

An Efficient Method of Tooth Segmentation Under Massive Medical Data

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ABSTRACT

To accurately and efficiently complete tooth segmentation from a large amount of oral medical data, the burden of doctors should be reduced. An automatic seed picking method based on 2D projection of the occlusal plane was proposed. First, the authors establish a two-dimensional seed data set for tooth segmentation. Then, this article built a prediction network of teeth seeds based on YOLOv4 to realize the prediction of teeth position as well as the recognition of teeth categories. Finally, according to the statistical optimal seed position, the two-dimensional seeds are calculated and mapped back to the three-dimensional space by the reverse projection transformation method to realize the final picking up of the three-dimensional seeds. Furthermore, combined with the previous work of division line detection, the automatic segmentation of the 3D dental model was realized. The experimental results show that the proposed method has high accuracy and real-time performance, which significantly reduces the burden of human-computer interaction in dental model segmentation.

KEYWORDS

Artificial Intelligence, Machine Learning, Oral Medical Data, Seed Picking, Teeth Segmentation, YOLOv4

INTRODUCTION

In the digital information age, with the application of all kinds of electronic sensors, the data that people can obtain is becoming more and more fine, and the medical industry has always been an industry closely related to people's life, and a large number of medical data are produced all the time (Fiori et al., 2016; Conrad et al., 2002; Pestian et al., 2006), among which oral medical data are deeply concerned by patients, doctors and researchers. On the one hand, this kind of data is real-time, and doctors need to deal with it in time to develop a reasonable and efficient treatment plan for patients (Tan et al., 2021); on the other hand, such data are closely related to patients' privacy, and hospitals or research institutions need to establish intelligent management methods to strictly restrain the dissemination, sharing, and use of such data (Tan et al., 2022; Wang et al., 2021). Therefore, how to use and manage these data efficiently and safely has become a hot topic (Yang et al., 2021).

One of the uses of oral medical data is dental correction. Traditional orthodontic methods generally use plaster models to simulate the teeth and jaws of patients, but this plaster model has many inconveniences in preservation and use, such as breakage and breakage. It takes up space, which is

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not conducive for doctors to understand the dental conditions of patients in different treatment stages, and finally affect the effect of dental correction. At the same time, the orthodontic appliance used in the traditional correction method also has the shortcomings of long correction time, complex wearing mode and easy to cause. These factors lead doctors and patients to hope for new ways of correction.

In recent years, with the development of computer graphics technology and the improvement of modern medical level, computer aided design system has been widely used in more and more fields (Yu et al., 2021; Rodby et al., 2014; Tian et al., 2021; Reighard et al., 2021; Dovramadjiev et al., 2021; Rakishev et al., 2022). Virtual orthodontic system plays an important role in the field of oral medicine. The system uses the data of dental model collected by 3D scanning equipment as input to record and save the shape and parameters of teeth. A computer was used to simulate the entire course of the patient's orthodontic treatment, recording the changes in tooth position at each stage. Based on these data, the invisible braces were designed at different stages, Patients simply need to wear different invisible braces at different times according to the design, can make the upper or lower occlusal teeth move according to the design, Eventually, the patient's teeth become even. Patients can also see the virtual treatment process before treatment and know the correction results in advance.

It is an important preprocessing of virtual orthodontic system to accurately segment teeth from dental models (Kau et al., 2011; Petrescu et al., 2022; Choi et al., 2021). Its purpose is to separate the single crowns from the dental models, and separate the crowns from each other. It lays the foundation for the movement and arrangement of teeth. At present, many 3D model segmentation methods have been proposed in the field of computer graphics, but there are still some challenges in the complete automatic segmentation of 3D models. Although teeth have obvious geometric features, teeth of different people have obvious morphological differences, and due to the influence of scanning accuracy and 3D mesh reconstruction accuracy, there are often uneven and adhesive areas on the surface of dental models. These factors make it difficult for traditional methods to achieve completely automatic and accurate segmentation.

According to the minimum rule of human vision theory, the dividing line between teeth and gums is located in the region with large negative curvature of the model. The methods based on curvature information usually detect these negative curvature regions and segment teeth. However, due to the uneven areas between teeth and gums, these areas will cause serious interference to the segmentation method based on curvature information, and it is difficult to achieve accurate segmentation of the model.

In order to improve the robustness of the algorithm, many scholars provide prior knowledge for the segmentation process through human-computer interaction, such as manually marking seeds for each tooth or manually repairing the segmentation errors after the completion of segmentation (Zhang et al., 2020). This method effectively improves the segmentation accuracy, but too much human-computer interaction greatly increases the burden of doctors.

In recent years, deep learning has become a research hotspot in the field of three-dimensional vision. Deep learning methods represented by convolutional neural networks show strong robustness and universality in the field of two-dimensional image segmentation. However, because of the irregular characteristics of mesh data, the network can not be directly applied to the processing of 3D mesh model. Therefore, many scholars proposed to map the three-dimensional model to the two-dimensional space. After the segmentation is completed on the two-dimensional image, it is mapped back to the three-dimensional space. In this way, the 3D model can be segmented. In recent years, the deep learning methods directly acting on 3D models have also made great progress, and have a good segmentation effect (Qi et al., 2017; Qi et al., 2017; Wang et al., 2019; Wang et al., 2019; Wu et al., 2019). However, these methods require a large amount of 3D dental model data support, and the patient's dental data are usually difficult to obtain, and the two-dimensional image data enhancement methods are more mature. Moreover, most of the mainstream methods currently used are still to improve the Marker-Controlled Interactive method, and to improve the efficiency

of segmentation by replacing the segmentation algorithm of deep learning, which increases the risk and instability of enterprise products.

Aiming at the current mainstream method and the problem that seeds need to be picked manually in the preliminary work of the research group, the researchers propose a method to automatically pick up the seeds of 3D dental model based on the occlusal plane image of 3D dental model, and realize the complete automatic segmentation of 3D dental model based on the existing work achievements.

RELATED WORK

Segmentation of 3D mesh model is one of the hot issues in 3D model processing and many methods of 3D model segmentation are proposed. According to the input data format, the researchers divide these methods into two categories, namely, image-based methods and 3D mesh-based methods.

Many scholars have proposed effective segmentation methods based on two-dimensional images.

Some researchers proposed the depth image segmentation method: Firstly, the depth images and panoramic depth images of the dental and maxillary models were obtained from the occlusal plane, Then the researchers combined the edge features of the two images to get the tooth segmentation boundary (Kondo et al., 2004). Some investigators proposed a segmentation method based on multi-layer depth images, which avoided the problem of poor accuracy caused by relying only on a single image. The method first detects the tooth contour and the non-convex vertices between the teeth in each layer image. Then these non-convex vertices are connected and mapped back to the 3D space to obtain the tooth segmentation boundary (Grzegorzek et al., 2010).

The segmentation method based on 3D mesh is a mainstream method. Some people proposed a fast dental model segmentation algorithm based on mesh extraction. The algorithm simplifies the grid model and optimizes the traditional stack operation into container operation, which improves the segmentation efficiency effectively (Ma et al., 2018). A method of tooth segmentation based on harmonic field is also proposed, which can not only deal with severely deformed teeth, but also deal with blurred tooth edges. However, this method needs to manually set the segmentation constraint point of each tooth, so manual intervention is more, and when the number of vertices is large, it will be impossible to solve the situation (Li et al., 2016; Zou et al., 2015). Some pursuers improved the interactive tooth segmentation method based on harmonic field and realized the automatic tooth segmentation method, which improved the efficiency of tooth segmentation. However, its adaptability is relatively weak, and when the quality of the model is poor or the shape of the teeth is irregular, the quality of the gingival line will also be poor or even wrong (Liao et al., 2015). Some investigators proposed a mesh segmentation method based on ant colony optimization, which has high accuracy and improved processing speed, but the segmentation quality is not good (Zhang et al., 2018). Some people proposed a tooth segmentation algorithm based on feature line segmentation technology, which effectively improved the segmentation efficiency. However, when the feature of the dental model is not obvious or the quality of the mesh is poor, the algorithm needs to carry out some preprocessing operation before extracting the feature line of the dental model (Xiao et al., 2017). Some researchers proposed a novel automatic segmentation method for single tooth based on path planning technology, which effectively solved the problems of dividing line fracture, branch interference and manual interaction, and had less parameter adjustment. However, for the case of blurred tooth boundary, the method still needs some manual adjustment (Wu et al., 2018).

With the deepening of deep learning research at home and abroad, deep learning has been widely used in the processing of three-dimensional models. Some investigators mapped the 3D dental model to the 2D harmonic parameter space. In the two-dimensional space, the model is segmented by CNN network, and finally mapped back to the three-dimensional space. But there are many requirements for input data, and it is greatly affected by the results of neural network prediction (Zhang et al., 2020). Some people proposed a tooth recognition method based on two-level feature learning, which can improve the accuracy of tooth labeling and reduce misclassification among teeth with high similarity.

However, due to the limitation of training samples, the generalization ability of the network is weak (Tian et al., 2019). Some researchers proposed an automatic tooth feature recognition method based on DBSCAN and K-means mixed clustering. This algorithm can accurately detect the feature points of teeth, which is simpler and more accurate than the existing recognition algorithms (Zhu et al., 2018). Some people proposed a neural network that directly utilizes the original dental and jaw models by borrowing ideas from PointCNN (Li et al., 2018), and this network achieved accurate tooth segmentation. However, this network consumes a large amount of memory resources when running and has some limitations for implementation (Zanjani et al., 2021). Several investigators have extended PointNet (Qi et al., 2017) to propose an end-to-end neural network. The multi-scale contextual features are learned directly from the 3D dental model and then combined with feature fusion to accomplish tooth segmentation. However, the training time of this algorithm is too long and the memory consumption is too large (Lian et al., 2020). Some pursuers proposed a two-stage neural network, which consists of a tooth plenum prediction network and a single tooth segmentation network. This method first detects all the teeth by the tooth plenum and then segments each detected tooth (Cui et al., 2021). Some researchers proposed a dual-flow graph convolutional neural network, which has two branches receive the vertex and normal vector information of the dental triangular mesh model and extract unique geometric features, respectively, and then fuse the geometric features obtained from the two branches and predict the tooth segmentation results (Zhang et al., 2021).

Some investigators have used the idea of multimodality to process the 2D slice image and intraoral scan model of Cone-Beam Computed Tomography (CBCT) separately, and merge the processing results to complete tooth segmentation (Deleat-Besson et al., 2021). Some researchers designed a graph attention convolutional layer structure and a global branching structure to complete the local and global feature extraction of the dental model, respectively (Zhao et al., 2021). Some people proposed a multi-scale bidirectional enhancement module to enhance both geometric and semantic information to achieve tooth segmentation (Li et al., 2022). Some researchers designed both label prediction network and offset computation network, and used static and dynamic convolution to learn tooth geometric features to complete tooth segmentation (Zheng et al., 2022).

The segmentation methods of 3D models are constantly optimized and improved. However, the main curvature-based segmentation algorithm has a heavy task in human-computer interaction. Although the method of deep learning realizes the automation of segmentation tasks, it is limited by the shortage of training samples and weak in generalization ability. This paper presents an automatic seeds picking method based on two-dimensional image. By adjusting the observation Angle and using image processing technology, the data set can be expanded effectively. Combined with the existing method based on curvature segmentation (Ma et al., 2020), it can not only overcome the problem of insufficient sample size, but also reduce the risk of replacing the segmentation algorithm.

METHOD

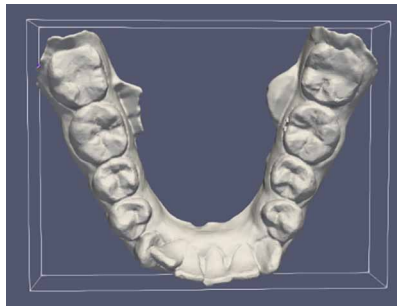
The automatic picking method of tooth seeds proposed in this paper mainly includes four stages:

1. Preprocessing and data set construction phases. The researchers obtained the occlusal plane two-dimensional projection images of different malformed teeth, and used the LabelImg tool to label the occlusal plane image data, so as to obtain the occlusal plane image set with label.
2. Tooth classification and seeds picking. The tagged occlusal plane image set was input into the object detection network for training, to complete tooth classification and seed point picking in two-dimensional space.
3. Seeds projection. The seeds identified in 2D occlusal plane images were projected onto 3D dental model in 3D space.
4. Combined with the previous results of the research group on 3D model segmentation, the 3D dental model can be completely automated segmentation.

PREPROCESSING AND DATA SET CONSTRUCTION

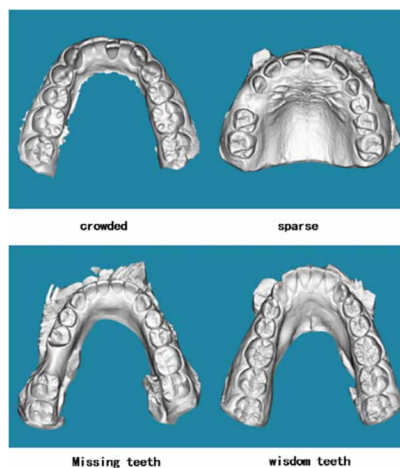
In this paper, the occlusal plane image data set acquisition tool is developed under the VTK environment. The 3D model data of dental were read in and the model was adjusted to make the occlusal plane face the camera, as shown in Figure 1. The model is orthographic projected to xOz plane to get the vertical view of the model, and then combined with the filter `vtkwindowtoimageFilter` to achieve the capture and preservation of graphic display window.

Figure 1. Model adjustment results



In order to ensure the effectiveness and correctness of the automatic seeds picking method, the experimental data set should include as many occlusal plane images of different malformations as possible according to the clinical manifestations of malocclusion. The data set constructed manually in this paper contains occlusal plane images of four deformities, including crowded dentition, scattered dentition space, missing teeth and wisdom teeth. As shown in Figure 2.

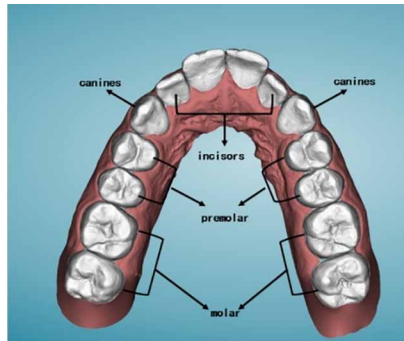
Figure 2. Types of dental malformations



According to the morphological characteristics and functions of teeth, they can be classified into the following categories: incisors, canines, premolars, and molars. The incisors are located in the front of the mouth, with eight teeth on the top, bottom, left and right. The canines are located near

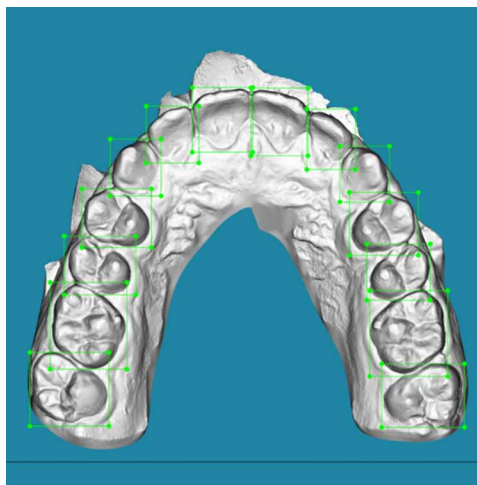
the corner of the mouth, with four teeth on the top, bottom, left and right. The premolars are located behind the canines, with eight teeth on the top, bottom, left and right. Molars are located behind the premolars, with eight teeth on the upper, lower, left and right sides. As shown in Figure 3.

Figure 3. Classification of teeth



Use the LabelImg tool to create a bounding box for each tooth on the occlusal plane image, as shown in Figure 4.

Figure 4. Creating data set



Save the location and size information of the bounding box, and set the category number for each tooth (for example, the teeth are divided into four categories: incisor, canine, premolar and molar in this paper, then set the labels as 0, 1, 2 and 3 in turn). The format of each line of the label file is as follows:

$[label \ x \ y \ w \ h]$

Each row of data corresponds to information about the bounding box of one tooth in the occlusal plane image. From left to right, each row of data represents the category number, normalized center point X coordinate, normalized center point Y coordinate, normalized width W, normalized height H.

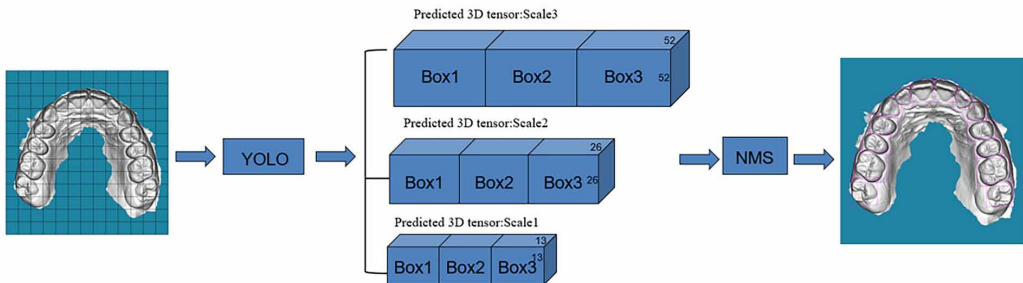
In the medical field, due to the privacy of patient case data and the high cost of annotation, there are very few data available for training. Therefore, in the research and processing of medical images, it is necessary to enhance the data set. In this paper, the enhancement of the data set is mainly achieved through perspective adjustment, image mirroring, rotation and cropping.

TOOTH CLASSIFICATION AND TWO-DIMENSIONAL SEEDS PICKING BASED ON YOLOV4

YOLOv4 is the fourth version of the target detection algorithms in the YOLO series (Bochkovski et al., 2020; Redmon et al., 2016). Compared with the previous algorithms, YOLOv4 perfectly combines the recognition accuracy and speed.

In order to apply YOLOv4 to pick up seeds of teeth, the YOLOv4 configuration file needs to be modified to adapt to the detection of teeth. First of all, classes in voc.data file are set to 4, indicating that the detection range of this system includes four categories: molars, premolars, canines and incisors. At the same time, the data set information in this file is modified into the data set information of this experiment. Then modify the file YOLOv4-voc.cfg. Including classes set to 4 and filters set to 27. Among them, filters = 3*(classes + 4 + 1). The number 3 indicates that each grid cell is responsible for predicting three Bounding boxes. The numbers 4 and 1 represent position coordinate information and confidence, respectively. The processing process is shown in Figure 5.

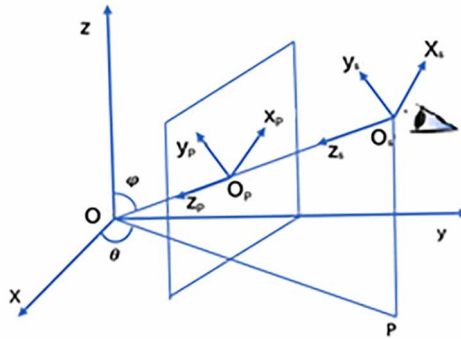
Figure 5. YOLOv4 processing process



SEEDS PROJECTION

The real world is three-dimensional, the objects that can be seen are also three-dimensional, while the computer monitor display image is two-dimensional, so to display three-dimensional objects on the computer screen will need to go through a series of graphic transformation. Mainly including the user coordinate system to observe the conversion of the coordinate system and then to the screen coordinate system conversion. As shown in Figure 6. The origin of the user coordinate system, the observation coordinate system and the screen coordinate system are at the points O , O_s and O_p , respectively.

Figure 6. Perspective transformation coordinate system



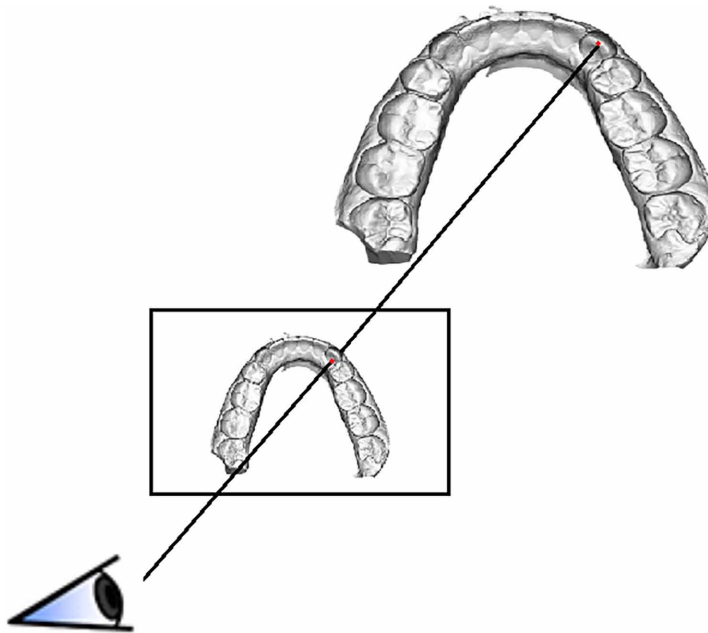
The occlusal plane image of the dental model was used as the input of the trained network model in 3.2. In this way, the category of each tooth and the location of seeds in the two-dimensional occlusal plane image can be predicted. The final segmentation process is carried out in the three-dimensional space, so the seeds identified in the two-dimensional occlusal plane image are mapped back to the three-dimensional dental model in the three-dimensional space by the reverse projection transformation method. The reverse projection transformation matrix is expressed as follows:

$$T_r = \begin{bmatrix} -\sin \theta & -\cos \varphi \cos \theta & 0 & \frac{-\sin \varphi \cos \theta}{d} \\ \cos \theta & -\cos \varphi \sin \theta & 0 & \frac{-\sin \varphi \sin \theta}{d} \\ 0 & \sin \varphi & 0 & \frac{-\cos \varphi}{d} \\ 0 & 0 & 0 & \frac{R}{d} \end{bmatrix}^{-1} \quad (1)$$

here R denotes the length of the coordinate origin O and the viewpoint O_s , and d denotes the apparent distance, i.e., the distance between the viewpoint O_s and the view center O_p .

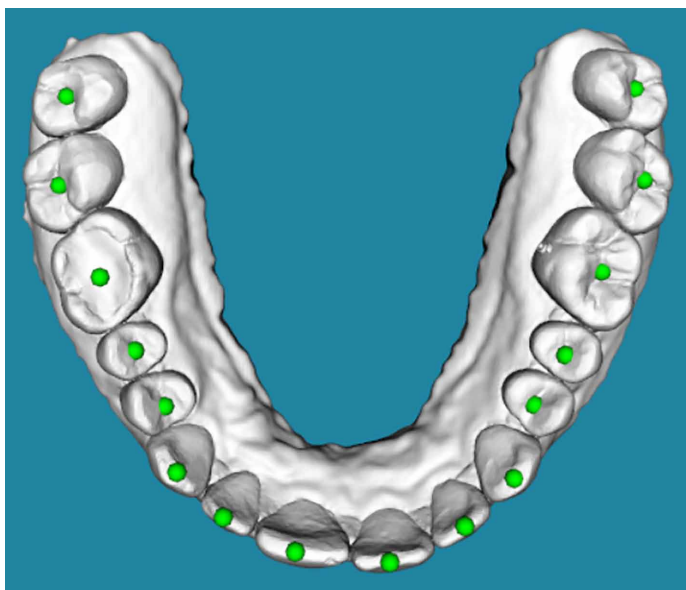
The process of projection from the seeds recognized on the two-dimensional occlusal plane image to the three-dimensional dental model is to realize the transformation from the two-dimensional screen to the three-dimensional space, that is, the inverse process of the three-dimensional object display to the screen. In this paper, the projection of two-dimensional seeds to three-dimensional seeds is realized based on the inverse projection transformation method and mouse picking algorithm. In this experiment, the location of seeds predicted by YOLOv4 model was substituted for mouse click operation. As shown in Figure 7.

Figure 7. Mouse picking



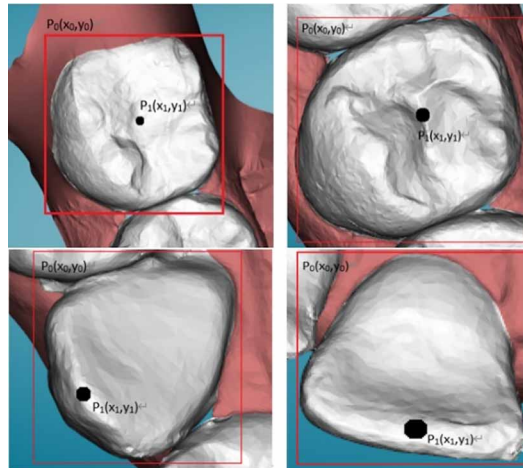
When the user marks the seeds, the seeds of incisors are generally marked at the midpoint of the incisor ridge. The seeds of the canines are generally marked at the tips of the canines. The seeds of premolars are generally marked at the center of the central sulcus. The seeds of molar is generally marked in the center of the fovea. As shown in Figure 8.

Figure 8. Seeds pickup standards



The position information of the bounding box of molars, premolars, canines and incisors was compared with the position of the seed points marked by hand, as shown in Figure 9.

Figure 9. Comparison of location of bounding box and seed points



Assume that the coordinates of the upper left corner of the bounding box are $p_0(x_0, y_0)$, the position of the seed points is $p_1(x_1, y_1)$, and the width and height of the bounding box are w and h respectively. Calculate the position of the seed point relative to the bounding box, i.e

$$ScaleX = \frac{x_1 - x_0}{w} \quad (2)$$

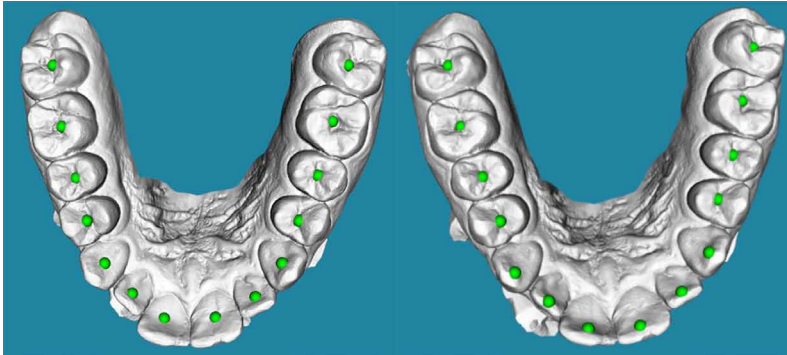
$$ScaleY = \frac{y_1 - y_0}{h} \quad (3)$$

ScaleX represents the relative position of the seeds from the Mesio-distal sides, and ScaleY represents the relative position of the seeds on the Labial-tongue side. The relative positions of the tooth bounding box and the seeds manually marked in the left part of the occlusal plane images of 50 dental models were statistically averaged, as shown in Table 1.

According to the above method, by comparing the identification results of the tooth bounding box with the manually marked seeds, it was found that the seeds of molars and premolars were basically located in the center of the bounding box. The seeds of the canines were located in the labial and distal sides of the bounding box. The incisor seeds is generally located in the center of the Mesio-distal side of the incisor, and in the direction of the Labial-tongue, it is basically located in the fourth position of the labial side of the surrounding box. To sum up, the following adjustments were made for different teeth based on the size of the bounding box automatically recognized: the center of the bounding box was taken for the seeds of molars and premolars; The seed points of canines were located at 0.3671 on the labial side and 0.2917 on the distal side. The incisor seeds were located at 0.2535 on the labial

side of the bounding box and at the center of the distal middle side. The position comparison of seed points automatically recognized before and after adjustment is shown in Figure 10.

Figure 10. Seeds adjustment effect



After adjustment, the seed points of canines and incisors were basically the same as those picked up manually, and a few of the seeds deviated slightly from those selected manually.

EXPERIMENTAL RESULTS AND ANALYSIS

The hardware and software platforms of this experiment are: Intel(R) Core(TM) I5-9300HF CPU 2.40GHz processor, NVIDIA GeForce GTX1660TI graphics card computer for training; Deep learning framework: Darknet; Development environment: VS2019.

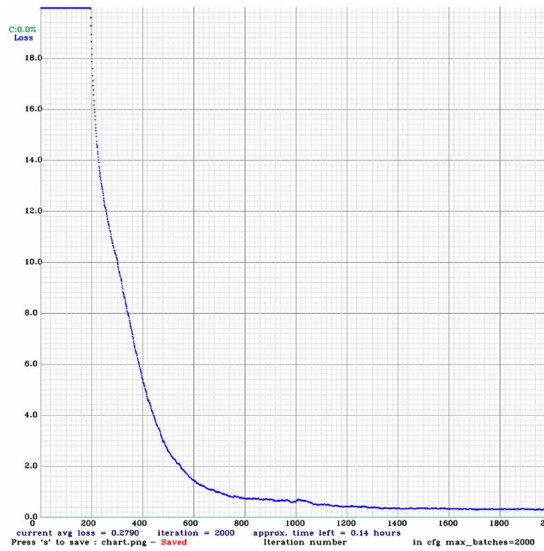
The evaluation of the experimental results in this paper is divided into two parts. The first part is to evaluate the performance of the object detection algorithm using the results of seed picking and tooth classification. The second part is to verify the effect of automatic seed picking by combining the experiment of seed picking with the existing 3D dental model segmentation method.

COMPARISON OF PICKING EFFECT OF SEED POINTS

In this paper, the object detection algorithm is based on YOLOv4 network. The input data is the square occlusal plane image, and the output is the tooth category and the position of the prediction box. In order to verify the effectiveness of the method in this paper, the researchers made a occlusal plane image data set of 100 teeth and enhanced the data set to 1000 teeth through mirroring, cropping, rotation and other methods. The LabelImg tool is used to manually complete the annotation of the data set. The dental models used in this study were all from clinical data, and all patients' personal information was deleted. In this experiment, 150 images of occlusal plane were randomly selected as the test set, and the remaining 850 images were used as the training set and verification set.

Start training after modifying the configuration file. In this paper, the experiment was iterated for 2000 times. The loss function curve is shown in Figure 11, where the abscissa represents the number of iterations and the ordinate represents the loss value. As can be seen from the figure, at the beginning, the curve of the loss function declines rapidly, and after iteration to 1200 times, it decreases slowly, and finally converges to about 0.3.

Figure 11. Loss function curve



As shown in Figure 5, YOLOv4 divides the input image into $S \times S$ grids uniformly, and if the center of an object falls in one of the squares in the figure, that square is responsible for predicting that object. For each image of the input, YOLOv4 predicts three different size tensors, and each cell is responsible for predicting B enclosing box location information and its confidence, as well as the probability of C categories. Therefore, the model will finally output three tensors with different sizes of $13 \times 13 \times 27$, $26 \times 26 \times 27$, and $52 \times 52 \times 27$, respectively. where the YOLOv4 border prediction equation is as follows:

$$b_x = \sigma(t_x) + c_x \quad (4)$$

$$b_y = \sigma(t_y) + c_y \quad (5)$$

$$b_h = p_h e^{t_h} \quad (6)$$

$$b_w = p_w e^{t_w} \quad (7)$$

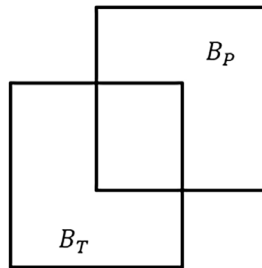
where c_x c_y indicates the cell offset, p_h p_w are the sizes of the pre-defined anchor boxes, and t_x t_y t_w t_h are the four predicted values in the YOLOv4 convolution model.

The confidence level is the degree of confidence that the bounding box of each box prediction contains objects and is calculated as follows:

$$confidence = \Pr(object) \times IOU_{pred}^{truth} \quad (8)$$

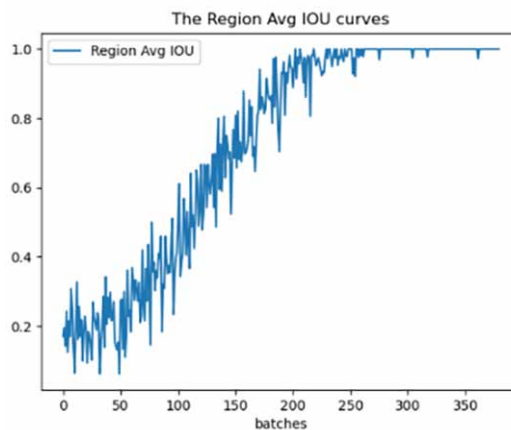
where $\Pr(object)$ has a value of 1 or 0, indicating whether the target object exists in this box; IOU is the Intersection over Union, which is the ratio of the intersection and union of the predicted bounding box and the actual bounding box. As shown in Figure 12.

Figure 12. Intersection over Union (IOU)



The performance of object detection model can be evaluated by positioning accuracy. Positioning accuracy can be measured by the degree of overlap between the detection window and the manually tagged object, known as the Intersection over Union (IOU). In this experiment, with the increase of training times, the IOU increased continuously and finally fluctuated around 0.86. The variation trend of IOU is shown in Figure 13.

Figure 13. IOU curve



The accuracy of tooth position prediction is very important in seeds recognition. Therefore, mmAP was used as the evaluation index of tooth classification task in this study. The calculation of mmAP first needs to set different IOU thresholds, and take the average value of the mean accuracy

(mAP) under each threshold. Table 2 shows the identification accuracy (AP) of YOLOv4 for various teeth under different IOU thresholds. Table 3 shows mAP and mmAP under different IOU thresholds.

As can be seen from Table 2, YOLOv4 has a good detection effect on all kinds of teeth. However, when the IOU threshold was set high, the detection effect of canines and incisors was inferior to that of molars and premolars. It can be seen from Table 3 that the average detection accuracy decreases with the increase of IOU threshold. Finally, the average value of mmAP is calculated to be 93.882, which has a good recognition effect.

Table 1. Position of manually picked seed points relative to the predicted bounding box

Tooth type	Molar	preMolar	Canine	Incisor
Mesio-distal side	0.5161	0.4713	0.3571	0.2535
Labial-tongue side	0.4912	0.5455	0.2917	0.4717

Table 2. Recognition accuracy of various teeth under different IOU thresholds(%)

Type	AP ₅₀	AP ₆₀	AP ₇₀	AP ₇₅	AP ₈₀
Molar	100	100	99.71	98.73	91.31
preMolar	100	99.71	98.41	93.99	75.88
Canine	100	99.42	98.66	85.94	62.74
Incisor	100	100	99.51	95.98	77.66

Table 3. mAP and mmAP under different IOU thresholds(%)

IOU thresholds	50	60	70	75	80	mmAP
mAP	100	99.78	99.07	93.66	76.90	93.882

Table 4. Comparison of mmAP and detection time of different algorithms

Algorithm	mmAP/%	Average detection time /s
YOLOv2	76.918	0.07023
YOLOv3	84.734	0.1167
YOLOv4	93.882	0.1884
Faster-RCNN	98.638	2.4440

Table 5. Comparison of the recognition accuracy of different algorithms for all kinds of teeth

Tooth type	YOLOv2	YOLOv3	YOLOv4	Faster-RCNN
Molar	96.154	93.442	97.95	99.99
preMolar	89.106	86.976	93.958	99.99
Canine	69.752	81.482	89.352	98.638
Incisor	52.658	76.438	94.63	94.546

In the experiment, the mmAP values of YOLOv2 (Redmon et al., 2017), YOLOv3 (Redmon et al., 2018), YOLOv4 and Faster-RCNN (Ren et al., 2015) algorithms and the detection time of images are compared and displayed, as shown in Table 4. It can be seen that the mmAP value of YOLO series algorithm gradually increases with the improvement of versions. The testing time also increased gradually. Compared with the algorithms of YOLO series, Faster-RCNN has a higher detection accuracy, but the detection speed is slower, and the detection time is more than 13 times that of the algorithms of YOLO series.

The accuracy of YOLOv2, YOLOv3, YOLOv4 and Faster-RCNN algorithms for the recognition of different types of teeth are shown in Table 5. It can be seen that different algorithms have good detection effect on molars and premolars, but YOLOv2 and YOLOv3 have poor detection effect on incisors. YOLOv4 and Faster-RCNN have good detection effect on all kinds of teeth, but the detection effect of canine and incisor among the four types of teeth is still worse than that of molars and premolars, so targeted training data can be added for training in the later stage.

Considering the recognition accuracy and speed comprehensively, YOLOv4 carries out a good balance between the two aspects, which ensures the segmentation accuracy and improves the detection speed.

Figure 14 shows the category prediction effect of the network model trained in this paper. The teeth of different deformities were tested. It can be seen that the method in this paper has a good category detection effect and lays a foundation for the subsequent adjustment of seeds.

Figure 14. Category detection effect

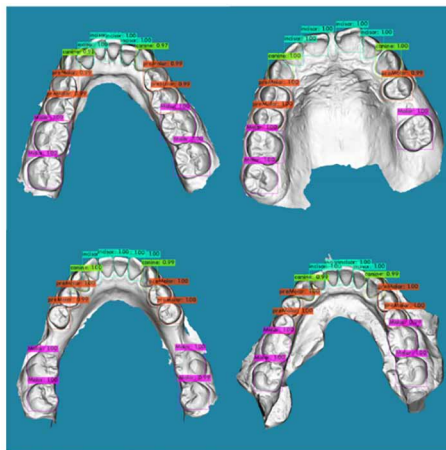
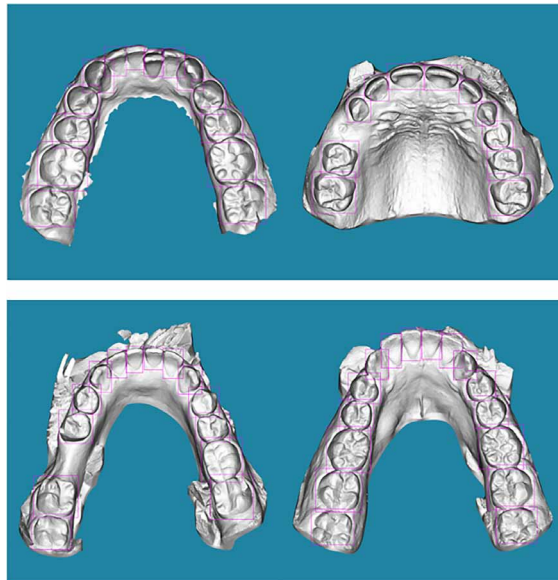


Figure 15 shows the effect of tooth position recognition in this paper, which has been tested for teeth of different deformities. It can be seen that there is no obvious difference between the learning effect and the manual box selection. It is proved that the proposed method can identify the position of teeth well in two-dimensional images, and the adjusted seed position deviates less from the manually marked seed position by the user, which lays a foundation for the subsequent projection of the seeds to the three-dimensional model.

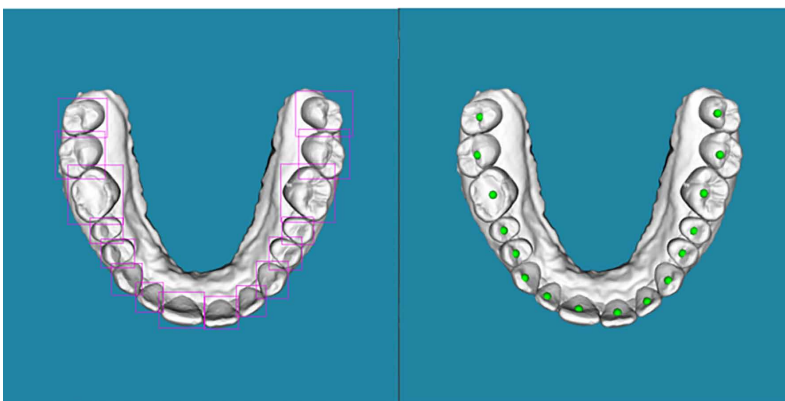
Figure 15. Detection effect of tooth position



APPLICATION EFFECT OF AUTOMATIC TOOTH AND OCCLUSAL MODEL SEGMENTATION

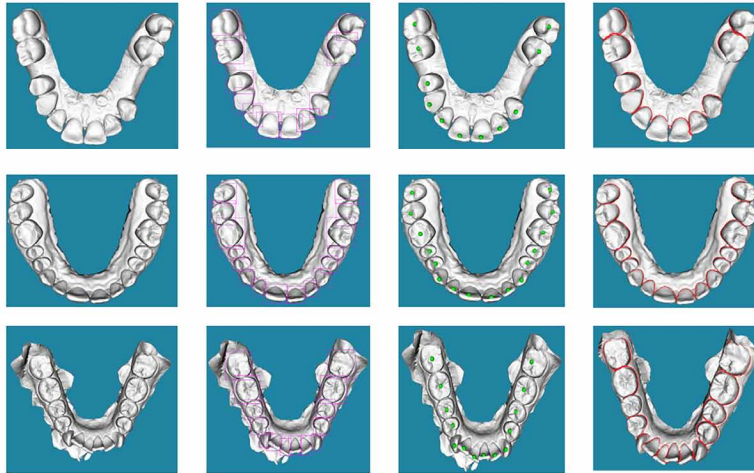
Based on the location of seeds predicted in the 2D image in 4.1, the mapping of 2D seeds to 3D seed points is realized by using the reverse projection transformation method. The mapping results are shown in Figure 16.

Figure 16. Seeds project results



Finally, based on the previous work of the research group, the full automatic segmentation of the dental model was realized. The researchers show the seeds picking and segmentation effect pictures of three malformations of dentition crowding, dentition space dispersion and wisdom teeth respectively. As shown in Figure 17.

Figure 17. Automatic segmentation process and results



THEORETICAL AND PRACTICAL CONTRIBUTIONS

The main contributions of this paper are as follows:

1. Constructing occlusal plane image data set. The occlusal plane images of the dental model were intercepted and labeled.
2. Constructing YOLOv4 network to adapt to the detection of teeth. It can be seen from Table 2, Table 3, Table 4, and Table 5. The different algorithms have good detection results for both molars and premolars, but YOLOv2 and YOLOv3 have poor detection effect on incisors. YOLOv4 and Faster-RCNN have good detection effect on all kinds of teeth, but the detection effect of canine and incisor among the four types of teeth is still worse than that of molars and premolars. Considering the recognition accuracy and speed comprehensively, YOLOv4 carries out a good balance between the two aspects, which ensures the segmentation accuracy and improves the detection speed. As shown in Figure 14. The method in this paper accurately identifies the category to which each tooth belongs, and lays a foundation for the subsequent adjustment of seeds.
3. The researchers counted the location of the optimal seeds of all kinds of teeth, and selected the seeds by combining the tooth categories predicted by the network. As shown in Table 1. In this paper, after comparing the statistics, it is concluded that the adjustment of the tooth bounding box recognition result can get extremely close to the manually marked seeds. This is shown in Figure 15. The proposed method can identify the position of teeth well in two-dimensional images, and the adjusted seed position deviates less from the manually marked seed position by the user, which lays a foundation for the subsequent projection of the seeds to the three-dimensional model.
4. Combined with the existing division line detection method of the research group, the automatic segmentation of dental model is realized. As shown in Figure 17. Even if the dental model has three types of malocclusion conditions, such as dentition crowding, dentition space dispersion and wisdom teeth, good tooth segmentation results can still be obtained.

CONCLUSION

In order to solve the problem of more human-computer interaction in the traditional segmentation method of dental model, this paper designed and implemented an automatic seeds picking method based on the two-dimensional target detection method, which effectively reduced the defects of more human-computer interaction in the dental model segmentation, greatly reduced the burden of physicians, and improved the efficiency of segmentation. In addition, this method does not change the segmentation algorithm itself, but only replaces the operation of human-computer interaction, thus greatly reducing the risk and instability caused by algorithm change in enterprise products. In this paper, the researchers construct the occlusal plane data set by ourselves. Experiments using this method prove that the YOLOv4 network can effectively realize automatic seeds picking. However, the acquisition of occlusal plane image requires some manual adjustment of the model. Automatic acquisition of occlusal plane image by learning other features of the model is a research direction in the future. It is worth mentioning that since the 3D dental model has richer geometric information compared with the occlusal plane image, better results may be achieved by predicting the seed point positions directly on the 3D dental model using deep learning methods. However, limited by hardware resources, can the seed point position bias caused by the downsampling of the original tooth and jaw model to a few times of the original be avoided to the greatest extent? This is a debatable question.

CONFLICT-OF-INTEREST STATEMENT

The authors declared that they have no conflicts of interest to this work.

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