Teeth3DS+: An Extended Benchmark for Intraoral 3D Scans Analysis

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Abstract

Intraoral 3D scans analysis is a fundamental aspect of Computer-Aided Dentistry (CAD) systems, playing a crucial role in various dental applications, including teeth segmentation, detection, labeling, and dental landmark identification. Accurate analysis of 3D dental scans is essential for orthodontic and prosthetic treatment planning, as it enables automated processing and reduces the need for manual adjustments by dental professionals. However, developing robust automated tools for these tasks remains a significant challenge due to the limited availability of high-quality public datasets and benchmarks. This article introduces Teeth3DS+, the first comprehensive public benchmark designed to advance the field of intraoral 3D scan analysis. Developed as part of the 3DTeethSeg 2022 and 3DTeethLand 2024 MICCAI challenges, Teeth3DS+ aims to drive research in teeth identification, segmentation, labeling, 3D modeling, and dental landmarks identification. The dataset includes at least 1,800 intraoral scans (containing 23,999 annotated teeth) collected from 900 patients, covering both upper and lower jaws separately. All data have been acquired and validated by experienced orthodontists and dental surgeons with over five years of expertise. Detailed instructions for accessing the dataset are available at https://crns-smartvision.github.io/teeth3ds

Keywords: Teeth3DS, Teeth3DS+, intraoral 3D scans, 3D point cloud, 3D segmentation, dentistry

1. Introduction

Computer-aided design (CAD) tools are becoming increasingly popular in modern dentistry for highly accurate treatment planning. Advanced intra-oral scanners (IOSs) are particularly popular in orthodontic CAD software as they provide an accurate digital surface 3D representation of the dentition. Such 3D representation can greatly assist dentists in simulating tooth extraction, realignment, and smile design, making the treatment’s final results more predictable. As a result, digital teeth models have the potential to relieve dentists from time-consuming and tedious tasks.

Although IOSs are becoming ubiquitous in clinical dental practice, there are only a few contributions on teeth segmentation/labeling available in the literature, e.g., [1, 2, 3, 4, 5, 6], and, most importantly, no publicly available benchmark. A fundamental challenge in IOS data analysis is the ability to accurately segment and identify teeth. Teeth segmentation and labeling are challenging due to inter-class variations, such as inherent similarities between tooth shapes and ambiguous positions on jaws, as well as intra-class variations such as damaged teeth or braces. This is in addition to the tight

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borders between surrounding teeth and gingiva as well as abnormalities like crowded, misaligned, or missing teeth.

Despite several efforts, developing an accurate and a fully automated dental segmentation and labeling tool remains challenging. Most former approaches are based on the teeth geometric characteristics, such as curvature thresholding [7] or active contour computing [8] in order to separate between teeth and gingiva. However, these solutions lack robustness with respect to teeth shape variations and usually require additional manual interventions that include teeth pre-selection or contour initialization. Recent advances in 3D shape analysis based on machine learning techniques can also be used for 3D dental scan analysis. In general, they follow two main strategies. Some researchers proposed to convert the 3D scans into 2D images so that existing convolutional neural networks (CNNs) can be used for both teeth segmentation and classification [9]. This strategy may lead to acceptable results in the 2D space. Meanwhile, the reconstruction of the obtained segmentation into the 3D space will systematically decrease the segmentation accuracy. Other studies proposed to directly process the 3D scans and to apply deep learning architectures [10] with the aim of detecting and segmenting teeth present in the IOSs. Although this approach may be faster, it still has to deal with different challenges such as point cloud irregularity, downsampling, and 3D pose variations. Overall, it should also be noted that the lack of a publicly available dataset or benchmark is an obstacle to the development of this research area, as no fair comparison can be conducted among state-of-the-art approaches.

In this article, we introduce a freely available teeth dataset of 1800 intra-oral scans collected from 900 patients covering the upper and lower jaws separately. These data were first used for the 3DTeethSeg 2022 [11, 12] scientific challenge held during the 25th International Conference on Medical Image Computing and Computer Assisted Intervention (MICCAI) (https://3dteethseg.grand-challenge.org/), which reflects the research community’s interest in our proposed dataset. The provided data can be used by researchers of different backgrounds for the development and evaluation of machine learning methods not only for teeth detection, segmentation and labeling, but also other tasks such as 3D shape modeling and reconstruction from 2D intra-oral photos.

2. Methods

2.1. Patients and intra-oral scans collection

In compliance with the European General Data Protection Regulation (GDPR) agreement, we obtained 3D intra-oral scans for 900 patients acquired by orthodontists/dental surgeons with more than 5 years of professional experience from partner dental clinics located mainly in France and Belgium. All data is completely anonymized, and the identity of the patients cannot be revealed. Two 3D scans are acquired for each patient, covering the upper and lower jaws separately. The following IOSs were used for scan acquisition: the Primescan from Dentsply, the Trios3 from 3Shape, and the iTero Element 2 Plus. These scanners are representative and generate 3D scans with an accuracy between 10 and 90 micrometers and a point resolution between 30 and 80 pts/mm2. No additional equipment other than the IOS itself was used during the acquisitions. All acquired clinical data are collected for patients requiring either orthodontic (50%) or prosthetic treatment (50%). The provided dataset follows a real-world patient age distribution: 50% male 50% female, about 70% under 16 years-old, about 27% between 16-59 years-old, about 3% over 60 years old.

2.2. Data annotation and processing

2.2.1. Teeth detection, segmentation, and labeling

The data annotation, i.e., teeth segmentation and labeling, was performed in collaboration with clinical evaluators with more than 10 years of expertise in orthodontistry, dental surgery, and endodontics. The detailed process is depicted in Figure [1]. It consists of eight steps. First, the 3D scans are preprocessed (steps 1 and 2 in Figure [1]) by removing all degenerated and redundant mesh faces, as well
as duplicated and irrelevant vertices. The dental mesh coordinates are then automatically centered and aligned with the occlusal plane by principle component analysis. This improves teeth visibility while also normalizing the 3D pose of all the input 3D IOSs. Then, we used a custom tool to manually crop each tooth from the 3D scans with a tight sphere that includes the detected tooth as well as its surroundings (i.e., neighboring teeth and gingiva). We decided to perform UV mapping in step 3 to flatten the cropped 3D meshes and show the maximum 3D curvature to make the annotation of tooth boundaries easier. This transformation is ensured by harmonic parameterization, a fixed boundary parameterization algorithm that calculates the 2D coordinates of the flattened cropped tooth as two harmonic functions. These vertices are then mapped to a circle, and the 2D coordinates of the remaining vertices are calculated using two harmonic functions and the circle boundary constraints. The benefits are twofold: the annotator can annotate the 2D polygons delimiting the tooth without changing the 3D point of view, and the 3D curvature overlay is informative on the boundaries of teeth.

After the manual annotation of the UV maps (step 4 of Figure 1), we back-propagate the tooth boundaries to the 3D crops in step 5. At this point each separate tooth candidate has been manually segmented, however they have been represented in the same 3D coordinate system. The aim of the next step is to gather all the teeth crowns and prepare them for manual labeling as shown in step 7 of...
Figure 1. We followed the FDI World Dental Federation numbering system for teeth labeling depicted in Figure 2.

The final step 8 of the annotation process consists of the visual inspection and validation of the produced annotated 3D IOS. This step is carried out by our clinical partners, who are experienced orthodontists, dental surgeons, and endodontists. Their inspection targeted the identification of annotation issues, such as a missing tooth annotation (return to step 2), inaccurate tooth boundary annotation (return to step 4), or incorrect tooth labels (return to step 7). This validation/correction cycle was repeated until the entire dataset was correctly annotated and clinically validated.

2.2.2. Dental Landmarks

In the context of the 3DTeethLand Challenge associated with MICCAI 2024, specifically targeting the task of landmark detection on 3D intraoral scans, accurate identification of 3D landmarks is essential for various orthodontic and dental applications. This process not only advances automation but also harnesses AI to enhance the precision and efficiency of orthodontic treatments. Participation in this challenge enables researchers to drive innovative developments with the potential to transform clinical practices, improve treatment accuracy, and ultimately enhance patient care.

To support this effort, we introduced landmark annotations on a dataset consisting of 340 intraoral scans (IOS). This dataset is divided into two main groups: 240 scans from the Teeth3DS dataset, used as the training set for the 3DTeethLand Challenge and containing segmentation and labeling annotations, and an additional 100 scans without segmentation or labeling annotations, designated as the hidden private test set.

To facilitate accurate analysis and understanding of tooth positioning and alignment, we define specific dental landmarks on each tooth, as illustrated in Figure 3. These landmarks provide crucial reference points for various dental assessments:

1. Mesial (red) and Distal (green) Points: These points are located on the proximal surfaces of the tooth. The mesial point is on the side of the tooth closer to the midline of the mouth, while the distal point is on the side farther from the midline. These points are important for determining the alignment and positioning of the tooth in the dental arch.

2. Cusp Point (blue): The cusp is the pointed or rounded mound on the chewing surface of a tooth. The cusp point is located at the highest point of the cusp. It is significant for understanding the occlusion (bite) relationship between the upper and lower teeth.

3. Inner (yellow) and Outer (cyan) Points: These points are located at the boundaries of the tooth, where the tooth meets the gingiva (gum tissue). The inner point is on the inner side of the tooth.

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1FDI World Dental Federation numbering system, Wikipedia, last modified May 20, 2022.
https://en.wikipedia.org/wiki/FDI_World_Dental_Federation_notation
closer to the tongue or palate, while the outer point is on the outer side of the tooth, closer to the cheek or lips. These points are indeed important for determining the pose of the tooth, including its orientation.

4. Facial Axis (magenta) Point: This point is located at the midpoint of the facial surface of each tooth. The facial surface is the surface of the tooth that is visible from the front of the mouth. The facial axis point is important for determining the angulation and inclination of the tooth.

3. Data records

A total of 1800 3D intra-oral scans have been collected for 900 patients covering their upper and lower jaws separately. Figure 6 shows some examples.

The data are hosted at the OSF platform. For the purpose of the segmentation and labeling challenge held at MICCAI 2022, the 3D scans data (obj format) are separated into training (1200 scans, 16004 teeth) and test data (600 scans, 7995 teeth). The dataset structure is depicted in Figure 4. Patients are anonymized by their universally unique identifier (uuid). The ground truth tooth labels and tooth instances for each vertex in the obj files are provided in JavaScript Object Notation (JSON) format. A JSON file example is shown below:

```json
{
  "id_patient": "YNKZHRPO",
  "jaw": "upper",
  "labels": [0, 0, 44, 33, 34, 0, 0, 45, 0, ... , 41, 0, 0, 37, 0, 34, 45, 0, 31, 36],
  "instances": [0, 0, 10, 2, 12, 0, 0, 9, 0, ... , 10, 0, 0, 8, 0, 1, 9, 0, 1, 8]
}
```

[https://github.com/abenhamadou/3DTeethSeg22_challenge](https://github.com/abenhamadou/3DTeethSeg22_challenge)
Figure 4: Dataset structure for both training and testing phases. All data are structured by jaws and patient ID. Stl files represent the raw intra-oral scans (3D mesh). They are converted to obj files for commodity. Json files provide the annotation corresponding to the obj files.

The length of the tables "labels" and "instances" is the same as the total number of vertices in the corresponding 3D scan. The label and instance "0" are reserved by default for gingiva. And, other than "0", the unique numbers in table "instances" indicate the number of teeth in the 3D scan.

In the other hand, the landmarks annotations are provided in JavaScript Object Notation (JSON) format for each IOS scan in the Teeth3DS dataset.
An example of the scanname_arch_kpt.json file format is shown below:

```json
{
  "version": "1.0",
  "description": "landmarks",
  "key": "01A6HAN6_lower.obj", # lower arch of scan named 01A6HAN6, which can be found in Teeth3DS files.
  "objects": [ # list of landmarks
    {
      "key": "uuid_0", # unique id for the keypoint
      "class": "Mesial", # the class of the keypoint
      "coord": [ # xyz coordinate of the keypoint
        2.3146634105298736,
        -14.671770076868356,
        -82.42080180486484
      ]
    },....
  ]
}
```

**Technical Validation**

As previously mentioned, the annotation of our dataset was performed and validated in collaboration with clinical evaluators with over ten years of experience in orthodontistry, dental surgery and endodontics. We divided the dataset into training and testing subsets as detailed in Table 1. We selected two-thirds of the scans for training and the rest for testing, totaling 1200 and 600 scans, respectively. The scan selection is performed in such a way that the same training/testing proportion is validated at the level of tooth labels as well, ensuring balanced data. For example, there are 591 teeth in the training subset out of a total of 888 teeth with the label 12, which reads approximately 66.55%.

We also validated the statistics related to teeth distributions across upper and lower jaws. As depicted in figure 5, we observe a comparable distribution of number of teeth per jaw when comparing the upper and lower jaws. For example, we find 10.7% for 13-teeth upper jaws while 13-teeth lower jaw represents 10.3%. From another perspective, jaws with 14 teeth are the most representative, accounting for 53.4% and 58.9% for upper and lower jaws, respectively. Even if there are significantly
fewer jaws with missing teeth (e.g., 0.1 % and 0.8 % for 8 and 9 teeth on the upper jaws), the overall statistics are still representative according to our clinical experts.

To provide use case scenarios for our Teeth3DS dataset, it was successfully processed by the competing algorithms in the 3DTeethSeg 2022 challenge. The obtained results showed that the majority of the proposed deep learning algorithms can perform accurate and reliable 3D teeth localization, 3D scan segmentation and labeling tasks. In terms of evaluation metrics, they obtained a teeth localization accuracy between 45.3% and 96.58%, a teeth segmentation accuracy between 81.26% and 98.59% and a teeth identification rate between 68.36% and 91%. These results demonstrate that Teeth3DS can be useful for segmenting and labeling each instance of visible teeth in 3D dental scans, allowing for example orthodontists to simulate teeth extraction, deletion, and rearrangement and improve the treatment outcome prediction. Nevertheless, in order to develop a fully automated CAD system, all of these three mainstream tasks should be significantly improved. For example, depending on the application requirements, teeth miss detection should ideally be lower than 1/100. Also, we envision further refining the tasks and metrics in order to evaluate the quality of the algorithms in the accurate delimitations of these limits. Beyond the explored tasks, this dataset will be also useful for a wider range of applications such as 3D teeth modeling and reconstruction or dentition anomaly detection.

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|                  | Training | Testing | Total  |
|------------------|----------|---------|--------|
| **# patients**   | 600      | 300     | 900    |
| **# scans**      | 1200     | 600     | 1800   |
| **# teeth**      | 16004    | 7995    | 23999  |
| **Total**        |          |         | 11898  |
| **Upper jaw**    |          |         |        |
| Label 18         | 28       | 14      | 42     |
| Label 17         | 417      | 205     | 622    |
| Label 16         | 592      | 298     | 890    |
| Label 15         | 591      | 290     | 881    |
| Label 14         | 586      | 293     | 879    |
| Label 13         | 556      | 278     | 834    |
| Label 12         | 591      | 297     | 888    |
| Label 11         | 599      | 300     | 899    |
| Label 21         | 599      | 300     | 899    |
| Label 22         | 598      | 299     | 897    |
| Label 23         | 561      | 283     | 844    |
| Label 24         | 592      | 297     | 889    |
| Label 25         | 584      | 286     | 870    |
| Label 26         | 590      | 300     | 890    |
| Label 27         | 425      | 213     | 638    |
| Label 28         | 24       | 12      | 36     |
| **Total**        | 7933     | 3965    | 11898  |
| **Lower jaw**    |          |         |        |
| Label 38         | 31       | 16      | 47     |
| Label 37         | 458      | 224     | 682    |
| Label 36         | 586      | 296     | 882    |
| Label 35         | 585      | 293     | 878    |
| Label 34         | 589      | 292     | 881    |
| Label 33         | 588      | 295     | 883    |
| Label 32         | 600      | 300     | 900    |
| Label 31         | 598      | 299     | 897    |
| Label 41         | 598      | 300     | 898    |
| Label 42         | 598      | 300     | 898    |
| Label 43         | 589      | 297     | 886    |
| Label 44         | 594      | 297     | 891    |
| Label 45         | 581      | 289     | 870    |
| Label 46         | 589      | 292     | 881    |
| Label 47         | 456      | 225     | 681    |
| Label 48         | 31       | 15      | 46     |
| **Total**        | 8071     | 4030    | 12101  |
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