In Research on Computer Aided Dental Implant

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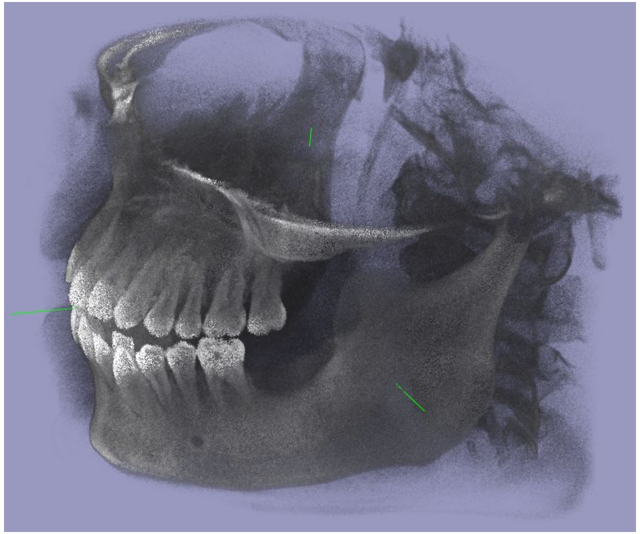
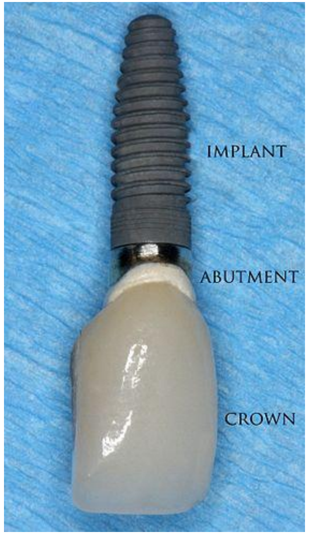
任务

- 已知病人的有至少一处的牙齿缺失，拍摄CBCT图像。
- 已知一个种植牙牙根和连接体的数据库。
- 输入CBCT图像，求出最适合种植的位置，以及最合适的牙根和连接体的型号。



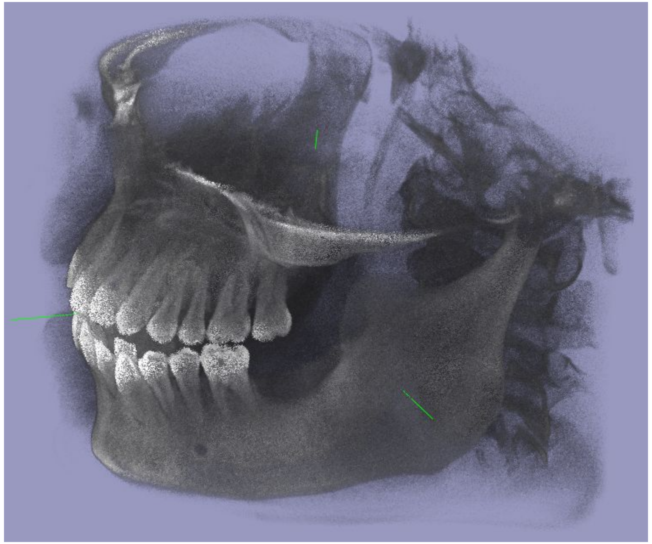


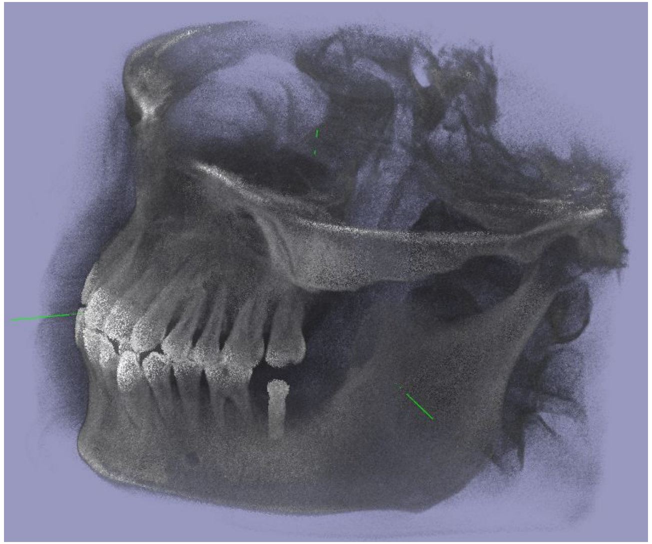
方法:第一步

- 提取种植区域ROI。
- 理想情况下，求术前术后图像的差即可得到种植的位置。
- 实际上两次拍照有位置和姿势的差别，所以需要先进行配准，根据配准结果选择提取ROI的方法（求差法，阈值法等）。
- 为了优化配准，裁剪图片，只取用牙齿部分，并调整对比度。

数据

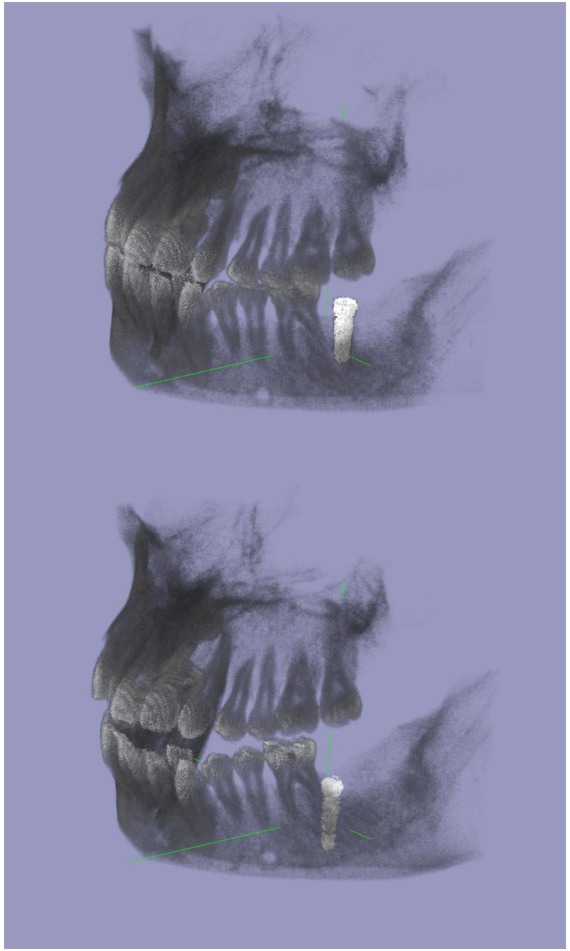
- 现有数据:病人进行植牙手术前后的CT图像。目前经数据清洗后共36对数据。





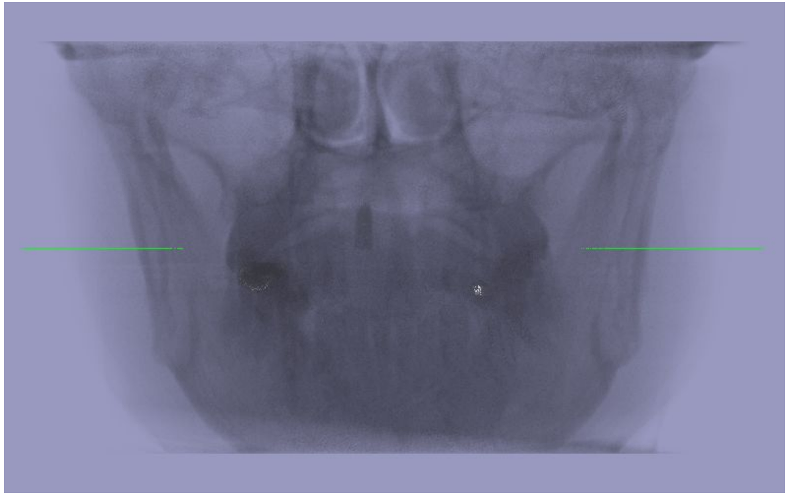
第一次尝试

- 效果不理想。
  - 找不到正确的种植牙 Mask。
  - 配准结果不理想。



分析原因并改进

- ✓ 先在术后CT上用阈值法提取出可能是种植牙区域的Mask。
- 筛选种植牙Mask(无监督分类)。
- ✓ 重新裁剪并进行下采样，舍弃细节信息，去除可能影响配准结果的部分(种植牙和其他治疗痕迹等)。
- ✓ 只对牙齿和骨骼的轮廓进行配准。
- 将配准生成的Displacement field 应用到种植牙的Mask上，即可将Mask映射到术前CT上



Dental pathology detection in 3D cone-beam CT

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Dental pathology detection in 3D cone-beam CT

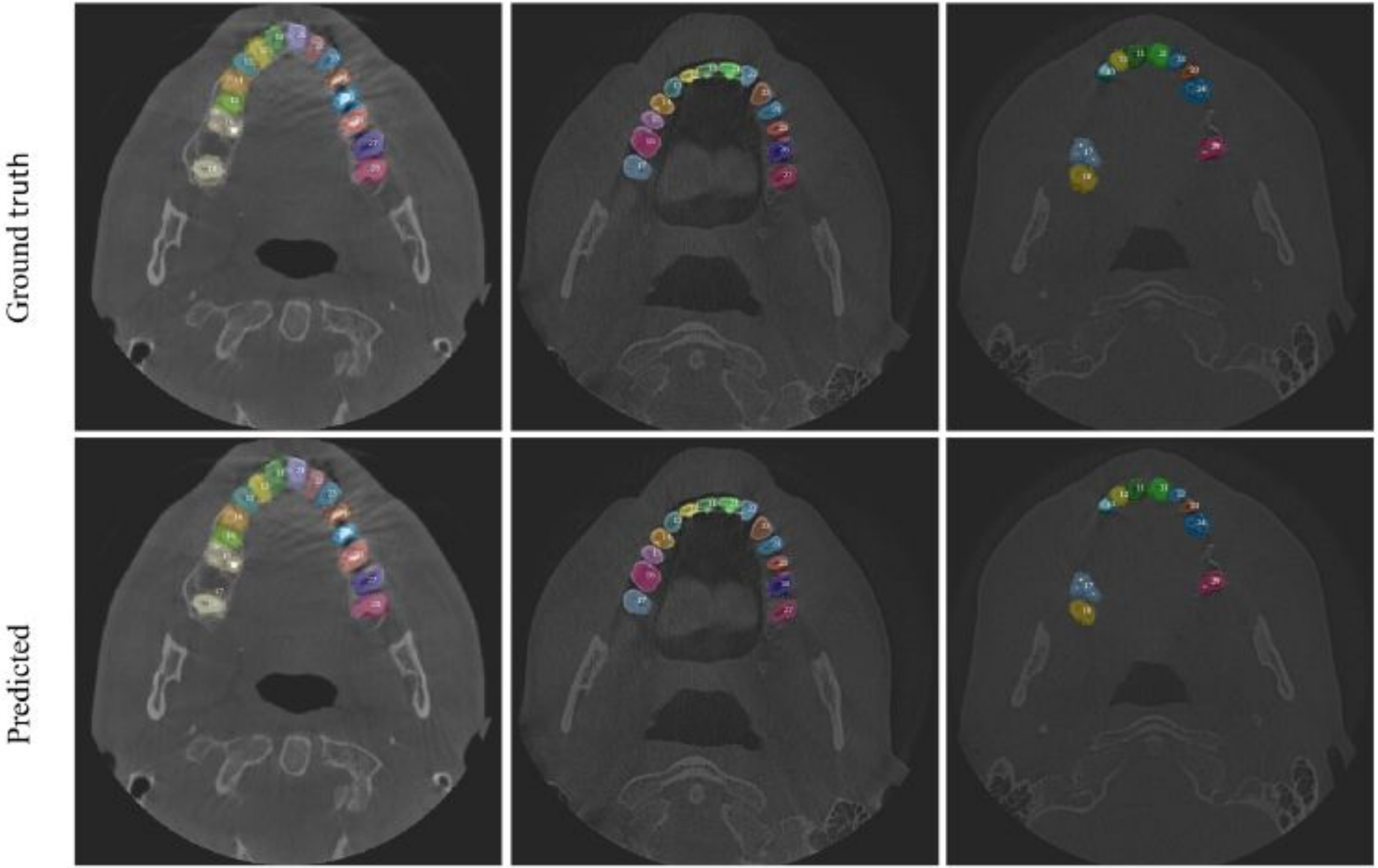
- Task
  - Find locations of each present tooth inside a 3D image volume.
  - Detect several common tooth conditions in each tooth.
    - Fillings, artificial crowns, implants, filled canals, missing teeth.
- Dataset
  - Localization dataset.
    - Annotated 517 studies.
  - Pathology dataset.
    - 39888 examples from 1284 studies.

Dental pathology detection in 3D cone-beam CT

- Methods
  - Data preprocess.
  - Localization.
  - Extracting the tooth volumetric image together with the surrounding context.
  - Predict condition.
- Sparse annotated location to segmentation mask
  - 32+1 masks, one for each tooth and one for background.
  - Energy = distance to center of the bbox for each tooth, or a trainable value for background.
  - Energy_intensities = intensities + k * energies.
  - Use argmax to obtain the label.

Dental pathology detection in 3D cone-beam CT

- CNNs
  - 6 levels V-Net for localization. Soft negative multi-class Jaccard similarity loss.
  - DenseNet for classification. Weighted BCE loss.
- Result
  - 96.3% accuracy in tooth localization.
  - 0.94 AUROC for 6 common tooth conditions.


Ground truth
Predicted

AUTOMATIC DETECTION AND CLASSIFICATION OF DENTAL RESTORATIONS IN PANORAMIC RADIOGRAPHS

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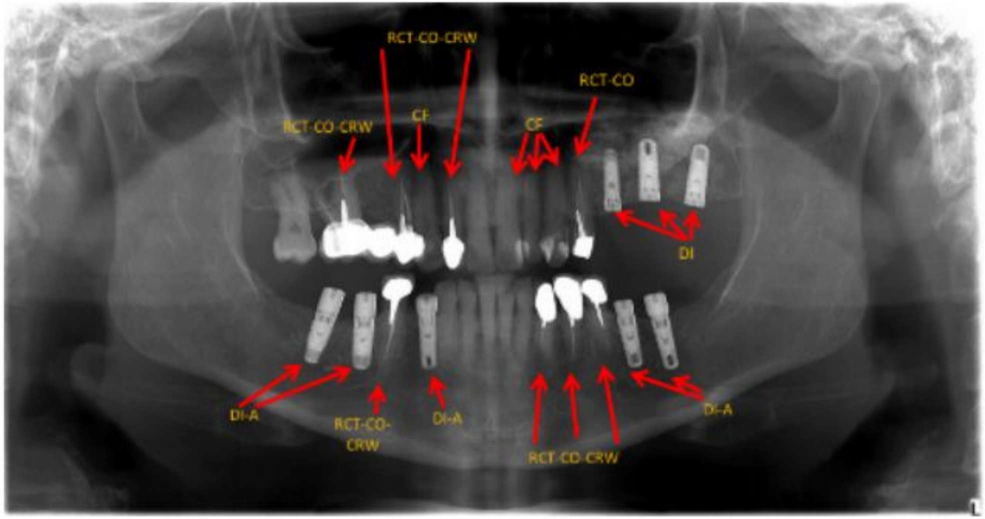
Automatic Detection and Classification of Dental Restorations in Panoramic Radiographs

- Task
  - Develop a prototype of an information-generating computer tool designed to automatically map the dental restorations in a panoramic radiograph.

Automatic Detection and Classification of Dental Restorations in Panoramic Radiographs

Table 1. Division of dental restorations into categories

Group number	Type of Restoration	Acronyms
1	Crown (only)	CRW
2	Root Canal Treatment with Core	RCT-CO
3	Root Canal Treatment with Core & Crown	RCT-CO-CRW
4	Dental Implant (only)	DI
5	Dental Implant with Abutment	DI-A
6	Dental Implant with Crown	DI-CRW
7	Amalgam Filling	AF
8	Composite Filling	CF
9	Connected Restorations	MULTI



Automatic Detection and Classification of Dental Restorations in Panoramic Radiographs

- Methods
  - Crop ROI.
  - Adaptive threshold segmentation.
  - Remove regions adjacent to image borders.
  - Classification.
- Results
  - 95% detection rate, 92% classification accuracy.

ToothNet: Automatic Tooth Instance Segmentation and Identification from Cone Beam CT Images

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ToothNet: Automatic Tooth Instance Segmentation and Identification from Cone Beam CT Images

- Task
  - Tooth instance segmentation and identification.
- Dataset
  - 20 CT scans, 12 for training, 8 for testing.
  - Crop 150 patches of size 128 * 128 * 128 around alveolar bone ridge to obtain 1800 patches.
  - Annotated witha tooth-level bbox, mask and label.

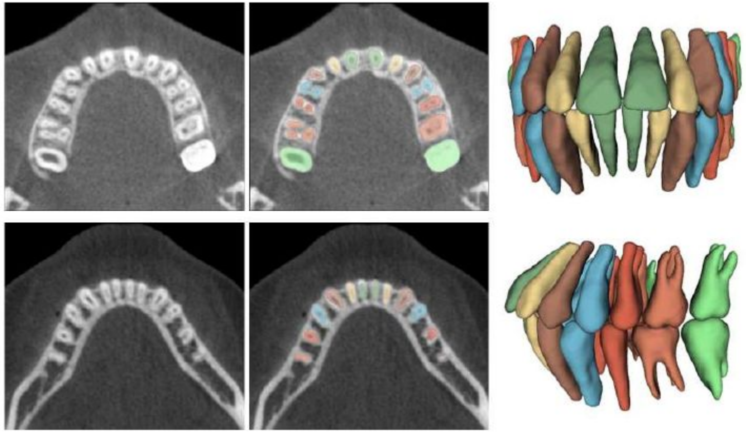
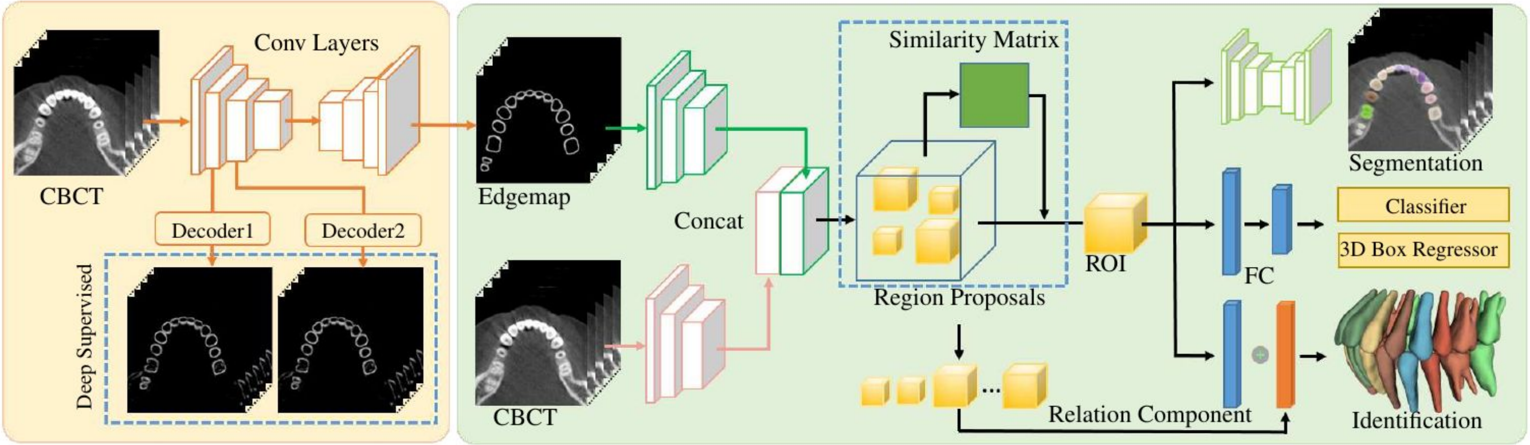


Figure 1. An example of tooth segmentation and tooth identification. The first column shows a CBCT scan in the axis view, the second column shows its segmentation results, and the last column shows the 3D segmentation results with different colors for different teeth respectively.

ToothNet: Automatic Tooth Instance Segmentation and Identification from Cone Beam CT Images

- Methods
  - Deep supervised edge map extraction stage.
  - Concat edgemap with CBCT, input to RPN.
  - Use a similarity matrix instead of NMS to remove duplicate proposals.



ToothNet: Automatic Tooth Instance Segmentation and Identification from Cone Beam CT Images

- Similarity Matrix
- Relation Conponent
- Result
  - Dice similarity coefficient 91.98%
  - Detection accuracy 97.75%
  - Identification accuracy 92.79%

Ideas

- Weak or semi supervised teeth segmentation.
    - Atlas based methods may work.
- Supernumerary tooth detection.