Contribution Title

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Abstract. we used 3D model cascade models to segment airway from medical images. The code of efficientSegNet developed by Fan Zhang was publicly in: https://github.com/Shanghai-Aitrox-Technology/EfficientSegmentation .

Keywords: Airway Segmentation, Deep Learning, U-net.

1 Introduction

Airway segmentation is one of the most attractive topics in the field of medical image analysis, which plays an important role in supporting clinical workflows such as disease diagnosis and treatment planning of asthma, bronchiectasis, and emphysema. Competition organizers present ATM2022, an airway segmentation benchmark. It provides 500 CT scans from multi-sites[1,2,3,4]. The airway tree structures are carefully labeled by three radiologists with more than five years of professional experience.

To addressing airway segmentation task, we employed efficientSegNet network developed by Fan Zhang[5].

2 Method

Preprocess

a. Images was reorientated to target direction.
b. The HU value was clipped to the range [-1024, -546], then z-score normalization was is applied.
c. The input of coarse model was resampled to 160*160*160 in the x, y and z direction. The input of fine model was resampled to 256*256*256 in the x, y and z direction.
d. Data augmentation. Random crop, rotate and HU value changes was used to improve coarse model's generalization. Besides, elastic transform and gaussion noise was employed in fine model.

Model

EfficientSegNet was used to segment airway from CT scans[5].

Postprocess

A connected component analysis of segmentation mask is applied model output.

3 Dataset and Evaluation Metrics

3.1 Dataset

The datasets collected from multi-sites and the airway masks were carefully labeled by three radiologists with more than five years of professional experience.

The datasets totally include 500 CT. Task splits 350 CT as training cases, 50 CT as validation cases and 150 CT for testing.

Table 1. Data splits of ATM2022.

Modality	Training	Validation	Testing
CT	350	50	150

3.2 Evaluation Metrics

Dice Similarity Coefficient (DSC)

False Negative Error (FNE)

False Positive Error (FPE)

Tree length detected rate (TD)

Branches detected rate (BD)

Precision

4 Implementation Details

4.1 Environments

The environment of the methods is shown in Table 2.

Table 2. The environment of the methods.

	Parameters
operating system	Linux
CPU	AMD Ryzen Threadripper 3990X 64-Core
GPU	NVIDIA GEFORCE RTX 3090
CUDA version	11.5
Deep learning framework	Pytorch 1.11.0

References

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