

Automated Pulmonary Airway Tree Segmentation Based on UNet

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Abstract. Pulmonary airway tree segmentation is important for lung cancer related surgical treatment and analysis of pulmonary diseases. To achieve more accuracy and complete reconstruction results remain a meaningful subject in deep learning field. We develop an automated airway tree segmentation network based on U-Net architecture. This network achieves end to end airway tree segmentation using CT scans, and achieves SOTA performance in ATM 2022 dataset.

Keywords: Airway Tree Segmentation, U-Net, Coarse-to-fine.

1 Introduction

Pulmonary airway tree segmentation is important for lung cancer-related surgical treatment and analysis of pulmonary diseases. In today’s clinical process, most pulmonary airway tree annotation work is manual – it is a labour-intensive and error-prone task. With the development of deep learning in the medical image process, end-to-end automated airway tree segmentation achieves better results. Achieving more accuracy and complete segmentation results remains a meaningful subject in the deep learning field. We develop an automated airway tree segmentation network based on U-Net. This network achieves end-to-end airway tree segmentation using X-Ray computed tomography (CT scans), and achieves SOTA performance in the Airway Tree Modeling challenge 2022 dataset [1-4].

2 Methods

2.1 ATM Dataset

The CT scans data used in these experiments is provided by the Airway Tree Modeling challenge 2022 dataset [1-4]. This dataset contained 500 CT scans, which are collected from multi-centres and labeled by three experienced radiologists. All CT scans have a spacing of $0.7441 \times 0.7441 \times 0.5$. However, broken of the branch of the airway tree in the provided ground truth is very often, as Fig. 1. shown, which may impact segmentation results.

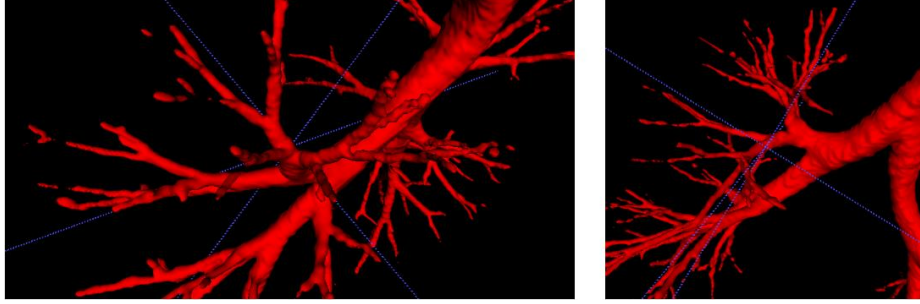


Fig. 1. Examples of Dataset

2.2 Network architecture

As Fig. 2. shown, this network adopts encoder-decoder architecture with skip connection, based on U-Net [5]. In the experiment, we use convolutional layers with strip = 2 to conduct the downsample and use ConvTranspose to conduct the up sample. We use instance normalization for both downsample and upsample. The training is patch-wise training and the patch size used in this network is 96, 160, 160. **75% patches are labeled and 25% are sampled randomly.**

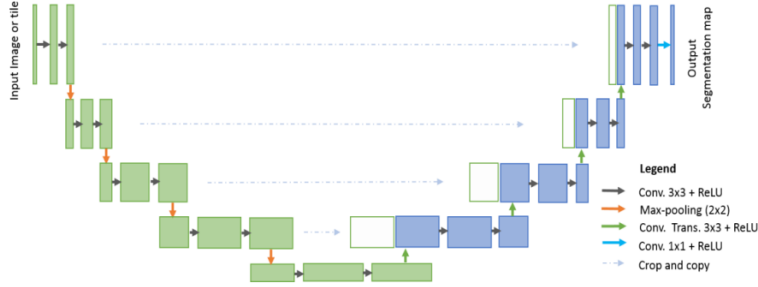


Fig. 2. U-Net architecture

To predict high-level airway tree more accurately, we adopt coarse-to-fine architecture in this work. Attention UNet is used for the fine part [6]. Compare to the coarse model, fine model has shallower network architecture (4 ups and downs compare to 5 for coarse model) and smaller patch size 48, 80, 80. **The patches are sampled with 25% randomly and 75% contained high level airway tree.**

2.3 Pre-processing and Training

The HU value of input data is limited from -1028 to 266 and conducted standard normalization. To alleviate the bottleneck of memory, we use patch-wise training, patch size is 96, 160, 160. Patches are extracted randomly, 50% of patches contain area that has airway label. We use cross-entropy loss combined with dice loss in the experiment.

We divide the training set into training set and validation set in 7:3 randomly, totally 209:90.

3 Results

The results of dice score and recall score are shown below, and the segmentation results shown as Fig. 3.

Table 1. Results in ATM Training Set.

Training/Validation	Metrics	Results
Training	Dice Score	0.8957
Validation	Dice Score	0.8962
Training	Recall Score	0.9079
Validation	Recall Score	0.9043

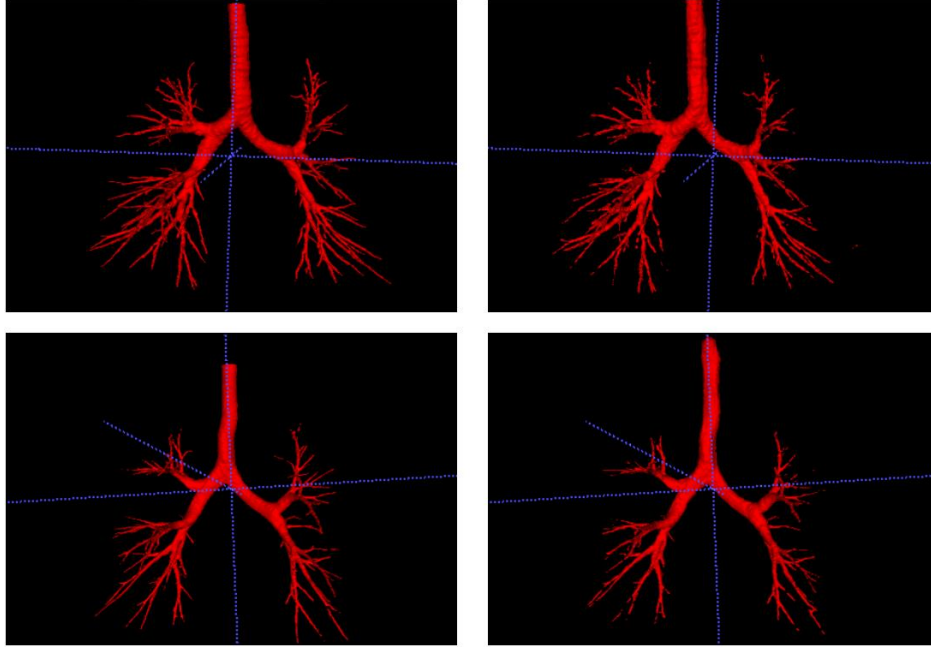


Fig. 3. Segmentation Results (GT vs Pred)

Our coarse-to-fine design has higher dice and FP FN than the single UNet model.

Table 2. Single Model with Coarse-to-fine Model.

Model	Metrics	Results
Single	Dice Score	0.8893
Coarse2fine	Dice Score	0.8957
Single	False Negative Rate	0.0952
Coarse2fine	False Negative Rate	0.0921
Single	False Positive Rate	0.1224
Coarse2fine	False Positive Rate	0.1136

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