Airway Segmentation With Two Stage UNet

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Abstract. Airway Segmentation is very import in the pulmonary surgery and disease diagnosis. In this paper, we propose deep learning method with a two stage UNet to promote the accuracy of the airway segmentation. The first net is aim to get the whole binary result of the airway. Then, the second net is aim to refine the end bronchioles with the broken part. We train the net with the same network structure, but with the different training strategy. They play different role on the segmentation process.

Keywords: Deep Learning, Airway Segmentation, Two Stage, UNet.

1 Introduction

The accurate airway topology structure and segmentation result is very crucial for many medical research and application. Typically, it is very important to generate the plan path before the surgery such as bronchoscopy and lung puncture. The first step is to segment the airway with the chest non-contrast CT scan. As the deep learning become the advanced technology in the medical research, more and more scholars and experts do their research with neural network such as organ segmentation or lesion detection and so on.

Some paper presents a fully automatic airway segmentation with the separate trachea and bronchi segmentation, it said this can improve the segmentation accuracy respectively[1]. Other paper gets the segmentation from the centerline tracking. It predicts the diameter of the points in the centerline using a CNN-based orientation classier[2]. Another paper present a novel approach of multi parametric freeze-and-grow (FG) propagation which starts with a conservative segmentation parameter and captures finer details through iterative parameter relaxation mixed with deep learning[3]. To further address the intra-class imbalance between large and small airways, one paper designs a kind of loss function that obviates the impact of airway size by distance-based weights and adaptively tunes the gradient ratio based on the learning process.

In this paper, we also propose a method to fine the distal small airways using two model trained by the general UNet[5], which has been proved significantly effective on medical image segmentation. The fist model get the whole airway segmentation result, and the second one refine the distal bronchi when trained emphasizing these small places.

2 Data

The training data are all from the Grand Challenge of Airway Tree Model 2022. It included 299 thorax CT scans with paired images and labels. We do the 8-2 split on the training data randomly, so we got 239 train samples and 60 valid samples.

3 Method

3.1 Preprocess

We perform statistics on the train samples. We resample all samples with the median spacing as (0.7813, 0.7813, 0.5). The mean, std, 0.05 percentile and 99.5 percentile value is -998, -217.5, -1024 and -225. We use them to normalize the samples.

3.2 Network

The network is the basic U-Net architecture. It has five time down sampling with the convolution of the stride 2. Each layer has two convolution blocks with the convolution, instance normalization and leaky relu structure. The basic feature channels are set to be 32. The feature channels got double until the largest number 320 as the feature map got half. We use the deconvolution to up sample feature maps and concatenate feature maps from the same stride layer of the encoder. The outputs are passed through the soft max function to generate the probability map to compute the loss.

3.3 Training strategy

We use the common data augmentation transform such as color transform, spatial transform, noise transform. Then we randomly crop the image and mask pair and then pass into the net to do the front propagation and back propagation. The patch size is set to (112, 128, 160) also form the data statistics. The initial learning rate is 1e-3 and we use the Adam optimizer to find the best optimization direction. It reduced the learning rate with the learning rate schedule adaptively. The loss is weighted dice and cross entropy loss.

When training the second net to supplement the distal small airway, we sample the patch on the distal part of the foreground with a certain probability to focus on this part training because of the specific task.

3.4 Validation

We do the validation on the validation set with the patches cropped from the image in turn. The overlap between the neighboring patches is set to be half of the patch size across each axis to discard the noisy part around the patch. Then we resample the reconstructed image back to the original size. Finally, we leave the largest connected component of the result.

4 Results

We calculate the Dice on the validation set and got the metric value of 92.3% temporarily. We will optimize the algorithm according to the actual test results.

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