Improved nnUNet for Airway Segmentation*

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Abstract. Airway segmentation on LIDC-IDRI images is a crucial premise for the analysis of pulmonary diseases, which enables the quantitative measurements of airway dimensions and wall thickness and helps for navigation in bronchoscopic-assisted surgery. Many factors including difficulty in labeling coronary lumens, various morphologies in stenotic lesions, thin structures and small volume ratio with respect to the imaging field complicate the task. In this work, we propose improvements to the nnUNet[1]. It has two main parts: 1)Pre-processing. In this stage, the pixel value of the image is setted from 0 to 4095 by normalization, and z-score standardization is used to process the image during training. At the same time, the image is resampled so that the image size is 1:1:1. 2)Post-processing. In this stage, the reasoned image is reprocessed, so as to suppress false segmentation due to region similarity. On the basis of training on the same dataset, the improved nnUNet improves by 2.2% on validation set compared with traditional methods. The results show that the ability of neural network to perceive the characteristics of tubular structures and the quality of bronchial segmentation are improved by the improvement of pre-processing and post-processing.

Keywords: Pulmonary airway segmentation · nnUNet · Airway models.

1 Introduction

Airway segmentation is a crucial premise for the analysis of pulmonary diseases including asthma, bronchiectasis, and emphysema. The accurate segmentation based on X-Ray computed tomography (CT) enables the quantitative measurements of airway dimensions and wall thickness, which reveal the abnormality of patients with chronic obstructive pulmonary disease (COPD). Besides, the extraction of patient-specific airway models from CT images is required for navigation in bronchoscopic-assisted surgery.

But it is still a challenging task for accurate airway segmentation owing to the following difficulties: Challenge 1: Thin structures. Thin structures have numerous hard-to-segment regions and will make the network more prone to over-segmentation or under-segmentation. Challenge 2: Small volume ratio. The airway only accounts for a small part of the area in images which makes the target and the background have large-scale differences. The differences cause

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the class imbalance so that the network will show weak segmentation on the minority classes.

Bruijne et al. [2] held the âĂŸExtraction of airways from CT (EXACT'09)âĂŹ challenge in 2009 and achieved a great contribution to the field of airway segmentation. They focused on semi-automated and automated algorithms mainly based on multi-threshold, template matching, and region growing, aiming to relieve the burden of manual delineation and help clinicians explore the influence of pneumonia on airways. These traditional algorithms face difficulty in extracting small peripheral bronchi and suffer the risk of airway leakage. With the advance of deep learning methods, fully convolutional networks (FCNs) achieved state-of-the-art performance in the segmentation task of volumetric medical data. Most of the deep learning methods are data-driven while the EXACTâĂŹ09 contains only 20 CT scans for training and 20 CT scans for testing, which is not sufficient for the artificial intelligence era.

In order to improve the index performance, we add pre-processing and post-processing on the basis of the original nnUNet network.1) Before training, normalize the training image to make the pixel value between 0 and 4095, and resampling to make the image size ratio 1:1:1. During training, z-score normalization is performed on the image to make the pixel values conform to the standard normal distribution. 2) After the training is completed, the model is used to infer the image, and at the same time, the lung is segmented. The lung and the results are superimposed, and the false positive region is removed by outputting the overlapped part.

2 Methodology

2.1 Preprocessing

As shown in Fig. 1(a), after resampling and normalizing the input image, the size of the image is 1:1:1, and the pixel value is 0 to 4095. This operation improves the convergence speed and accuracy of the model during later training. As is shown in Fig. 1(b), during training, we standardize the z-score on the image to make the data conform to the standard normal distribution and eliminate the magnitude risk brought by the data itself.

2.2 Reprocessing

After reasoning on the validation set with the trained model, we find that there are false positive region around the bronchus in some images, as shown in Fig2. (a) These false positive region exist outside the lung. First, we segment the lung information of each image, as shown in Fig2. (b), and superimpose the lung information with the predicted image. The non overlapping parts are the areas outside the lung and the non bronchial parts in the lung, so that the false positive region can be effectively removed, as shown in Fig2. (c).

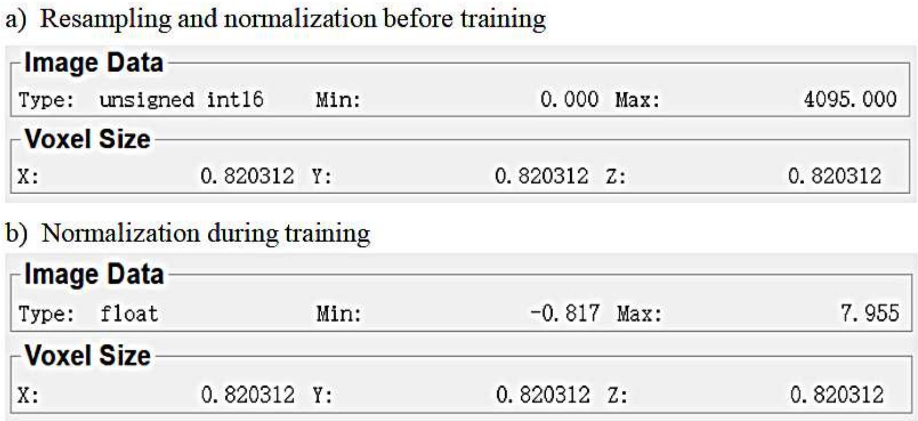

Fig. 1. Preprocessing:a)shows the normalization and resampling results of images before training nnUNet. b)shows the result of further normalization of the image when training nnUNet

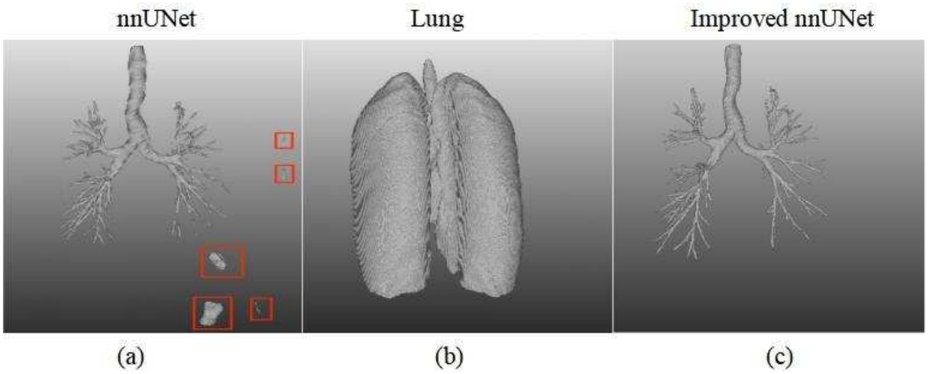

Fig. 2. Reprocessing:a)shows the image output by nnUNet with false positive region. b)shows the result of segmented lung image. c)shows the image after superposition of (a) and (b)

3 Experiments configurations

Our experiments mainly involve the thoracic CT scans from the public LIDC-IDRI dataset[3-6] and the Shanghai Chest hospital, which is used to train our nnUNet and shows the ability to perceive tubular structures.

The original image is 512 × 512 per slice, with about 700 slices per image. Each thoracic CT scan is first preprocessed by some strong deep learning models and ensemble strategy to acquire the preliminary segmentation result and then carefullt delineated and double-checked by three radiologists with more than five years of professional experience to acquire the final refined airway tree structure. 249 of them are used as a training set and the other 50 as the test set. The region of interest(ROI) is extracted and these lung ROIs are cropped into smaller region online before been fed into the network to increase training speed. Resampling and normalization are used to improve training effect.

Our nnUNet is optimized by Adam with the original learning rate of 0.001. The training batchsize is 2 and the network is trained iteratively with 300 e-poches. Our implementation uses Pytorch.

To see the effect of the nnUNet, the Dice coefficient is used to evaluate the similarity of the foreground regions in the two images.

4 Results and discussion

In this section, we evaluate the effectiveness of the improved network by comparing the classical UNet[7], nnUNet and the improved nnUNet. The results show that the performance index is improved by pre-treatment and post-treatment.

We train the network on the training set provided by the competition, and then predict the output on the verification set. For the classical UNet, the prediction are shown in Fig. 3(a). The average Dice value on the validation set is 83.5%. There are problems such as insufficient prediction of bronchial stages and too many false positive region. The Dice value of 83.5% is mainly due to the large area occupied by the main branches of the bronchus. The results predicted by the nnUNet network are shown in Fig. 3(b). The average Dice value on the validation set is 90.2%. It is seen that the bronchus are inferred to the tertiary bronchial tree, but there is a false positive region problem. The improved n-nUNet is used for reasoning. As shown in Fig. 3(c), the average Dice value on the verification set is 92.3%, and the problem of false positive region is overcome on the basis of the original nnUNet.

5 Conclusion

In this paper, on the basis of nnUNet, our network further increases the operation of pre-processing and post-processing. 1) Before training, normalize the training image to make the pixel value between 0 and 4095, and resampling to make the image size ratio 1:1:1. During training, z-score normalization is performed on the image to make the pixel values conform to the standard normal

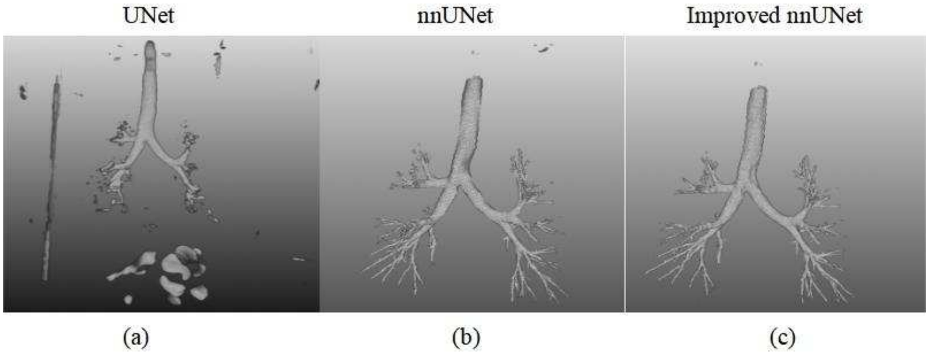

Fig. 3. Predicted comparison:a)shows the predictionof the classical UNet. b)shows the prediction of the nnUNet. c)shows the prediction of the improved nnUNet)

distribution. 2) After the training is completed, the model is used to infer the image, and at the same time, the lung is segmented. The lung and the prediction results are superimposed, and the redundant plaque is removed by outputting the overlapped part. In our mission, the performance indicators are improved through pre-processing and post-processing.

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