Heatmap Regression-based Segmentation of Airway Trees*

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Abstract. Segmentation of airway trees from thoracic Computed Tomography (CT) images is crucial for diagnosis of pulmonary diseases, localization of abnormal airway walls and surgical navigation. However, fully automatic segmentation of airway from volumetric CT images is challenging due to anatomical variation of pathologies, low contrast at peripheral branches and complex tree-like structures. In this study, we propose a method for fully automatic heapmap regression-based segmentation of airway trees. The dataset is randomly split with a ratio of 80%/20% into train and validation sets for model training and hyperparameter tuning, respectively. The proposed method achieves an average Dice ratio of 90.07% on validation dataset.

Keywords: Airway segmentation · Airway regression · ATM2022.

1 Introduction

Segmentation of airway trees from thoracic Computed Tomography (CT) images is crucial for diagnosis of pulmonary diseases, localization of abnormal airway walls and surgical navigation. However, fully automatic segmentation of airway from volumetric CT images is challenging due to anatomical variation of pathologies, low contrast at peripheral branches and complex tree-like structures.

The airway tree is composed by a series of hierarchy-connected tubular structures with varying length and diameter. Despite local appearance variances, human airway trees have certain priors in global connectivity and topologically structure. To capture such global anatomical information of airway tree, we design a heatmap-based detector to first regress the location and dimension of the airway tree using low resolution CT images. The heatmap encodes the pseudo-probability of a point on the airway centerline being located at a certain pixel position. Specifically, the pseudo-probability of a point in the heatmap is set to be 1.0 on the airway centerline and decreases smoothly to 0.0 at the edge of the airway. The heatmap encodes information about the dimension and location of the airway and is used as additional input to improve the performance of subsequent segmentation network.

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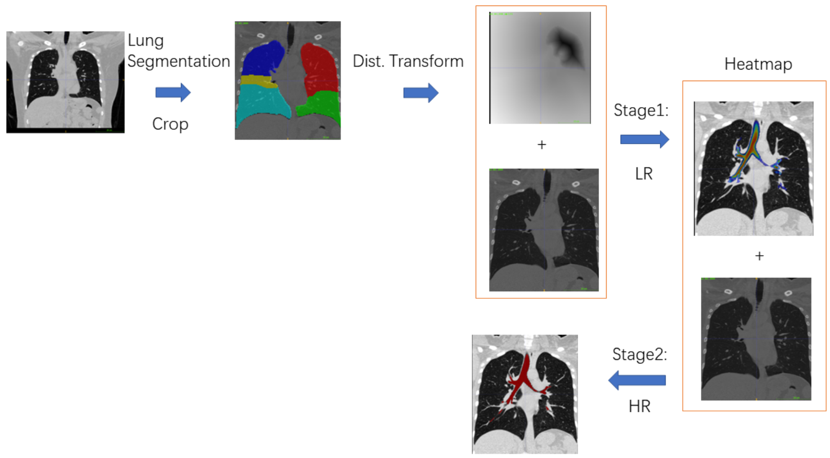

Fig. 1. Overview of our proposed heatmap regression-based airway tree modeling method.LR:low-resolution. HR:high-resolution

2 Methods

In this work, we propose a two-stage Airway Tree Modeling (ATM) method. As shown in Fig.1, we first trained a model to obtain lung segment segmentation. Next, distance maps of different lung segments are concatenated to the cropped lung field volume and feed into the network of the first stage. The network at the first stage expects low-resolution CT images as inputs, while outputs predicted airway tree heatmaps. The airway tree heatmaps are then up-sampled and concatenated to the high-resolution CT images to be used as the input to the network at stage 2. During training, the network at stage 2 receives high-resolution 3D patches as input to reduce computational complexity as well memory requirement. During inference, we adopt a sliding window approach to obtain segmentation of airway tree. A 3D-UNet-like network architecture is used for both stages.

3 Results

The released training set consists of 299 thoracic CT images. The dataset is randomly split with a ratio of 80%/20% into train and validation sets for model training and hyperparameter tuning, respectively. The proposed method achieves an average Dice ratio of 90.07% on validation dataset. In Fig.2, we shows an input CT volume from the validation dataset with airway heatmap, segmented airway and 3D reconstruction for ground truth (first row) and predictions (second row), respectively.

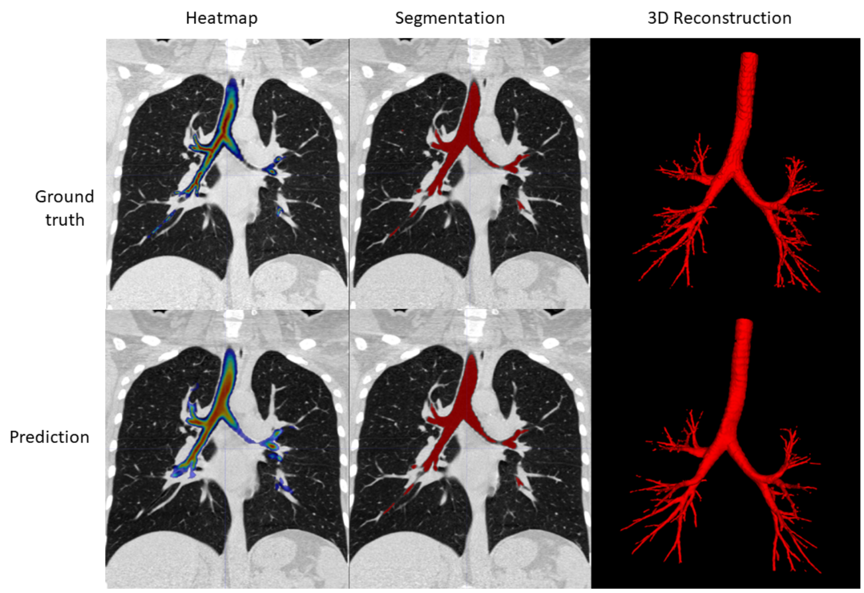

Fig. 2. An input CT volume from the validation dataset with airway heatmap, segmented airway and 3D reconstruction for ground truth (first row) and predictions (second row), respectively.