Improvement of fully automated airway segmentation on computed tomographic images using 2.5D and 3D convolutional neural net

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Abstract

We proposed novel airway segmentation methods in volumetric chest computed tomography (CT) using 2.5D convolutional neural net (CNN) and 3D CNN. A method with 2.5D CNN segments airways by voxel-by-voxel classification based on patches which are from three adjacent slices in each of the orthogonal directions including axial, sagittal, and coronal slices around each voxel, while 3D CNN segments by 3D patch-based semantic segmentation using modified 3D U-Net. The extra-validation of our proposed method was demonstrated in 20 test datasets of the EXACT'09 challenge. The detected tree length and the false positive rate was 60.1%, 4.56% for 2.5D CNN and 61.6%, 3.15% for 3D CNN. Our fully automated (end-to-end) segmentation method could be applied in radiological practice.

1 Introduction

Airway tree segmentation plays an especially important role in pulmonary disease analysis, because it quantifies the anatomical features, including the airway wall thickening, wall–lumen diameter ratio, and changes in lumen diameter. Most previous methods made an effort to overcome the trade-off between increasing the airway tree length and reducing the number of leakage [1]. However, fine-tuning the parameters that influence this trade-off is often a difficult and tedious task and may also depend on the quality of the CT scan. In this paper, we proposed novel airway segmentation methods based on the convolutional neural nets (CNNs) which self-learn the informative features directly from image dataset. We designed and compared 2.5D CNN and 3D CNN based airway segmentation methods. These methods were extra-validated on the 20 test datasets of the EXACT'09 challenge [2], which is an internationally recognized open contest for airway segmentation.

2 Airway Segmentation Using 2.5D and 3D CNN

We selected multi-center thoracic CT scans from the Korean obstructive lung disease (KOLD) cohort, which includes stable patients with obstructive lung disease who were prospectively obtained from the pulmonary clinics of 11 hospitals in South Korea between June 2005 and September 2009 [3]. We randomly selected 69 COPD patients who had undergone volumetric CT with the same type

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of scanner (Somatom Sensation; Siemens Medical Systems, Erlangen, Germany) at seven selected hospitals. This study was approved by the institutional review boards of all hospitals, and each patient provided written informed consent. The CT images were represented by a 512 x 512 matrix, and pixel dimensions were ranged depending on the participant's body size.

2.1 2.5D CNN based airway segmentation

A method with 2.5D CNN segments the airways by voxel-by-voxel classification based on the patches around each voxel (see Figure 1). We selected 2,250 sample points per one thoracic CT scan (1,000 and 1,250 sample points from the airway and nonairway regions, respectively) and then extracted airway-candidate patches which are from three adjacent slices in each of the orthogonal directions including axial, sagittal, and coronal slices. The patch size was fixed at 32 x 32 pixels, ensuring complete capture of the surrounding information.

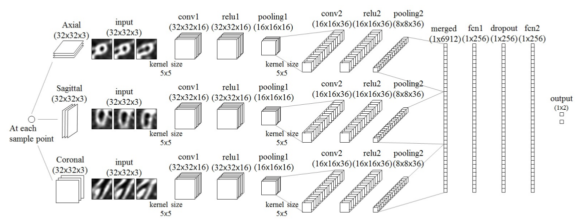

Figure 1: Architecture of 2.5D CNN for airway segmentation.

2.2 3D CNN based airway segmentation

A method with 3D CNN segments the airways by patch-based semantic segmentation using modified 3D U-Net [4] (see Figure 2). Instead of selecting a single model, we made an ensemble of three models which were trained using different 3D patches; each model was trained using 1) 64x64x64 patches from large airways, 2) 64x64x64 patches from small airways, 3) 32x32x32 patches from small airways, respectively. In order to compensate discrepancy between training and inference, we employed batch renormalization [5].

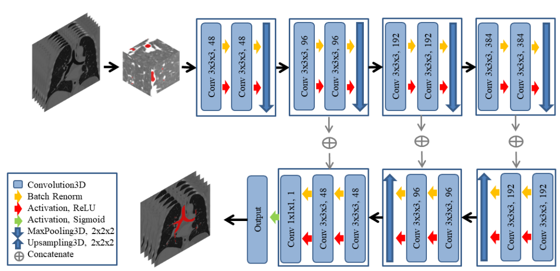

Figure 2: Architecture of 3D CNN for airway segmentation.

3 Experiments and Results

The proposed 2.5D and 3D CNN were trained on the inspiratory thoracic CT scans of 69 patients. The performances of our methods were compared with those of the 15 algorithms in the EXACT'09 challenge [2]. The airway segmentation algorithms in EXACT'09 were evaluated by seven performance measures, as mentioned in [2]. For a fair comparison, we evaluated our method by the same measures. Table 1 summarizes the computed performance measures in the 20 test cases of EXACT'09. Figure 3 compares the performances of the proposed deep-airway segmentation methods and the 15 algorithms of EXACT'09. 3D CNN achieved better performance than 2.5D CNN in regard to both detected tree length and false positive rate. Our method was outperformed by the leakage reduction algorithm of Charbonnier et al. [6], with a detected tree length of 65.4% and a false positive rate of 1.68%. However, our fully automated (end-to-end) segmentation method lowers the execution time to 2–8 min (2 min in all except 2 cases), without any additional processing or user interactions.

Table 1: Performances of the proposed deep-airway segmentations on EXACT'09 challenge data

	2.5D CNN	3D CNN
Branch count	163.4±79.4	164.8±85.7
Branch detected (%)	65.7±13.1	66.5±14.4
Tree length (cm)	129.3±66.0	136.4±79.7
Tree length detected (%)	60.1±11.9	61.6±13.0
Leakage count	94.1±61.9	87.8±77.9
Leakage volume (mm^3)	726.4±779.0	763.4±813.3
False positive rate (%)	4.56±3.73	3.15±2.78

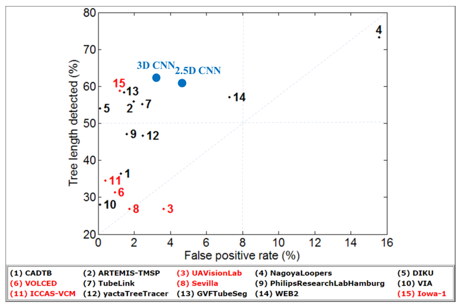

Figure 3: Performance comparison of our proposed methods with 2.5D and 3D CNN for airway segmentation on EXACT'09 challenge data

4 Discussion and Conclusion

Computerized analyses related to the human airway require accurate identification of the airway tree. Semi-automated detection of a human airway tree is possible in theory but typically infeasible in practice; therefore, fully automated methods are highly desired. By training end-to-end model on CT scans, we predicted the segmentation of the entire volume at once. This fully automated segmentation method provides a robust segmentation that is free from user bias.

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