Robust Airway Extraction based on Machine Learning and Minimum Spanning Tree

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ABSTRACT

Recent advances in MDCT have improved the quality of 3D images. In thoracic radiology, Virtual Bronchoscopy has been used for evaluating airways. However, Virtual Bronchoscopy has become widely used only for the evaluation of proximal airway diseases. The reason is that conventional airway extraction methods often fail to extract peripheral airways with low image contrast. In this paper, we propose a machine learning based method which can improve the extraction robustness remarkably. The method consists of 4 steps. In the first step, we use Hessian analysis to detect as many airway candidates as possible. In the second, false positives are reduced effectively by introducing a machine learning method. In the third, we obtain airway trees by utilizing a minimum spanning tree. In the fourth, we extract airway regions by using graph cuts. Experimental results show that our method can extract peripheral airways very well.

Keywords: MDCT, Airway Extraction, Virtual Bronchoscopy, Machine Learning, AdaBoost, Minimum Spanning Tree

1. PURPOSE

Because conventional airway extraction methods often fail to extract peripheral airways with low image contrast, Virtual Bronchoscopy has become widely used only for the evaluation of proximal airway diseases. Aiming to expand applications of Virtual Bronchoscopy, our purpose is to propose a novel method which can extract both proximal and peripheral airways robustly.

2. METHOD

The method consists of 4 steps. In the first step, we use Hessian analysis to detect as many airway candidates as possible (Fig. 1 (a)). In the second, false positives are reduced effectively by introducing a machine learning method (Fig. 1 (b)). In the third, we obtain airway trees by utilizing a minimum spanning tree (Fig. 1 (c)). In the fourth, we extract airway regions by using graph cuts.

2.1 Candidate Point Detection

Airways have tube-like structures, where airway walls surround air regions. To detect the airways, we apply Hessian analysis on multiple resolution images generated from input CT images [1]. The Hessian Analysis discriminates tubular structures by thresholding the lineness calculated from three eigenvalues of Hessian matrix. Here we use a low threshold value to prevent false negatives. As a result, this step detects as many airway candidates as possible, and also many false positives.

2.2 False Positive Reduction

Because the airways do not have clear tubular appearances, especially at the peripheral, the Hessian analysis cannot discriminate them from other objects accurately. To tackle this problem, we use a machine learning method for learning about the appearance of the airways.

We train a classifier in advance as follows.

① Creating training samples. The positive training samples were prepared from training data by manually labeling centerlines and airway contours. The negative training samples were collected from false positives generated from the Hessian analysis. Orientation and scale of each training sample are normalized as shown in Figure 2. Here the orientation corresponds to the smallest eigenvector. And the scale corresponds to the kernel size of the Hessian filter.

② Learning a classifier. An airway classifier is learned by using the AdaBoost algorithm from the two sets of training samples [2,3].

The learned classifier is applied to reduce the false positives from the candidates detected by the Hessian analysis. Notice that, because the orientation and scale information of each candidate has been estimated approximately by the Hessian analysis, the reduction process is computationally efficient.

2.3 Airway Tree Construction

After the false positive reduction, airway trees are constructed from the remaining candidates. Here, we define a cost function between the candidates. The function outputs weights of connection likelihood depending on the intensity, orientation and scale of each node pair. Then, the candidates are connected to generate a minimum spanning tree by Prim's method [4]. Finally, we express the airway by the tree represented as graph nodes and edges.

2.4 Airway Region Segmentation

After airway tree construction, centerlines and approximated radii of airways are known. Based on this information, we use 3D Graph Cuts to segment airway regions accurately [5]. This process is applied to every node in the airway tree, where s-links are set based on the node position (airway center), t-links are set based on the radius at the node (airway size), and n-links are set between neighboring voxels. Here weights of n-links depend on intensity differences.

3. EXPERIMENTAL RESULTS

The proposed method was evaluated by a standardized evaluation framework, which was presented at "Extraction of Airways from CT 2009 (EXACT09)" workshop [6]. In this framework, 20 chest CT datasets were provided for testing. Extraction results obtained by our method were sent to the organizers of EXACT09. In return, seven evaluated performance measures were reported.

Table 1 shows a summary of the evaluation results. Detected tree length which represents the true positive rate is 83.1% on average, and is ranked 1st position compared with the other methods. Generally, the airways become thinner toward the distal side. The higher the rate becomes, the more distal airways have been extracted. Two examples are shown in Figure 3 and 4, our method detected many more peripheral airways than the others [7]. On the other hand, the false positive rate is 13.8 %, and is ranked second worst. However, the organizers indicated that the false positive rate had been overestimated compared to the actual performance for two reasons. First, since the reference segmentation data was established by taking the union of correct segmentation results of the participants to EXACT09, new branches detected only by our method were counted as false positives. Second, the segmentation results of our method were a little thicker than the reference segmentation. Unfortunately, boundary regions were counted as false positives. In summary, the method achieved a high detection rate due to the extraction ability of the peripheral airways, with a competitive rate of false positives.

Note that the average processing time per dataset was 57.4 seconds, on a Core i7-2600 3.4 GHz PC with 12 GB RAM.

4. NEW OR BREAKTHROGH WORK TO BE PRESENTED

A novelty of the proposed method is applying machine learning for 3D airway extraction. Since the airway classifier is learned from a large number of training samples, the classifier can discriminate airways despite the wide variety of appearance. In learning a classifier, there is the difficulty that 3D objects have high rotational freedom. We solved it by using orientation and scale information estimated by the Hessian analysis. The classifier can be learned in rotationally invariant, and the detection is computationally efficient.

5. CONCLUSION

In this paper, we proposed a novel airway extraction method based on machine learning and a minimum spanning tree. The experimental results show that the proposed method can extract peripheral airways well. Our proposed method makes it possible to evaluate peripheral airways by Virtual Bronchoscopy.

6. WHETHER THE WORK IS BEING, OR HAS BEEN, SUBMITTED FOR PUBLICATION OR PRESENTATION ELSEWHERE

The work is not being, and has not been submitted for publication or presentation elsewhere.

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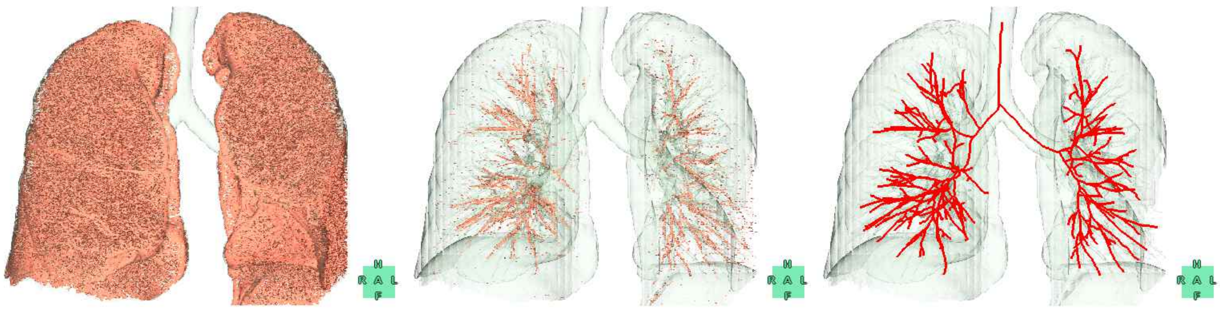

(a) (b) (c)

Figure 1 : Snapshots of each steps of the proposed method, (a) airway candidates obtained by Hessian analysis, (b) airways candidates after false positive reduction, (c) the constructed airway tree by connecting the airway candidates.

Table 1 : Experimental result.

	Branch count	Branch detected (%)	Tree length (cm)	Tree length detected (%)	Leakage volume (mm^3)	False positive rate (%)
Mean	206.7	83.0	184.2	83.1	3930.8	13.79

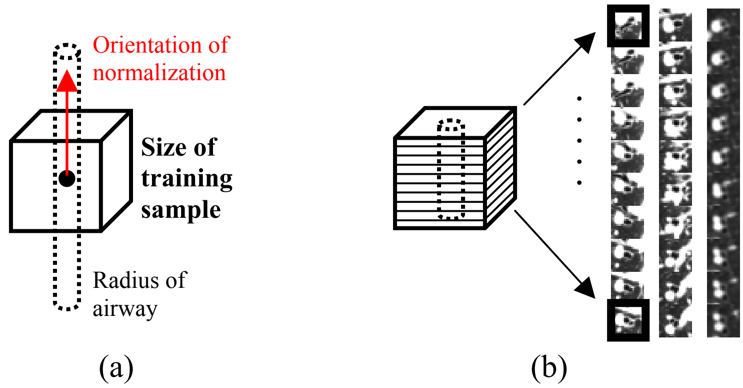

Figure 2 : (a)Normalization method of a training sample. (b)Positive training samples.

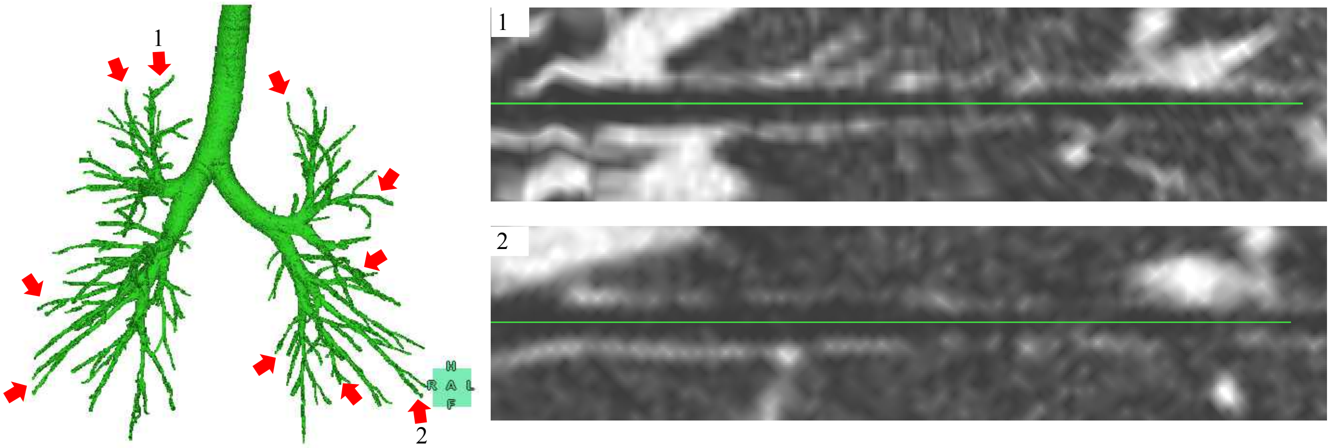

Figure 3 : (LEFT) Extraction results of the CASE 22, (RIGHT) CPR(Curved Planar Reformation) images of the airways indicated by the index numbers. The green line in CPR images shows the centerline of the airway. Compared with the best method presented at EXACT09, branches extracted only by our method are indicated by red arrows. Detected tree length and false positive rate for this case are 89.6% and 6.92%, respectively.

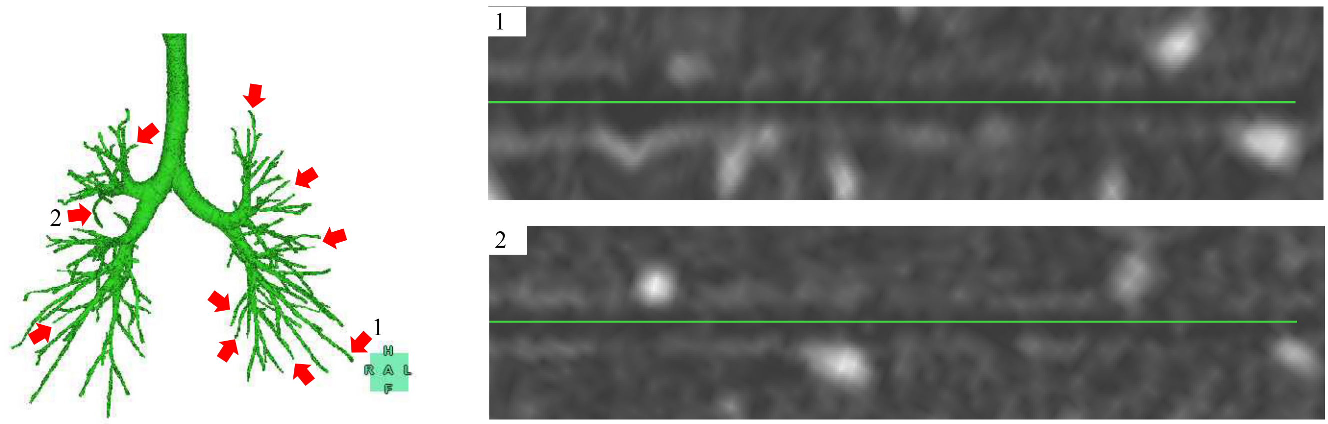

Figure 4 : (LEFT) Extraction results of the CASE 23, (RIGHT) CPR(Curved Planar Reformation) images of the airways indicated by the index numbers. The green line in CPR images shows the centerline of the airway. Compared with the best method presented at EXACT09, branches extracted only by our method are indicated by red arrows. Detected tree length and false positive rate for the case are 91.7% and 8.47%, respectively.