Segmentation of the Airway Tree from Chest CT using Local Volume of Interest

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Abstract. Lung diseases such as COPD and asthma affect airway morphology. Automated segmentation is an essential first step toward the analysis of airways. We propose a fully-automated algorithm to segment the airway tree from chest CT scans. The proposed algorithm requires no manual intervention and uses a 3D region growing based method and allows for accurate detection of leakage by growing regions within a locally-defined envelope. The algorithm is run within a tree segmentation framework which breaks down the problem into the segmentations of individual branches. The method was evaluated using 20 chest CT scans from EXACT09 challenge. The provided scans were taken from the patients with various health conditions. The results show that the algorithm is able to segment the airway tree while keeping the leakage level low, as only 0.11% of the segmentation was classified as false positive and the average number of leakage was less than 1 per patient.

1 Introduction

The physical appearance of human airway tree is affected by lung diseases such as COPD and asthma. Technological advances in volumetric chest CT provide the opportunity to study how airways are affected by a certain disease or respond to a therapeutic treatment. Segmentation of the airway tree structure from a chest CT scan is an essential first step to further studies on airway morphology.

There has been a considerable amount of interest in segmenting airway tree structure from chest CT. The vast majority of the segmentation methods are based on 3D region growing technique. [1–6] This is due to the high contrast between airway lumen with low intensity and airway wall with high intensity. A seed point is identified inside the top-most airway segment (trachea), and the rest of the airway structure is derived from the seed point. A major problem with the growing-based approach is a leakage into the lung parenchyma region which has similar intensity as airway lumen. The airway segmentation is performed as a first step in analysis of the airway segments. The segmentation algorithm was optimized to avoid any leakage since each leakage may cause false measurements.

Although the basic principles of most growing-based algorithms are similar, the algorithms use different approaches to prevent a leak. The algorithm presented in this paper uses two levels of preventive measures to avoid a leak. First, 3D growing itself is carried out conservatively by using strict criteria for growing a voxel. Second, leak that could not be prevented using conservative growing is subsequently detected locally and eliminated.

Since the different papers evaluate the algorithms using different datasets and evaluation metrics, it is difficult to compare different algorithms. The data used in this work is from EXACT09 (http://image.diku.dk/exact/), a segmentation challenge with the goal of comparing the results of various algorithms for extracting the airway tree from chest CT scans using a common dataset and performance evaluation method. [7]

This paper presents the details of our algorithm, provides a description of the data, and the results. In the results section, we report the performance of the presented algorithm with the evaluation metrics used in the challenge.

2 Method

The proposed algorithm has three main stages. First, a seed point is automatically identified from a given CT scan. Then, starting with the trachea using the seed point, individual branches are grown within localized cylindrical volumes. Finally, any detected leaks are removed from the segmentation.

2.1 Pre-processing

The entire CT scan is pre-filtered with 3x3 median filter to reduce noise. Kiraly et al. [5] suggested that the median filter increased the robustness of the segmentation algorithm. However, such filtering may reduce the sensitivity to identify small airway segments.

2.2 Tree Segmentation Framework

The segmentation algorithm was implemented within a framework that discovers the tree structure of the airways for subsequent segment analysis. Within this framework, each individual branch in the airway tree is represented as a node with the pointers to its parent and children, if any.

Each node may be in one of two states, “open” or “closed”. A node is in an open state when it is first created, meaning that the segmentation is not completed for the given branch. When the segmentation is complete (i.e. an end point or a bifurcation point is detected), the current node is closed, and if necessary, the child nodes are newly allocated with open states.

The growing process searches for any open node and performs segmentation on the corresponding branch. The program terminates when there are no more open nodes. Following airway segmentation airway analysis may proceed by measuring parameters of each detected airway segment.

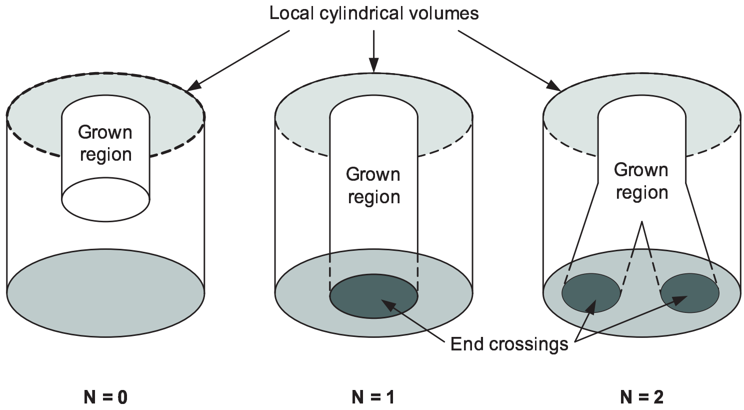

Fig. 1. Illustration of different number of end crossings (N). A view looking up at the cylinders is shown. The number of end crossings determines how the algorithm will proceed in the next iteration.

2.3 Seed Point Detection

The seed point is a point where the growing process starts and is typically located in the trachea. For this work the seed point was automatically identified in each scan from the slice 50 mm below the top-most image. The 50 mm distance was selected to be below the region of the scan where there is high noise but high enough to still be within the trachea.

The search space for a seed point was limited to a rectangular region centered on the slice of interest. The dimension of the rectangle is set to half of the scan size in x and y dimensions. Within the search space, the image is thresholded at -750 HU, and the largest connected component is found. The seed point is estimated by computing the center of mass of this component.

2.4 Local Growing

Each airway branch is grown iteratively by advancing a volume of interest. This idea is similar to the methods proposed in [3, 4]. A volume of interest is initially formed by placing a cylinder toward a given direction. The very first volume of interest is for growing the trachea and is placed on the seed point in a downward direction ($d = <0,0,1>$).

Each voxel is added to the segmentation if all of the following conditions are met:

1. It is connected to the currently grown voxel using 6-connectivity.
2. It has an intensity below a threshold.
3. At least half of its 26 neighbors have intensity below a threshold.

The third criterion is a modification to a typical region growing method and serves as the first level of leakage prevention.

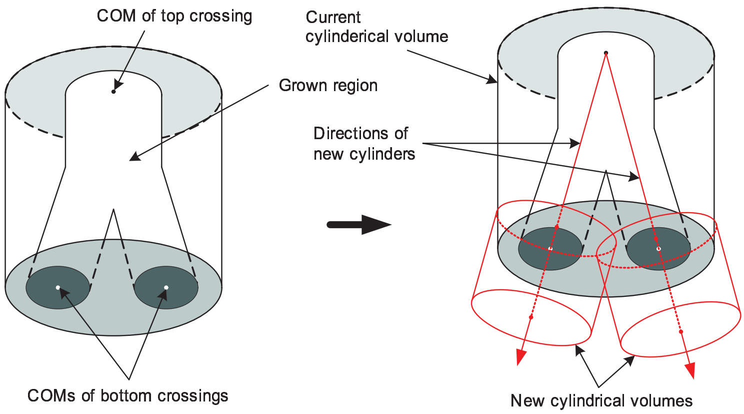

Fig. 2. Illustration of new cylindrical volume construction (N=2). A view looking up at the cylinders is shown. The left figure shows the current cylindrical volume, and the right figure shows both current and new cylindrical volume. The directions of the new cylindrical volumes are determined by connecting the center of masses of crossings.

Once a region is grown within current cylindrical volume, a new volume of interest is established based on how the grown volume crosses the current cylindrical volume. The number of crossings toward the end of the cylinder (N) determines how the growing proceeds. There are three possible categories for values of N as shown in Figure 1:

1. $N = 0$: The current segment has ended, and no children branches will be created.
2. $N = 1$: The current branch has not yet been fully grown.
3. $N > 1$: The current segment has ended, and children branches will be initiated.

When N is greater than 0, one or more new cylindrical volumes need to be constructed. Four parameters are needed to construct a cylinder: a start point, a direction, a diameter, and a length.

Figure 2 shows an illustration of how new cylinders are created for the case of $N = 2$. The direction of the newly constructed cylinder is determined using start and end crossing regions. A vector connecting the centers of masses of the start crossing and the end crossing defines the direction of a new cylinder. The starting point of a new cylinder is offset from the end crossing's center of mass in the opposite direction. This offset is introduced in order to eliminate a gap between two subsequent cylindrical volumes. The offset value is set to 10% of the cylinder's height. The diameter and length parameters were empirically determined using the training data as described in Section 2.6.

2.5 Leak Detection and Threshold Adjustment

Although growing step itself has some degree of leakage prevention, leaks may still occur. Growing airway branches iteratively allows for local detection of a leakage. Using a localized growing algorithm, a leak may be detected more accurately, and it is possible to locate where the leak has occurred.

Two criteria were used for detecting a leak in the current cylindrical volume:

1. If any of the crossing regions has a surface area greater than the α times entire cylinder's surface area. ($0.0 \leq \alpha \leq 1.0$)
2. If the grown volume is increased by β times when compared to the grown region in the previous iteration.

The probability of a leak has a direct relationship to the threshold used for growing. A high threshold makes the airway detection more sensitive but increases the chance of a leak. The optimal threshold value is determined adaptively for each case. The algorithm initially uses the threshold value of -950 HU. The threshold is incremented by 5 HU until a leak is detected. A leak detected in a cylindrical volume is removed from the segmentation output by unsetting all grown voxels within the cylinder.

2.6 Parameter Optimization

Four parameters were optimized with the training data set:

1. diameter of the cylindrical volume
2. length of the cylindrical volume
3. α - leak detection parameter (defined in Section 2.5)
4. β - leak detection parameter (defined in Section 2.5)

The only requirement for cylinder's diameter was that it must be greater than the diameter of airway branch of interest. Based on the training data, the cylinder diameter was set to 40 mm for the very first branch (the trachea) and 30 mm for all other branches. Setting the diameter to any greater value should not affect the outcome of the segmentation.

The length of the cylinder determines how much to advance in each iteration of growing. A short length means that the growing is constrained to smaller local space and is preferred since it would allow for localized detection of leakage. However, the length should be proportional to the diameter of the airway for robust placement of new cylindrical volumes. For this work, cylinder height was varied depending on branch generation. The empirically determined cylinder length based on the segmentation outcome for the training data were 20 mm for the trachea (1st generation), 17.5 mm for the main bronchi (2nd generation), 15 mm for the 3rd generation bronchi, and 10 mm for the branches with higher generations.

The values of α and β have effect on the performance of the leak detection. Smaller α and β values would mean that the leak will be detected with higher sensitivity. Based on close observation of the leakages in the training data, α and β were set to 0.5 and 4.0, respectively.

2.7 Post-processing

Once the growing process is complete (i.e. there are no open nodes), the outcome is further processed to obtain the final segmentation. The main purpose of this step is to correct any artifacts and voids that may exist due to noise present in the CT scan. First, a 3D morphological closing operation is performed on the grown binary image with a 3x3x3 spherical kernel. Then, any voids enclosed within the segmentation are filled.

3 Data

The dataset for the experiment included two sets of 20 chest CT scans provided for EXACT09 challenge. The scans were acquired at different sites using different scanners and parameters. The scans were taken from healthy volunteers as well as the patients with mild to severe lung disease and taken at various degree of inspiration and expiration. The radiation dose of the scans ranged from clinical dose to low dose.

The first 20 scans were used as a training set, and the algorithm parameters were optimized using these scans. The second set of 20 scans were used as a test set to evaluate the algorithm.

4 Results

The algorithm's performance using the evaluation metrics defined by EXACT09 challenge is shown in Table 1. The ground truth was defined as the union of all valid airway segments from all segmentations submitted to the challenge [7]. On average, the algorithm successfully segmented 81 branches (32.8% of the ground truth segmentation) with the false positive rate of 0.11%.

5 Discussion

A fully automated method for segmenting airway tree has been presented. Once an optimal threshold was found for a given case, the algorithm took less than 30 seconds to process a CT scan on a workstation with Intel Xeon 3.00 GHz CPU.

The proposed method performs segmentation in a conservative manner to prevent leakage into the lung parenchyma. When conservative growing fails to avoid a leak, the second level of leakage prevention is carried out using a local leak detector. Figure 3 shows an example of leak detection and elimination.

The algorithm was able to segment 79 airway branches for each scan on average, which corresponds to approximately the 6th to 7th branch generations. The number of successfully segmented branches corresponded to approximately one third of the number of branches in the ground truth. While the proposed algorithm may exhibit a low sensitivity, the false positive rate was very low (0.11%). It should also be noted that the number of leakages was less than 1 per scan on average.

Table 1. Evaluation measures for the twenty cases in the test set.

	Branch count	Branch detected (%)	Tree length (cm)	Tree length detected (%)	Leakage count	Leakage volume (mm^3)	False positive rate (%)
CASE21	76	38.2	43.6	39.5	0	0.0	0.00
CASE22	175	45.2	131.4	39.7	4	155.2	1.09
CASE23	152	53.5	106.8	41.0	2	26.8	0.22
CASE24	53	28.5	46.7	28.7	0	0.0	0.00
CASE25	75	32.1	58.2	23.1	0	0.0	0.00
CASE26	31	38.8	20.9	31.8	0	0.0	0.00
CASE27	33	32.7	23.9	29.5	0	0.0	0.00
CASE28	41	33.3	30.3	27.6	0	0.0	0.00
CASE29	60	32.6	36.5	26.4	0	0.0	0.00
CASE30	43	22.1	28.9	18.9	0	0.0	0.00
CASE31	59	27.6	40.6	23.1	0	0.0	0.00
CASE32	72	30.9	50.5	23.2	1	60.4	0.61
CASE33	62	36.9	44.5	30.3	0	0.0	0.00
CASE34	221	48.3	150.0	42.0	0	0.0	0.00
CASE35	99	28.8	66.5	21.5	1	42.9	0.36
CASE36	44	12.1	39.8	9.7	0	0.0	0.00
CASE37	48	25.9	40.9	23.0	0	0.0	0.00
CASE38	34	34.7	26.6	40.1	0	0.0	0.00
CASE39	110	21.2	88.1	21.5	0	0.0	0.00
CASE40	98	25.2	80.9	20.9	0	0.0	0.00
Mean	79.3	32.4	57.8	28.1	0.4	14.3	0.11
Std. dev.	51.1	9.6	36.2	8.8	1.0	37.2	0.28
Min	31	12.1	20.9	9.7	0	0.0	0.00
1st quartile	43	25.9	30.3	21.5	0	0.0	0.00
Median	61	32.3	44.1	27.0	0	0.0	0.00
3rd quartile	110	38.8	88.1	39.7	1	26.8	0.22
Max	221	53.5	150.0	42.0	4	155.2	1.09

The low leakage level was achieved by using a conservative segmentation approach. The algorithm parameters were chosen to prevent the leak as much as possible. By varying the parameters α, β, and threshold, we expect that the algorithm would achieve a higher sensitivity at the cost of increasing false positive rate (or level of leakage).

6 Conclusion

A fully-automated algorithm for segmenting airway tree from a chest CT scan has been developed and was evaluated using the data and performance metrics provided by EXACT09 challenge. The presented method segmented one third of the branches in the ground truth and exhibited an average leakage count of less than one per case.

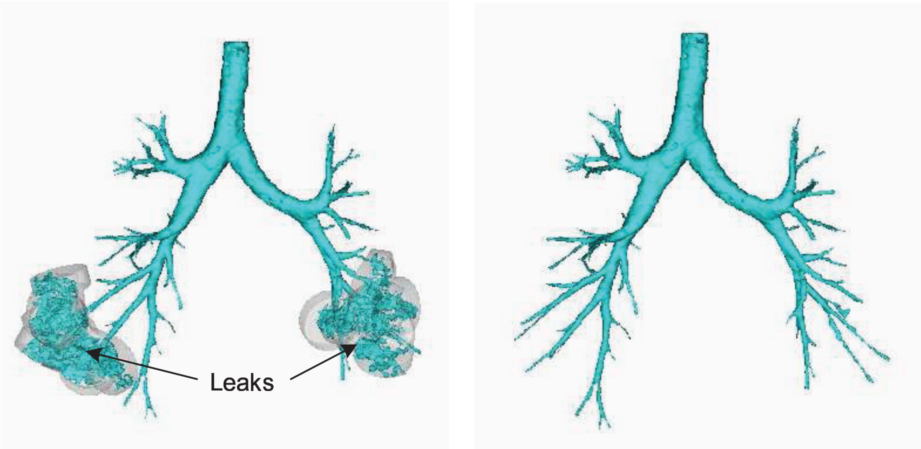

Fig. 3. An example of leak handling (CASE23). The visualization on the left shows the segmented airway with the transparent cylindrical volumes in which the leaks were detected. The right image is the visualization of the final segmentation after elimination of the detected leaks.

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