

8—13

A Fully Automatic Segmentation Method for Virtual Bronchoscopy

Kyobum Ku Dongsung Kim *

Jonghyo Kim †

School of Electronic Eng.
Soongsil Univ.

Department of Diagnostic Radiology
Seoul National Univ.

Abstract

This paper presents a fully automatic segmentation method for the virtual bronchoscopy, which requires the segmentation of a trachea and left/right bronchi. A trachea region is automatically detected, based on medical knowledge and DICOM header information, and its center point is selected as a seed point for the slice-based 3D Seeded Region Growing (SRG). The slice-based 3D SRG grows a region by collecting its homogeneous neighbors in a single slice, and makes seed points at adjacent slices. The seed points grow at their own slices, recursively. While growing, a region size constraint between adjacent slices is preserved to prevent from leakage problem of conventional SRG methods. The slice-based 3D SRG can segment a complex tubular shaped organ whose center axis can be represented by a high order curve. Segmentation results are presented using CT slice image data sets.

1 Introduction

Bronchoscopy is a medical diagnostic examination of the major air passages of the lungs. Since bronchoscopy requires insertion of a bronchoscope, which is a flexible tube about the width of a pencil, through patient's nose or mouth, it is very painful for a patient. For this reason, a virtual bronchoscopy is performed with CT slice images. A trachea and left/right bronchi are segmented, and the results are visualized. In order to use virtual bronchoscopy as a routine diagnosis tool, it is necessary to develop a fully automatic segmentation method.

Medical image segmentation methods can be divided into three major categories: thresholding methods, boundary based methods, and region based methods. The thresholding methods are simple and efficient to segment high contrast organs such as trachea [1], but have difficulties in separating a bronchus and a lung because they are homoge-

neous and connected to each other, inherently. They should accompany manually editing the connected volumes. For boundary based method, segmentation methods based on 2D/3D deformable models have received much attention in segmentation of human organs, and produced good results for organs with noisy boundary [2]. Robustness to the noise may give difficulties in recovering severely protrusive boundary [3], which may be overcome by incorporating shape prior [4]. In general, incorporating shape prior to bronchi segmentation is difficult, because shape variation of bronchi branches among the patients are very large.

Finally, for the region based methods, level set approaches have been used to segment organs with a complex shape such as brain [3]. Shape prior was also introduced to attack the leakage problem of the level set [5], which is not suitable for segmentation of a bronchus whose shape variation is large. The conventional SRG may be used to segment bronchi [6], but suffers leakage problem due to connection between a bronchus and a lung.

Although many previous methods might be modified for fully automatic segmentation, we could not find any method claimed fully automatic segmentation for this particular virtual bronchoscopy.

This paper proposes a fully automatic segmentation method for virtual bronchoscopy. The proposed method performs in two steps: automatic seed selection and the slice-based 3D SRG. For the seed selection, a trachea is found in a slice image using medical knowledge and DICOM header information, and its center position is selected as a seed point.

The slice-based 3D SRG grows a region slice by slice. A seed grows only in its own slice, and makes a region disc. The region disc generates seeds for adjacent upper/ lower slices. These processes are repeated until seeds are exhausted. While region growing, size constraint between adjacent slices is preserved to overcome the leakage problem.

Section 2 describes automatic seed selection. Section 3 explains the slice based SRG. Section 4 provides results of the segmentation method. Finally, Section 5 concludes the paper.

Address: 1, Sangdo-Dong, Dongjak-Ku, Seoul, 156-743, Korea
E-mail: dongsung@saint.soongsil.ac.kr
Address: 28, Yeongun-Dong, Jongno-Gu, Seoul, Korea

2 Automatic Seed Selection

The proposed method is designed for routine diagnosis of the virtual bronchoscopy in a hospital, where images are acquired and stored by PACS(Picture Archiving and Communication System). For this, the method needs to read DICOM(Digital Imaging and Communications in Medicine) data that is a standard format for PACS images. The DICOM data consists of an image data and a header. The header contains information about patient and image acquisition, which are used for automatic seed selection.

Image data set is initially sorted to have descending order from neck to abdomen. An image data filename has a sequence number, however the number is not necessarily coincident with actual order. Increasing sequence number represents descending order in an image data set while ascending order in another data set. Sometimes, the sequence number of the file name is given irregularly. All files are sorted to have correct descending order using the DICOM header information.

The DICOM header information is also used to compute actual size of a region. Each image data set can have different scale in acquiring images, so the area of a trachea varies for different image sets. The scaling effect can be resolved by computing actual size from DICOM header information. The actual size information is provided for automatic seed selection.

A seed point is selected as a center position of a trachea. A trachea is detected in the two steps: body detection and trachea detection. At the first step, the largest object is selected by thresholding an image. A pixel whose value is greater than the threshold becomes foreground. Otherwise, it becomes background. Among the foreground pixels, the largest connected component is selected as a body. At the second step, a trachea is detected inside the detected body by selecting air filled objects whose sizes and locations are met with trachea constraints. The air filled objects whose center of mass is located in near the center of a body are selected as trachea candidates. Among them, a candidate whose actual size is within a trachea range is detected as a trachea. If there are more than one candidate, the current slice is discarded and the next one is processed to avoid false detection of a trachea.

Figure 1 illustrates automatic seed selection. The detected trachea is marked as gray and its seed point is represented as a white cross.

3 Slice-based 3D SRG

The slice-based 3D SRG consists of two modules: a 2D SRG and seed generation for adjacent slices.

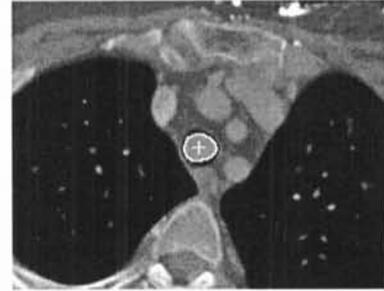


Figure 1: Automatic Seed Selection

The 2D SRG grows a region in a slice. Adjacent neighbors only in the work slice are collected as the same region if they are homogeneous. The homogeneity is verified with gray level difference. The details of the 2D SRG can be found in [6]. For seed generation, a region disc is introduced to represent a segmented region in a slice. From the region disc, seed points for adjacent upper/lower slices are generated.

3.1 Seed generation

A region disc needs to generate seed points for upper/lower slices. An initial seed point is not necessarily selected at the top slice of the trachea. When it is selected at a mid slice, it should grow to both upper and lower slices. Moreover, a bronchus branch could be bent like a hook, or forked to both upper and lower slices. In such cases, the seed generation in both upper and lower slices are also required.

A region disc is able to make multiple seed points in an adjacent slice. A single branch can be forked to several branches at an adjacent slice. All forked branches should have their own seeds to follow. That is, disconnected regions at an adjacent slice need to be classified.

Seed generation module is composed of the following two steps. At the first step, homogeneous pixels are found in an adjacent slice from a region disc. A region disc initially masks an area in its adjacent slice. Among the masked area, homogeneous pixels are found. At the second step, seed points are selected for all connected components of the homogeneous pixels. Homogeneous pixels are grouped into connected components, and their representative points are selected as seed points. Computing of connected components requires two scans of an image [1]: one for labeling, the other for substituting equivalent labels. Finding the seed point for each connected component may require another scan. The one scan algorithm is developed for efficient computation, which finds both connected components and seed points in a single scan.

The one scan algorithm makes a point as a seed

point if its upper and left pixels are not homogeneous, and gives new label for the pixel. If either of upper/left pixels is homogeneous, a label for the homogeneous pixel is given to the current pixel. When both upper/left pixels are homogeneous, their label may be different. For the case of the same label, the label is given to the current pixel. For the case of different labels, higher label is given to the current pixel. In addition, the seed point for lower label is deleted to keep a single seed for a single connected component. Figure 2 illustrates the one scan algorithm. Scan starts from A0 pixel, and moves right and bottom direction. C1 pixel is labeled as 1, and is stored as a seed point. D1 is labeled as 1 because of a homogeneous neighbor. B2 pixel is labeled as 2, and is stored as new seed point. Because C2 has left and upper homogeneous pixels whose labels are different, C2 is labeled as higher label. In addition, seed point for the label 1 is deleted. Thus, a single seed point for a connected component is preserved.

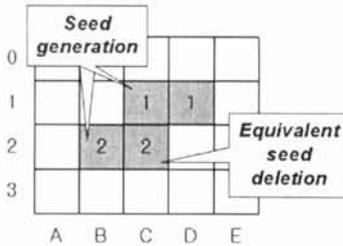


Figure 2: One Scan Algorithm

3.2 Leakage prevention

A bronchus is connected to a lung, which causes leakage problem in segmentation. The leakage can be overcome with the constraint of bronchus area change between image slices. When leakage occurs at a slice, the area of the slice is much larger than that of its adjacent slice. Leakage is detected when size of areas changes abruptly between adjacent slices. Once leakage is detected, an area is conservatively segmented as a bronchus. A region disc of an adjacent slice is ANDed with the current leaked region. Only the common area is segmented as a correct region. Because such common area has low confidence, a segmented region at its adjacent slice would have lower confidence if it leaks again. If leakages occur in several consecutive slices, no further seed generation is performed with the low confidence region not to make false segmentation. If the leakage stops at a slice, the segmented region gets back to full confidence.

Figure 3 shows an image slice and its segmented results. In the image, the bronchi are connected to the lung. The segmentation results successfully

contain bronchi without leakage, although region boundary has some errors due to AND operation with the region disc of the adjacent slice.

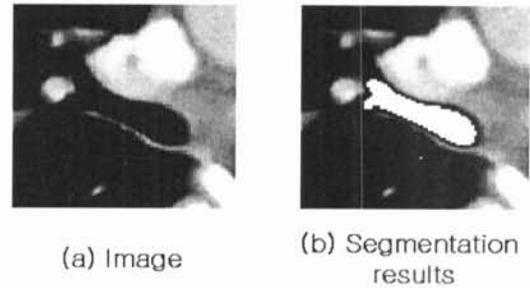


Figure 3: Leakage Detection

3.3 Algorithm of Slice-based 3D SRG

The slice-based 3D SRG grows its volume like an exhaustive searching algorithm. From a seed, it grows a region with the 2D SRG. The grown region generates seed points if it is valid. These steps are repeated until no more seed is available. Such an exhaustive approach enables the algorithm to segment a complex tubular shape whose center axis is represented by a high order curve. Because a seed is fetched from a stored data structure such as a queue, it needs to keep all necessary information for region growing and leakage prevention. The information is kept in a seed class composed of seed point, slice number, size of parent region, and leakage depth. The seed point and its slice number are required for region growing while the others are for leakage prevention.

The slice-based 3D SRG algorithm is described in Figure 4. The initial seed point is input from the automatic seed detection module. The seed point is enqueued as a seed object. A seed object is dequeued to find a 2D region. The 2D region generates seed objects if it is valid. The validity is computed from confidence value of the region described in Section 3.2. These processes stop when the queue is empty.

4 Results

The proposed method has tested with bronchoscopy CT image data sets acquired from Seoul National University Hospital. The CT image has size of 512×512 , and has gray values from -1024 to 3071. A trachea and bronchi are segmented by the proposed method, and visualized by a volume rendering tool developed by the 3D-Med specialized in medical image visualization.

Figure 5 shows automatic segmentation results from 70 image slices with 2mm thickness. 3D volume is reconstructed by volume rendering method

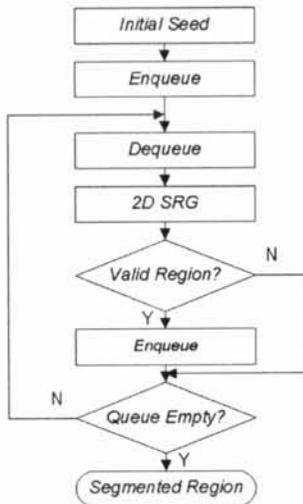


Figure 4: Algorithm of the Slice-based 3D SRG

with linear interpolation of the slice-based 3D segmentation results. Left and right bronchi as well as a trachea are successfully extracted without leakage. Small branches in bronchi are also segmented. The computation time took 1.7 seconds on a Pentium III 550 PC. Optimization will speed up the algorithm.

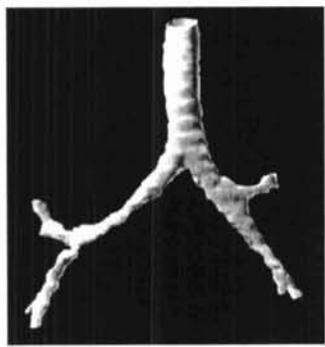


Figure 5: 3D of Segmentation Results

Figure 6 illustrates segmentation results of a image set consisting of 85 image slices with 1mm thickness. Bronchus of this data has abnormally narrow volume in the right bronchus, where a stencil is inserted by an operation. The whole bronchus is successfully segmented. The computation time took 2.0 seconds on a Pentium III 550 PC.

5 Conclusions

A fully automatic segmentation method is developed for virtual bronchoscopy. A seed point in a trachea region is detected using medical knowledge and the DICOM header information. Then, a volume is grown from the seed with the slice-based 3D SRG that can overcome leakage problem of the conven-

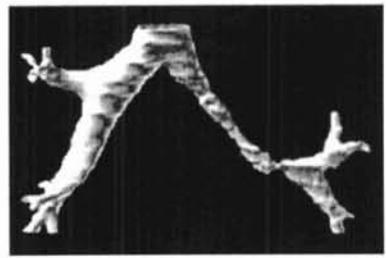


Figure 6: Results for an abnormal bronchus

tional SRG with the constraint of region area change between adjacent slices. The slice-based 3D SRG can segment a complex tubular shaped organ whose center axis can be represented by a high order curve, and can follow all branches at a junction in an organ. The method is also applicable to other tubular organs such as angiography blood vessels if automatic seed selection is modified. Future research will focus on recovering correct region boundary where a leakage occurs.

Acknowledgments

This work was supported by a grant(#HMP-98-G-1-011) of the 1998 Highly Advanced National Projects on the Development of Biomedical Engineering and Technology

References

- [1] R.C. Gonzalez and R.E. Woods, "Digital Image Processing," Addison Wesley, 1993
- [2] L.D. Cohen and I. Cohen, "Finite Element Methods for Active Contour Models and Balloons for 2D and 3D Images," *IEEE Trans. on the Pattern Analysis and Machine Intelligence*, vol .15, no. 11, pp. 1131-1147, Nov. 1993
- [3] R. Malladi, J.A. Sethian, and B.C. Vemuri, "Shape Modeling with Front Propagation: A Level Set Approach," *IEEE Trans. on the Pattern Analysis and Machine Intelligence*, vol .17, no. 2, pp. 158-175, Feb. 1995
- [4] L.H. Staib and J.S. Duncan, "Model-Based Deformable Surface Finding for Medical Images," *IEEE Trans. Medical Imaging*, vol. 78, no. 5, pp. 720-731, Oct. 1996
- [5] M.E. Leventon, W.E.L. Grimson, and O. Faugeras, "Statistical shape Influence in Geodesic Active Contours," *Proc. Computer Vision and Pattern Recognition(CVPR)* pp. 316-323, 2000
- [6] R. Adams and L. Bischof, "Seeded Region Growing," *IEEE Trans. on the Pattern Analysis and Machine Intelligence* , pp. 641-647, vol. 16, no.6, June 1994