Reliable Airway Tree Segmentation Based on Hole Closing in Bronchial Walls

Michał Postolski[12], Marcin Janaszewski[12], Anna Fabijańska[1], Laurent Babout[1], Michel Couprie[3], Mariusz Jędrzejczyk[4], and Ludomir Stefańczyk[4]

[1] Computer Engineering Department,Technical University of Łódź, Stefanowskiego 18/22, 90-924 Łódź, Poland
mpostol,janasz,an_fab,lbabout@kis.p.lodz.pl
[2] Department of Expert System and Artificial Intelligence, The College of Computer Science in Łódź, Rzgowska 17a, 93-008 Łódź, Poland
[3] Université Paris Est, LABINFO-IGM, A2SI-ESIEE 2, boulevard Blaise Pascal, Cité DESCARTES BP 99 93162 Noisy le Grand CEDEX, France
coupriem@esiee.fr
[4] Department of Radiology and Diagnostic Imaging, Medical University of Lodz, S. Żeromskiego 113, 90-710 Łódź, Poland
mariusz82@gmail.com, stefanczyk_l@wp.pl

Summary. Reliable segmentation of a human airway tree from volumetric computer tomography (CT) data sets is the most important step for further analysis in many clinical applications such as diagnosis of bronchial tree pathologies. In this paper the original airway segmentation algorithm based on discrete topology and geometry is presented. The proposed method is fully automated, reliable and takes advantage of well defined mathematical notions. Holes occur in bronchial walls due to many reasons, for example they are results of noise, image reconstruction artifacts, movement artifacts (heart beat) or partial volume effect (PVE). Holes are common problem in previously proposed methods because in some areas they can cause the segmentation algorithms to leak into surrounding parenchyma parts of a lung. The novelty of the approach consists in the application of a dedicated hole closing algorithm which closes all disturbing holes in a bronchial tree. Having all holes closed the fast region growing algorithm can be applied to make the final segmentation. The proposed method was applied to ten cases of 3D chest CT images. The experimental results showed that the method is reliable, works well in all cases and generate good quality and accurate results.

1 Introduction

Modern medical computer tomography which uses multidetector spiral CT scanners can produce three-dimensional volumetric images of very high quality and allows to look into inside of a human body. This is a very powerful and useful technique being used in a variety of medical application.

3D volumetric scans of human organs provide an excellent basis for virtual colonoscopy (VC) [1], virtual angioscopy (VA) [2], virtual bronchoscopy application (VB) [3], surgical planning [4] or quantification of anatomical structures [5]. In all presented applications accurate and reliable segmentation is the first and crucial step. However proper segmentation of many human organs, for example an airway tree, is very difficult and is a challenging problem because of the complex anatomy and the limitations in image quality or errors in image acquisition.

Airway tree segmentation algorithms operate on a CT chest image represented by a large 3D array of points with associated values. Each point is represented as a quadruple (x, y, z, v) where the first three values represent it's spatial location in 3D space. The last element v represents attenuation coefficient of a small portion of the tested object with the centre in (x, y, z) and is measured with Hounsfield units (HU). In well calibrated CT images points which represent an interior of an airway tree should be at approximately -1000HU (air) surrounded by walls which points having relatively high value at approximately -100 to 200HU (soft tissues). Unfortunately, this situation is very rare in real applications. Noise, image reconstruction artifacts, movement artifacts (heart beat), non standard patient anatomy, airway obstruction or partial volume effect (PVE) significant decrease the difference between HU for bronchial wall points and points which represent surrounded air. Therefore, values of airway wall points at different bronchial parts can present different intensity values and can be similar to values of interior points of a tree, in particular for high order branches. In addition, different reconstruction kernels (smooth kernels) can increase this effect. As a result small holes in a wall structure appear and high order segments of a tree disappear which cause leakages of segmentation algorithms in surrounding parenchyma parts of a lung (see Fig. 1). Leakage is a main problem in segmentation of airway tree. A lung has very similar texture to the small airways, which leads to a failure of simple segmentation algorithms like region growing [6] and the user has to adjust the algorithm parameters manually for each image separately. However, manual adjustment is impractical and not reliable because it is very hard or, in some cases, even impossible to find suitable parameters.

Previous work on airway segmentation can be divided into five groups: region growing based methods [7][8][9], mathematical morphology based methods [10][11], and combination of the two [12], rule based methods [13] and energy function minimalization [14]. However previously published methods focus on how to detect and eliminate leakages when they occur or how to avoid them using complex rules. Some of these algorithms must be run several times with different parameters, another ones analyse very large sets of points using complicated nonlinear filters or semantic rules.

In this paper we propose a new segmentation algorithm based on 3D hole closing in bronchial walls. The presented method eliminates the leakage problem by closing all holes in an airway tree wall and then performs the standard

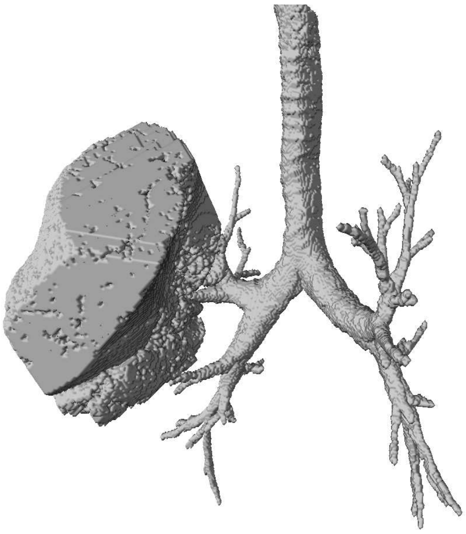

Fig. 1. Example of a severe segmentation leak. Result of segmentation with the standard region growing algorithm.

region growing algorithm. Thanks to the 3D hole closing algorithm (HCA) [15] the method is simple, reliable and based on well defined mathematical notions like simple points, square Euclidean distance and a hole defined on the basis of discrete topology. Moreover the method is fast and fully automated.

This paper is organized as follows. In section 2 the proposed method is explained in detail. Section 3 describes our experimental results. Discussion and summary are given in section 4.

2 Methodology

2.1 Histogram analysis and preliminary wall extraction

The first, important step in presented segmentation method is airway wall extraction (see Fig. 2). After histogram analysis of ten CT scans we can distinguish three intensity ranges with are of great importance from the bronchial tree segmentation point of view (see Fig. 3). The first one represents air voxels, the second one corresponds to voxels of internal border of bronchial walls and the last one represents soft tissue and blood voxels. Bronchial walls belongs to soft tissue range. However, differences in wall pixel intensities and wall thickness, at low and high level of an airway tree and common occurrence of other soft tissues, make very difficult to extract walls directly from borders of the range as threshold parameters. Fortunately, in our application, we do not need to segment walls, instead the algorithm extracts only internal border of bronchial walls which is enough to perform a hole closing procedure. The lower threshold value for this purpose is approximately situated on the border between air voxels range and internal border of bronchial walls. The higher threshold value is approximately situated between the range which represents internal border of bronchial walls and soft tissue range. Using this values, which can be easily and automatically selected, the algorithm can extract internal border of the walls on different levels of an airway tree. Moreover, small number of points in this range leads to a "clear" output image (without unnecessary soft tissues).

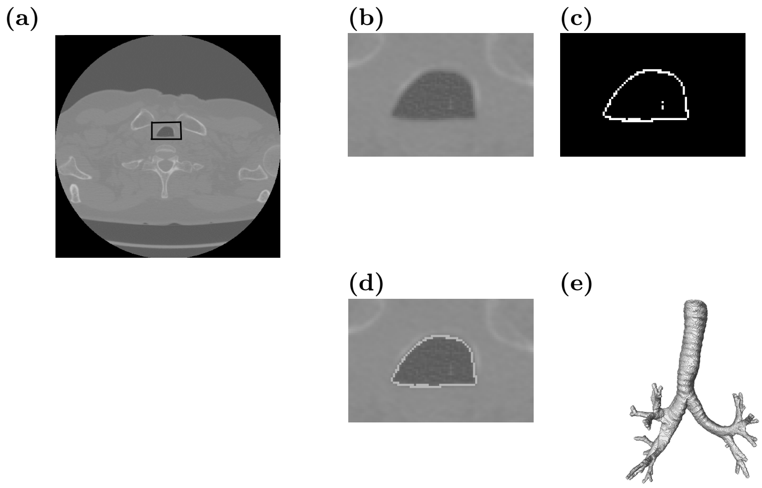

Fig. 2. Airway tree segmentation: a) One 2D slice obtained from a 3D CT data set b) zoomed fragment of the airway tree c) extracted airway walls d) an input image merged with the (c) image e) Example of a final segmentation result.

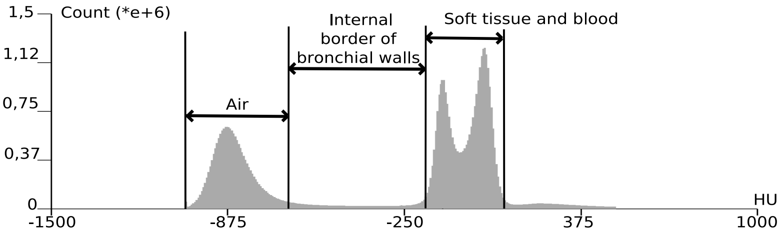

Fig. 3. A typical histogram generated from a 3D chest image. Marked ranges (air, internal part of bronchial walls, soft tissue and blood) have been determined based on histogram analysis from ten lung scans with different airway pathologies.

2.2 3D hole closing in airway walls

3D hole closing algorithm [15] is linear in time and space complexity. Because of a space limitation we can not present the algorithm with all mathematical details. Interested readers can refer to [15] for more details. The short presentation of the algorithm might be as follows: first it computes a bounding box Y which has no cavities and no holes and which contains the input object X. Then it iteratively deletes points of $Y \setminus X$ which are border and which deletion does not create any hole in $Y \setminus X$. The deletion process is ordered by a priority function which is defined as the Euclidean distance from X. The algorithm repeats this deletion of points until stability. An example of the algorithm results when applied to a torus is presented in Fig. 4.

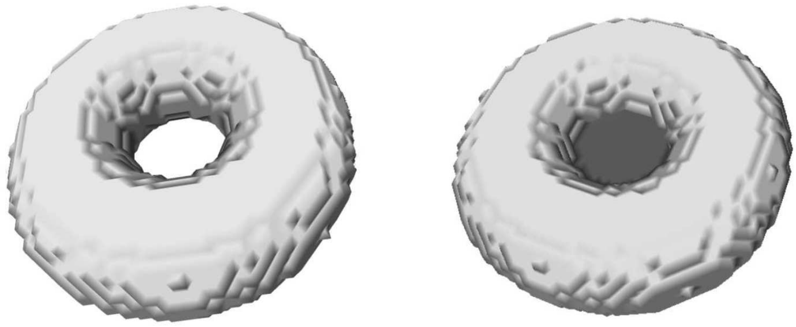

Fig. 4. An example result of hole closing applied to a torus object. The hole closing volume is represented in dark grey colour.

2.3 Merging and final segmentation

On the last step, the algorithm combines the binary image B, produced in previous step, with an input data set A. The algorithm sets intensity of a voxel from image A to a priori defined maximal possible HU value H_{max}, only if the corresponding voxel from the image B has value 1. Then the standard region growing algorithm (RGA) is applied to produce the final segmentation result. The RGA needs two parameters: the first represents a threshold value which constrains the growth process, the second one corresponds to a starting point which is called the seed. The first parameter is set to the H_{max} value and the seed can be selected manually or automatically using, for example, a simple method proposed in [16].

3 Results

The proposed method has been applied to test the segmentation of ten chest CT images acquired using GE LightSpeed VCT multidetector CT scanner. The set of stack images is of size 512x512 and voxel dimentions are: $x = y = 0.527$ mm, $z = 0.625$ mm. All tests were performed on standard PC platform computer (CPU: INTEL 2Ghz). Fig. 5 shows the comparison between the proposed method and standard region growing approach on the same set of images.

The experimental results showed that presented method works well in all tested cases. The leakage problem is fully eliminated and results are of much better quality than for simple region growing approach. The numbers of extracted branches by the proposed method and region growing method with optimal parameters selected manually are presented in table 1. It occurs that for all tested cases our algorithm gives better results than RGA. Moreover, for the first two cases (3D images of healthy patients with well defined airway tree) almost 100% of the branches are extracted up to 5th order of a bronchi using the proposed method. The superiority of our approach is also clearly visible for the next two cases (case 3 and 4 in Fig. 5) which corresponds to unhealthy patients. The presented method extracted 100% branches up to 4th level in both cases, while RGA extracted only 37% or finished with a severe leak (bottom image of case 4 in Fig. 5). The computation time for these two algorithms has been also evaluated. The proposed algorithm is much slower than RGA but it's runtime does not exceed several minutes per volume, and

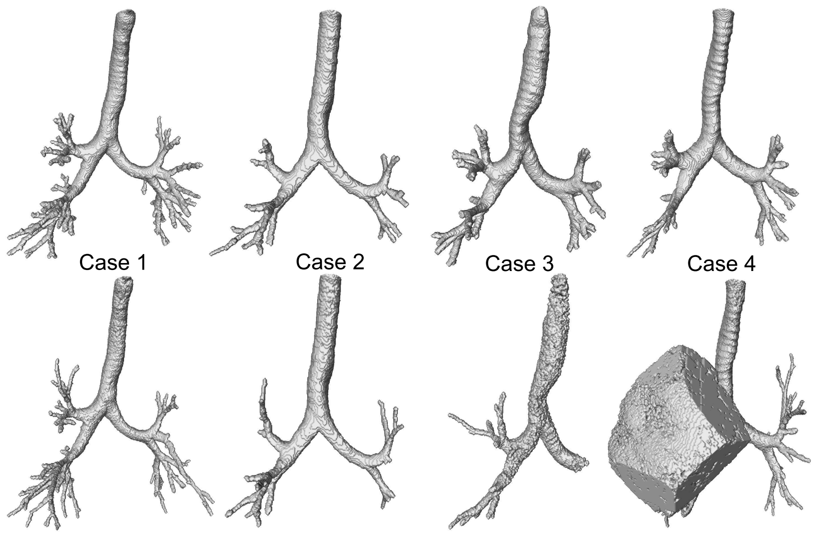

Fig. 5. 3D visualization of segmentation results. Upper row - proposed method, lower row - the region growing procedure [6].

it is faster than previously presented approaches e.g. [16][17]. It is worth mentioning that the presented segmentation method is optimal (linear complexity) because it is only based on linear complexity algorithms. Compared to other methods like the one proposed in [16][17], our method resolves less orders of the bronchi. However, it has been found that these approaches are not optimal as well, and the complexity of their algorithm makes it difficult to estimate their respective time complexity.

Table 1. Fraction (in %) of extracted branches at different levels of the airway tree. Results obtained using the proposed method (HC) and region growing method (RG) with manually selected optimal parameters.

	case 1		case 2		case 3		case 4	
	HC	RG	HC	RG	HC	RG	HC	RG
2nd level[%]:	100	100	100	100	100	50	100	-
3rd level[%]:	100	100	100	62,5	100	50	100	-
4th level [%]:	100	87,5	68,7	25	100	37,5	100	-
5th level[%]:	93,7	62,5	12,5	0	68,7	6,2	62,5	-
Working time[sec]:	360	4,5	270	3	340	3	340	8

4 Conclusions

The authors has presented a bronchial tree segmentation algorithm which is flexible, fast (runtime, for a PC, does not exceed several minutes per volume), efficient and based on well defined mathematical notions. Firstly, the algorithm eliminates sources of leaks using HCA, and secondly performs a very fast region growing procedure. By doing so, the approach is, for the authors point of view, the simplest among all well known solutions, published so far. Moreover the algorithm is fully automated. The set of measurements carried out to estimate the efficiency of the proposed approach have shown that the algorithm is reliable as it produces accurate segmentation results from all the tested cases. It should be emphasise that, from the medical point of view, the results are good enough to become an input for quantitative analysis which, in turn, is considered to be a baseline for an objective medical diagnosis. Although the presented algorithm does not segment as many tree segments as the best published algorithms [16][17], it is far more easier to implement and is less time consuming. Moreover it is possible to obtain better results with simple improvements on which we are working on. Taking into account all above considerations, it is worth emphasising that the main goal of the work - construction of a simple and fast algorithm of bronchial tree segmentation which gives good enough results for clinical applications - has been achieved.

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