EFFICIENT APPROACHES TO INTRATHORACIC AIRWAY TREE SEGMENTATIONS

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Abstract

In this paper, an improved method for intrathoracic airway tree segmentation is proposed. We present efficiency and robustness enhancements to a segmentation procedure previously proposed by Tschirren et al. IEEE TMI, 24(12), 2005. Their method is reviewed and our approach is described. Our method is demonstrated on experimental CT data. Finally, we give some concluding remarks and discuss future implementations.

1 Introduction

Airway Tree segmentation is the process of identifying and extracting from medical images the structures of the respiratory system that lead the air into the lungs. The intrathoracic airway tree is also called the lower airway tree and encompasses the trachea, bronchi and bronchioles. With the result of the segmentation, physicists and practitioners can make measurements, search for abnormalities and generally be assisted in diagnosing diseases in the respiratory system. Due to the natural complexity of the airway structure, however, its segmentation is a very difficult task.

The primary aims of this work are computational fluid dynamics (CFD) applications that try to numerically model the airflow properties of patients [8-10]. The 3D model obtained from the segmentation is used as geometric domain for finite element algorithms that solve the governing airflow equations (Navier-Stokes) [6, 7]. Using patient specific image segmentation and numerical boundary conditions, this process helps understanding the flow properties and medication efficacy for each of them. In the latter case, pre- and post-medication patients are submitted to CT scans and the process indicates if inhaled medication is reaching the expected regions of the lungs, according to that individual's airflow model. The precision required by the correct numeric modelling of the airflow demands very accurate segmentation results.

2 Methods

In this section we present possible ways of achieving the desired segmentation results. We also briefly review the previously proposed algorithm [1] and propose new techniques to increase its robustness and efficiency.

2.1 Semi-automatic Segmentation

Semi-automatic segmentation of the airway tree can be achieved with the use of region growing algorithms [2-5]. In this process, the user provides a seed pixel inside the airway structure. From this point, a region is grown by the recursive aggregation of pixels that pass a certain test of similarity. Common similarity tests check differences in intensity between neighbour pixels. Assuming that the image to be segmented is represented as a 3D grid, neighbour pixels are usually defined as those sharing a vertex, an edge or a face.

One common problem of region growing algorithms is leakage: if the walls of the desired structure are not clear at a certain step of the segmentation, points outside the structure can pass the test of similarity and eventually be incorrectly aggregated to the growing region. The results in this case can be catastrophic and useless for the desired applications. In the case of the airway tree segmentation, a thin wall separates the structure from the air inside the lungs. Since both have similar pixel intensities, the entire lung can be aggregated to the region. User intervention is required in this case to detect the leakage point, remove the leak, close the wall and restart the segmentation, possibly adding more seed points. Another specific problem of airway tree segmentation is the early collapse of branches. A much more time consuming user intervention is needed in this situation, to detect the collapsed branches and add more seed points to restart the segmentation, possibly having to manually connect disconnected regions at a later step. It is easy to notice that a high level of user intervention is needed to detect and correct the problematic cases. An experienced user can take more than 3 hours segmenting the image of a single patient. Since this is a very concentration demanding task, it can be exhausting and extremely prone to error.

2.2 Automatic Segmentation

Tschirren et al. recently proposed an automatic region growing algorithm that takes advantage of the fact that the airway tree is a hierarchical combination of cylindrically shaped objects [1]. An iterative process places adaptive cylinders (called regions of interest, or ROIs) around the region to be grown. These ROIs bound the region growing and can set a dead end to possible leaks. Branching is detected by computing the skeleton of a grown region. The size of the intersections of the region with the borders of the cylinder and the number of branches of the skeleton and their spatial orientation are used to estimate the size and orientation of the cylinders of the next step, respectively. ROIs are inserted in a priority queue and this process continues until no more pixels are aggregated. One important aspect to be noted is that leaks are not avoided, but controlled. This requires a leak detection step, which is executed in every iteration of the algorithm. The proposed leak detector assumes that leaks have a "spongy" structure, with many holes and tunnels. Once a leak is detected with a special morphological operator, the algorithm goes back to the previous step and repeats the segmentation, now using what the authors call "directional affinity". This strategy only makes the similarity tests with neighbours lying in the direction of the cylinder. The authors also discuss other ROI based approaches and make direct comparison between their algorithm and a traditional region growing approach, with improved results.

2.2.1 Drawbacks

The assumption that leaks always have a spongy structure might not be true. Emphysema, for instance, can appear as a solid object in a CT image, having the same pixel intensity of the air inside the airway tree. A leak towards the diseased region can go undetected in this case. Moreover, a leak that appears to be spongy in one step might have grown from a smaller, solid structure in the previous step. The airway wall, in this case, will be incorrectly segmented. The algorithm is not capable of telling if a "correctly" segmented branch is expected to exist at a certain step of the overall segmentation process.
In terms of efficiency, computing the skeleton of the currently segmented region in order to determine the orientation of the next cylinders can be a very time consuming task. Even using a simple skeletonization algorithm, it is expected that the complexity of the process will be at least *O(n)*, where *n* is the volume of the current cylinder, in number of voxels.

2.2.2 Proposed Modifications

To overcome some of the weaknesses of the described algorithm, which we consider to be the state of the art in airway tree segmentation, we propose some improvements in this work. First, for efficiency reasons, we do not use the skeleton of a region to estimate the orientation of the cylinder of the next step. As already mentioned, calculating the skeleton can be a very time consuming task, especially if executed in every step of the algorithm. Since the barycentres of the intersections of the region with the cylinder are originally used as anchor points of the skeleton, we propose to use them directly as a spatial orientation estimator. The walls of the cylinder are classified in top, bottom and side borders. The top border is where the segmentation always starts (where the seed pixel is placed). Without loss of generality, a start intersection region and its corresponding barycentre are always assumed to exist at the top border. The segmentation process can naturally stop inside the current cylinder or by intersecting any of its borders. The regions obtained from these intersections have their barycentres calculated. When the intersection occurs at the bottom border, the barycentres of the start and end regions are connected. For intersections with side and top borders, a "global" barycentre (barycentre of the barycentres) is computed and connected to the respective side and top barycentres. This is a very straightforward approach which is also very fast. Despite not being as precise as the skeleton, the estimation of the orientation of new cylinders proved to be very satisfactory. Figure 1 depicts the original and the proposed situations.

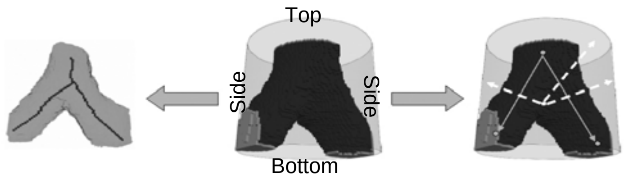

Figure 1 – Centre: segmented region, ROI and intersections. Left: skeleton. Right: proposed improvement with barycentres (the point in the middle is the "global" barycentre).

The second improvement deals with the detection of leaks. For this, we use gained knowledge about the structure of the lungs [11, 1]. For instance, it is easy to see that the diameter of the structure from one branching level to the other hardly ever increases. Moreover, branches are named and there are no more than 3 or 4 branches per level. These characteristics can be seen in figures 2 and 3.

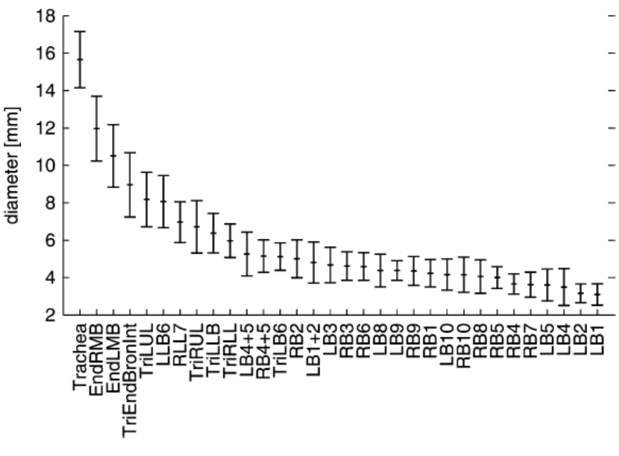

Figure 2 – Relative diameter between branches [1].

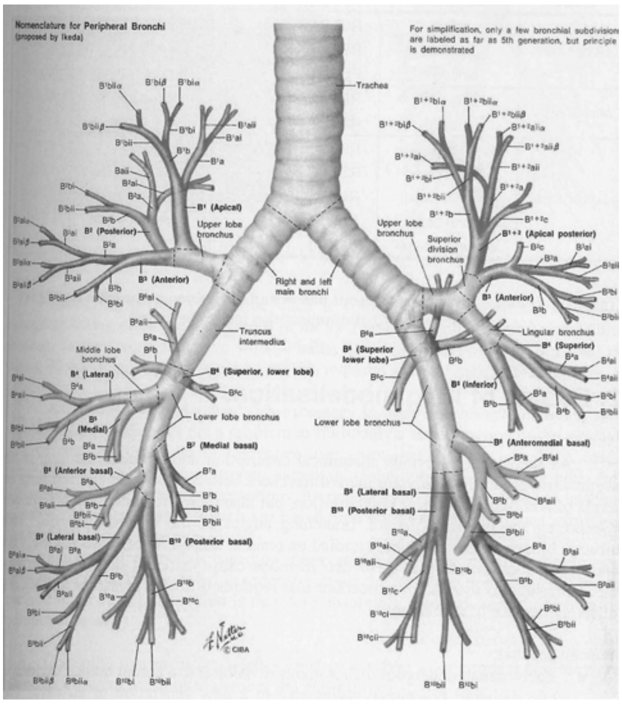

Figure 3 – Ikeda lung model [11].

In the method, the number of branches and their estimated diameters are obtained from the intersections between the regions and the cylinders. Whenever a branch intersects a cylinder, the areas of the regions of intersection are taken into account. A simple test can determine if the ratio between the area of the current branch and the area of a sibling branch is above a predefined threshold, in which case a leak is detected and the segmentation of that sibling branch stops. Detection results have also been satisfactory so far. After the leak is detected, as proposed in [1], the algorithm can go back to the previous step and repeat the segmentation using directional affinity, in order to prevent the occurrence of another leak.

3 Results

Our image database is composed of several low-dose CT scans of voluntary patients under treatment of respiratory diseases. Scans are taken prior to and after the use of medication. Each scanning event is divided into complete inspiration, in which the lungs and airway tree reach their full volume capacity, and complete expiration, when many of the branches naturally collapse. This database provides us with a great variety of situations and is a very good test bed for our algorithms. Figure 4 shows the results of a very well behaved segmentation, where no leaks occur. The *O(512x512x500)* image volume corresponds to an expiration scan and it is easy to see the early collapse of branches. The segmentation result is precise and very fast, running in less than 30 seconds on an Intel Pentium 4, 3GHz machine.

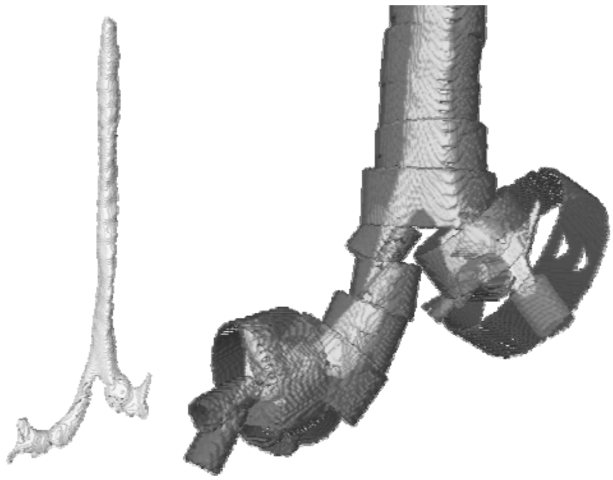

Figure 4 – Left: the full segmented structure of an expiration image set. Right: a closer look, with ROIs overlaid.

Figure 5 depicts the segmentation of a full inspiration scan. Contrary to the previous example, there are many leaks in this image, in several branching levels, but they were successfully detected and the segmentation was interrupted. The algorithm in this case ran in less than 80 seconds for an *O(512x512x524)* image volume.

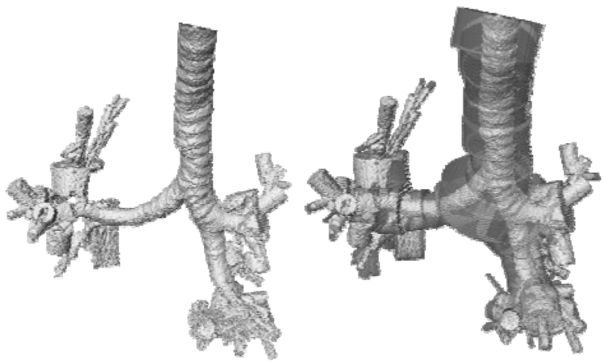

Figure 5 – Left: segmentation results with detected leaks in an inspiration image set. Right: another view, with ROIs overlaid.

4 Conclusions and Future Directions

We presented enhancements to a previously proposed intrathoracic airway tree segmentation algorithm [1]. Results so far indicated robustness improvements and considerable potential decrease in execution time when compared to the previous algorithm. Large CT image volumes have been used as experimental data.

One step still to be implemented is the identification of the leakage point. It is intuitive and easily proven that leakage points are those where the edges of the structure are weak. Once detected, the weak edge can be "closed" and the leak can be removed. The segmentation can normally continue from this stage.

A process to detect these points after the application of an edge detection filter on the images is under study at this moment.

Future improvements to the proposed techniques are also under consideration. First, we intend to use more prior knowledge, taking into account the length and location of branches and also the angle between them [12, 13]. Second, there is also a feeling that statistical shape modelling and segmentation [14] can further improve the method. Using only the skeletons [15, 16] of pre-segmented images as a training set, the point distribution model can be reduced and the establishment of correspondences can be simplified.

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