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Survey on Extraction of Airways and Nodules of Lungs

Rosebud Roy
Department of Computer Science& Engineering
Royal College of Engineering & Technology,Akkikavu
Thrissur,India

Mr.Sreeraj R
Head of the Department of CSE
Royal College of Engineering & Technology, Akkikavu
Thrissur,India

***Abstract*---The bronchial tree structure of lung airways is complex. So the accurate assessment of both the inner and outer airway wall surfaces from volumetric X-ray computed tomography (CT) data sets is required for diagnosing numerous major lung diseases like asthma and the chronic obstructive pulmonary diseases (COPD). In past years many research undergo for finding this, a graph search technique (LOGISMOS) can simultaneously identify the inter-related surfaces of branching airway trees.**

Keywords— Airway trees, bifurcation, complex topology, graph search technique, image segmentation, multiple surfaces.

I. INTRODUCTION

The segmentation of airway trees in chest volumetric computed tomography (CT) scans plays an important role in the analysis of lung diseases. Airway tree segmentation is useful in the measurement of airway lumen and wall dimensions, which is used to diagnose the presence of chronic obstructive pulmonary disease (COPD). As the lungs are subdivided anatomically based on the airway tree, airway tree segmentation is also a useful input for other segmentation tasks such as segmentation of nodules and lobes. We start by subdividing each segmented airway tree into its individual branch segments. Each branch segment is then obseved by trained observers to determine whether or not it is a correctly segmented part of the airway tree.

Several automated methods have been proposed to segment the airway tree from CT images. Evaluation of these methods has been problematic. Manual segmentation of airways is a difficult and very time consuming task due to the complexity of the 3-D structure of the airway tree. In addition, low contrast in the peripheral branches may make manual detection, inevitably performed in 2-D views, unreliable. Most methods have been evaluated qualitatively based on visual inspection or were compared quantitatively to more basic techniques such as region growing.

A drawback of such different segmentations is that they may be based to the algorithms used in their construction and are thus less suitable for comparing different methods.Different type of algorithms are used for image segmentation.

Although not very common, in some cases, a ground truth was constructed fully manually for evaluation. These graph search based schemes first transform the image segmentation problem to computing a minimum-cost closed set in a derived vertex-weighted directed graph using an algorithm, from there an optimal segmentation of human lungs is produced. The methods have been successfully applied to non-branching airway segmentation.

This paper considers such issues and describes the methods to do better extraction of airways and also diagnosing of maliguous nodule.

II. ARCHITECTURAL DESCRIPTION OF AIRWAYS

This section covers the details regarding the architectural description of Airways.

A. *Overview of Airways*

This section covers the details regarding the diagram description of Airways.

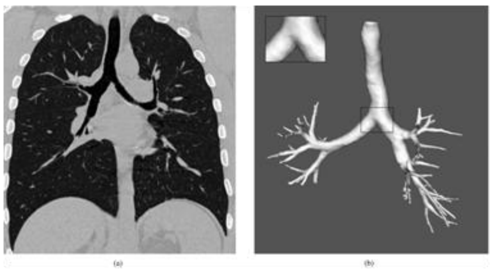

Fig. 1. The architecture of a airways

The human respiratory system is used for respiration process. Lungs have important role in this process. Respiration starts from the nose and mouth and continues through the airways and the lungs. Air enters through the nose and mouth and air passes down the throat (pharynx) and then through the voice box, or larynx.The process of entering air into lungs with air is called inhalation and other process of expelling air out with carbondioxide is expalation. The entrance to the larynx is covered by a small flap of tissue called epiglottis that automatically closes while swallowing, thus preventing food from entering the lung airways.

The largest airway is the windpipe called trachea, which branches into two smaller airways: the right and left bronchi, which lead to the two lungs. Each lung is divided into lobes, two in the left lung and three in the right lung. The left lung is a little smaller since it shares space in the left side of the chest with the heart. Because of the topological complexity, its very difficult to do segmentation in airway bifurcations and measurement in the airway tree .It is of clinical importance to improve assessment accuracy on these areas.

The bronchi themselves branch many times into smaller airways, ending in the narrowest airways called bronchioles, which is one half of a millimeter across. The structure of lung airways resemble an upside-down tree structure, so this part of the respiratory system is often called the bronchial tree.

The major challenges of segmentation are;

1. Complex structure
2. Small in size
3. CT Scan taken on Inhale/Exhale
4. Expensive

III. Related Works

The diseases can be diagnosed by the thickness of airways. There are several surveys in the literature on extraction of airways and an attempt is made to present below and discuss the existing differences between them. Previous work on airway segmentation includes mainly region growing–based methods, morphology-based methods, combinations of the two, hybrid multi scale method, fuzzy connectivity method, rule-based methods, energy function minimization and Gradient Vector Flow Method.

The paper [3] conventional region-growing methods deals with the existing contrast between the air (black on CT) and the airway wall (bright on CT). If this contrast locally decreases, because of an imaging artifact or a thin airway wall, this growing approach may allow the growing process to jump from the inside of the airway to the outside pulmonary parenchyma, which usually carries similar gray-level properties on CT images. Once the growth starts outside the airway lumen as “leaks”, there is no way to stop it and large parts of the lungs are erroneously marked as the airway tree. So a result, one of the biggest problems when segmenting airway trees by automated methods is leakage into the extralumenal regions. This best region-growing result was then used for the anatomic labeling.

Another common problem with region growing method airway segmentation algorithms is when segmenting low-dose scans and scans of heavily diseased lungs.It is very difficult. Example is the lungs of patients suffering from emphysema. In the case of low-dose scans, the segmentation either stops early or by growing leaks. The user then must run the segmentation algorithm several times in an attempt to find an optimal combination. In the case of diseased lungs, heavy leaking is not unusual. The region-growing algorithm was run on each data 12 times, each using different combinations of inputs. The best region-growing result was hand-selected by obseving all segmentation results and choosed the one result with the highest number of branches and no significant leaks. The anatomic labeling uses the best region-growing result.

Paper [4] is a new airway segmentation method based on fuzzy connectivity. The segmentation algorithm is based on fuzzy connectivity as proposed by Udupa and Samarasekera and Herman and Carvalho. Here, growth of the foreground region and growth of the background region compete against each other. Fuzzy method has the great advantage that it can overcome lack of image contrast between the airways and the airway walls and the effects of noise. This algorithm was run only once on every CT dataset, using the same input parameter for all datasets.

Paper [5] [6] proposes hybrid multi scale method uses intensity based and morphology based methods together; so it is called hybrid. Most airway characterization on CT scans is done manually, but is often too labor intensive ,time consuming process for routine clinical practice and also expensive. Therefore, it is required to have semi- and fully-automatic airway segmentation algorithms are crucial for the diagnosis. A fundamental challenge in airway tree segmentation is the highly varing intensity levels within the lumen, which leads to a segmentation method to leak into adjacent lung parenchyma through non-definite airway walls or through soft boundaries. This paper present a new hybrid multi-scale airway segmentation approach to solve these problems through proposing a new fuzzy connectivity.This algorithm combines multiple features to identify airways at different scales. The performance of this method was qualitatively and quantitatively evaluated on pulmonary CT images from different human patients suffering from diverse lung diseases with promising results.

Paper [7] is an automated gradient vector flow approach for the segmentation of lung airways in CT scans. The approach utilizes the Gradient Vector Flow and consists of two main processing steps. In first step, airway-like structures are identified and their centerlines are extracted. These centerlines are used in a second step to initialize the actual segmentation of the corresponding airways. An evaluation on 20 clinical datasets achieves a good average airway branch count (63.0%) without any major leakage.

Paper [8] is a Multi-scale Vessel-guided Airway Tree Segmentation method for airway tree segmentation .This method uses a combination of a trained airway appearance model, vessel and airway orientation information, and region growing method. The method uses a voxel classification based appearance model, use a classifier that is trained to differentiate between airway and non-airway voxels.The vessel and airway orientation information are used in the form of a vessel orientation similarity measure, which indicates how similar the orientation of the airway candidate is to the orientation of the neighboring vessel. The method is evaluated in EXACT'09 on a diverse set of CT scans by 15 different algorithms. Results show a favorable combination of a relatively large portion of the tree detected correctly with very few false positives.

Paper [9] is a method for fully automated extraction of airways from volumetric computed tomography images. This is based on a self-adapting region growing process. The method consists of 3 main steps. Firstly, the histogram of a dataset is well analyzed. Secondly, the trachea is searched and segmented into sections. And thirdly, the bronchial tree is segmented by a self-adapting region growing process. This method has been applied to 40 patient datasets provided by EXACT09, which is a comparative study of airway extraction algorithms. Former versions of this method have been used extensively in many clinical studies and is effective.

IV. OPTIMAL GRAPH SEARCH METHOD

The graph search based algorithms solve the image segmentation problem by transforming it to finding a minimum cost closed set. Our graph search based image segmentation approach consists of the following four major steps.

1) Pre-segmentation and meshed surface representation
2) Image re-sampling.
3) Graph construction.
4) Graph search.

A. Presegmentation

The humans lung airway trees are presegmented using the commercially available PW+ software . This presegmentation produces only the luminal (inner) wall and is approximate with respect to the positioning of the luminal surface. This approximate segmentation was formaly used for double-wall segmentation in airway segments between bifurcations. The bifurcation areas were not previously segmented since no appropriate approach was available for this task.

Once a labeled image is generated by the pre-segmentation, the inner wall surface is transformed into a triangulated mesh using the marching cube algorithm.

A pre-segmentation is done to get basic information on the object's global topological structure. It is not necessary for the pre-segmentation to be locally accurate. However, it is crucial to preserve the topology of the target object. If the pre-segmentation does not yield a surface mesh, we need to transform the volumetric result into a mesh representation.

B. Image Resampling Based on Medial Axes

To segment an optimal surface in the image using the given preliminary meshed surface, we performs a re-sampling of the input 3-D image for every meshed surface vertex along the normal direction of the meshed surface at that vertex, resulting in a column of voxels for each vertex.For resampling, a linear interpolation kernel was used.In this process, we are trying to avoid two "bad" situations: (1) The length of a voxel column is too short, so that it fails to capture enough information about the sought surface; (2) the length of a column is too long, so that it interferes or intersects with other columns (see Fig. 2). In situation (1), the use graph search algorithm would fail to find the correct surfaces. In situation (2), the graph we constructed from the re-sampling would contain wrong topological relations among the involved columns as shown in [Fig. 3(a)], which is determined by the base graph.

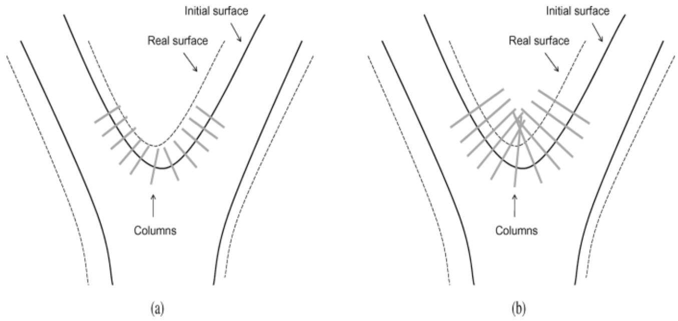

Fig: 2. Possible graph construction problems. a) Column lengths are too short to capture the true surface. (b) Column length too long

The possible graph construction problems are column lengths are too short to capture the true surface and other one is column lengths are too long and the columns interfere with each other. The solid curves represent the presegmented surface, and the dashed curves represent the true surface.

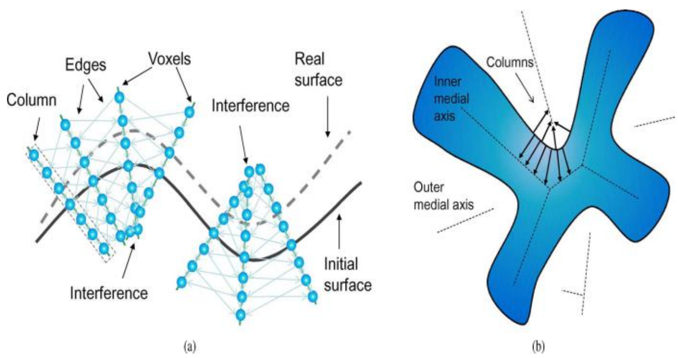

Fig. 3. Image resampling and graph construction. (a) Interferences caused by inappropriate column lengths introduce disordered structures in the constructed graph. (b) 2-D example of image resampling based on medial axes to obtain columns with no interference.

Using the outcome of the pre-segmentation, the image is re-sampled based on each vertex of the initial surface mesh directly, resulting in a set of vectors (called *columns*) of voxels. Here, medial axes are applied to determine the directions and lengths of the re-sampling voxel columns.

Approximate solutions can be obtained using computational geometry techniques. An algorithm for computing an approximate medial axis and the column lengths is summarized as follows.

1) Let be the set of vertices of the mesh. We compute the Voronoi diagram VD of and the dual Delaunay triangulation of in the 3-D image.
2) The points of both the inner and outer medial axes for a vertex are approximated by the poles in VD, which are computed as the centers of selected big Delaunay balls (i.e., circumscribed spheres of the Delaunay tetrahedra in) adjacent to the vertex .
3) The inner and outer poles and are assigned to each mesh vertex by selecting the largest poles among the nearest neighbors of (on both sides of the surface, Fig. 4), to reduce the impact of possible noise on the surface. The -nearest neighbors were identified using . See Fig. 5 for an example of the resulting medial axes.
4) The column lengths are obtained by computing the distances from each mesh vertex to its corresponding medial axis points *Vp1* and *Vp2* (on both the inner and outer medial axes of the preliminary surface, Fig. 4.

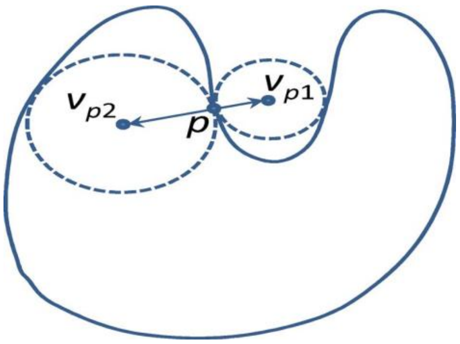

Fig 4: Illustrating the poles.

C. Graph Construction

A graph G= (V,E) has a set of V nodes (or vertices) that are connected by edges in . In this paper, the nodes in V of G are voxels in the re-sampled volumetric image, organized by the columns. Each column of nodes is associated with a vertex of the preliminary mesh, and is sampled along the normal direction of the meshed surface at that vertex. The mesh vertices are connected by edges of the mesh. Below we show how to assign edges to connect nodes in G and to enforce two important geometric constraints (e.g., the *smoothness constraint* and the *separation constraint* on the sought surfaces. After the graph is constructed with the above three types of edges (intra-column, inter-column, inter-surface) between the nodes in the columns, cost values are assigned to each of the nodes.

D. Cost Functions

An airway tree has two surface walls: the inner wall and outer wall. Distinguishing the inner wall is quite easy from the airway lumen, but the detection of the airway outer wall is difficult since the outer surface is often surrounded by nearer adjacent tissues with similar gray-scale intensities in MDCT images. Then only we can diagnosis whether any disease get affected in airways of lungs.

For that purpose we are using cost functions for calculating. So on optimal method we are considering this cost function as an important step. We need to find the difference between walls by calculation.We are considering graphs vertices for finding this. In our graph search based segmentation, a cost function used must reflect the possibility for a voxel (node) to belong to a certain surface. It should also distinguish voxels that belong to different surfaces.

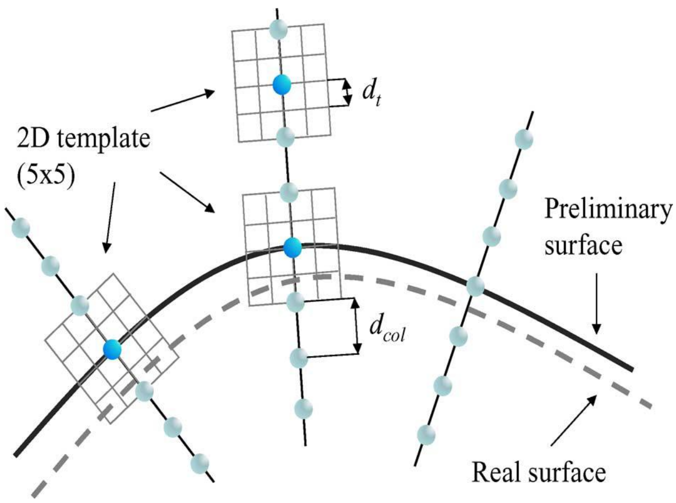

Fig. 5. Cost function values are computed for each node of the graph.

The voxels are sampled at the interval size dt such that

$$dt = dcol / 2$$

where *dcol* is the interval between consecutive voxels in a re-sampled column. In our experiments, the re-sampling interval *dcol* is set to be 0.25 voxel unit. This value was chosen empirically to balance between the accuracy and efficiency of the algorithm(.Fig 5)

For airway wall detection, the two surfaces differ from orientation of image edges . Since the airway lumen is darker than the airway wall, the intensity increases from low to high at the inner border. Conversely, the intensity decreases from high to low at the outer border when only parenchymal tissue is adjacent. Edge strength associated with the outer wall locations may be very weak. However, even small differences in brightness are utilized by the algorithm for positioning the outer wall. More importantly, even in the presence of non-parenchymal surrounding tissues or adjacent vessels, it is very likely that at least one section of the airway wall will not be immediately adjacent to such structure considering a spherical surrounding of the airway. A combination of this spherical context and the image intensity information is utilized to position the outer wall surface when the airway is touching non-parenchymal structures.

The cost function we use for airway tree segmentation is a combination of the first and second derivative edge detectors
and is based on a previously proposed cost function. This is due to the property that the two edge detectors tend to yield the maximum magnitude on one or the other side of the true edge, causing certain overestimate or underestimate of the airway wall position. Thus, a weighted sum of the first and second derivatives works better for the accurate border location. The value of the weight is determined by the size of the airway and was computed based on the method. One notable difference that likely caused differences in the values compared to was that the focus was on minimization of the wall thickness errors (or joint positioning of both surfaces) while the previous work sought minimization of the surface positioning errors for each individual surface. In our problem, the local size is actually the same as the inner column length (i.e., the distance from each point on the pre-segmented surface to the inner medial axis). The coordinates of the endpoints of each piece-wise linear intervals are determined. The coordinates of the endpoints are empirically adjusted to provide good performance in phantoms. Fig. 6 illustrates the piecewise linear function of the weight used in the validation for a double surface bifurcating phantom.

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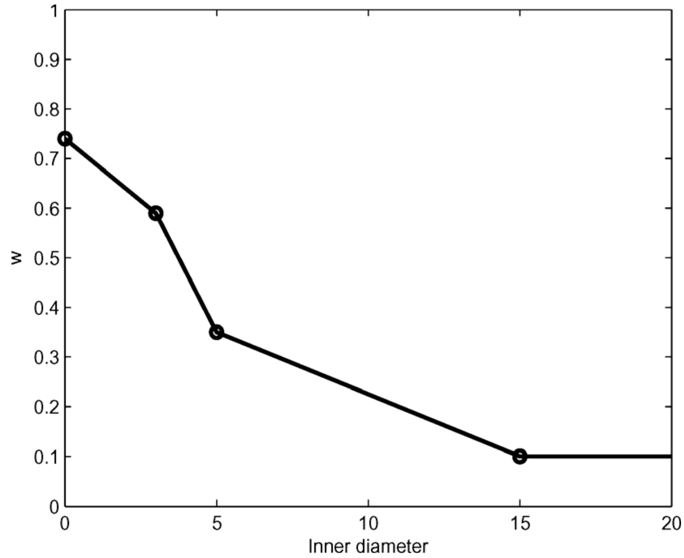

Fig. 6. Piece wise linear function depicting weights of the cost function as a function of the presegmented luminal diameter. Parameters of this function were determined in phantoms and employed for the analysis of *in vivo* human CT data.

E. Determining an Optimal Solution

To determine an optimal solution for segmenting airway double surfaces in a 3-D image , the problem is transformed to computing a minimum-cost closed set in a directed graph G’
.

V. CHALLENGING FACTORS

Accurate assessment of the inner and outer airway wall surfaces of a complete 3-D tree structure is difficult due to their complex nature, particularly around the branch areas. [10]

The major factors affecting the Segmentation are;
1. Image Clarity
2. Inhale/Exhale Image
3. Expensive

VI. PERFORMANCE ASSESSMENT ON PHYSICAL PHANTOMS

A. Identification of Airway Bifurcations and Carina Regions

In a tree-like topology such as the airway tree, parental generations typically split into two child airways at the site of a bifurcations. Trifurcations can be modeled as a series of two bifurcations in a rapid succession. The region where two child airways separate forms a 3-D V-shape. To assess the accuracy of airway wall segmentation and wall thickness measurement in the segments between successive bifurcations and within the bifurcation regions, subsets of the airway wall surface must be identified to allow performance comparisons. For this purpose, the tree structure can be represented by its 3-D skeleton that holds useful information about the tree topology, branching points, three segments, etc. The skeleton can therefore be used to define regions of specific properties within airway bifurcations. Two such region labeling are utilized in this work. Consequently, each point of the airway tree surface is labeled with two labels: as belonging to a bifurcation or non-bifurcation region as well as belonging to a carina or non-carina region.

1) Identifying Bifurcation Regions: An airway tree skeleton is computed using a 3-D thinning algorithm by Lee *et al*. This algorithm iteratively removes the *simple points* from a given object while preserving the object topology (such as the connectivity, holes and cavities of the object, etc.). The output skeleton of this thinning algorithm is a one- voxel wide centerline structure. Next, a tree-labeling process identifies the branching points and non branching points in the skeleton using a depth-first search. Each of the branching and non branching points is associated with a corresponding generation number. It is a well-known phenomenon that an object skeleton/medial axis is sensitive to local changes of the object surface—possibly forming undesired skeleton branches. Since it is important to remove such false branches, the length of each branch is determined and the branches that are too short compared to the corresponding local diameter are pruned.

The bifurcation regions are defined as the subset of surface points with smaller than a specified distance from the branching point. To conveniently define surface subsets, spheres of desired diameters are centered at each branching point. To cope with the varying airway sizes, the sphere diameters are set proportional to the corresponding local branch diameters. In Fig. 8(a), the diameter of the sphere was selected twice as large as the local diameter in order to incorporate the entire bifurcation. However, in this situation, some of the branches [e.g., in generations 3–6 of the example in Fig. 8(a)] that are short compared to the local diameter may become partially included in the bifurcations (covered in red).

2) Identifying Carina Regions: The tracheal carina is a cartilage- rich saddle region within the trachea that separates the trachea and the two main stem bronchi. Carina regions exist at each higher generation bifurcations. The carina regions can be defined as the V-shaped saddle areas.

VII. CONCLUSION

In airways several researches are going based on the different methods. This method now allows for the separate measurements of the airway wall thickness in the bifurcation and carina regions of the airway trees using a globally optimal approach. The quantification of wall properties in bifurcations offers an effective basis for novel disease-specific studies of the intra thoracic airway tree morphology and function. Our method is general and can be applied to segmenting other complex objects with multiple inter-related surfaces in 3-D and higher-D images. Early diagnosis of malignant nodule is only found for early assessment of cancer.

The Optimal Search Method try to solve this problem and to produce scalable and efficient extraction. They segment the airways and efficiently and fusion diagnose lung diseases.

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