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Extraction of Samples From Airway and Vessel Trees In 3D Lung CT Based On A Multi-Scale Principal Curve Tracing Algorithm

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Abstract— **The extraction of airway and vessel trees plays an important role in the diagnosis and treatment planning of lung diseases. However, this is a challenging task due to the small size of the anatomical structures, noise, or artifacts in the image. The similar intensity values between the lung parenchyma and airway lumen, the airway wall and the blood vessels make extraction particularly difficult. Our method detailed herein presents an automatic extraction of samples of both the airways and vessels from the three-dimensional computed tomography (3D-CT) based on the multi-scale principal curve algorithm. The image is first thresholded to find airway or vessel candidates according to their corresponding Hounsfield units (HU). The Frangi filter is then used to extract the tubular structures and remove background noise. Finally, a multi-scale principal curve projection and tracing algorithm is applied on the filtered image to identify the centerlines of the airway and vessel trees.**

I. Introduction

Segmentation and localization of pulmonary tube structures, such as bronchi and blood vessels, are critical to the diagnosis and treatment of lung diseases [7]. Analyzing the airway or vessel trees can help diagnose some pulmonary diseases. Moreover, registration of the lung CT scans is also an important step for many clinical applications. The lung deforms and changes shape during respiration, making registration across the breathing cycle critical to accurate segmentation in four-dimensional computed tomography (4D-CT). Fortunately, the airways and vessels are distinctive anatomical structures. Registration of the lung within 4D-CT scans based on the geometrical curve or branchpoints of airway and vessel trees as a set of landmarks influences the local deformations and offers a more robust and efficient registration compared with the intensity based registration. To facilitate these applications, automatic, reliable, robust, and fast extraction of samples from the airway and vessel trees in CT scans becomes critical.

However, segmenting the airways and vessels from CT datasets is difficult and complex. Limited image resolution and high level of noise lead to heterogeneous intensity values of the voxels inside the airway lumen. Furthermore, the leakage into the lung is a common issue for airway segmentation due to the low contrast between the air and the lung parenchyma. Some other problems, such as similar intensity values between the blood vessel and the airway walls, may also affect the extraction.

Numerous airway tree segmentation techniques have been previously been presented [7]. 3D region growing algorithms are the most common and widely used methods for airway tree segmentation [5]. This is a simple and fast method that assumes no prior knowledge about the shape, size and location of the airways. However, as the airways have similar intensity values as the lung parenchyma, if choosing a global HU threshold, the voxels of the lung parenchyma are misclassified. Various region growing based approaches using different techniques have been presented to avoid leakage, such as smoothing the image before the region growing [3]. However, filtering often removes important small airways. Several other methods have also been proposed such as morphological, wave front propagation, template matching, fuzzy techniques or combinations of these methods.

Level set methods [8], and vessel enhancement filters [4] integrating with different image matching techniques are among the existing approaches to extract the vessel trees from the lung CT images.

Our goal in this paper is to develop an algorithm to extract samples from both pulmonary airway trees and vessel tress in 3D-CT images. Our method combines the tube enhancement filters and the locally defined multi-scale principal curve approaches. The main advantage of the proposed algorithm is that tube enhancement and centerline extraction are both based on the gradient and the Hessian matrix of the image intensity. The kernel widths of the kernel interpolation of the tubular measure in the principal curve projection and tracing step for centerline detection directly uses the optimal scales measured in the tube enhancement step. Using the integration of the tubular structure enhancement filter, - the Frangi filter, and the tubular structure tracing method, -multi-scale principal curve tracing, provides a simple, fast, and reliable method for the extraction of both the airway trees and the vessels. This serves as a useful starting point for 4D-CT lung image registration based on the curves or branchpoints as interior landmarks of the airway and vessel trees.

II. METHODOLOGY

The algorithm consists of three steps: (1) The image is pre-thresholded to select the airway candidates and the vessel candidates, respectively. (2) The tube enhancement filter, the Frangi filter, is used to enhance the tubular structures and remove some noise voxels misclassified by pre-thresholding. (3) Centerlines of the airway trees and vessel trees are

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extracted using the multi-scale principal curve projection and tracing algorithm.

A. Preprocessing

In multi-detector computed-tomography (MDCT), the voxel intensities are measured in HU. The air has an intensity around -1000HU. An airway tree conducting air into the lungs appears as tubes of low-intensity airway lumen surrounded by high intensity airway walls. The voxels with intensities below -800HU are loosely segmented as air filled regions. As both the airway lumen and lungs are filled with air, background noise inside the lung is often misclassified. For the vessel trees, the lung field is first extracted from the CT images. The blood and soft tissue have intensities around 50-200HU. The voxels with intensities above -500 HU are classified as the foreground.

B. Tube Enhancement Filter

To extract voxels having tubular structures and to remove the noise voxels misclassified in the pre-processing step, we employ a tube enhancement filter by Frangi [4]. The Frangi filter analyzes the eigenvalues of the Hessian matrix of the image intensity at multiple scales, σ, of the Gaussian smoother to obtain tubeness measure. Let $\mathbf{p}$ be the voxel location in the image. If a scale is approximate to the radius in $\mathbf{p}$, the maximum filter response in $\mathbf{p}$ is obtained at that scale. For dark airway tubes and bright background, the Frangi filter response is $w_\sigma(\lambda(\mathbf{p})) = (1-\exp(-\frac{R_A^2}{2a^2}))\exp(-\frac{R_B^2}{2b^2})(1-\exp(-\frac{S^2}{2c^2}))$ if $\lambda_2(\mathbf{p}), \lambda_3(\mathbf{p}) > 0$. For bright vessel tubes and dark background, the Frangi filter response is obtained if $\lambda_2(\mathbf{p}), \lambda_3(\mathbf{p}) < 0$. $\lambda_1, \lambda_2, \lambda_3$ are the eigenvalues corresponding to three orthonormal directions of the Hessian matrix of the image intensity, and their magnitudes are sorted in an ascending order, $|\lambda_1| \leq |\lambda_2| \leq |\lambda_3|$. $R_A = |\lambda_2|/|\lambda_3|$ is the ratio that distinguishes between plate-like and line-like structures; $R_B = |\lambda_1|/\sqrt{|\lambda_2\lambda_3|}$ distinguishes blob-like structures; $S = \sqrt{\lambda_1^2+\lambda_2^2+\lambda_3^2}$ eliminates background noise; a, b, c are normalizing constants. The filtered image has maximum response along the centerlines of the tubular structures, reduced near the boundary and close to zero outside the tubular-like regions. Therefore, both airway and vessel tubes are enhanced by the Frangi filter. The locally defined multi-scale principal curve tracing algorithm will be implemented in these filtered images.

C. Locally Defined Multi-Scale Principal Curve Tracing

Locally defined principal curves are discussed in previous papers by Ozertem and Erdogmus [2], [6]. Following this concept, we employ a subspace constrained tracing method [1] to trace the centerlines of the airway and vessel trees in the filtered image. Given a seed point and an initial tangent direction, the proposed method uses the gradient and Hessian of the kernel interpolation of the tubeness measure to calculate the principal curves in the data having locally similar characteristics with the seed points. The voxels in the vicinity of the seed point in the constrained normal subspace iteratively converge to the principal curve, and the algorithm then traces the curve along the center of the tube in the tangent subspace.

Let $\{\mathbf{p}_i\}_{i=1}^N$ be the voxel locations of the filtered image, where $\mathbf{p}_i \in \mathbb{R}^n$. The kernel interpolation of the tubeness measure is given as,

$$f(\mathbf{p}) = \sum_{i=1}^{N} w(\mathbf{p}_i) k_{\mathbf{\Sigma}_i}(\mathbf{p}-\mathbf{p}_i)$$

where $w(\mathbf{p}_i)$ is the tubeness measure for each voxel in the filtered image; $\mathbf{\Sigma}_i$ is the covariance of the Gaussian kernel $k_{\mathbf{\Sigma}_i}(\mathbf{p}) = C_{\mathbf{\Sigma}_i} e^{-\frac{1}{2}\mathbf{p}^T\mathbf{\Sigma}_i^{-1}\mathbf{p}}$. The gradient and the Hessian of the kernel interpolation are:

$$\mathbf{g}(\mathbf{p}) = -\sum_{i=1}^{N} w(\mathbf{p}_i) c_i \mathbf{u}_i$$

$$\mathbf{H}(\mathbf{p}) = \sum_{i=1}^{N} w(\mathbf{p}_i) c_i (\mathbf{u}_i\mathbf{u}_i^T - \mathbf{\Sigma}_i^{-1})$$

where $c_i = k_{\mathbf{\Sigma}_i}(\mathbf{p}-\mathbf{p}_i)$, $\mathbf{u}_i = \mathbf{\Sigma}_i^{-1}(\mathbf{p}-\mathbf{p}_i)$. The local covariance inverse based on the gradient and Hessian is defined as:

$$\mathbf{\Sigma}^{-1}(\mathbf{p}) = -f(\mathbf{p})^{-1}\mathbf{H}(\mathbf{p}) + f(\mathbf{p})^{-2}\mathbf{g}(\mathbf{p})\mathbf{g}^{\mathbf{T}}(\mathbf{p})$$

$((\lambda_1(\mathbf{p}), \mathbf{v}_1(\mathbf{p})), ..., (\lambda_n(\mathbf{p}), \mathbf{v}_n(\mathbf{p}))$ are the eigenvalue - eigenvector pairs of local covariance inverse, where the eigenvalues are sorted such that $\lambda_1(\mathbf{p}) < \lambda_2(\mathbf{p}) < ... < \lambda_n(\mathbf{p})$ and $\lambda_i \neq 0$. Here $n = 3$. $\mathbf{v}_1(\mathbf{p})$ corresponding to the smallest eigenvalue forms a tangent subspace. It indicates the direction along the tubes with the minimum intensity variation. The normal subspace is spanned by the remaining eigenvectors, $\mathbf{V}_\perp = [\mathbf{v}_2(\mathbf{p})\ \mathbf{v}_3(\mathbf{p})]$. Mean-shift updates constrained in the normal subspace, $\mathbf{m}_\perp(\mathbf{p})$, iteratively force $\mathbf{p}$ to converge to the principal curve, where $\mathbf{m}_\perp(\mathbf{p}) = \mathbf{V}_\perp\mathbf{V}_\perp^{\mathbf{T}}\mathbf{m}(\mathbf{p})$; $\mathbf{m}(\mathbf{p}) = (\sum_{i=1}^N k_{\mathbf{\Sigma}_i}(\mathbf{p}-\mathbf{p}_i)\mathbf{\Sigma}_i^{-1})^{-1}\sum_{i=1}^N k_{\mathbf{\Sigma}_i}(\mathbf{p}-\mathbf{p}_i)\mathbf{\Sigma}_i^{-1}\mathbf{p}_i$. A point is on the principal curve iff the gradient $\mathbf{g}(\mathbf{p})$ is orthogonal to the normal subspace. Propagating through the tangent subspace with proper directions and the step length will trace the locally defined principal curve at $\mathbf{p}$. If $\mathbf{p}$ has been previously traced, is out of the image boundary, or the kernel interpolated tubeness measure is lower than a threshold, then the tracing terminates. This iterative tracing algorithm combines the correction in the constrained normal subspace and propagation in the tangent subspace with proper directions to trace the locally defined principal curves. The kernel widths of the kernel interpolation of the tubeness measure in each location are varied based on the scale at which the maximum response of the Frangi filter is obtained. Therefore, the proposed algorithm is referred to as the multi-scale principal curve algorithm.

III. EXPERIMENTAL RESULTS

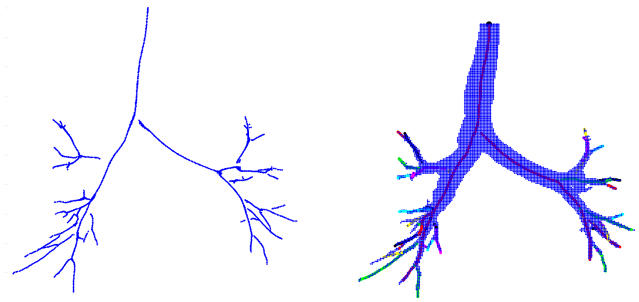
We apply our method to a 3D-CT data set. The size of the image is $512 \times 512 \times 307$, and the resolution is $0.78 \times 0.78 \times 1mm^3$.

A. Airway Trees

Presegmentation of airways is done by selecting voxels with $\leq$ 800 HU intensity. However, since the lung parenchyma has intensity values near this range, global thresholding may select those voxels. Frangi filter is used to enhance the airways and remove some non-tubular structures. In the filtered image, airway structures have high tubeness measurement compared to the non-tubular region. The filtered image still contains small holes. Since the airway tree is 26 connected, the 26 - connected voxels are selected to extract the airway trees and small and disconnect holes are removed.

The centerline tracing is implemented in the filtered image. A seed point and an initial direction are manually selected. Kernel interpolation of the tubeness measure gives more weights to the center voxels. The kernel widths in the kernel interpolation are the optimal scales of each voxel obtained from the Frangi filter response measurement. Principal curve projection of the whole dataset is first obtained by iteratively converging the points to the principal curve in the constrained normal subspace. Then tracing starts from the seed point and follows the given direction until it terminates. At each iteration, the direction of the principal curve is calculated, and the immediate neighbor voxel in that direction is selected as the next approximate curve sample. After each termination of branch tracing, the projected principal curve subset is used to check if there are any nearby branches bifurcating from the previously traced branch. If there are bifurcating branches, a new principal curve trace is initialized until all branch candidates are visited.

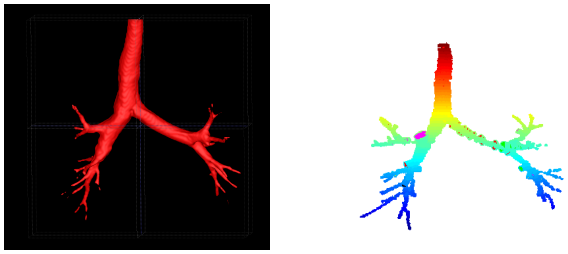
Fig. 1 shows the projected airway tree and the extracted centerlines of the airway tree. The Frangi filter produces disconnections at the thin branches. A complete airway tree can be reconstructed based on the extracted centerlines and scales.



(a) (b)

Fig. 1. Centerline extraction of airways: (a) Principal curve projection of airways; (b) Segmented airway trees (blue) with traced centerlines overlayed. The black dot is the selected seed point.

Fig. 2 shows the mask obtained for the pre-extracted airway tree after thresholding, tube enhancement, and hole removal using ITK-SNAP and the reconstructed airways based on the center points and the corresponding radius.



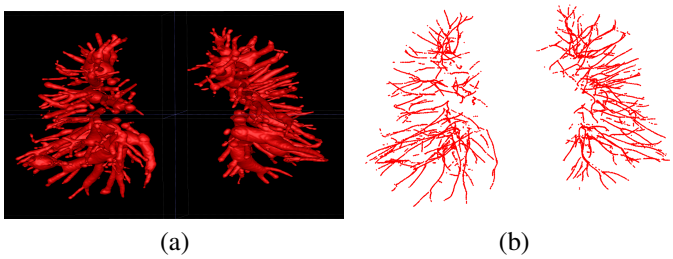
(a) (b)

Fig. 2. The pre-extracted airway tree and the reconstructed airway tree.

B. Vessel Trees

For vessel extraction, the lung field is first extracted to limit the vessel extraction to the interior of the lung. Since the lung is full of air, the image is pre-thresholded to roughly extract the lung field. Morphological operations are then used to fill the cavities caused by the structures with higher intensities, such as the blood vessels, airway walls, and other soft tissues. Finally, the binary lung field mask is mapped with the original image.

HU ≥ -500 HU is used to select the vessel candidates. Then the Frangi filter is employed to enhance the tubular structures. 26-connected voxels are then selected to extract the vessel trees, and small holes are removed. As the extracted vessel branches are disconnected due to the low resolution of the image, a large amount of seed points need to be provided in order to trace all of the disconnected branches. Instead, the centerlines of vessel trees are extracted by iteratively projecting the vessel tree candidates to converge on the principal curve in the constrained mean-shift normal subspace without tracing along the tangent subspace. Fig. 3 shows the vessels enhanced by the Frangi filter using ITK-SNAP and the extracted centerlines of the vessel trees.



(a) (b)

Fig. 3. (a) Vessels enhanced by the Frangi filter; (b) The extracted centerlines of the vessel tree.

IV. DISCUSSIONS AND CONCLUSION

In this paper, we present a method that combines the tube enhancement filter and the locally defined multi-scale principal curve projection and tracing algorithm to extract the samples from airway and vessel trees. Our method uses the gradient and Hessian of the image intensity to calculate the principal curves in the data having locally similar characteristics with the seed points. The voxels in the vicinity of

the seed points in the constrained normal subspace iteratively converge to the principal curve, and propagating along the tangent subspace, the algorithm can trace the principal curve along the center of the tube. Selection of the airway seed points is manual. Optimal scales obtained from the Frangi filter are employed as the kernel widths for the kernel interpolation of the tubeness measure. In tracing branching curves, new seed points are given to initialize another tracing. Our ultimate goal is to perform the deformable registration of the lung within 4D-CT scans based on the curves or branching points as a set of landmarks for the airway or vessel trees. Therefore, we have not to pay much attention extracting the small, peripheral branches. Our future work will focus on performing registration within 4D-CT scans based on these landmark samples of the airway and vessel trees.

REFERENCES

[1] E. Bas and D. Erdogms, *Principal curve tracing*, in European Symposium on Artificial Neural Networks (2010), 405–410.

[2] D. Erdogmus and U. Ozertem, *Self-consistent locally defined principal surfaces*, Processing of ICASSP'07 (2007), II–549–II–552.

[3] A. Fabijariska, M. Janaszewski, M. Postolski, and L. Babout, *Airway tree segmentation from ct scans using gradient-guided 3d region growing*, Progress in Pattern Recognition, Image Analysis, Computer Vision, and Applications **5856** (2009), 247–254.

[4] A.F. Frangi, W.J. Niessen, K.L. Vincken, and M.A. Viergever, *Multiscale vessel enhancement filtering*, in MICCAI **1496** (1998), 130–137.

[5] M.W. Graham, J.D. Gibbs, and W.E. Higgins, *Robust system for human airway-tree segmentation*, Proc. of SPIE Medical Imaging **6914** (2008), 69141J–1–69141J–18.

[6] U. Ozertem and D. Erdogmus, *Local conditions for critical and principal manifolds*, Proceedings of ICASSP'08 (2008), 1893–1896.

[7] I. Sluimer, A. Schilham, M. Prokop, and B. van Ginneken, *Computer analysis of computed tomography scans of the lung: A survey*, IEEE Transaction Medical Imaging **25** (2006), 385–405.

[8] G. Yu, Y. Miao, P. Li, and Z. Bian, *Multiscale vessel segmentation: A level set approach*, Progress in Pattern Recognition, Image Analysis and Applications (2005), 701–709.