GPU-Based Pulmonary Vessel Segmentation using a Tubular Spline Model

Erik Smistad, Anne C. Elster and Frank Lindseth
Norwegian University of Science and Technology, Dept. of Computer and Information Science

We describe a fully automatic method for segmenting the pulmonary vessels from CT scans. Our method uses a tubular spline model to detect the vessels. An airway and fissure segmentation is performed to eliminate any false responses from other pulmonary structures. The method has not been designed for any specific scans or pathologies and does not require any training. Our method also uses graphic processing units (GPUs) and parallel processing to accelerate the segmentation.

1 Tubular Detection Filter

A new Tubular Detection Filter (TDF) is used to detect the pulmonary vessels. The TDF uses the eigenvectors of the Hessian matrix to detect the direction and the cross-sectional plane of the vessel. The eigenvectors, $\vec{e}_1$, $\vec{e}_2$ and $\vec{e}_3$ are sorted so that their corresponding eigenvalues have the following relation: $|\lambda_1| < |\lambda_2| < |\lambda_3|$. The first eigenvector, $\vec{e}_1$, will then point in the same direction as the vessel at that voxel and the two other eigenvectors will define the cross-sectional plane of the vessel. We use a similar model-based approach as the circle fitting method by Krissian et al. [4]. But instead of fitting a circle, we create a spline in the cross-section using line searches in the gradient vector field to find the control points of the spline. The TDF response is calculated as the average dot product of the inward normal of the spline and the direction of the underlying gradient vector field. As previously done by Bauer et al. [1], [2], we also use Gradient Vector Flow (GVF) to handle vessels of different sizes instead of the Gaussian scale-space method. The advantage of our spline model is that it can model tubular structures with different cross-sectional profiles. The method of Krissian et al. [4] assumes a perfect circular profile and tubes deviating from this circular shape gets a lower response. Also, false responses at curved areas are eliminated because a max radius on the line searches is used and it is robust against noise.

2 Airway Segmentation

The challenge defined the airway wall as non-vessel and thus to eliminate any false segmentation of this wall an Airway segmentation was performed and dilated to include the airway wall. This segmentation was then excluded from the provided lung mask. The Airway segmentation was done by means of 3D region growing similar to the one used by Graham et al. [3]. The seed is found automatically inside the trachea by looking for a small and circular region with very low intensity in one of the top slices. The region growing is started with a low intensity threshold equal to the seed's value. The threshold is increased gradually until a segmentation leakage is detected. This is detected by measuring the volume of the segmentation result. When a segmentation leakage is detected, the threshold is decreased until the leakage is removed.

3 Fissure Segmentation

The lung is divided into lobes by fissures and the TDF can create false responses at these fissures. A fissure segmentation is performed to remove these false responses. This is done using a method similar to that of Wiemker et al. [5]. First a fissure enhancement F is performed on each voxel where λ_3 is less than zero as shown in Eq. 1. This enhancement filter uses the eigenvalues and a Gaussian model of the fissure's intensity (μ, σ). Neighboring voxels that have a high F and very similar directions are grouped together into a segmentation.

Finally, a morphological closing is performed and any small objects are removed from the segmentation. The fissure segmentation is removed from the mask so that false vessel segmentations on the fissures are avoided.

$$F(\vec{v}) = \frac{\lambda_3 - \lambda_2}{\lambda_3 + \lambda_2} e^{-(I(\vec{v})-\mu)^2/2\sigma^2} \tag{1}$$

4 Linking

The next step is to identify valid links between two voxels and then perform segmentation in each valid link, similar to that done by Graham et al. [3]. Voxels with a high TDF response are selected for linking. A link between two voxels, $\vec{x}_a$ and $\vec{x}_b$, can be established if they are close (Eq. 2 and their directions are similar (see Eq. 3, 4, 5).

$$|\vec{x}_a - \vec{x}_b| \leq 4 \tag{2}$$

$$\arccos(|\vec{e}_1(\vec{x}_a) \cdot \vec{e}_1(\vec{x}_b)|) < 60^\circ \tag{3}$$

$$\arccos(|\vec{e}_1(\vec{x}_a) \cdot \frac{\vec{x}_b - \vec{x}_a}{|\vec{x}_b - \vec{x}_a|}|) < 60^\circ \tag{4}$$

$$\arccos(|\vec{e}_1(\vec{x}_b) \cdot \frac{\vec{x}_b - \vec{x}_a}{|\vec{x}_b - \vec{x}_a|}|) < 60^\circ \tag{5}$$

5 Segmentation

For each valid link, a region growing segmentation is performed. The growing procedure starts with one of the two endpoints as a seed. The starting threshold is set equal to the minimum of the intensity of the two endpoints. The threshold is gradually lowered until a segmentation leakage is detected. Segmentation leakage is detected using the splines of the endpoints and the tube segment that they define. If the procedure grows outside of this segment it is identified as a segmentation leakage. When leakage is detected, the threshold is increased. If the other endpoint was reached, the segmentation is considered valid and added to the segmentation result. In the end, any small objects in the segmentation result are removed.

6 Speed

Most of the data parallel steps of our implementation such as blurring, TDF, GVF, morphological closing, fissure enhancement etc. are written in OpenCL and run on the GPU. Some of the other steps that are task parallel such as the final segmentation is performed in parallel on the CPU using OpenMP. The runtime of our system varies a lot with the size detected pulmonary vessel tree. The average runtime was measured to be 2m and 51s with minimum 2m 3s and maximum 4m 22s. This was done on a machine with an NVIDIA Tesla C2070 GPU, Intel i7 CPU with 24GB of memory.

References

[1] C. Bauer and H. Bischof. A novel approach for detection of tubular objects and its application to medical image analysis. *Pattern Recognition*, pages 163–172, 2008.

[2] C. Bauer, H. Bischof, and R. Beichel. Segmentation of airways based on gradient vector flow. In *International Workshop on Pulmonary Image Analysis, Medical Image Computing and Computer Assisted Intervention*, pages 191–201. Citeseer, 2009.

[3] M. W. Graham, J. D. Gibbs, and W. E. Higgins. Robust system for human airway-tree segmentation. *Proceedings of SPIE*, 6914:69141J–69141J–18, 2008.

[4] K. Krissian. Model-Based Detection of Tubular Structures in 3D Images. *Computer Vision and Image Understanding*, 80(2):130–171, Nov. 2000.

[5] R. Wiemker, T. Bülow, and T. Blaffert. Unsupervised extraction of the pulmonary interlobar fissures from high resolution thoracic CT data. *International Congress Series*, 1281:1121–1126, May 2005.