Airway Segmentation in 3D using Dynamic Hyperpolarized He-3 Multi-Echo VIPR

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Introduction

The feasibility of airway segmentation using hyperpolarized helium 3 MRI has been demonstrated using multiple methods[1,2]. This technique uses inspiratory dynamics to primarily isolate the He-3 signal in the airway lumen rather than the parenchyma. However, the time resolution needed for this approach has limited this technique to 2-dimensions (2D), with a single slice typically selected to encompass the major branches of the airway tree in the coronal plane. However, accurate evaluation and measurement of the airway tree, requires 3-dimensional (3D) information such as that performed in quantitative CT methods for measuring the airways in obstructive lung disease. Here we present an acquisition and segmentation algorithm capable of complete 3D airway segmentation down to the 4th generation.

Methods

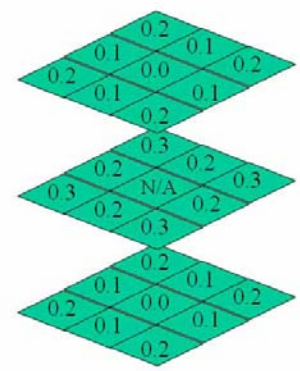
Imaging: Imaging was performed on a normal volunteer with a 1.5T clinical scanner equipped with broadband capability (GE HealthCare, Milwaukee, WI). An excite/receive vest coil tuned to ~48MHz, the resonance frequency of He-3 at 1.5T, was used (Medical Advances). A Multi-Echo-VIPR (3D PR) acquisition was used, parameters were 42cm FOV, BW = +/- 125 kHz, reconstructed resolution of 256x256x256 mm^3, modulated RF flip angle[3], gradient correction[4], and a 20 s inspiration maneuver using a 8 half-echo PR acquisition[5]. Data was acquired using a TR of 4.4ms, and reconstructed using HYPR[6] with a 5s wide composite and a 1s temporal resolution.

Airway Segmentation: The airway segmentation algorithm is an automatically seeded, manually thresholded region growing algorithm with a linearity constraint imposed in order to better segment the small airways. The core segmentation algorithm is a 26 connectivity (3x3x3 cube) iterative 3D region growing[6] method implemented in C++. This works well for high contrast regions, but the algorithm does not perform as well in smaller airways when the contrast-to-noise ratio is much lower. In these regions the linearity constraint is used to prevent the segmentation from including regions that fall outside of the airways such as lung parenchyma and reconstruction artifact. The linearity constraint is implemented by artificially increasing, or weighting the voxel graylevels not on the axis of growth using a cubic kernel with a side length of 3. The kernel is adapted using all 26 possible directions of growth and is computed using 6 connectivity distance map seeded along the axis of travel. Equation 1 shows the equation used to determine the temporary voxel value. Table 1 shows the weighting kernel when the growth is proceeding along the y (vertical) axis. As the orientation of growth changes, the mask is reshaped so the zero values are oriented along the axis of growth. Note that using the weighting values of 0, 10, 20, or 30% of the voxel value does not change the segmentation in the larger airways because the voxel values are already well above the threshold, and the growing proceeds in all directions. However, in smaller airways which are at most a few voxels wide, the linearity constraint is thereby enforced, and the region growing does not deviate from the airway unless a sufficiently strong lateral signal is present. This allows for a more sensitive segmentation of the small airways than would otherwise be achieved. Results were then compared qualitatively to a Multi-Detector CT (MDCT) airway segmentation using commercial software (VIDA; Iowa City, IA) on a different normal volunteer.

Equation 1: Equation used to impose the linearity constraint

Threshold=(voxel value)+(voxel value)(weighting kernel value)*

Table 1: Vertically Oriented 3x3x3 Weighting Kernel



Results

Figure 1 shows a lung segmentation result using MDCT which provides a similar segmentation to equivalent generations when compared to the HP MRI segmentation result. As seen in Figures 2 and 3, the segmentation clearly depicts airways down to the 3rd to 4th generation. This is aided by the 3D contiguous dataset acquired at 1s temporal resolution so allowing for separation of parenchymal and airway signal. The 3D data allows viewing of the segmentation in 3D, which allows for visualization along any axis desired which improves the accuracy of airway measurements.

Figure 1: Coronal Rendering, MDCT Result

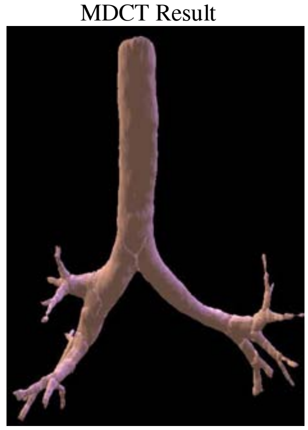


Figure 2: Coronal MIP, 3D MRI Result

Figure 3: Oblique Sagittal MIP, 3D MRI Result

Conclusion and Discussion

Dynamic lung ventilation imaging using the techniques presented makes it possible to quantitatively evaluate the airway lumen in a manner approaching that achieved in MDCT. By incorporating a linearity constraint into the segmentation during region growing, the small, linear airways can be well depicted allowing automatic segmentation with minimal human intervention. Future work will combine quantitative measures of regional gas dynamics within the context of airway lumen size to better identify regions of functional obstruction compared to regions of restriction on an airway by airway basis.

References

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