KU Medical Image Analysis

Assignment 1

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1 Introduction

The aim of this assignment sheet was to extract the lung from a 3D CT volume of a thorax. This was done by using ROF denoising, which removes the small details in the lung, i.e. vessels. The remaining dark structure is then the lung which shall be extracted as a mask by using a Otsu theshold and shape labeling.

2 Methodology

In order to get a lung segmentation from the provided 3D CT volume the primal-dual algorithm for the ROF model can be used.

2.1 Primal-dual ROF algorithm

The primal-dual ROF algorithm is an edge-preserving denoising algorithm that can also be used for shape-denoising. It solves a saddle point problem by alternating gradient descent and ascent and achieves a global optimizer for the denoising solution.
The algorithm uses a pre-defined number of iterations. For each iteration the algorithm performs a primal update followed by a dual update. The implemented algorithm handels these as follows:
For the primal update a discretized divergence of the dual variable is calculated as follows

$$\nabla \cdot \boldsymbol{p} = (p^1_{i,j,k} - p^1_{i-1,j,k}) + (p^2_{i,j,k} - p^2_{i,j-1,k}) + (p^3_{i,j,k} - p^3_{i,j,k-1}) \ \forall i, j, k$$

For the boundaries a constant boundary condition is used (meaning the values outside the boundary are the same as the ones inside).
Afterwards the following minimization step for u is calculated:

$$\boldsymbol{u}^{t+1} = \boldsymbol{u}^t - \tau_P(-\nabla \cdot \boldsymbol{p} + \lambda(\boldsymbol{u}^t - \boldsymbol{f}))$$

After the primal update the dual update is applied. For the dual update a discretized gradient of the primal variable is calculated as follows

$$\nabla \boldsymbol{u} = \begin{bmatrix} u_{i+1,j,k} - u_{i,j,k} \\ u_{i,j+1,k} - u_{i,j,k} \\ u_{i,j,k+1} - u_{i,j,k} \end{bmatrix} \ \forall i, j, k$$

For the boundaries the zero flux Neumann boundary conditions was used (meaning everything outside is zero).

Afterwards the following maximization step for p is calculated:

$$\tilde{\boldsymbol{p}}^{t+1} = \boldsymbol{p}^t + \tau_D \nabla \boldsymbol{u}$$

Then the constraint $||\boldsymbol{p}||_2 \leq 1$ needs to be handeld. This is done via a projection onto the ℓ_2 ball of radius 1 for each gradient of a voxel.

$$\boldsymbol{p}^{t+1} = \frac{\tilde{\boldsymbol{p}}^{t+1}}{\max\{1, ||\tilde{\boldsymbol{p}}^{t+1}||_2\}}$$

All the steps above are applied simultaneously to all elements of the primal variable followed by all elements of the dual variable.
The algorithm terminates if the ℓ_∞-norm of the difference between two iterations for both the primal and the dual variable is less than ε. With ℓ_∞-norm denoting the biggest absolute value of a given tensor.

2.2 Confidence Connected filter for region growing segmentation

Region-growing algorithms are a better segmentation approach than thresholding techniques. The `ConfidenceConnected` filter is a ITK filter, that estimates the range of the threshold from predefined seeds. The seeds are chosen from the original 3D CT volume.

3 Results

3.1 Input image

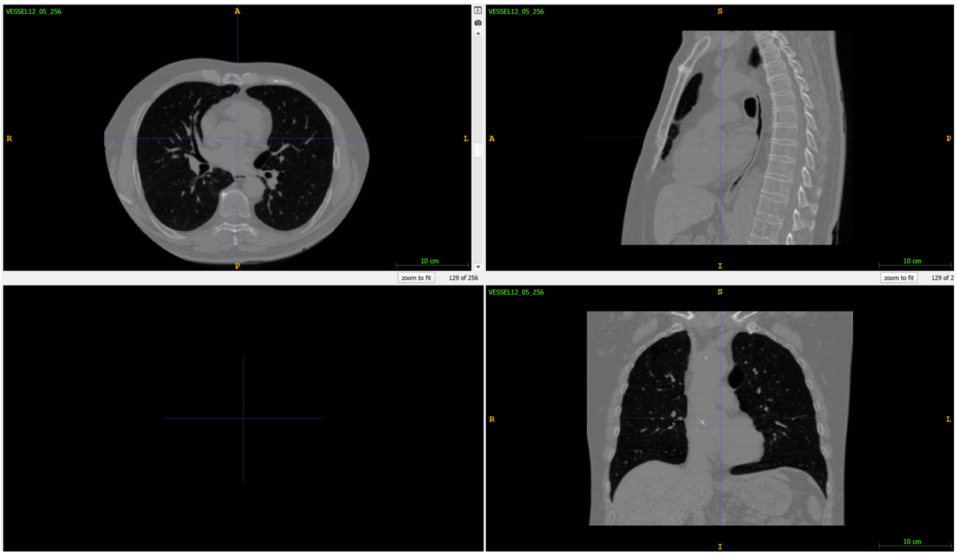

Figure 1: Input image: 3D CT volume of a thorax.

3.2 Experiment results for studying the effect of different values for λ and for different numbers of iterations

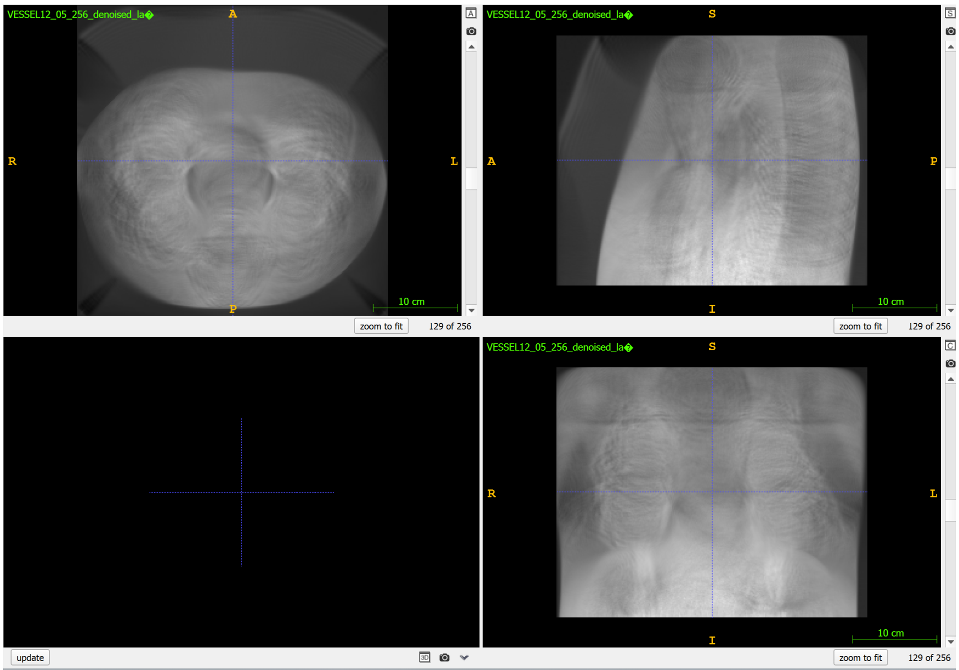

Figure 2: ROF denoising with the number of iterations being set to 300 and $\lambda = 0.1$.

Figure 3: ROF denoising with the number of iterations being set to 300 and $\lambda = 1$.

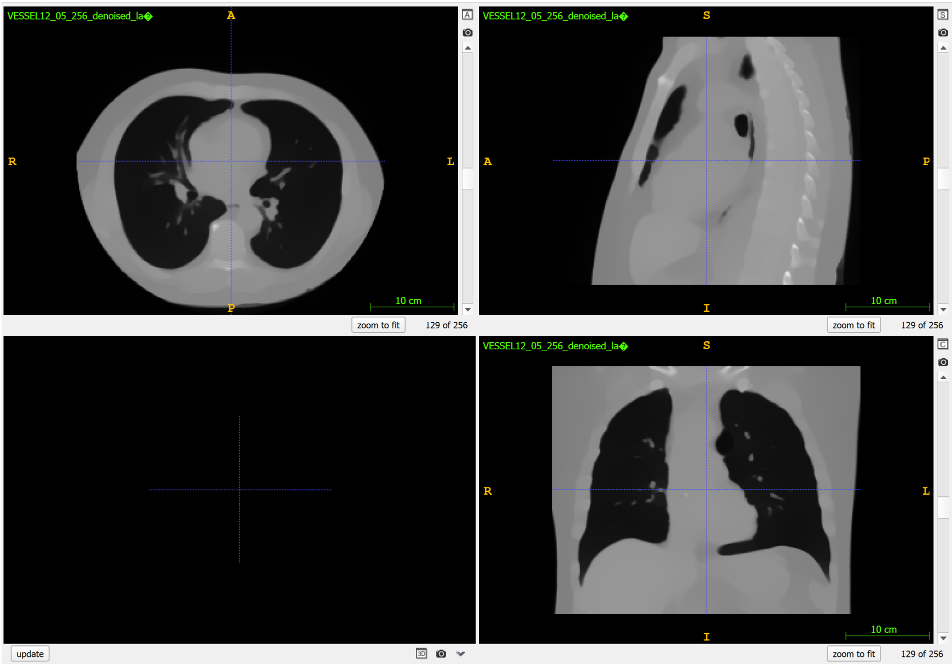

Figure 4: ROF denoising with the number of iterations being set to 300 and $\lambda = 5$.

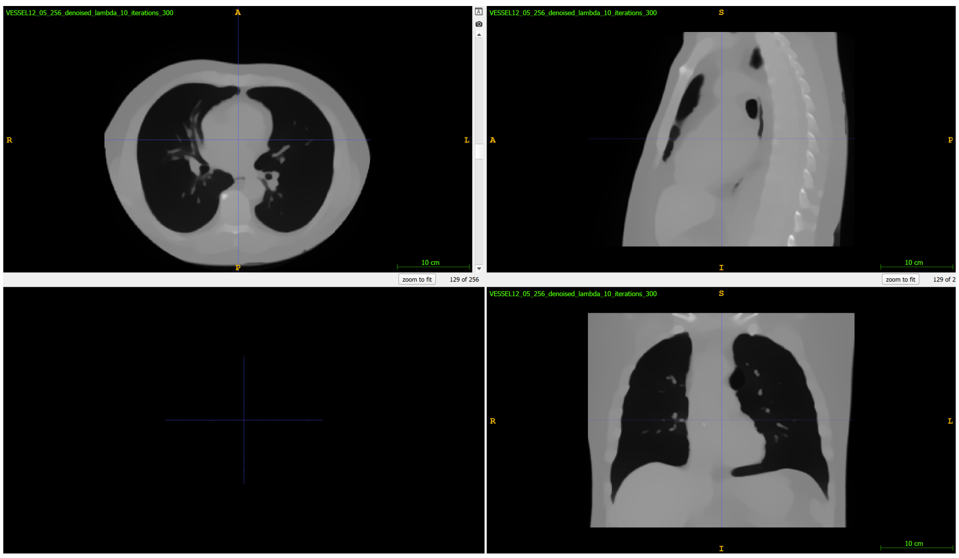

Figure 5: ROF denoising with the number of iterations being set to 300 and $\lambda = 10$.

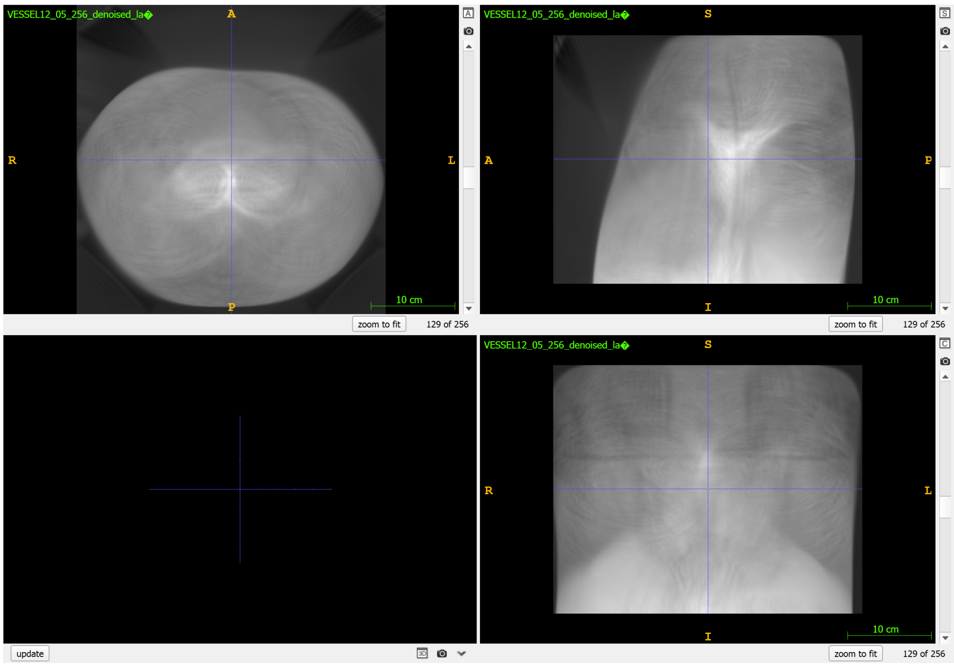

Figure 6: ROF denoising with the number of iterations being set to 500 and $\lambda = 0.1$.

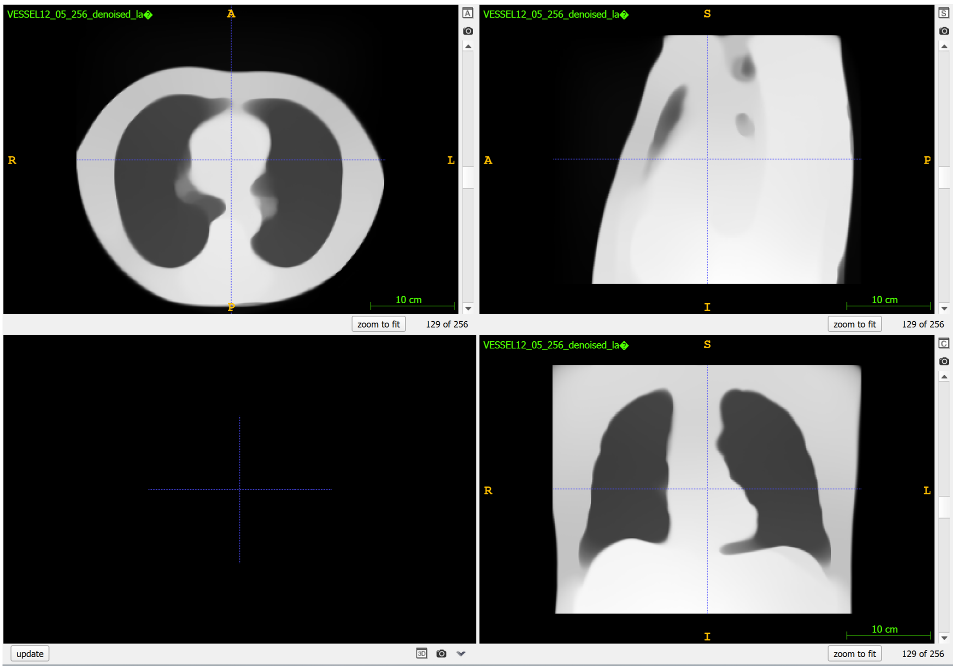

Figure 7: ROF denoising with the number of iterations being set to 500 and $\lambda = 1$.

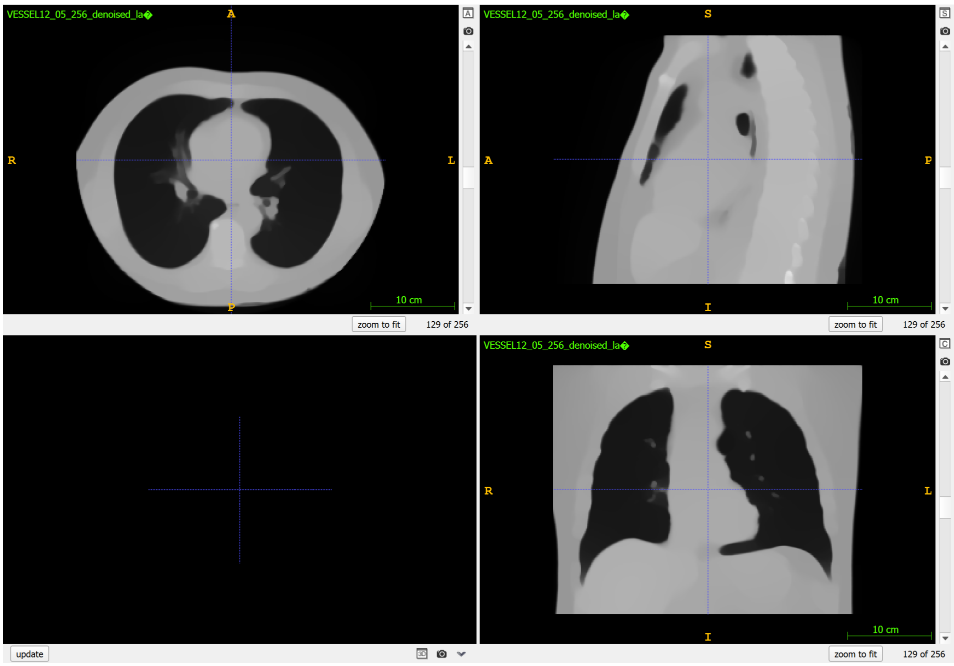

Figure 8: ROF denoising with the number of iterations being set to 500 and $\lambda = 5$.

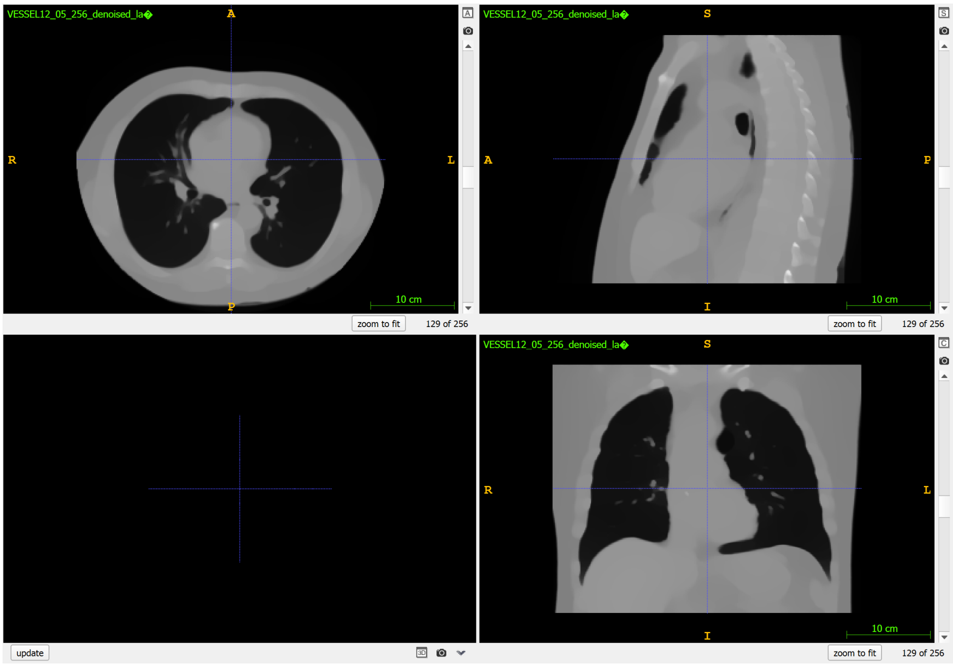

Figure 9: ROF denoising with the number of iterations being set to 500 and $\lambda = 10$.

3.3 Otsu threshold

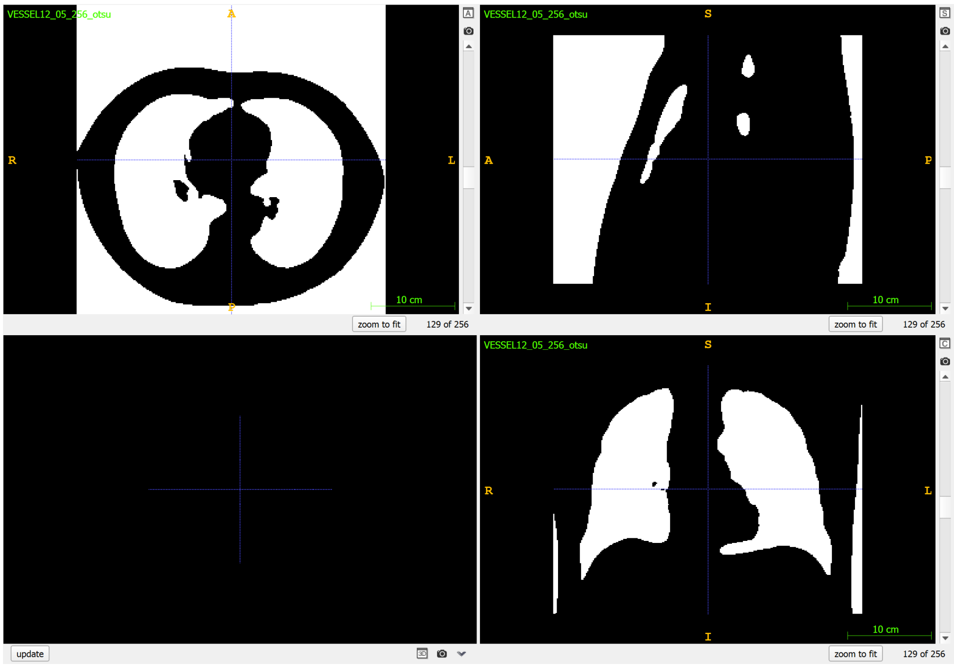

Figure 10: Otsu threshold with a bin size of 128 for the histogram ($\lambda = 5$, number of iterations = 500).

3.4 Shape labeling

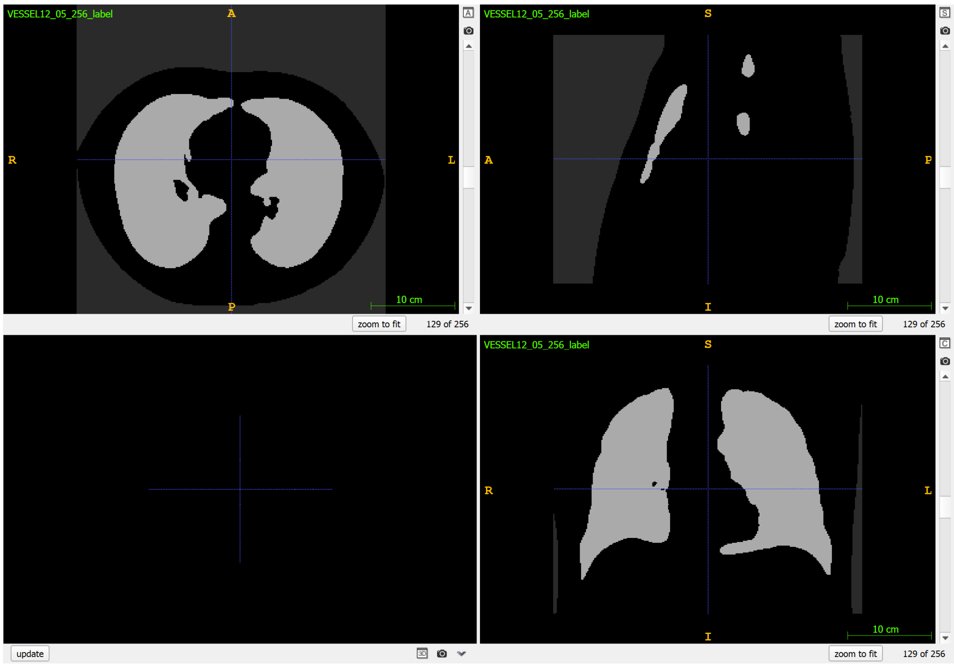

Figure 11: Shape labeling to find the connected components in the thresholded image.

3.5 Lung segmentation

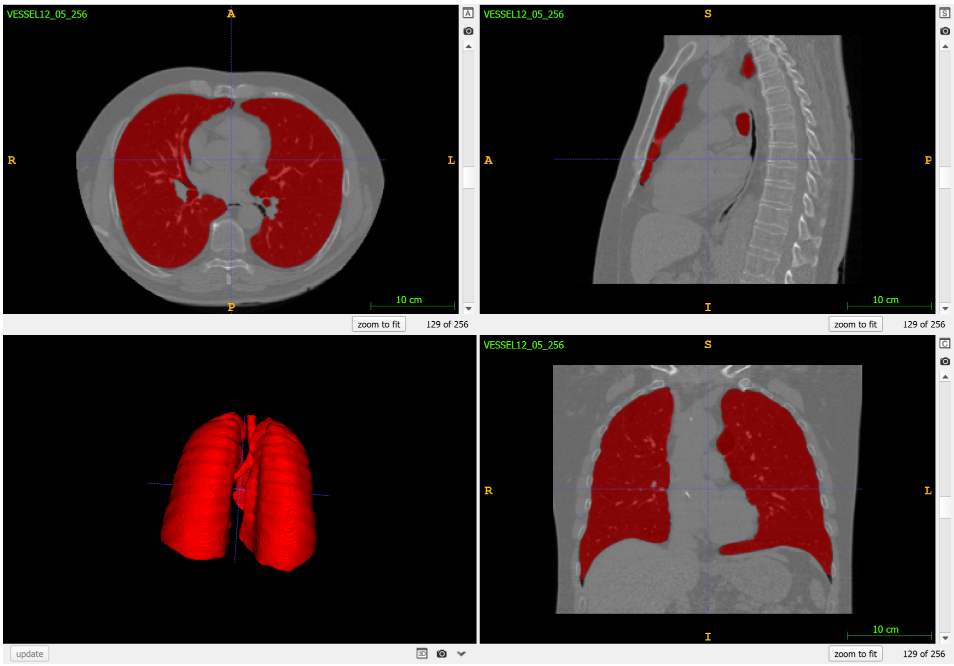

Figure 12: Result of lung segmentation for $\lambda = 5$ without region growing.

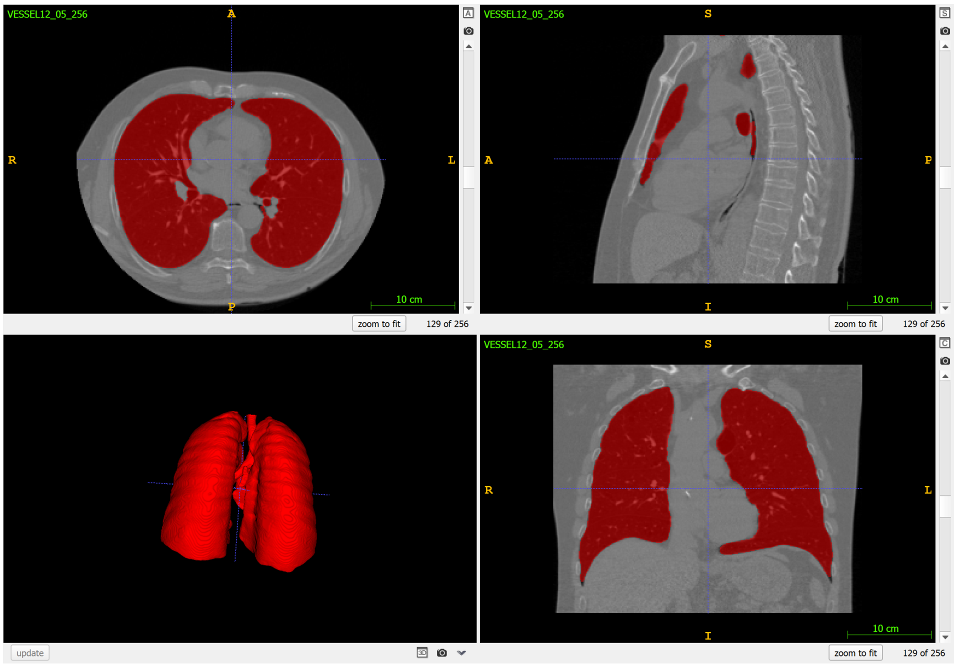

Figure 13: Result of lung segmentation for $\lambda = 5$ with region growing (confidence connected).

4 Discussion

When comparing the images with different values for λ one can see that the smaller λ gets the stronger the denoising of the image will become. For $\lambda = 0.1$ the image becomes unrecognizable (see figure 2 and 6). For $\lambda = 5$ the small vessels in the lung have nearly disappeared, however also the edges of the lung start to vanish, especially in the corners near the diaphragm (see figure 4 and 8). This is even more defined for $\lambda = 1$ (see figure 3 and 7). Here the vessels have completely disappeared, however the smoothing of the edges is even stronger. For a greater value of λ, like 9 or 10 not all vessels could be removed, however, the edges are better persevered (see figures 5 and 9). The reason for this is that for a small λ the difference between the original image and the denoised image has a small impact onto the saddle point problem. This means the number of iterations would need to be a lot higher to reach the actual optimum.
There is no significant difference visible between the images where the iteration was set to 300 and the ones where the number of iterations was set to 500. Also, the early stopping did not stop as the maximum absolute difference of both variables was always greater than the selected ϵ. In the end, I decided to use $\lambda = 5$ and 500 iterations for the lung segmentation.
The output image of the Otsu thresholding can be seen in figure 10 for $\lambda = 5$ and number of iterations = 500. One can see that most parts of the lung were recognized as one image area (foreground), and the rest of the thorax was recognized as another image area (background). Since not all vessels were removed by the denoising these were also classified as background by the Otsu threshold.
Shape labeling was then used to define the connected components in the thresholded image and the lung was chosen according to the labeled shape sizes. Since we know that the background is the largest connected dark region, we can say that the lung is the second largest dark region, which would be the white area in the Otsu-filtered image. With this information and the size of the individual labels it is possible to extract a mask for the lung.
The final lung segmentation can be seen in figure 12. One can see that some vessels were not recognized as part of the lung. Also, there are some gaps near the diaphragm.
To fill some of the gaps near the diaphragm a region-growing algorithm was used. For the seeds data points inside the lung were chosen from the denoised image with the tool ITK-snap. The result can be seen in figure 13. Here the gaps are now slightly smaller between the lung and the diaphragm. Also, gaps between the lung and the edges decreased.