# Automatic Lung Segmentation in MDCT Images

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Case 01
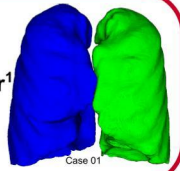
Introduction

A fast and reliable segmentation of the lung tissues is of fundamental importance for many clinical applications like emphysema quantification or lung nodule detection. We present a method for fully automated extraction of the lungs from volumetric computed tomography (CT) images. The method is part of our in-house software *yacta*.
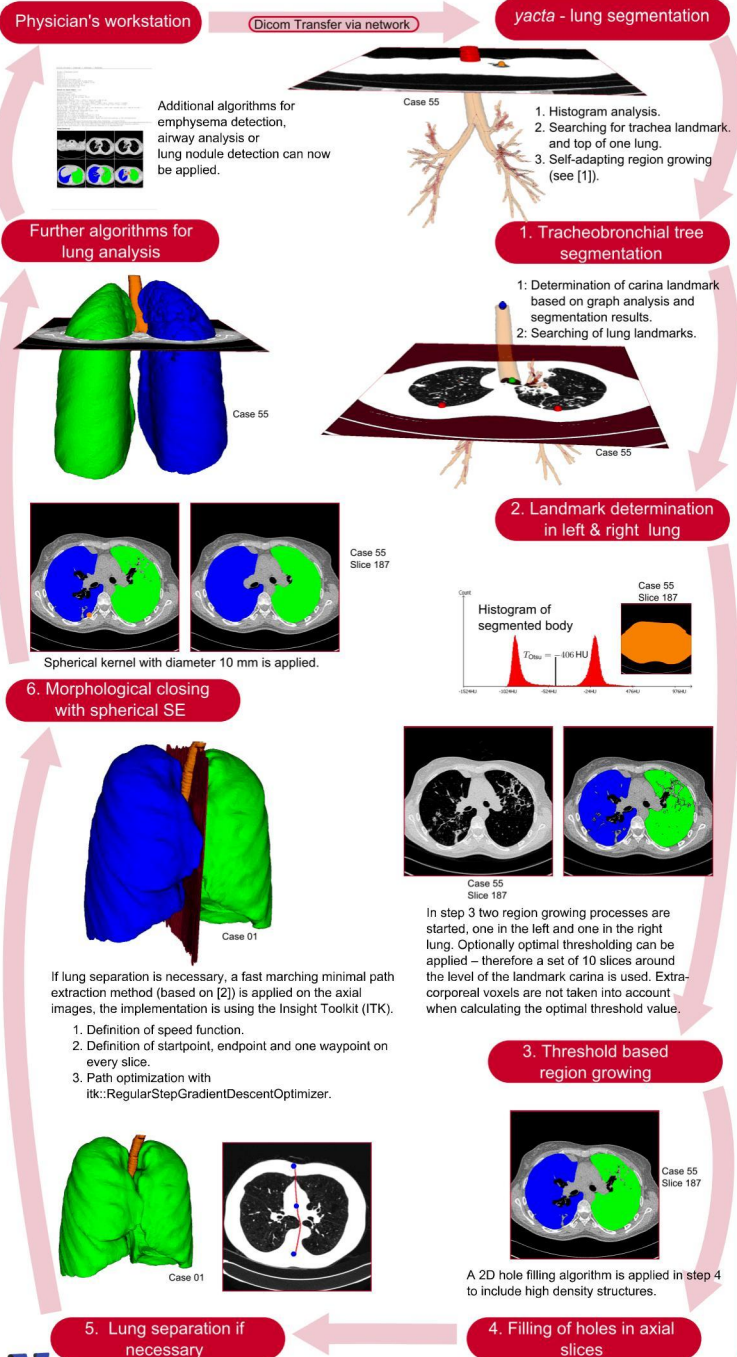
Depending on anatomical variations and pathological changes lung segmentation can be demanding. On the one hand clinical applications should be able to handle severe pathologic lung CT images, e.g. for longitudinal studies. On the other hand they should also be sensitive enough to find pathologic lung changes in an early state because a precocious diagnosis is the best way to ensure the success of a treatment.

An evaluation on 55 clinical datasets (LOLA11-datasets) shows that the segmentations of our method achieves a good average volumetric overlap (97%) against manually generated reference segmentations.

Automatic Lung Segmentation in MDCT Images

The algorithm currently used in *yacta* can be classified as an advanced conventional method and consists of following steps:

1. Segmentation of tracheabronchial tree.
2. Landmark determination in left and right lung.
3. Threshold based region growing.
4. Filling of holes in axial slices.
5. Lung separation if necessary.
6. Morphological closing operation with a spherical structural element.

Physician's workstation — Dicom Transfer via network → yacta - lung segmentation

Additional algorithms for emphysema detection, airway analysis or lung nodule detection can now be applied.

Case 55

1. Histogram analysis.
2. Searching for trachea landmark. and top of one lung.
3. Self-adapting region growing (see [1]).

Further algorithms for lung analysis

Case 55

1. Tracheobronchial tree segmentation

1: Determination of carina landmark based on graph analysis and segmentation results.
2: Searching of lung landmarks.

Case 55

Case 55

2. Landmark determination in left & right lung

Case 55 Slice 187

Spherical kernel with diameter 10 mm is applied.

Histogram of segmented body

C_{opt}

$T_{Otsu} = -106\ HU$

Case 55 Slice 187

6. Morphological closing with spherical SE

Case 01

If lung separation is necessary, a fast marching minimal path extraction method (based on [2]) is applied on the axial images, the implementation is using the Insight Toolkit (ITK).

1. Definition of speed function.
2. Definition of startpoint, endpoint and one waypoint on every slice.
3. Path optimization with itk::RegularStepGradientDescentOptimizer.

Case 55 Slice 187

In step 3 two region growing processes are started, one in the left and one in the right lung. Optionally optimal thresholding can be applied – therefore a set of 10 slices around the level of the landmark carina is used. Extra-corporeal voxels are not taken into account when calculating the optimal threshold value.

3. Threshold based region growing

Case 55 Slice 187

Case 01

A 2D hole filling algorithm is applied in step 4 to include high density structures.

5. Lung separation if necessary

4. Filling of holes in axial slices
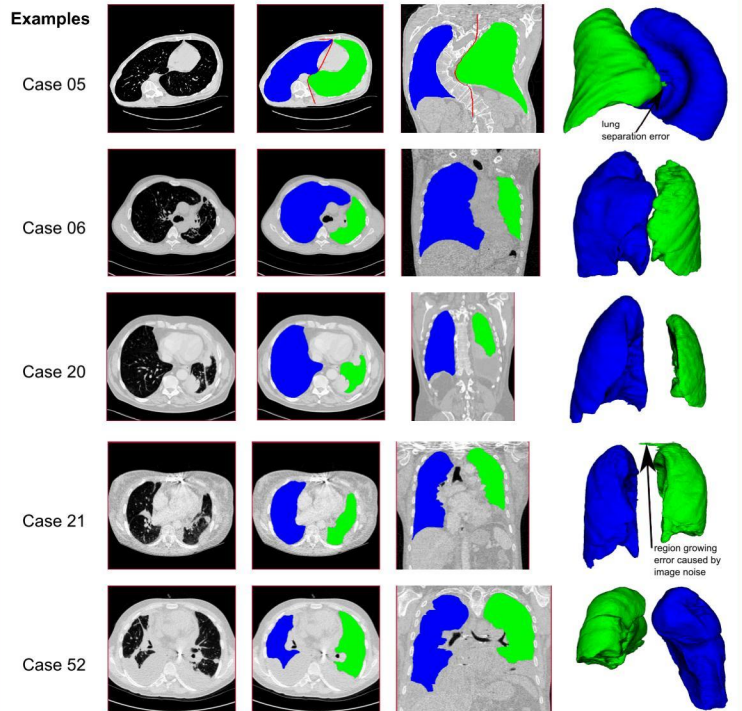
Results

The automatic lung segmentation methodology implemented in *yacta* was applied to all 55 LOLA11-datasets. The achieved results were compared with manually generated reference segmentations. As measure the volumetric overlap fraction was used, which compares the relative volumetric overlap of two binary segmentations: $O(V_1, V_2) = \frac{\|V_1 \cap V_2\|}{\|V_1 \cup V_2\|}$.

The segmentation results with morphological closing (score: 0.970, step 6, see Table 1) are with respect to this measure slightly better as the results without closing (score: 0.964). The average runtime on a PC (Intel Xeon CPU, 2.83 GHz, 4GB RAM) per case was 7.3 minutes without morphological closing and 11.4 minutes with morphological closing. For details on the set-up of the study, collection of data and evaluation of segmentations see http://www.lola11.com/.

Table 1. Results of lung segmentation for the 55 scans in LOLA11 - with morphological closing.

	mean	SD	min	Q1	median	Q3	max
left lung	0.971	0.0925	0.309	0.982	0.988	0.992	0.997
right lung	0.969	0.134	0	0.986	0.99	0.993	0.998
score	0.970						

Examples

Case 05 — lung separation error

Case 06

Case 20

Case 21 — region growing error caused by image noise

Case 52

It is worth to mention, that *yacta* is integrated (running on a virtual server) in the daily routine of the Department of Radiology at the Thoraxklinik Heidelberg. Just there, more than 2500 datasets were analysed by *yacta* until now. If errors occur in the segmentation process, they are analyzed and the algorithms are modified accordingly, difficult datasets are captured in a database. New releases of *yacta* are tested on a database containing currently more than 150 scans from different sources. This gives the possibility to develop the software step by step, without losing quality achieved already.

Conclusion

We presented a method for fully automated segmentation of the lungs from CT scans. Our method worked well on the challenging datasets of LOLA11, nevertheless we have gathered valuable information for our future work. Generating a common database covering a wide range of possible CT scans is an important step for improving and comparing different lung segmentation methods.

Our implementation can be classified as advanced conventional method. The good score achieved with this method shows that it is a suitable solution for lung segmentation. Nevertheless there are still problems to solve and ideas to improve the method , e. g.: (1) Using a higher HU threshold for the threshold based segmentation in step 3 can lead to a better segmentation. (2) The minimal path algorithm is implemented in 2D, working on axial slices. This should be a real 3D method. (3) Integration of a robust lobe segmentation. (4) Faster runtime. (5) Better airway tracer.

Literature

[1] Weinheimer, O., Achenbach, T., Düber, C.: Fully automated extraction of airways from ct scans based on self-adapting region growing. In: Proceedings of the SecondInternational Workshop on Pulmonary Image Analysis. (2009) 315–321

[2] Mueller, D.: Fast marching minimal path extraction in itk. The Insight Journal (2008)

Further Information

Please contact mail@oliwe.com. More information on this and related projects can be obtained at www.oliwe.com. You can find an online PDF-version of this poster here: www.oliwe.com/publications/Weinheimer_2011_LOLA11_Poster.pdf

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