AUTOMATIC LIVER AND TUMOR SEGMENTATION IN LATE-PHASE MRI USING FULLY CONVOLUTIONAL NEURAL NETWORKS

Grzegorz Chlebus, Hans Meine, Nasreddin Abolmaali and Andrea Schenk
Background

- Liver & tumor segmentation is required for many liver interventions

- Radioembolisation
  - Basis for tumor load computation
  - Required for dose computation

- Manual or semi-automatic segmentation
  - Tedious and time consuming
  - Inter-observer variability

- Well studied problem for CT
  - LiTS challenge 2017 (3rd place out of 28 teams) [1]

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Goal

- Develop automatic DL-based algorithm for:
  - Liver segmentation
  - Liver tumor segmentation

- Comparison with:
  - Reference annotations
  - Clinical routine segmentations
  - Results reported in the literature

- Extends our previous work [1]

Data

- 90 patients with primary liver cancer and/or liver metastases
  - 76 scheduled for radioembolisation
- DCE-MRI
  - Acquired at Städtisches Klinikum Dresden, Germany
  - 3T Discovery MRI, GE Healthcare Systems, USA
  - Contrast agent Gd-EOB-EDPA (Primovist®, Bayer Healthcare)
  - LAVA sequence

Native 20s 60s 120s 15 min
Manual segmentations

- **Reference**
  - Very precise and time consuming
  - Done by radiological assistants and reviewed by a radiologist
  - Used for training of deep learning models

- **Routine**
  - According to clinical routine standards
  - Defined by one radiologist and two residents
  - Contouring and interpolation software [1]


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Segmentation Pipelines

- Axial
Segmentation Pipelines

- OrthoMean [1]


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Neural network architecture

- U-net like [1]
- 4 resolution levels
- 9M trainable parameters
- Receptive field 94x94 voxels

- 3x3 convolution kernels
- Short skip connections [2]
- Batch normalization
- Spatial dropout

Data preprocessing

- Normalization
  - 2nd and 98th percentiles mapped to [0, 1] range

- Resampling to a 2mm isotropic voxel size

- Training data augmentation
  - Random rotations
  - Random intensity shifts

- Training/validation/evaluation split
  - 57/5/28 liver
  - 60/5/20 liver tumor
Results: Training Data Size

Liver segmentation quality

Axial

OrthoMean
Examples: Liver

*White – Reference*

*Solid black – Axial*

*Dashed black – OrthoMean*
Examples: Liver tumors

White – Reference

Solid black – Axial

Dashed black – OrthoMean
## Results

### Axial vs OrthoMean

<table>
<thead>
<tr>
<th></th>
<th>DICE</th>
<th>RVE[%]</th>
<th>t[s]</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Liver</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Axial</td>
<td>0.946 ± 0.018</td>
<td>4.20 ± 3.34</td>
<td>2.05 ± 0.34</td>
</tr>
<tr>
<td>OrthoMean</td>
<td>0.951 ± 0.018</td>
<td>4.20 ± 3.65</td>
<td>7.32 ± 0.36</td>
</tr>
<tr>
<td><strong>Tumor</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Axial</td>
<td>0.627 ± 0.241</td>
<td>48.9 ± 53.3</td>
<td>1.73 ± 0.73</td>
</tr>
<tr>
<td>OrthoMean</td>
<td>0.647 ± 0.210</td>
<td>35.9 ± 28.2</td>
<td>7.63 ± 2.23</td>
</tr>
</tbody>
</table>
Results: Comparison with routine segmentations of the liver

- Manual routine segmentations: 10 ± 4 min
- OrthoMean: 7.3 ± 0.4s

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## Comparison with literature

<table>
<thead>
<tr>
<th></th>
<th>DICE</th>
<th>#</th>
<th>Sequence</th>
<th>Scanner</th>
<th>Resolution [mm]</th>
<th>Slice thickness [mm]</th>
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</thead>
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<td>Axial, OrthoMean</td>
<td>0.946 ± 0.018</td>
<td>90</td>
<td>LAVA</td>
<td>3T Discovery(GE)</td>
<td>0.74-1.76</td>
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<tr>
<td>Christ et al. [6]</td>
<td>0.870</td>
<td>31</td>
<td>n/a</td>
<td>1.5T Avanto(Siemens)</td>
<td>n/a</td>
<td>5.0</td>
</tr>
<tr>
<td>Suzuki et al. [7]</td>
<td>0.936 ± 0.017*</td>
<td>23</td>
<td>LAVA, THRIVE</td>
<td>1.5T Signa HDx/HDxt(GE), 1.5T Achieva(Philips)</td>
<td>1.17-1.72</td>
<td>4.0-5.0</td>
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<tr>
<td>Le et al. [8]</td>
<td>0.910 ± 0.028</td>
<td>10</td>
<td>VIBE</td>
<td>1.5T Avanto(Siemens)</td>
<td>1.18-1.40</td>
<td>3.5-4.0</td>
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<tr>
<td>Bereciartua et al. [9]</td>
<td>0.902 ± 0.086</td>
<td>18</td>
<td>VIBE</td>
<td>1.5T Avanto(Siemens)</td>
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<td>Huynh et al. [10]</td>
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<td>VIBE, LAVA, THRIVE</td>
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<tr>
<td>Ivashchenko et al. [11]</td>
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<td>mDIXON</td>
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* Average for CT and MRI dataset.

- **Direct comparison not possible due to differences in datasets**

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Summary

- Liver segmentation quality of our segmentation approaches was comparable to that of manual routine segmentations
- Tumor segmentation is a more difficult task than liver segmentation
- Acquiring more training data has a positive impact on the model performance
- Direct comparisons with other methods remain difficult due to lack of publicly available data

Future work
- More extensive validation
- Evaluation of 3D architectures
Thank you for your attention 😊

Questions?
What does the neural network see?