Left Atrial Segmentation in a Few Seconds Using Fully Convolutional Network and Transfer Learning

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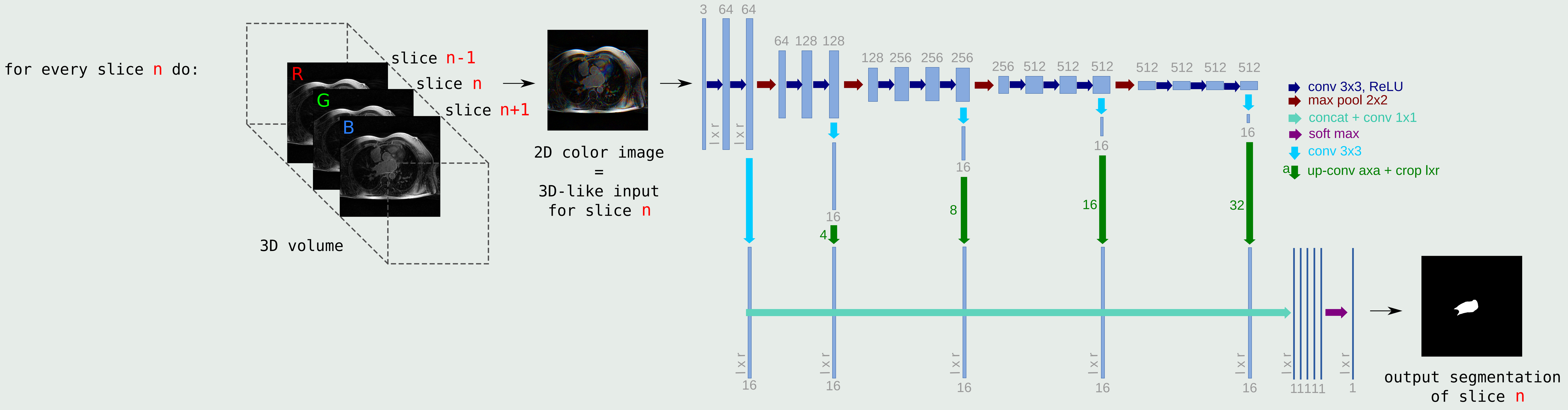
At a glance



Problem:

- We want a precise segmentation of left atrial in MRI heart volumes...
- ...and we want it quick!

Why our approach is intersting:

- it is simple, light, and versatile

Conclusion:

- a novel approach to handle 3D volumes with 2D CNN [1, 2]
  → the *"3D-like"* approach
- transfer learning works for medical image segmentation
- state-of-the-art results... obtained in a few seconds

Most important stuff

What people do:

- 3D patches at every voxel [6]
- 2,5 D patches = 3 × 2D patches at every voxel [7]
  → that is heavy / slow
- a dedicated network [...]
  → a large dataset for training is required

What we propose:

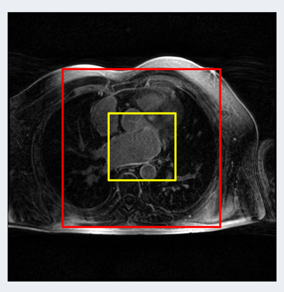
- input a FCNN network with a series of 2D images
  → 3 slices of a 3D volume = 1 color 2D image
  ⇝ these **2D images** are **3D-like**
- reuse a fast and pre-trained base network (VGG-16 [3])
  → transfer learning [5]

And it's generic:

- applied to *MRI brain volumes* for structures segmentation [1] (results on [4]) and for white matter hyperintensities segmentation [2]

Training

- Tools: GNU/Linux, Keras over Tensorflow, NVIDIA GPU
- ADAM optimization procedure to minimize the loss, 10 epochs
- Parameters: learning rate = 0.002, $\beta_1 = 0.9$, $\beta_2 = 0.99$, $\epsilon = 0.001$
- Images are cropped (red frame) and gray-levels are normalized wrt the center histogram (yellow)



- Training database is split: 80 volumes for training and 20 for validation
- Training time: 1 epoch takes less than 5 min
- Inference lasts 1.8 second

Preliminary results

- Light post-processing: spacial regularization using 1D and 2D median filters + largest component selection + hole fill-in
- Cross-validation with 5-fold procedure (80/20):

	basic	with normalization	+ with regularization
Dice	0.86	0.91	**0.92**

- Qualitative results: in yellow: true positive, in green: false negative

Selected bibliography

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[2] Y. Xu, É. Puybareau, T. Géraud, and J. Chazalon, "**White matter hyperintensities segmentation in a few seconds using fully convolutional network and transfer learning**," in *BrainLes (MICCAI 2017 competition)*, pp. 501–514, vol. 10670 of LNCS, Springer, 2018.

[3] K. Simonyan and A. Zisserman, "**Very deep convolutional networks for large-scale image recognition**," *CoRR*, vol. abs/1409.1556, 2014.

[4] A. M. Mendrik *et al.*, "**MRBrainS challenge: Online evaluation framework for brain image segmentation in 3T MRI scans**," *Computational Intelligence and Neuroscience*, 2015. ⇝ http://mrbrains13.isi.uu.nl/results.php

[5] J. Long, E. Shelhamer, and T. Darrell, "**Fully convolutional networks for semantic segmentation**," in *CVPR*, pp. 3431-3440, 2015.

[6] H. Chen *et al.*, "**VoxResNet : Deep voxelwise residual networks for volumetric brain segmentation**," https://arxiv.org/abs/1608.05895, 2016.

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