Laboratoire d'Informatique, du Traitement de l'Information et des Systèmes

Segmentation of Organs at Risk in CT Images using Deep Anatomical Constraints Learning

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Collaborations

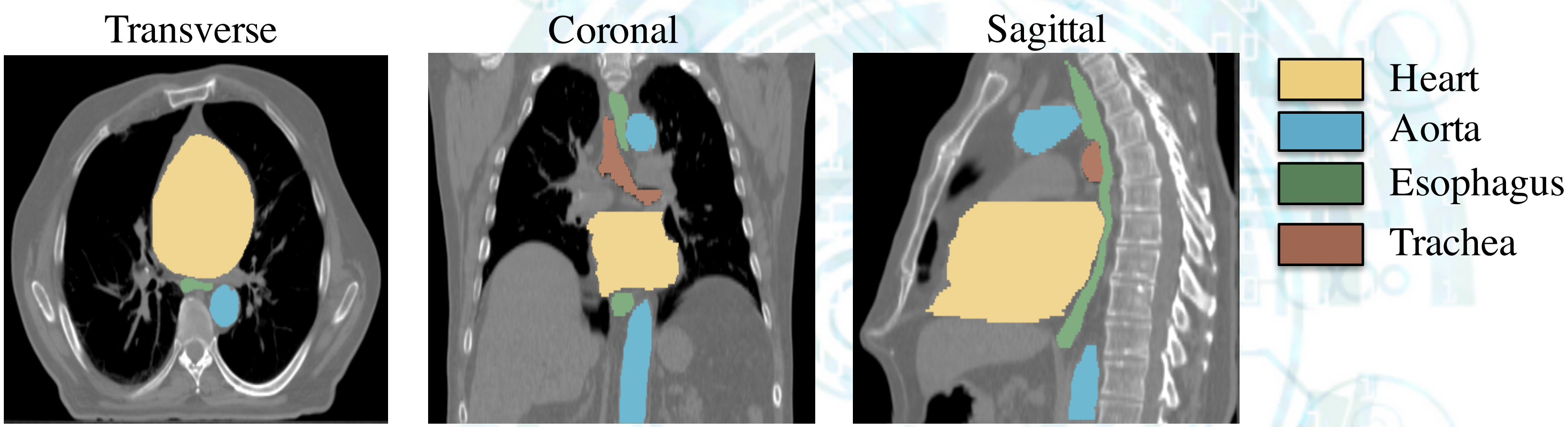
- Joint work with
  - S. Ruan, C. Petitjean (co-supervisors)
  - B. Dubray (radiotherapist)
  - D. Nie and Prof. D. Shen (IDEA Lab UNC)
- Funded by M2NUM Project
  - Regional and European grant

Context

- Cancer is a leading cause of death worldwide.
- Radiotherapy, alone or combined with chemotherapy, is a standard treatment.
- First step is to identify the target volumes to be treated and the healthy organs at risks to be protected.

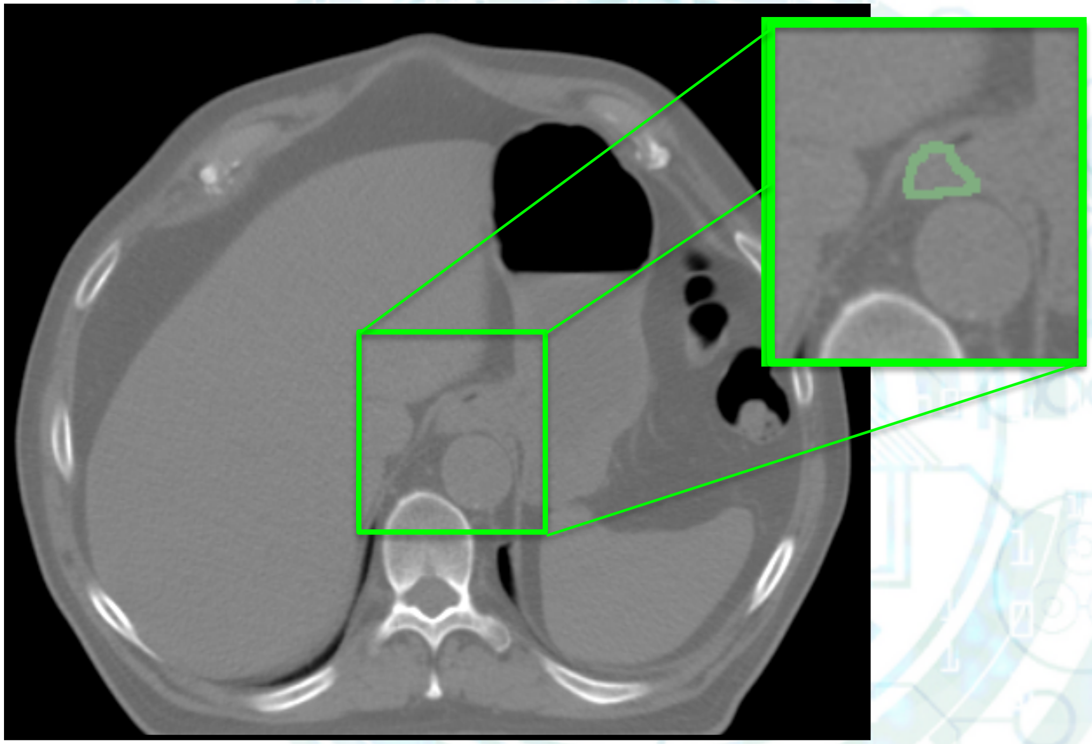
Context

- We work on the automatic segmentation of 4 Organs at risk



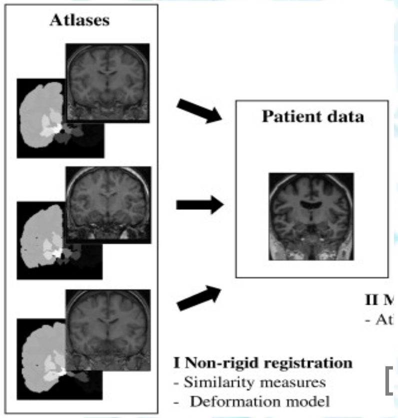
Context

- Esophagus is particularly challenging due to low contrast



Related Works and Limitations

- Multi-atlas based segmentation methods (-) High accuracy registration needed
  - Majority Voting (MV)

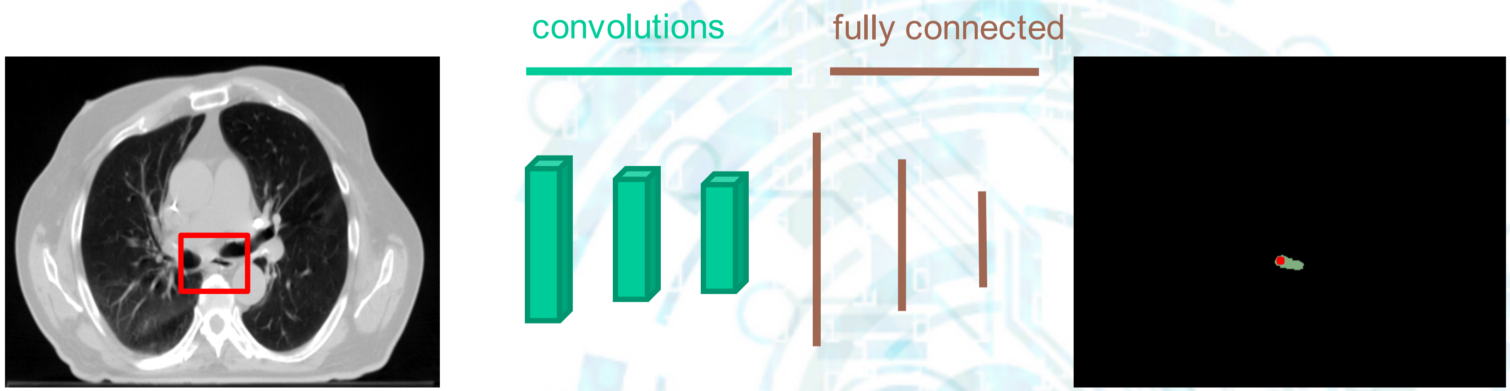


[Lotjönen et al, Neuroimage 2010]

- Learning-based segmentation methods (-) Manual designed features
  - Random Forest (RF), LINKS

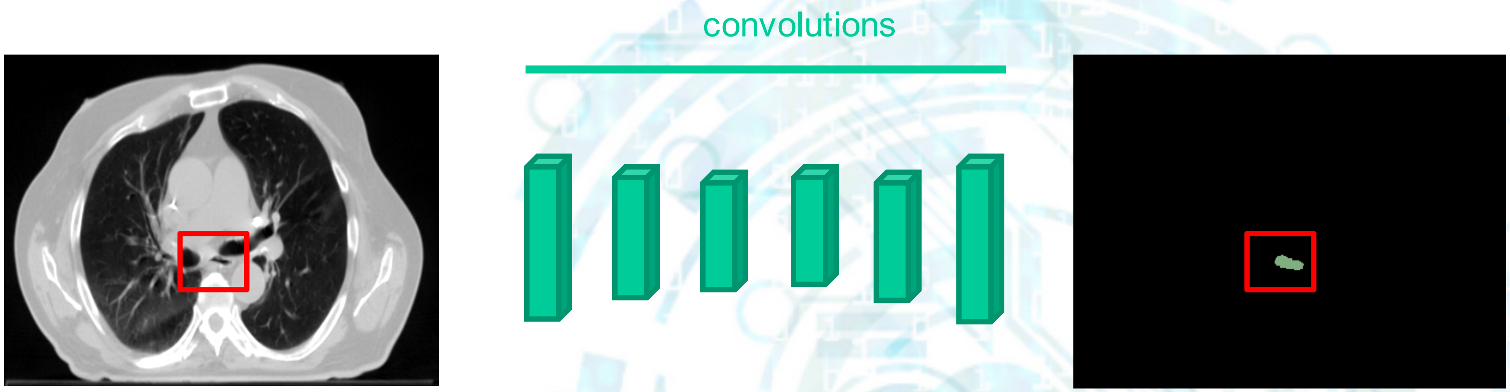
CNNs could (partially) address these limitations

Convolutional Neural Networks



(+) Learn features automatically
(-) Lose spatial information
(-) Slow

Fully Convolutional Networks



(+) Retain spatial information
(+) Fast

FCN Improvement

Input Image

FCN Result

Ground-Truth

FCNs tend to produce coarse outputs and do not encourage structure

Conditional Radom Fields (CRF)

- Discriminative graphical model that can be used to encourage structured outputs

$$E(X) = \sum_i \phi_u(x_i) + \sum_{ij} \phi_p(x_i, x_j)$$

- Typically, CRFs has been used to boost the performance of simple classifiers

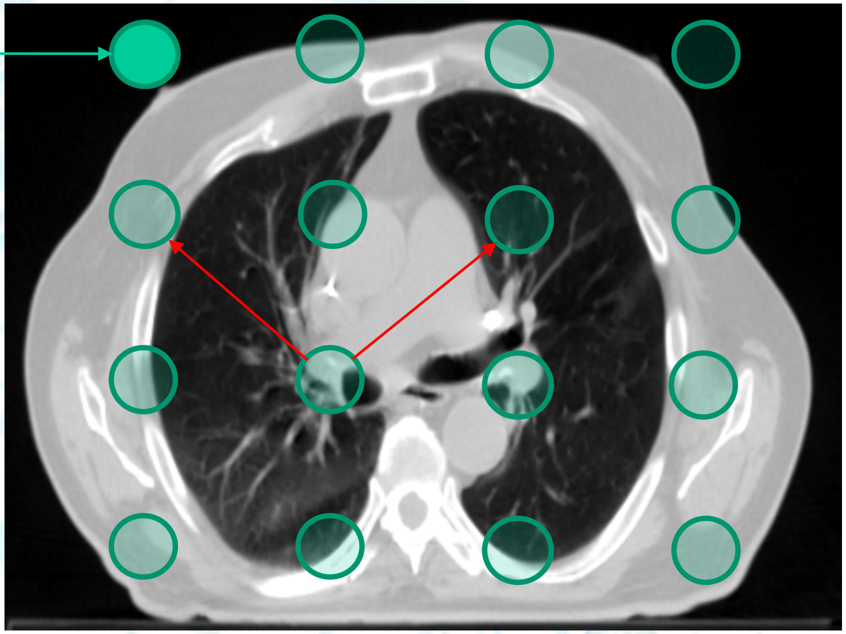
CRF Illustration

Unary Term

- Depends on individual nodes
- Pay a penalty if the label assignment does not agree with the initial probability (classifier)

Pairwise Term

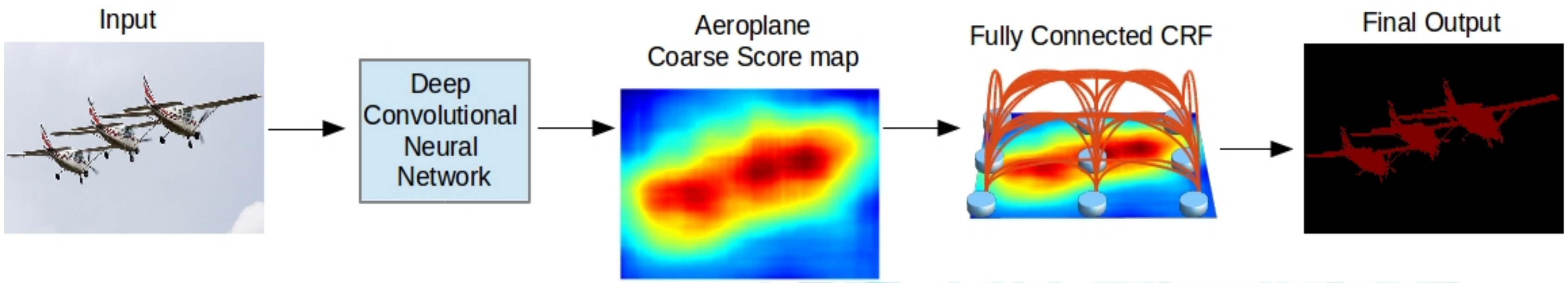
- Depends on pairs of nodes
- Pay a penalty if two similar nodes have a different label assigned



$$w_1 exp\left(-\frac{\|I_i - I_j\|^2}{2\sigma_\beta^2}\right) + w_2 exp\left(-\frac{\|p_i - p_j\|^2}{2\sigma_\gamma^2}\right)$$

CRF to Improve FCN

- Use CRF as a post-processing step



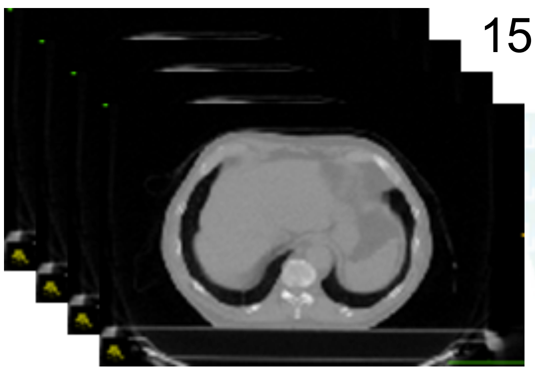
[Chen et al. ICLR 2015]

- CRFasRNN [Zheng et al ICCV'15]
  - Perform Inference using Recurrent Neural Networks (RNNs).
  - Not anymore a separated step, it can be trained as an additional layer of the network.

Experimental Setting

- **60 CT scans where the patients have either lung cancer or Hodgkin lymphoma**
- Volume sizes of 512x512x(150~284) voxels
- Spatial resolution of 0.98x0.98x2.5 mm^3

- **6 Fold Cross Validation**
- 50 subjects for training and 10 for testing at each fold

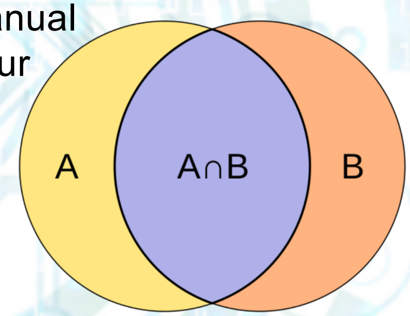


150 ~ 284

512

512

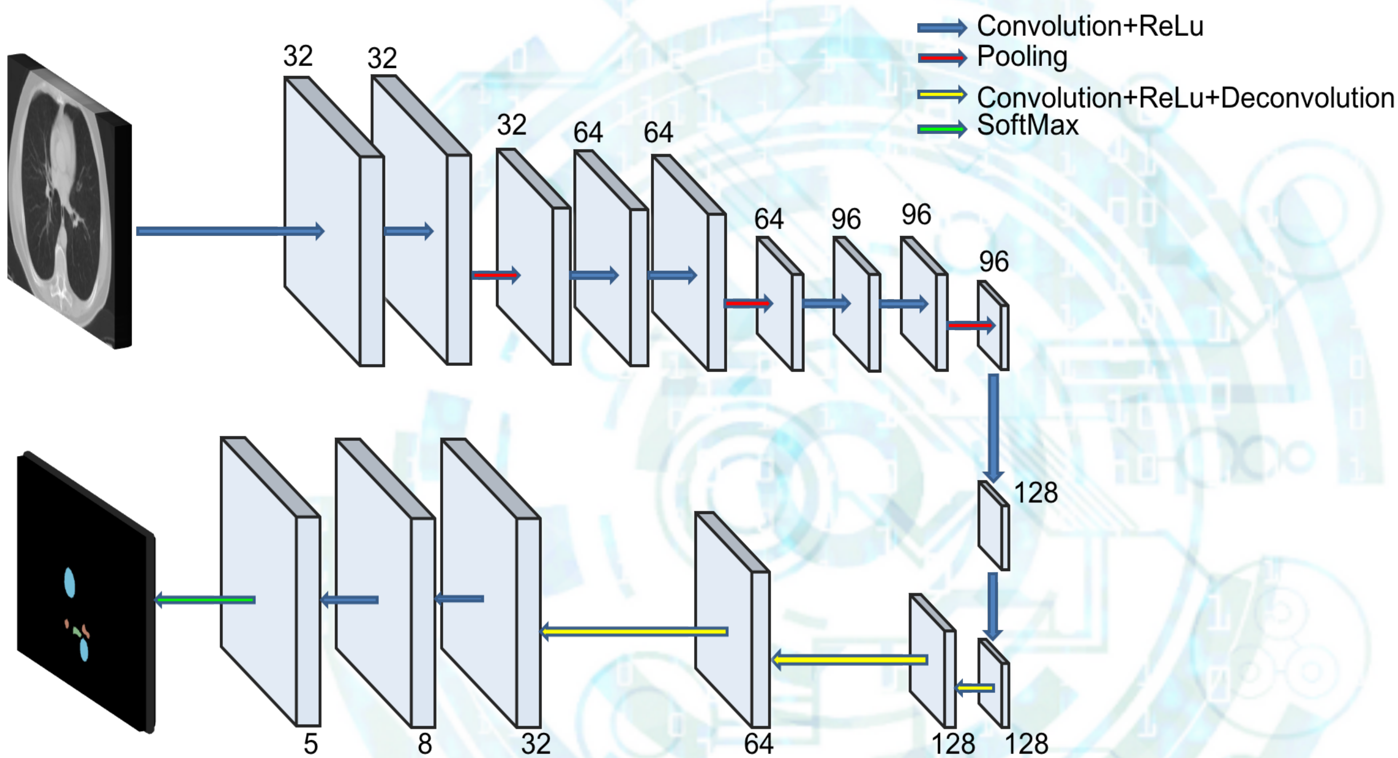
A: Manual contour



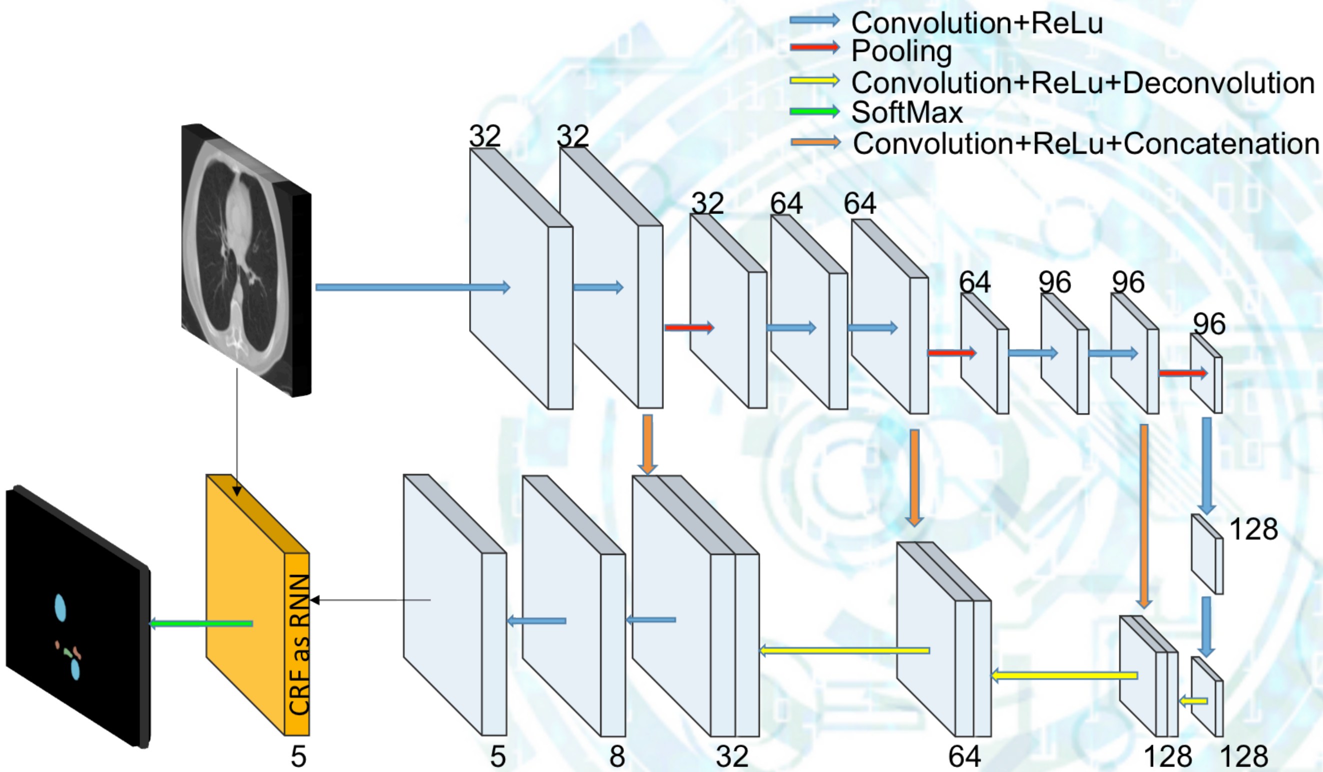
B: Contour with our method

$$Dice\ index = \frac{2|A \cap B|}{|A|+|B|}$$

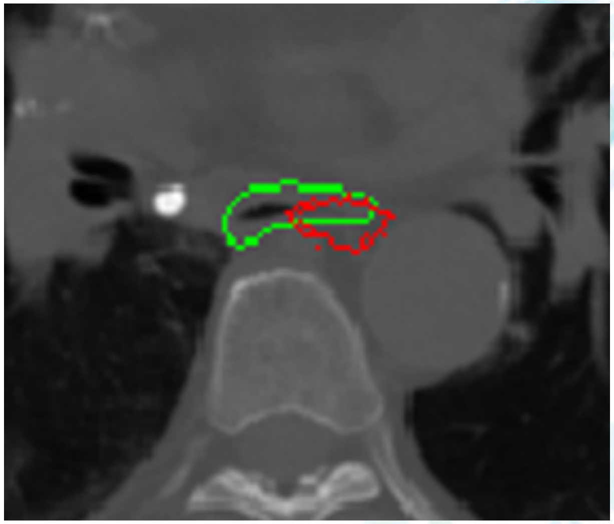
FCN Model


Convolution+ReLu
Pooling
Convolution+ReLu+Deconvolution
SoftMax
32
32
32
64
64
64
96
96
96
128
128
128
64
32
8
5

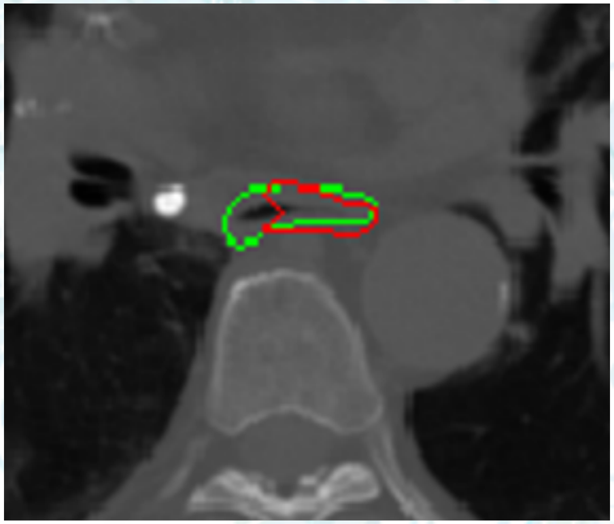
Skip-connection architecture (First Framework)



Visual Results

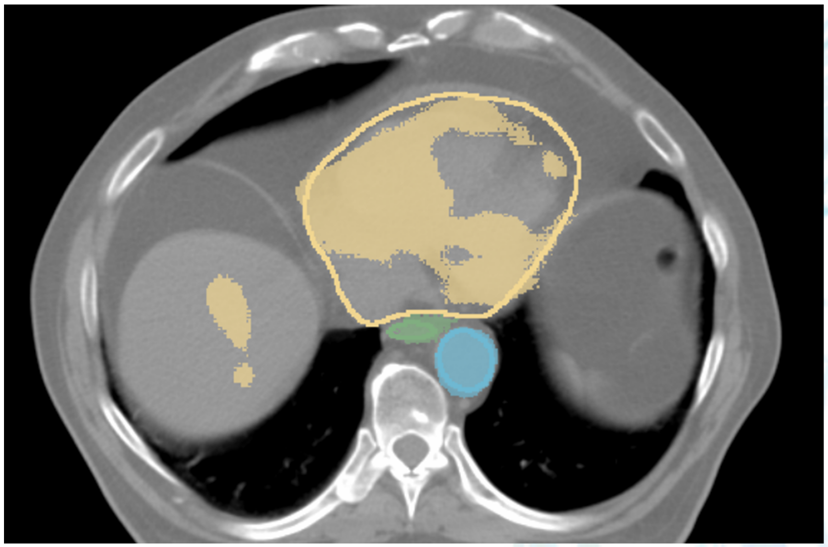


FCN

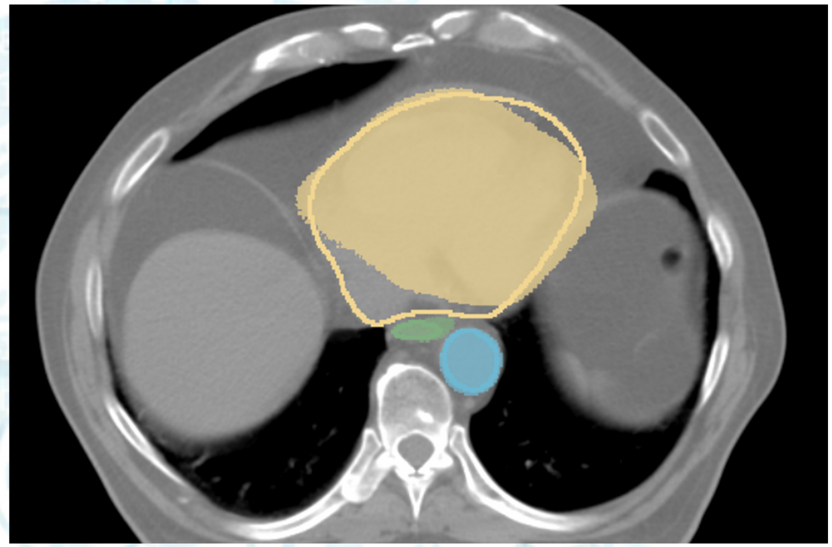


SM

Visual Results



SM



SM+CRF

Anatomical Constraints Learning

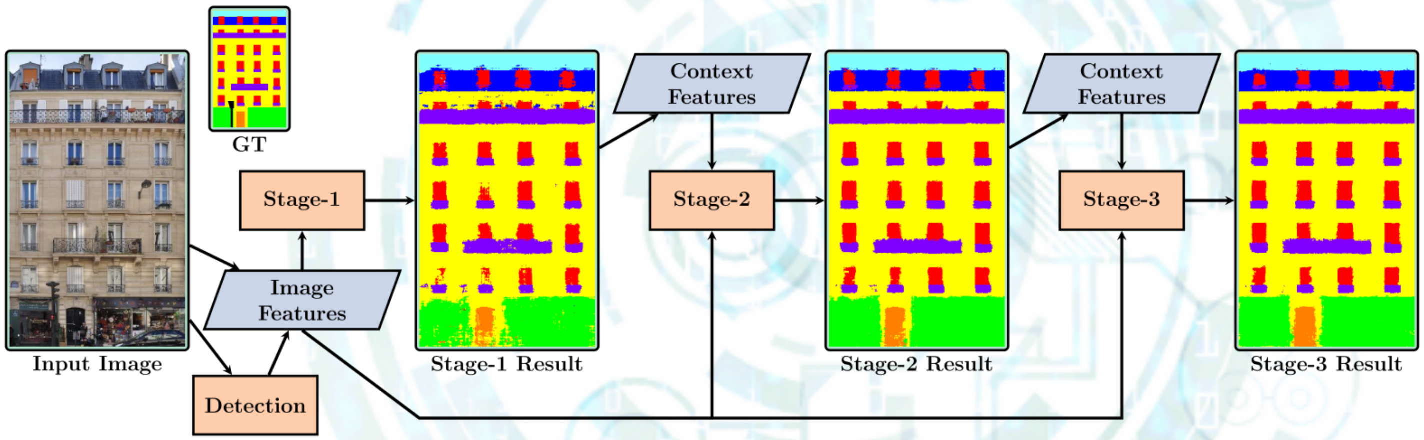
- Radiotherapists use anatomical knowledge to segment the OARs.

- Our goal: learn automatically this type of anatomical constraint via deep networks

Autocontext model- ACM

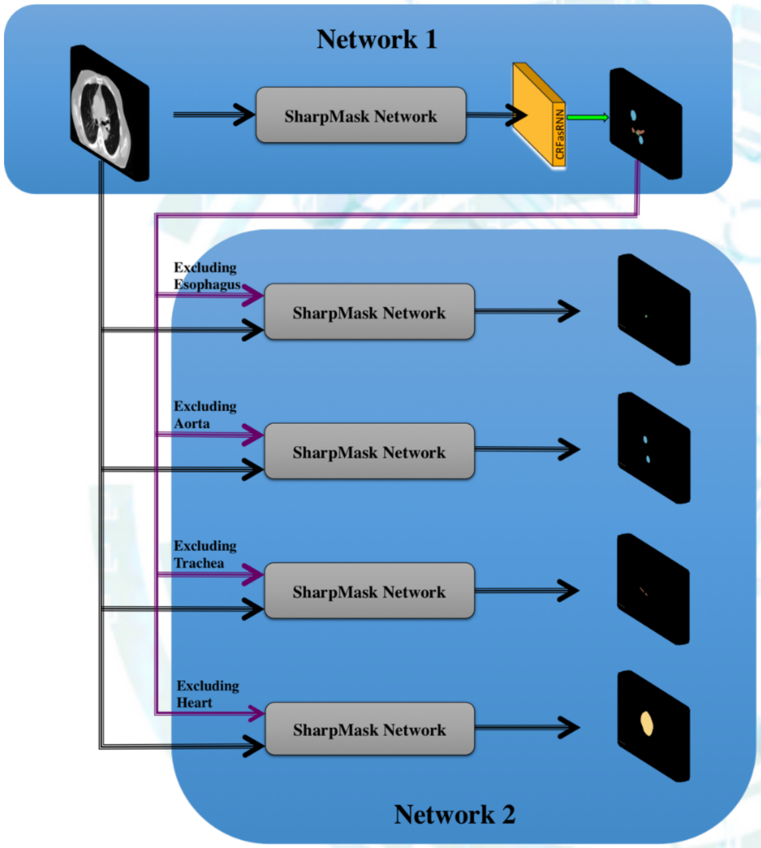
Tu et al IEEE PAMI'10

- Cascade system where the classifier at one stage uses the segmentation result of the previous one

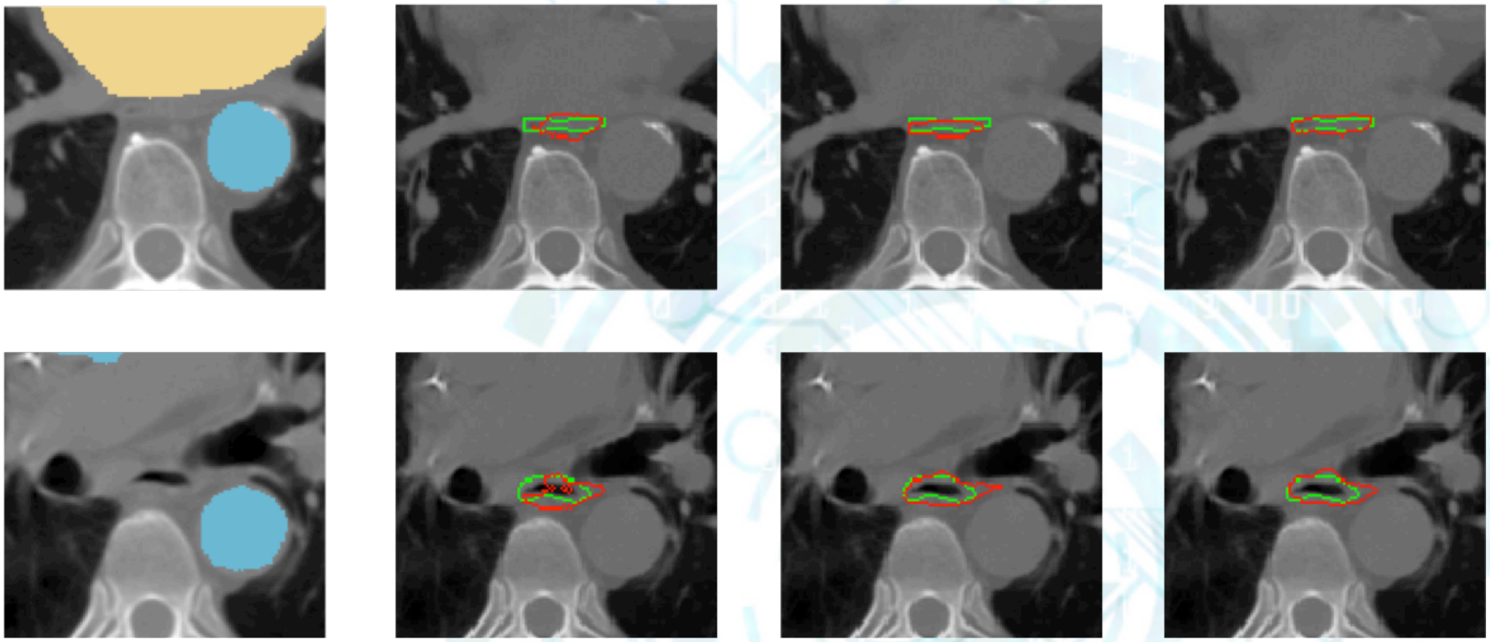


Source:
http://segmentation.is.tuebingen.mpg.de/facadesegmentation/

Anatomic Information (Second Framework)



Visualizations



(a) *Input*

(b) *SM*

(c) *SM+Constraints GT*

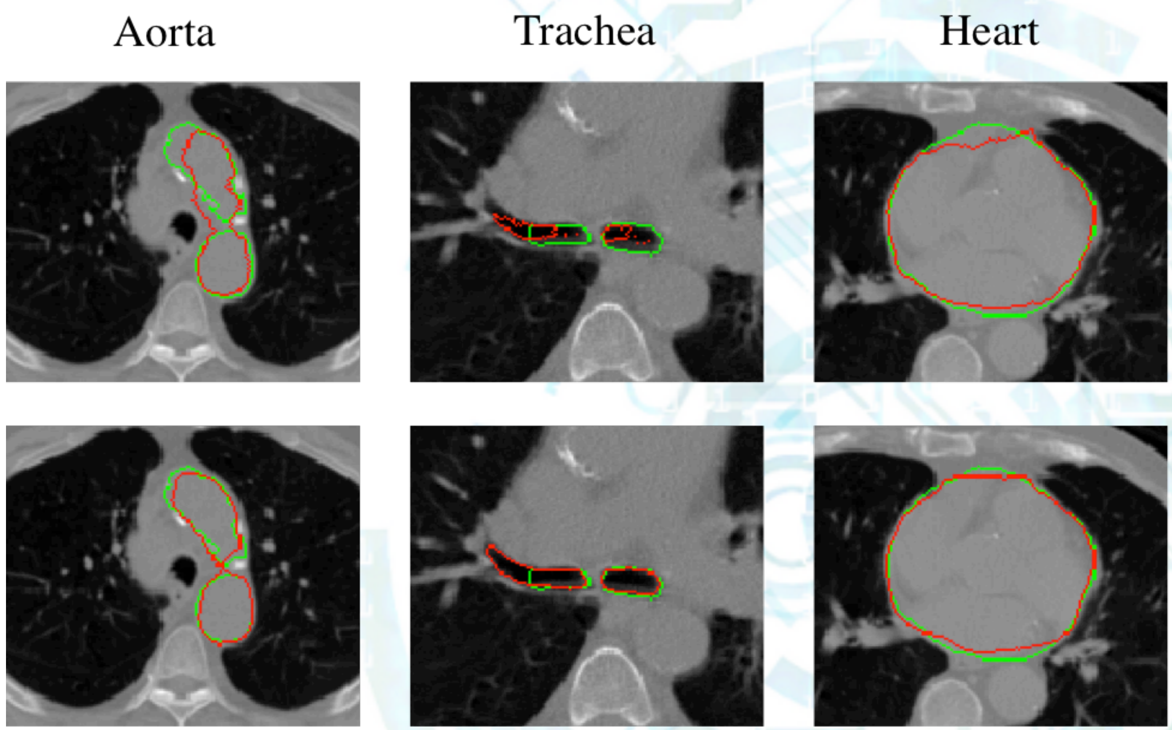
(d) *SM+Constraints 1^{st} net*

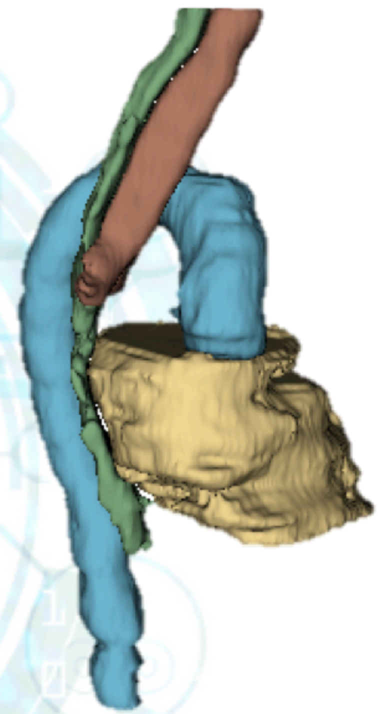
Esophagus

Visualizations

w/o constraints

With constraints





Results

Organ	Method				
	Patchmtch.	SM	SM+CRF	SM+ ACM	SM+ Constraints
Esophagus	0.39+-0.05	0.66+-0.08	0.67+-0.04	0.67+-0.04	**0.69+-0.05**
Heart	0.62+-0.07	0.89+-0.02	0.90+-0.01	**0.91+-0.01**	0.90+-0.03
Trachea	0.80+-0.03	0.83+-0.06	0.82+-0.06	0.79+-0.06	**0.87+-0.02**
Aorta	0.49+-0.10	0.85+-0.06	0.86+-0.05	0.85+-0.06	**0.89+-0.04**

Dice Ratios

Joint segmentation of multiple thoracic organs in CT images with two collaborative deep architectures. MICCAI'17 workshop Deep Learning in Medical Image Analysis, 2017.

Conclusions and Future Works

- We presented a Deep Learning based framework for the segmentation of OARs in CT images.
- Hierarchical, auto-context based architecture improves the performance
- Dynamic loss functions preform better
- Future/ Ongoing works
  - GAN for segmentation
  - Handle 3D with RNNs
  - Apply the method to other datasets

Thanks!

Questions?