Deep Reinforcement Learning for Organ Localization in CT

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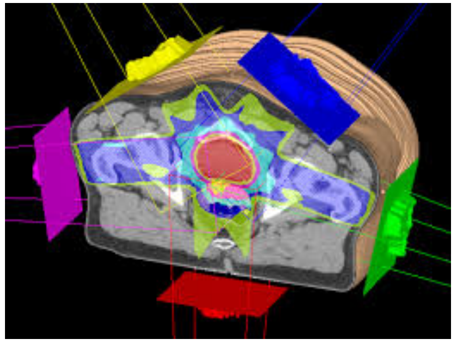
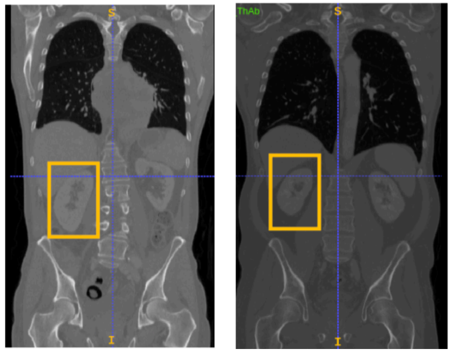
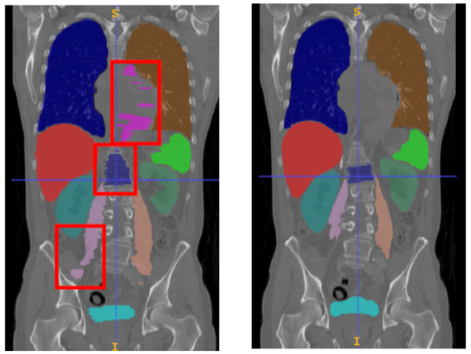
Motivation

- Radiation Therapy Planning
- Registration
- Segmentation Analysis





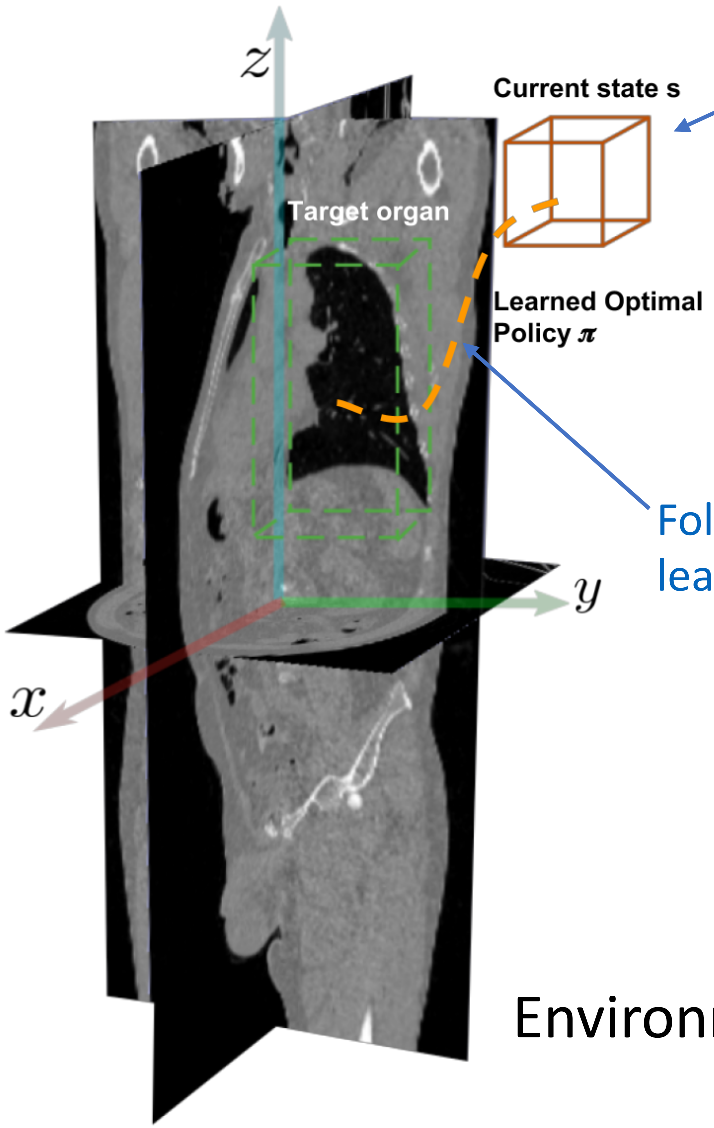


Contributions

- We show for the first time that deep reinforcement learning (RL) can be effective for the task or organ localization.
- The introduction of a new set of 11 actions, which are tailored for organ localization in RL to account for the variability of organs' sizes and shapes.
- We show that for the task of organ localization, RL can learn under a limited data regimen compared to CNNs.

Method

Random Initialized 3D box in CT scan

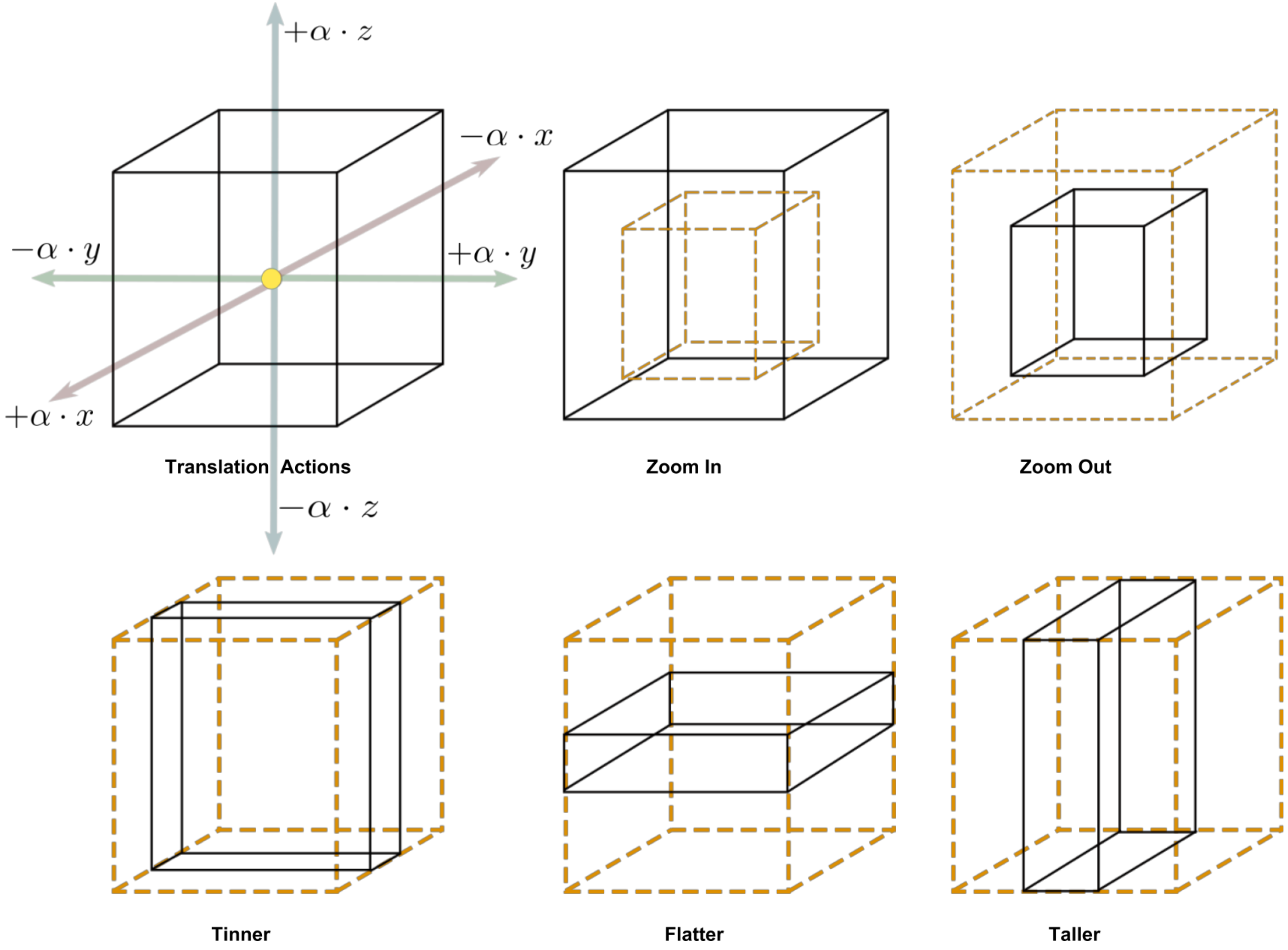


Follows the optimal learned policy

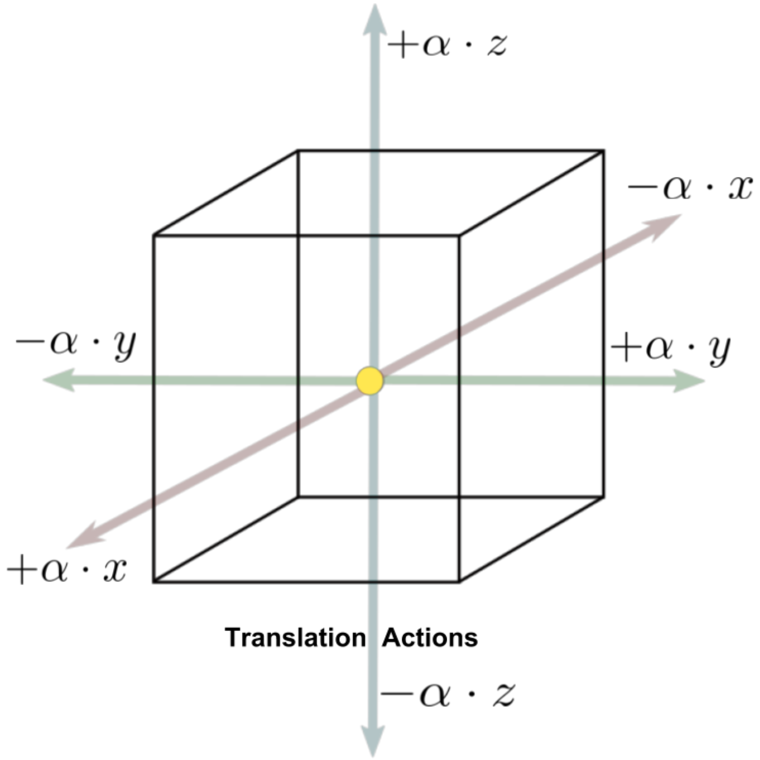
The organ localization follows a sequential process selecting optimal actions in every time step

Environment $\mathcal{E}$: 3D CT scan

The Action Space

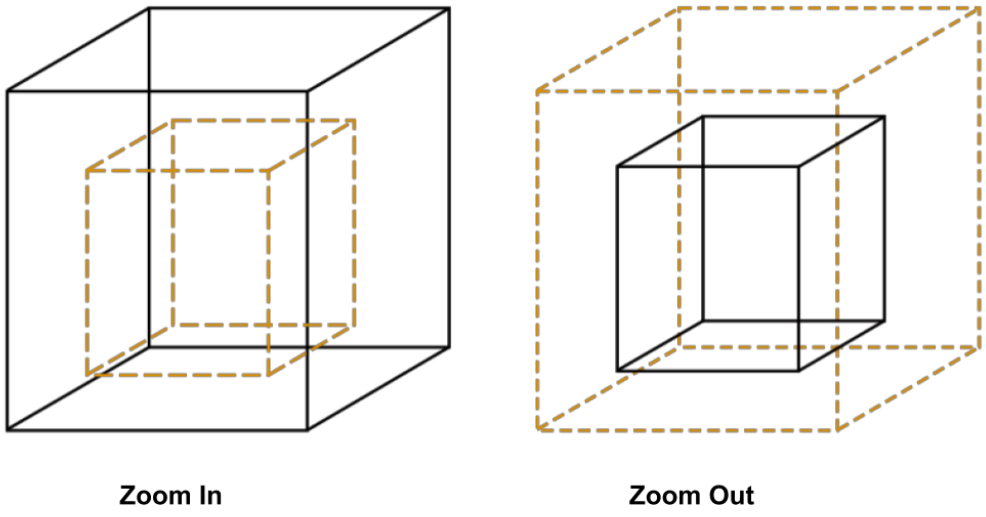


Translation



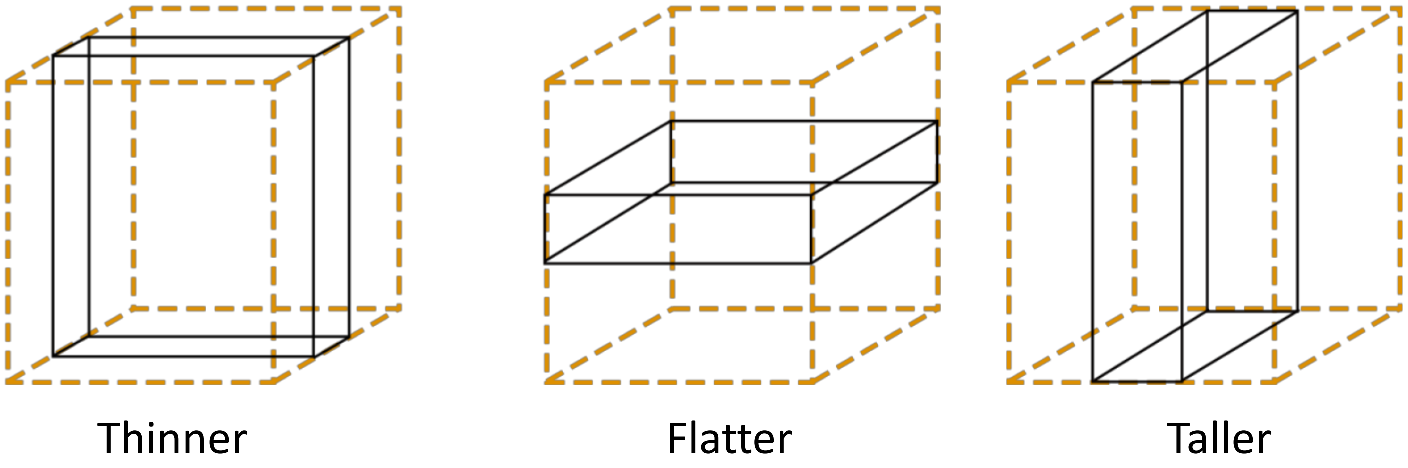
- Translation actions do not change the neither the size nor the aspect ratio of the box.

Global Scaling



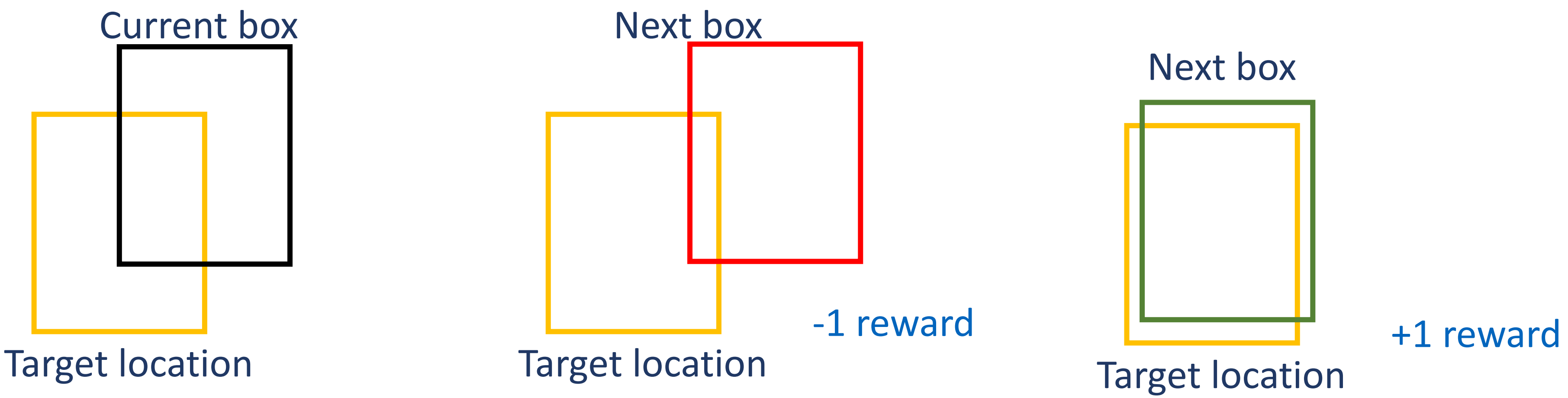
- These actions change the size of the box but preserve the aspect ratio.

Aspect Ratio Actions



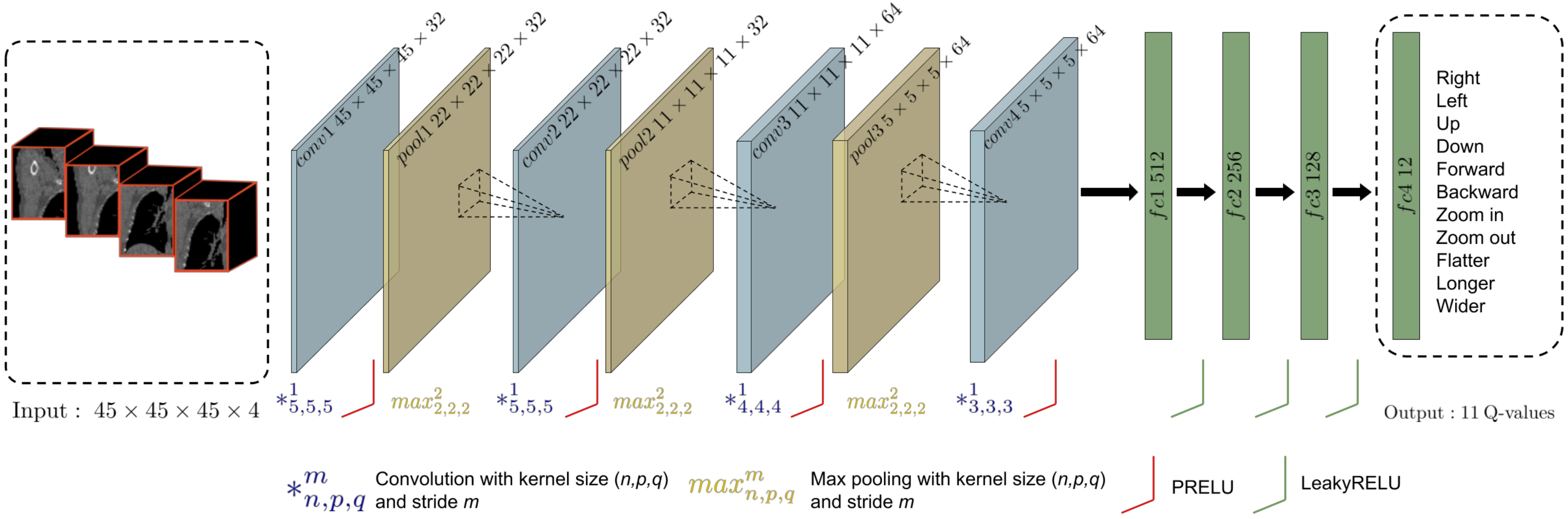
- The actions deform on one of the faces of the bounding box.
- These actions are responsible for changes in the aspect ratio of the box

Reward Function



$$R_a(s, s') = sign(IoU(b', g) - IoU(b, g))$$

Finding the Optimal Policy



- Loss function to optimize:

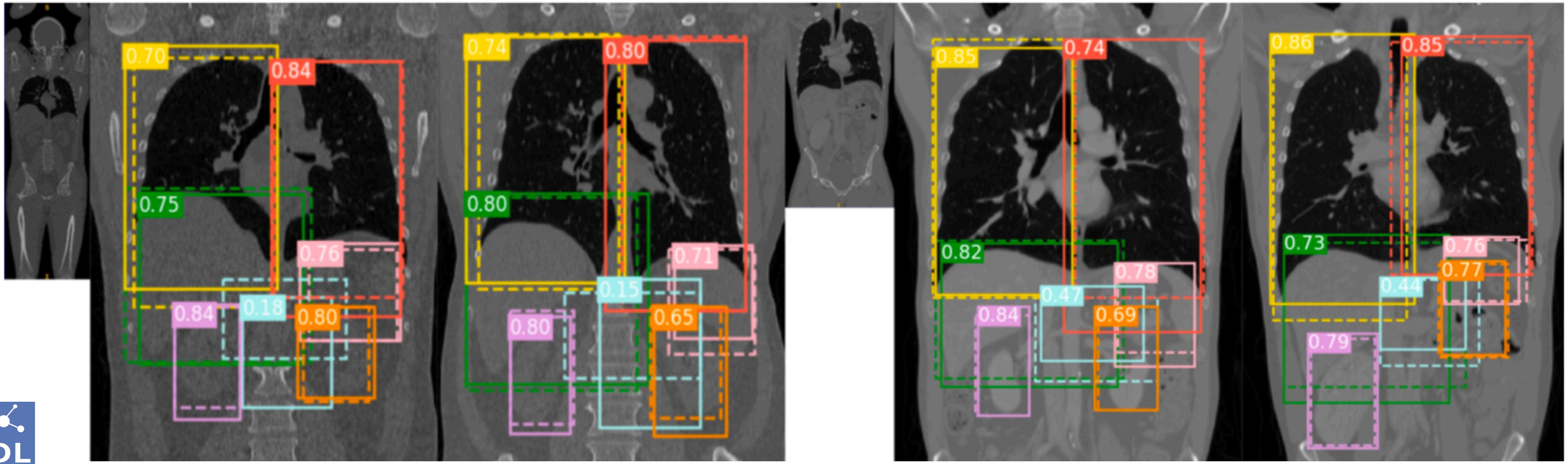
$$L_i(\theta_i) = \mathbb{E}_{(s,a,r,s',a')\sim U(D)}\left[\left(r + \gamma \max_{a'} Q(s',a';\theta_i^-) - Q(s,a;\theta_i)\right)^2\right]$$

[1] Mnih, et. Al . Human-level control through deep reinforcement learning. Nature, 2015.
[2] Amir Alansary, et al. Evaluating reinforcement learning agents for anatomical landmark detection. Medical image analysis, 2019.

Experiments and Results

Dataset: Visceral3 [1]

	Avg IoU	Wall dist [mm]	Centroid dist [mm]
Right Lung	0.77	3.46 ± 5.28	6.06 ± 10.25
Left Lung	0.73	4.91 ± 7.38	10.32 ± 17.09
Right Kidney	0.60	2.96 ± 2.91	5.69 ± 5.67
Left Kidney	0.57	4.06 ± 4.98	7.52 ± 9.02
Liver	0.80	2.41 ± 0.70	3.36 ± 1.34
Spleen	0.60	5.25 ± 7.23	9.20 ± 12.03
Pancreas	0.32	12.26 ± 13.60	20.79 ± 20.38
Global	0.63	5.04 ± 6.01	8.99 ± 10.82
Median	0.60	2.25	3.65



[1] Oscar Jimenez-del Toro, et al. Cloud-based evaluation of anatomical structure segmentation and landmark detection algorithms: Visceral anatomy benchmarks, TMI.

Comparison to SOTA

Method	# Scans	Organs							Time (s)
		L Lung	R Lung	L Kidney	R Kidney	Liver	Spleen	Pancreas	
RF (Criminisi et al., 2013)	400	12.90	10.10	13.60	16.10	15.70	15.50	-	4
RF (Gauriau et al., 2015)	130	-	-	5.50	5.60	10.70	7.90	-	3.2
RF (Samarakoon et al., 2017)	100	-	-	11.52	10.98	15.82	14.84	-	2.2
CNNs (Mamani et al., 2017)	553	2.87	2.60	5.68	5.82	8.19	7.17	-	-
CNNs (Humpire-Mamani et al., 2018)	1884	**2.31**	**1.99**	**2.67**	3.03	5.84	**3.37**	-	4.0
3D RCNN (Xu et al., 2019)	118	5.1	4.9	4.3	3.9	8.5	6.3	**9.2**	**0.3**
Ours (100% data) RL	70	4.91	3.46	4.06	**2.96**	**2.41**	5.25	12.26	3.1
Ours (10% data) RL	**7**	8.28	7.90	9.25	6.60	6.16	7.91	17.83	3.1

Visualizing the training

Liver beginning of training

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https://openreview.net/forum?id=UHtZuvXHoA

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