JULY 12–16 2020 VIRTUAL JOINT AAPM | COMP MEETING
EASTERN TIME [GMT-4]

Incorporating explicit dose-volume constraints in deep learning improves prediction of deliverable dose distributions for prostate VMAT

S. WILLEMS [1], L. VANDEWINCKELE [2], E. STERPIN [2 3], K. HAUSTERMANS [2], W. CRIJNS [2] and F. MAES [1]
1 Department ESAT/PSI, KU Leuven & MIRC UZ Leuven, Leuven, Belgium
2 Department Oncology – Laboratory of Experimental Radiotherpay, KU Leuven & Radiation Oncology, UZ Leuven, Leuven Belgium
3 UC Louvain, Dept. of Radiation Oncology, Cliniques universitaires Saint-Luc, B-1200 Woluwe-Saint-Lambert,Belgium

KU LEUVEN

INTRODUCTION

In the last decades, overall plan quality in radiotherapy (RT) has improved as a result of continuous evolution in RT delivery approaches, such as intensity modulated radiotherapy (IMRT) and volumetric modulated arc radiotherapy (VMAT). Apart from quality benefits, these more complex treatment modalities enlarge planning time, hereby hampering the clinical implementation of adaptive strategies, which are expected to have a positive effect on tumor control probability and post-treatment complications. In conventional RT planning, a complex inverse optimization procedure including a prior set of dose constraints is used to determine the optimal machine parameters for administering the prescribed dose to the target volume (TV) while minimizing the dose to the organs at risk (OAR). Recently, the research focus of RT has shifted towards knowledge-based planning strategies, which exploit information from previous treatment cases to more efficiently generate RT treatment plans for new cases. More specifically deep learning by convolutional neural networks (CNNs) has been applied successfully in RT for segmentation tasks [1] and for voxelwise dose prediction [2], assuming availability of contours and learning the contour-dose relationship.

AIM

- To investigate the benefit of incorporating explicit flexible constraints imposed on the dose volume histogram (DVH) when training a convolutional neural network (CNN) for 3D dose prediction.
- To evaluate deliverability of the predicted dose distributions using the dose mimicking functionality of the treatment planning workstation.
- To assess the feasibility of automated treatment planning for prostate VMAT RT.

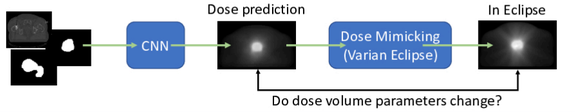
METHOD

Dataset

- 73 CT scans and manually delineated contours of prostate VMAT patients
- Prescription dose: 77Gy
- 31 of 73 patients with a simultaneously integrated boost (SIB) of 95Gy

Experiments

A U-net regression CNN (CNN1) was trained to predict the 3D dose distribution from the planning CT and contours as input, using mean squared difference as loss function and 5-fold cross-validation. A second, identical CNN (CNN2) was trained identically with an additional term in the loss function that directly compared the DVHs of the predicted and the ground truth dose distributions, thus incorporating domain-specific knowledge considered during plan optimization. For one fold (13 patients), deliverable RT plans were generated in Varian Eclipse™ using the DVH of the predicted dose distributions as dose-volume objectives for plan optimization, i.e. dose mimicking. Performance of both CNNs was evaluated by the difference between predicted and ground truth dose distributions of clinically relevant dose-volume parameters (DVPs). These DVPs were also evaluated after dose mimicking to assess the impact of imposing deliverability.



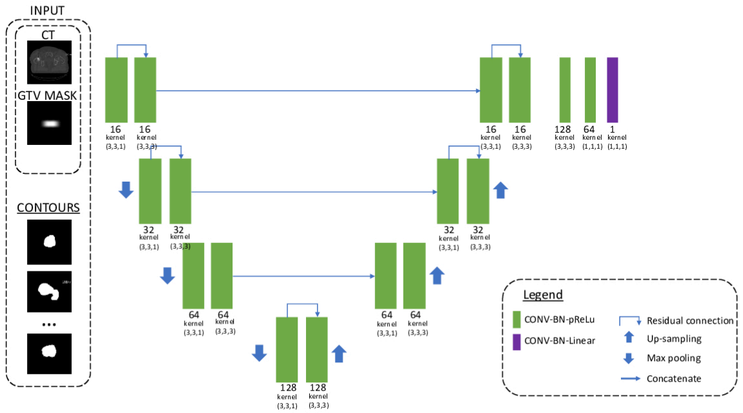


Figure 1. 3D UNET architecture with residual connections.

RESULTS

DVH Loss function[2].

Given a binary mask of structure s (M_s) and a volumetric dose distribution D, the volume for a certain dose threshold d_t can be defined as:

$$v_{s,d_t} = \frac{\sum_{i,j,k} Sigmoid(D(i,j,k) - d_t) M_s(i,j,k)}{\sum_{i,j,k} M_s(i,j,k)}$$

with i,j, and k representing the voxel indices for the 3D images. The t is an index for the dose threshold values which are constrained to be monotonically increasing with increasing index. Finally, the DVH for any structure s, can be reconstructed and the mean squared difference over two DVHs can be calculated as additional loss term (L_{DVH}):

$$DVH(D, Ms) = (v_{s,d_1}, v_{s,d_2}, \cdots, v_{s,d_{nt}})$$

$$L_{DVH} = \frac{1}{n_s}\frac{1}{n_t}\sum_s \left\| \mathrm{DVH}(D_p, M_s) - \mathrm{DVH}(D_T, M_s) \right\|_2^2$$

Validation Metrics

The two CNNs are compared using the clinical dose volume parameters (DVPs, i.e. dmax,d95,d50,d2), derived from the dose volume histograms. The percentage error on these dose constraints relative to the prescription dose is calculated as follows for each structure:

$$\%\Delta DVP_i = 100 * \frac{|DVP(D_{P,i}) - DVP(D_{T,i})|}{D_{pr,i}}$$

with DVP equal to the dose volume parameter of interest (dmax, d99, d98, d50 or d2), $D_{P,i}$ and $D_{T,i}$ representing the predicted dose resp. the ground truth dose in organ i for a specific patient. $D_{pr,i}$ defines the prescription dose for the organ of interest more specifically 95Gy for the SIB, and 77Gy for all other organs.

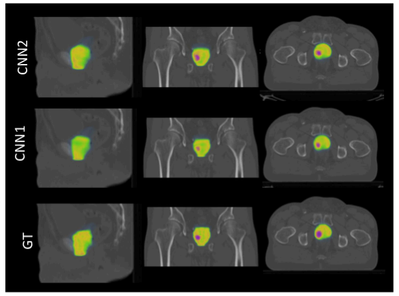


Figure 2. Example of predicted dose distributions for CNN1, CNN2 and ground truth (GT).

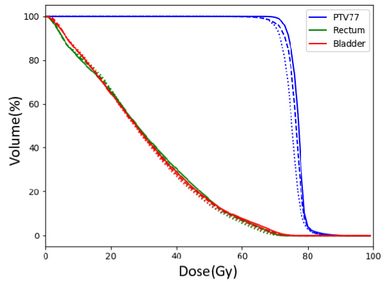


Figure 3. Average dose volume histograms for CNN1 (dotted), CNN2 loss (dashed) and ground truth (solid) for PTV, rectum and bladder.

Table 1. Percentage error on DVPs for OAR and PTV for a CNN trained with L2-loss function (CNN1) and a CNN trained with L2+ DVH loss function (CNN2) before dose mimicking. The lowest error value is indicated in bold.

	CNN1				CNN2			
	dmax	d2	d50	d95	dmax	d2	d50	d95
PTV66	2.67(2.56)	2.32(2.09)	2.17(1.77)	4.40(2.86)	**1.76(1.61)**	**1.60(1.34)**	**1.30(1.10)**	**2.64(2.66)**
PTV77	2.96(2.83)	2.69(2.04)	2.78(1.37)	3.21(1.84)	**2.46(2.40)**	**1.97(1.90)**	**1.21(0.93)**	**2.09(2.40)**
PTV_SV	**3.02(2.51)**	**3.20(2.54)**	**2.15(1.67)**	**2.29(1.93)**	3.58(2.40)	3.38(2.40)	2.17(1.62)	2.61(3.01)
Bladder	2.73(2.18)				**2.28(1.72)**			
Rectum	1.98(1.80)				**1.52(1.14)**			
FemoralJoint_L	**3.86(3.69)**				4.34(3.70)			
FemoralJoint_R	4.03(3.42)				4.03(3.23)			
SIB	4.03(2.05)				**3.52(2.73)**			

Dose mimicking

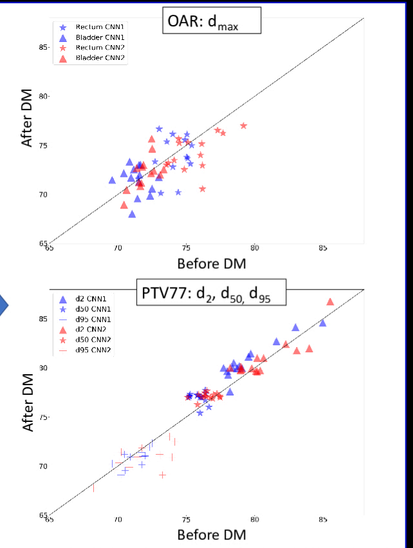


Figure 3. Scatter plot with dose-volume parameters before dose mimicking on the x-axis and after dose mimicking on the y-axis for PTV (left), rectum and bladder (Right). Dose distributions from CNN1 are shown in blue, CNN2 in red.

CONCLUSIONS

Including the DVH constraints explicitly during CNN training improved dose prediction performance for almost all dose volume parameters (DVPs). When performing dose mimicking, a higher change in these DVPs is observed for the network which is trained without the DVH loss compared to the network trained with DVH loss. However the subsequent dose mimicking decreased differences in DVPs between both methods, the number of acceptable treatment plans was still larger for CNN2 than for CNN1 (10/13 vs 8/13).

ACKNOWLEDGEMENTS

Siri Willems is supported by a Ph.D. fellowship of the Research Foundation – Flanders (FWO) under grant number 1SA6419N.

fwo Research Foundation Flanders Opening new horizons

CONTACT INFORMATION

siri.willems@kuleuven.be

REFERENCES

1. Van der Veen, J., Willems, S., Deschuymer, S., Robben, D., Crijns, W., Maes, F., & Nuyts, S. (2019). Benefits of deep learning for delineation of organs at risk in head and neck cancer. Radiotherapy and Oncology, 138, 68-74.
2. Nguyen, D., McBeth, R., Sadeghnejad Barkousaraie, A., Bohara, G., Shen, C., Jia, X., & Jiang, S. (2020). Incorporating human and learned domain knowledge into training deep neural networks: A differentiable dose-volume histogram and adversarial inspired framework for generating Pareto optimal dose distributions in radiation therapy. *Medical physics*, *47*(3), 837-849.