Attention Mechanism on Dose-Volume Histograms for Deep Dose Predictions

Paul Dubois, Nikos Paragios, Paul-Henry Cournède, Pascal Fenoglietto

Submitted for SFRO 2024 (Paris, France)

Introduction:

Radiotherapy treatment planning aims to deliver a targeted radiation dose while minimizing damage to healthy tissues. Traditionally, dosimetrists define constraints for dose delivery through a semi-manual process. Deep learning techniques have emerged to automate parts of this planning by predicting the 3D dose distribution based on patient scans, and then use "dose mimicking" techniques to compute the plan. However, these techniques lack interactive feedback for dosimetrists within the treatment planning system (TPS). This study proposes using attention mechanism to incorporate target Dose-Volume Histograms (DVHs) into the dose prediction model. This enables interactive modifications of the plan, by modifying the target DVHs.

Material and Methods:

We used a cohort of 168 patients (with split 80-10-10 for training-validation-test). The models input CT scans, Principal Target Volume (PTV) contour, and Organs at Risk (OARs) contours; and output a 3D dose. We trained the models with a voxel-wise Mean Absolute Error (MAE), combined with a DVH L1 loss.

The backbone of the models is a convolutional Unet of depth three. Then, we compared three architectures. First, a vanilla Unet-0 (with no DVH information). Second, a Unet-1 with DVH information incorporated using the DAFT technique. Third, a Unet-2, with DVH added via a cross-attention mechanism (our contribution).

The cross attention takes queries from the 3D data, and keys/values from the target DVHs. Finally, the attention output is re-injected in the Unet-3 model via a simple addition.

Results:

Models incorporating DVH data (Unet-1 and Unet-2) achieved superior performance. The MAE and mean DVH deviation were improved by Unet-1 and Unet-2, with a minor advantage for the Unet-2.

Performances of the three models			
Metric	**Unet-0**	**Unet-1**	**Unet-2**
3D dose MAE	3.093 Gy	2.254 Gy	2.210 Gy
Mean DVH deviation	1.942 Gy	1.051 Gy	0.930 Gy

The dataset included patients prescribed for either 62 Gy or 78 Gy on the PTV. The Unet-1 model was not able to adapt to varying prescriptions, consistently predicting a dose resembling a 65 Gy prescription. Conversely, Unet-1 and Unet-2 adjusted their dose predictions suggesting that these models adapted their predictions to be conform with the provided DVHs.

Conclusions:

This study demonstrates the feasibility of incorporating DVH data into deep learning models for dose prediction. The inclusion of DVHs resulted in improved dose prediction accuracy and enhanced model adaptability to varying prescriptions. This approach paves the way for a novel dose optimization workflow where dosimetrists primarily focus on designing desired DVHs. The TPS would then compute the deliverable plan that best matches the specified DVHs. Furthermore, DVHs offer greater inter-patient comparability compared to 3D dose distributions. This enables the establishment of a standardized target DVH per treatment center.