An OAR Sparing Preference Prior Guided Lung RT Plan Dose Prediction Model

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ABSTRACT

Purpose: We developed an efficient mathematical representation of achievable Pareto optimal OAR dose sparing objectives for lung cancer RT planning. We further incorporated these preferences in a RT planning model for individualized RT dose prediction.

Method: A vanilla model to predict plan dose distribution from patient CT and structure contours was first trained to separate the plan dosimetrics variations due to patient anatomical variability from those due to OAR sparing preferences. A non-dominant sorting algorithm was used to order the deviations of the predicted dosimetric objectives: Esophagus_V60, Heart_V50, and Lung_V20 from the actual plan values and to extract the non-dominant objective subset. A denoising auto-encoder (DAE) was then employed to extract a 2D compressed latent representation of a sparsely populated Pareto set by utilizing its bottleneck architecture. It was then used to augment the inputs of the dose prediction model. VMAT lung RT plans for 98 patients were included in this study with an 80/20 training/testing split ratio. The quality of the 2D latent space representation of the Pareto surface (PS) and the prediction accuracy improvement of the augmented model was assessed.

Results: The non-dominant subset of predicted dosimetric deviations from the actual plans shows a wide range of different sparing preferences and strong non-convex behavior. The Mean Squared Distances of the dosimetric deviations to the latent space representation is 1.56 (in % of organ volume). The Mean absolute error (MAE) of the predicted 3D dose distribution by the augmented model is 3.6 Gy, compared with the MAE of 4.4 Gy from the vanilla model.

Conclusion: The DAE provides efficient compressed representations for non-convex PS of RT plan DVH metrics. The augmented model can better account for the clinical trade-off decisions in clinical data and can provide individualized dose prediction.

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INTRODUCTION

Radiation-induced side effects to the esophagus and heart develop frequently in advanced stage lung cancer patients. To reduce the side effects, individualized OAR sparing preference is needed. To explore the OAR sparing trade-off considerations, One method is the ensemble method which exhaustively sample the decision space with varying optimization weights or objectives. This is a very inefficient computing intensive approach with computing complexity of O(Nd) for planning parameters dimension of d. thus it is impractical to use it for individual patient in routine clinical practice. another method aims to improve the efficiency by taking advantage of the convex condition of some dosimetrics to reduce the search space dimension. However, it can only be applied to limited dose metrics due to convex requirements. In this study, we developed an efficient mathematical representation of achievable Pareto optimal OAR dose sparing objectives for lung cancer RT planning without convex requirements. We further incorporated these preferences in a RT planning model for individualized RT dose prediction.
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METHODS AND MATERIALS

Our dataset consists of 98 locally advanced stage lung cancer patients treated in our department with an 80/20 training/testing split ratio. A vanilla model to predict plan dose distribution from patient CT and structure contours was first trained to separate the plan dosimetrics variations due to patient anatomical variability from those due to OAR sparing preferences. A non-dominant sorting algorithm was used to order the deviations of the predicted dosimetric objectives: Esophagus_V60, Heart_V50, and Lung_V20 from the actual plan values and to extract the non-dominant objective subset. A denoising auto-encoder (DAE) was then employed to extract a 2D compressed latent representation of a sparsely populated Pareto set by utilizing its bottleneck architecture (Figure 1).

The denoising autoencoder: DAE is a neural network trained by self-supervised learning. In this study, both the encoder and decoder of the DAE consist of a single hidden layer, while the bottleneck layer has a latent space dimension of 2. The DAE was trained in 350 epochs. The OAR sparing preferences for each case were determined by projecting the dosimetric deviation to this latent representation in the objective space. The DAE reduces computational complexity of trade-off space to O(N2) and it can handle all DVH metrics and complicated trade-off scenarios.

OAR sparing augmented dose prediction model: The 2D latent space variables extracted from the bottle neck layer of the DAE was used as OAR sparing prior and entered the dose prediction model. They are concatenated with the encoded CT and contour features at the bottle neck layer. The vanilla dose prediction model has a U-Net architecture. The Encoder and Decoder of model consists of 32, 64, 128, 256 and 512 feature channels in each layer. Where each layer includes two 3D convolutions, rectilinear activation, instance normalization and dropout modules. The vanilla and augmented models were trained in 340 and 280 epochs, respectively. The architectures of the auto-encoder and the augmented model is shown in Figure 1.

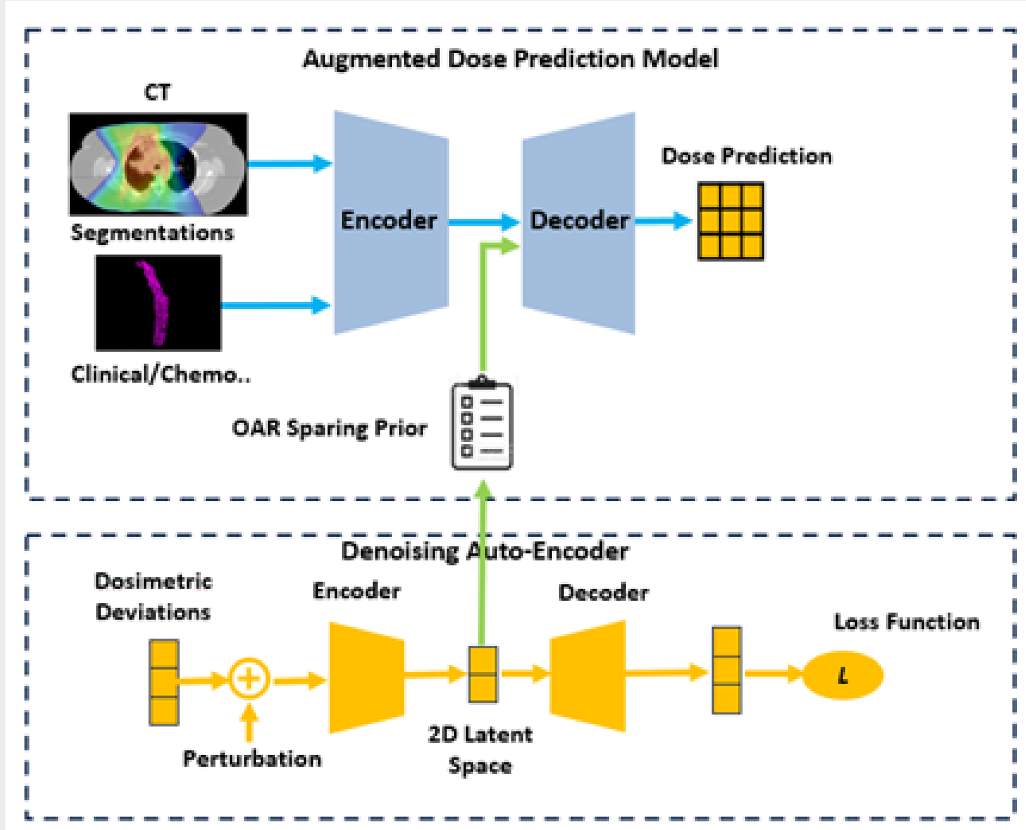

Figure 1. The architectures of the auto-encoder (DAE) and the augmented dose prediction model.

RESULTS

The non-dominant subset of predicted dosimetric deviations from the actual plans shows a wide range of different sparing preferences and strong non-convex behavior. The Mean Squared Distances of the dosimetric deviations to the latent space representation is 1.56 (in % of organ volume). The Mean absolute error (MAE) of the predicted 3D dose distribution by the augmented model is 3.6 Gy, compared with the MAE of 4.4 Gy from the vanilla model.
In Figure 2, Deviations of the predicted dose metrics: Esophagus_V60, Heart_V50, and Lung_V20, by the vanilla dose prediction model for the training cases shown as dots. They are color coded based on the order of Pareto optimality using the non-dominant scoring algorithm. Colder color indicates more superior plans. The reconstructed OAR sparing preferences on the PS representation are shown as red diamonds. The dominated dosimetric objectives and their projections on the PS are linked by lines.

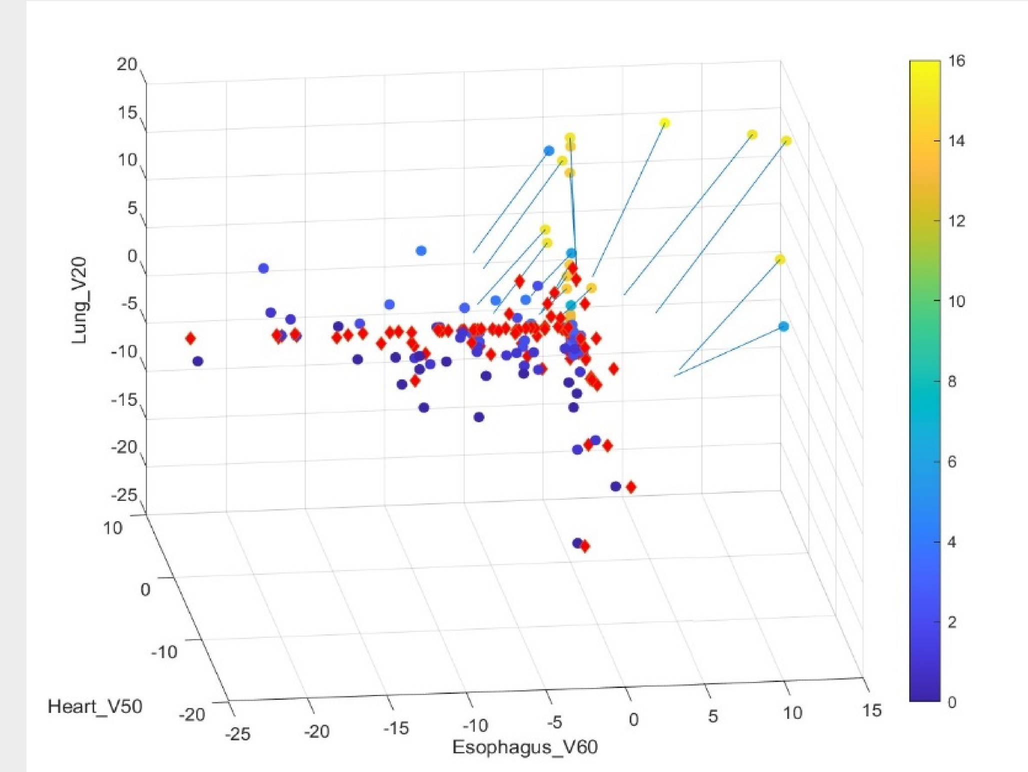

Figure 2. The deviations of the predicted dose metrics by the vanilla dose prediction model from the actual values for all the training cases. They color coding represent the order of Pareto optimality using the non-dominant scoring algorithm.

CONCLUSIONS

The Denoising Auto Encoder provides an efficient compressed representations for the non-convex Pareto optimal trade-off of RT plan DVH metrics. The augmented dose prediction model can better account for the clinical trade-off decisions in clinical data and can provide individualized dose prediction.

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