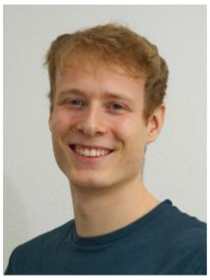
Deep Learning based Monte Carlo Dose Denoising for Radiation Therapy

Raphael Joost

Supervisor(s): Prof. Dr. Peter Manser, Prof. Dr. Stavroula Mougiakakou, Prof. Dr. Michael K. Fix, Hannes A. Löbner
Institution(s): University Hospital Bern (Inselspital), Division of Medical Radiation Physics
University of Bern, ARTORG Center for Biomedical Engineering Research



Introduction

Monte Carlo (MC) dose calculation is widely considered as the gold-standard for calculating dose distributions of radiotherapy plans, owing but not limited to its ability to accurately simulate dose distributions in inhomogeneous media. However, its clinical applicability is limited due to its long calculation-time for dose distributions with low statistical uncertainty. The purpose of this work is to develop a fast, deep learning based approach to denoise Monte Carlo dose distributions (MCDD) of high statistical uncertainty for 6, 10 and 15 MeV volumetric modulated arc therapy and to integrate it into the Swiss Monte Carlo Plan (SMCP)[1].

Materials and Methods

The proposed approach first calculates a MCDD of low statistical uncertainty, approximately 60%, of each field/arc of a radiotherapy treatment plan using 1.5 million primary particles. The resulting MCDD is subsequently denoised by a 4-layer 3D-U-Net, to predict a denoised MCDD of low statistical uncertainty, <1%. The model is trained on dose distributions of 106 clinically motivated VMAT arcs applied on 29 CTs. The plans are augmented to 3074 different arcs by random changes of machine parameters. MCDDs of low statistical uncertainty are used as ground truths (targets) to train the model. Different model input sizes are evaluated in this work. Patient-geometries that are smaller than the input size are padded with zero voxels, larger geometries are handled using a patch-based approach.
The final model accuracy is evaluated by means of gamma passing rates (3% (global)/ 3 mm, 10% threshold) and root-mean-squared error (RMSE) between target and denoised dose distributions for 307 samples from the test set, as well as a radiotherapy plan for a lung case consisting of two arcs. Dose distributions of individual arcs are summed to yield the full treatment dose distribution of the lung case. The case is additionally evaluated using a dose line plot and gamma map. Model performance is assessed by computation time.

Results

Model accuracy on the test set shows an average gamma passing rate of 94.0±2.3% (standard deviation) and RMSE of 0.12±0.02 mGy/MU for voxels with dose values greater than 10% of the maximum dose. Model performance on a CPU is on average 32.7±7.5 s for the input MCDD. The subsequent data-loading, preprocessing, and denoising take on average of 2.6±0.3 s on a GeForce RTX 3090 GPU.

This compares to a MCDD with low statistical uncertainty taking on average 3.3±0.7 h on a CPU.
The clinical lung case achieves an average gamma passing rate per arc of 97.37% and 99.83% for the full treatment (figure 1). The average computation time per arc is 32.5 s (input: 30.0 s, denoising 2.5 s).

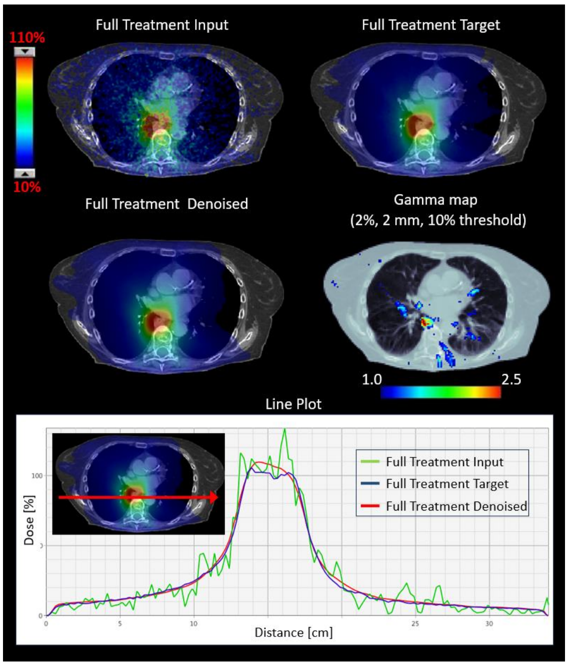


Fig. 1 2D slices of input, target and denoised dose distributions of the full treatment plan. The dose values are represented relative to the prescribed dose. The line plot shows dose values along the red arrow. The gamma map shows voxels that do not pass the gamma criterion (2% (global)/ 2 mm, 10% threshold), resulting in a gamma passing rate of 97.66% for this criterion.

The proposed approach is integrated into the SMCP framework and can be selected on its graphical user interface. All calculations are executed on the high-performance computing cluster UBELIX.

Discussion

A deep learning based approach to denoise MCDD is successfully developed and integrated into the SMCP framework. It offers a substantial reduction in computational time compared to a full MCDD calculation, while achieving reasonable accuracy.

References

[1]Fix et al., An efficient framework for photon Monte Carlo treatment planning, Phys. Med. Biol. 52, 2007.