Combining Monte Carlo with a Generative Adversarial Network to predict High-Resolution Low-Noise Dose Distributions

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

INTRODUCTION

- Monte Carlo (MC) simulation is considered the gold standard for accuracy in radiotherapy dose calculations due to its detailed modelling of individual physical interaction processes.
- However, simulating individual physical processes results in long computational time. This limits the clinical use of MC simulations.
- Can we use the power of deep learning to circumvent the long calculation times without sacrificing the accuracy of MC calculations?

AIM

- Train a Generative Adversarial Network (GAN) to predict high-resolution low-noise (HRLN) dose distributions from low-resolution high-noise (LRHN) MC dose distributions.
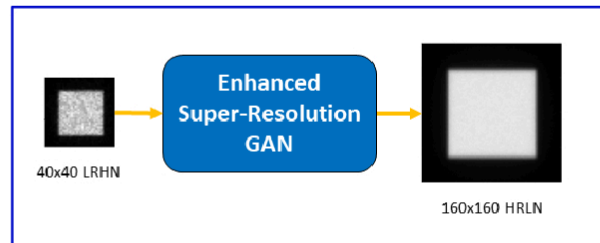
METHODS

Figure 1. Supervised learning using Enhanced Super-Resolution Generative Adversarial Network (ESRGAN). Super-Resolution enables us to create images with higher spatial resolution and less noise.

- A model of a clinical 6MV photon beam was constructed using schematics and phase space data.
- Simulations were performed in the dosxyznrc and BEAMnrc user codes of EGSnrc where dose distributions were generated at multiple depths for a 10x10cm2 field.
- Voxel resolutions of 4mm3 and 1mm3 in a homogeneous water phantom, with corresponding simulation uncertainties of 5% and 0.7%, were considered.
- ESRGAN was trained using dose distributions from depths 2, 5, and 10 cm.
- Each training sample consisted of an input-output pair of a LRHN and HRLN dose distribution, respectively.
- Testing was performed on dose distributions from the trained depths plus unseen depths of 3, 4, 7, 15, & 20 cm.
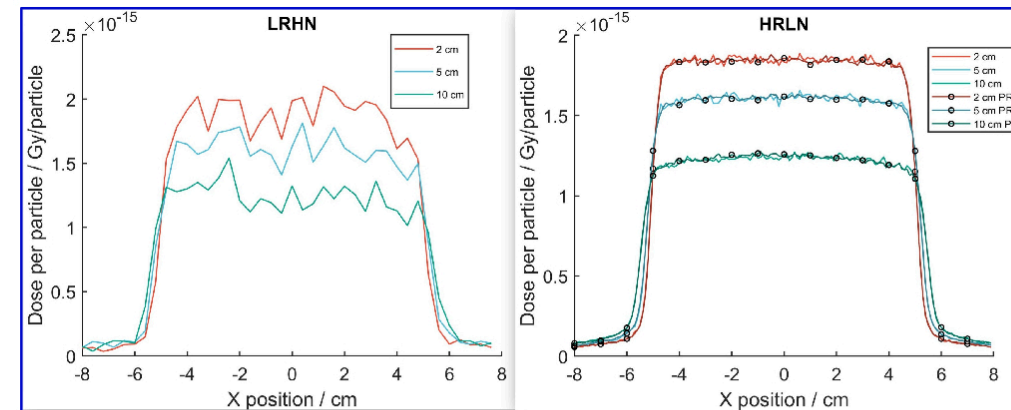
RESULTS

Figure 2. Dose profiles for test data at seen depths of 2, 5 and 10 cm. **Left:** Low resolution high noise input. **Right:** High resolution low noise prediction (PR) and the corresponding ground truth.
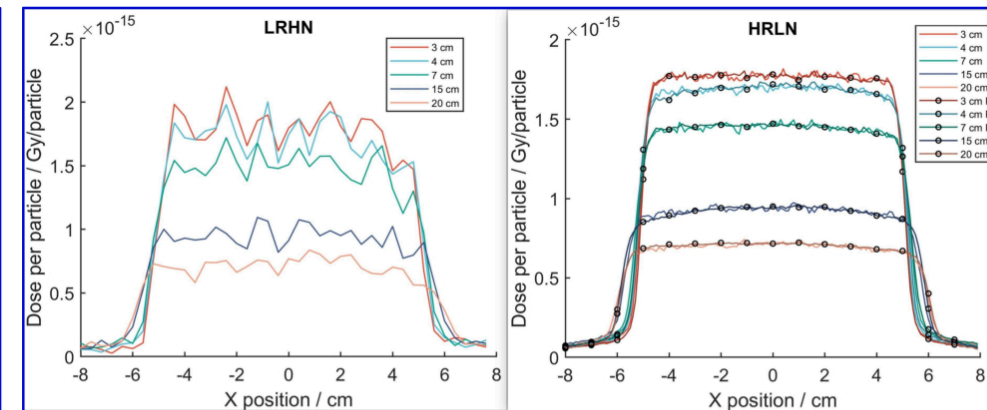

Figure 3. Dose profiles for test data at unseen depths of 3, 4, 7, 15 and 20 cm. **Left:** Low resolution high noise input. **Right:** High resolution low noise prediction (PR) and the corresponding ground truth.

- The trained model accurately predicts HRLN dose distributions at the
    1. Trained depths, 2, 5, and 10 cm;
    2. At in-between depths unseen during training, e.g., 3, 4 and 7 cm; and
    3. At depths beyond 10 cm, unseen during training, e.g., 15 and 20 cm.
- For the qualitative assessment of the predicted dose distributions refer to the dose profiles on **test data** shown in figures 2 and 3.
- In Figure 2, the left panel shows the dose profiles for the low-resolution high-noise input at depths 2, 5, and 10 cm. The right panel shows the corresponding high-resolution low-noise ground-truth and prediction. As seen in the figure, the predicted profiles are close to the ground truth profiles.
- In Figure 3 the dose profiles are shown at depths that were not included during training.
- Figure 4. contains boxplots representing the % relative error in the predicted dose distributions across the central 80% for all the samples in the dataset.
- The % relative error is calculated as $\frac{(\|y-\bar{y}\|)\times100}{\|y\|}$, where y and $\bar{y}$ represent the ground-truth and prediction respectively.
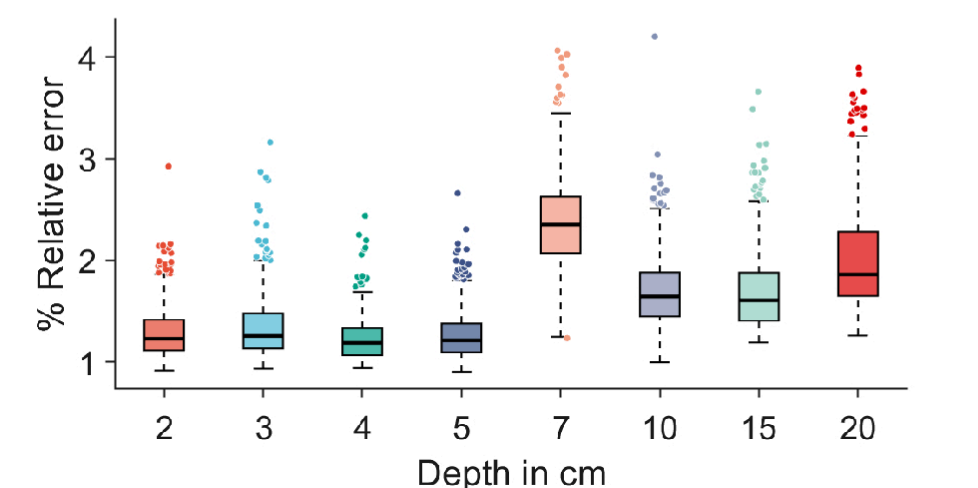- The relative errors are well within 5% for all the depths.

Figure 4. Boxplots representing the percentage relative error in the predicted dose distributions across the central 80% for the entire dataset. Observe that the relative error is less than 5% across the samples and depths.

CONCLUSIONS

- Our main message is that a Generative Adversarial Network (GAN) could be trained to accurately predict high resolution low noise (HRLN) dose distributions from low resolution high noise (LRHN) dose distributions obtained via Monte Carlo (MC) simulations.
- To the best of our knowledge, this work is the first attempt using a GAN to substantially reduce HRLN MC dose calculation times. The required computation time to generate the HRLN data used in this work was approximately 76 hours (CPU time) to simulate 2.5×10^9 primary particles using 60 parallel simulations. Using the trained model we can generate the same data in a few seconds.
- Our experiments show that the generated dose distributions are comparable to those generated from analog HRLN MC simulations.
- Future research includes expanding the model to include:
    - Smaller radiation field sizes;
    - Asymmetric shapes; and
    - Heterogeneous media.

ACKNOWLEDGEMENT

RELATED WORK

- Javaid U, Souris K, Dasnoy D, Huang S, Lee JA. Mitigating inherent noise in Monte Carlo dose distributions using dilated U-Net. Medical physics. 2019 Dec;46(12):5790-8.
- Wang X, Yu K, Wu S, Gu J, Liu Y, Dong C, Qiao Y, Change Loy C. Esrgan: Enhanced super-resolution generative adversarial networks. In Proceedings of the European Conference on Computer Vision (ECCV) 2018 (pp. 0-0).

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