ESTRO

Abstract

Title

Fast Monte-Carlo dose simulation with recurrent deep learning

Authors

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Purpose or Objective

Designing deliverable radiotherapy treatments under clinical time constraint require fast and precise calculation of dose distribution maps. However, current clinically used algorithms do not match the precision of Monte-Carlo (MC) radiation transport calculation. Nevertheless, because MC simulations account for all particles-matter interactions, they are prohibitively time-consuming to compute which prevents their clinical adoption.

To circumvent this issue, we introduce a 2D ConvLSTM (Shi et al. 2015) based neural network to infer high-particles and computationally expensive MC dose distributions from sequences of low-particles and cheap to compute MC simulations of VMAT plans. We show that our proposed model gives promising results compared to non-local means method (NLM) (Darbon et al, 2008).

Materials and Methods

We retrospectively generate Monte-Carlo simulations of 50 patients VMAT plans using OpenGate with the phase space information of a 6MeV Varian Truebeam. The training set comprises slices from 40 patients while the validation and test sets each draw slices from 5 patients. Our model has 5 ConvLSTM cells stacked on top of each other. The input sequence of the model consists of 4 slices of a patient's dose volume simulated with respectively 5e8, 1e9, 5e9 and 1e10 particles using MC. The denoised slice comes from the corresponding dose simulated with 1e11 particles. We select the slices in areas within 30%-100% of the maximum dose in the denoised simulations. Thus, the model is trained to infer highly sampled dose simulations from lower precision simulations. The training strategy is patch-based for robustness with patch size of 64x64 pixels i.e. 12.8x12.8 cm2 for each slice. We use random horizontal and vertical flipping as sole augmentation techniques. We use AdamW as optimizer and a hybrid loss summing the Mean Squared Error (MSE) and the Structural Similarity Index Measure (SSIM).

Results

We evaluate the model on the test set according to the Gamma Index Passing Rate (GIPR), MSE and SSIM. GIPR is computed using a dose threshold of 0.1 and various dose-to-agreement / dose tolerance ratios.

We compare the model's performance to the NLM algorithm. For the comparison, we set NLM to denoise simulations with 1e10 particles, i.e. the last slice of our model's input sequence.

Figure 1 displays qualitative results. The table and Figure 2 highlight that our model yields competitive results compared to NLM.

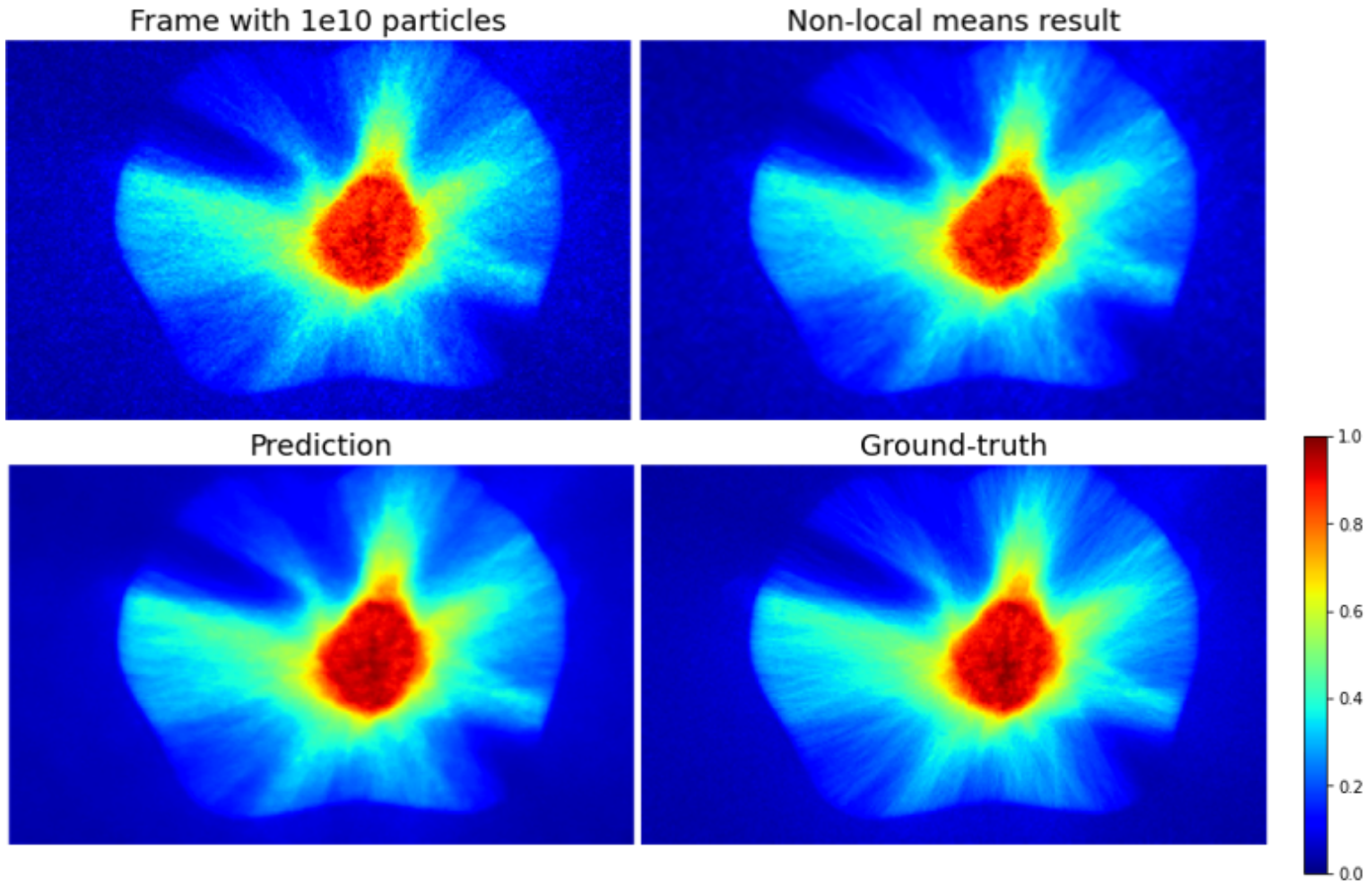

Figure 1. Slices of noisy dose, NLM denoising, model's prediction, highly sampled dose.

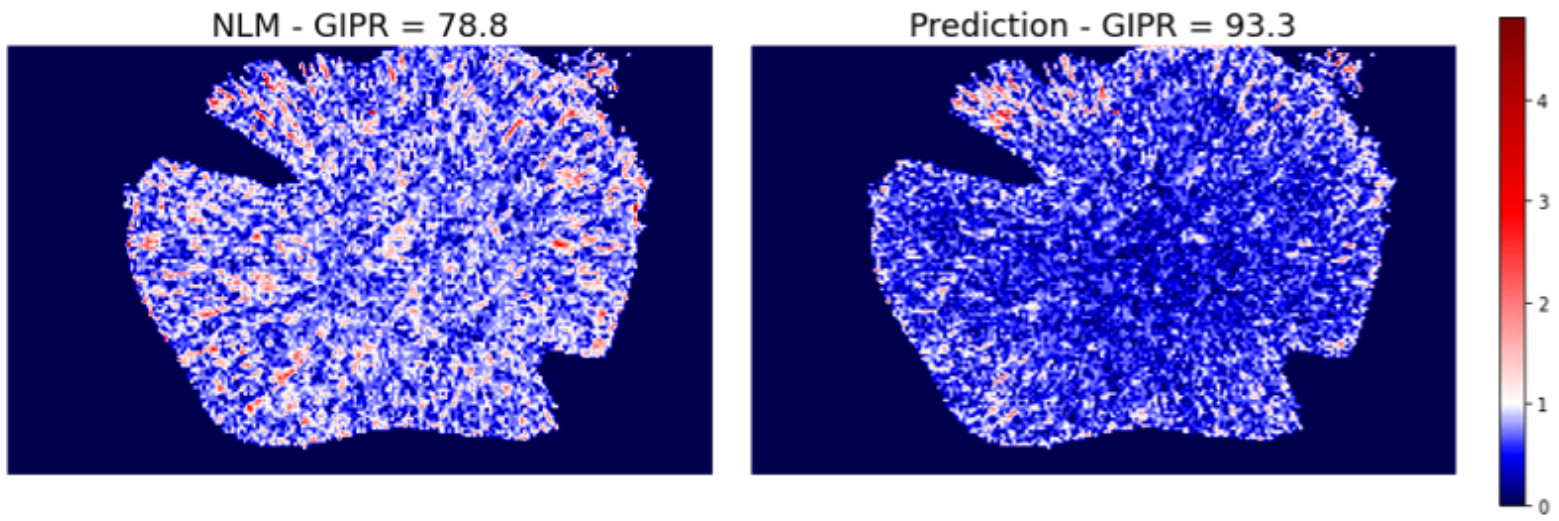

Figure 2. Visualization of gamma index slices of the NLM denoised dose and model's predicted dose.

Method / Metric	MSE	SSIM (%)	GIPR 5%/5mm (%)	GIPR 3%/3mm (%)	GIPR 2%/2mm (%)
Slice 1e10 particles	3.13e-4	87.5	99.2±0.49	81.6±7.04	31.3±8.73
NLM on 1e10 particles	2.04e-4	94.4	98.2±1.92	80.5±11.2	35.9±13.2
Stacked ConvLSTM	**9.73e-5**	**97.3**	97.7±3.43	**83.2±12.9**	**42.7±15.2**

Conclusion

The results highlight that recurrent neural networks show promise to accelerate dose distribution MC simulations.

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