Weakly supervised 3D ConvLSTMs for Monte-Carlo radiotherapy dose simulations

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Introduction

The **most precise** method to compute clinical dose volumes in radiotherapy is **Monte-Carlo** simulation, but it remains **prohibitively time consuming** if well converged results are required.

Goal: to infer high precision dose volumes from noisy Monte-Carlo dose simulations [1].

Contributions and intuition

Intuition:

ConvLSTM [2] derives meaningful features from the sequential nature of the input to infer the next logical step.

Contributions:

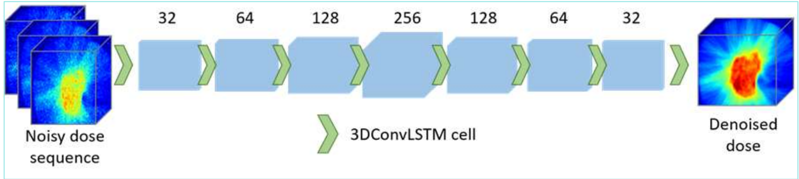
1. Investigate 3D ConvLSTM-based architecture
   → To infer high-precision dose volumes from a sequence of noisy Monte-Carlo generated dose distributions.
2. Noise-to-noise [3] training scheme on VMAT [4] cases
   → Reduces the computation time required to generate the training set.

Dataset

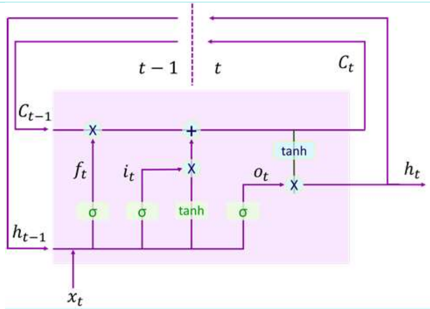
- 50 VMAT patients
- Resolution: 2 mm^3
- For 1 patient:

#Particles	#Simulations	Computation time
5e8	5	5 hours
1e9	5	10 hours
5e9	5	50 hours
1e11 Reference	1	4000 hours

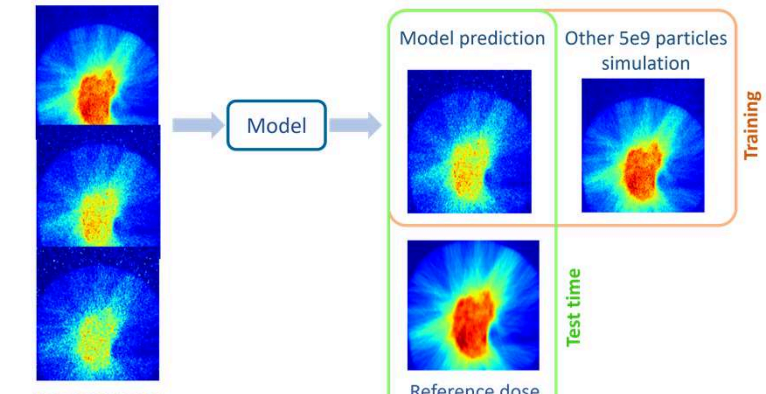
Model: Stacked 3D ConvLSTMs



- Fully convolutional model
- 3D ConvLSTM cells
- Designed for 4D dataset
- No spatial downsampling



Training scheme : Noise-to-noise



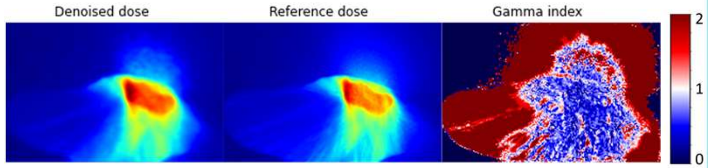
Noise-to-noise training does not require expensive-to-compute ground-truth.

- Train / validation / test sets: 40 / 5 / 5 patients.
- Patch-based training: 64 x 64 x 64 pixels
- Hyperparameters for AdamW: learning rate=0.001, weight decay=0.01.
- Loss function - weighted sum of SSIM and L1:

$$Loss = SSIM(y_{model}, y_{5e9}) + 20 * L1(y_{model}, y_{5e9})$$

Results

- Evaluation with gamma index and clinical metric Gamma Passing Rate [5]
- Dose-to-agreement / tolerance on dose values = 3mm / 3% within 30% - 100% of maximum dose.
- Benchmark with BiONet [6] adapted to handle 3D data.
- Gamma index < 1 = ✔



Model	#Weights	SSIM (%)	L1	GPR (%)
3D BiONet (seq. input)	178 M	**91.1 ± 2.2**	0.102±0.022	50.5 ± 4.8
3D BiONet (5e9 input)	178 M	90.4 ± 3.4	**0.072±0.011**	71.9 ± 5.1
Stacked 3DConvLSTMs	5 M	86.4 ± 5.2	0.104±0.022	**83.8 ± 3.4**

Future work

In future studies, we will:
1. Assess sensitivity of the model to input noise
2. Perform ablation studies to size up the potential of 3D ConvLSTMs

References

[1] T. Bai, et al. Deep dose plugin towards real-time monte carlo dose calculation through a deep learning based denoising algorithm. Machine Learning: Science and Technology, 2020.
[2] X. Shi,et al. Convolutional lstm network: A machine learning approach for precipitation nowcasting. NIPS 2015.
[3] J. Lehtinen, et al. Noise2noise: Learning image restoration without clean data. ICML, 2018.
[4] K. Otto. Volumetric modulated arc therapy: Imrt in a single gantry arc. Medical Physics, 2008.
[5] D. Low, et al. A technique for the quantitative evaluation of dose distributions. Medical Physics, 1998.
[6]T. Xiang, et al. Bio-net: Learning recurrent bi-directional connections for encoder-decoder architecture. MICCAI 2020.