Acceleration of Monte Carlo radiation dose simulations using deep learning: Proof of principles for CT and radiotherapy dosimetry

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INTRODUCTION

Monte Carlo (MC) simulation is the most accurate method for calculating x-ray interactions with the patient's body and voxel-wise dose distributions. However, the large number of photons need to be simulated for MC dose calculation in CT and radiotherapy to achieve acceptable statistical uncertainty (nearly noise-free dose maps), requiring MC methods to be accelerated to a level suitable for clinic applications. This paper reports a recent study to reduce the statistical uncertainty using a novel deep-learning based "denoising" approach [1].

AIM

To train a convolutional neural network (CNN), called Monte Carlo Denoising Net (MCDNet) [1], to directly predict the high-photon (low-noise) dose maps from the low-photon (high-noise) dose maps obtained from MC dose calculations in CT and radiotherapy.

METHOD

1) Data processing

- Generating high-photon dose maps and low-photon dose maps
- Normalizing dose value to (0, 1)
- Extracting dose patches
- Data augmentation including rotation and flip

2) Training neural network, MCDNet [1]

- 5 convolutional and 5 deconvolutional layers with 32 filters
- Activation function: Rectified Linear Unit (ReLU)
- Loss function: Mean Square Error
- 5-fold cross-validation

3) Evaluation

- Calculating Gamma Index Passing Rate (GIPR) (3mm/3%) [2]

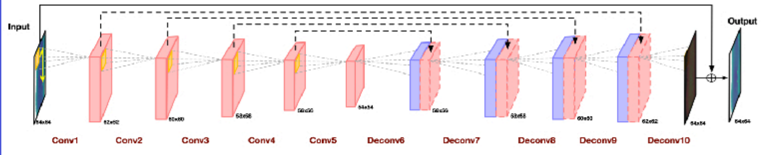

Fig. 1. The proposed MCDNet structure

RESULTS

1) Dose calculation in CT [1]

- 5 full-body anatomically realistic adult voxel phantoms of various sizes.
- Low-photon dose maps: $1.6x10^4$, $1.6x10^5$, $1.6x10^6$, $1.6x10^7$ photons (input)
- High-photon dose maps: $1.6x10^9$ photons (ground truth)
- Testing results are shown in Table 1 and Fig. 2.

2) Dose calculation in radiotherapy [3]

- 30 rectal cancer patients with intensity-modulated radiation therapy (IMRT)
- Low-photon dose maps: $1.0x10^7$ photons (input)
- High-photon dose maps: $1.0x10^{10}$ photons (ground truth)
- Testing results are shown in Table 2 and Fig. 3.

Table 1. The computational time and GIPR for MC simulations and MCDNet predictions in CT. The prediction time of MCDNet is <3s.

Number of photons	MC simulations		MCDNet
	Time (min)	GIPR	GIPR
1.6×10^4	0.185	0.4448 ± 0.0676	0.4447 ± 0.0659
1.6×10^5	0.235	0.5676 ± 0.0658	0.9678 ± 0.0285
1.6×10^6	0.275	0.7862 ± 0.0529	0.9962 ± 0.0033
1.6×10^7	0.465	0.9767 ± 0.0173	0.9996 ± 0.0005
1.6×10^8	2.515	0.9999 ± 0.0003	None
1.6×10^9 (ground truth)	21.92	None	None

Table 2. GIPR for MC simulations and MCDNet predictions in radiotherapy

Method	MC simulations				MCDNet
	1.0×10^7 (input)	1.0×10^8	1.0×10^9	1.0×10^{10} (ground truth)	
GIPR	0.7849 ± 0.0801	0.9753 ± 0.0157	0.9999 ± 0.0001	None	0.9820 ± 0.0130

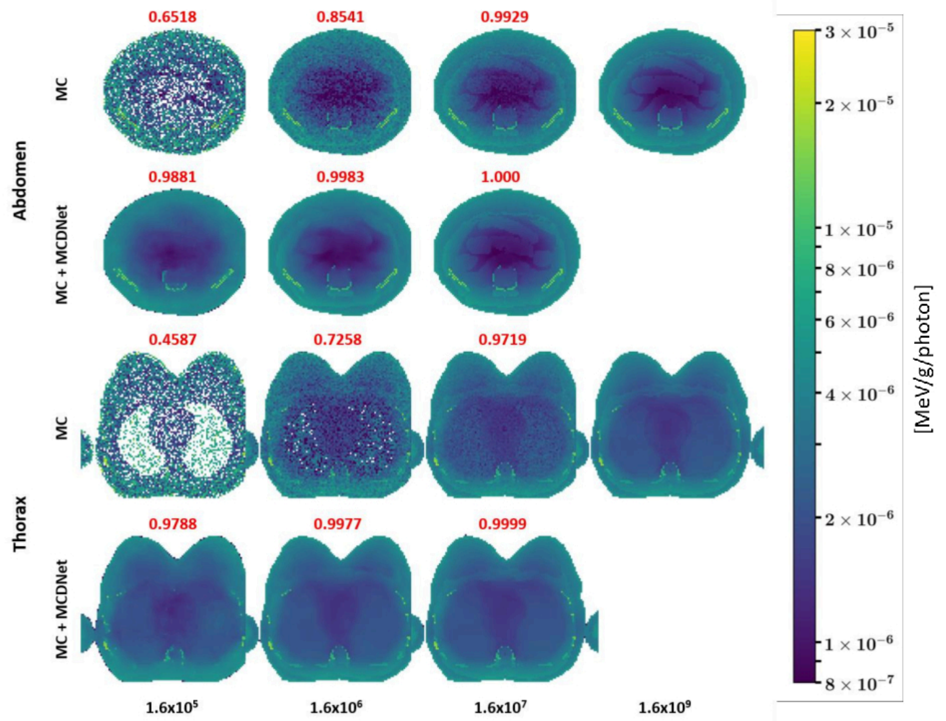

Fig. 2. The original MC simulated dose maps and MCDNet predicted dose maps for CT using the RPI female phantom as an example. Each column represents dose maps in different number of photons (denoted by the black numbers at the bottom). The red number at the top of each dose map represents the corresponding GIPR for 1.6×10^9 photons (i.e., the ground truth).

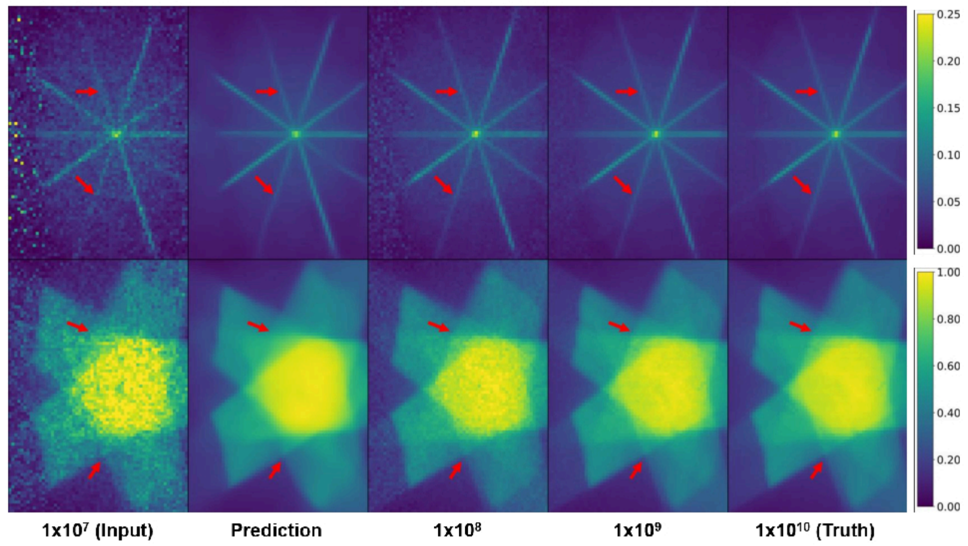

Fig. 3. The dose maps in the radiotherapy predicted by MCDNet and simulated by MC with a different number of photons. The edge slices (first row) and center slices (second row) are shown separately.

CONCLUSIONS

- For the MC simulations of CT imaging doses, MCDNet is found to have the ability of predicting dose maps of $9.9x10^7$ photons from corresponding dose maps of $1.3x10^6$ photons, yielding a 76x speed-up in terms of photon numbers. When the low-photon dose maps are generated with very few photons, MCDNet is not convergent due to insufficient training information.
- For the MC simulations of IMRT, the MCDNet can improve the GIPR of dose maps of 1×10^7 photons over that of 1×10^8 photons, yielding over 10× speed-up in terms of photon numbers.

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