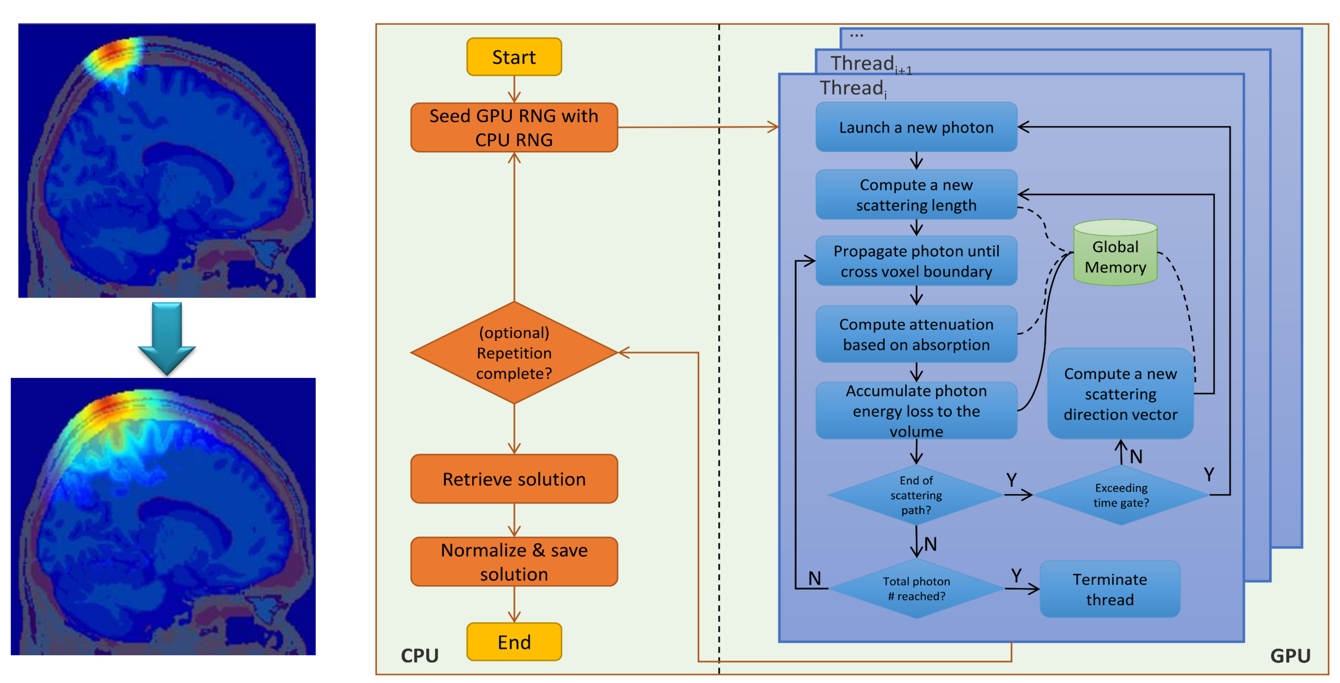
Denoising in Monte Carlo Photon Transport Simulation Using Neural Networks

Leiming Yu[1], Yaoshen Yuan[1], Zhao Hang[3], David Kaeli[1] and Qianqian Fang[2]
[1] Dept. of Electrical and Computer Engineering, and [2] Dept of Bioengineering, Northeastern University
[3] Dept. of Electrical Engineering and Computer Science, Massachusetts Institute of Technology

Abstract

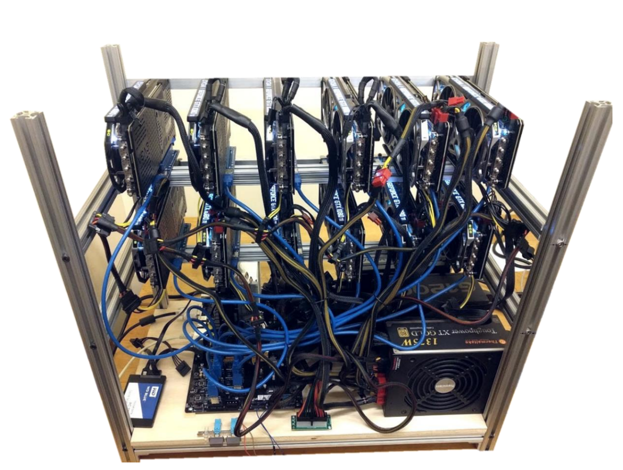
- The Monte Carlo (MC) method is deemed as the gold standard for modeling light propagation in turbid media, such as human tissues.
- MC-based simulations have inherent stochastic noise, which can be reduced by increasing the number of simulated photons (SNR~$\sqrt{N}$) but at the cost of proportionally increased runtimes.
- A 12x GPU server has been built to accelerate the simulation.
- Previously, GPU-accelerated noise-adaptive non-local mean (ANLM) filter [1] was proposed to improve the quality of low-photon MC simulations.
- We present a significantly more efficient neural network model to remove spatially-varying noise present in MC outputs. It improves filtering results by 4x as compared to ANLM.

Monte Carlo eXtreme



- Monte Carlo eXtreme (MCX [2]) is a fast photon transport simulation software accelerated by Graphics Processing Units (GPUs).
- It initializes simulation parameters, such as domain settings, optical properties and random seeds, on the host and copies them to the GPU.
- GPU threads run concurrently, where each thread carries out multiple photon transport simulations.
- The host waits for the GPU to complete the computation and reads the data (3D fluence maps and detected photons) back to the host memory.

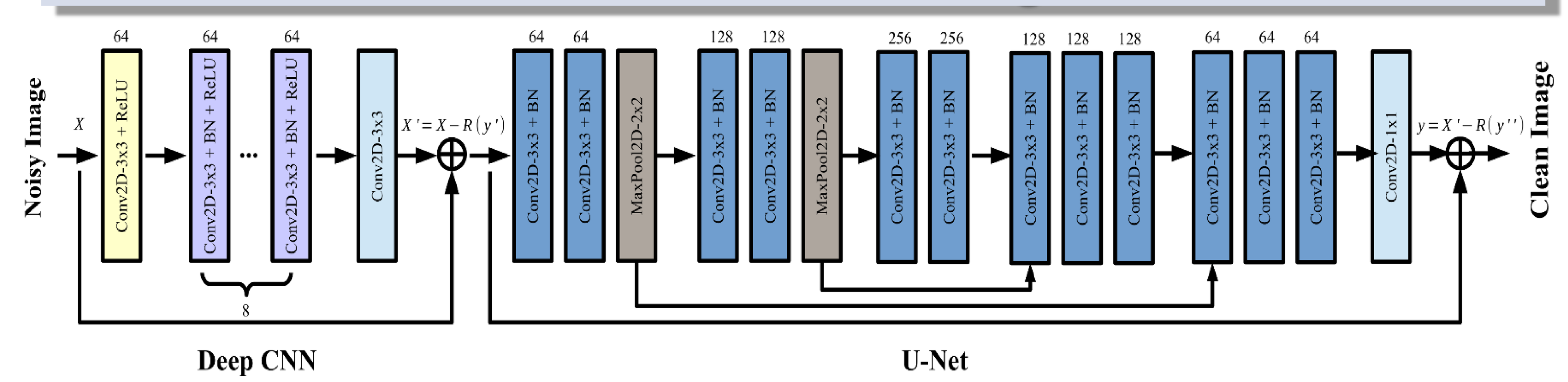
Platform



Hardware
- CPU: Intel i7-7700K @ 4.2GHz
- GPU: 12 x NVIDIA GTX 1080 Ti
- Motherboard: BIOSTRA TB250-BTC Pro (12x PCIe)
- Power supplies: 1200W+1300W+1000W

Software
- OS: Ubuntu 14.04
- Matlab R2016a
- Tensorflow 1.4 with GPU support

Neural Network Denoising Model



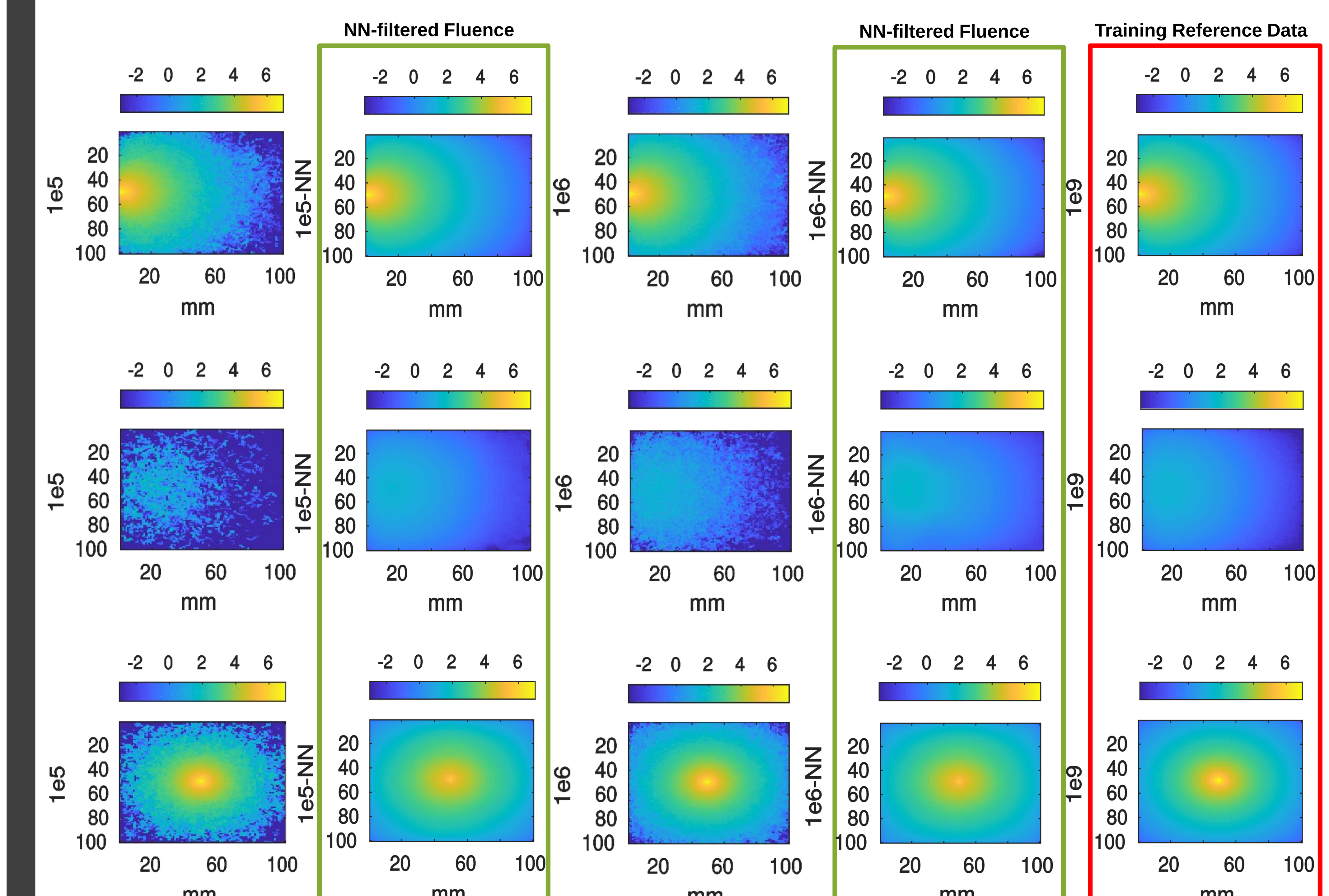
- Our proposed denoising neural network model combines two popular convolutional neural network (CNN) models.
- Deep CNN [3] to learn the noise, U-Net [4] to learn the photon energy degradation contour.
- Residual learning is applied to the outcome as the feedback, enabling the model to learn the stochastic noise.

Evaluation

Environment Setup
- 100x100x100 homogeneous cube (1 mm³ voxel)
- absorption coefficient = 0.005 mm⁻¹, scattering coefficient = 2 mm⁻¹, anisotropy = 0, refractive index = 1.37
- Pencil beam source is applied for simulation.

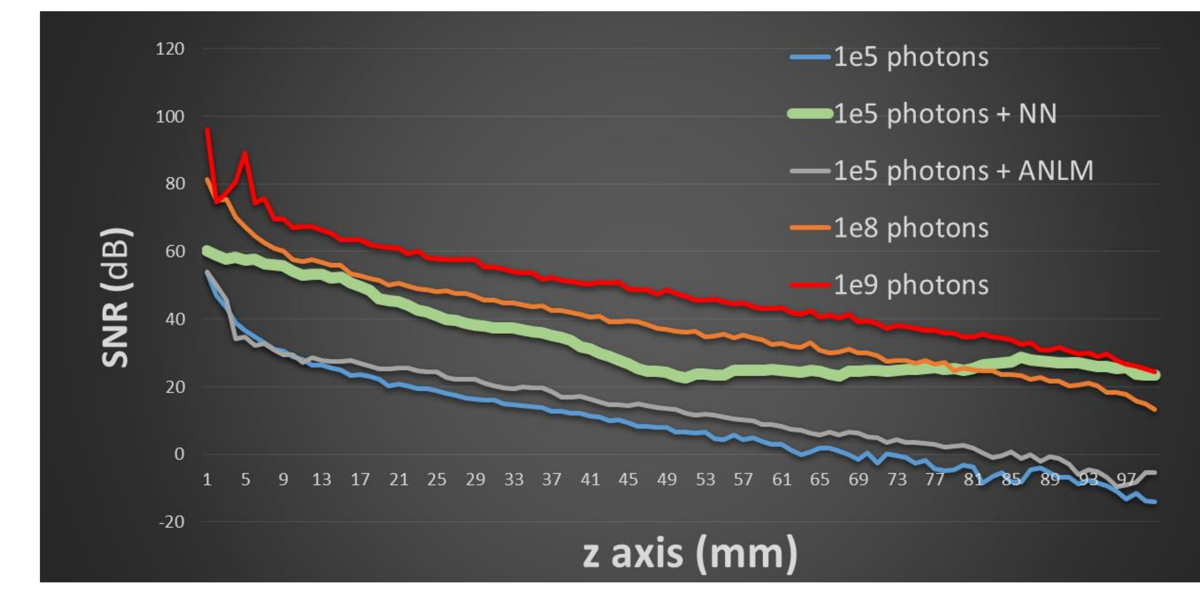
Training
- 1e5 photon simulation images for the input and 1e9 photon simulation results for the ground truth.

Testing
- Apply neural network (NN-Filtering) on the 1e5 and 1e6 simulation results by varying the light source location.



Evaluation (cont.)

- Signal-to-Noise Ratio $SNR_k(dB) = 20 + \log_{10}\frac{\mu_k}{\sigma_k}$, where k is the photon number, μ_k is the averaged fluence rate, σ_k is the variance.
- We measure SNR using a slice along the z axis (y = 50) in the cube.



- On average, NN-Filtering improves the SNR by 25 dB and 20 dB over the 1e5 simulation and ANLM filtering, respectively.

Discussion and Future Work

- In this study, we proposed a neural network model to filter stochastic noise inherent in Monte Carlo photon transport simulation.
- As a result, a denoised low-photon simulation result can attain comparable quality as those generated from simulating photons 2 to 3 orders of magnitude more.
- It is shown that the neural network based denoising algorithm can improve the SNR of the simulation by 25 dB. This is more than 4-fold improvement compared to the 5 dB improvement from the ANLM filter.
- We are currently developing a new approach to improve the intensity of the light source using the neural network model.

References

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Acknowledgement

This research is supported by National Institutes of Health (NIH) grants # R01-GM114365 and R01-CA204443.