# Neural Network Denoiser for Monte Carlo Photon Transport Simulations


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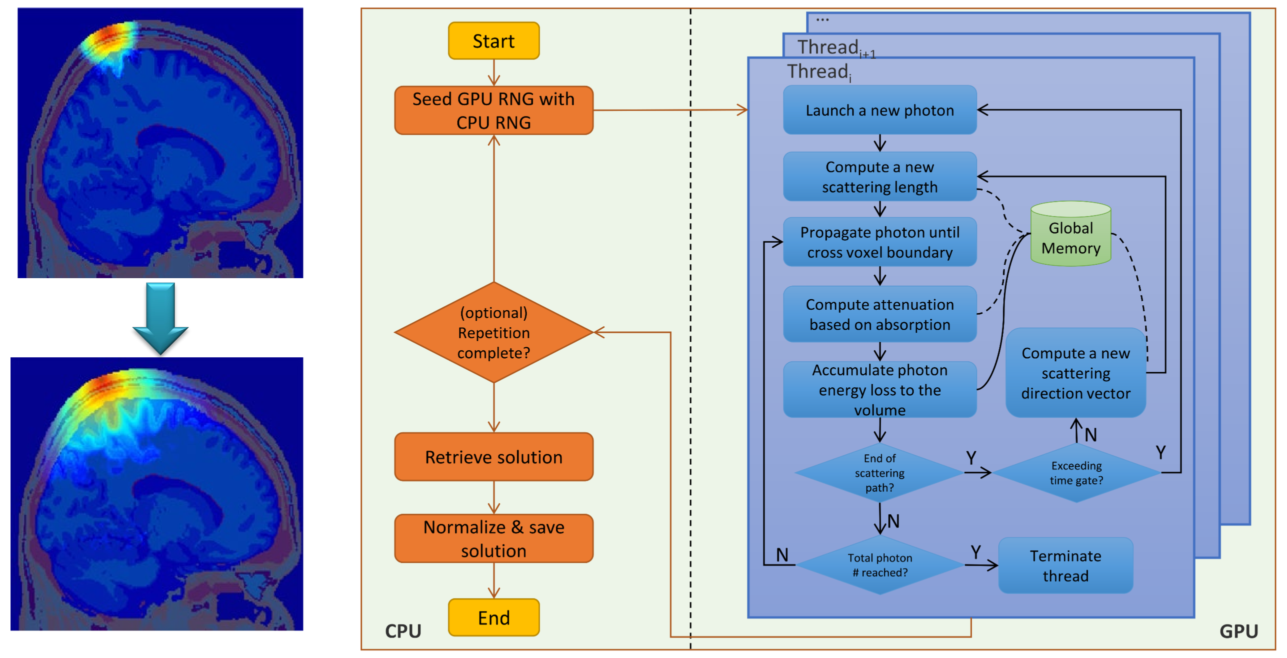
## Abstract

- 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.
- Previously, we proposed GPU-accelerated noise-adaptive non-local mean (ANLM) filter [1] 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.
- Most conventional CNN denoising models designed for photos fail to process MC images due to 1) high dynamic range in image data, 2) spatially varying noise, and 3) lack of image features.


## Monte Carlo eXtreme




- Monte Carlo eXtreme (MCX [2,3]) 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

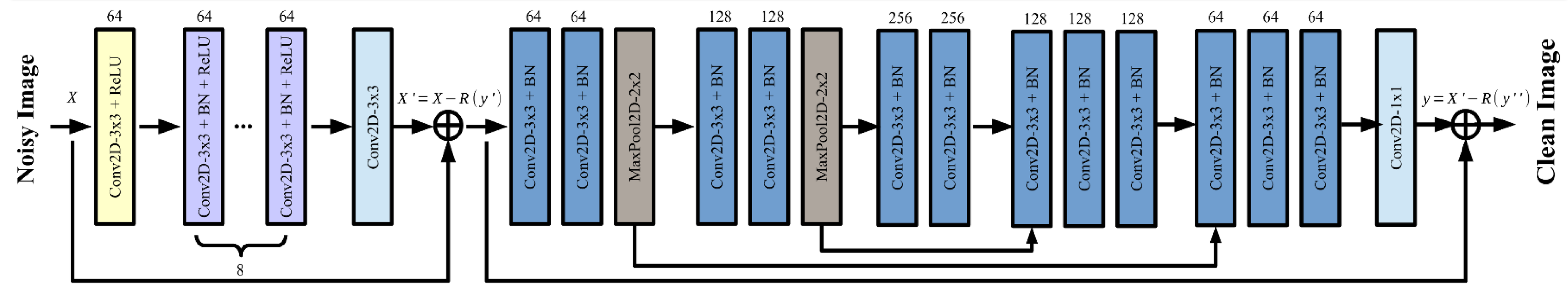
### Hardware

- 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 [4] to learn the noise, U-Net [5] 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

### Homogeneous Case

- 100x100x100 homogeneous cube (1 $mm^3$ voxel)
- Tissue-like optical properties: $\mu_a$= 0.005 $mm^{-1}$ , $\mu_s$= 2 $mm^{-1}$, g = 0, n = 1.37
- Pencil beam source is applied for simulation.

### Training (12K simulation images)

- Input: $10^5$ photon simulations; output: $10^9$ photon simulations. Each image rotate 90 degree for 4 times.

### Testing

- Apply neural network (NN-Filtering) on the $10^5$ and $10^6$ simulation results by varying the light source location.

### Heterogeneous Case

- 100x100 2D domains with random letter-like patterns
- Random optical properties
- Random Point source locations

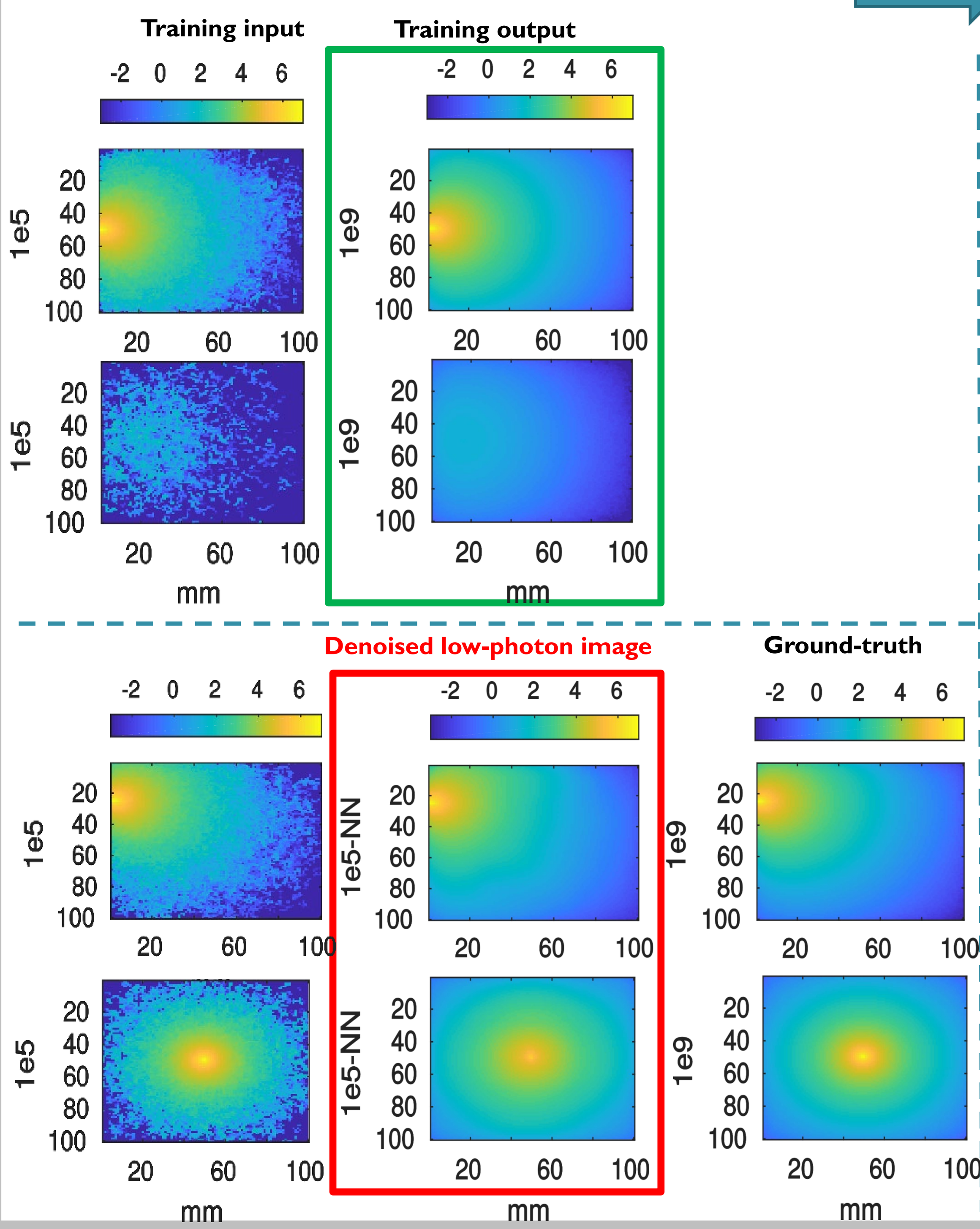
### Training (20K simulation images)

- Input: $10^7$ photon simulations; output: $10^8$ photon simulations..

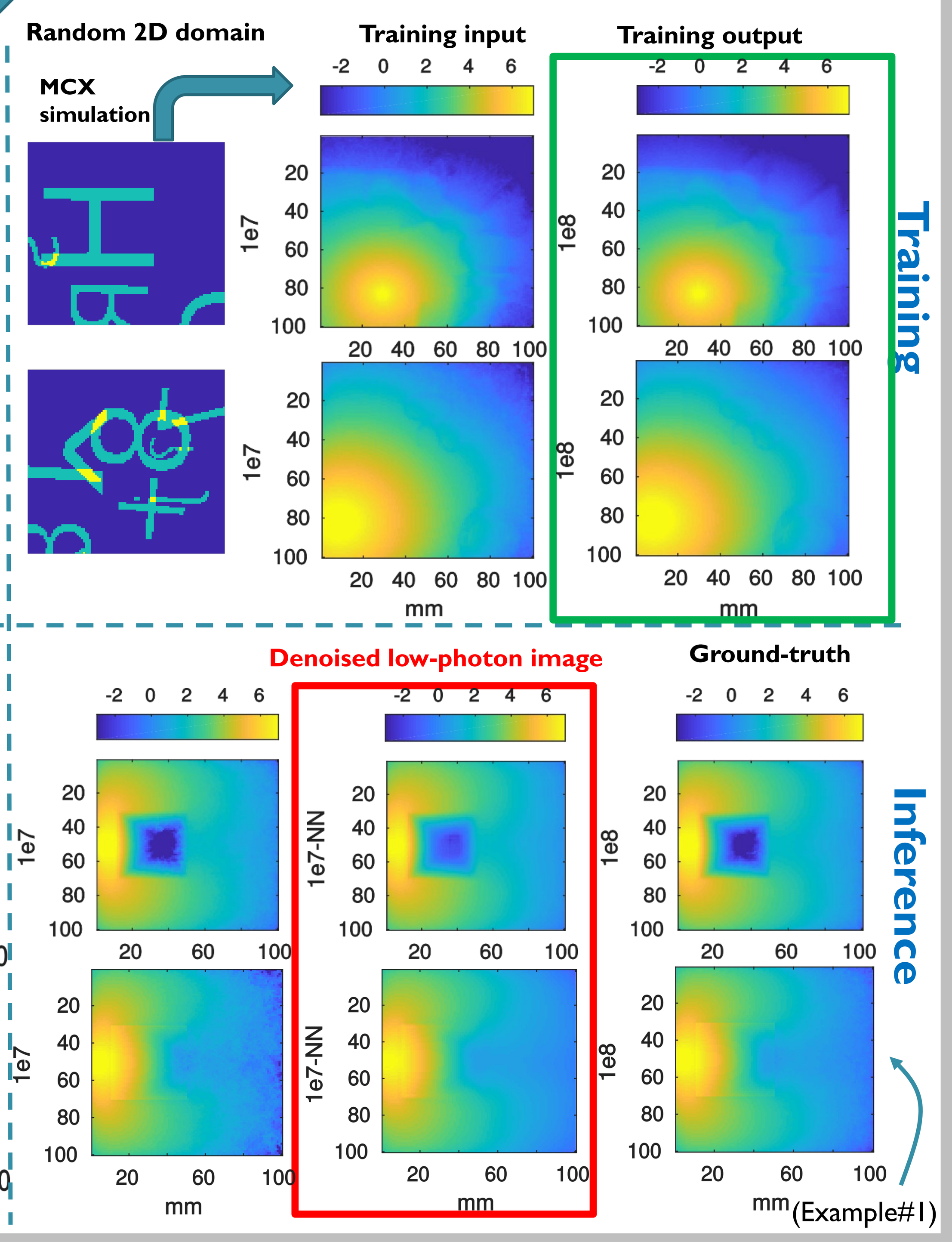
### Testing

- [1] Example#1: 100x100 2D domain with a 40x40 inclusion: $\mu_a$= 0.02 $mm^{-1}$ , $\mu_s$= 30 $mm^{-1}$, g = 0, n = 13.7
- Apply neural network (NN-Filtering) on the $10^7$ simulation results.

### Homogeneous domain

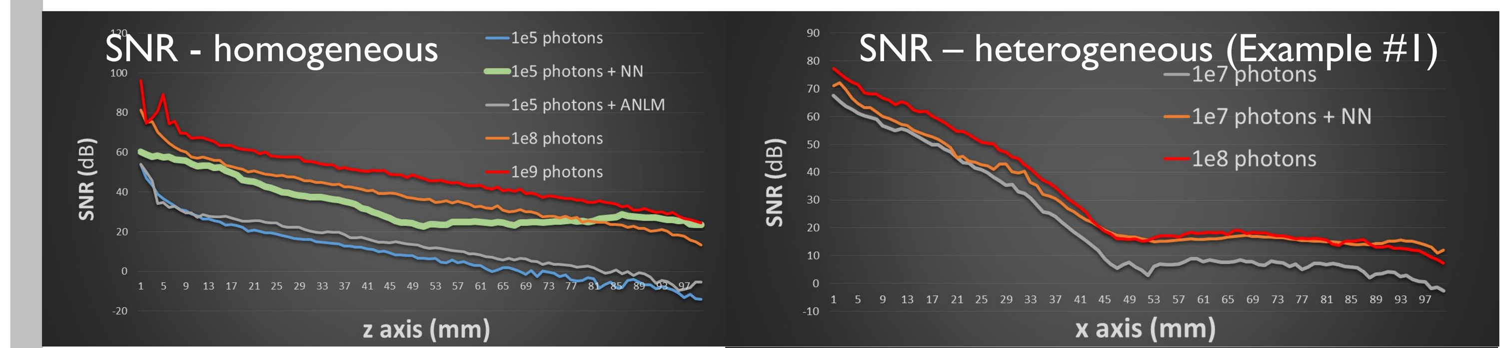


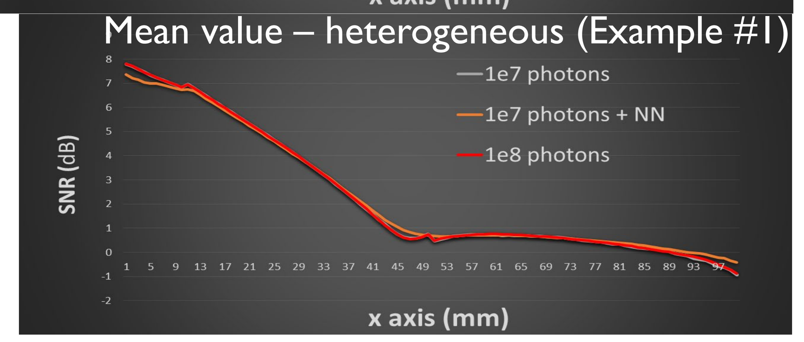

### Heterogeneous domain




## Evaluation (cont.)

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




- For homogeneous domains, NN-Filtering improves the SNR by 25 dB and 20 dB over the $10^5$ simulation and ANLM filtering [1], respectively.
- For heterogeneous domains, NN-Filtering typically produce smooth images preserving image features. The SNR improvement is 7dB given the training data; the mean-values overall agree with the ground-truth.

## 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.
- We tested the denoiser for both homogeneous domains and heterogeneous domains; in the former case, it improves SNR by 25 dB. This is more than 4-fold improvement compared to the 5 dB improvement from the ANLM filter.


## References

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