doi:10.1017/S1431927622007917
Microsc. Microanal. 28 (Suppl 1), 2022

Neural Networks for Dose Reduced Reconstruction Image Denoising in Neutron Tomography

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Neutron imaging employs the unique characteristics of neutrons' interactions with matter to probe materials in a mode that is highly complementary to X-rays. More specifically: neutrons interact with the nuclei of a material's constituent atoms, while X-rays interact with the electron shell. While these modes are highly complementary, the flux of neutron sources is significantly lower than typical X-ray sources. To contextualize the extreme discrepancy in flux, consider modern synchrotron sources are around $10^9 \times$ brighter than the sun. In this astral context a neutron source yields fluxes comparable to the stars outside the solar system ($10^7 \times$ less bright than the sun). For imaging experiments, this generally means that exposure times are much higher for neutron sources than for X-ray sources. This temporal problem is even more problematic for tomography which integrates a series of angular image projections into a unified volumetric image (tomogram). Depending on the size of the object being imaged, high-resolution tomograms can require on the order of thousands of projection images. Overcoming this limitation via dose reduction can render time-dependent and high-throughput neutron tomography much more feasible and enable novel insights in areas of research such as batteries, fuel cells and water transport in porous media.

In the context of this work, *dose reduction* refers to sparser angular projection sampling density than optimal (i.e., as determined by the Nyquist-Shannon sampling theorem) and not lower photon counts per projection. When dose reduction is employed for tomography, reconstructions tend to be noisy with streaking artifacts, which deeply corrupt the fidelity of reconstructed data. This has led to a variety of techniques for reconstructing sparsely sampled projections including, most recently, neural networks (NN). NNs have been employed toward many image processing tasks achieving state of the art results and recently have been applied to a variety of X-ray CT dose reduction approaches such as the *Filtered Back Projection Convolutional Network* [1] and *Residual Encoder-Decoder Convolutional Neural Network* [2]. The work herein contrasts these (and other [3, 4]) neural network-based approaches with both traditional de-noising methods (TV minimization, Gaussian Filtering) and an iterative reconstruction method (SIRT: 10 iterations).

Raw projection images of an alkaline AAA battery were cropped and converted to attenuation space where they were filtered by the method of Vo et al. [5] to remove stripe artifacts. These images henceforth are referred to as *ground truth*. There were 5 down-sampling conditions used which comprise taking every n^{th} projection with n = 2,4,8,16, and 32 (400, 200, 100, 50, and 25 projections respectively). These constitute the *down-sampled* data sets where each method was assessed on a single set of down-sampled images (n = constant) paired with the ground truth (n = 1; 800 projections). All NN models were trained on the reconstruction image space where the data were split into training (80%) and validation (20%) sets to ensure the models did not over-fit. Likewise, to assist in data augmentation the models were trained with random cropped (128 × 128) portions of the images to avoid memorizing the data set.

Figure 1 shows the results of employing the FBPConvNet architecture to the different down sampled datasets along with the inputs and ground truth. This method performed the highest of the tested methods in the peak-signal-to-noise-ratio (PSNR) metric that indicates the pixel-wise similarity of two images. The PSNR distributions for each method at each down sampling condition are shown in Figure 2. In conclusion, the neural-network-based methods perform higher than all the traditional de-noising methods at removing this structured noise that arises from dose reduction, enabling a pathway to accelerate 4D tomography [6].

https://doi.org/10.1017/S1431927622007917 Published online by Cambridge University Press

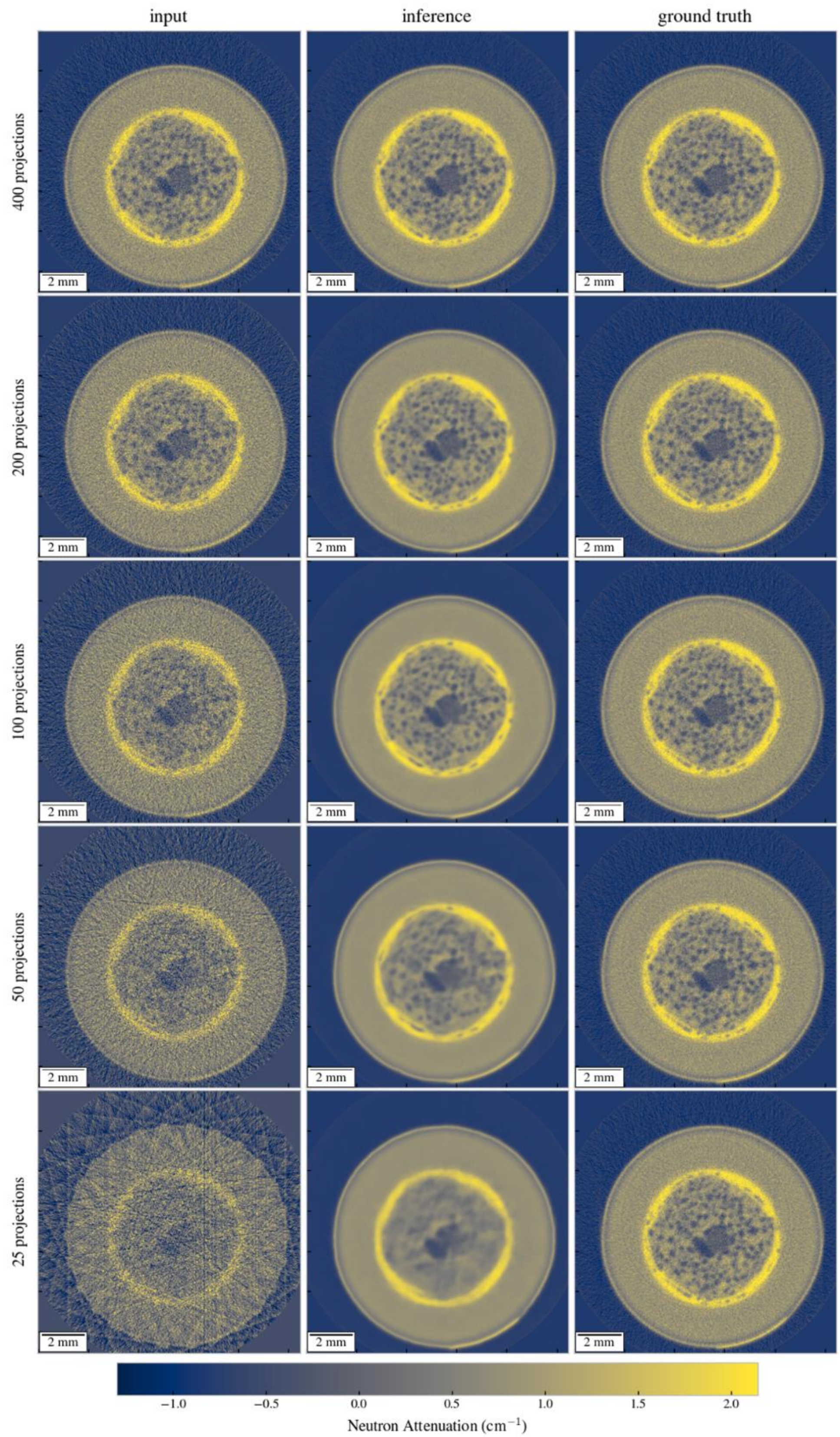
input
inference
ground truth
400 projections
200 projections
100 projections
50 projections
25 projections
2 mm
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
Neutron Attenuation (cm^{-1})

Figure 1: Demonstration of FBPConvNet results (highest performing method) on different sparsely sampled input data.

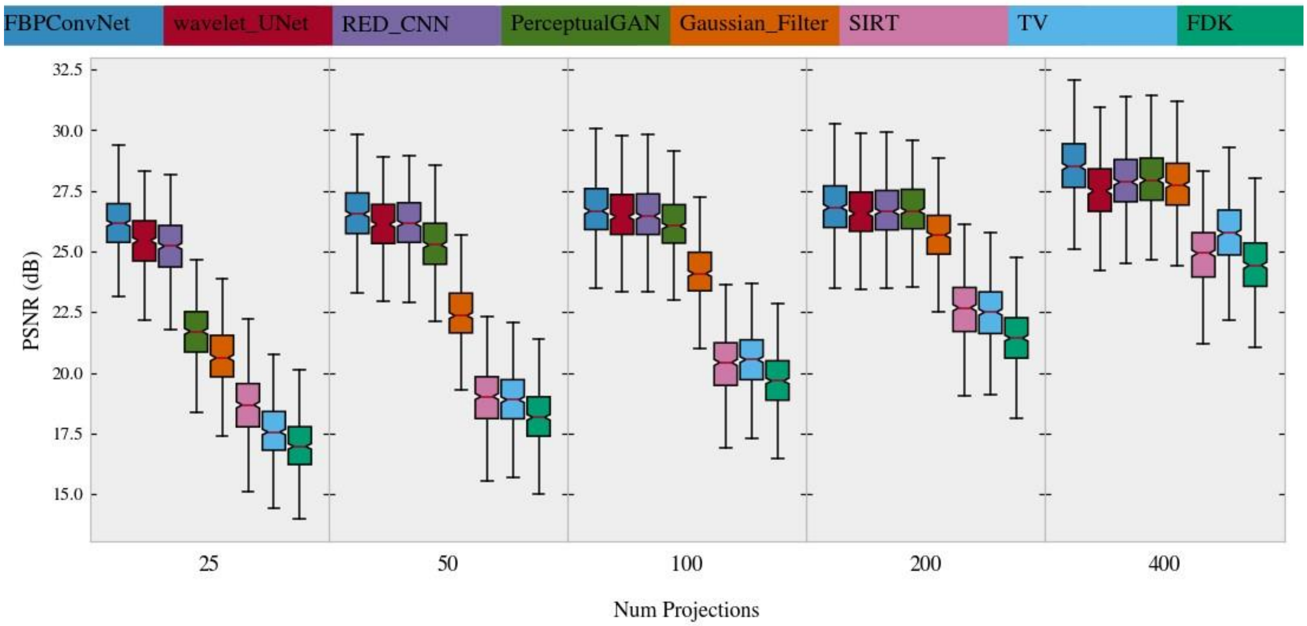

Figure 2: Comparison of denoising methods on PSNR for each down sampled dataset (with respect to fully sampled FDK). FBPConvNet is the highest in each down sampling condition.

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[6] Acknowledgements: Research was sponsored by the DEVCOM Army Research Laboratory (ARL) and was funded under Cooperative Agreement (CA) Number W911NF-20-2-0284. The views and

https://doi.org/10.1017/S1431927622007917 Published online by Cambridge University Press

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