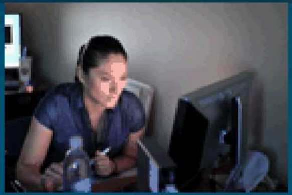
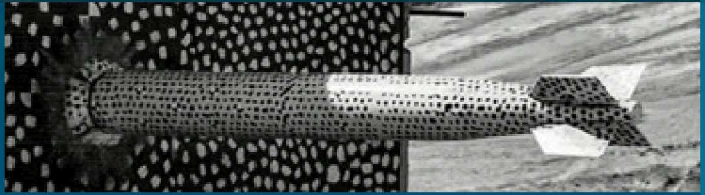
SAND2019-9430C

Machine Learning-Based Image Reconstruction for Undersampled XPCI Datasets





Srivathsan P. Koundinyan, Collin Epstein, Kyle R. Thompson, Edward S. Jimenez, Amber L. Dagel

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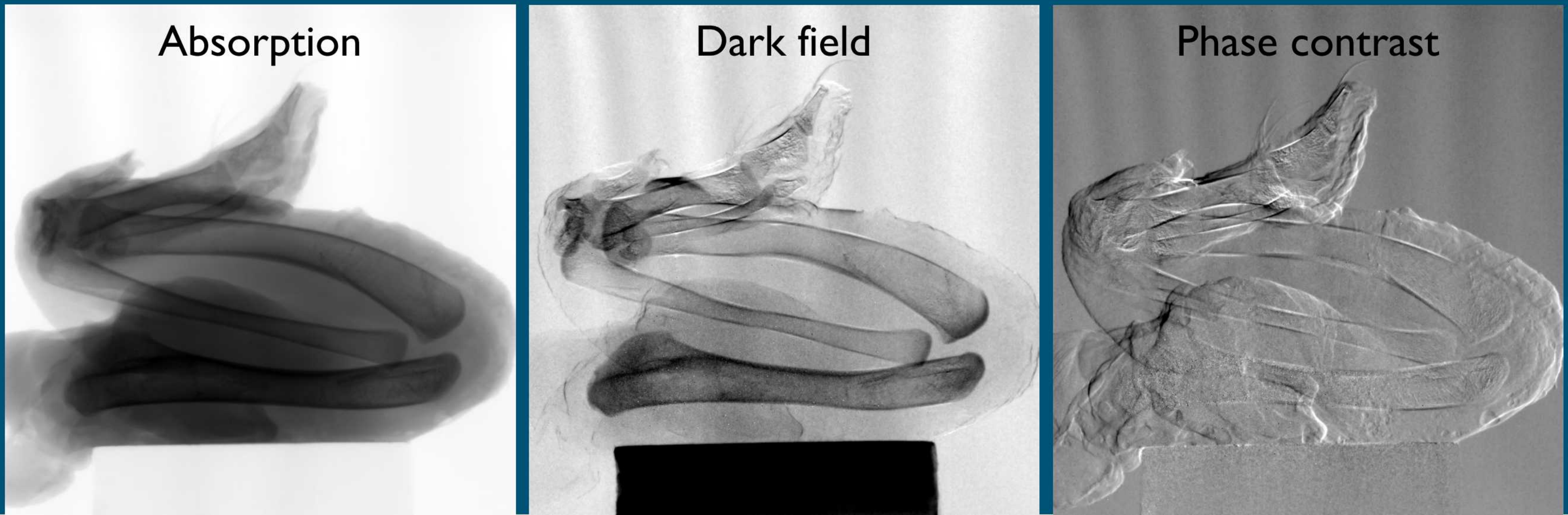
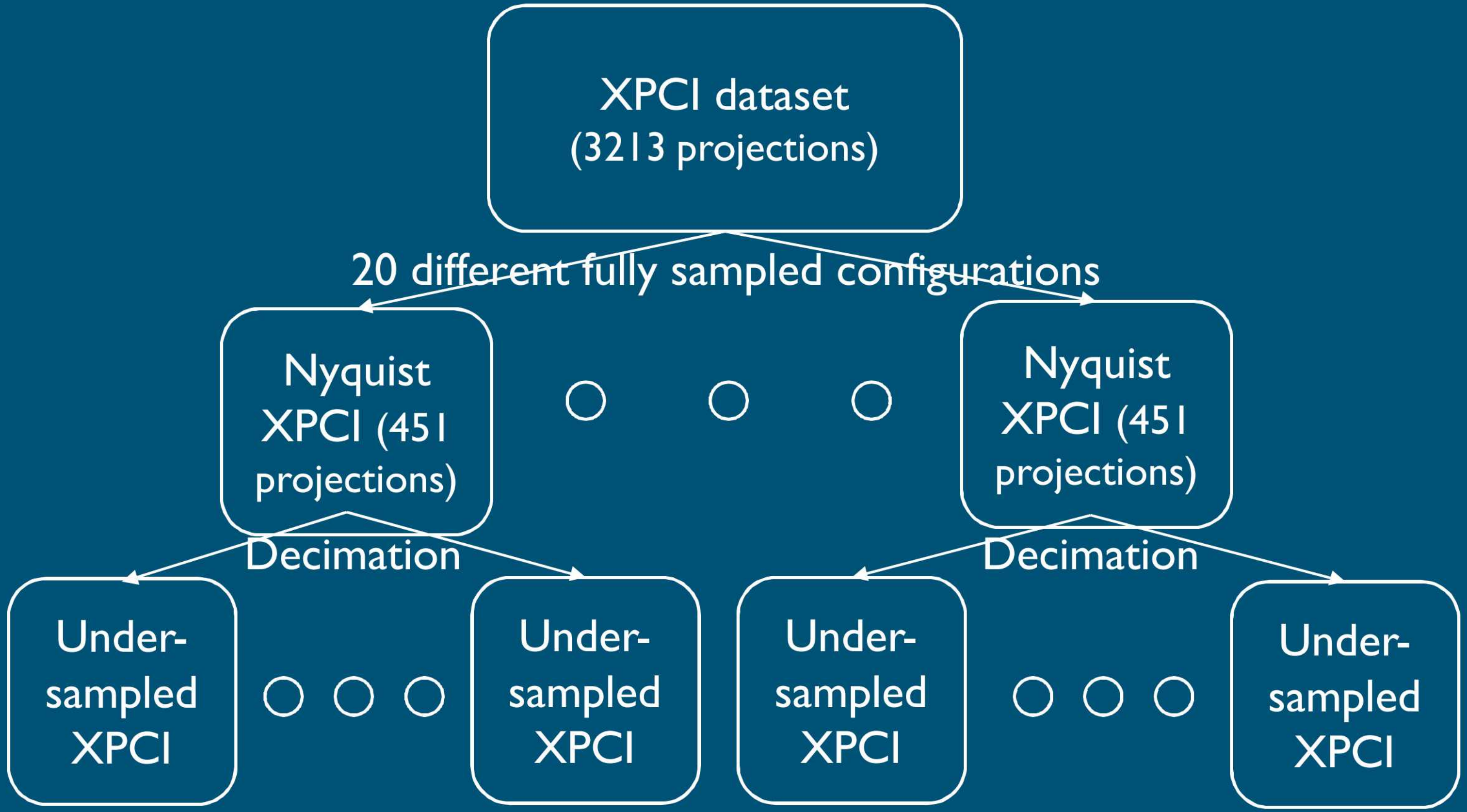
Introduction

- X-Ray Phase Contrast Imaging (XPCI)
  - Useful for visualizing weakly absorbing/low-density materials
  - Provides three image products compared to conventional x-ray CT
  - Limitation:
    - Very slow acquisition of data
  - Undersampling accelerates data collection at the cost of image artifacts
- Purpose: can we apply machine learning algorithms to reconstruct few-view XPCI data with high fidelity?



Training Data

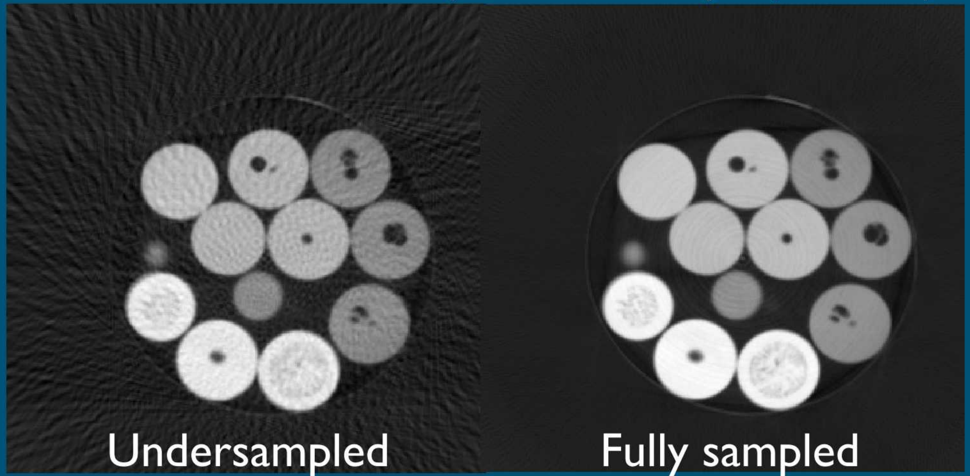
- Single XPCI dataset acquired with 3213 projections
  - Talbot-Lau-based system with three gratings
  - Six types of plastics in a cup
  - Fully sampled dataset requires 451 projections → oversampling factor of 7x
- Short term focus on reconstruction of undersampled absorption images



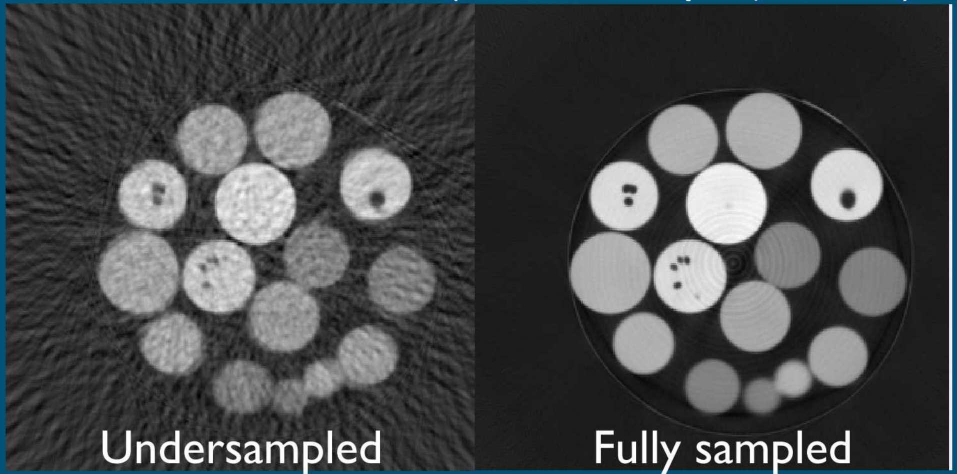
Decimation Factors

Different machine learning models trained for each decimation factor

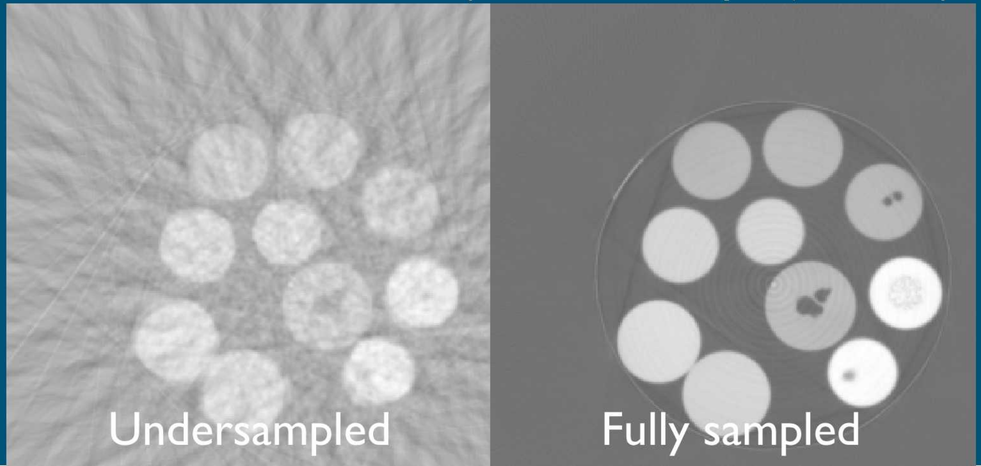
Decimation factor 4 (451/4 = 112 projections)



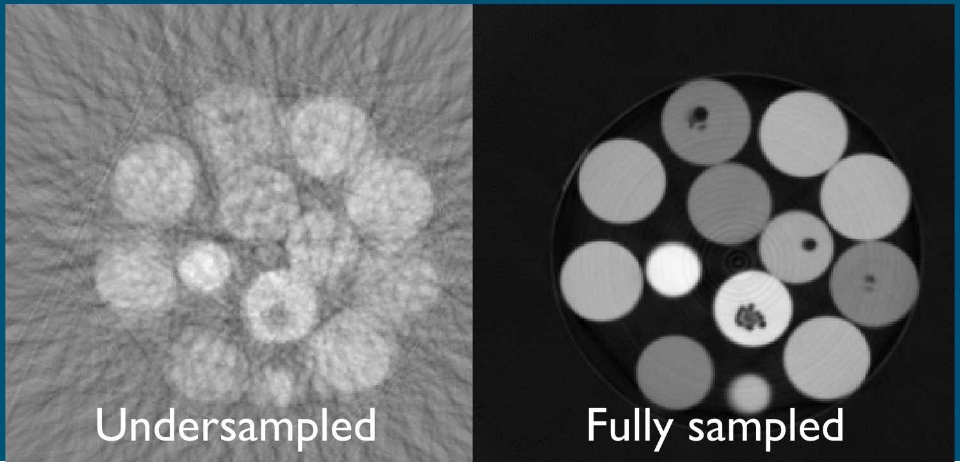
Decimation factor 8 (451/8 = 56 projections)



Decimation factor 12 (451/12 = 38 projections)

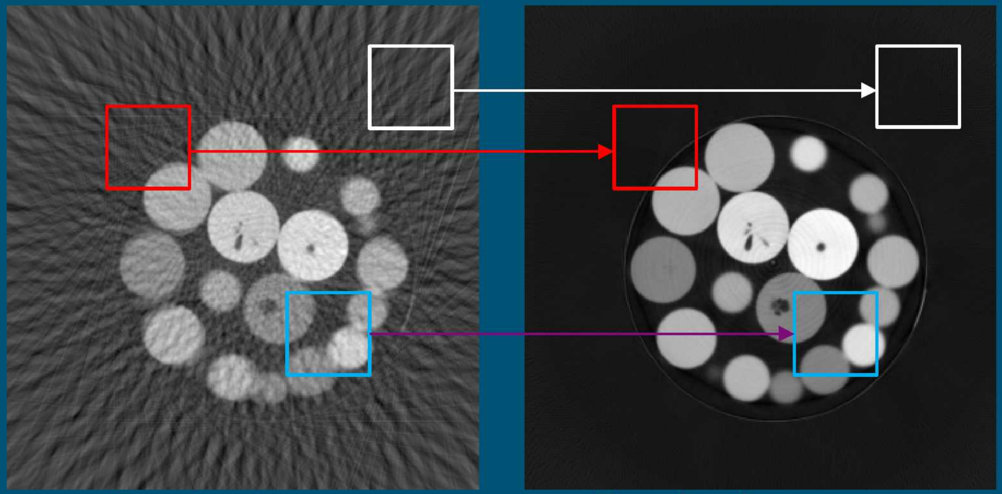


Decimation factor 16 (451/16 = 28 projections)



Methods

- Convolutional neural network (CNN)
  - Input: undersampled image
  - Output: de-aliased image
- Slice-by-slice de-aliasing of 3D volume
  - Minimizes memory requirements
- Patch-based training for additional memory efficiency and data augmentation
  - For a given slice (357 x 357), 64 random patches of size 64 x 64 extracted

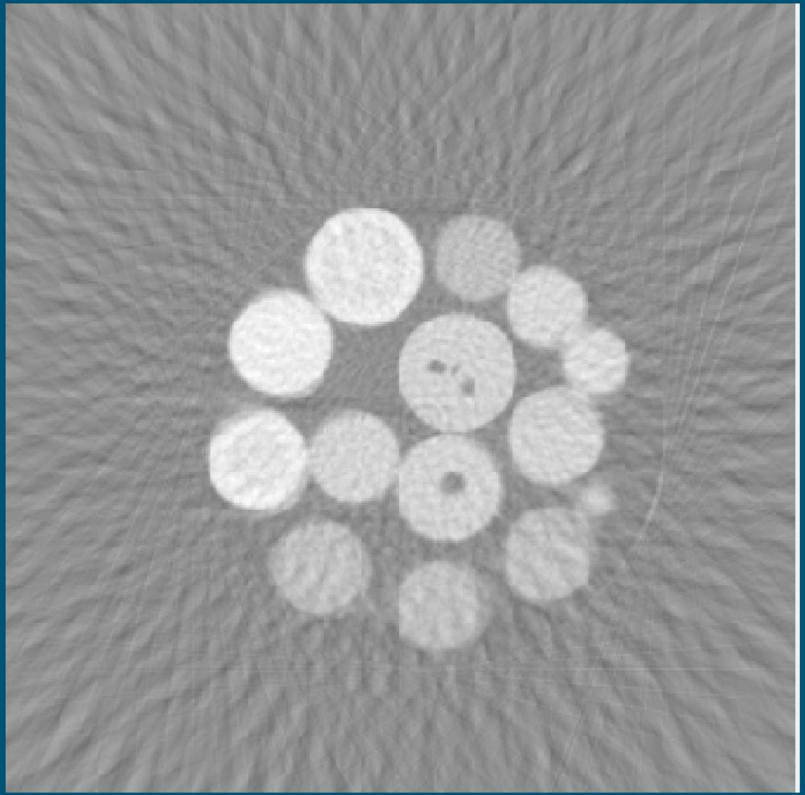


Patched input Patched output

Methods

- Input (undersampled image) and output (fully sampled image) spatially misaligned following reconstruction
  - Consequence of FDK reconstruction with commercially available Volume Graphics software

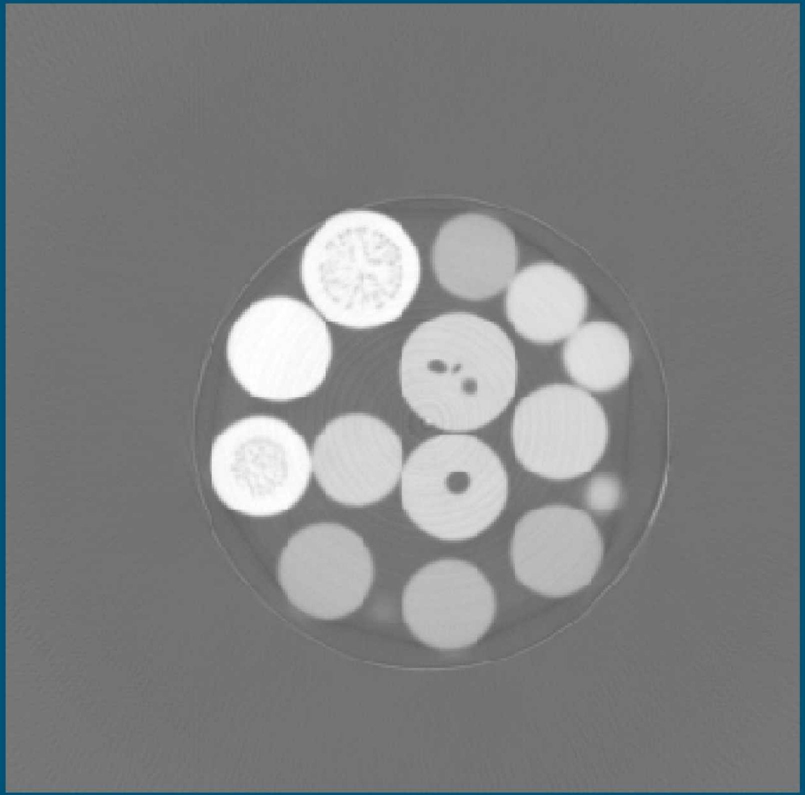
Sample input



Methods

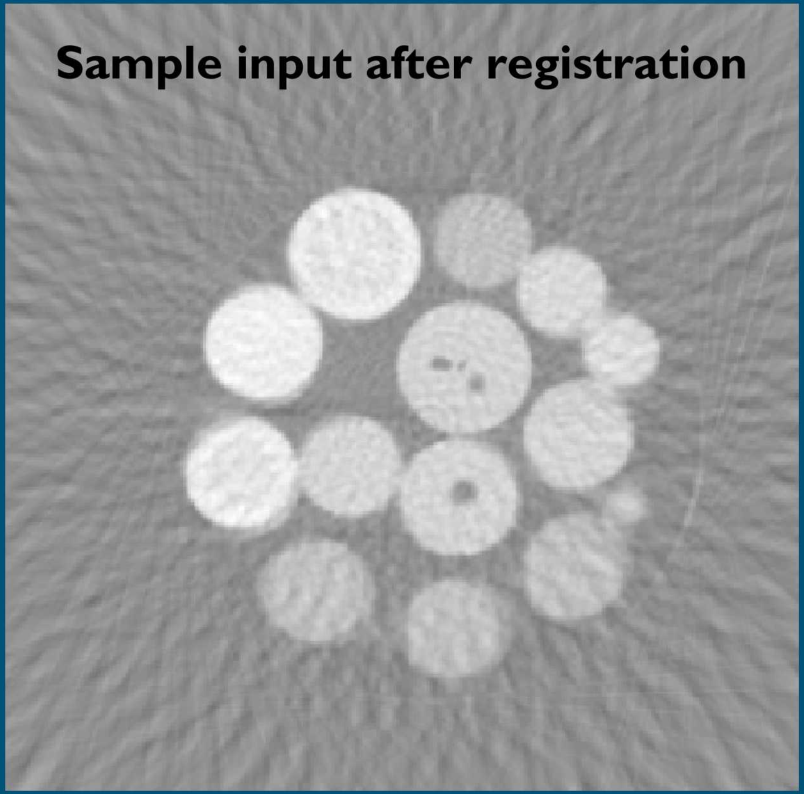
- Input (undersampled image) and output (fully sampled image) spatially misaligned following reconstruction
  - Consequence of FDK reconstruction with commercially available Volume Graphics software

Sample output



Methods

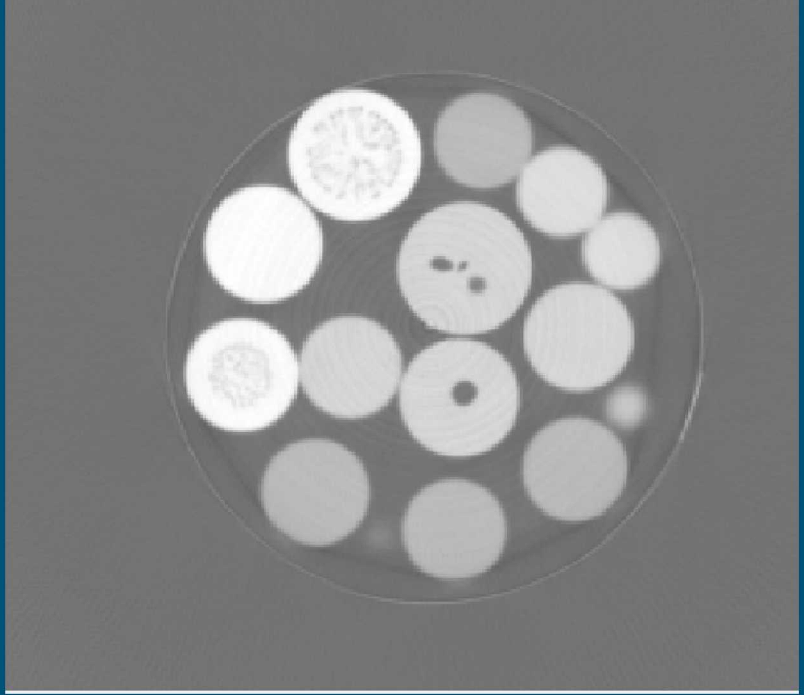
- Input and output spatially misaligned following reconstruction
- Affine registration technique implemented with four transformations to correct for misalignment
  - Translation, scale, shear, and rotation (12 total parameters)
  - Solver: Conjugate gradient; Optimization criteria: mean squared error



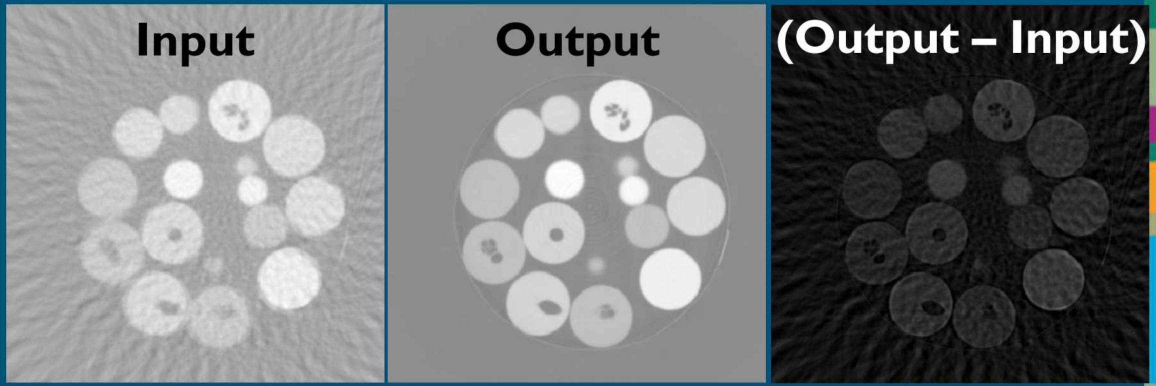
Methods

- Input and output spatially misaligned following reconstruction
- Affine registration technique implemented with four transformations to correct for misalignment
  - Translation, scale, shear, and rotation (12 total parameters)
  - Solver: Conjugate gradient; Optimization criteria: mean squared error

Sample output after registration



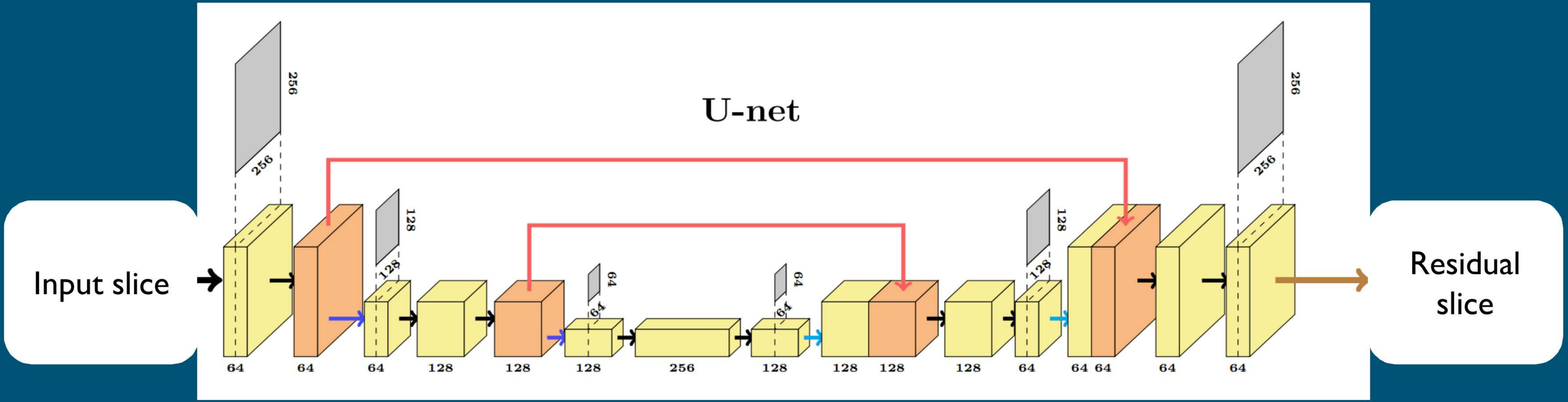
Methods



- **Residual U-Net Architecture**
  - Input: Undersampled image
  - Output: residual image (= fully sampled image – undersampled image)
  - Why? Sparse output is easier to learn

- Expansion/contraction Steps: 5
- Filters: 64 3x3 kernels per expansion/contraction
- Loss function: l_2

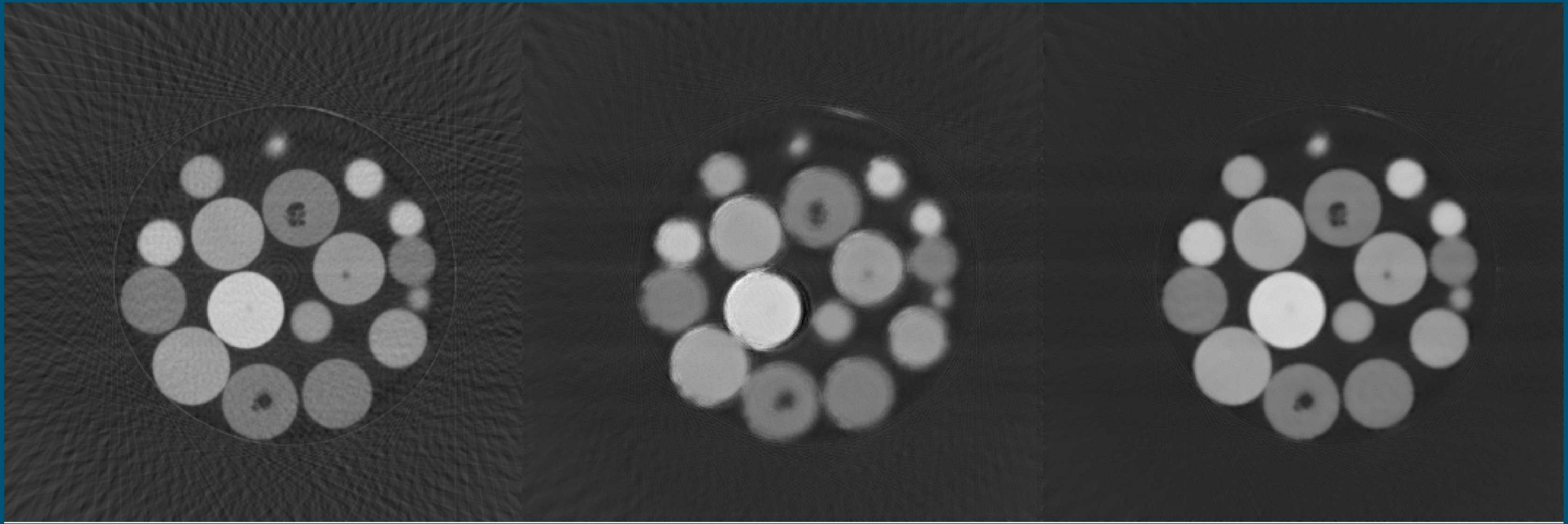
- Training parameters
  - Epochs: 200
  - Solver: Adam
  - Trained on NVIDIA GTX 1060



Jin et al. "Deep convolutional neural network for inverse problems in imaging." *IEEE TMI* 26.9 (2017): 4509-4522.

Results

Importance of affine registration to spatially align data



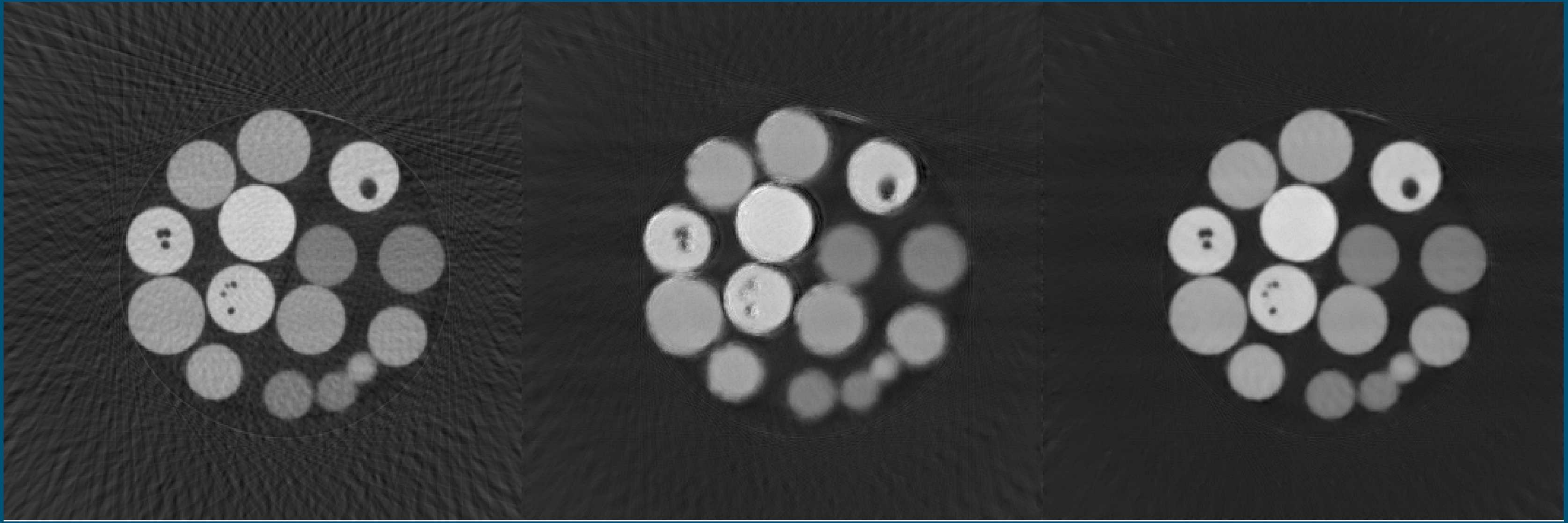
Input

Model output trained with misregistered data

Model output trained with registered data

Results

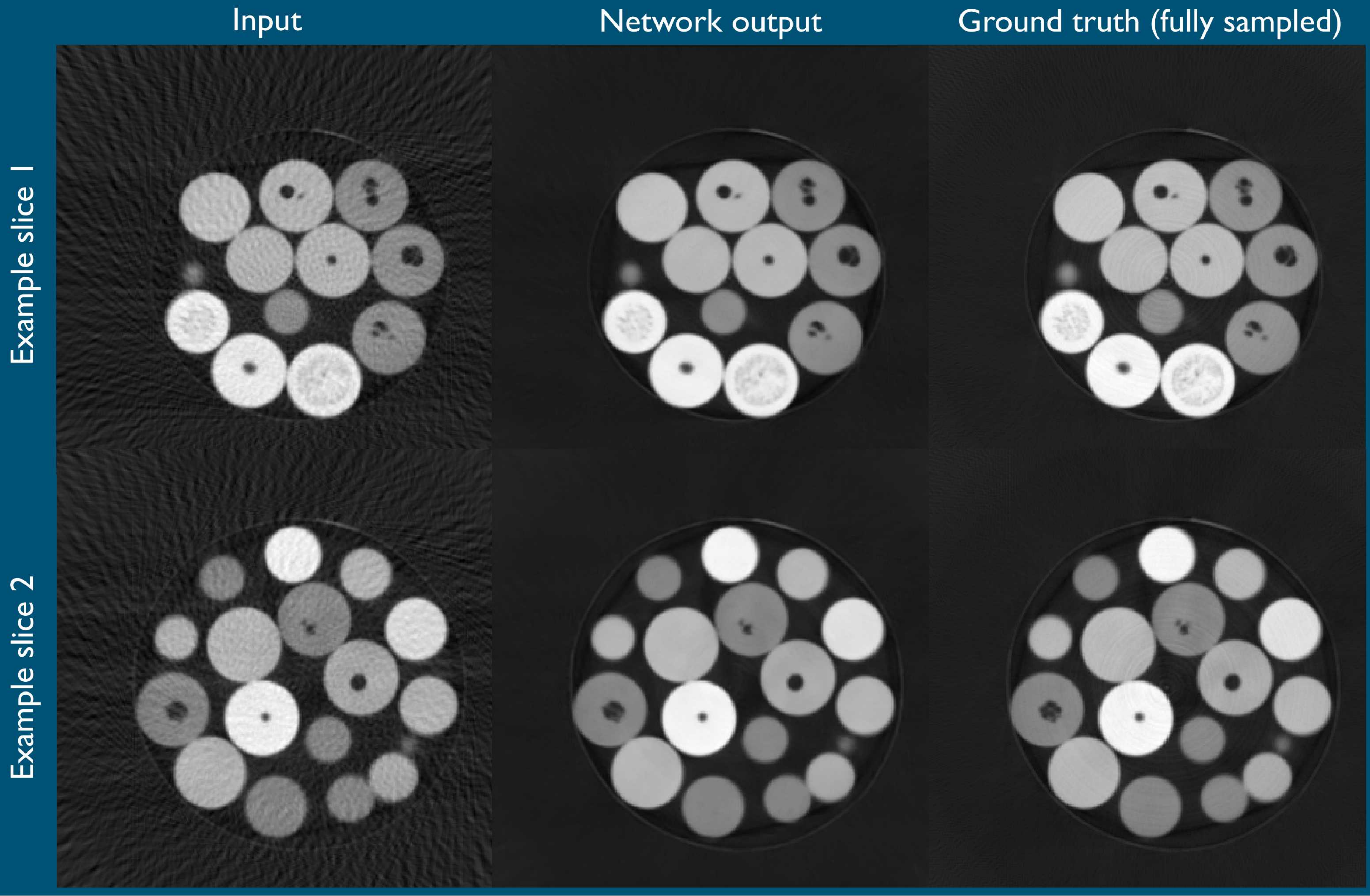
Importance of affine registration to spatially align data



Input | Network trained with misregistered data | Network trained with registered data

Residual regression with decimation factor **4** (112 projections)

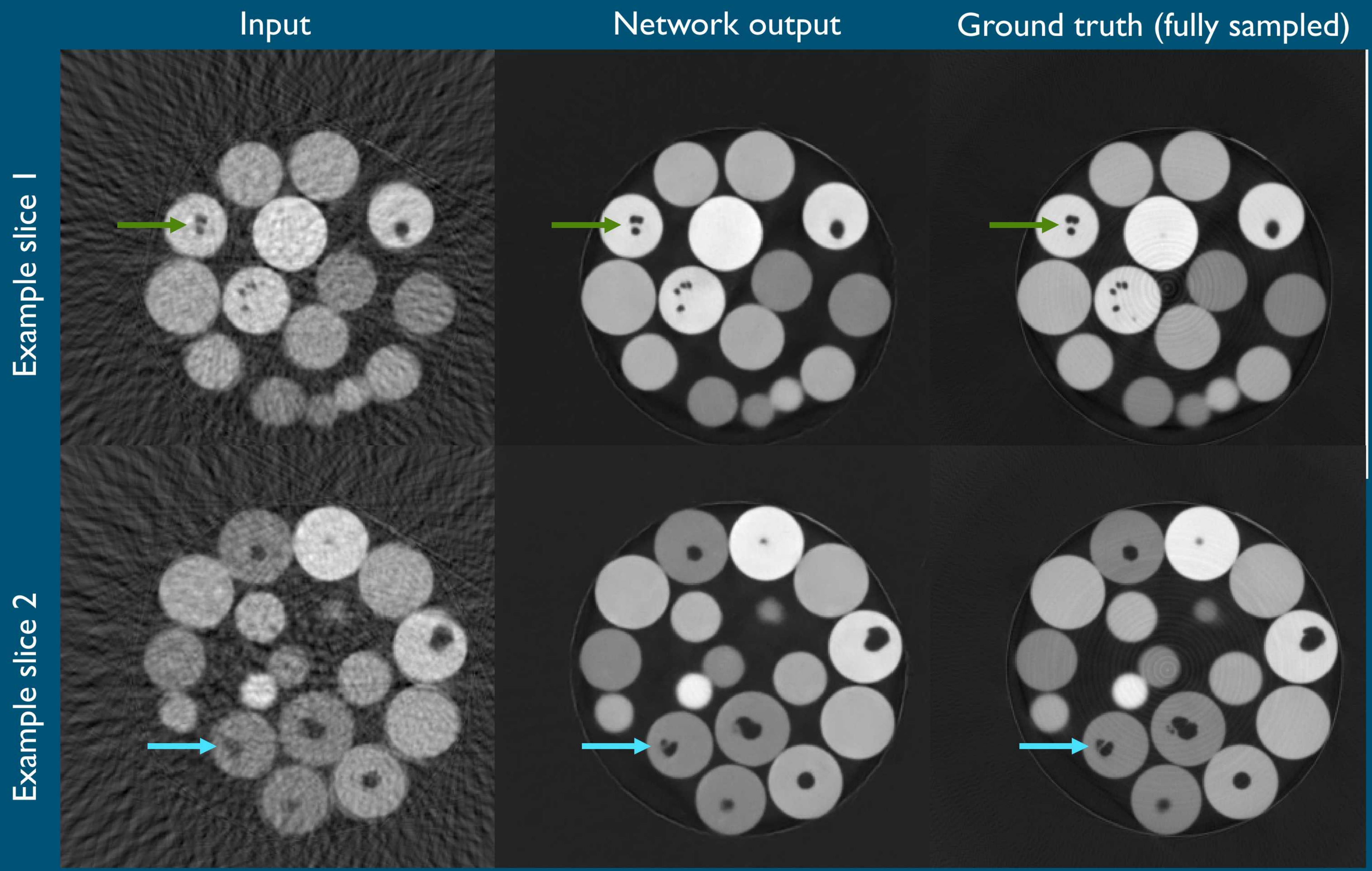
All models evaluated on unseen data and slices



Ring artifacts in ground truth image removed in network output

Residual regression with decimation factor **8** (56 projections)

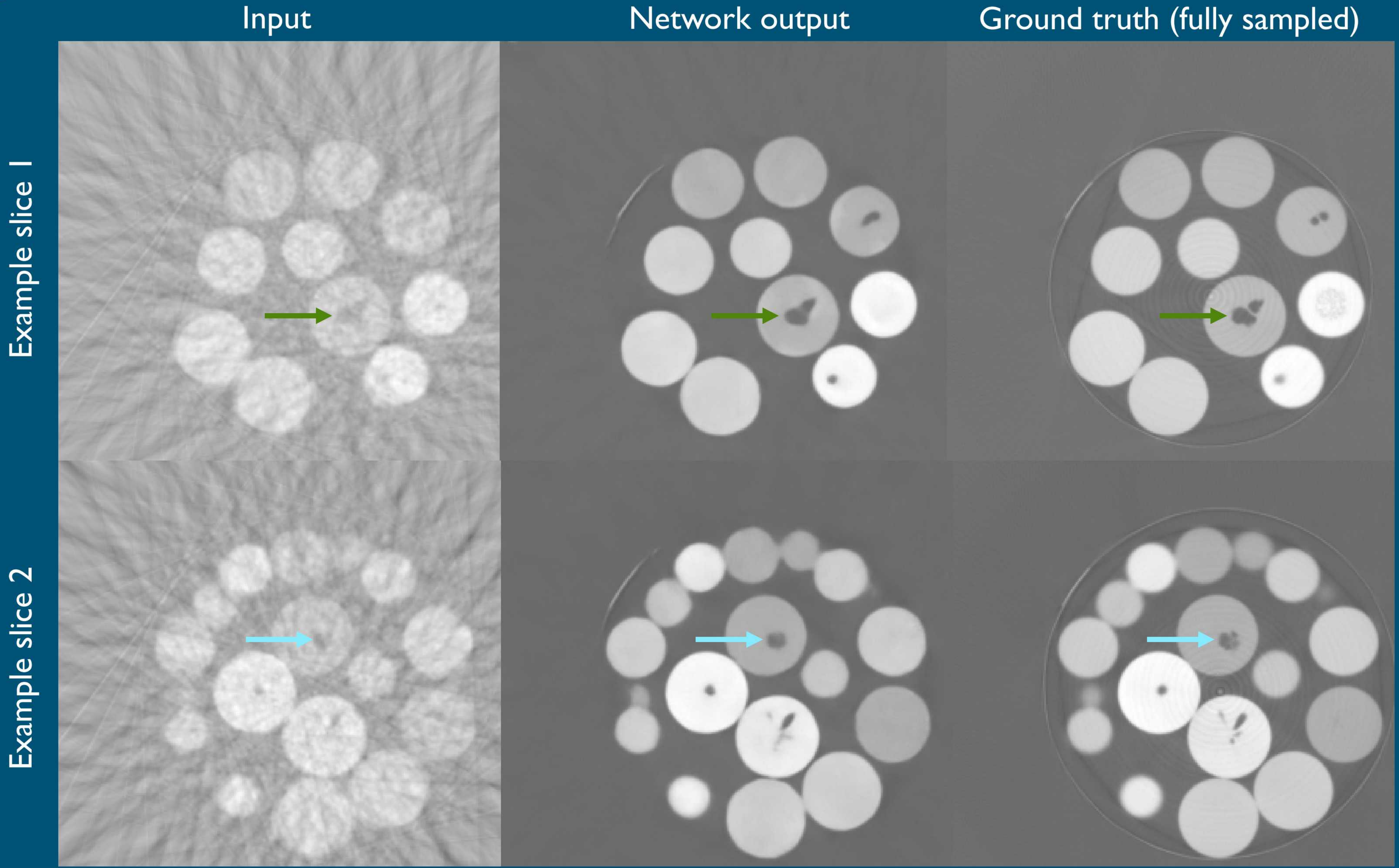
All models evaluated on unseen data and slices



Ring artifacts in ground truth image removed in network output

Residual regression with decimation factor 12 (38 projections)

All models evaluated on unseen data and slices



Ring artifacts in ground truth image removed in network output

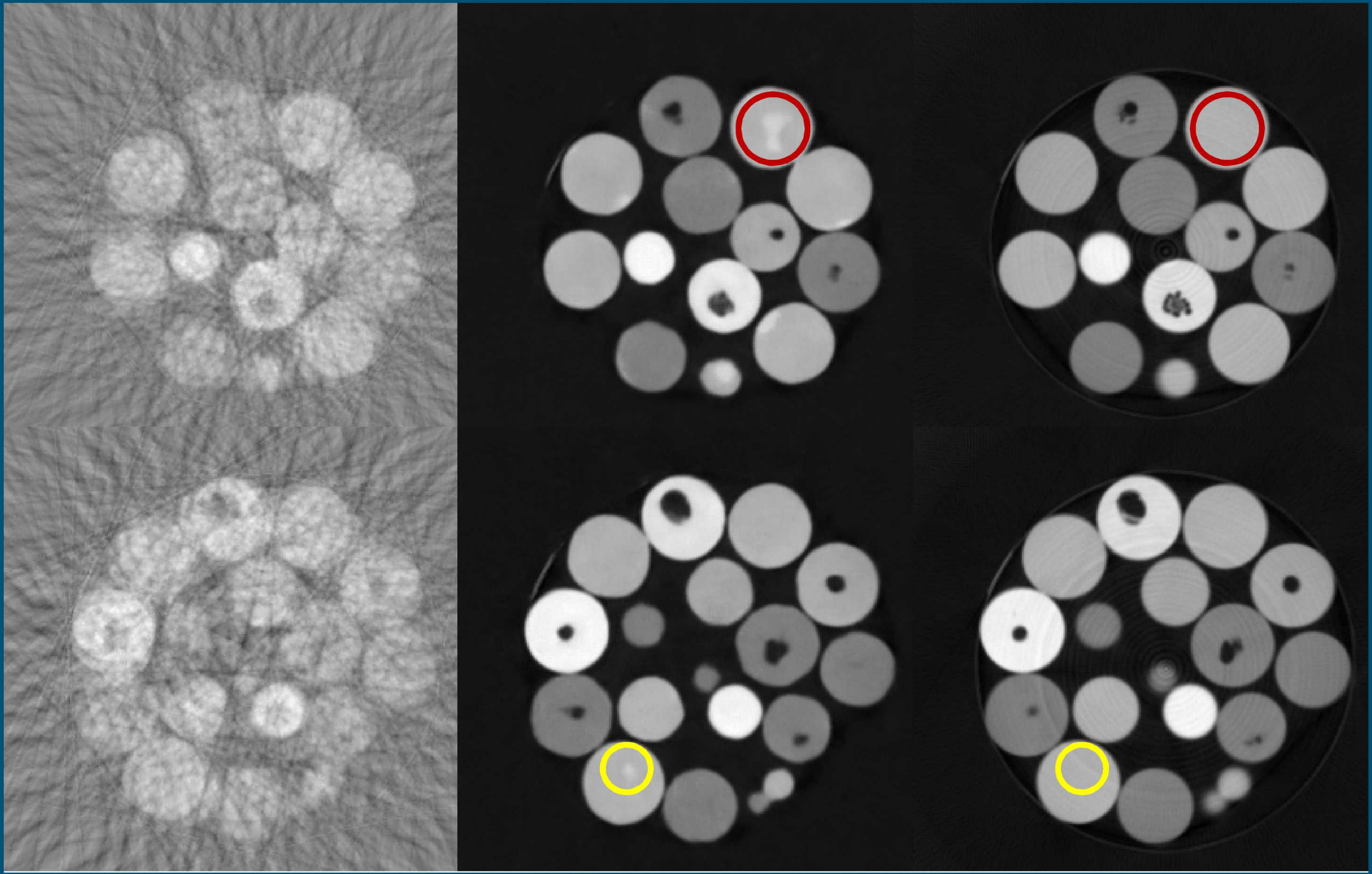
Residual regression with decimation factor **16** (28 projections)

All models evaluated on unseen data and slices

Input | Network output | Ground truth (fully sampled)

Example slice 1

Example slice 2

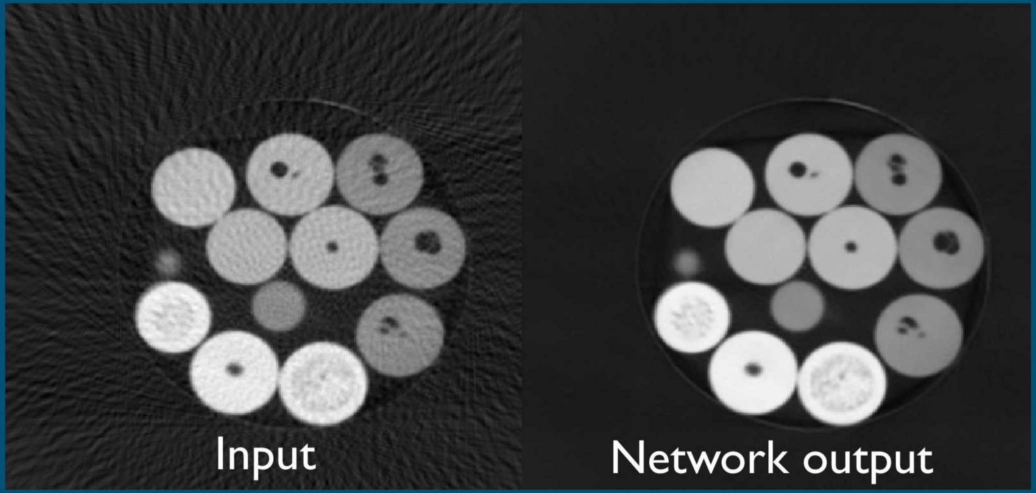


Ring artifacts in ground truth image removed in network output

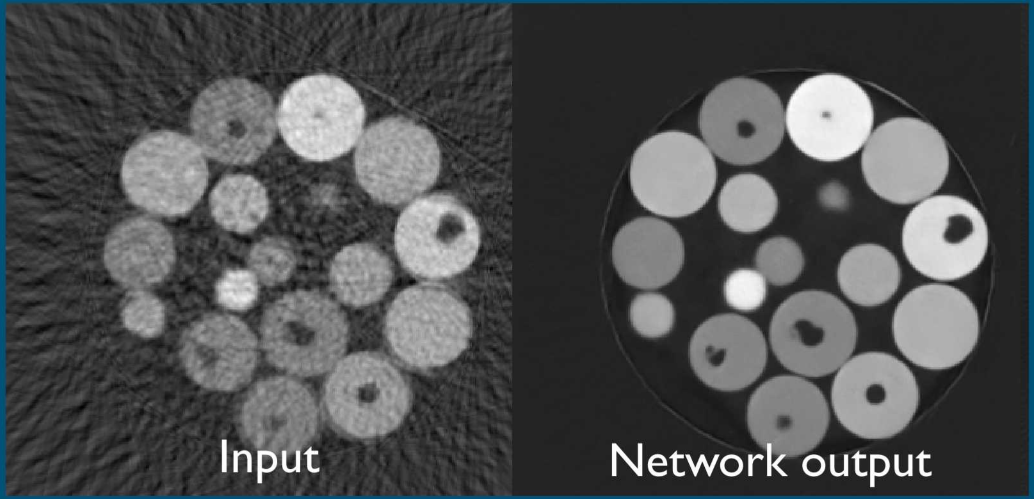
Comparison of outputs for all decimation factors

All models evaluated on unseen data and slices

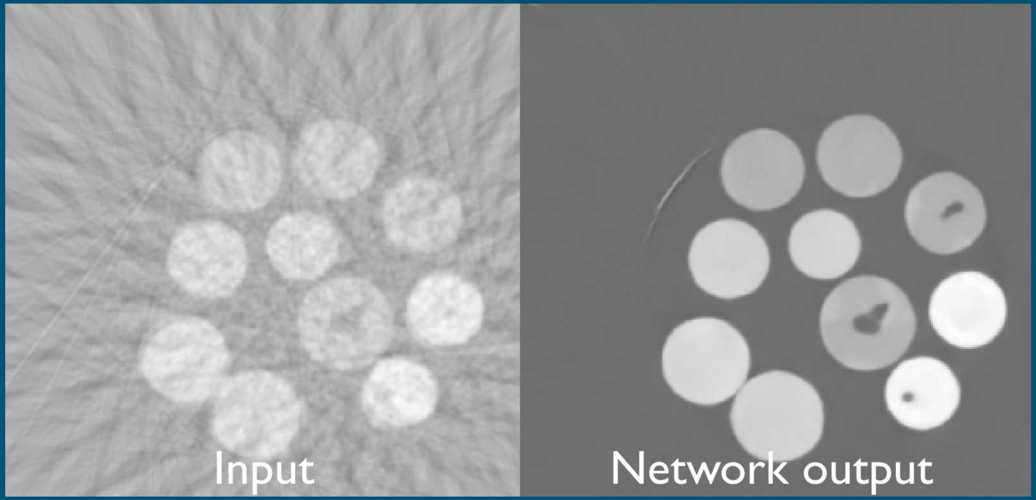
Decimation factor 4



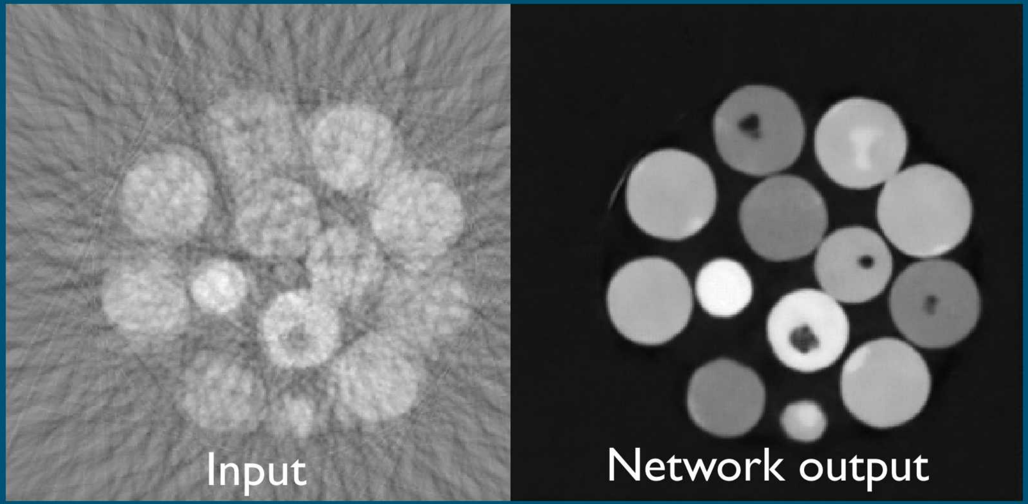
Decimation factor 8



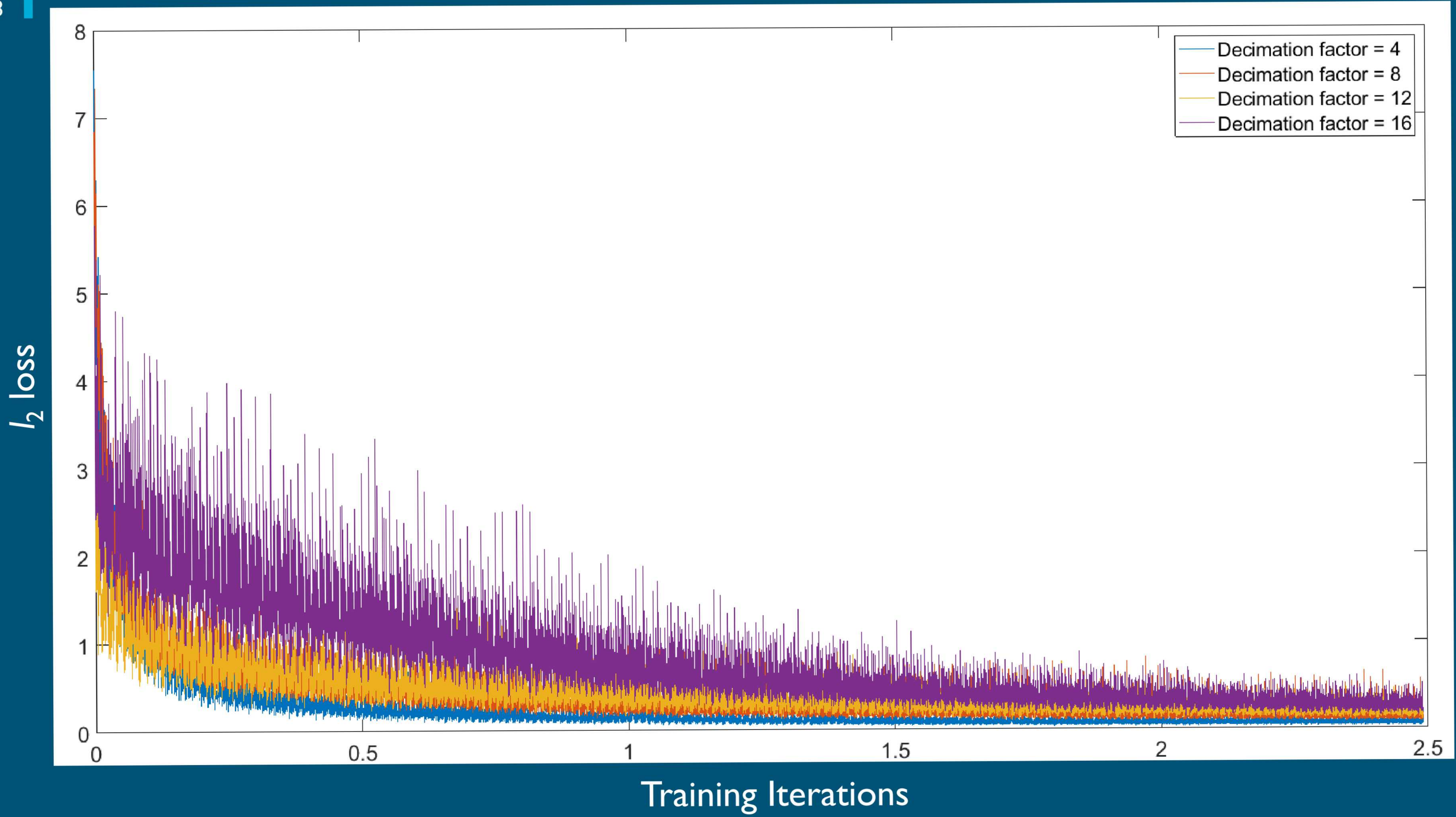
Decimation factor 12



Decimation factor 16



Training loss for all decimation factors



Discussion

- Convolutions neural networks enable reduction of under sampling artifacts in XPCI
  - Demonstrated application in decimation factors ranging from 4 to 16
    - Potential for significantly larger decimation factors
  - Network parameters are being tuned for improved performance
    - Network depth (= 5), number (= 64), and size (= 3x3) of filters, optimization routine (= Adam) etc.
    - Current network operates on 2D slices. A 3D network may further bolster performance
    - Requires better GPUs with larger memory (e.g., NVIDIA Titan V)
  - Work is underway to test more advanced network architectures (e.g., Dense, GANs)
- The current image reconstruction network does not incorporate known information about underlying physics
    - Hybrid iterative/deep learning routines are being implemented and tested

Thank you!
Questions?