U-net based deep neural networks for transmission tomography

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References:

Csaba Olasz, László G. Varga, Antal Nagy: Beam Hardening Artifact Removal by the Fusion of FBP and Deep Neural Networks; The 13th International Conference on Digital Image Processing (ICDIP 2021), May 20-23, Singapore.

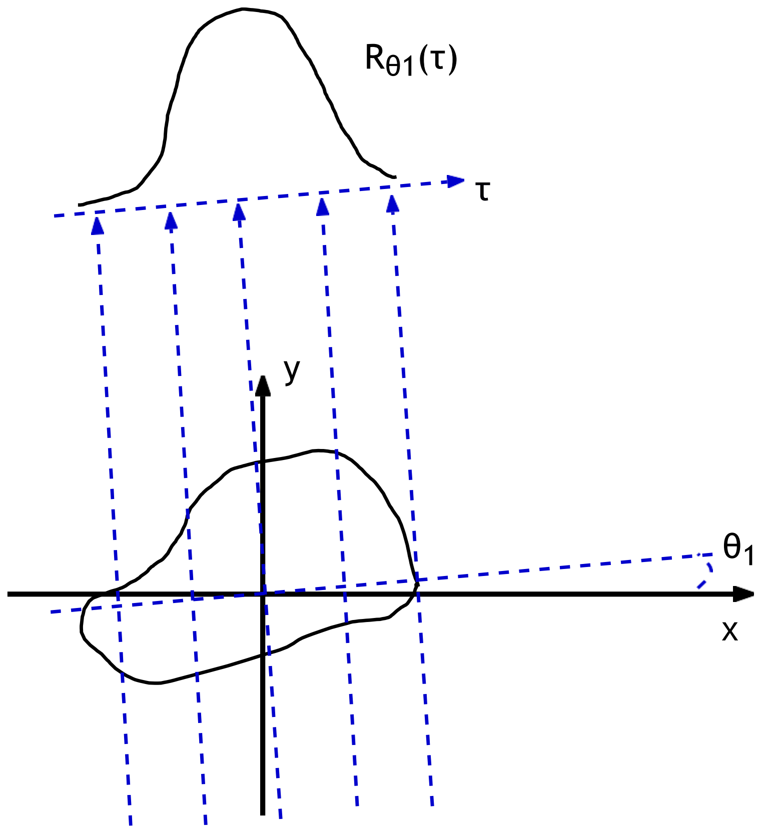
Olasz Csaba, Varga László Gábor, Nagy, Antal: Novel U-net based deep neural networks for transmission tomography. Journal of X-Ray Science and Technology, vol. 30, no. 1, pp. 13-31, 2022. DOI: 10.3233/XST-210962

The structure of the presentation

- Basics of computed tomography
- Beam hardening
- Neural networks and tomography
- Tested neural network structures
- Dataset for the neural networks
- Training and evaluation of the neural networks
- Results
- Conclusions

Basics of computed tomography I.

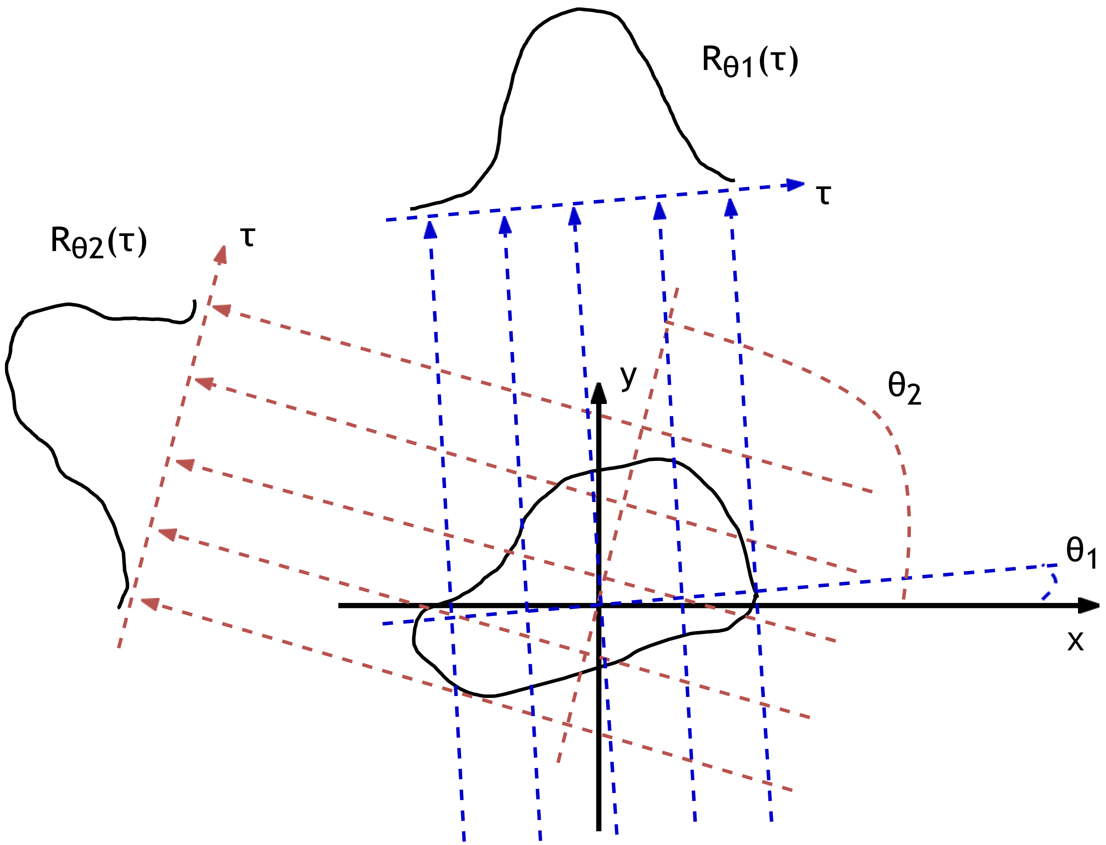
- Tomography is an imaging procedure such that the cross-sections of the studied 3D object are determined from their projections.
- The collection of projection lines having the same rotation angle are called projection.
- In real life the projections are mesaurements, where the values correspond to the summed attenuation coefficients along the X-ray beams (projection lines).
- The mathematical description of the projections is given by the Radon transformation.



$$R(\tau) = \int_{-\infty}^{\infty} f(\tau\cos\theta - y\sin\theta\,,\tau\sin\theta - y\cos\theta\,,)\,dy$$

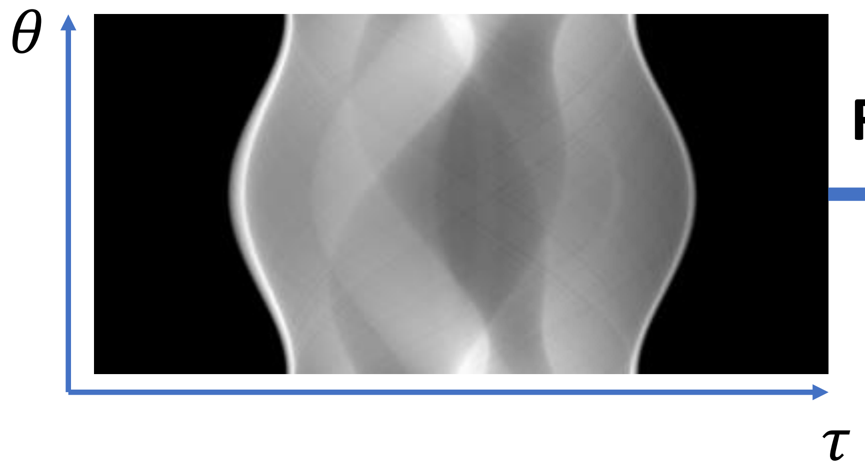
Basics of computed tomography II.

- It is possible to calculate the attenuation coefficients of the material at each position of an image of a cross-sections, if:
  - ✓we acquire projections from many different directions,
  - ✓the path taking by the lines are known
  - ✓and the measurements were taken perfectly.



Basics of computed tomography III.

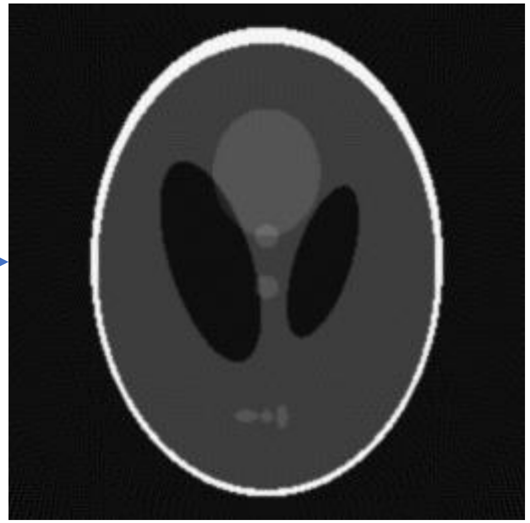
Projection data of a cross section



Filtered **B**ack **P**rojection

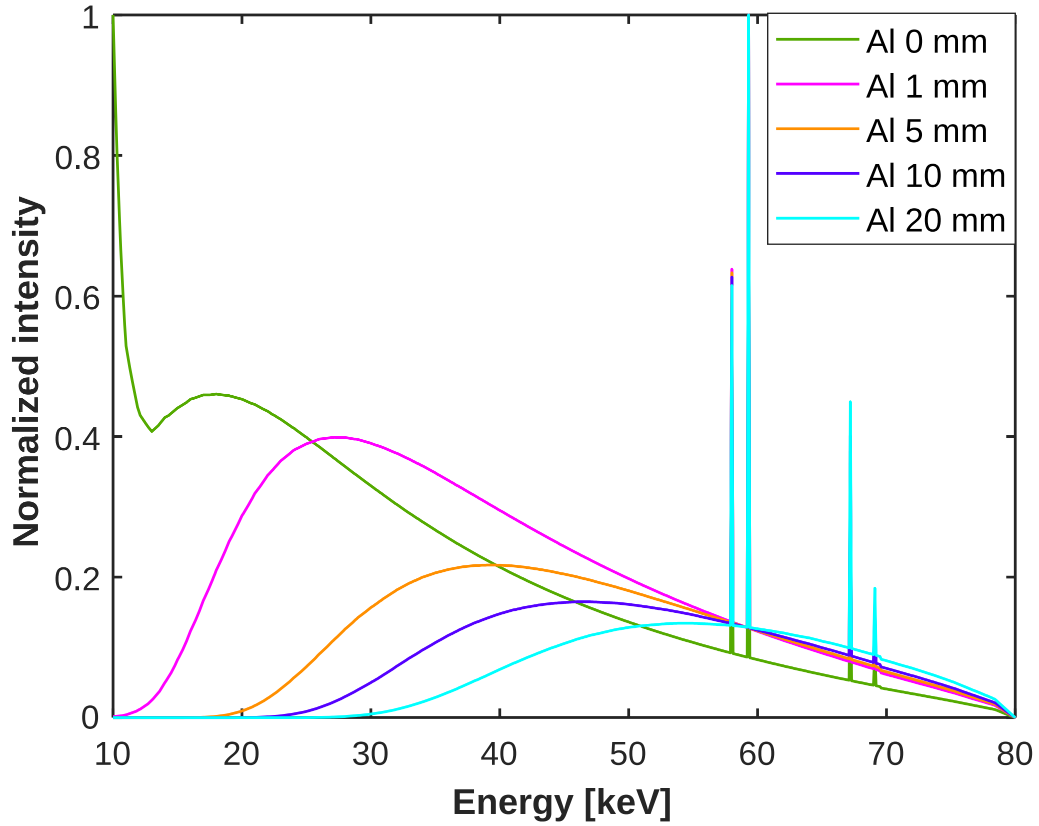
FBP

Reconstructed image of cross section

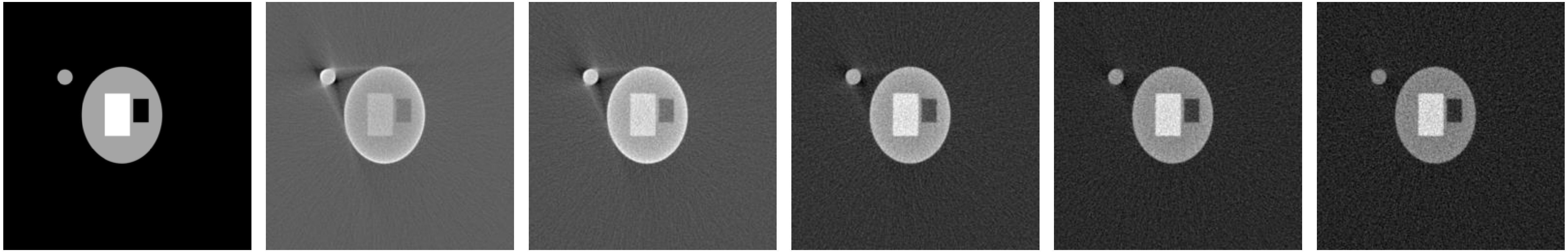


Beam hardening I.

- A physical phenomena causing distorsion on the projection data.
- The lower energy photons of the polychromatic radiation are more likely to be absorbed.
- Beam hardening artifacts appear as cupping and dark or light streaks on the reconstructed image.

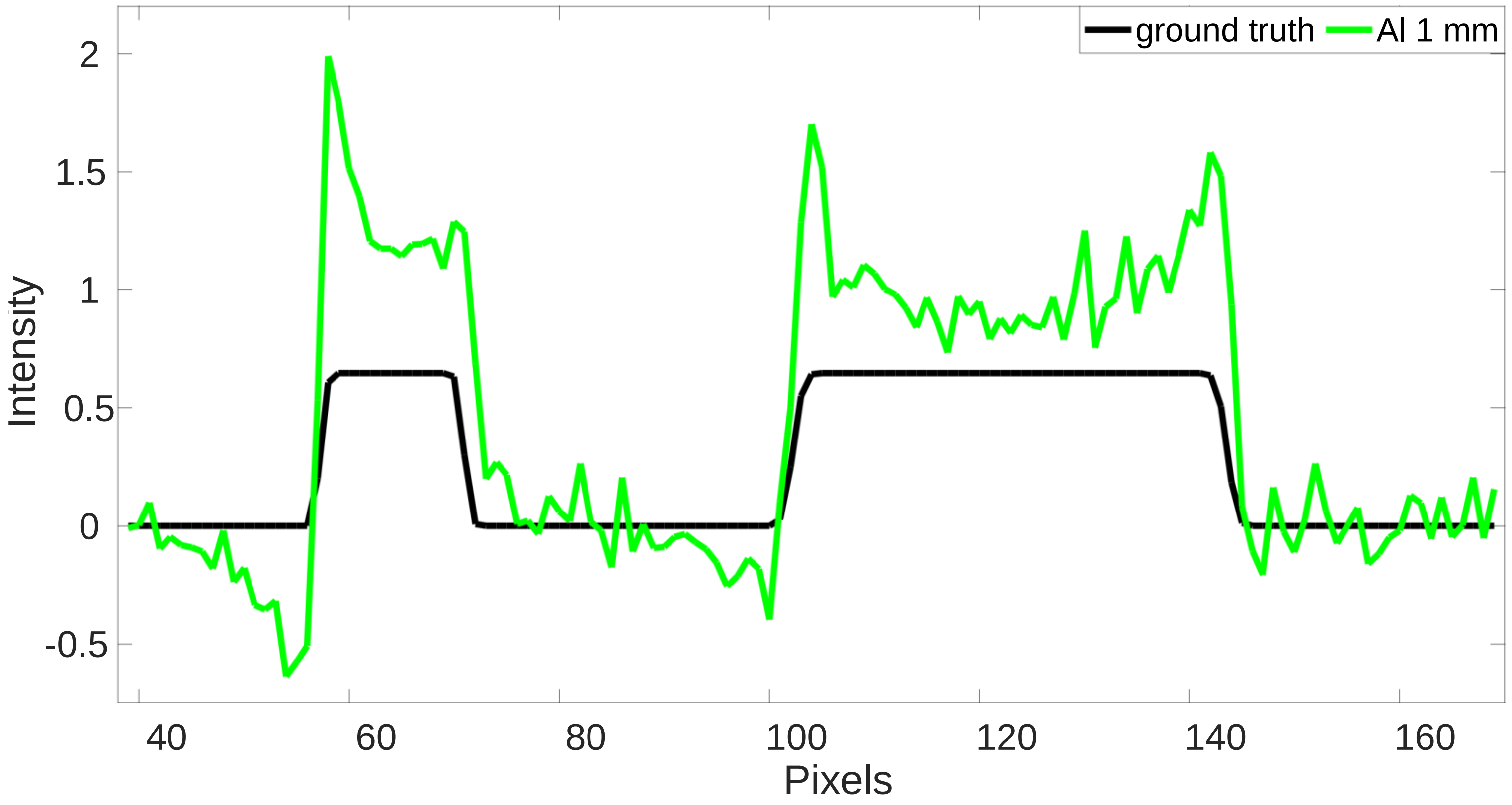


ground truth | Al 0 mm | Al 1 mm | Al 5 mm | Al 10 mm | Al 20 mm

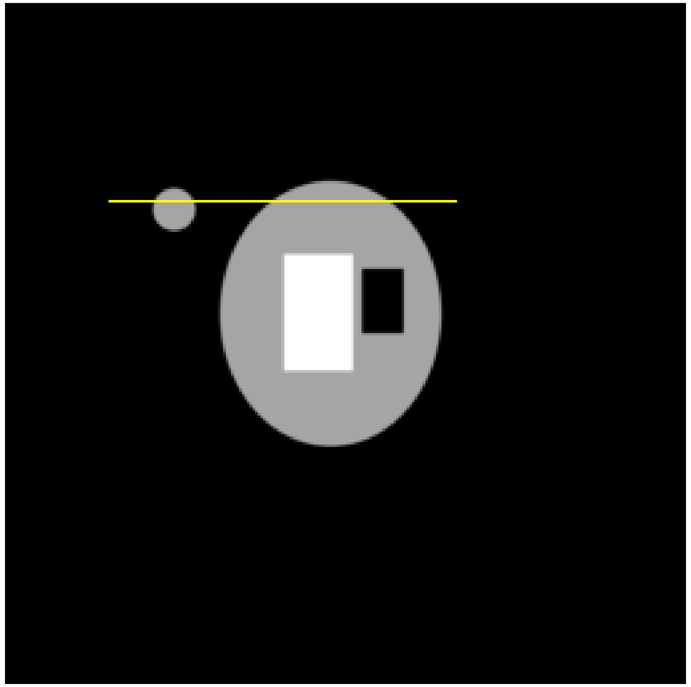


Beam hardening I.

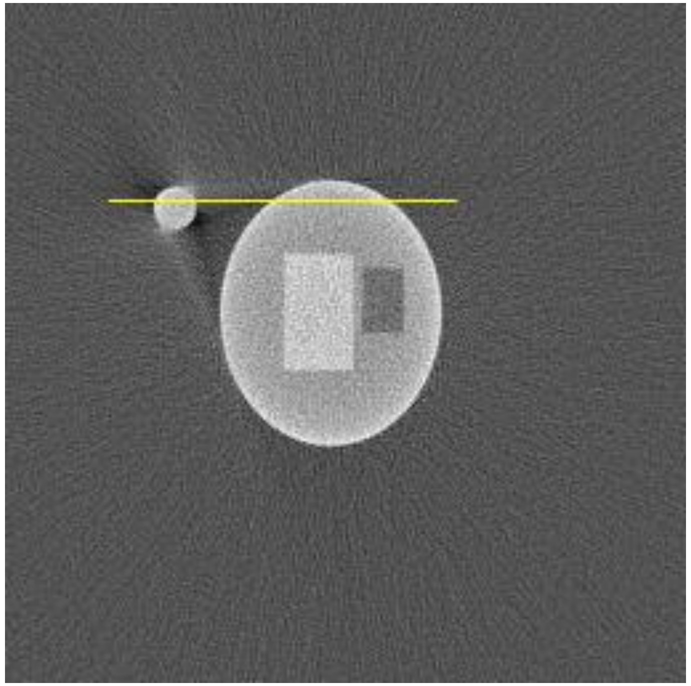
- Cupping



ground truth

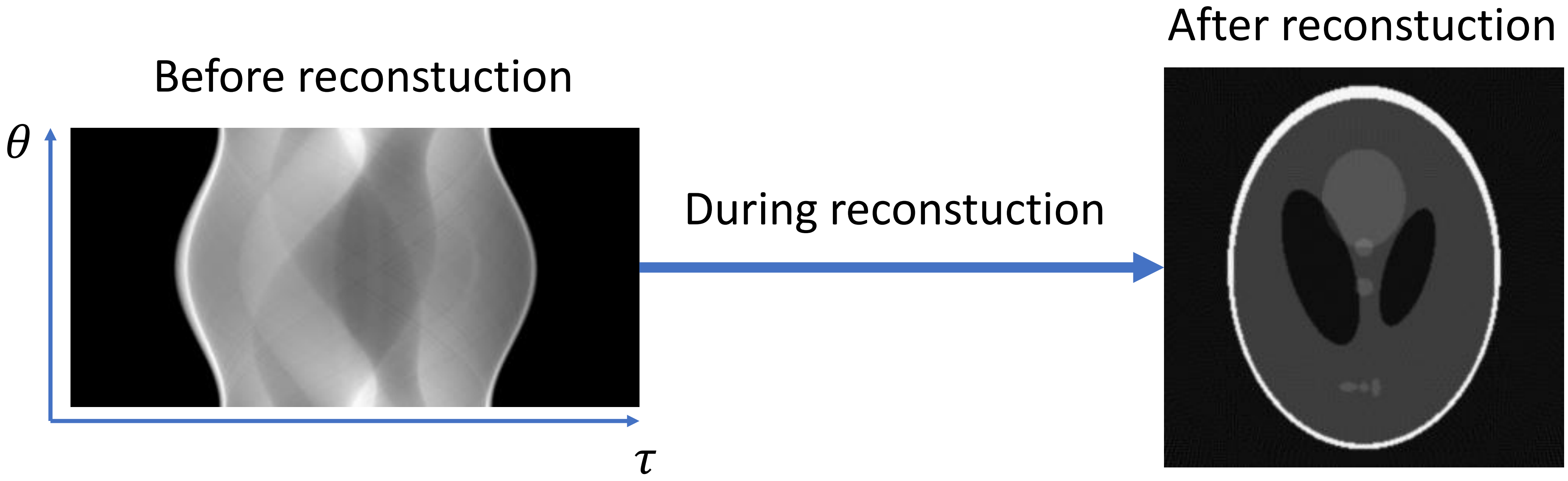


Al 1 mm

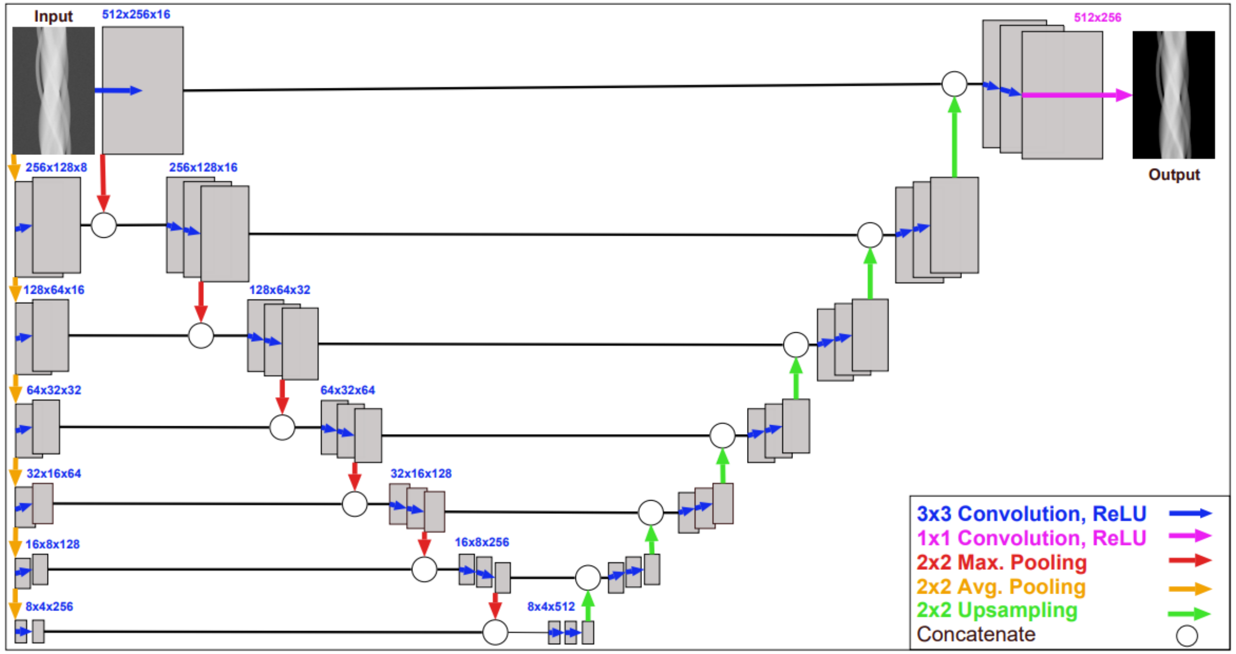


Neural networks and tomography

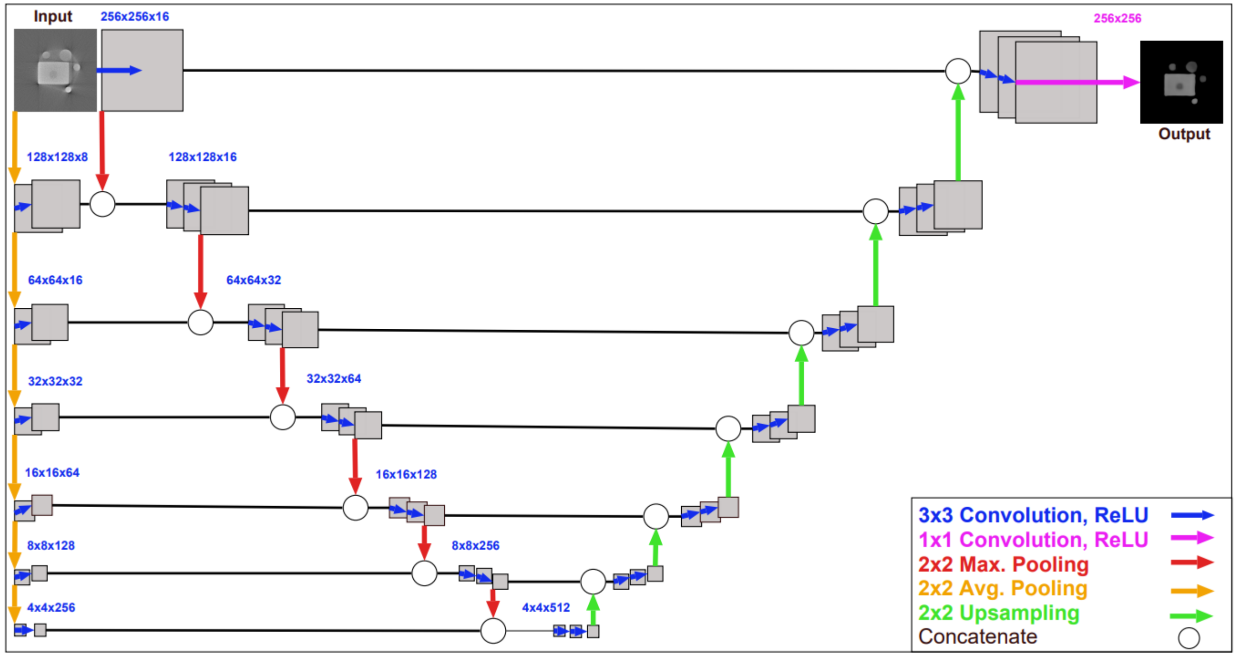
- We focused on methods using U-net.
- We studied the effect of the location of the U-net in the tomographic workflow.



Neural network structures I.



SinoNet
Input: projection data
Output: projection data



ReconNet
Input: reconstructed images
Output: reconstructed images

Neural network structures II.

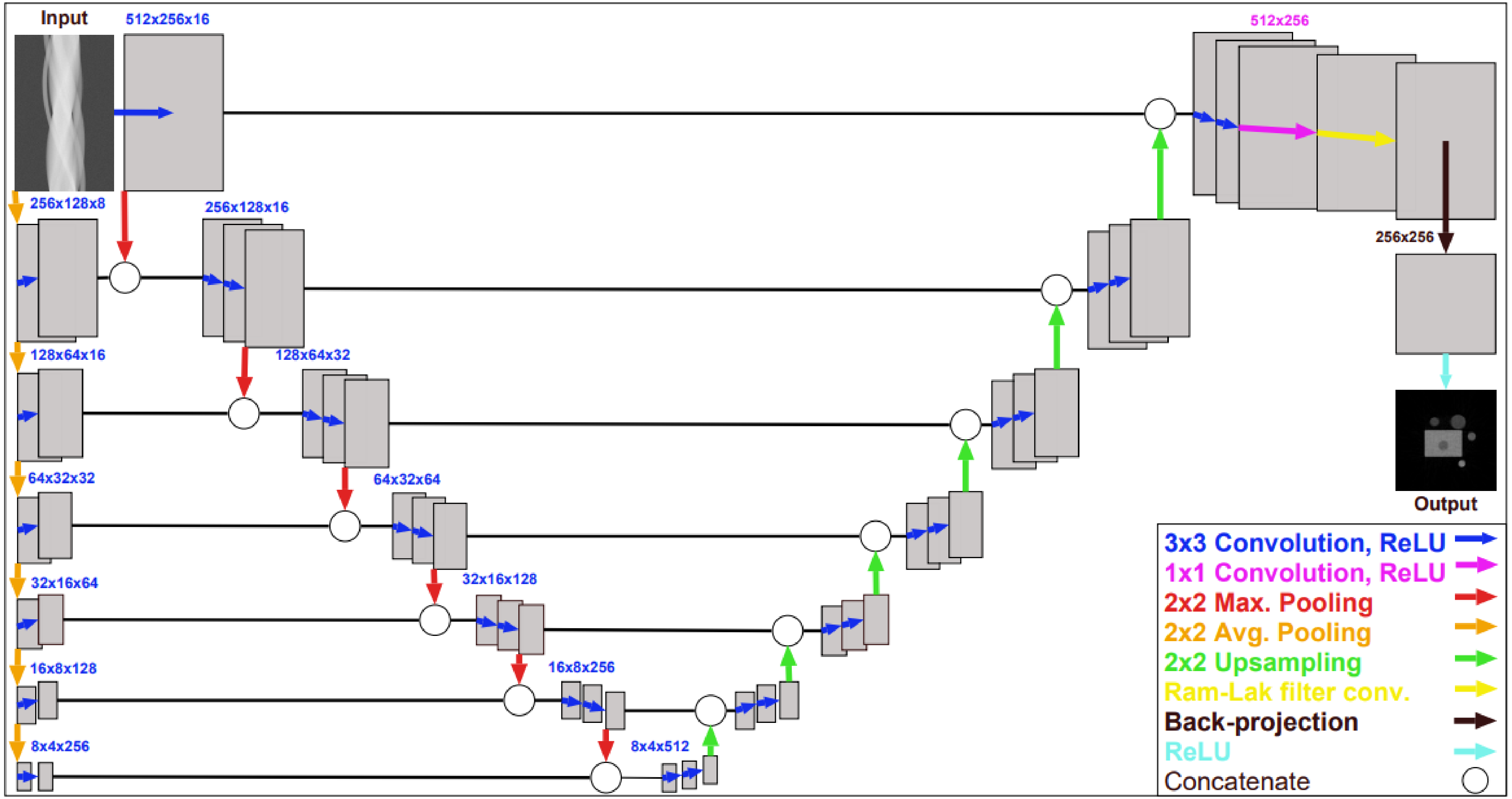
TomoNet1

Input: projection data

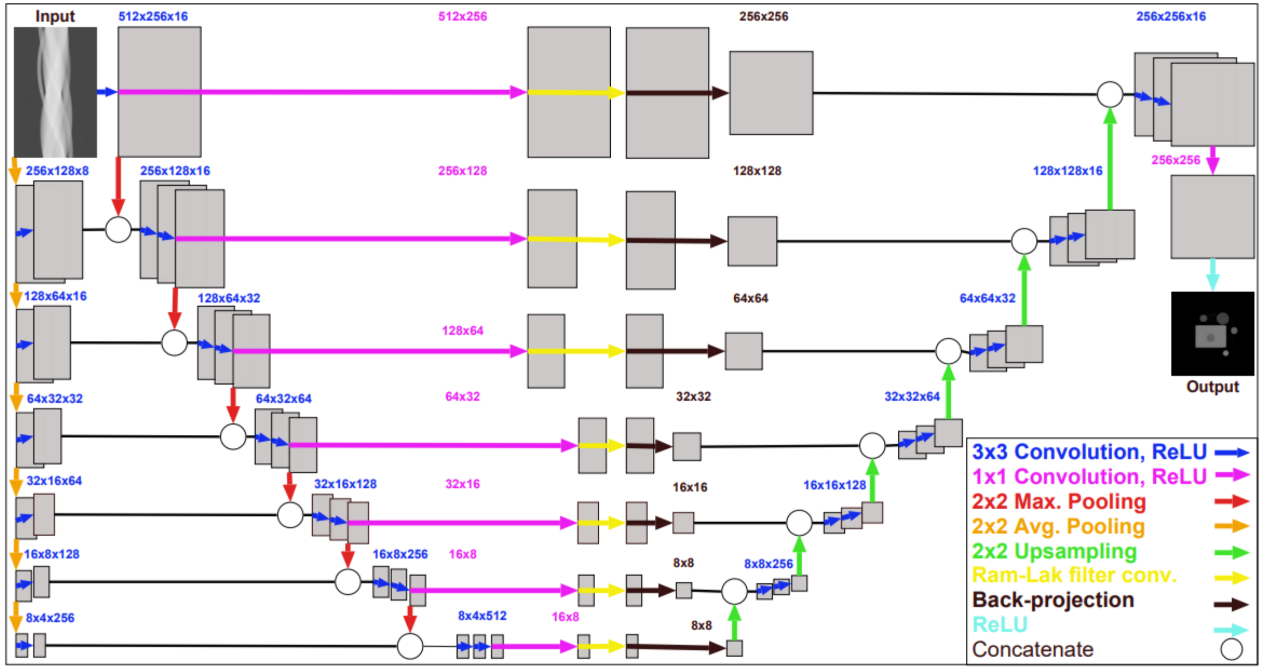
Output: reconstructed images

Additional elements:

- convolution with a Ram-Lak filter
- Back-projection
- ReLU activation layer



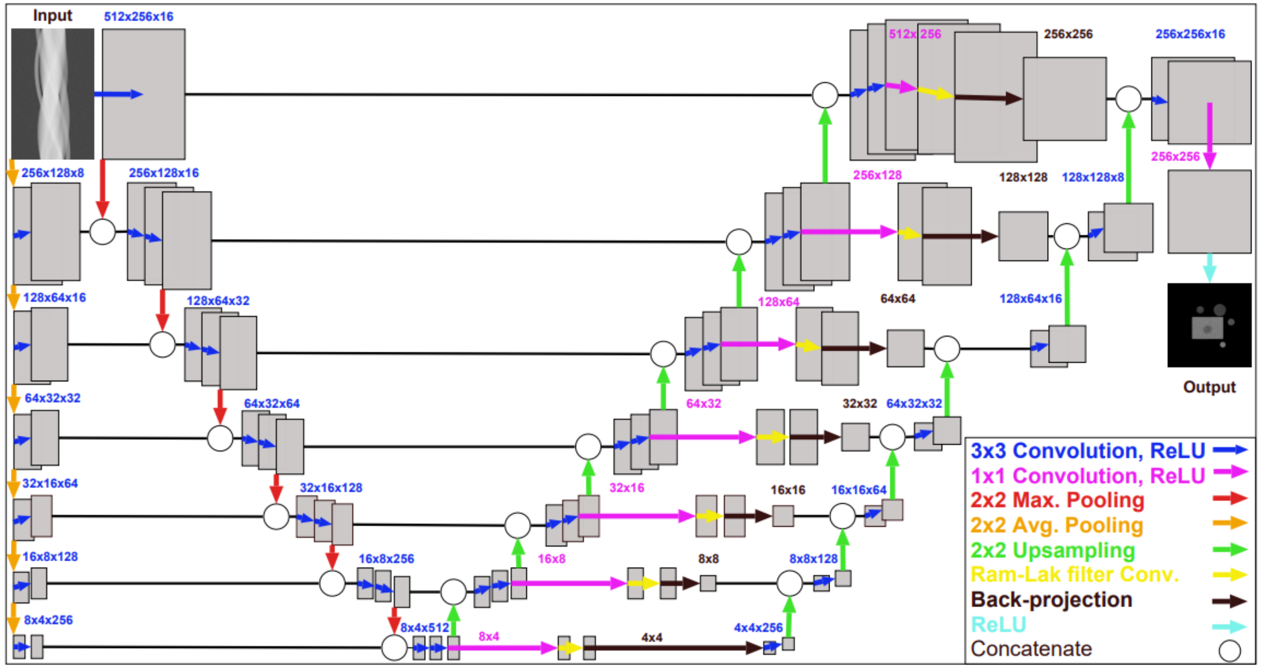
Neural network structures III.



TomoNet2

Input: projection data

Output: reconstructed images



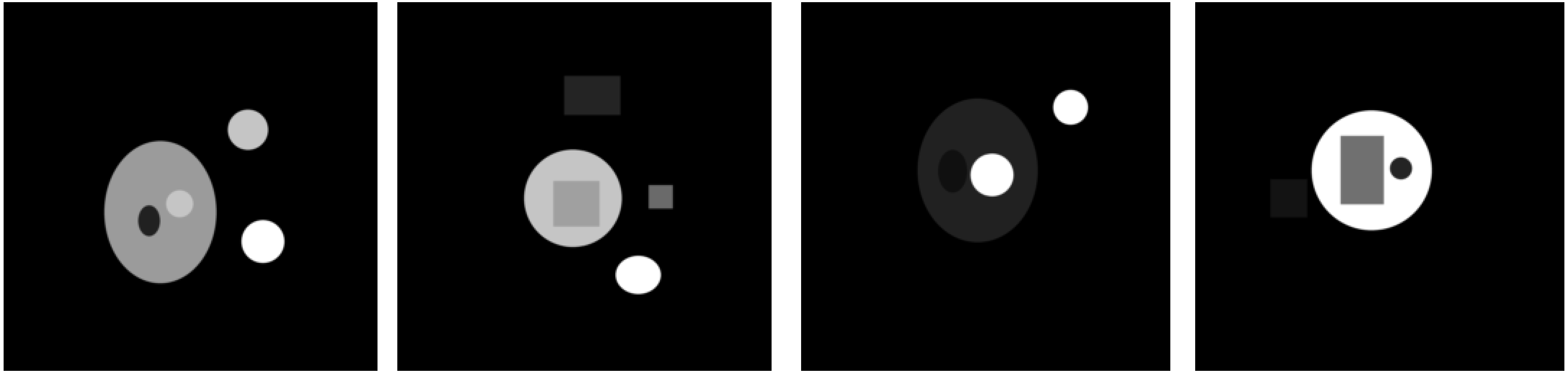
TomoNet3

Input: projection data

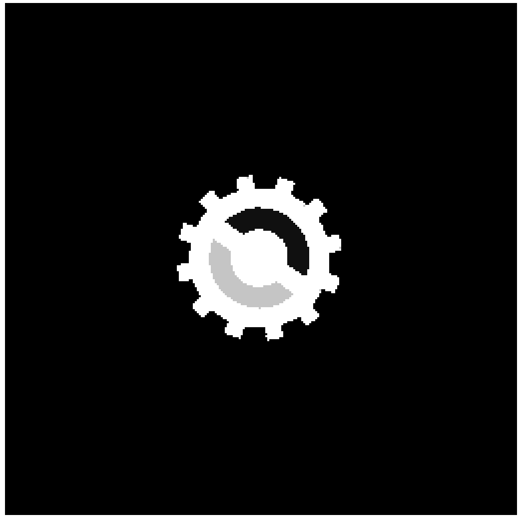
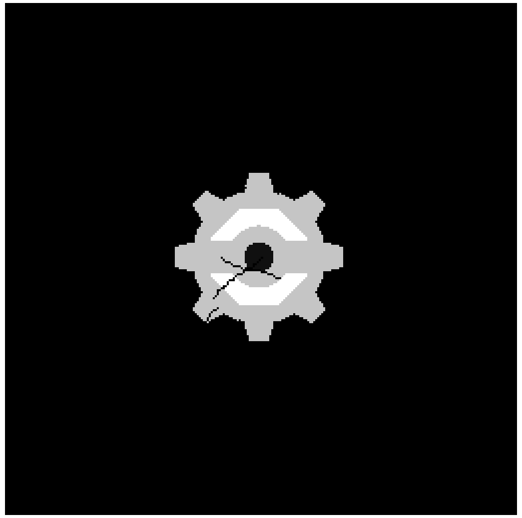
Output: reconstructed images

Dataset A

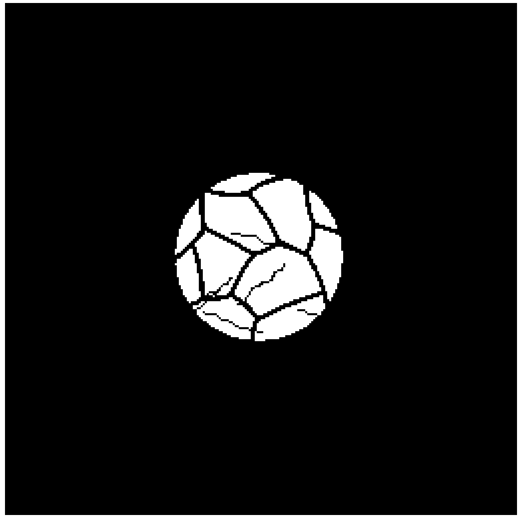
- Consists of 5000 artificial computer phantoms.
- Parallel beam GATE simulation.
- Random geometrical shapes (circles, ellipses, and rectangles)
- Splitted into 70 % training, 20 % validation and 10 % testing randomly.



Dataset B


- Only for testing.
- 11 different phantoms.
- In total 66 images in Dataset B, which can be partitioned into three groups with 22 phantom in each. (11 images with and without cracks)



- I. Group: Binary images
- II. Group: materials from the materials of the Dataset A.
- III. Group: every phantom contains one or two material, that was never seen by the networks during training or validation.

Training and evaluation

- Error measurements:
  - Peak-Signal-to-Noise-Ratio (*PSNR*),
  - Mean-Squared-Error (*MSE),*
  - Structural Similarity (*SSIM*).
- Best hyperparameters:

<table>
<tr><th>Parameters / Network type</th><th>Loss function</th><th>Optimizer</th><th>AMS Grad</th><th>Early Stopping</th><th>Activation function</th><th>Initial learning rate</th><th>Batch size</th></tr>
<tr><td>SinoNet</td><td rowspan="5">Mean Squared Error</td><td rowspan="5">Adam</td><td rowspan="5">True</td><td rowspan="5">True</td><td rowspan="5">ReLU</td><td rowspan="3">0.0001</td><td>43</td></tr>
<tr><td>ReconNet</td><td>7</td></tr>
<tr><td>TomoNet1</td><td rowspan="3">43</td></tr>
<tr><td>TomoNet2</td><td>0.001</td></tr>
<tr><td>TomoNet3</td><td>0.0001</td></tr>
</table>

Results: error measurements averages

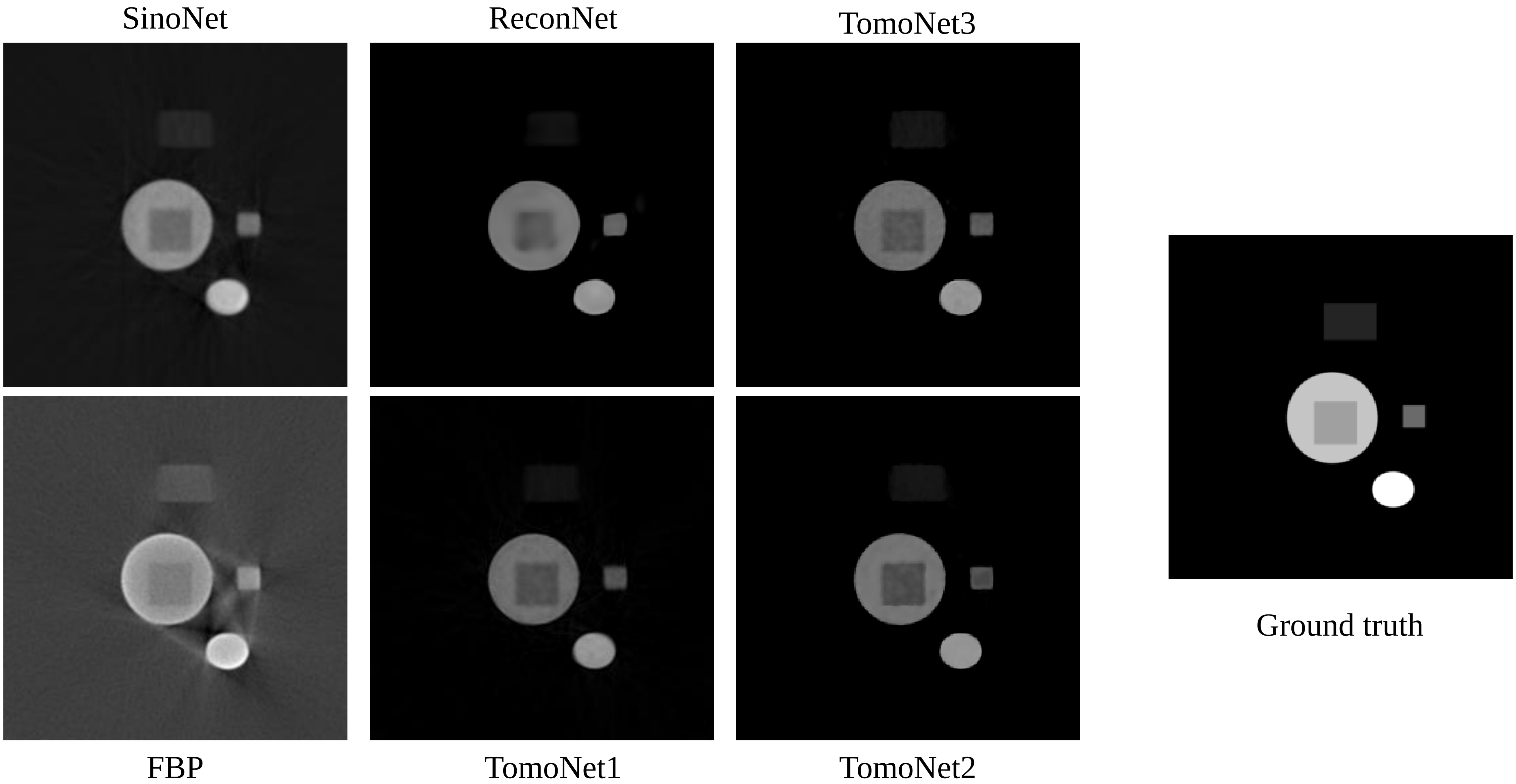
- The average values of the test phantoms of the datasets.

Network type / Error type	FBP	SinoNet	ReconNet	TomoNet1	TomoNet2	TomoNet3	Network type / Dataset
PSNR	27.5021	31.9951	33.0133	33.9611	**38.1958**	36.4728	**A**
SSIM	0.9372	0.9865	0.9935	0.9897	**0.9977**	0.9972	
MSE	0.0032	0.0010	0.0009	0.0007	**0.0003**	0.0005	
PSNR	25.5087	25.0291	14.4519	26.4300	**27.7960**	27.0588	**B**
SSIM	0.9519	0.9771	0.9581	0.9808	**0.9886**	0.9875	
MSE	0.0034	0.0037	0.7063	0.0027	**0.0018**	0.0023	

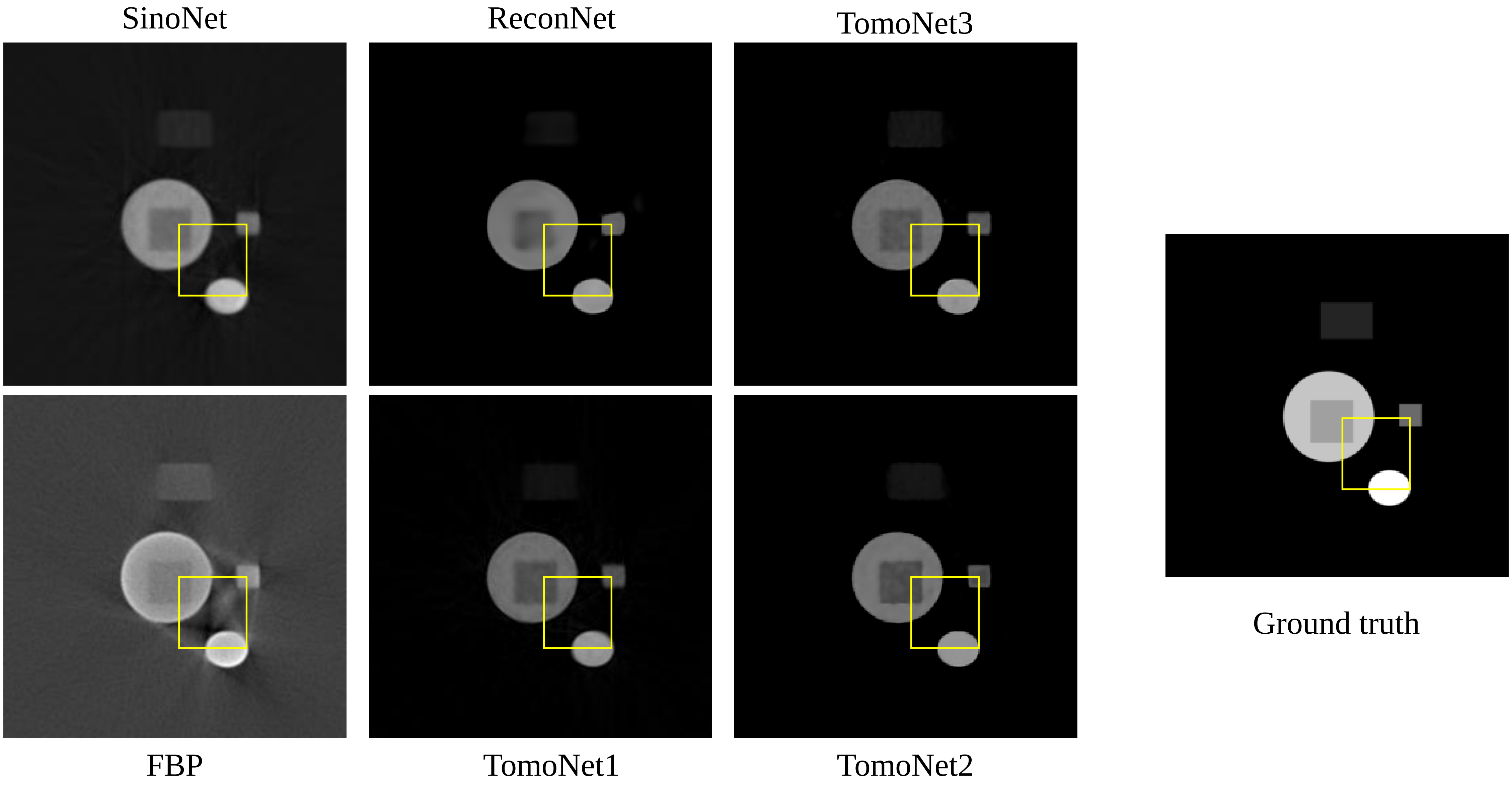
Results: error mesaurements Dataset B detailed

Network type / Error type	FBP	SinoNet	ReconNet	TomoNet1	TomoNet2	TomoNet3	Network type / Group
PSNR	22.9847	23.4377	7.6204	25.2104	**26.8979**	26.0787	**I.**
SSIM	0.9373	0.9728	0.9517	0.9756	0.9875	**0.9878**	
MSE	0.0051	0.0048	1.9855	0.0033	**0.0022**	0.0027	
PSNR	25.0866	25.3617	14.6258	26.9704	27.6045	**27.8985**	**II.**
SSIM	0.9476	0.9796	0.9584	0.9823	**0.9901**	0.9896	
MSE	0.0033	0.0031	0.1230	0.0021	**0.0018**	**0.0018**	
PSNR	28.4547	26.2879	21.1095	27.1091	**28.8856**	27.1993	**III.**
SSIM	0.9706	0.9789	0.9642	0.9845	**0.9881**	0.9850	
MSE	0.0017	0.0031	0.0105	0.0027	**0.0015**	0.0025	

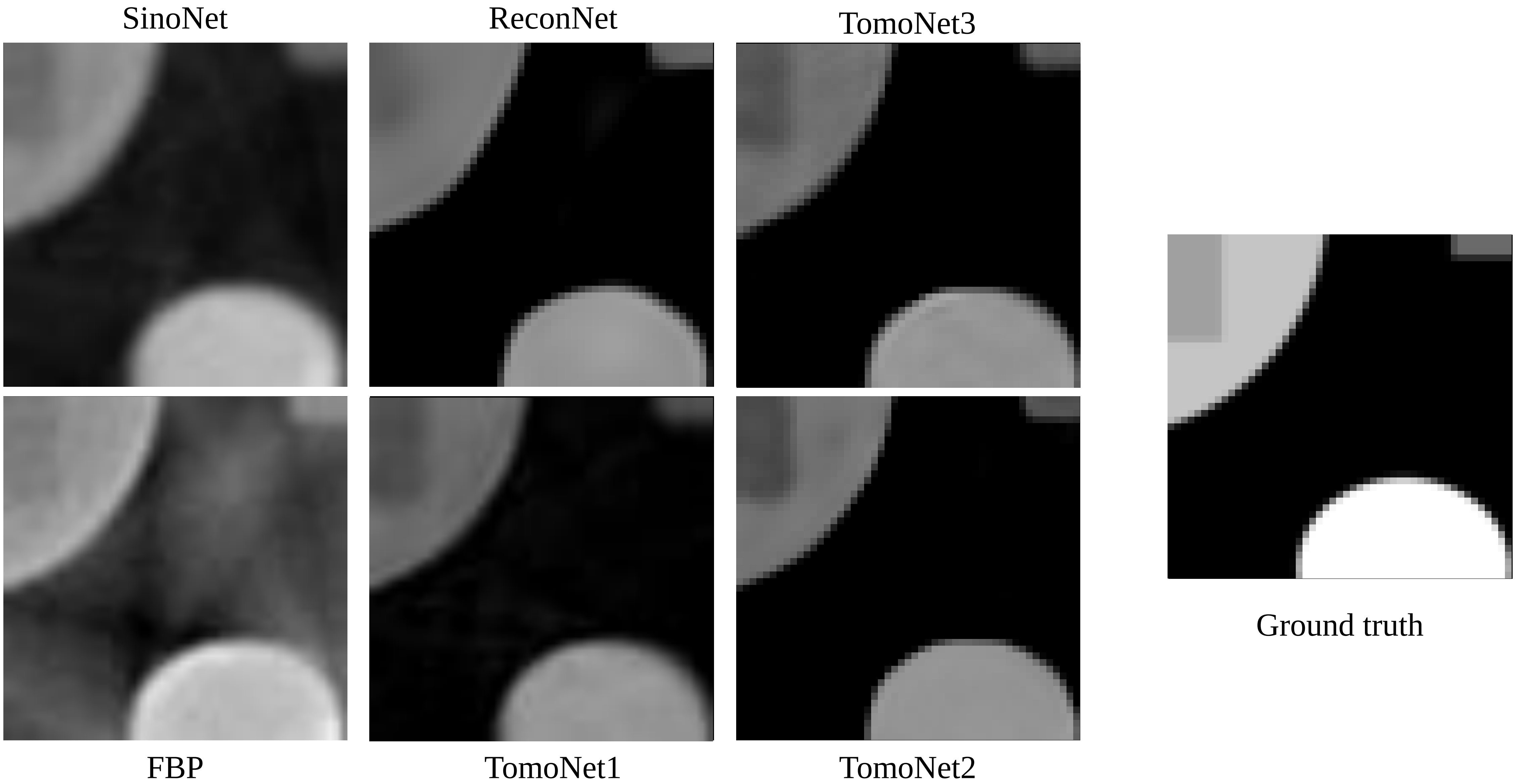
Results: Dataset A images



Results: Dataset A images



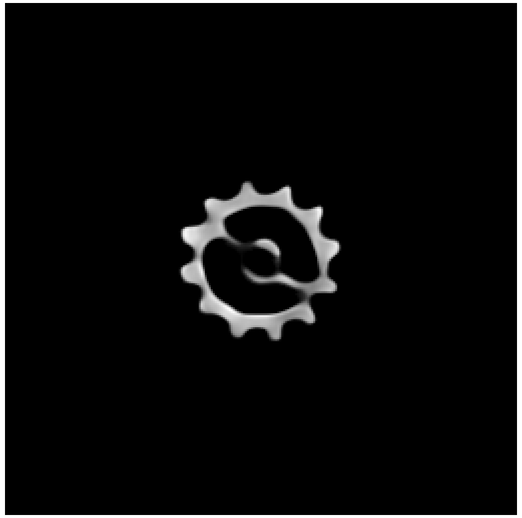
Results: Dataset A images



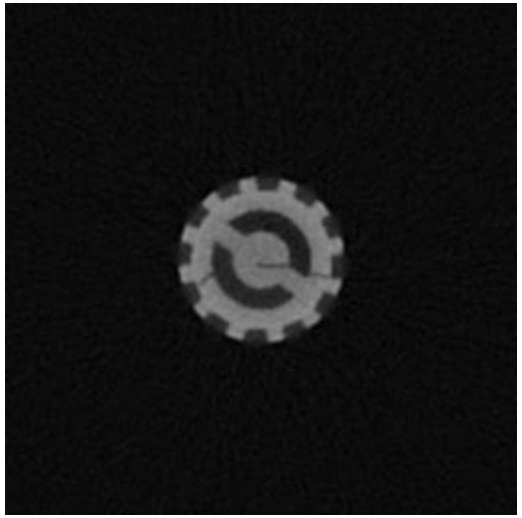
Results: Dataset B images

SinoNet

ReconNet



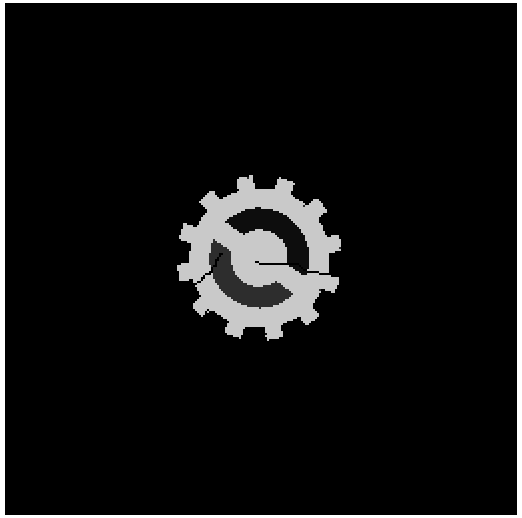
TomoNet3



FBP

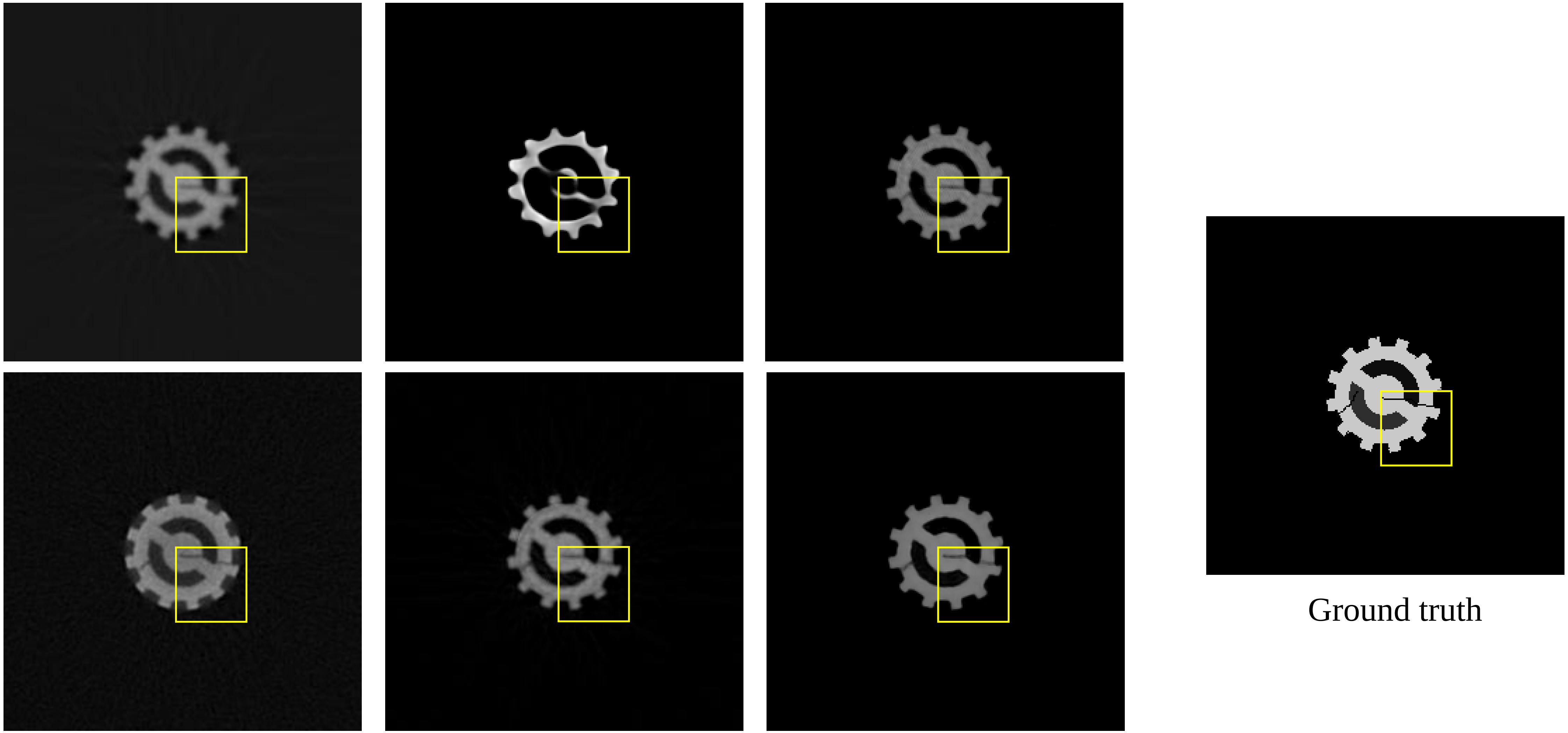
TomoNet1

TomoNet2



Ground truth

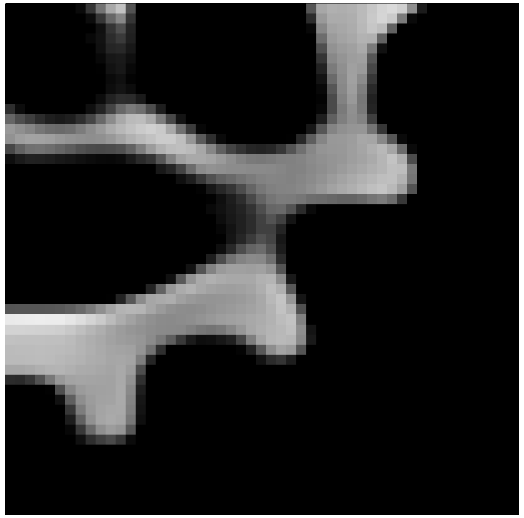
Results: Dataset B images



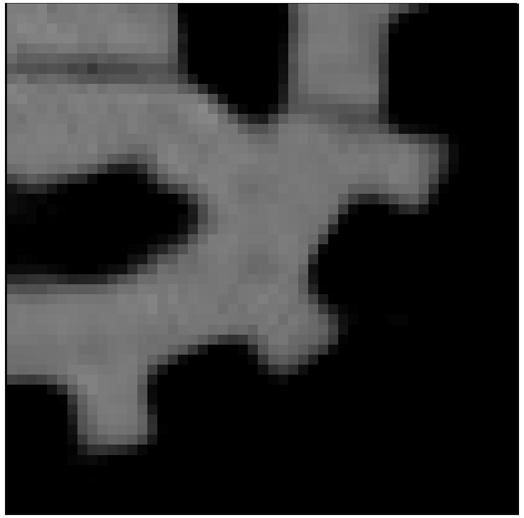
Results: Dataset B images

SinoNet

ReconNet

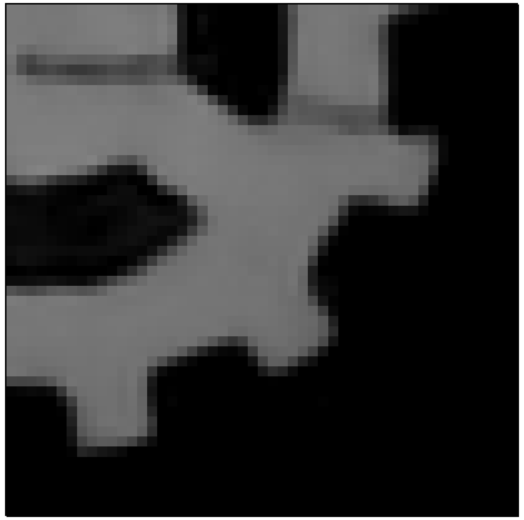


TomoNet3



FBP

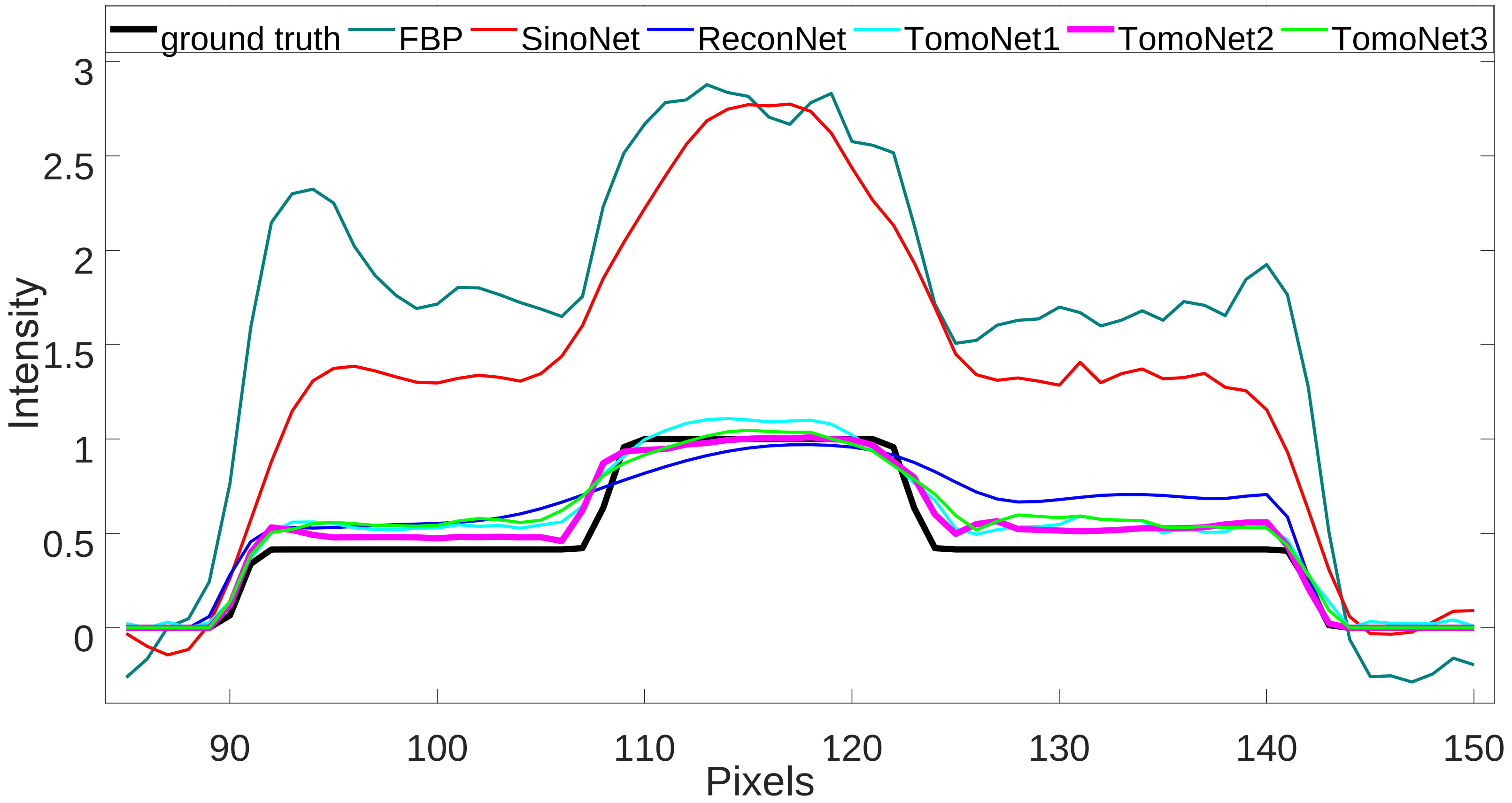
TomoNet1

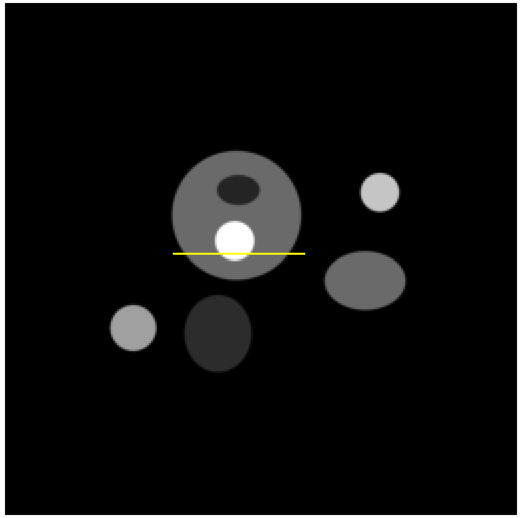


TomoNet2

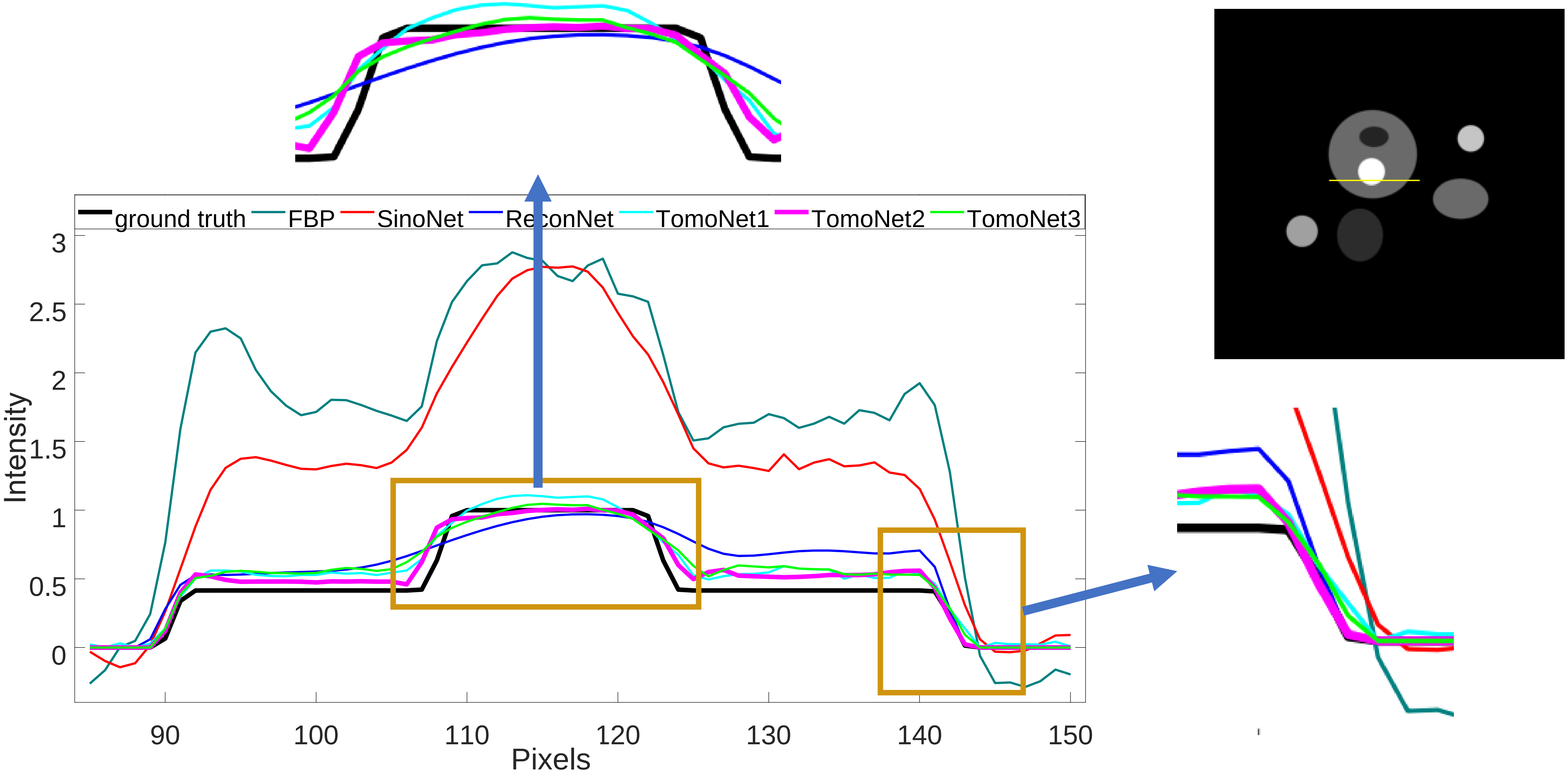
Ground truth

Results: Dataset A intensity profiles

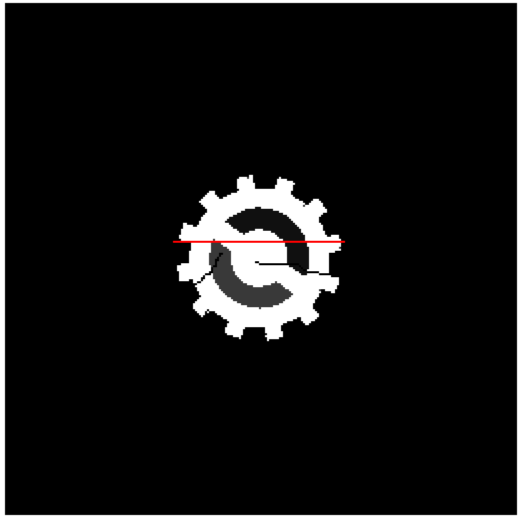


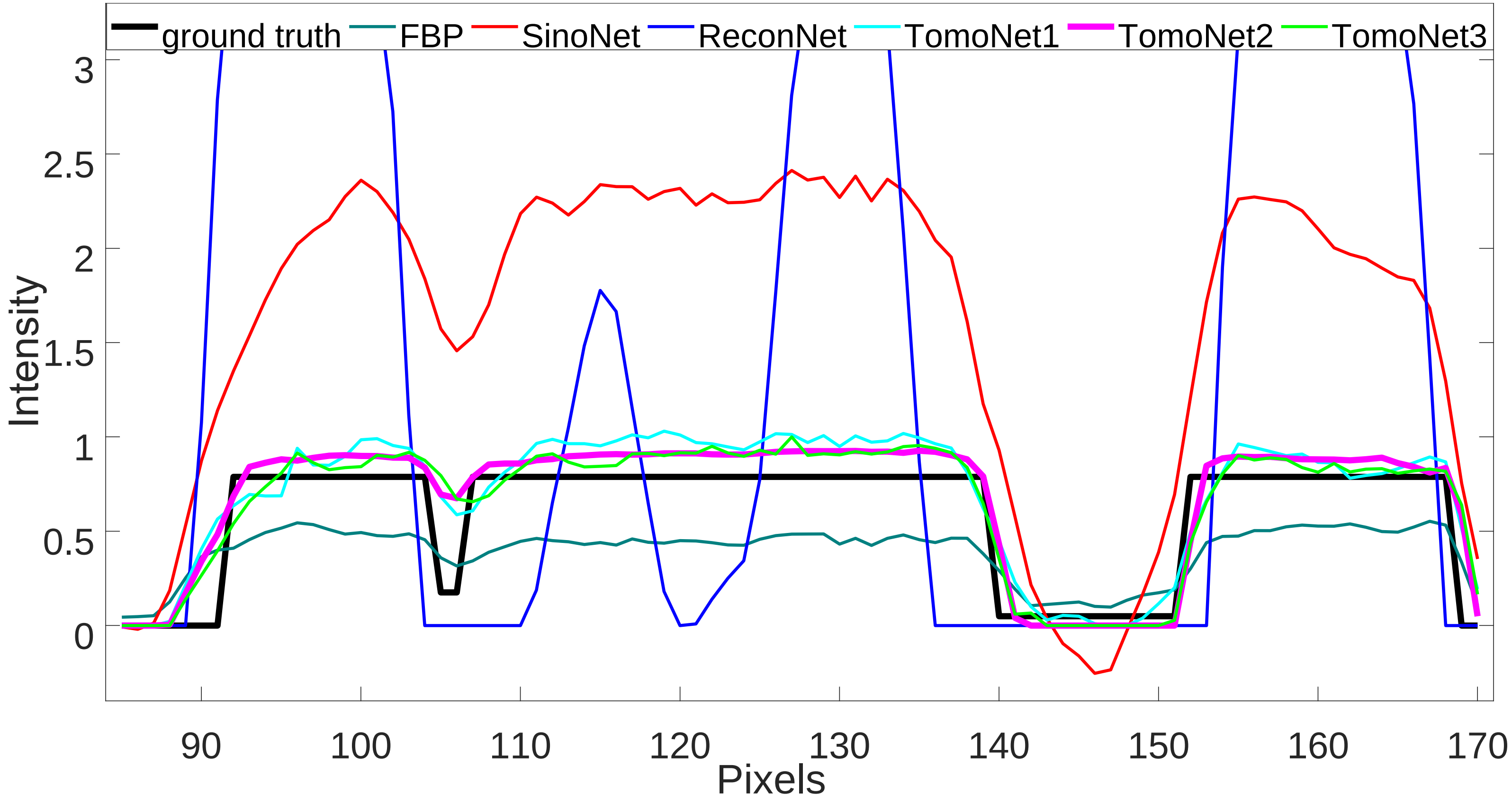


Results: Dataset A intensity profiles

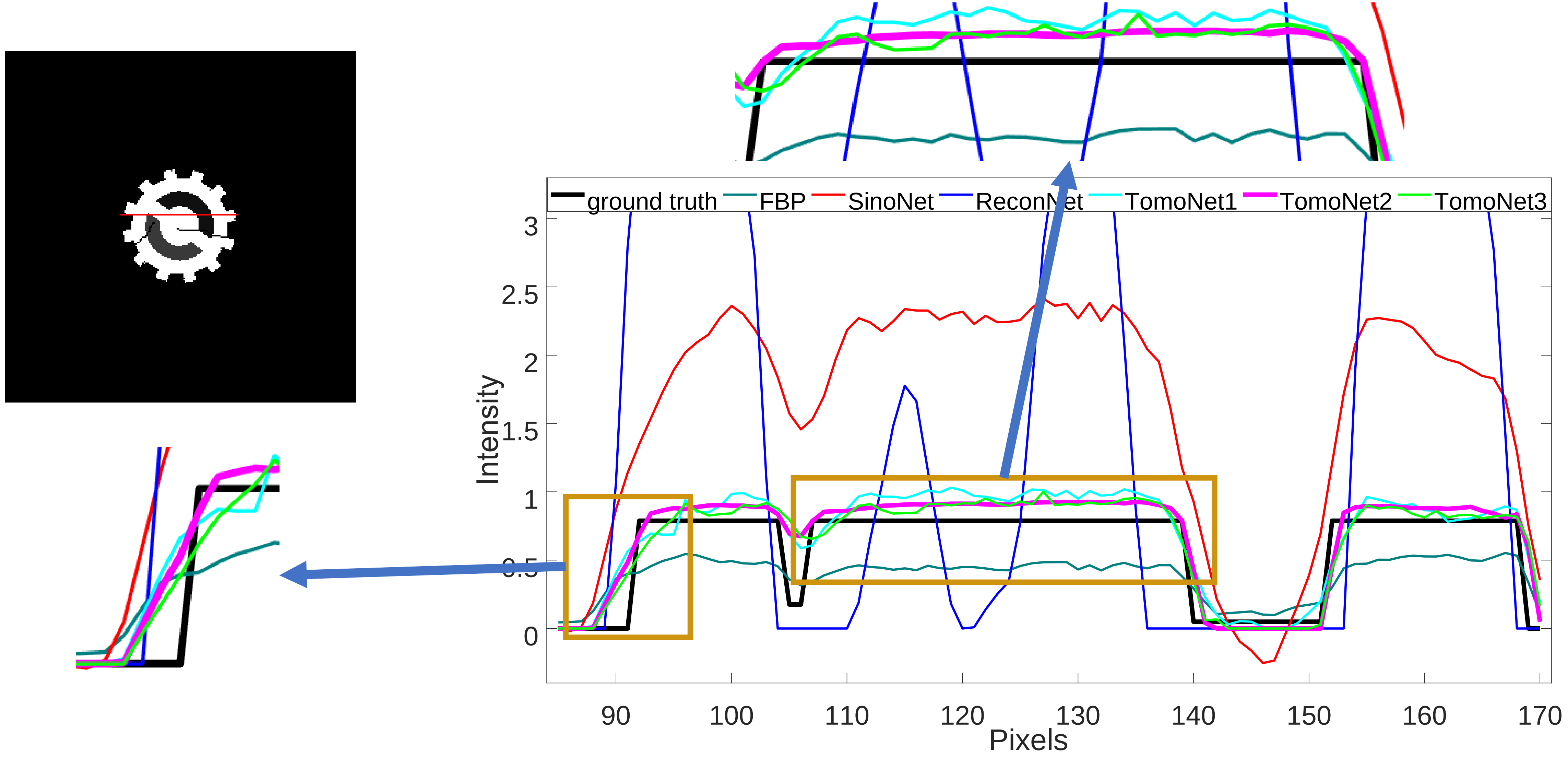


Results: Dataset B intensity profiles



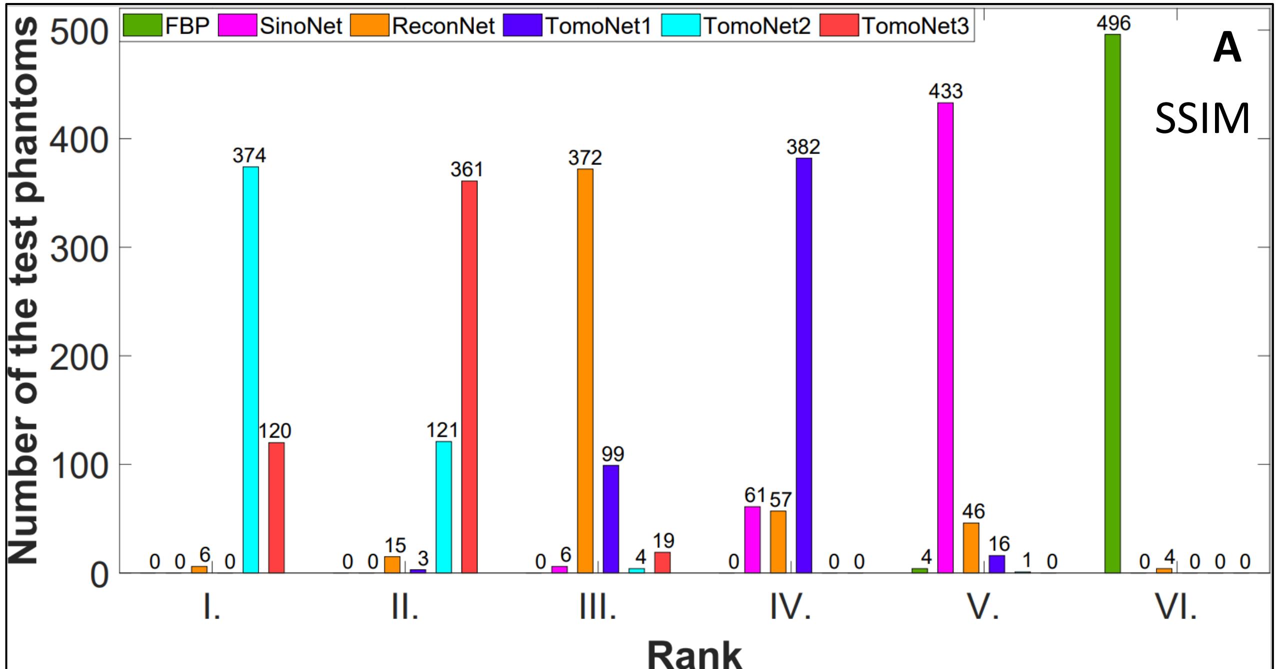


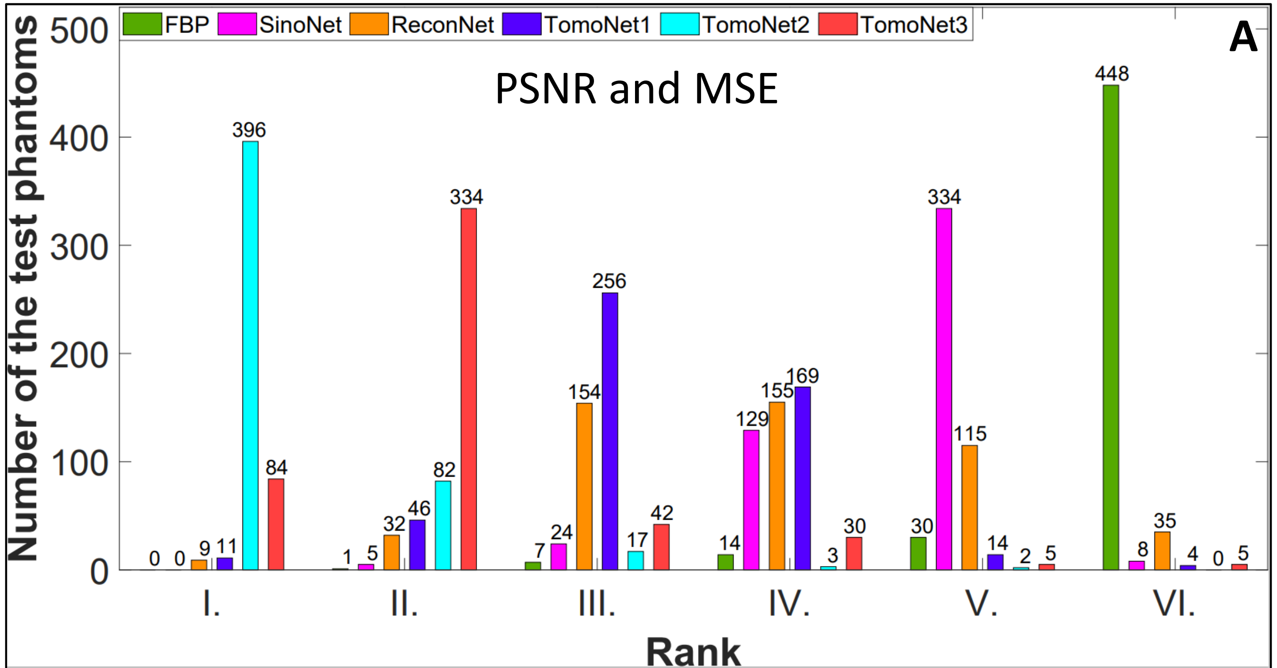
Results: Dataset B intensity profiles



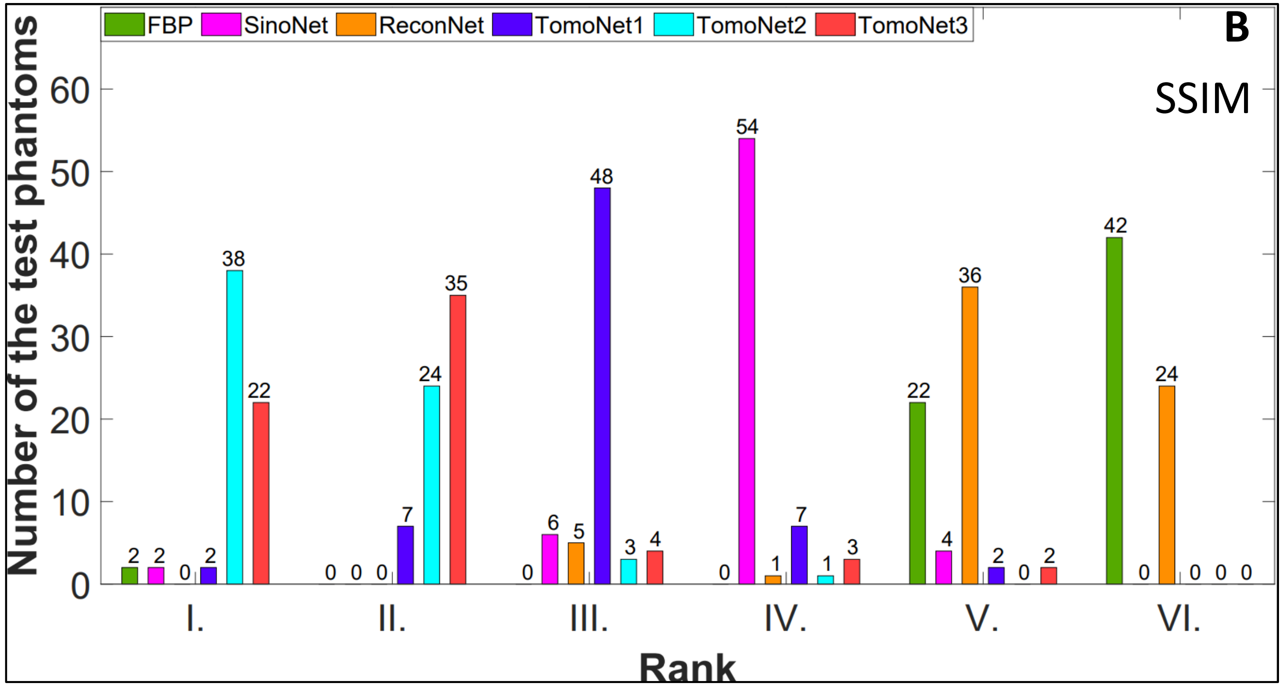
Results: ranking I.

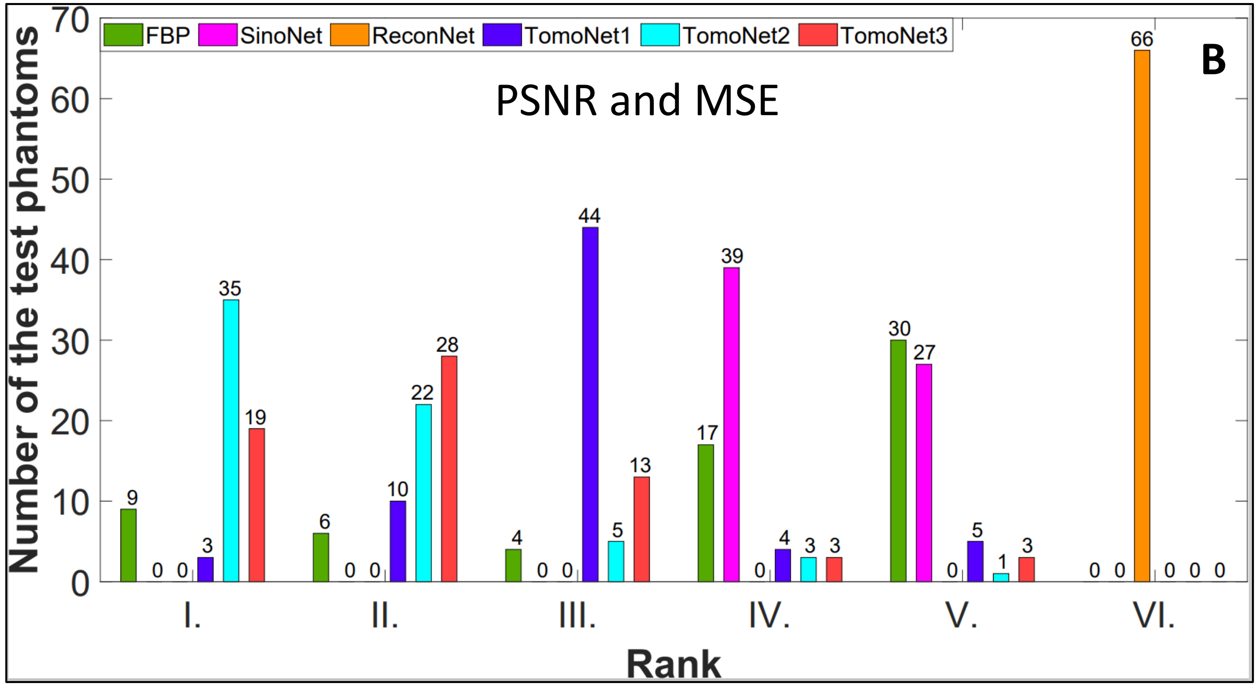
- For the better insight we checked the perfomance of every method for every phantom of the testing phase individually.
- We summed up, how many 1st, 2nd, 3rd, 4th, 5th and 6th best result were achieved by the methods.





Results: ranking II.





Results: ranking III.

- A so-called total score was calculated by the formula $\mathrm{Total\ Score} = \sum_{\mathrm{rank}=1}^{5} N_i\ rank$, where $\mathrm{rank}\ \in [1, 2, 3, 4, 5, 6]$ is the number corresponds to the rank and $\mathrm{N_i}$ is the number of the test cases at the given method and rank.

Final score	Error type	FBP	SinoNet	ReconNet	TomoNet1	TomoNet2	TomoNet3
Dataset A	PSNR and MSE	2917	2316	1940	1641	**633**	1053
	SSIM	2996	2427	1634	1911	**633**	899
Dataset B	PSNR and MSE	251	291	396	196	**111**	141
	SSIM	364	256	343	198	**99**	126

Conclusions

- Our experimental results showed that the reconstruction step used as an inner part of the U-nets improves the quality of the reconstructions.
- The phantoms of our database showed strong signs of beam hardening and a high level of electrical noise, but we were able to reduce the distorsions with U-net based methods, from which we would highlight our method called TomoNet2.
- We observed, that the usage of the back-projection at every level of the U-net as skip connections was benefical according to the results of TomoNet2.
- TomoNet2 were able to learn general enough to gain good results on the unseen phantoms of Dataset B.
- TomoNet2 proved to be a reliable method as all of our analysis showed the dominance of TomoNet2.

Future Work

- Real data.
- Implementing fan-beam or cone-beam projection geometry.
- Replacing the non-trainable Ram-Lak filter with a trainable one.
- Improving the structures of the networks.
- More testing with hyperparameters, especially try out more loss function during training.

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