

Computed Tomography 2.0

Photon-Counting and Artificial Intelligence

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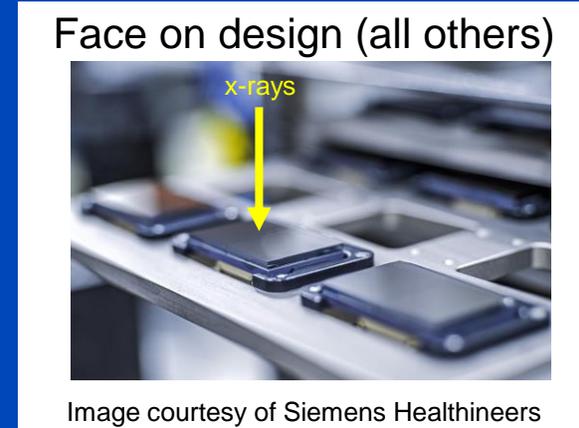
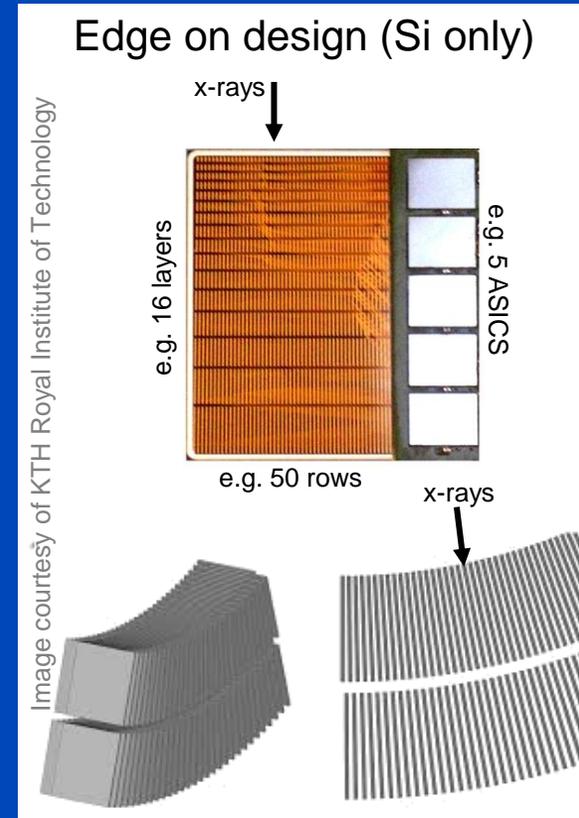


DEUTSCHES
KREBSFORSCHUNGSZENTRUM
IN DER HELMHOLTZ-GEMEINSCHAFT

PHOTON-COUNTING CT

Availability of Diagnostic Photon-Counting CT

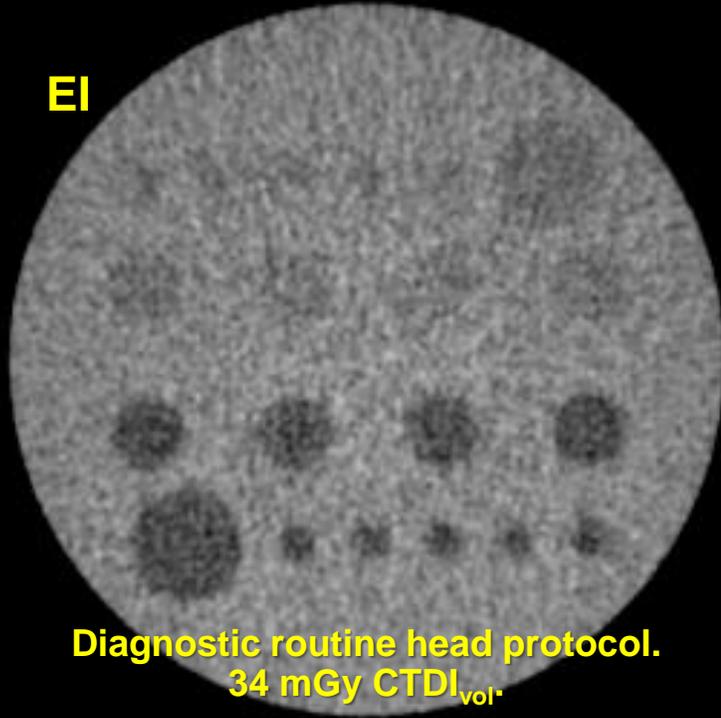
	Sensor material	Detector pixel size at iso	Pixel binning	FOM	Bins	FDA	Pubs	Installations
Canon	CdZnTe	210 μm	3x3, 1x1	50 cm	5	no	1	1 prototype (Japan)
GE	Si, edge on	400 x 400 μm	?	?	?	no		1 experimental (Sweden), 2 prototypes (USA)
Philips	CdZnTe	274 x 274 μm	?	50 cm	5	no	≈ 22	1 experimental setup (France)
Samsung Omnitom Elite	CdTe	703 x 707 μm / 351 x 423 μm / 117 x 141 μm	5x6, 3x3, 1x1	30 cm	3	yes	1	?
Siemens CounT	GOS/CdTe dual source	700 x 600 μm / 250 x 250 μm	2x2, 1x1	50 / 28 cm	4	no	≈ 50	3 experimental systems (Germany, USA)
Siemens CountPlus	CdTe	150 x 176 μm	2x2, 1x1	50 cm	4	no	≈ 11	3 prototypes (Czech, Sweden, USA)
Siemens Alpha	CdTe/CdTe dual source	2 · 150 x 176 μm	2x2, 1x1	50 / 36 cm	4	yes	≈ 40	about 100 worldwide



The additional factor 2 in the detector pixel size column indicates that some scan modes may use binning.

Diagnostic CT (Conventional Detector) of a Low Contrast Phantom

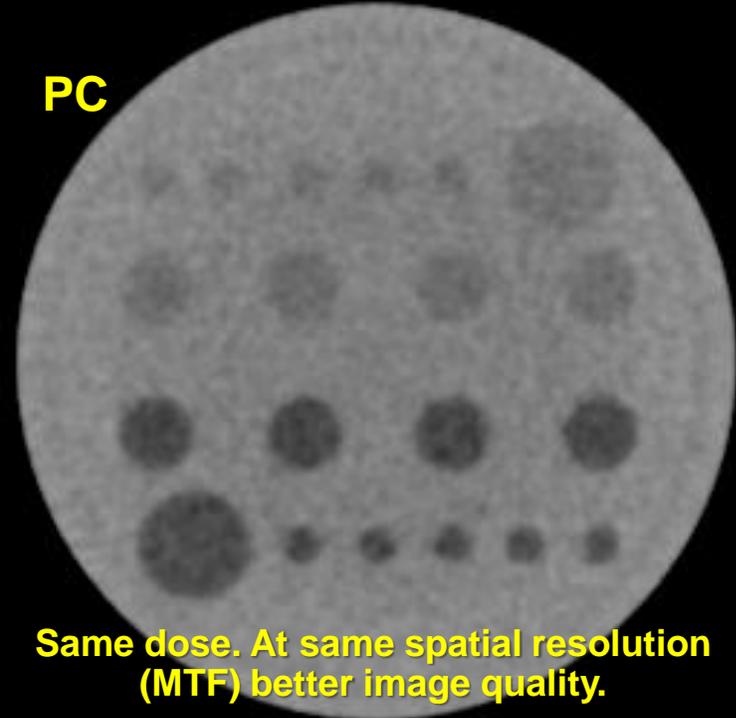
EI



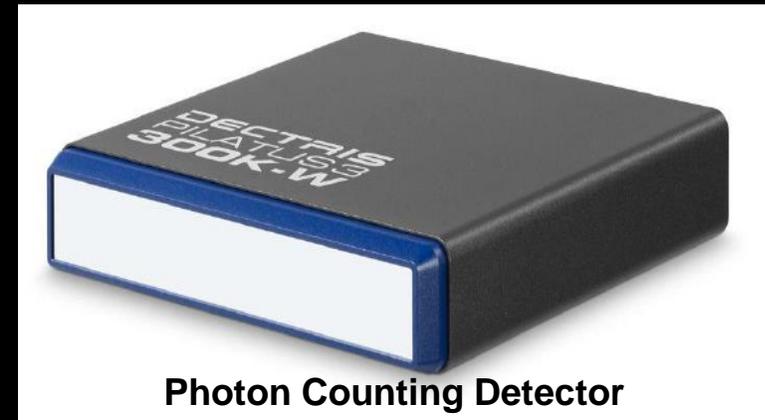
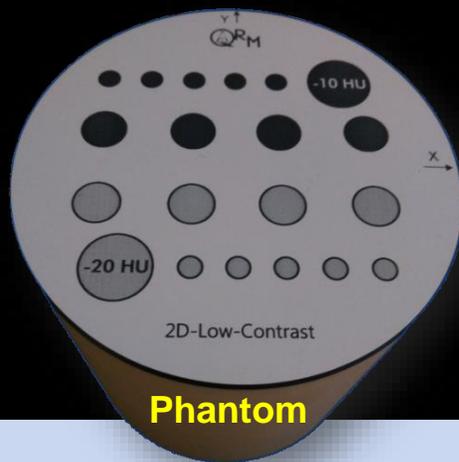
Diagnostic routine head protocol.
34 mGy $CTDI_{vol}$

Photon Counting Detector CT of a Low Contrast Phantom

PC



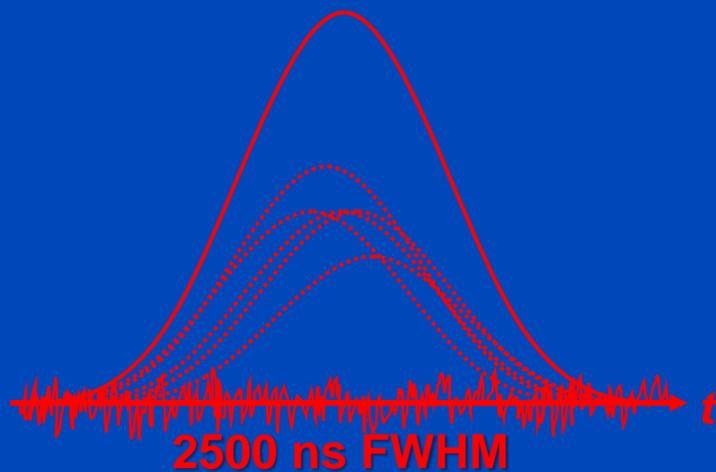
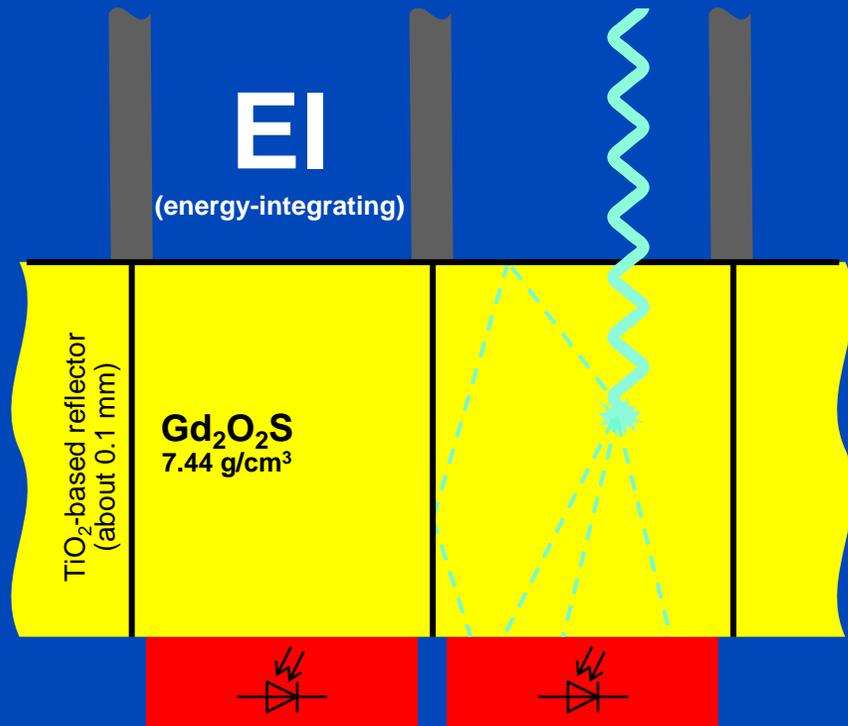
Same dose. At same spatial resolution (MTF) better image quality.



Photon Counting Detector

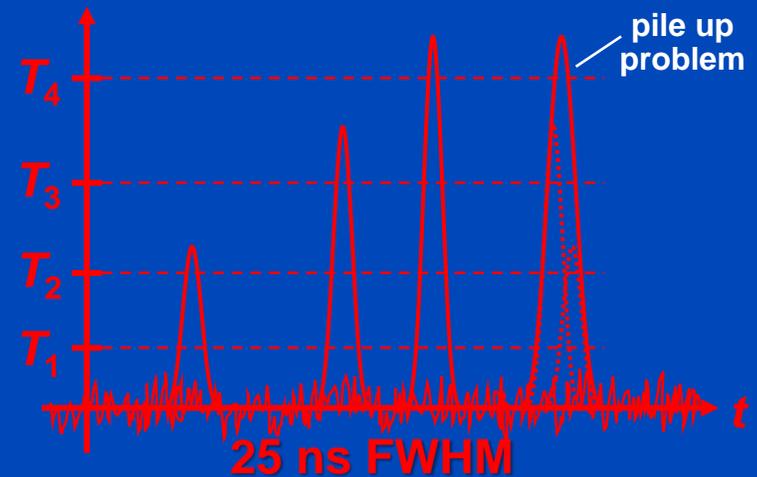
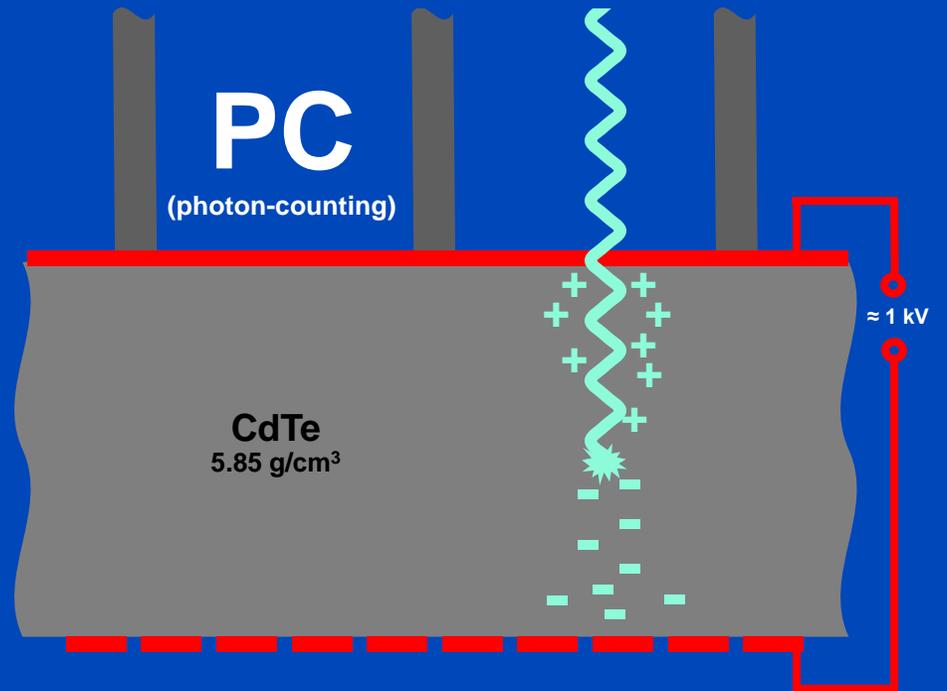
C = 0 HU, W = 80 HU

Indirect Conversion



i.e. max $O(40 \cdot 10^3)$ cps

Direct Conversion

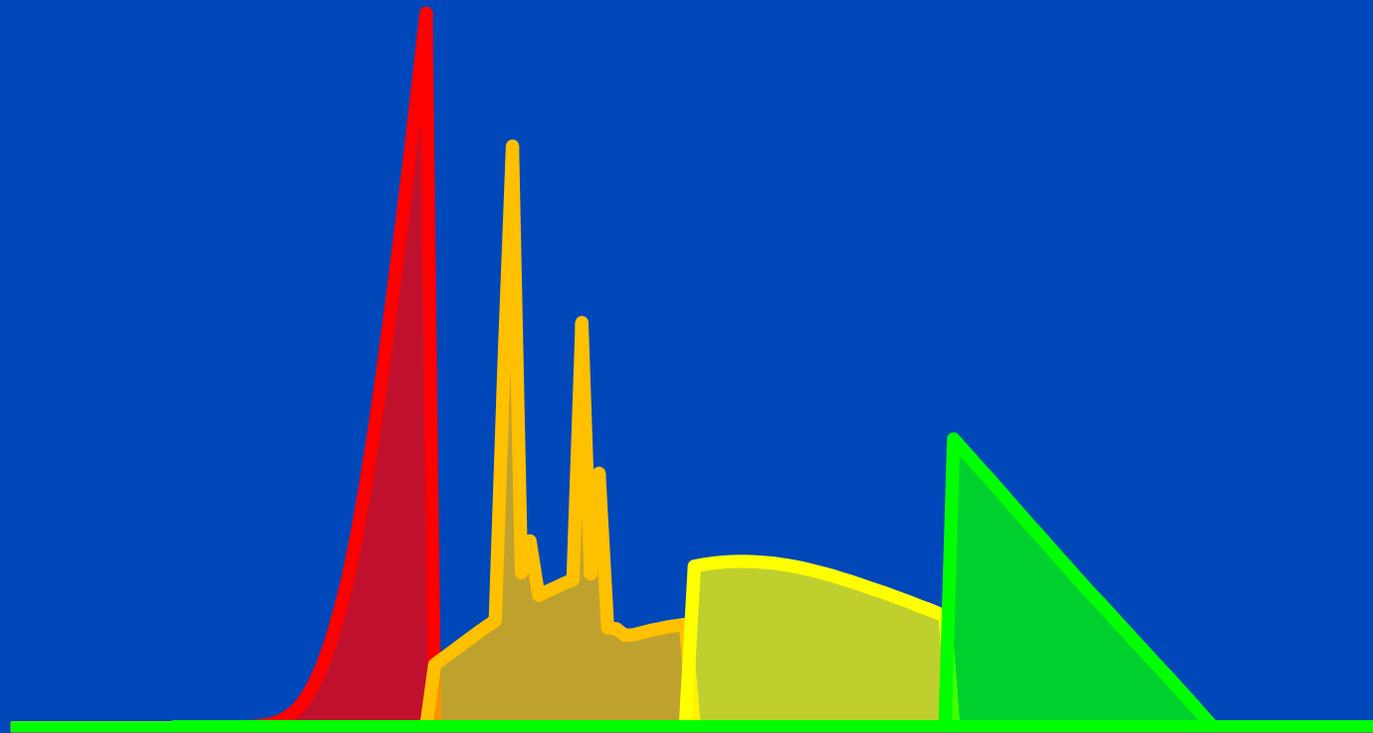


i.e. max $O(40 \cdot 10^6)$ cps

Requirements for CT: up to 10^9 x-ray photon counts per second per mm².
Hence, photon counting only achievable for direct converters.

Energy-Selective Detectors: Improved Spectroscopy, Reduced Dose?

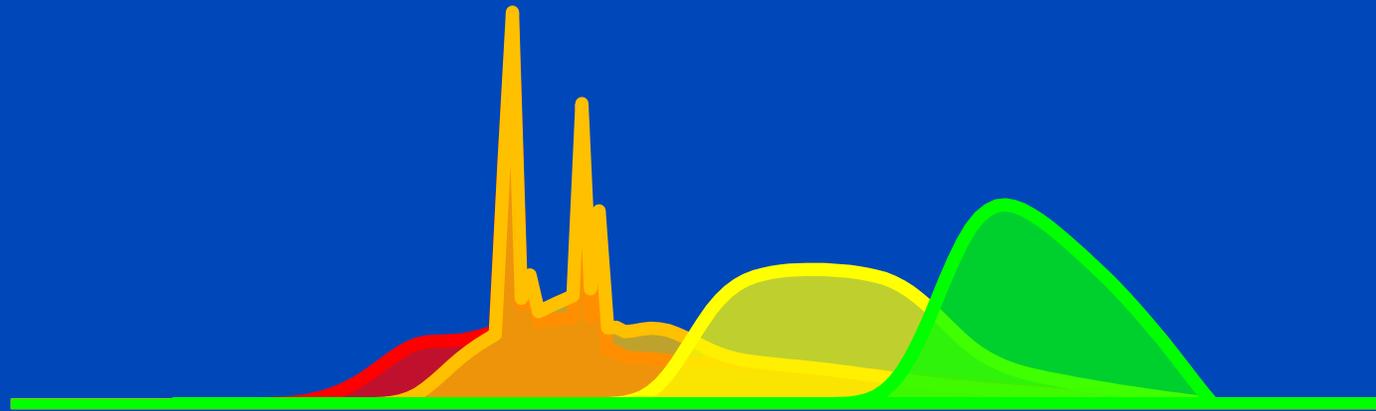
Ideally, bin spectra do not overlap, ...



Spectra as seen with 4 bins after having passed a 32 cm water layer.

Energy-Selective Detectors: Improved Spectroscopy, Reduced Dose?

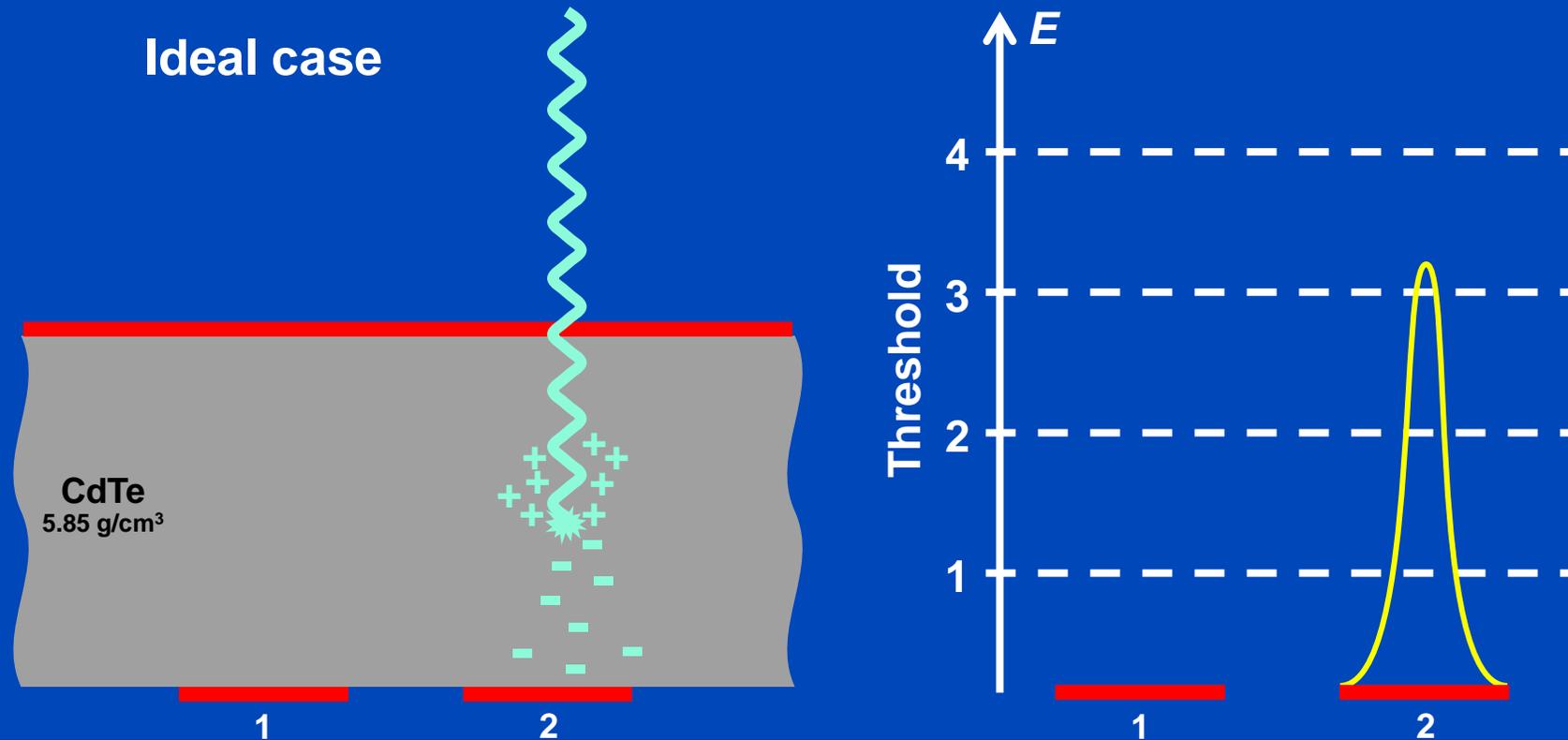
... realistically, however, they do!



Spectra as seen with 4 bins after having passed a 32 cm water layer.

Photon Events

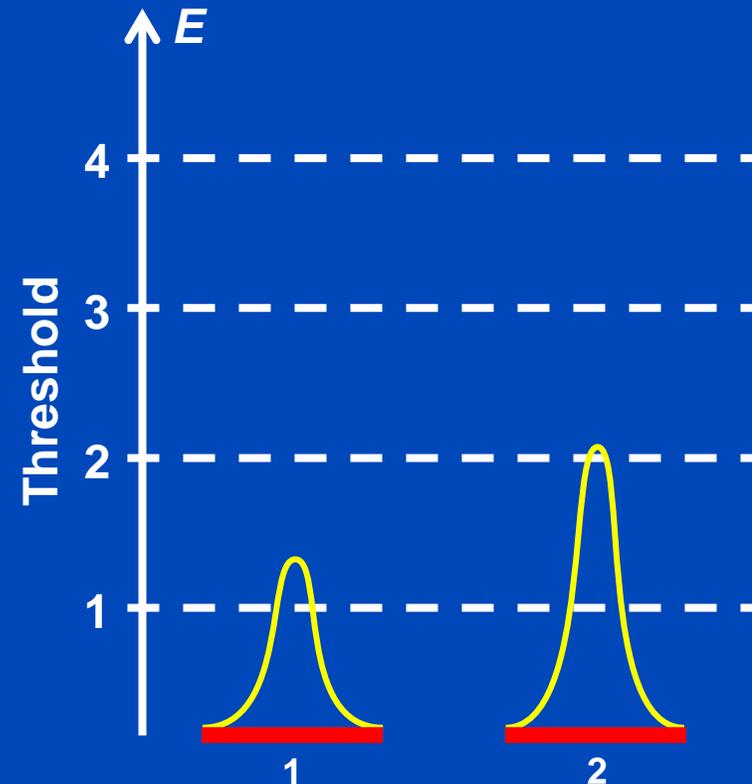
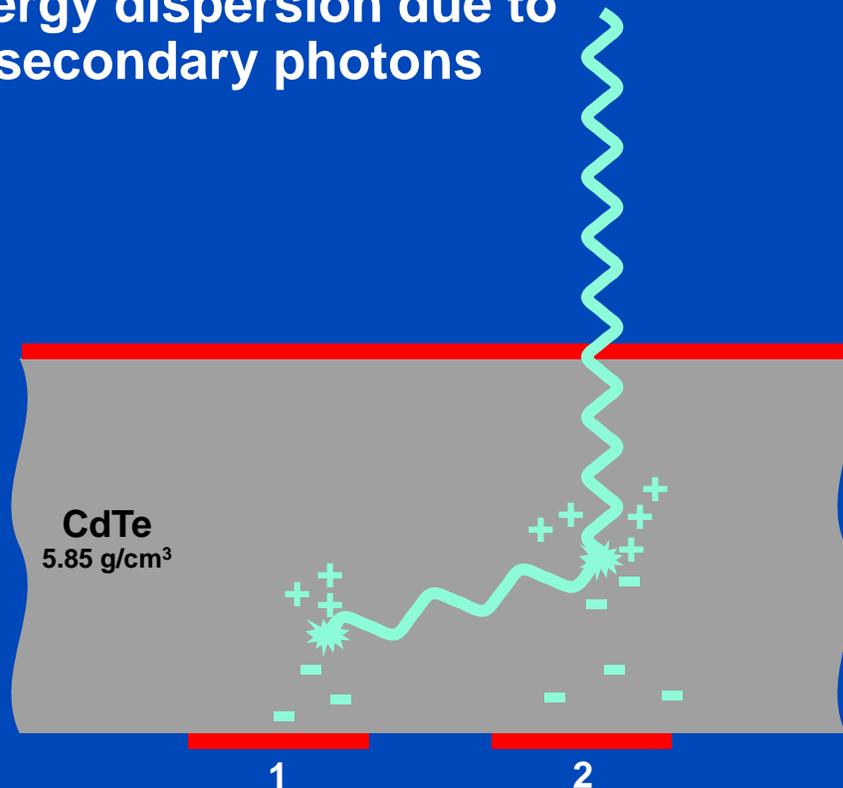
- Detection process in the sensor
- Photoelectric effect (e.g. 80 keV)



Photon Events

- Detection process in the sensor
- Compton scattering or K-fluorescence (e.g. 80 keV)

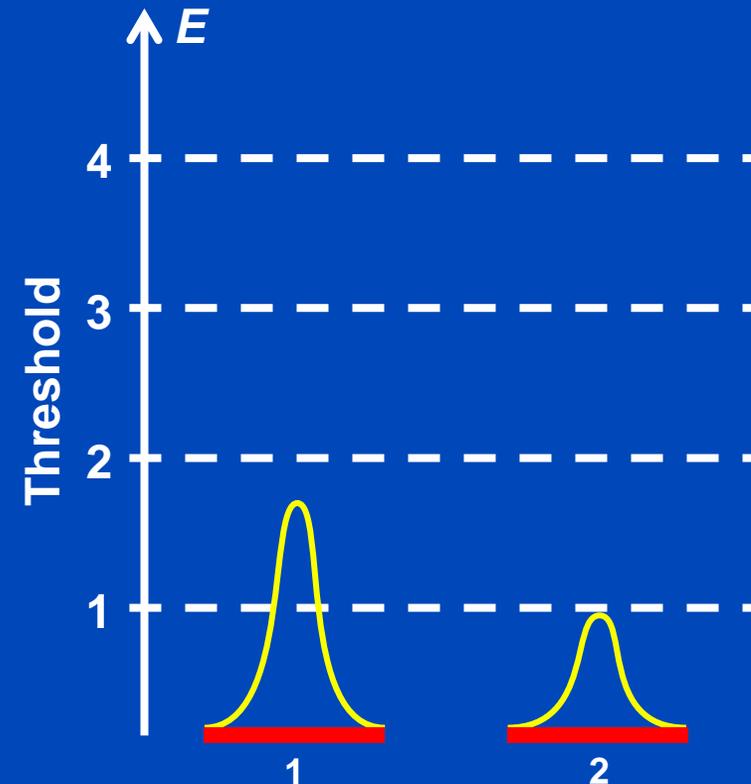
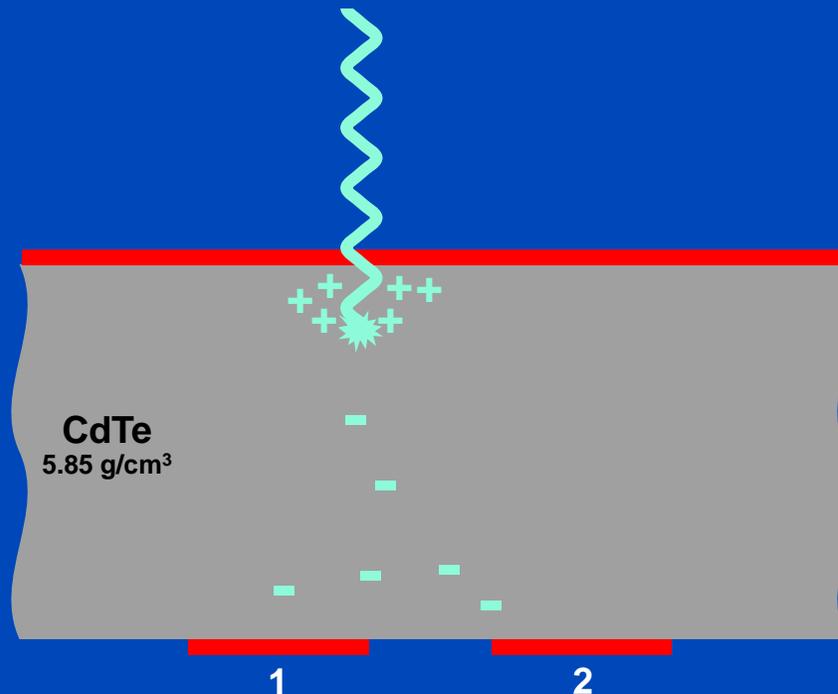
Energy dispersion due to secondary photons



Photon Events

- Detection process in the sensor
- Photoelectric effect (e.g. 30 keV), charge sharing

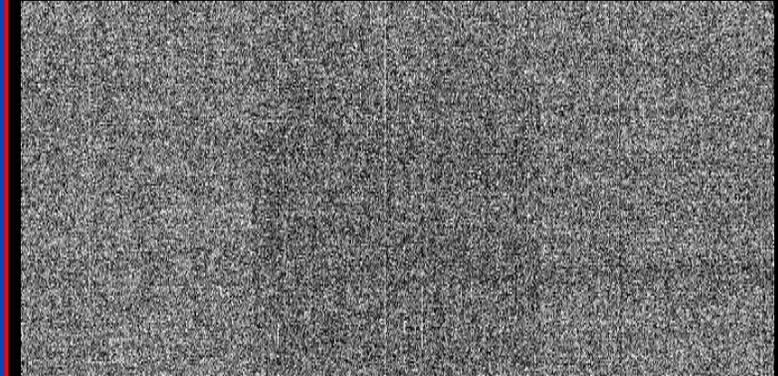
Energy dispersion due to charge diffusion



No Electronic Noise!

- Photon counting detectors have no electronic noise.
- Extreme low dose situations will benefit
 - Pediatric scans at even lower dose
 - Obese patients with less noise
 - **Industrial CT with very long exposure times per frame**
 - ...

EI (Dexela)



Readout noise only. Single events hidden!

PC (Dectris)



No readout noise. Single events visible!

18 frames, 5 min integration time per frame, x-ray off

Siemens Naeotom Alpha

The World's First Photon-Counting CT

- **Tubes**

- tube A: 120 kW
 - tube B: 120 kW
- } $\approx \frac{1}{4}$ MW
- Focal spot size down to 181 μm

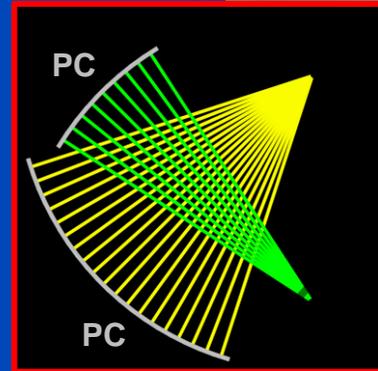
- **Detectors**

- pixel size down to 150 μm
- 288 detector rows
- 2752 detector columns

- **Speed**

- up to 4 rotations per second
- up to 737 mm/s scan speed

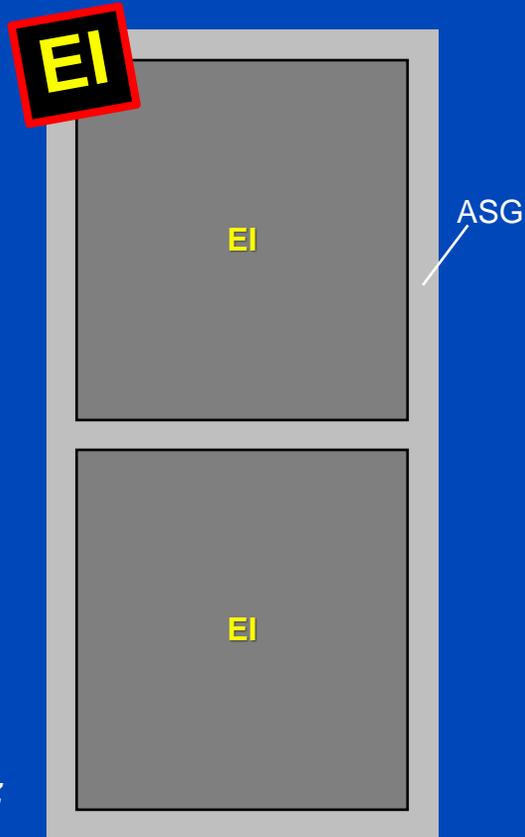
- **50 cm FOM**



Detector Pixel Force vs. Alpha

Force

920 × 96 detector pixels
 pixel size 0.52 × 0.56 mm at iso
 avg. sampling 0.56 × 0.6 mm at iso
 57.6 mm z-coverage



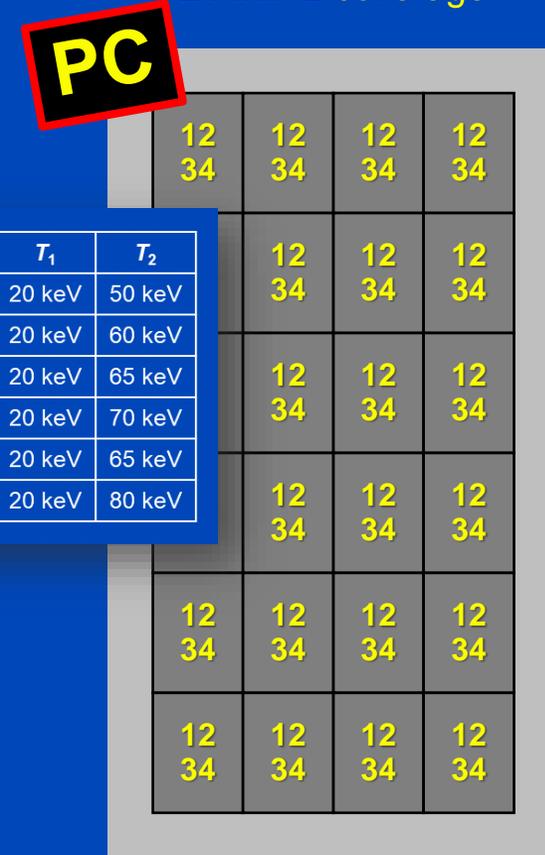
Alpha (Quantum Plus)

1376 × 144 macro pixels
 pixel size 0.3 × 0.352 mm at iso
 avg. sampling 0.344 × 0.4 mm at iso
 57.6 mm z-coverage



Alpha (UHR)

2752 × 120 pixels
 pixel size 0.151 × 0.176 mm at iso
 avg. sampling 0.172 × 0.2 mm at iso
 24 mm z-coverage



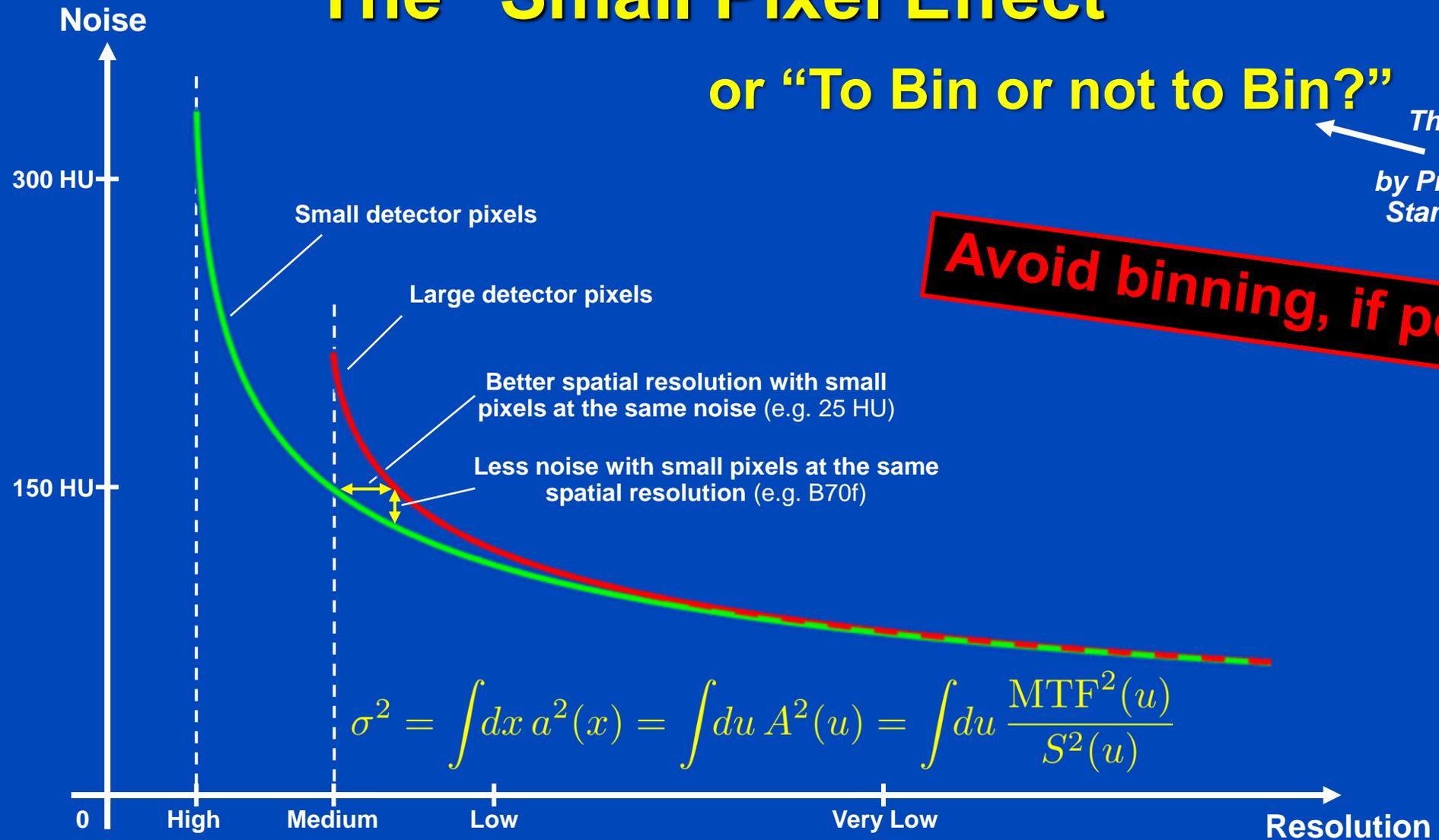
Spectrum	T ₁	T ₂
70 kV	20 keV	50 keV
90 kV	20 keV	60 keV
120 kV	20 keV	65 keV
140 kV	20 keV	70 keV
100 kV Sn	20 keV	65 keV
140 kV Sn	20 keV	80 keV

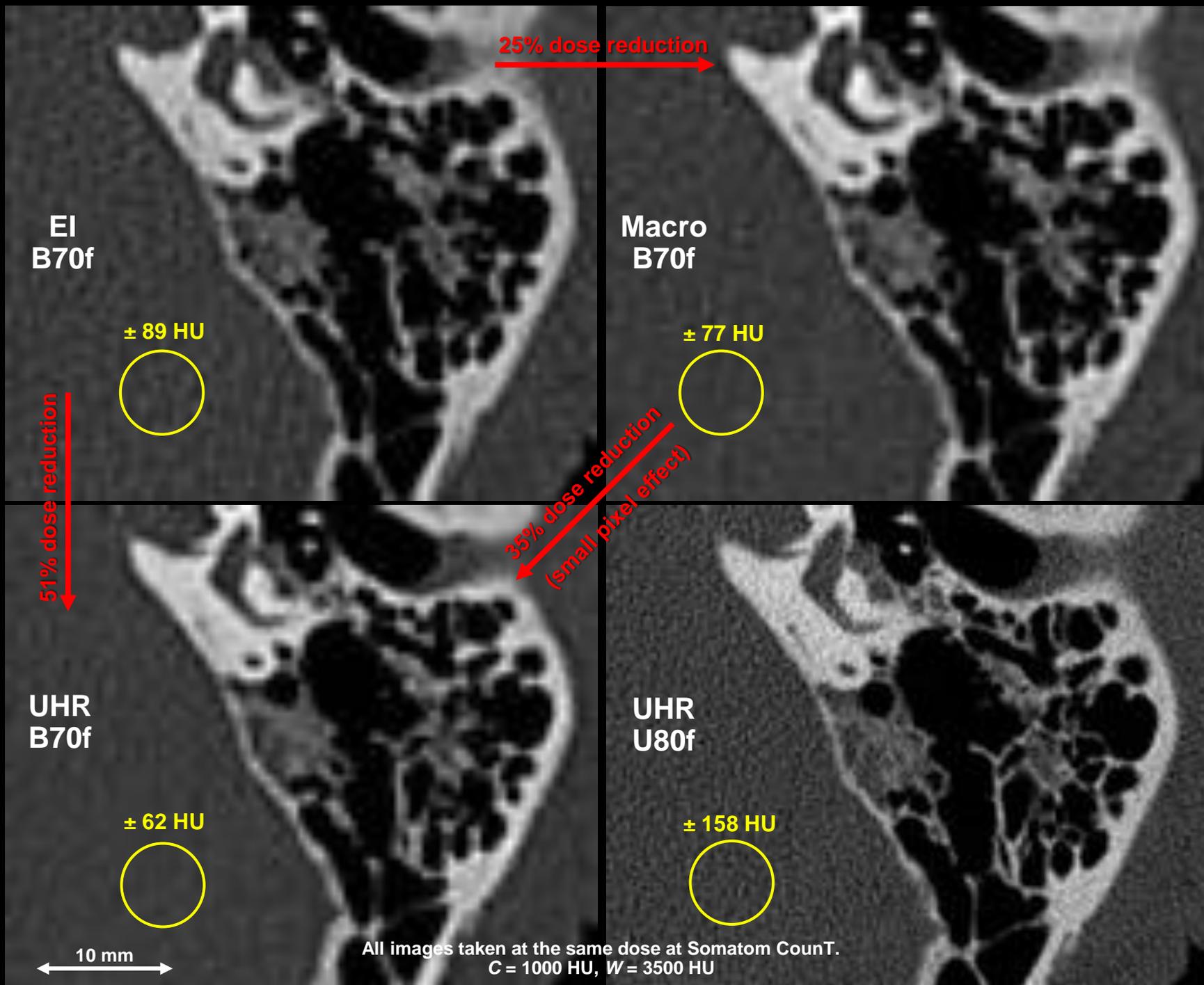
Focus sizes (Vectron): 0.181×0.226 mm, 0.271×0.7316 mm, 0.362×0.497 mm at iso
 which are 0.4×0.5 mm, 0.6×0.7 mm, 0.8×1.1 mm at focal spot

The "Small Pixel Effect"

or "To Bin or not to Bin?"

This nice phrase
was coined
by Prof. Norbert Pelc,
Stanford University.

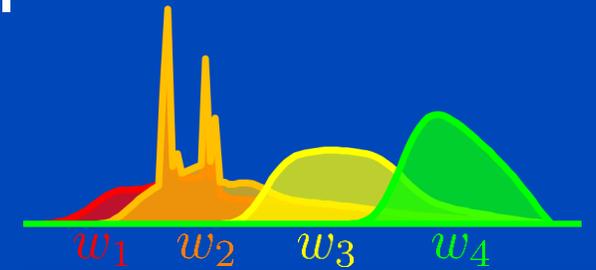




Photon Counting used to Maximize CNR

- With PC, energy bin sinograms can be weighted individually, i.e. by a weighted summation.
- To optimize the CNR the optimal bin weighting factor w_b is given by (weighting after log):

$$w_b \propto \frac{C_b}{V_b}$$

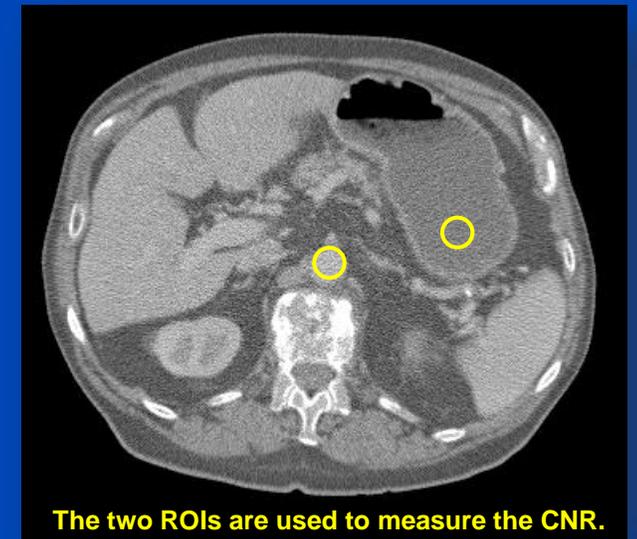


- The resulting CNR is

$$\text{CNR}^2 = \frac{(\sum_b w_b C_b)^2}{\sum_b w_b^2 V_b}$$

- At the optimum this evaluates to

$$\text{CNR}^2 = \sum_{b=1}^B \text{CNR}_b^2$$



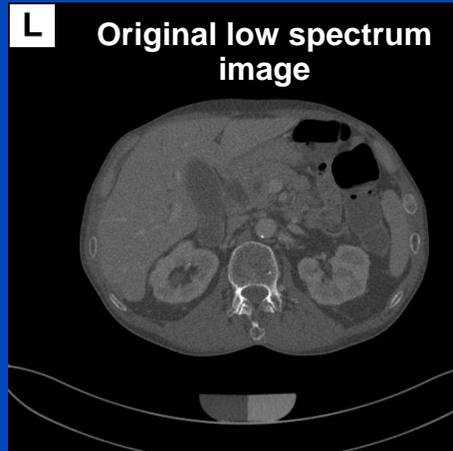
The two ROIs are used to measure the CNR.

Material Decomposition or CNR Maximization?

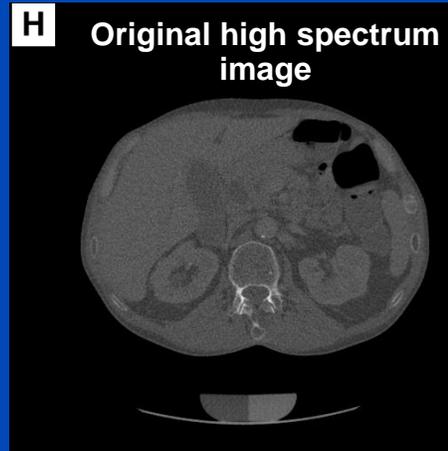
- W = soft tissue (water) signal, X = iodine signal
- Assume same noise N , e.g. 50 HU, in both bin measurements M_1 and M_2
 - $\text{Var } M_1 = \text{Var } M_2 = N^2$ regardless of whether iodine is present or not
- PCCT measurement
 - Measurement 1 (high bin): $M_1 = W + 0.25 X$ $\text{CNR}^2 = X^2 / 16 N^2$
 - Measurement 2 (low bin): $M_2 = W + 0.5 X$ $\text{CNR}^2 = X^2 / 4 N^2$
- Material decomposition
 - Estimated iodine: $4 (M_2 - M_1)$ **Variance = 16 (Var M_2 + Var M_1) = 32 N^2** $\text{SNR}^2 = X^2 / 32 N^2$
 - Estimated soft tissue: $2 M_1 - M_2$ **Variance = 4 Var M_1 + Var M_2 = 5 N^2** $\text{SNR}^2 = W^2 / 5 N^2$
- CNR maximization
 - Compute $(1 - w) M_1 + w M_2$ **Variance = $(1 - w)^2 N^2 + w^2 N^2 = (1 - 2 w + 2 w^2) N^2$**
 - Iodine value minus soft tissue value = **Contrast = $(1 - w) 0.25 X + w 0.5 X$**
 - Maximizing CNR yields $w = 2/3$ $\text{CNR}^2 = 5 X^2 / 16 N^2$

Linear Mixing Techniques

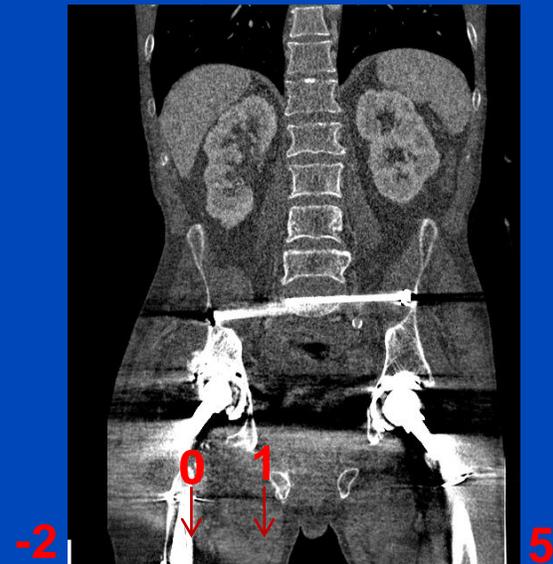
$\alpha = 0$



$\alpha = 1$



α



$C = 300 \text{ HU}, W = 1400 \text{ HU}$

Summary on PCCT

- **Higher efficiency**
 - better image quality
 - reduced measurement times
- **No electronic noise**
 - very long exposures possible
 - potential to overcome photon starvation
- **Spectral information on demand**
 - material discrimination
 - artifact reduction
 - combination with DECT acquisition possible and reasonable
- **High frame rates also for off-the-shelve PC detectors**
 - can be of interest for inspection tasks

ARTIFICIAL INTELLIGENCE

Overview

- Correction in sinogram/raw-data domain:
 - Nauwynck et al., Ring Artifact Reduction in Sinogram Space Using Deep Learning, Proc. CT Meeting 2020:486-489, 2020
- Correction in image domain:
 - Chang et al., A Hybrid Ring Artifact Reduction Algorithm Based on CNN in CT Images, Phys. 3D 11072:110726, 2019
 - Chao et al., Removal of Computed Tomography Ring Artifacts via Radial Basis Function Artificial Neural Networks, Phys. Med. Biol. 64(23):23519, 2019
 - Kornilov et al., Deep Neural Networks for Ring Artifacts Segmentation and Corrections in Fragments of CT Images, SPIE FRUIT conference:161-173, 2021
 - Wang et al., Removing Ring Artifacts in CBCT Images via Generative Adversarial Networks with Unidirectional Relative Total Variation Loss, Neural Computing and Applications 31(9):5147-5158, 2019
 - Ly et al., Image Denoising and Ring Artifacts Removal for Spectral CT via Deep Neural Networks, IEEE Access 8:22425-22435, 2020
- Correction in both, sinogram/raw-data and image domain:
 - Fang et al., Comparison of Ring Artifacts Removal by Using Neural Network in Different Domains, MIC, 2019
 - Fang et al., Removing Ring Artifacts for Photon-Counting Detectors Using Neural Networks in Different Domains, IEEE Access 8:42447-42457, 2020

A hybrid ring artifact reduction algorithm based on CNN in CT images

Chang, Shaolin, Chen, Xi, Duan, Jiyao, Mou, Xuanqin

Abstract: Ring artifacts in CT images are a common problem. This paper proposes a hybrid ring artifact reduction algorithm based on CNN in CT images. The algorithm consists of two parts: a ring artifact reduction algorithm based on CNN in CT images and a ring artifact reduction algorithm based on CNN in CT images. The results show that the proposed algorithm can effectively reduce ring artifacts in CT images.

Chang et al. (2019)

- The reference data for this image-based correction are taken from 10 full-dose clinical CT images.
- Ring artifacts are simulated on these data to generate a data base of 777 paired images for supervised training of a CNN.
- Two channel input: 64x64 image patches of uncorrected and WF (Wavelet-Fourier) corrected images are used as inputs.

The output of the CNN is directly the difference (difference image) of the original image and the WF corrected image. The WF corrected image is then added to the original image to get the corrected image. The results of this hybrid method do not look convincing at all. Even though there are fewer ring artifacts, the image is still blurry and the contrast is lower.

Chang et al. (2019)- Results and My Conclusion

Original image, UnCorrected image, CNN image, Combined image

The results of this hybrid method do not look convincing at all. Even though there are fewer ring artifacts, the image is still blurry and the contrast is lower. The proposed comprehensive model that uses information from image and projection domain.

Deep Neural Networks for Ring Artifacts Segmentation and Corrections in Fragments of CT Images

Ames Korabely¹, Ilya Salomon², Irena Kuznetsov¹, Ivan Yalitskiy¹
¹National Research University of Information Technologies
²National Research Nuclear University MEPhI Moscow, Russia
 National Research Nuclear University MEPhI Moscow, Russia
 National Research Nuclear University MEPhI Moscow, Russia
 National Research Nuclear University MEPhI Moscow, Russia

FRUCT = Finnish-Russian University Cooperation in Telecommunications

Kornilov et al. (2021)

- This work addresses corrections of remaining ring artifacts after vendor corrections (hard- and/or software-based) in micro CT. Actually those artifacts are typically area, not full rings.
- Their dataset consists of 8 reconstructions (6 for training, 1 for validation and 1 for testing) of sand and sandstone samples (from a Bruker SkyScan micro CT). They applied automated and manual segmentations to the ring artifact areas (in total ~2000 segmented artifacts). These artifacts are then transferred to "clean" regions in order to generate training and validation data pairs.
- A two stage correction is implemented: first a U-Net is used to find and segment the artifacts, and then a second CNN with some convolutional layers is used to perform an inpainting. The training of each stage is performed successively. A 2D U-Net and 3D U-Net are compared.

Kornilov et al. (2021)- Results and My Conclusion

Results for the segmentation part (left) and final images (right).

My conclusion:
 - Well written paper (or abstract) which addresses the problems of partial ring artifacts.
 - Unfortunately, they only show the result images above with different windows which do not really make the point that the 3D CNN is the best algorithm, which is what the labels show.

Chao et al. (2019)

Removal of computed tomography ring artifacts via radial basis function artificial neural networks

From the article: Shen and Han, August 2019, Proc. Med. Im. 48:2350-2351

Chao et al. (2019)- Results and My Conclusion

- An image-based correction is proposed which removes stripes in polar coordinates. The point of this paper is that the network architecture is very simple.
- The data consist of 160 clean brain images and 300 abdomen images, where the authors added 16, respectively 20 different simulated ring artifacts. For testing, data a set of 40 brain images is simulated and the algorithm is tested on measured abdomen data.
- Procedure:
 - Transformation of volume slices in polar coordinates and perform high-pass filtering
 - Low-pass along horizontal direction (after this step there needs to be a classification of artifacts)
 - Application of 3-layer neural network with 8 input nodes (trained on simulated artifacts). I guess the output is here an offset with respect to the original image (not mentioned).

Chao et al. (2019)- Results and My Conclusion

Results for the simulated validation data (left) and measured data (right).

My conclusion:
 - The results look good and also corrections of measured data are shown.
 - The network is extremely simple, but so is the problem: Selected lines are inpainted by this network. It is not clear to me whether the performed "mask" by good restoration of each artifact is really applied only in the artifact area. If so, the main problem and hardest task would be to determine the entire path of the artifact. If the authors did this by hand, the method shown here is useless. In this case another net in the fashion of Kornilov et al. (2021) should be used to segment the artifact lines.

Ring Artifact Reduction in Sinogram Space Using Deep Learning

M. Nauwynck¹, S. Kopylov², A. B. van Boven², J. De Boer¹, S. Afdel¹
¹School of Mechanical Engineering, Nanyang Technological University, Singapore
²Department of Physics, Nanyang Technological University, Singapore

Nauwynck et al. (2020)

- Here a ring artifact correction in sinogram space is proposed.
- Clean data from the Cancer Imaging Archive (45640 Images) are forward projected. Ring artifacts are extracted from measured data with ring artifacts (from Tomobank) and randomly sampled on the clean data to get training pairs. The dataset was divided into training (42240 samples), validation (1000 samples) and test set (2400 samples).
- A 2D U-Net is used with a custom loss function that consists of a L1-loss and a Sobel-loss.

Nauwynck et al. (2020) - Results and My Conclusion

Comparison of performance of the proposed method (RM) to other conditions on the simulated dataset regarding PSNR and SSIM.

My conclusion:
 - Their approach is the most intuitive to handle this issue in raw-data domain: simulate training pairs by using measured reference ring artifacts and use a 2D U-Net to train on the labeled data and finally perform the correction.
 - The results on measured data look good but they are not better than the comparison results. Low-frequency artifacts still remain. Maybe they were under-represented in this training data.

Removing ring artifacts in CBCT images via generative adversarial networks with unidirectional relative total variation loss

Zheng Wang¹, Xianyu Liu¹, Mengdie Sun¹

Received 12 November 2019; revised 12 December 2019; accepted 12 January 2020
 Published online 10 February 2020

Wang et al. (2019)

- Here a GAN is used to remove ring artifacts from CT volumes. The image is first transferred to polar coordinates, where ring artifacts appear as lines.
- 10 different ring artifacts are simulated on each of the 10000 brain CT images in the training dataset. The testing dataset contained 1000 simulated images and additionally 20 CBCT images with real ring artifacts.

Wang et al. (2019) - Results and My Conclusion

Corrected volume slices shown in the paper and the authors say it is 3588 slices. The authors say it is 3588 slices. The authors say it is 3588 slices.

My conclusion:
 - The paper is in general well written. It is shown that the transition to polar coordinates, as well as the L1-TV loss are beneficial for the correction.
 - The design of the results is very bad. Actually one is only able to see differences in the correction in the last image row, where an ROI is shown.

Comparison of Ring Artifacts Removal by Using Neural Network in Different Domains

Wei Fang, Liang Li, Senior Member, IEEE

Fang et al. (2019)

- This paper provides a comparison of different deep ring artifact correction methods: in projection domain, in image domain (Cartesian), in image domain (polar) and a combined "comprehensive" model. All use a 5-stage U-Net and the latter on both, raw-data and volume data simultaneously (backprojection layer implemented).
- Clean data is acquired from the AAPM Low Dose CT Grand Challenge. Ring artifacts are simulated by adding stripes in the sinogram data. The data was split into training (4800 images), validation (600 images) and testing datasets (526 images) and an MSE loss function is used.

Fang et al. (2019) - Results and My Conclusion

Results for different networks compared to a conventional Wavelet Fourier.

My conclusion:
 - The interesting point in this abstract is the comparison of different deep learning methods in different domains etc.
 - On simulated data the results look good but this study lacks a real experiment.
 - The paper of this work follows on the next slides.

Removing Ring Artefacts for Photon-Counting Detectors Using Neural Networks in Different Domains

WEI FANG¹, LIANG LI¹ (Senior Member, IEEE), AND ZHAOQIAN CHEN¹
¹School of Electronic Engineering, East China University of Science and Technology, Shanghai, China
 School of Electronic Engineering, East China University of Science and Technology, Shanghai, China
 School of Electronic Engineering, East China University of Science and Technology, Shanghai, China

Fang et al. (2020)

- This publication is the reviewed paper of the work shown on the previous slides. The same idea and similar experiments are shown. Here the authors additionally show results for measured noise data on a PCD (AKSIO, or PRODIGE 12, Sixelabs, PA) which has 256 pixels with pixel size 0.5 mm x 2 mm.
- As in Fang et al. (2019) the authors compare the ring artifact correction results of a deep learning correction in projection domain, in image domain (Cartesian), in image domain (polar), and a comprehensive model. The network architecture is that of a U-Net, and a comprehensive model.
- The training, validation and test data are the same as on slide 19. Their model to simulate ring artifacts on projection data consists of a constant factor and an offset.

Fang et al. (2020) - Results and My Conclusion

Architecture of the used U-Net.

My conclusion:
 - This paper is very helpful, especially because it compares different domains for deep learning correction.
 - Their method, combining projection and image domain, shows the best results.
 - It seems that a correction in projection domain outperforms image domain correction. Maybe the performance of an image domain correction could be improved by using a 3D U-Net.
 - The correction in image domain works better on Cartesian coordinates than on polar coordinates. This contradicts what Wang et al. (2019) show. Wang et al. first perform a stripe add to polar coordinates in order to get uniform stripes. As this paper is better overall, I would try on their options.

Image Denoising and Ring Artifacts Removal for Spectral CT via Deep Neural Network

MAHMOUD M. EL-BAYE¹, RENE BERG¹, FRANCESCO M. RUPI¹, AND JOHANNES L. SCHWENGER¹
¹Department of Electrical Engineering, Technical University of Munich, Munich, Germany

Lv et al. (2020)

- This work focusses on denoising and ring artifact reduction of PCD data in image domain via a CNN.
- They solely process measured data. To have ground truth data available they perform a noise suppression via a Split-Bregman algorithm and an iterative image-based ring artifact correction.
- The total number of CT images used for training, validation and testing was 2240 in the ratio 1:1:5. An MSE-like cost function is used.
- The PCD they are using is not specified, experiments were performed with 8 energy bins with thresholds ranging from 25 keV to 50 keV.

Lv et al. (2020) - Results and My Conclusion

Results for different energy bins.

My conclusion:
 - A good point about this paper is that they use measured data for training.
 - The results have some inconsistencies, e.g. where does the dark streak come from highlighted by the yellow arrow? Furthermore, the rest of the volume looks blurry. This might be a visual effect due to the noise suppression, however the authors show no TPs.
 - A more severe problem of this paper is that I don't know why this method is needed at all. They use some conventional methods to label their data. Are these methods computationally too expensive to be used routinely? No answer is given.

Deep Detruncation

Classification of DL-based reconstruction methods

1) Sinogram domain learning

2) Image domain learning

3) Dual-domain learning

- S:** Sinogram domain network
- I:** Image domain network
- P:** Projection operation
- R:** Reconstruction operation
- F:** Dual-domain information fusion operation

Wang, et al., A Review of Deep Learning CT Reconstructions from Incomplete Projection Data. IEEE Transactions on Radiation and Plasma Medical Sciences, doi: 10.1109/TRPMS.2022.3274349 (2022)

Deep learning-based sinogram extension method for interior computed tomography

Jusuo H. J. Ketola¹, Heikki Heino¹, Mikael A. K. Juntunen^{1,2}, Mika T. Nieminen^{1,3,4}, and Sota I. Takami¹

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²The South Savo Health Care Authority, Mikkeli Central Hospital, Oulu, Finland
³Department of Diagnostic Radiology, Oulu University Hospital, Oulu, Finland
⁴Medical Center Oulu, Oulu University Hospital and University of Oulu, Oulu, Finland

Results

Fig. 1. Example reconstructions: a) Original data from center, b) Algebraic Reconstruction Filtered by Filtered Back Projection, a Total Variation regularization, a FBP+GAN, a FBP+GAN+1-GAN Method. Reconstructions have been smoothed to facilitate the eye comparison.

Heikki Heino, et al., Deep learning-based sinogram extension method for interior computed tomography. Medical Imaging: Physics of Medical Imaging, doi: 10.1109/PMIP.2022.9813911 (2022)

Deep Detruncation

Classification of DL-based reconstruction methods

1) Sinogram domain learning

2) Image domain learning

3) Dual-domain learning

- S:** Sinogram domain network
- I:** Image domain network
- P:** Projection operation
- R:** Reconstruction operation
- F:** Dual-domain information fusion operation

Wang, et al., A Review of Deep Learning CT Reconstructions from Incomplete Projection Data. IEEE Transactions on Radiation and Plasma Medical Sciences, doi: 10.1109/TRPMS.2022.3274349 (2022)

Evaluation of novel AI-based extended field-of-view CT reconstructions

Gabriel Páris Ponnava¹

¹Department of Radiation Therapy (MALT/RT), CBWF School for Oncology and Developmental Biology, Maastricht University Medical Center, Maastricht 6229 XZ, The Netherlands

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 Senior Software Quality Engineers, Germany

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 Department of Radiation Therapy (MALT/RT), CBWF School for Oncology and Developmental Biology, Maastricht University Medical Center, Maastricht 6229 XZ, The Netherlands

(Received 29 February 2021; revised 27 April 2021; accepted for publication 30 April 2021; published 11 May 2021)

D. P. Ponnava, et al., Evaluation of novel AI-based extended field-of-view CT reconstructions. Med Phys, doi:10.1088/1361-6560/ab9121 (2021)

Results

Network Input Image Network Output Image HDDeepFov Result Image

D. P. Ponnava, et al., Evaluation of novel AI-based extended field-of-view CT reconstructions. Med Phys, doi:10.1088/1361-6560/ab9121 (2021)

Results

HDFOV (conventional) HDDeepFov (new)

D. P. Ponnava, et al., Evaluation of novel AI-based extended field-of-view CT reconstructions. Med Phys, doi:10.1088/1361-6560/ab9121 (2021)

Evaluation of novel AI-based extended field-of-view CT reconstructions

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Data Extrapolation From Learned Prior Images for Truncation Correction in Computed Tomography

Yinying Huang¹, Alexander Priebe¹, Michael Mariani¹, Guenter Lantusch¹, and Andreas Maier¹, Senior Member, IEEE

Huang, Yinying, et al., Data Extrapolation from Learned Prior Images for Truncation Correction in Computed Tomography. IEEE Transactions on Medical Imaging, doi:10.1109/TMI.2021.3081104 (2021)

Results

Huang, Yinying, et al., Data Extrapolation from Learned Prior Images for Truncation Correction in Computed Tomography. IEEE Transactions on Medical Imaging, doi:10.1109/TMI.2021.3081104 (2021)

Data Consistent CT Reconstruction from Insufficient Data with Learned Prior Images

Yinying Huang, Alexander Priebe, Michael Mariani, Guenter Lantusch, Andreas Maier

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Huang, Yinying, et al., Data Consistent CT Reconstruction from Insufficient Data with Learned Prior Images. IEEE Transactions on Medical Imaging, doi:10.1109/TMI.2021.3081104 (2021)

Generative adversarial networks improve interior computed tomography angiography reconstruction

Jusuo H. J. Ketola¹, Heikki Heino¹, Mikael A. K. Juntunen^{1,2}, Mika T. Nieminen^{1,3,4}, Samuli Siltanen¹ and Sota I. Takami¹

- 1) Input: truncated sinogram
- 2) Extended with sinogram extension GAN
- 3) Superimpose original measured data
- 4) reconstruction post-processing GAN is used to yield an improved reconstruction
- 5) original data is superimposed in the sinogram before final filtered backprojection

Heikki Heino, et al., Generative adversarial networks improve interior computed tomography angiography reconstruction. Frontiers in Deep Learning, doi:10.3389/fnlin.2021.786441 (2021)

Results

Heikki Heino, et al., Generative adversarial networks improve interior computed tomography angiography reconstruction. Frontiers in Deep Learning, doi:10.3389/fnlin.2021.786441 (2021)

Results

Huang, Yinying, et al., Data Consistent CT Reconstruction from Insufficient Data with Learned Prior Images. IEEE Transactions on Medical Imaging, doi:10.1109/TMI.2021.3081104 (2021)

Deep MAR Examples

Reducing Metal Streak Artifacts in CT Images via Deep Learning: Pilot Results

Lei Guo, Qingyao Tang, Yan Li, Binbin Chen, Tianxin Gu, Binbin Guo, Guo Wang

• Takes 32x32 input patch from NMAR image and produces 20x20 output patch
• Very basic CNN

Gjesteby, 2018

Deep Neural Network for CT Metal Artifact Reduction with a Perceptual Loss Function

Yong Yang, Qingyao Tang, Qingyao Tang, Yan Li, Binbin Chen, Tianxin Gu, Binbin Guo, Guo Wang

Gjesteby, 2018

• Inputs for the network are the NMAR image and the high-pass filtered original image
• Corrects streaks after NMAR
• Loss function is MSE or perceptual loss (from VGG work)
• SE shows over-smoothing
• L2-norm loss is used to reduce the residual error

Gjesteby, 2018

A dual-stream deep convolutional network for reducing metal streak artifacts in CT images

Lei Guo, Qingyao Tang, Yan Li, Binbin Chen, Tianxin Gu, Binbin Guo, Guo Wang

Gjesteby, 2019

Gjesteby, 2019

Gjesteby, 2019

- Same network as in previous work
- Detail image is the high-pass filtered original image
- Detail image and NMAR image are both put as inputs in 2 streams that converge later in the CNN
- Network uses residual error and cost function is a combination of MSE and perceptual loss

Metal artifact reduction for practical dental computed tomography by improving interpolation-based reconstruction with deep learning

Yong Yang, Qingyao Tang, Qingyao Tang, Yan Li, Binbin Chen, Tianxin Gu, Binbin Guo, Guo Wang

Xing, 2019

Xing, 2019

- Perform initial L1MAR to obtain images with interpolation artifacts
- Apply U-Net to pre-corrected images to reduce artifacts
- Network minimizes L2-norm loss outside of the metal regions

Metal artifact reduction on cervical CT images by deep residual learning

Lei Guo, Qingyao Tang, Yan Li, Binbin Chen, Tianxin Gu, Binbin Guo, Guo Wang

Zhang, 2018

Zhang, 2018

- Metal is placed in real CT images. Artifacts are created by forward and back-projecting soft tissue, bone, and metal
- Network input is patch of artifact image I and output is the residual, i.e. $R = I - G^T$
- Loss function is MSE of the residual
- Learning the residual is found to be better than learning the artifact-free image (no images)

Convolutional Neural Network Based Metal Artifact Reduction in X-Ray Computed Tomography

Wei Zhang, Senior Member, IEEE, and Hongping Yu, Senior Member, IEEE

Yu, 2018

Yu, 2018

- Training data are generated from clinical data with metal artifacts added afterwards through polychromatic forward- & back-projection
- Cost function is MSE
- CNN gets patches from the artifact BHC corrected, and LI corrected image as input, produces corrected patches
- Prior image is generated from CNN result by segmenting water and setting it to the average value of all water pixels and leaving bone intact
- Metal trace in the uncorrected sinogram is replaced with values from the prior image
- Having different types of MAR as input improves results

Metal-Artifact Reduction Using Deep-Learning Based Sinogram Completion: Initial Results

Reinhold E. H. Chen, Yuesha He, Lan X. Guo, Yan Li, Binbin Chen, Tianxin Gu, Binbin Guo, Guo Wang

Claus, 2017

- Trained and evaluated on simulated data with metal circle in the center (no other positions tested)
- Data are heavily simplified (random ellipses)
- Inputs are 2 81x21 sized patches from the sinogram next to metal patch. Won't work for complex metals
- Relatively small network (4 layers)

Deep Learning Based Metal inpainting in the Projection Domain: Initial Results

Thomas M. Gottschalk, Björn W. Kuhse, Rajeev Kumar, and Andreas Maier

Gottschalk, 2019

Gottschalk, 2019

- Corrects C-Arm projection data
- Data were obtained by placing metal on top of human knee cadavers
- Loss function is MSE
- Networks are based on U-Net with additional skip connection from original image to output
- Basic network can be used to implicitly segment the metal for the Mask-MAR-Net
- Providing a metal mask significantly improves results
- Results are blurred slightly

Gottschalk, 2019

Fig. 4. Inpainting results of sMAR-Net (c), Mask-MAR-Net (d) Dual-MAR-Net (e) and the corresponding input (b) and label (a) projections.

Deep Learning based Metal Inpainting in the Projection Domain using additional Neighboring Projection Information

Thomas M. Gottschalk, Björn W. Kuhse, and Andreas Maier

Gottschalk, 2020

N = Including neighbours, P = combining orig. with corrected

Gottschalk, 2020

- U-Net corrects CBCT projections
- Has metal mask and 10 neighbouring projections as additional input channels

Fast Enhanced CT Metal Artifact Reduction using Data Domain Deep Learning

Mohammad Oussou Ghani, W. Chen, Karl, Felix, IEEE

Ghani, 2019

Ghani, 2019

Generative Mask Pyramid Network for CT/CBCT Metal Artifact Reduction with Joint Projection-Sinogram Correction

Benli Lian, Wei An, Li, Zhishu Han, Leren Vongphoth, William J. Robert, S. Kevin Zhou, and Jiebo Luo

Liao, 2019

Fig. 7. MAR results on clinical images. Metallic implants are replaced with constant values (white) after MAR.

Liao, 2019

- First replaces metal trace in the projections (i.e. fixed angle but varying ξ and z)
- Then transforms the projections into sinograms and uses a second network to improve those
- Both networks are GANs with a U-Net generator and CNN discriminator
- Uses a Mask Pyramid to ensure the metal mask is seen by all stages of the U-Net
- Data are regular CT scans with metal traces from other patients imposed on them

DuoNet: Dual Domain Network for CT Metal Artifact Reduction

Wei An, Li, Benli Lian, Cong Peng, Xiaohang Tang, Jinghui Zhang, Jiebo Luo, Rene Chellappa, Shaohua Kevin Zhou

Lin, 2019

Lin, 2019

- Input are LI pre-corrected sinograms/images
- First improves the sinograms through a U-Net with mask pyramid (so all parts of the U-Net see the mask)
- Then applies FBP (Radon Inversion Layer) and uses the result as input for a second U-Net, which improves it in image domain
- Unclear how the LI and CNN results are combined

Deep MAR Examples

<p>Deep Learning-based Pre-scan Residual Metal Artifact Reduction in Computed Tomography</p>	<p>Nam, 2022</p>	<p>Nam, 2022</p>	<p>Kim, 2022</p>	<p>Kim, 2022</p>	<p>Kim, 2022</p>	<p>Wang, 2021</p>	<p>Wang, 2021</p>
<p>Unsupervised CT Metal Artifact Learning Using Attention-Guided U-NetGAN</p>	<p>Lee, 2021</p>	<p>Lee, 2021</p>	<p>Lee, 2021</p>	<p>Ann, 2021</p>	<p>Ann, 2021</p>	<p>Ann, 2021</p>	<p>Du, 2020</p>
<p>Du, 2020</p>	<p>Weller, 2020</p>	<p>Weller, 2020</p>	<p>Weller, 2020</p>	<p>Weller, 2020</p>	<p>Gjesteby, 2019</p>	<p>Gjesteby, 2019</p>	<p>Gjesteby, 2019</p>
<p>Deep Neural Network for CT Metal Artifact Reduction in a Pre-scan Loss Function</p>	<p>Gjesteby, 2018</p>	<p>Gjesteby, 2018</p>	<p>Gjesteby, 2017</p>	<p>Gjesteby, 2017</p>	<p>Xing, 2019</p>	<p>Xing, 2019</p>	<p>Metal artifact reduction on cervical CT images by deep residual learning</p>
<p>Zheng, 2018</p>	<p>Zheng, 2018</p>	<p>Convolutional Neural Network Based Metal Artifact Reduction in X-Ray Computed Tomography</p>	<p>Yu, 2018</p>	<p>Yu, 2018</p>	<p>Gottschalk, 2022</p>	<p>Gottschalk, 2022</p>	<p>Deep Learning based Metal Artifact Reduction in the Projection Domain using additional Noisy Training Data</p>
<p>Gottschalk, 2020</p>	<p>Gottschalk, 2020</p>	<p>Blum, 2022</p>	<p>Gottschalk, 2019</p>	<p>Gottschalk, 2019</p>	<p>Virtual Non-Metal Network for Metal Artifact Reduction in the K-edge Domain</p>	<p>Choi, 2022</p>	<p>Choi, 2022</p>
<p>Choi, 2022</p>	<p>Blum, 2022</p>	<p>Blum, 2022</p>	<p>Fai Enhanced CT Metal Artifact Reduction using Data Driven Deep Learning</p>	<p>Ghani, 2019</p>	<p>Ghani, 2019</p>	<p>Liao, 2019</p>	<p>Liao, 2019</p>
<p>Liao, 2019</p>	<p>Clauw, 2017</p>	<p>Clauw, 2017</p>	<p>Zhu, 2023</p>	<p>Zhu, 2023</p>	<p>Zhu, 2023</p>	<p>Wang, 2021</p>	<p>Wang, 2021</p>
<p>Yu, 2021</p>	<p>Yu, 2021</p>	<p>Yu, 2021</p>	<p>Yu, 2021</p>	<p>Yu, 2021</p>	<p>Peng, 2020</p>	<p>Peng, 2020</p>	<p>Peng, 2020</p>

Sparse View Restoration Example

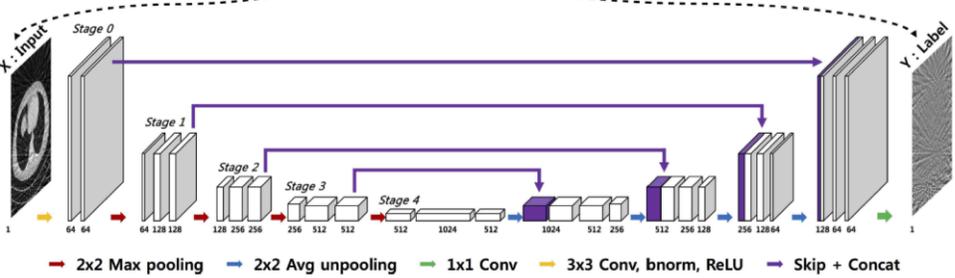
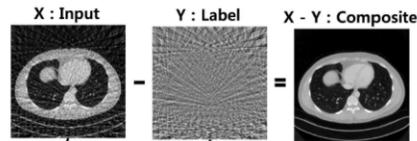
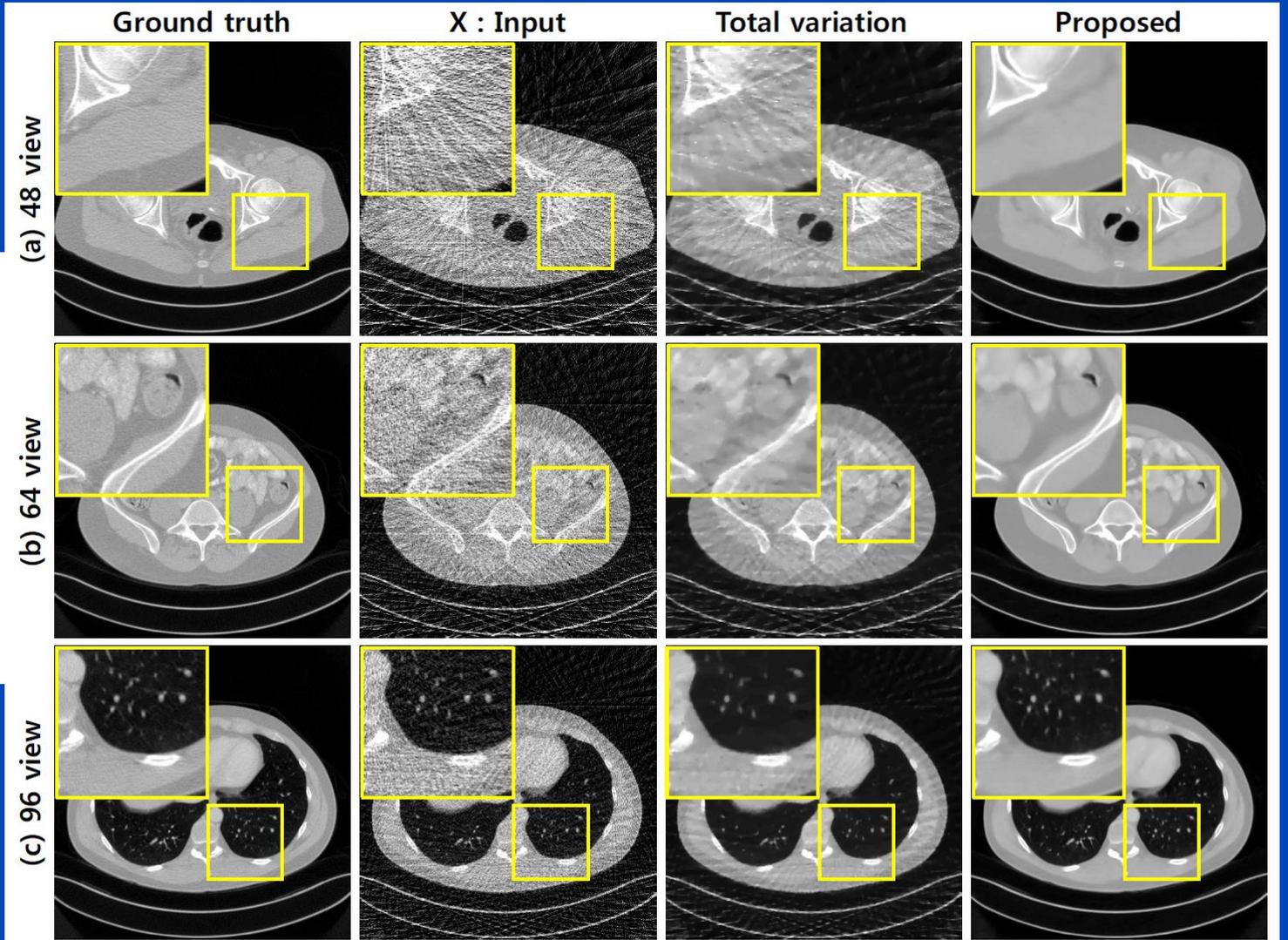
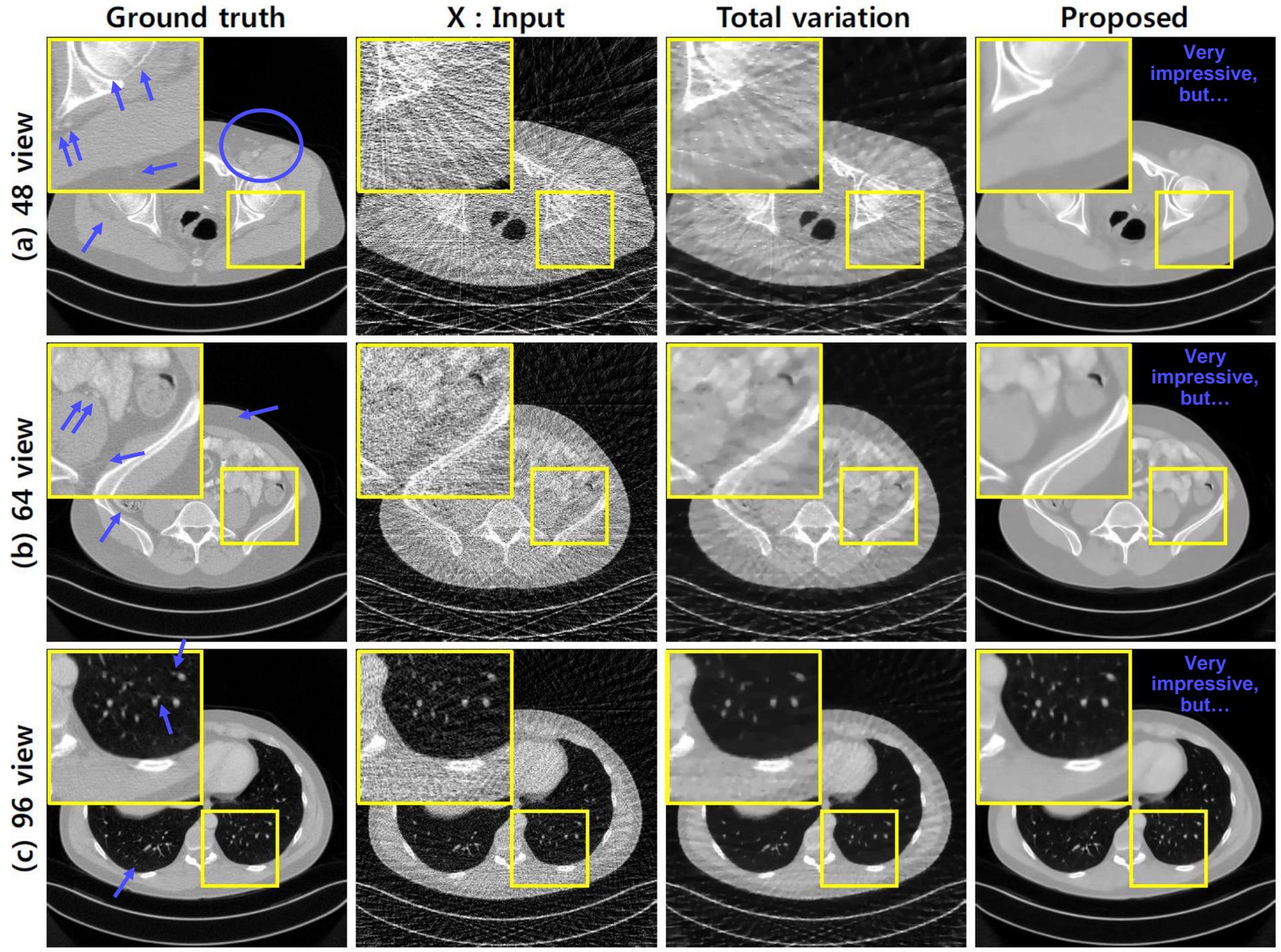


Figure 1. The proposed deep residual learning architecture for sparse view CT reconstruction.





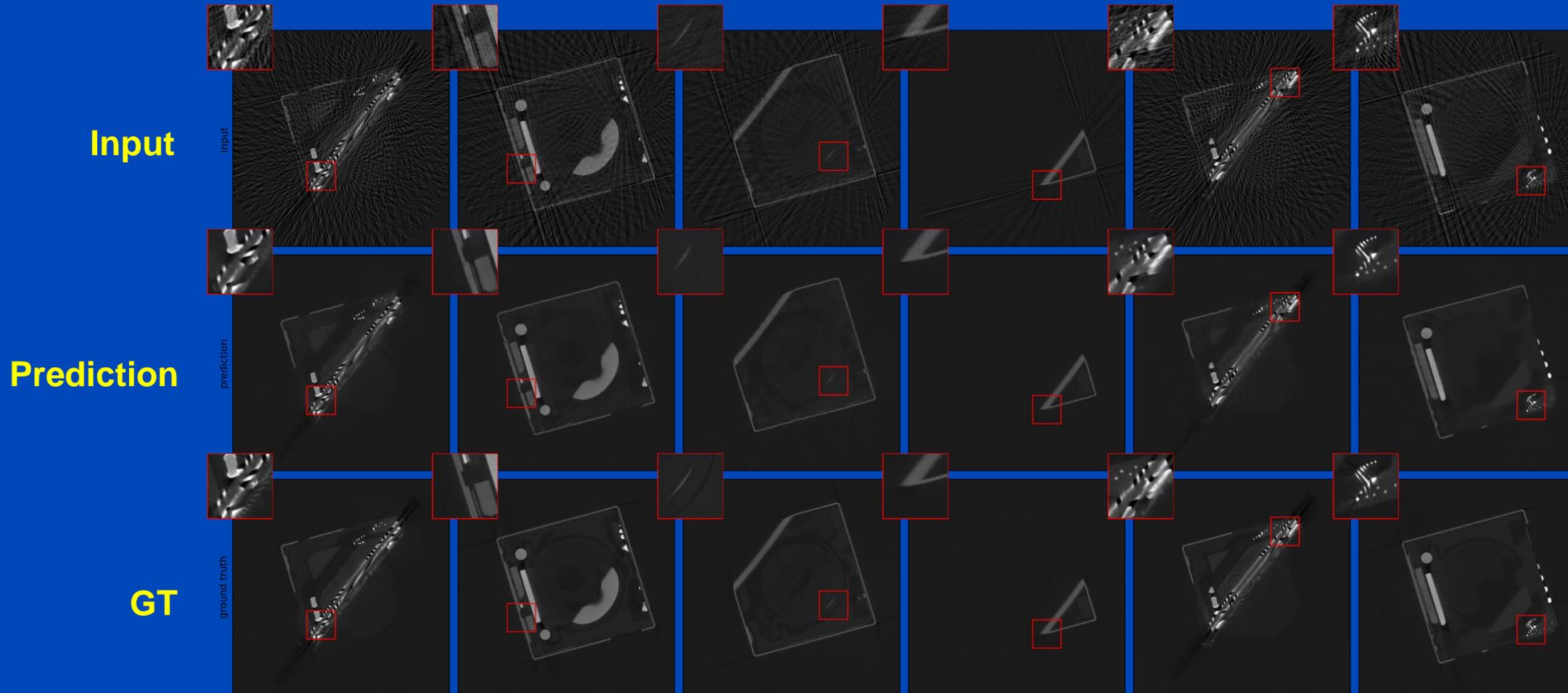
Component-Specific Denoising/Desparsifying

- We assume to have one long-acquisition scan of the component
- Generate training data via random transformations and deformations
- Generate datasets for training, validation and :
 - GT: Long-acquisition ground truth
 - UN: undersampled + noise reconstruction (80 projections, Poisson noise)
 - N: Noisy reconstruction (800 projections, with Poisson noise)
- Train three U-Nets
 - Sh-Unet-MSE: Shallow structure (3× downsampling, initial filter size: 16) with MSE
 - Unet-MSE: Deeper structure (4× downsampling, initial filter size: 16) with MSE
 - Unet-Adv: Deeper structure trained in WGAN-GP setting with perceptual and MSE component
- All networks are trained on patches of size 256^2 on the UN dataset

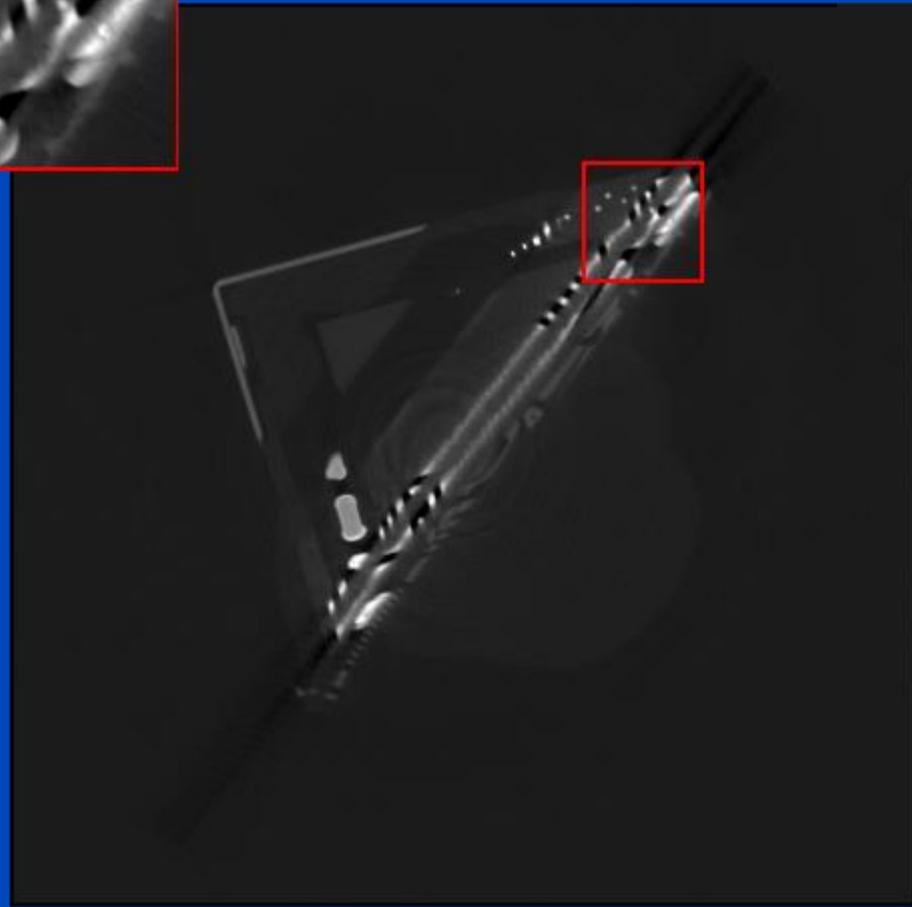
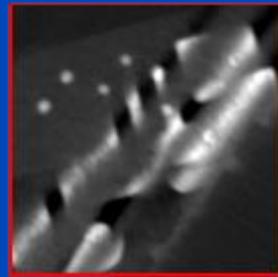
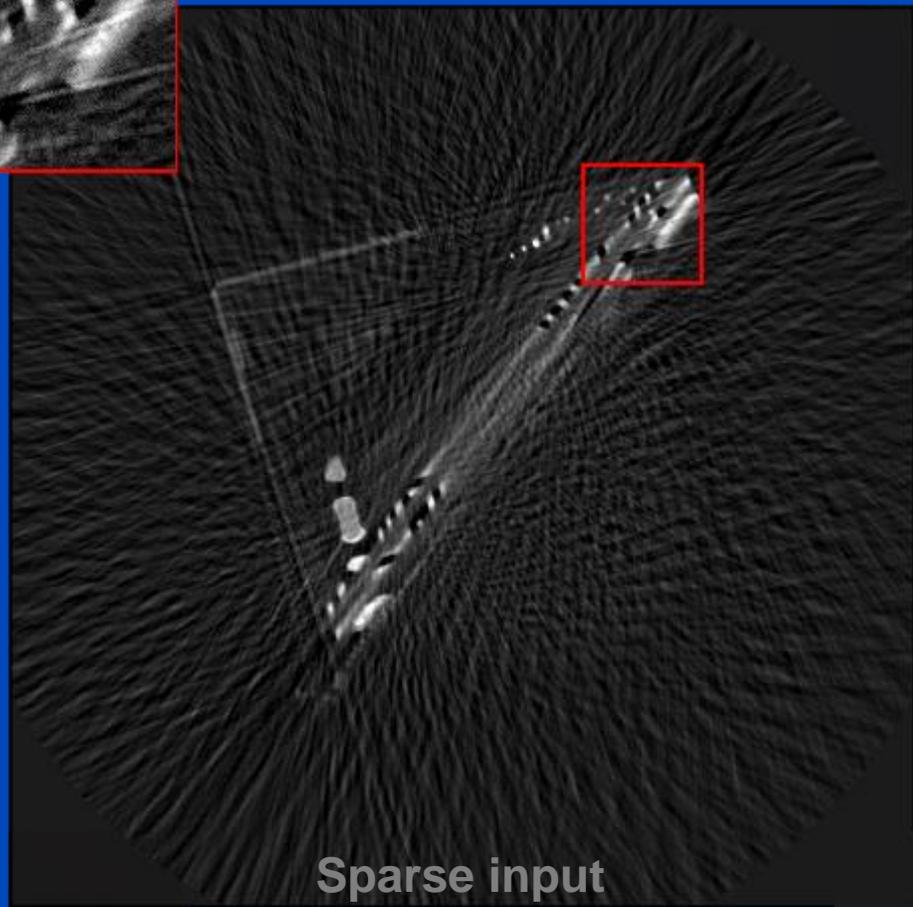


Results

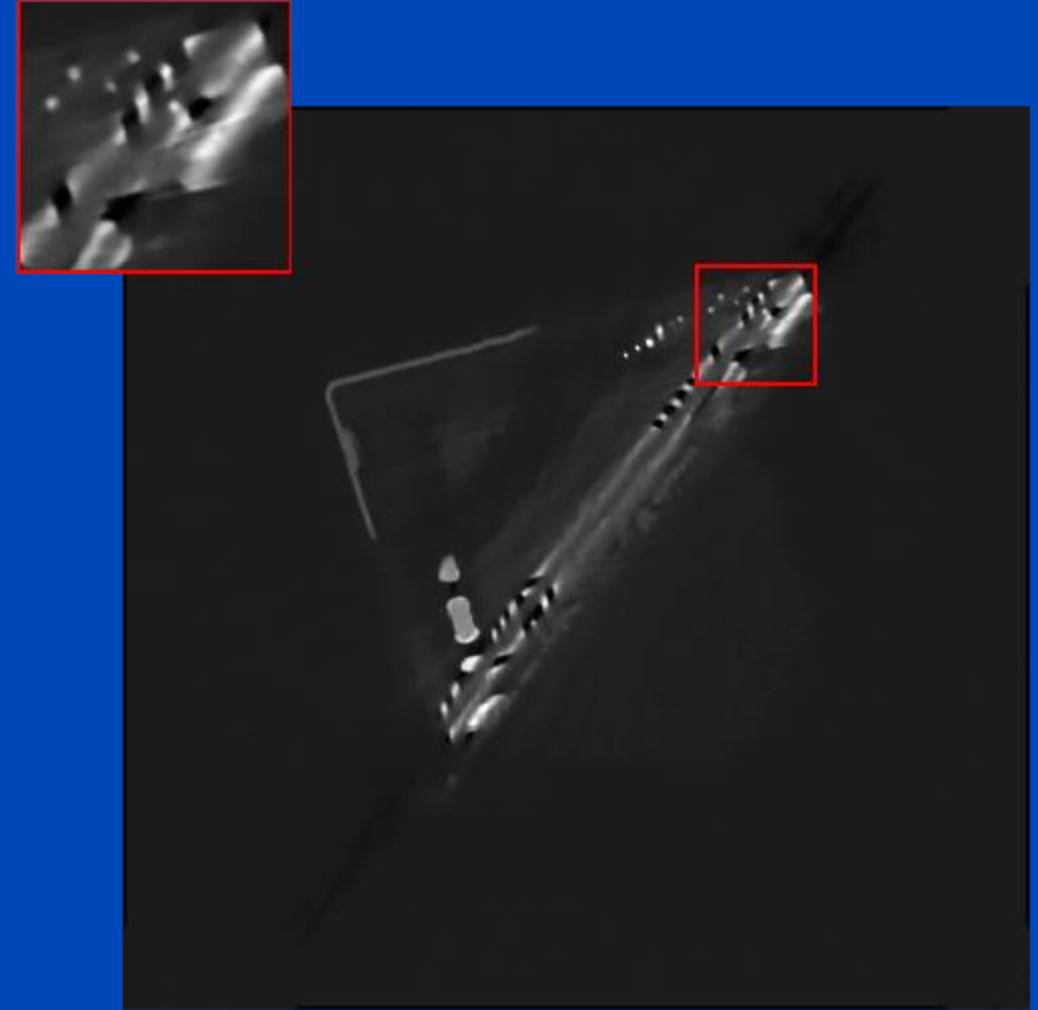
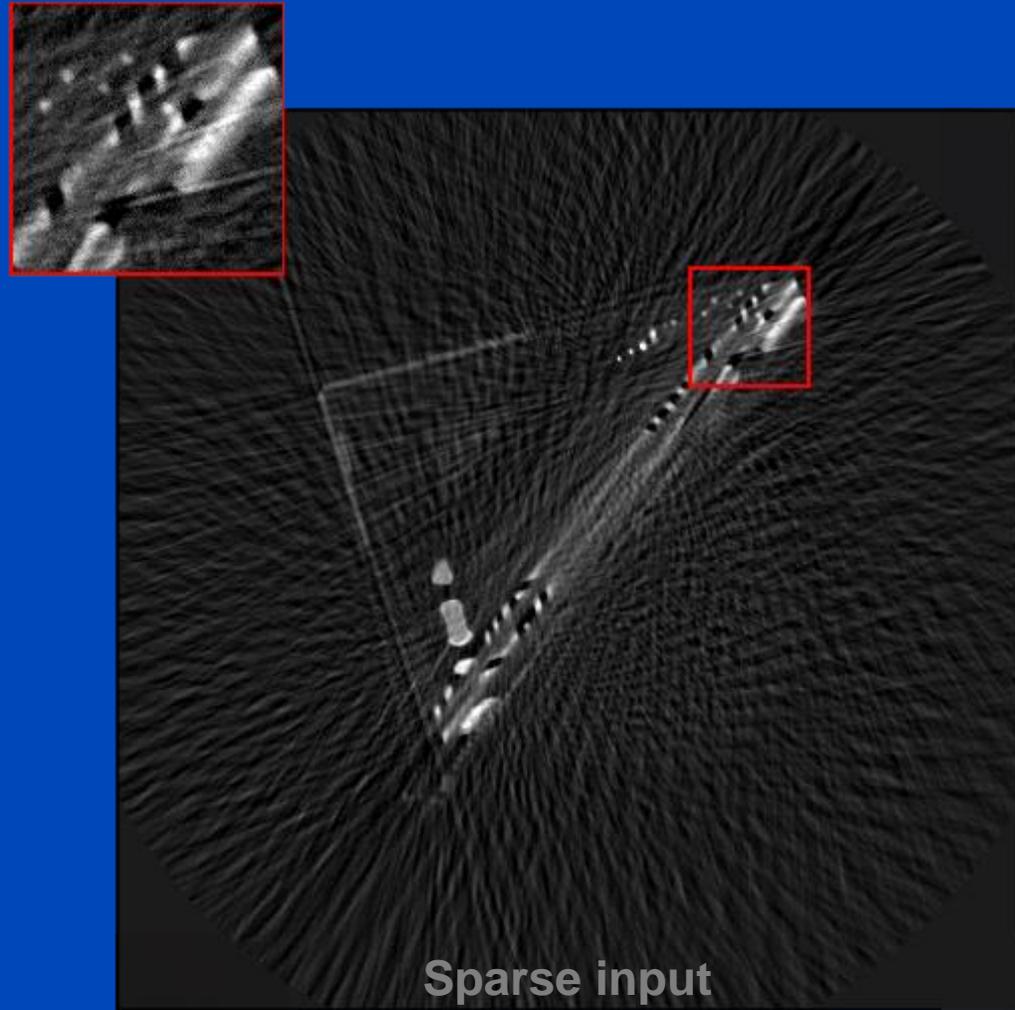
Test Data (UN) · Sh-Unet-MSE



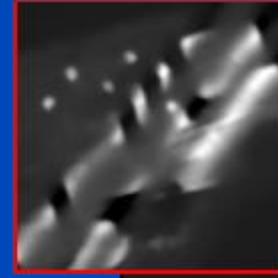
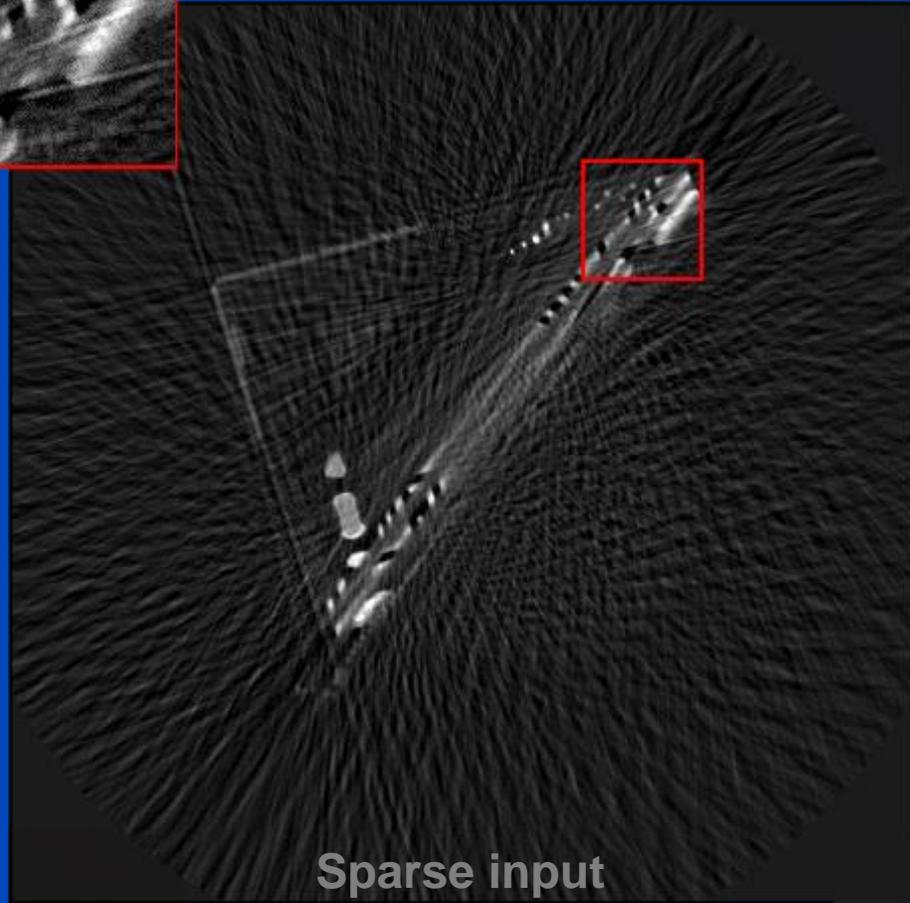
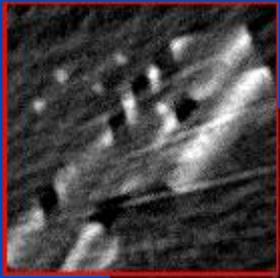
Ground Truth



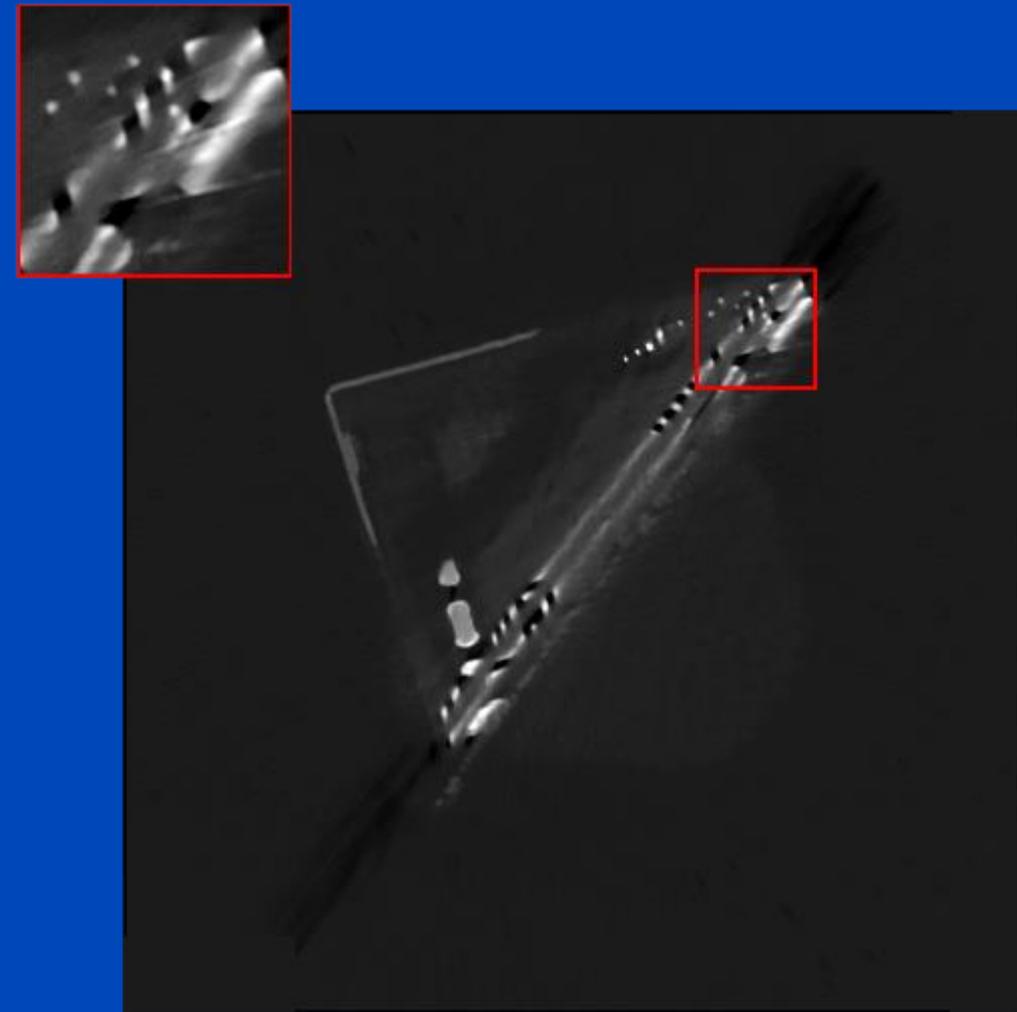
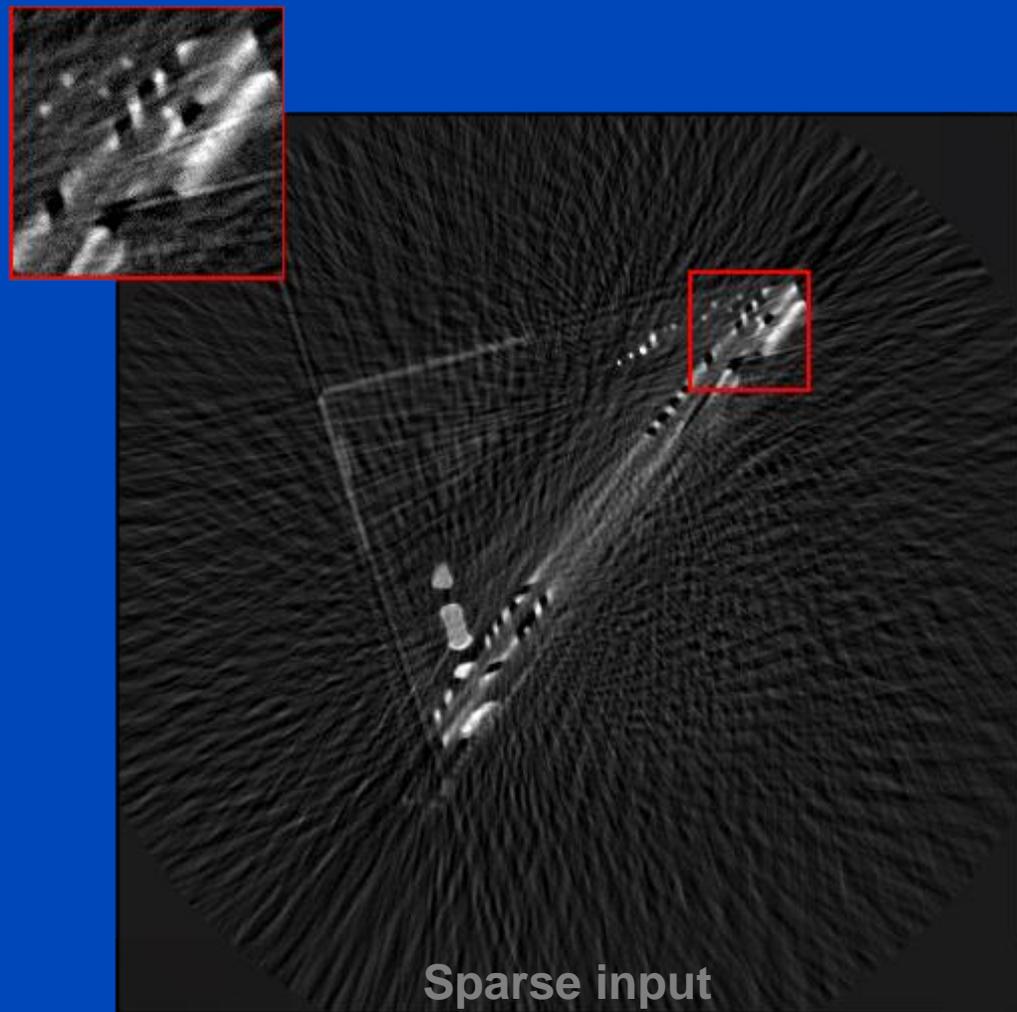
Shallow Unet



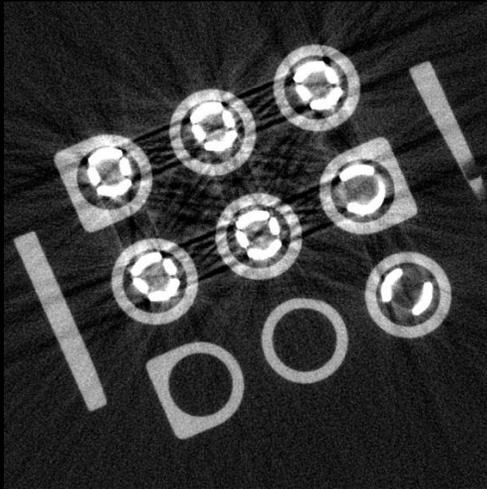
Deep Unet



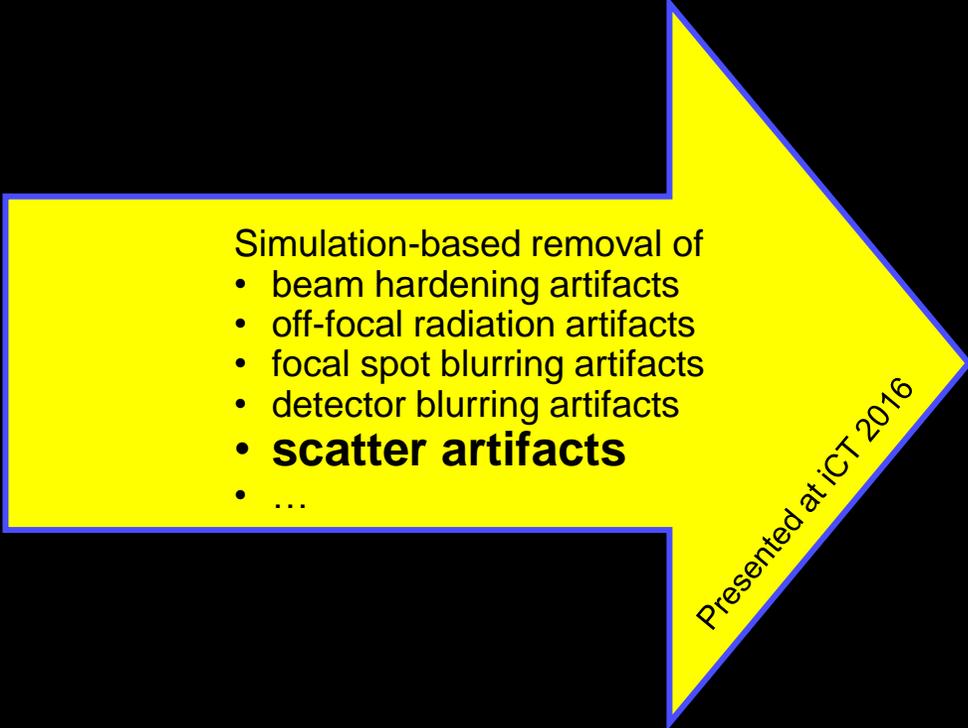
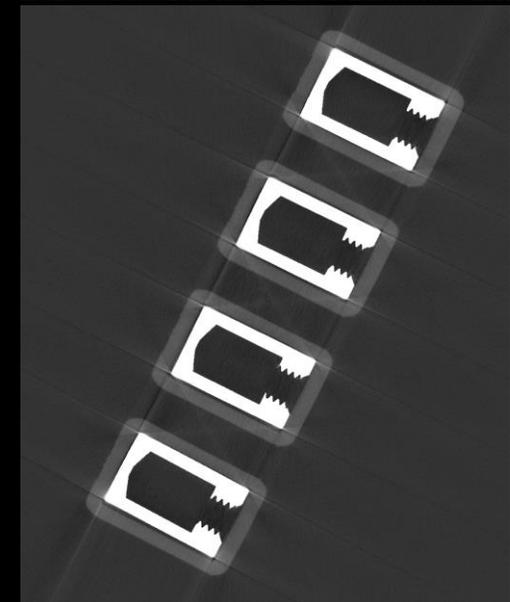
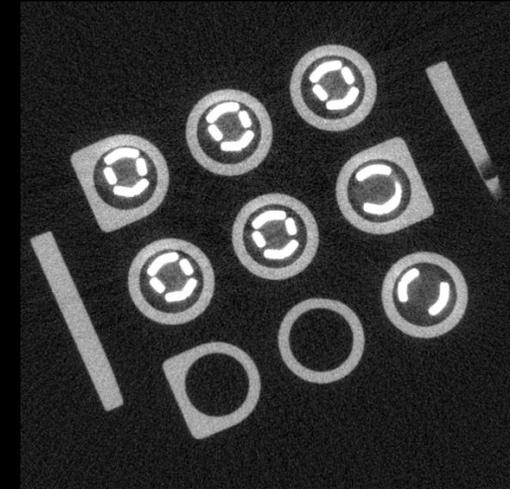
Deep Adversarial Unet



Standard reconstruction



Simulation-based artifact correction



- Simulation-based removal of
- beam hardening artifacts
 - off-focal radiation artifacts
 - focal spot blurring artifacts
 - detector blurring artifacts
 - **scatter artifacts**
 - ...

Presented at ICT 2016

Deep Scatter Estimation (DSE)



TOP DOWNLOADED PAPER 2018-2019

CONGRATULATIONS TO

Marc Kachelrieß

whose paper has been recognized as
one of the most read in

Medical Physics

This work received the
Behnken-Berger Award
at the DGMP annual meeting 2021

BEHNKEN-BERGER  STIFTUNG

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MEDICAL PHYSICS

The International Journal of Medical Physics Research and Practice

Congratulations — your work was one of the top
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Dear MARC,

We are excited to share that your research, published in [Medical Physics](#), is
among the top 10% most downloaded papers!

- [Real-time scatter estimation for medical CT using the deep scatter estimation: Method and robustness analysis with respect to different anatomies, dose levels, tube voltages, and data truncation](#)

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CONGRATULATIONS TO

Joscha Maier

whose paper has been recognized as
one of the most read in

Medical Physics

Monte Carlo Scatter Estimation

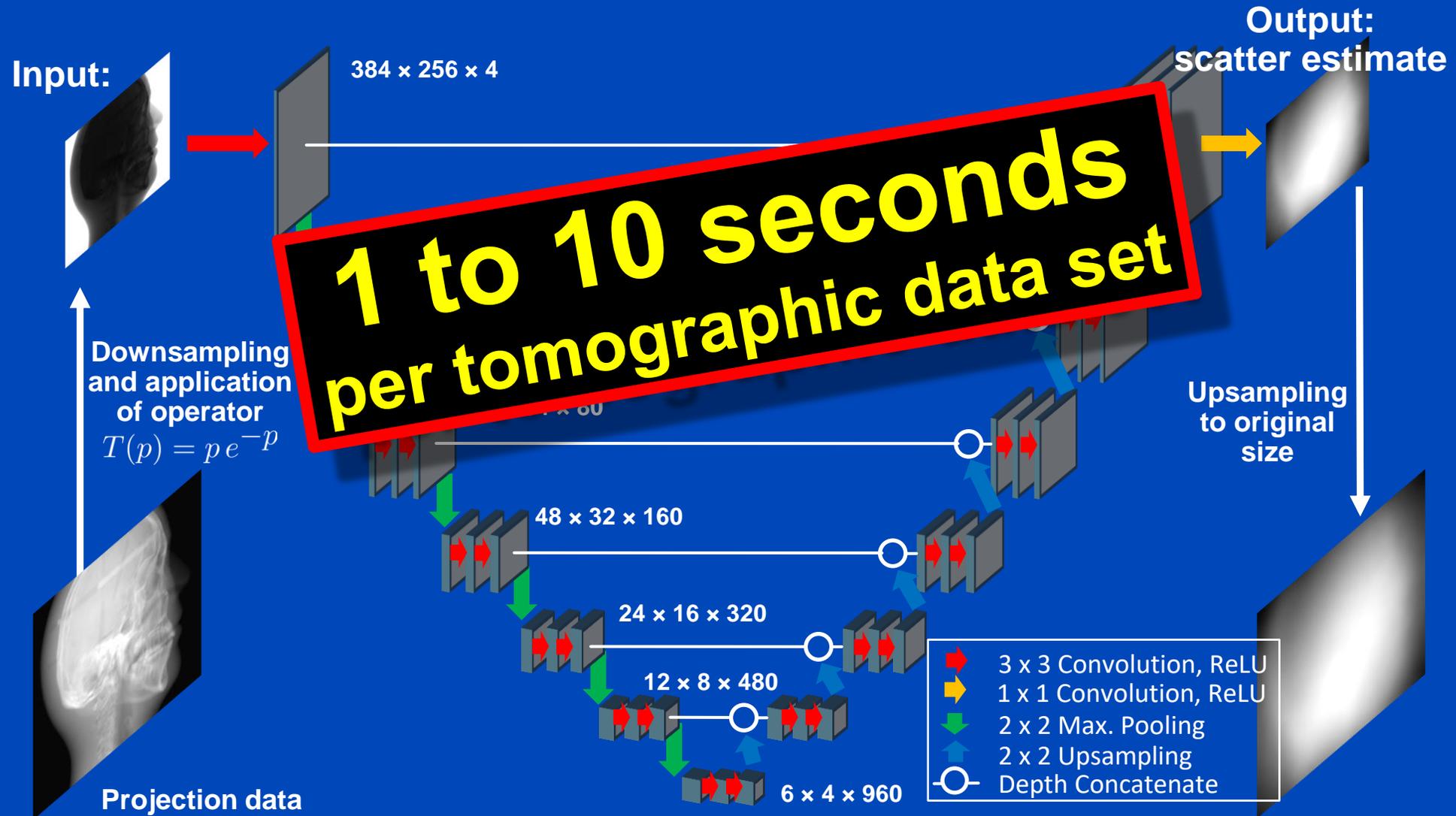
- Simulation of photon trajectories according to physical interaction probabilities.
- Simulating a large number of photons \rightarrow approximates the actual scatter distribution

**1 to 10 hours
per tomographic data set**



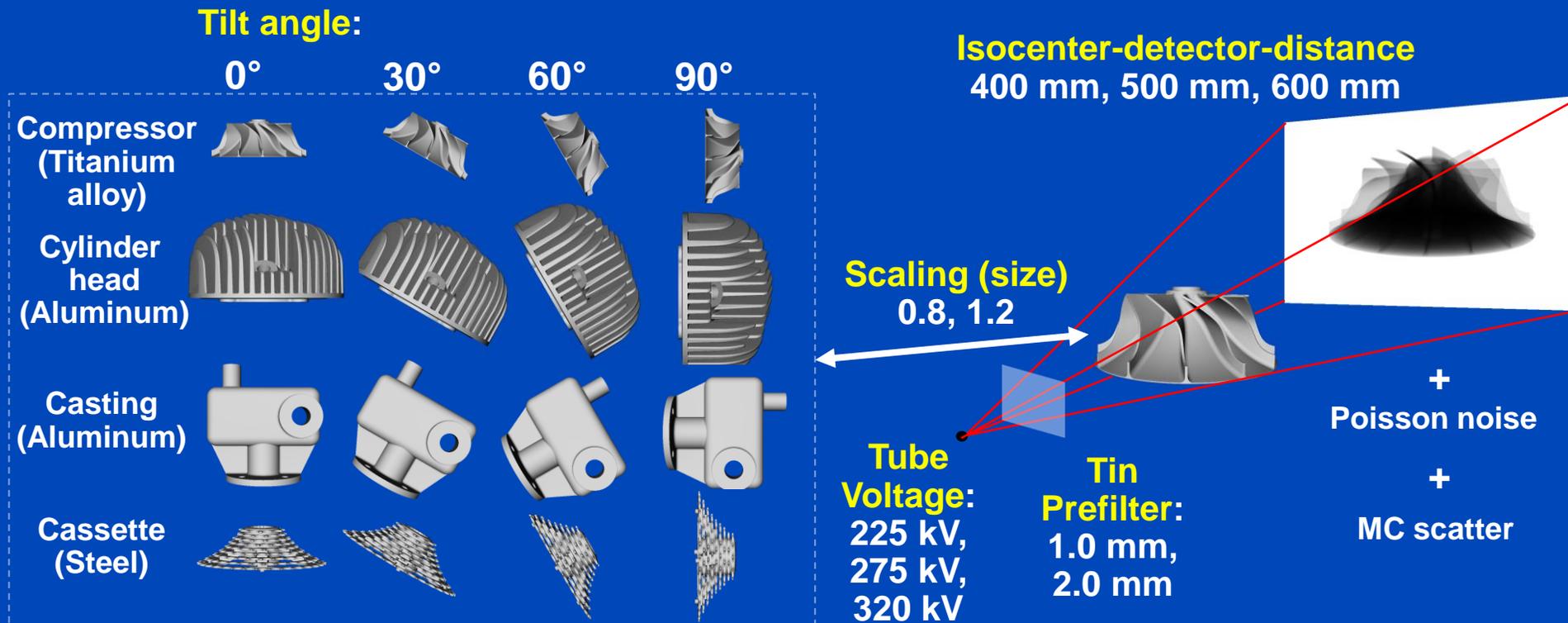
Deep Scatter Estimation

Network architecture & scatter estimation framework



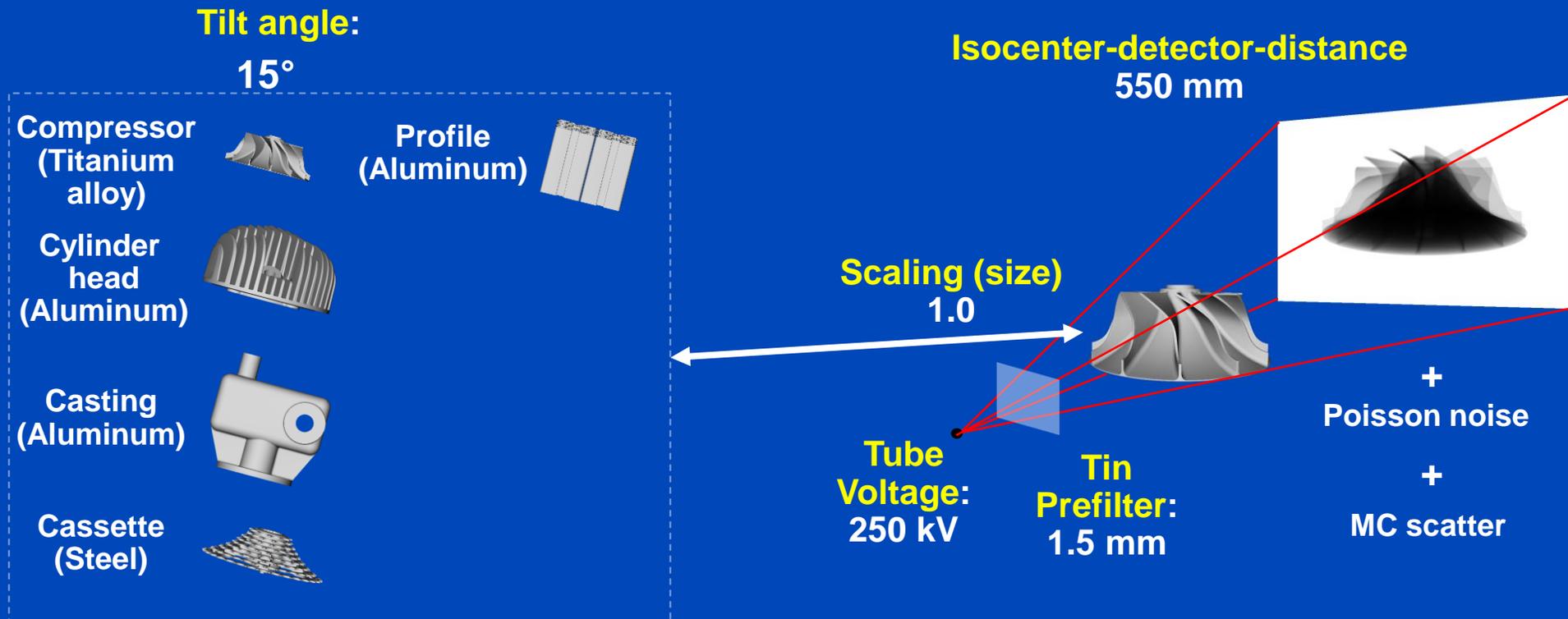
Simulation Study: Training Data

- Simulation of 16416 projections using different objects and parameter settings to train the DSE network.
- Training on a GeForce GTX 1080 for 80 epochs using the Keras framework, an Adam optimizer and a mini-batch size of 16.



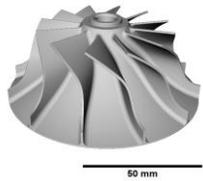
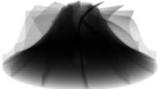
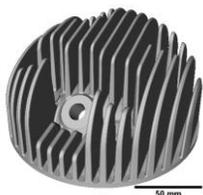
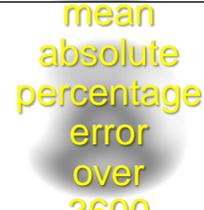
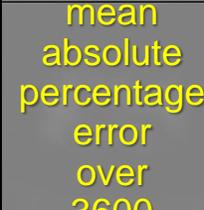
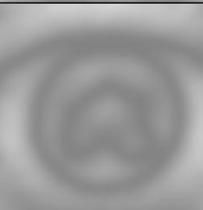
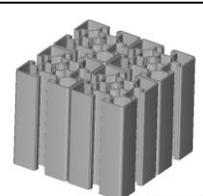
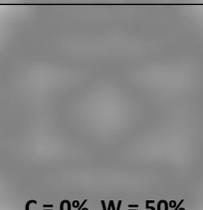
Simulation Study: Testing Data

- Simulation of a tomography (720 projection / 360°) of five components using acquisition parameters that differ from the ones used to generate the training data set.



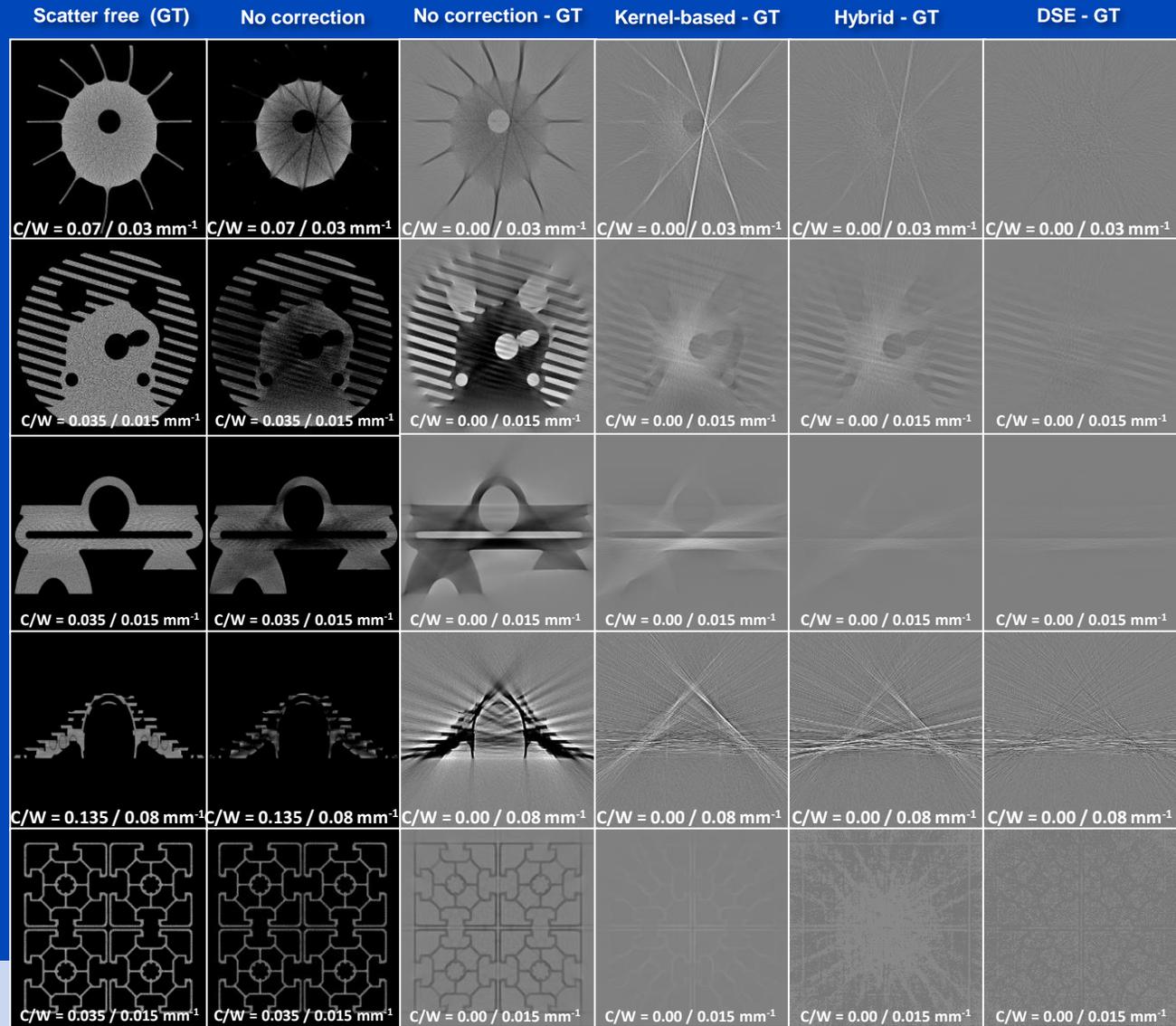
Results

Scatter estimates for simulated testing data

Model	Primary intensity	Scatter ground truth (GT)	$ \text{Kernel} - \text{GT} / \text{GT}$	$ \text{Hybrid} - \text{GT} / \text{GT}$	$ \text{DSE} - \text{GT} / \text{GT}$
			 13%	 7%	 1%
			 mean absolute percentage error over 3600 projections	 mean absolute percentage error over 3600 projections	 mean absolute percentage error over 3600 projections
			 projections	 projections	 projections
					
	 C = 0.5, W = 1.0	 C = 0.015, W = 0.020	 C = 0%, W = 50%	 C = 0%, W = 50%	 C = 0%, W = 50%

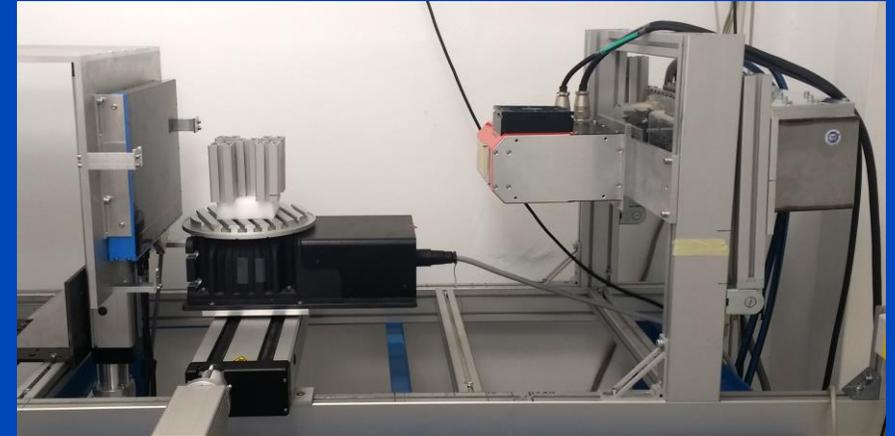
Results

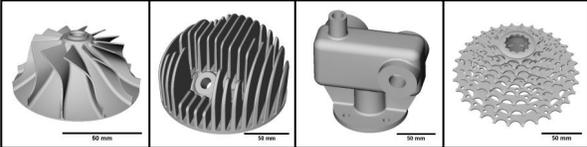
CT reconstructions of scatter corrected testing data



Application to Measured Data

- Measurement at DKFZ table-top CT
- Tomography of aluminum profile
- 720 projections, 360°
- 110 kV Hamamatsu micro-focus tube
- Varian flat detector

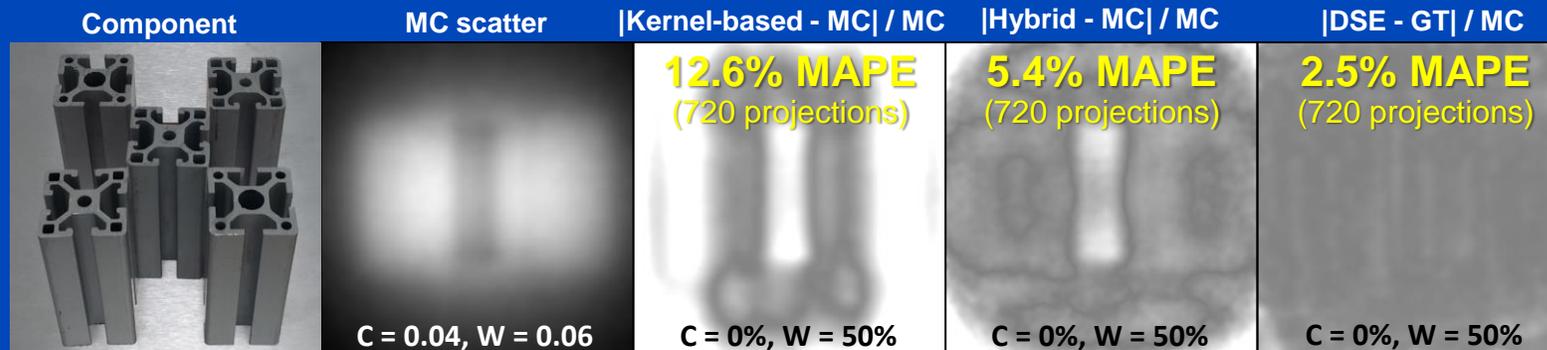


	Training	Testing
Components		
Detector elements	768x768	768x768
Source-detector distance	580 mm	580 mm
Source-isocenter distance	100 mm, 110 mm, 120 mm	110 mm
Tilt angle	0°, 30°, 60°, 90°	0°
Tube voltage	100 kV, 110 kV, 120 kV	110 kV
Copper prefilter	1.0 mm, 2.0 mm	2.0 mm
Scaling	1.0	-
Number of projections	8208	720

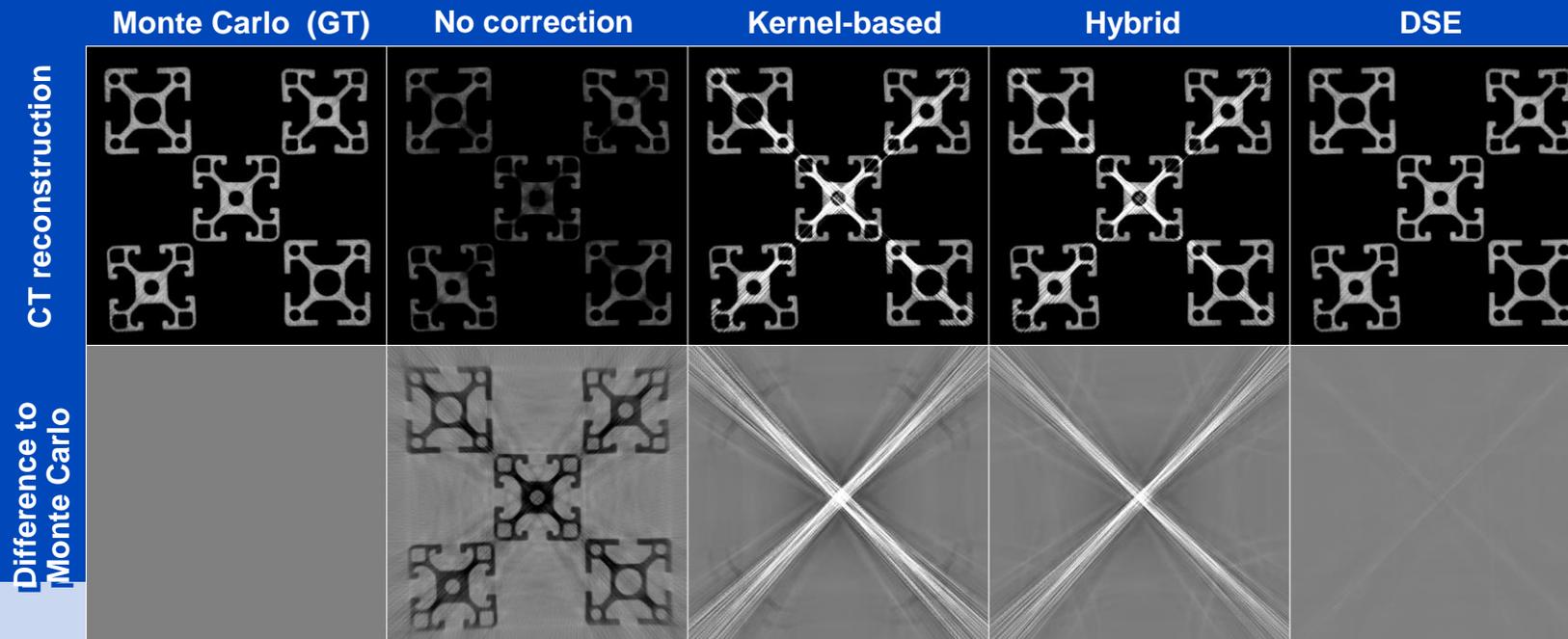
Results

Performance of DSE for measured data

Projection data

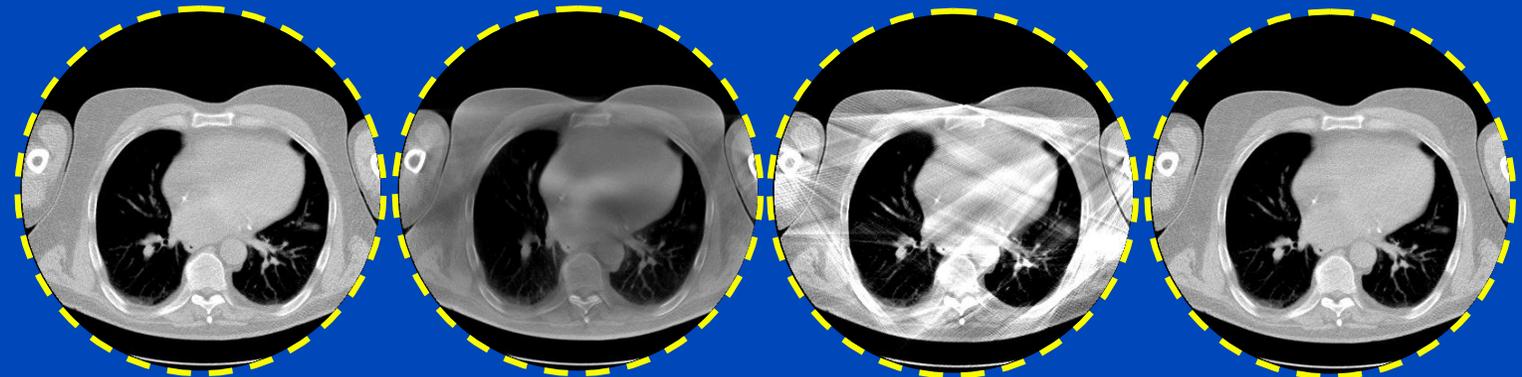
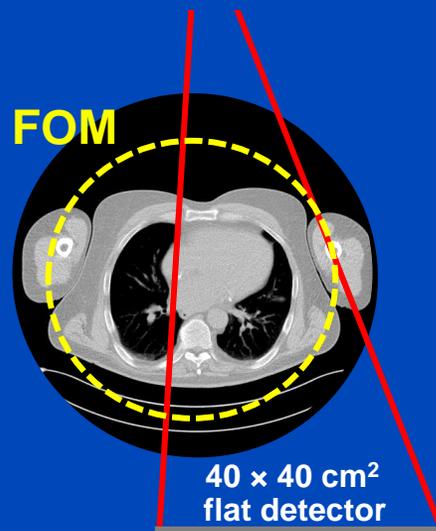
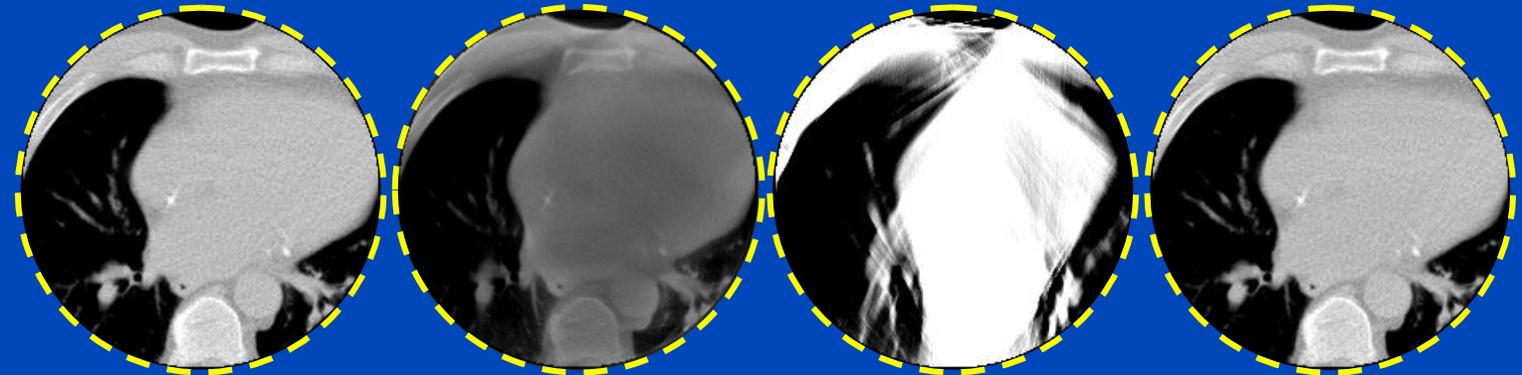
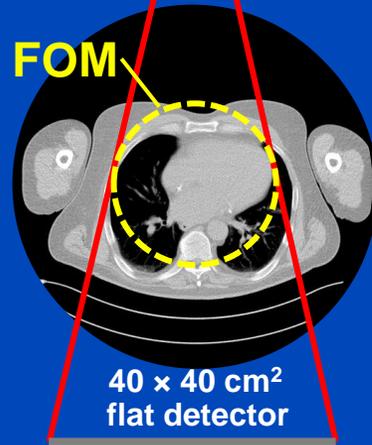


Reconstructions



A simple detruncation was applied to the rawdata before reconstruction. Images were clipped to the FOM before display. $C = -200$ HU, $W = 1000$ HU.

Truncated DSE

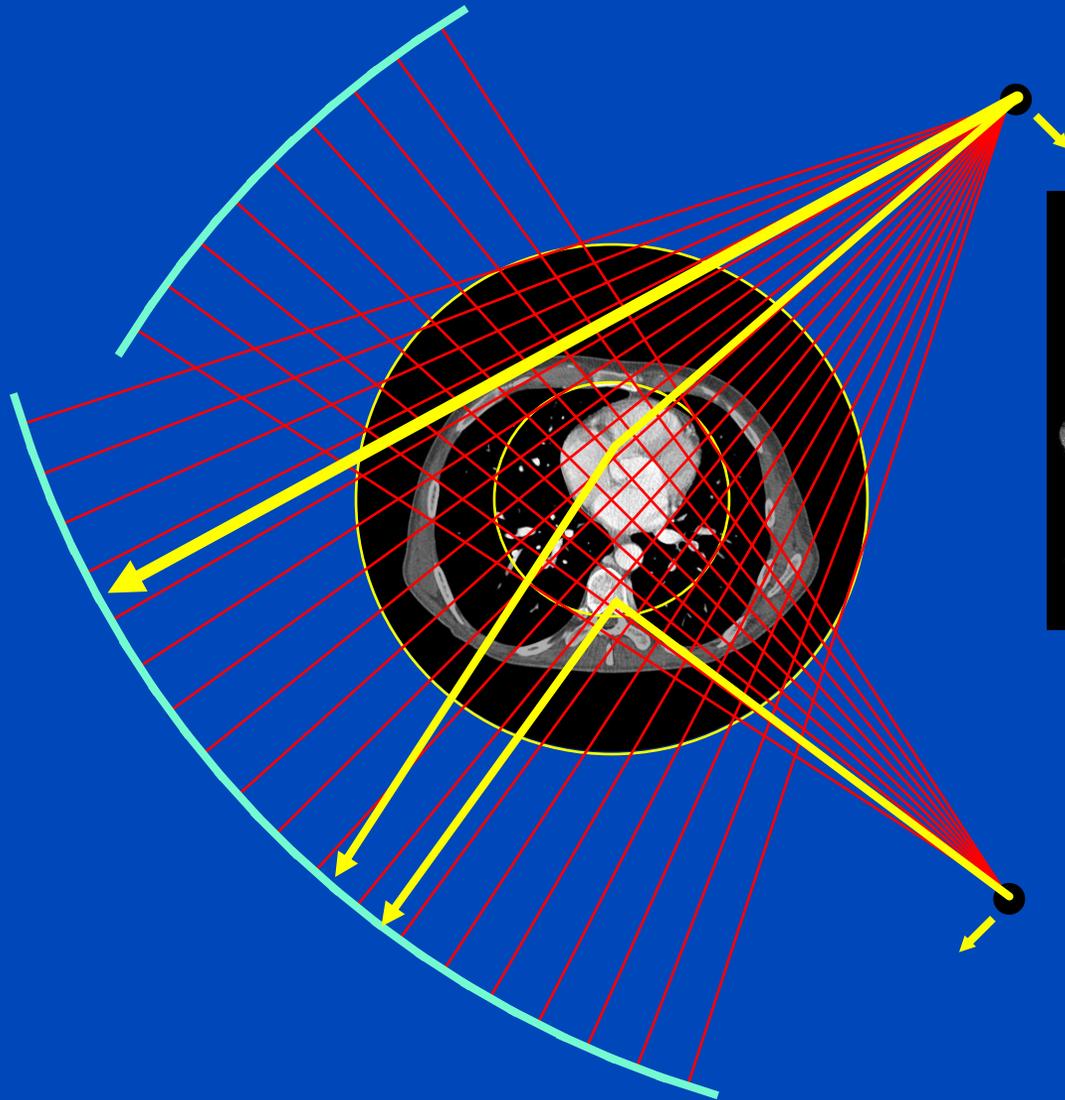


To learn why MC fails at truncated data and what significant efforts are necessary to cope with that situation see [Kachelrieß et al. Effect of detruncation on the accuracy of MC-based scatter estimation in truncated CBCT. Med. Phys. 45(8):3574-3590, August 2018].

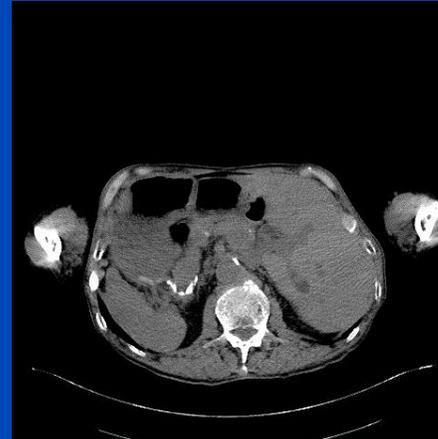
J. Maier, M. Kachelrieß et al. Deep scatter estimation (DSE). SPIE 2017 and Journal of Nondestructive Evaluation 37:57, July 2018.

J. Maier, M. Kachelrieß et al. Robustness of DSE. Med. Phys. 46(1):238-249, January 2019.

DSE for Cross-Scatter Correction (xDSE)



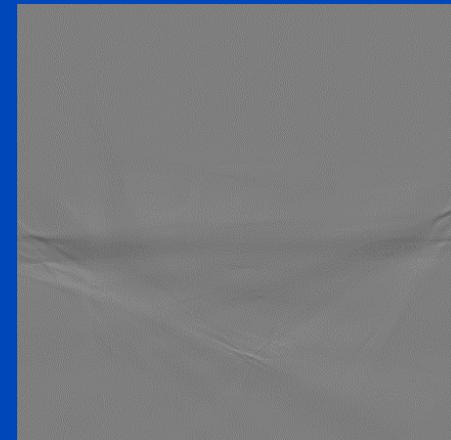
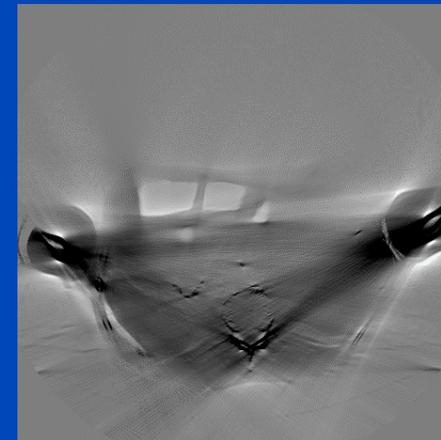
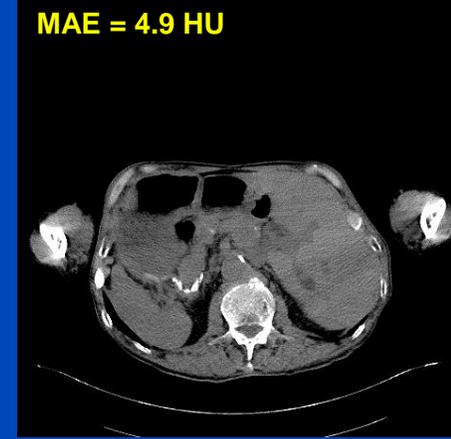
Ground Truth



Uncorrected



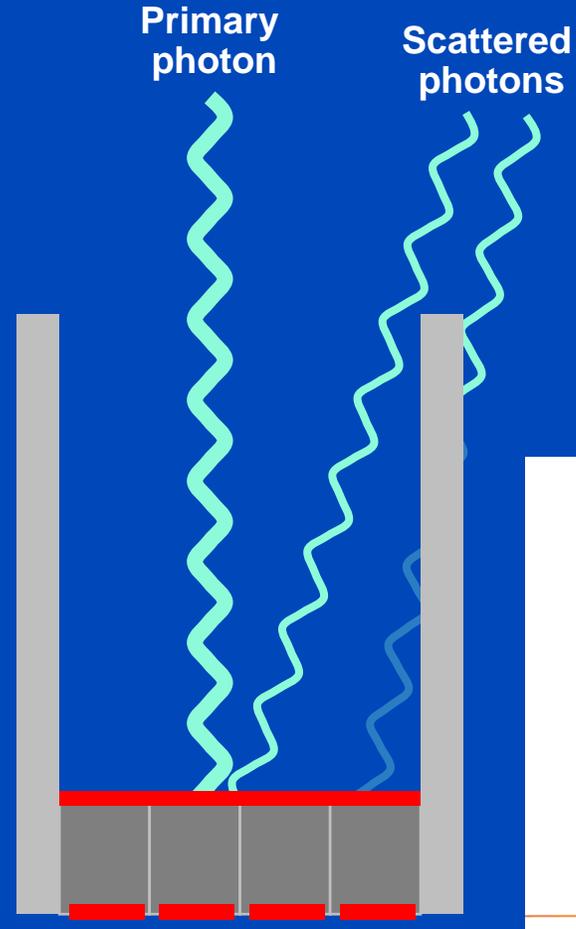
xDSE (2D, xSSE)



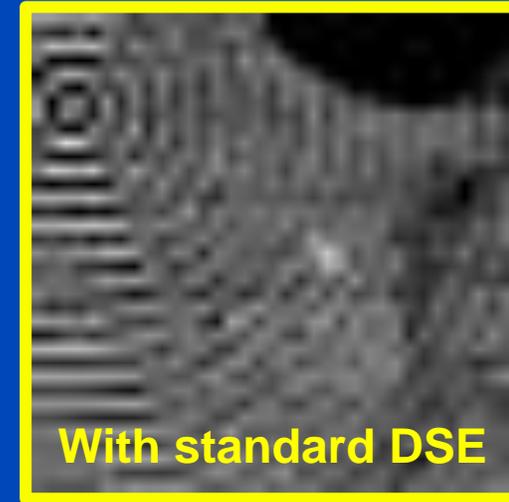
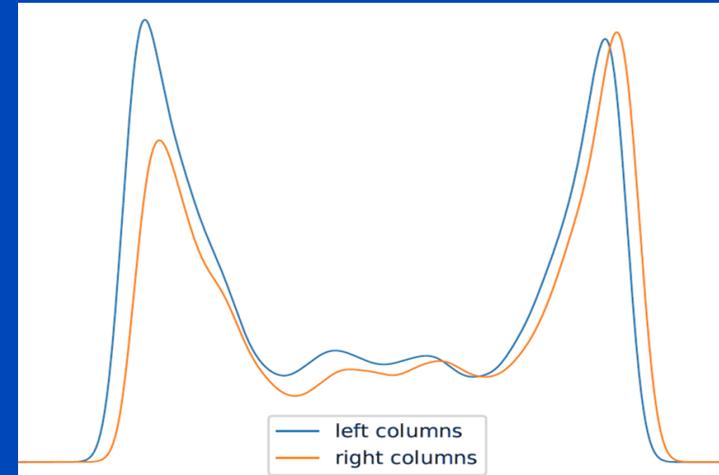
Images $C = 40$ HU, $W = 300$ HU, difference images $C = 0$ HU, $W = 300$ HU

DSE for Coarse ASG

Coarse ASG
Naeotom Alpha
1376 × 144 macro pixels
pixel size 0.3 × 0.352 mm at iso



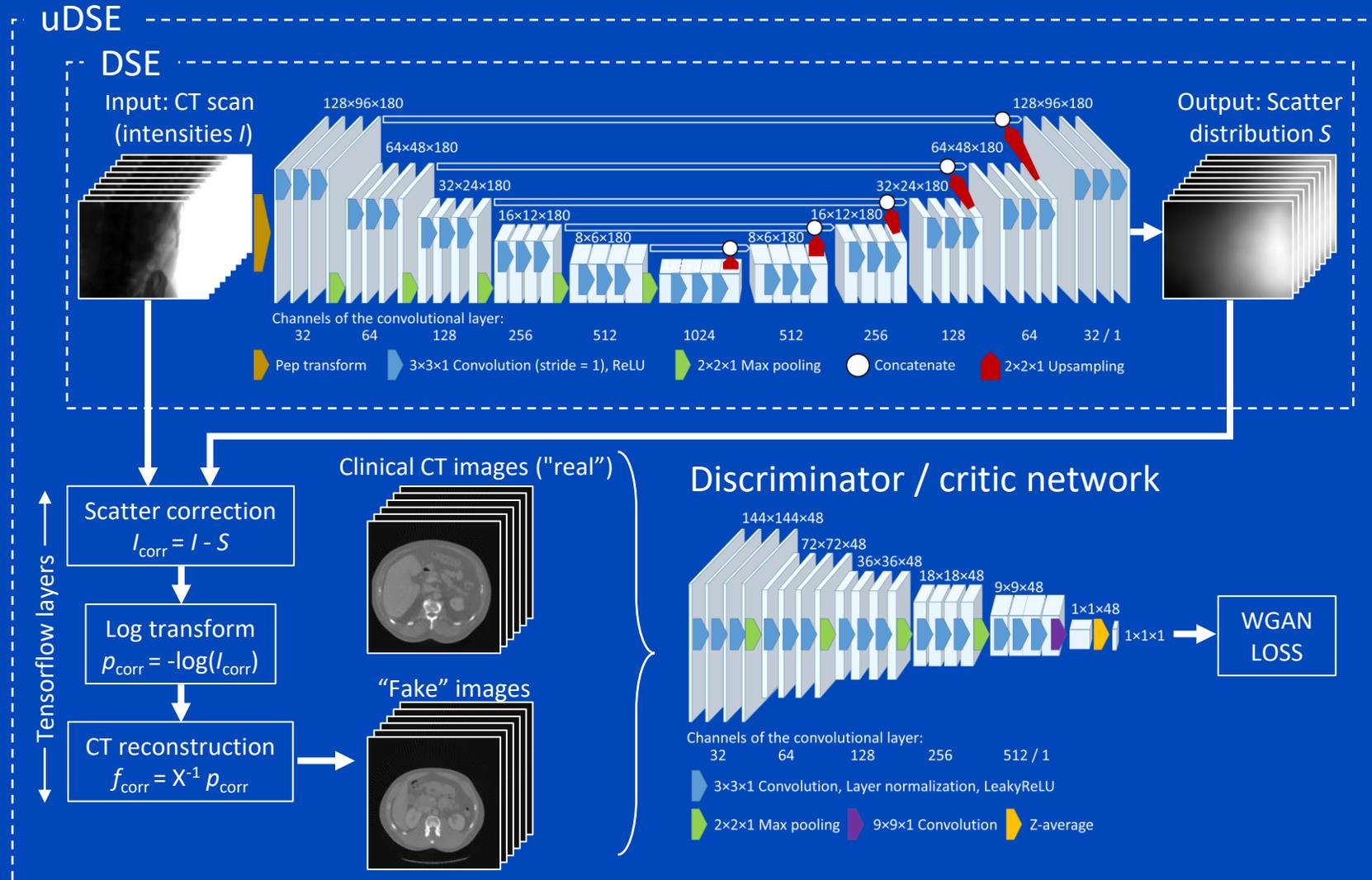
Coarse ASGs lead to changing scatter intensity between neighboring pixels.



Conclusions on DSE

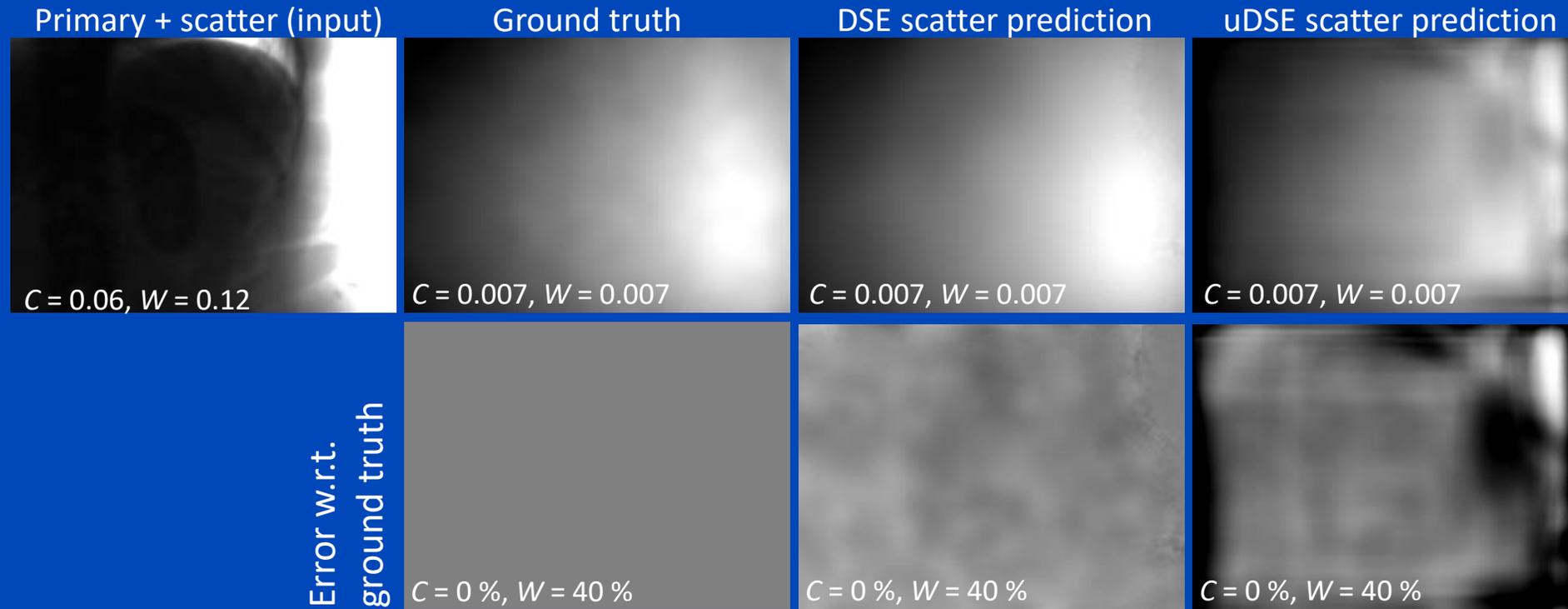
- DSE needs about 1 ms per projection.
- DSE is a fast and accurate alternative to MC simulations.
- DSE outperforms other approaches in terms of accuracy and speed.
- Facts:
 - DSE can estimate scatter from a single (!) x-ray image.
 - DSE generalizes well to different geometries, scanners and objects.
 - DSE variants for cross-scatter and coarse ASG scatter prediction are available.
 - DSE may outperform MC even though DSE is trained with MC.
- DSE is not restricted to reproducing MC scatter estimates.
- DSE can rather be trained with any other scatter estimate, including those based on measurements.
- DSE can also be used to simulate scatter (at somewhat lower accuracy).

uDSE – Basis Principle



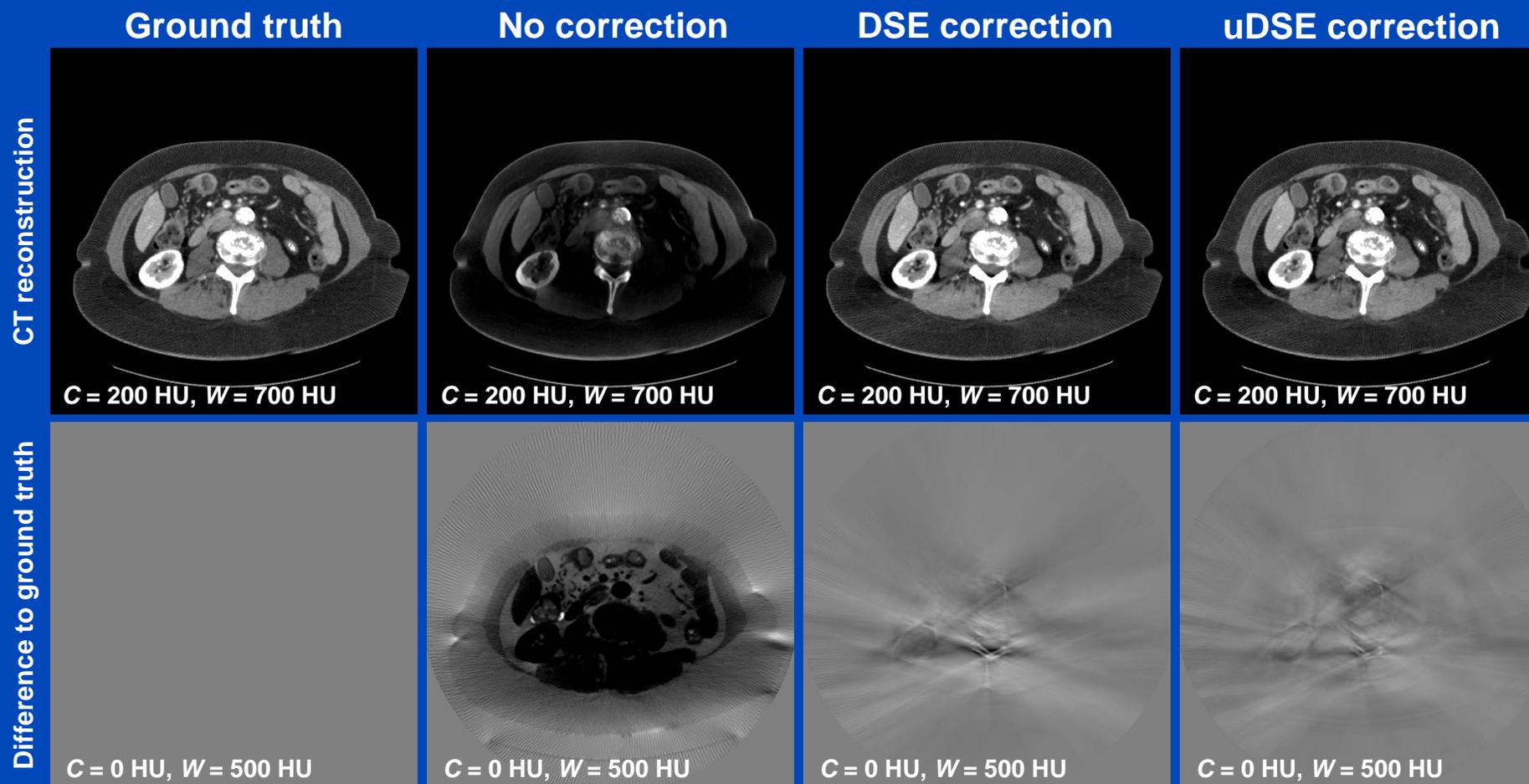
Results

Scatter Estimates



Results

CT Reconstructions



Summary on AI for CT Image Formation

- **Powerful tool that allows to solve yet unsolved problems**
 - Underdetermined situations, where AI brings in prior knowledge
 - Computational demanding problems, where AI reduces the compute time
 -
- **Results have to be taken with care**
 - Images often look great, but are they true?
 - Utilizing too much prior knowledge will result in fake content
 - Proves do not exist, the networks' output cannot be explained
 -
- **Vendors may tend to overemphasize the benefits from AI**
 - Sale by nice looking images

Thank You!

- This presentation will soon be available at www.dkfz.de/ct.
- Job opportunities through DKFZ's international PhD or Postdoctoral Fellowship programs (marc.kachelriess@dkfz.de).
- Parts of the reconstruction software were provided by RayConStruct[®] GmbH, Nürnberg, Germany.



The 8th International Conference on Image Formation in X-Ray Computed Tomography

August 5 – August 9, 2024, Bamberg, Germany
www.ct-meeting.org



Conference Chair

Marc Kachelrieß, German Cancer Research Center (DKFZ), Heidelberg, Germany

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