Deep Scatter Estimation (DSE): Accurate Real-Time Scatter Estimation for X-Ray CT using a Deep Convolutional Neural Network

Joscha Maier[1,2], Stefan Sawall[1,2], and Marc Kachelrieß[1,2]

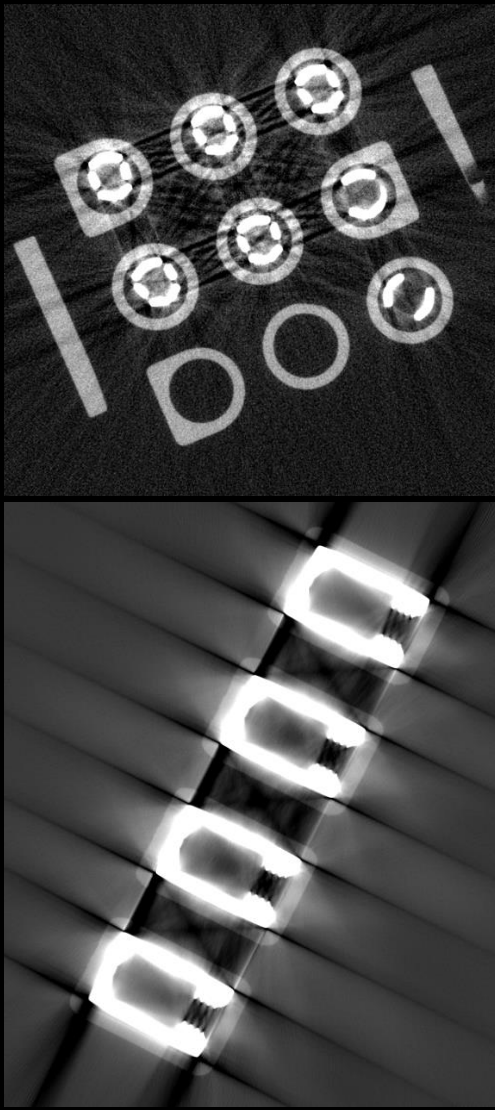
[1]German Cancer Research Center (DKFZ), Heidelberg, Germany

[2]Ruprecht-Karls-Universität, Heidelberg, Germany

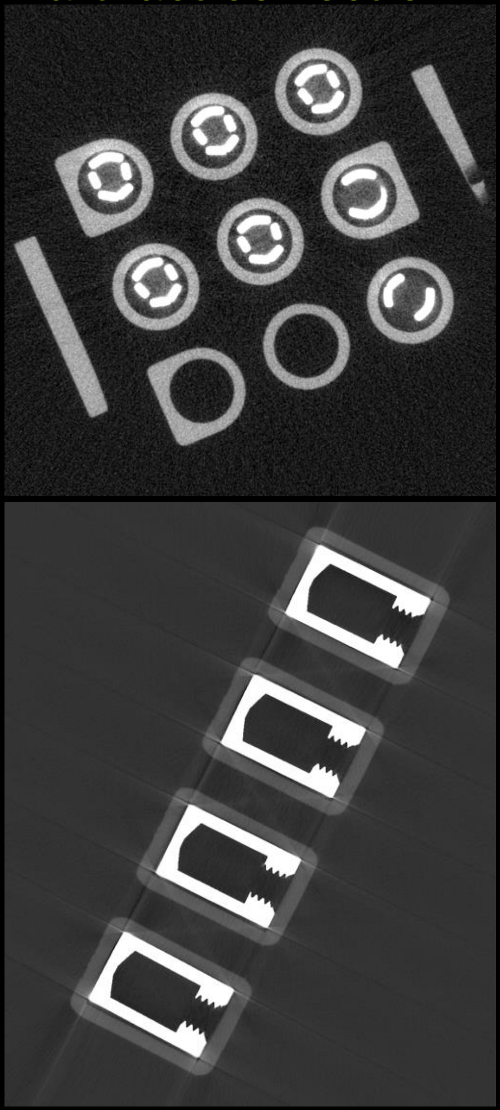
DEUTSCHES KREBSFORSCHUNGSZENTRUM IN DER HELMHOLTZ-GEMEINSCHAFT

Wels 2016

Standard reconstruction



Simulation-based artifact correction



Simulation-based removal of

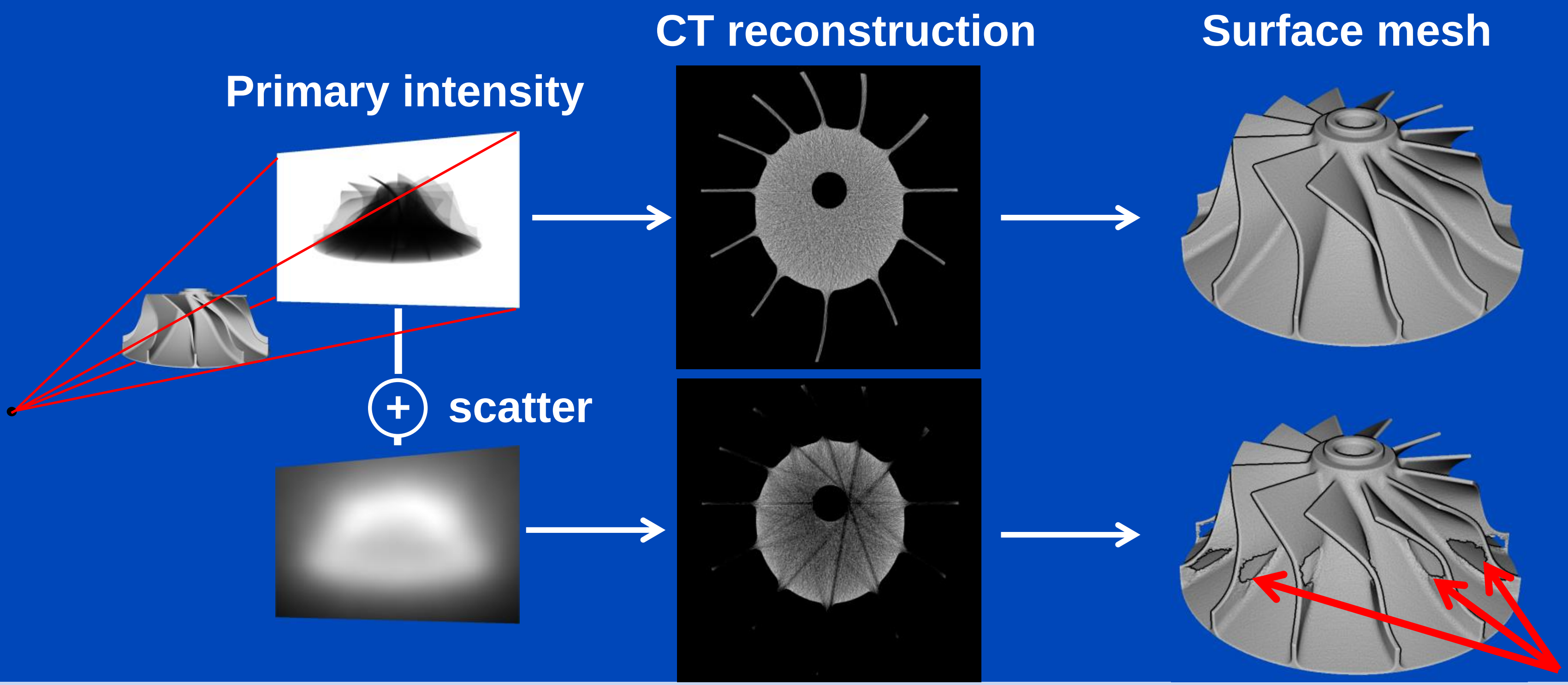
- beam hardening artifacts
- off-focal radiation artifacts
- focal spot blurring artifacts
- detector blurring artifacts
- **scatter artifacts**
- …

Presented at Wels 2016

J. Maier, M. Kachelrieß et al. Simulation-based artifact correction (SBAC) for metrological computed tomography. Meas. Sci. Technol. 28(6):065011, May 2017.

Motivation

- X-ray scatter is a major cause of image quality degradation in CT.
- Appropriate scatter correction is crucial to maintain the accuracy of the CT measurement.



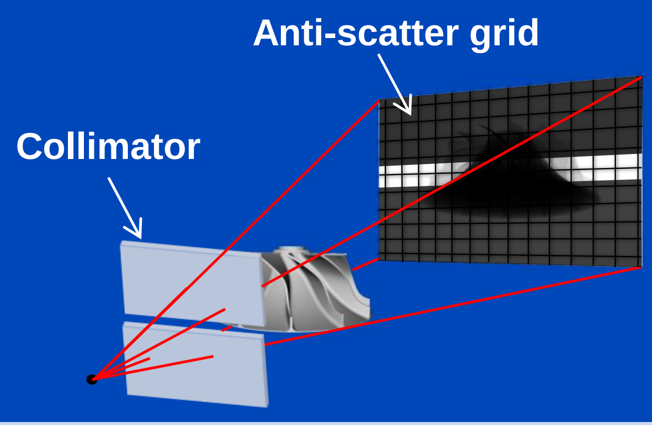
Scatter Correction

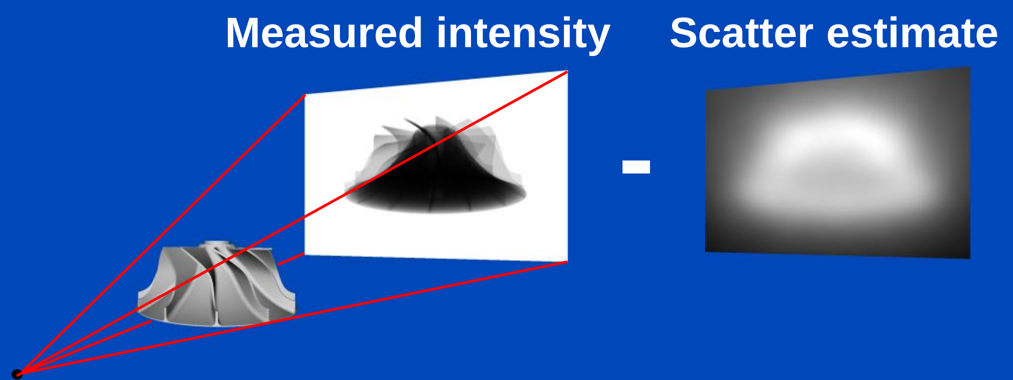
Scatter suppression

- Anti-scatter grids
- Collimators
- …

Scatter estimation

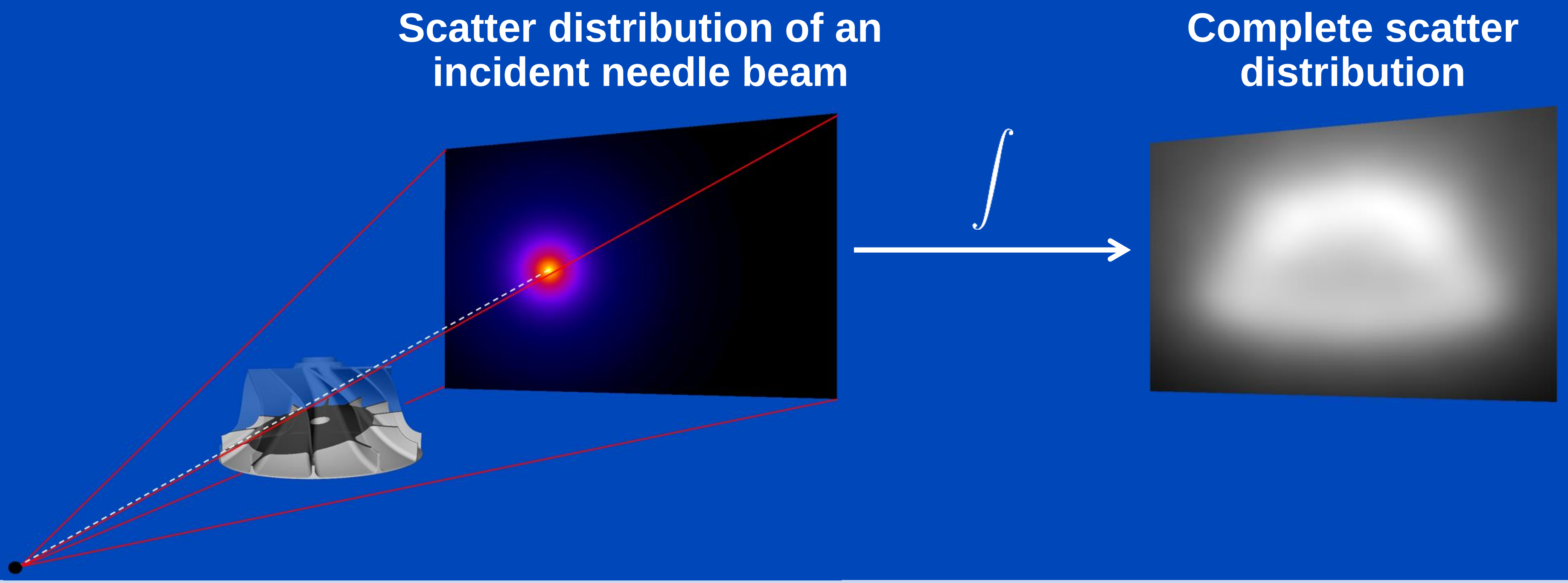
- Monte Carlo simulation
- Kernel-based approaches
- Primary modulation
- Beam blockers
- Boltzmann transport
- …





Monte Carlo Scatter Estimation

- Simulation of photon trajectories according to physical interaction probabilities.
- Simulating a large number of photon trajectories well approximates the expectation value of the actual scatter distribution.

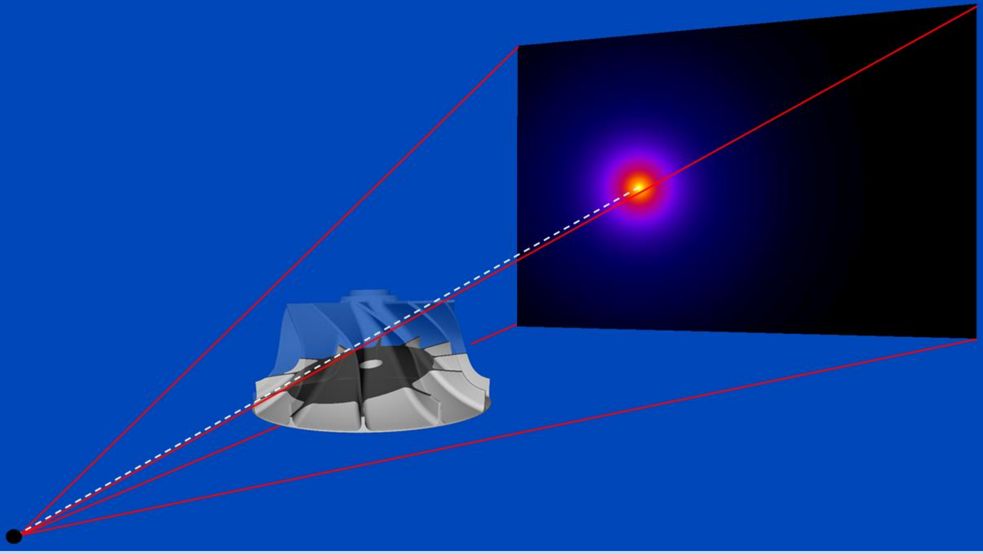


Kernel-Based Scatter Estimation

$T(p)$

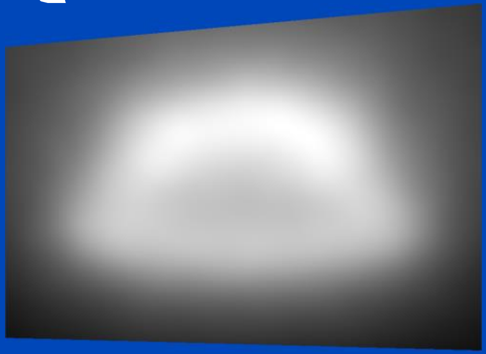
Estimate needle beam scatter kernels as a function of the projection data p

$$I_{\mathrm{s,\ est}}(\boldsymbol{u}) = \int T(p)(\boldsymbol{u}')G(\boldsymbol{u},\boldsymbol{u}',\boldsymbol{c})d\boldsymbol{u}'$$



Estimate mean scatter kernel that maps a function of the projection data p **to scatter distribution**

$$I_{\mathrm{s,\ est}}(\boldsymbol{u}) = T(p)(\boldsymbol{u}) * G(\boldsymbol{u},\boldsymbol{c})$$



Deep Scatter Estimation (DSE)

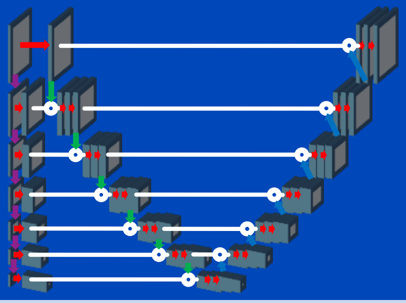
Idea

- **Use a deep convolutional neural network to estimate scatter using a function of the acquired projection data as input.**

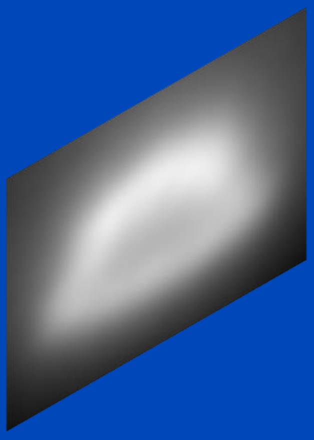
Input: $T(p)$

$$\int T(p)(\boldsymbol{u}')C(\boldsymbol{u},\boldsymbol{u}',\boldsymbol{c})d\boldsymbol{u}'$$

Convolutional neural network



Scatter estimate



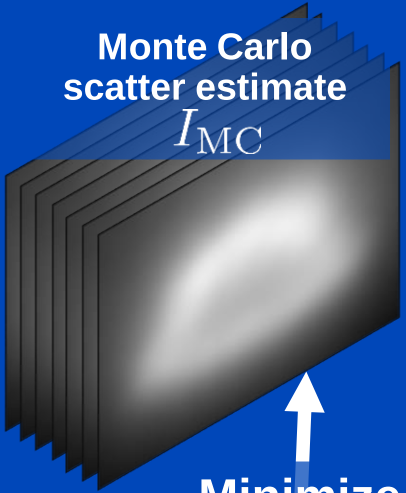
Deep Scatter Estimation (DSE)

Training of the network

- **Optimize weights and biases of convolutional network such that the mean squared error between the output and MC scatter simulations is minimal:**

$$\{w, b\} = \operatorname{argmin} ||DSE(T(p)) - I_{\mathrm{MC}}||_2^2$$

Monte Carlo scatter estimate I_{MC}

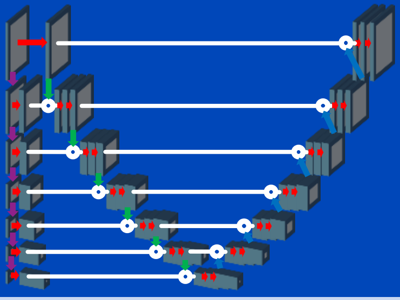


Minimize squared difference

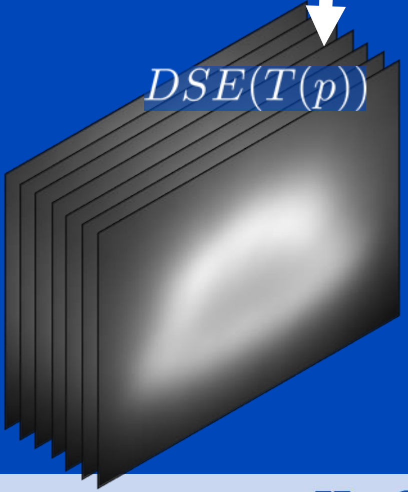
Input: $T(p)$

~~$\int T(p)(\boldsymbol{u}')C(\boldsymbol{u}, \boldsymbol{u}', \boldsymbol{c})d\boldsymbol{u}'$~~

Convolutional neural network

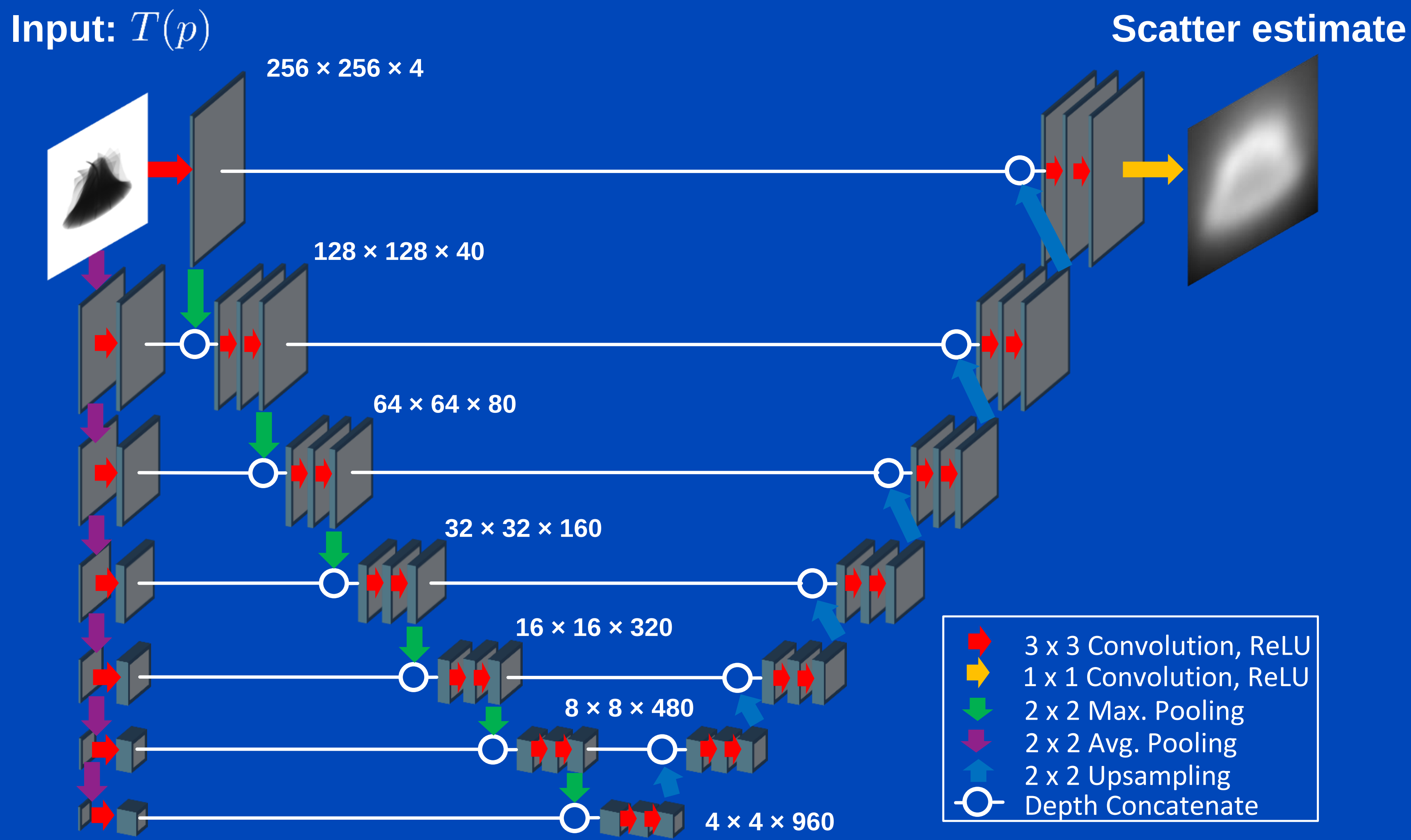


$DSE(T(p))$



Deep Scatter Estimation

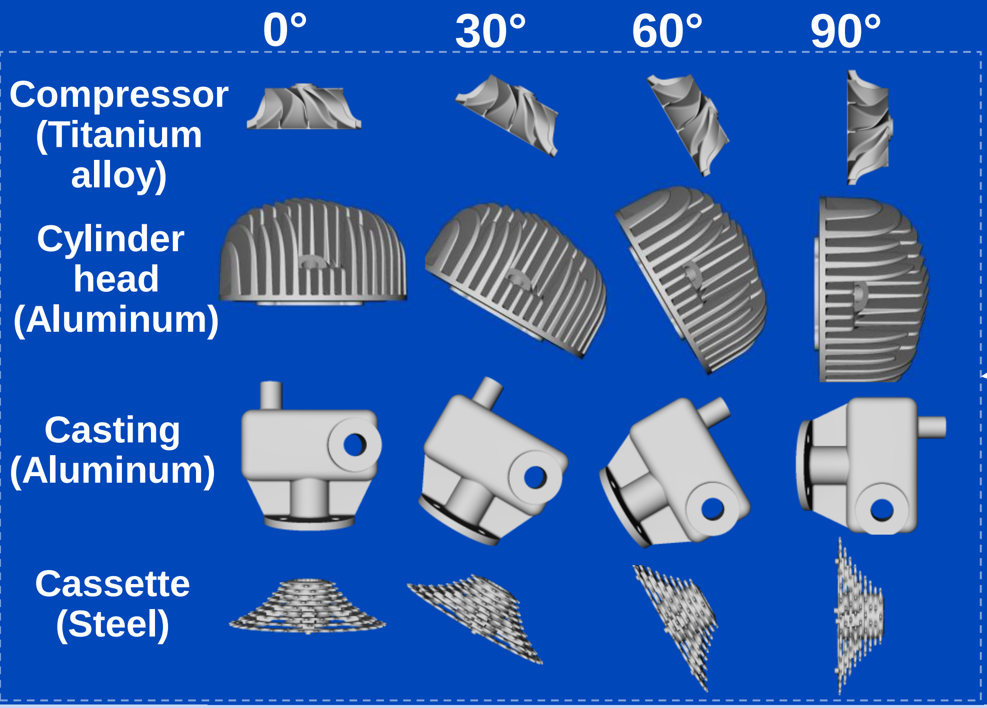
Network architecture



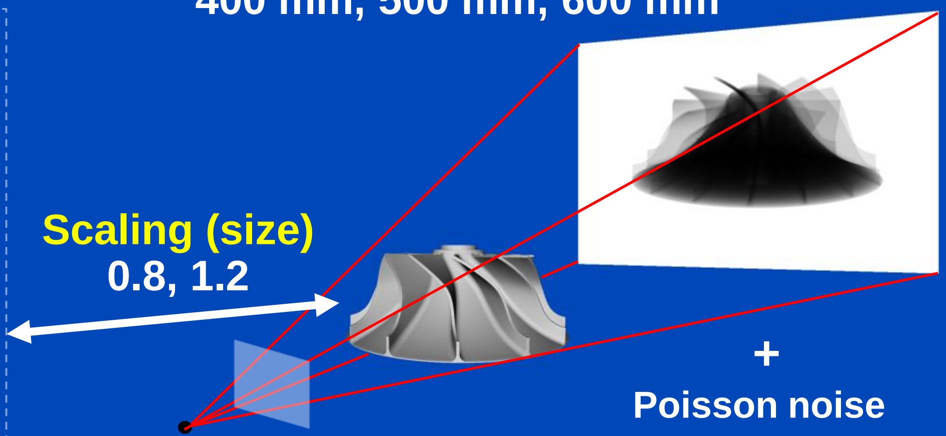
Simulation Study: Training Data

- 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.

Tilt angle:



Isocenter-detector-distance
400 mm, 500 mm, 600 mm



Tube Voltage:
225 kV,
275 kV,
320 kV

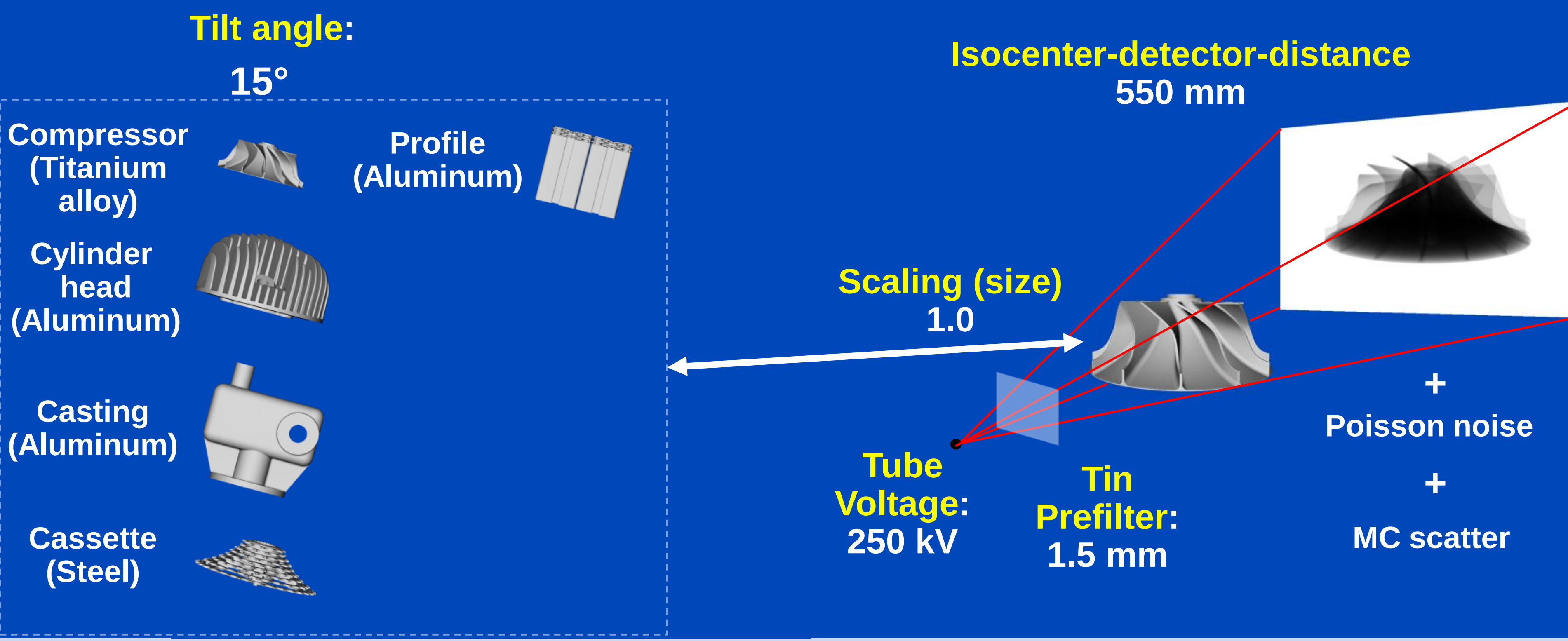
Tin Prefilter:
1.0 mm,
2.0 mm

\+ Poisson noise

\+ MC scatter

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.

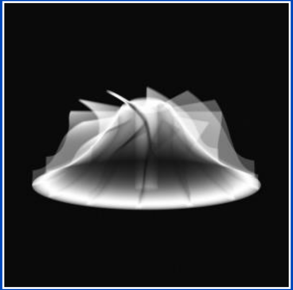


Reference 1

Kernel-based scatter estimation

- **Kernel-based scatter estimation[1]:**
  - **Estimation of scatter by a convolution of the scatter source term $T(p)$ with a scatter propagation kernel $G(\boldsymbol{u}, \boldsymbol{c})$:**

$$I_{\mathrm{s,\ est}}(\boldsymbol{u}) = \underbrace{\left(c_0 \cdot p(\boldsymbol{u}) \cdot e^{-p(\boldsymbol{u})}\right)}_{T(p)(\boldsymbol{u})} * \underbrace{\left(\sum_{\pm} e^{-c_1(\boldsymbol{u}\hat{\boldsymbol{e}}_1 \pm c_2)^2} \cdot \sum_{\pm} e^{-c_3(\boldsymbol{u}\hat{\boldsymbol{e}}_2 \pm c_4)^2}\right)}_{G(\boldsymbol{u},\boldsymbol{c})}$$



$T(p)(\boldsymbol{u})$

Open parameters: c_0

$G(\boldsymbol{u}, \boldsymbol{c})$

Open parameters: c_1, c_2, c_3, c_4

$$\{c_i\} = \operatorname{argmin} \sum_{n} \sum_{\boldsymbol{u}} \| I_{\mathrm{s,\ est}}(n, \boldsymbol{u}, \{c_i\}) - I_{\mathrm{s}}(n, \boldsymbol{u}) \|_2^2,$$

Samples of the training data set (n)

Detector coordinate ($\boldsymbol{u}$)

Scatter estimate

MC scatter simulation

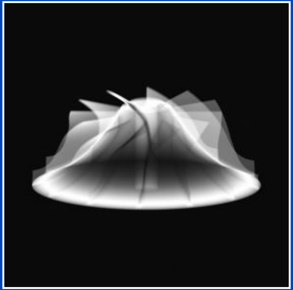
[1] B. Ohnesorge, T. Flohr, K. Klingenbeck-Regn: Efficient object scatter correction algorithm for third and fourth generation CT scanners. Eur. Radiol. 9, 563–569 (1999).

Reference 2

Hybrid scatter estimation

- **Hybrid scatter estimation[2] :**
  - **Estimation of scatter by a convolution of the scatter source term $T(p)$ with a scatter propagation kernel $G(\boldsymbol{u}, \boldsymbol{c})$:**

$$I_{\text{s, est}}(\boldsymbol{u}) = \underbrace{\left(c_0 \cdot p(\boldsymbol{u}) \cdot e^{-p(\boldsymbol{u})}\right)}_{T(p)(\boldsymbol{u})} * \underbrace{\left(\sum_{\pm} e^{-c_1(\boldsymbol{u}\hat{\boldsymbol{e}}_1 \pm c_2)^2} \cdot \sum_{\pm} e^{-c_3(\boldsymbol{u}\hat{\boldsymbol{e}}_2 \pm c_4)^2}\right)}_{G(\boldsymbol{u},\boldsymbol{c})}$$



$T(p)(\boldsymbol{u})$

Open parameters: c_0

$G(\boldsymbol{u}, \boldsymbol{c})$

Open parameters: c_1, c_2, c_3, c_4

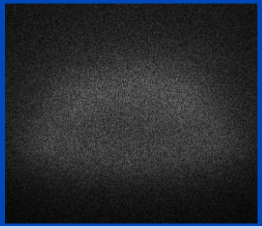
$$\{c_i\}_n = \operatorname{argmin} \sum_{\boldsymbol{u}} \| I_{\text{s, est}}(n, \boldsymbol{u}, \{c_i\}) - I_{\text{s}}(n, \boldsymbol{u}) \|_2^2,$$

Samples of the test data set

Detector coordinate

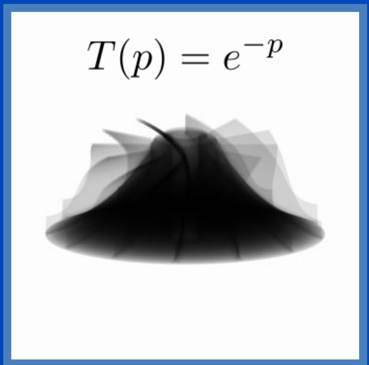
Scatter estimate

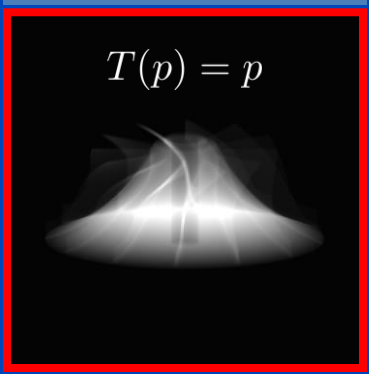
Coarse MC simulation

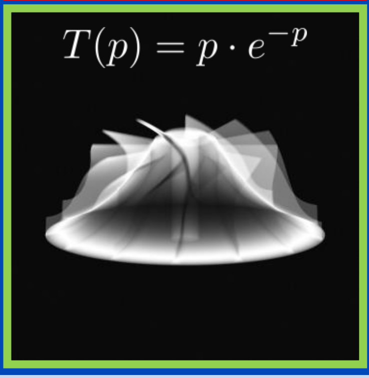


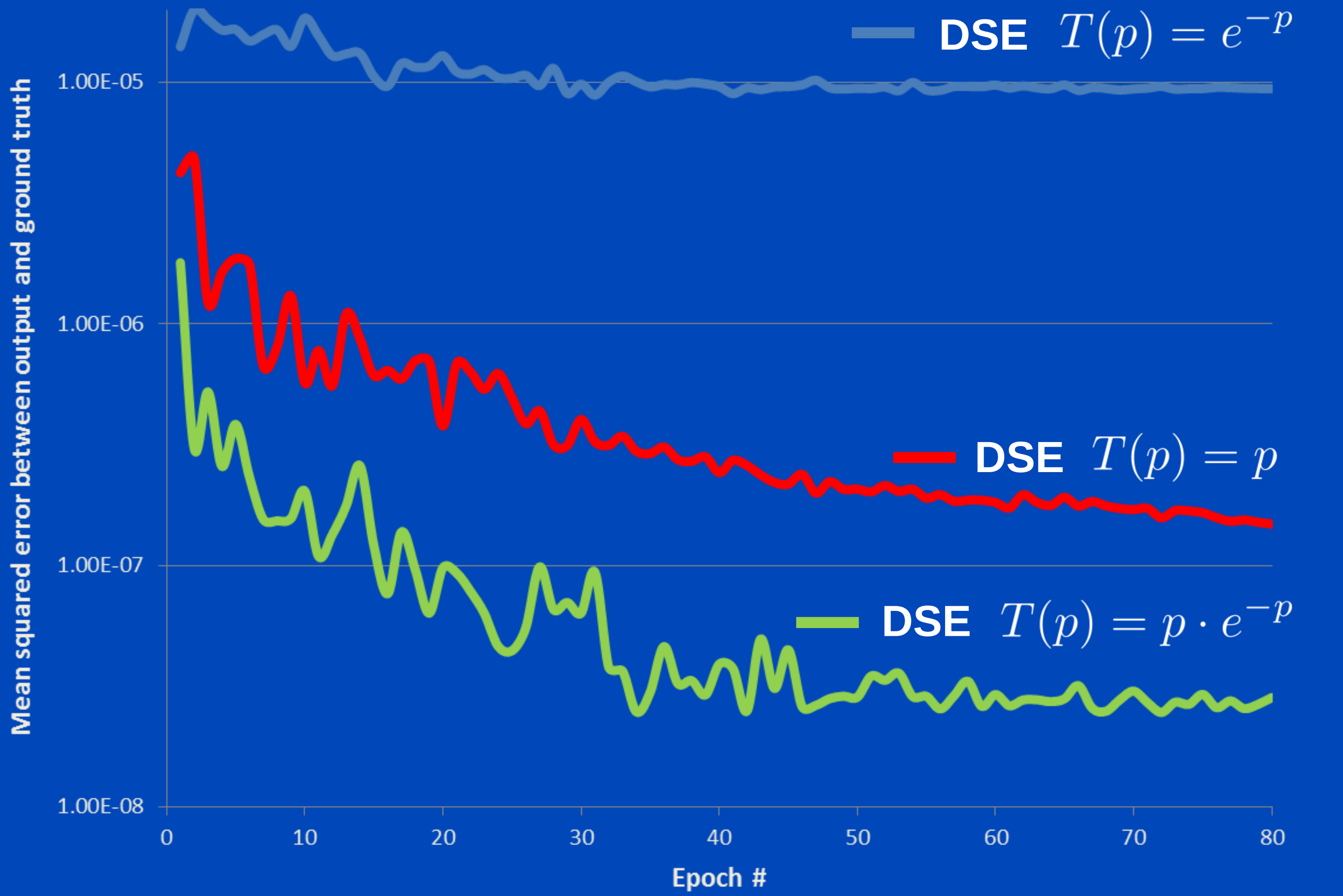
[2] M. Baer, M. Kachelrieß: Hybrid scatter correction for CT imaging. Phys. Med. Biol. 57, 6849–6867 (2012).

Performance on Testing Data for Different Inputs



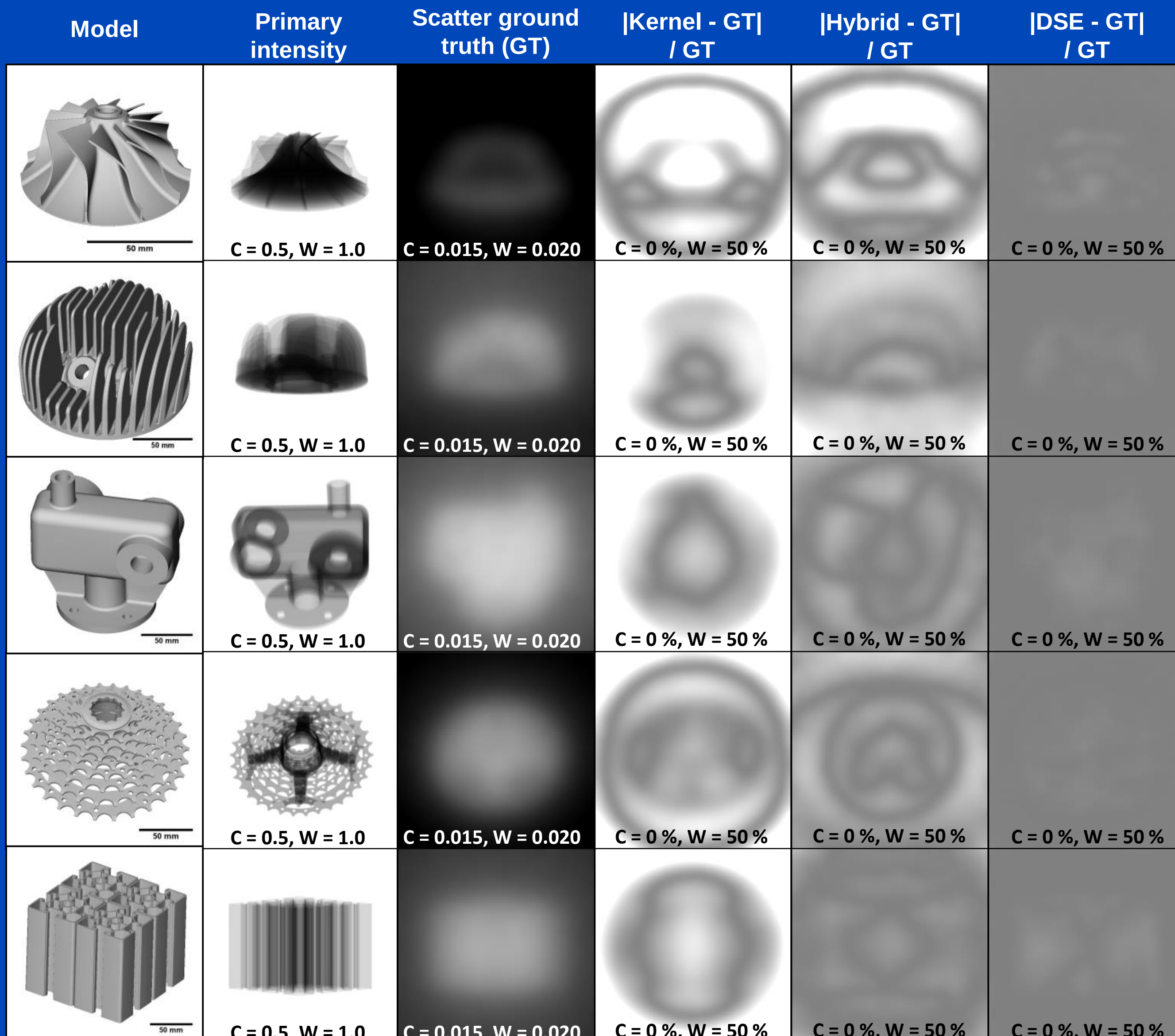






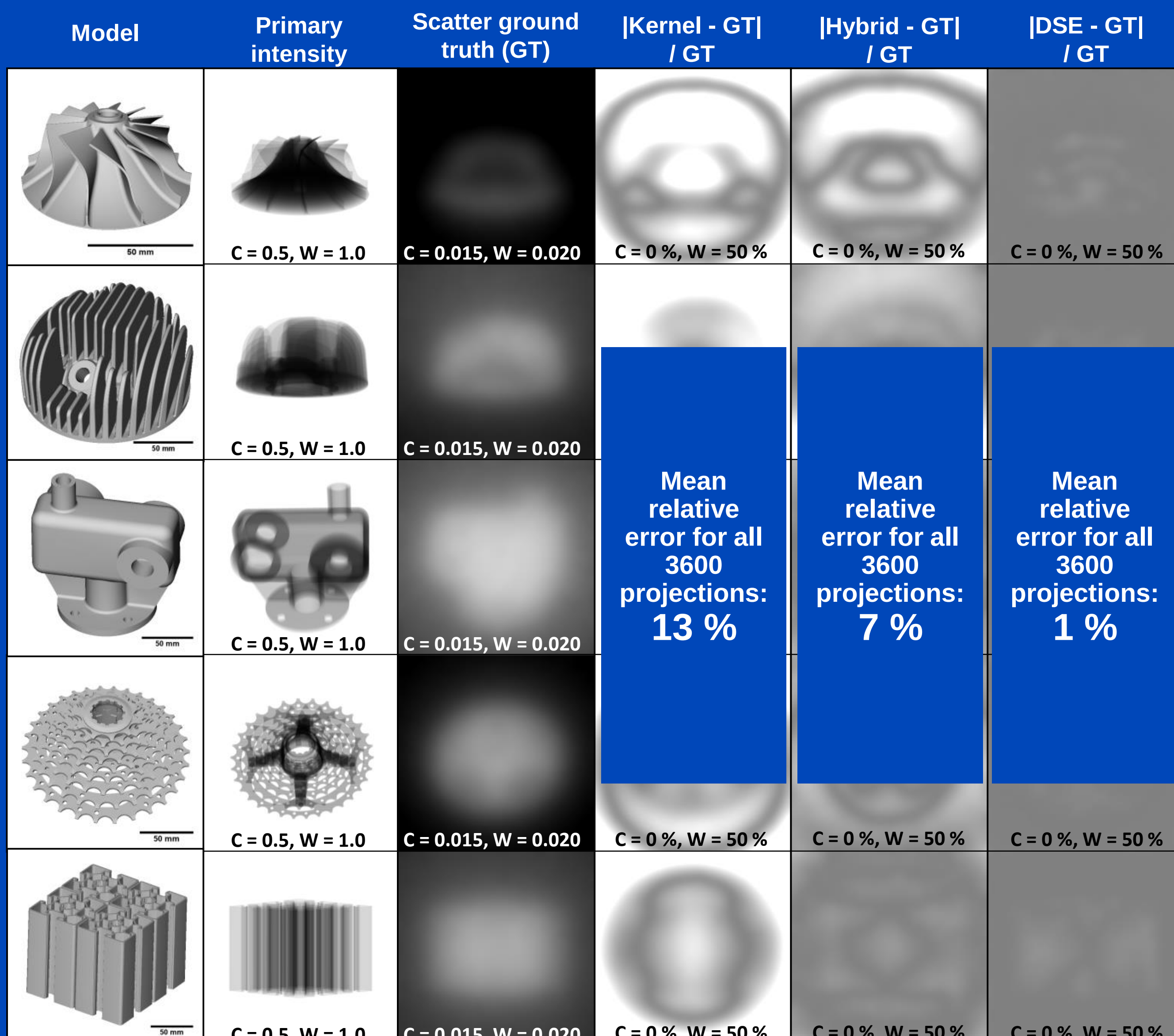
Results

Scatter estimates for simulated testing data



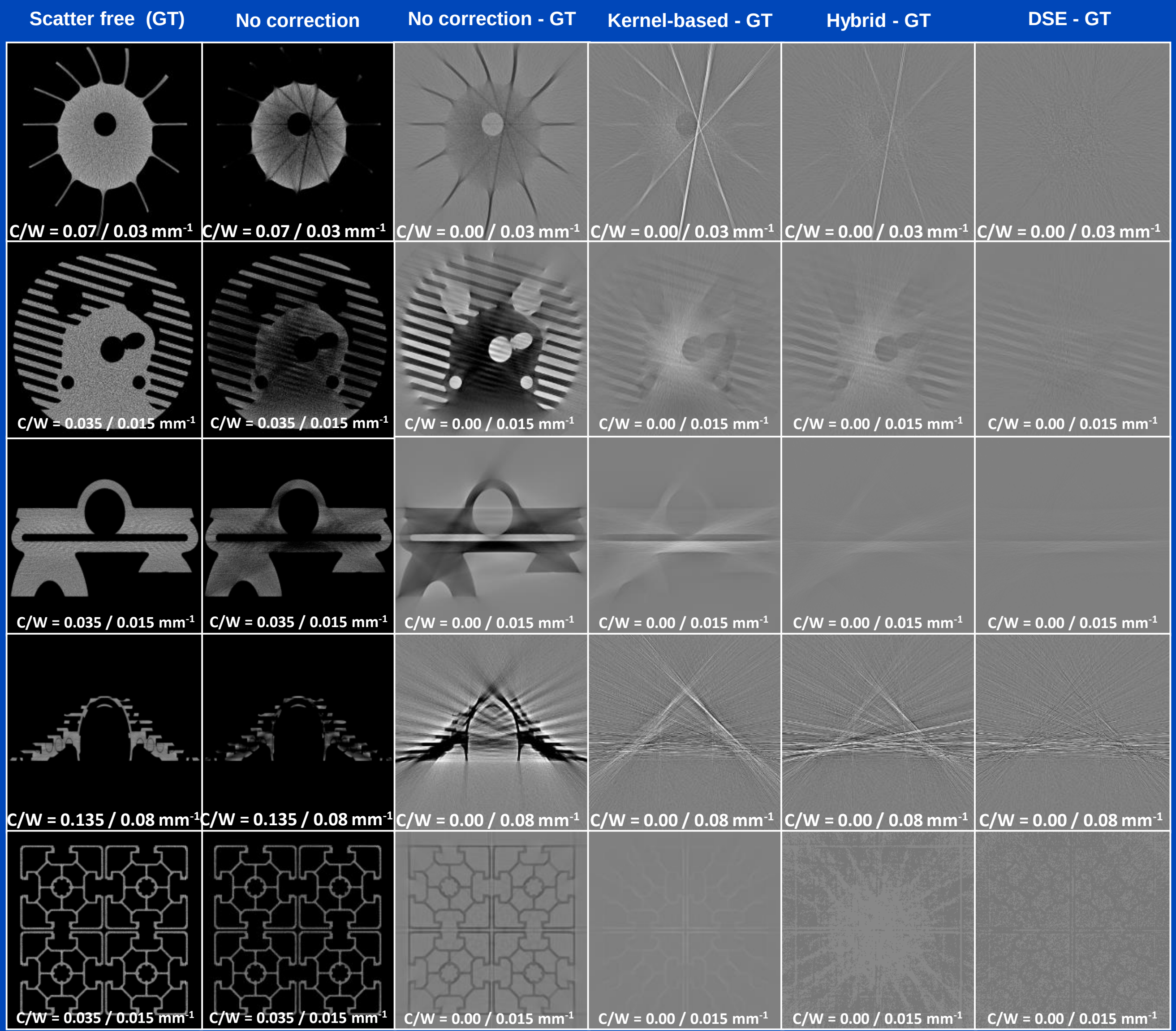
Results

Scatter estimates for simulated testing data

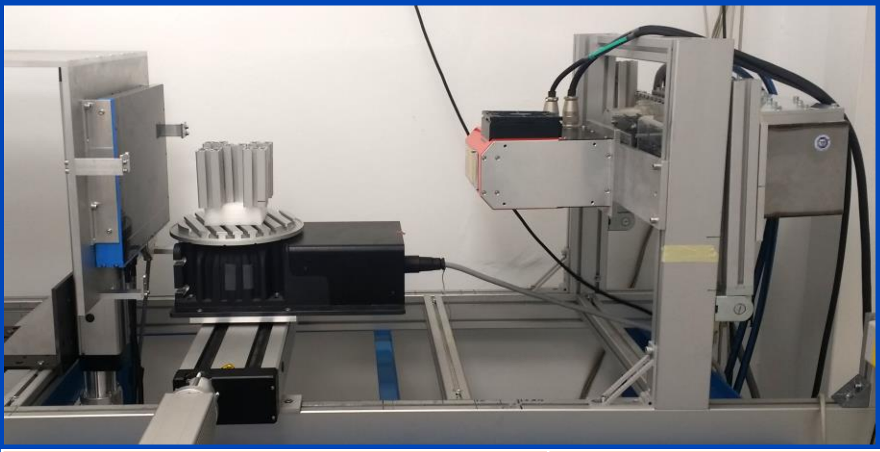


Results

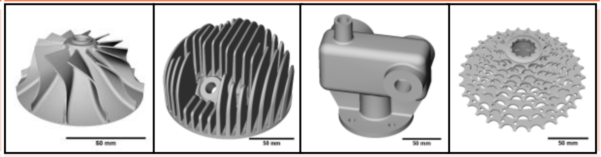
CT reconstructions of scatter corrected testing data



Application to Measured Data



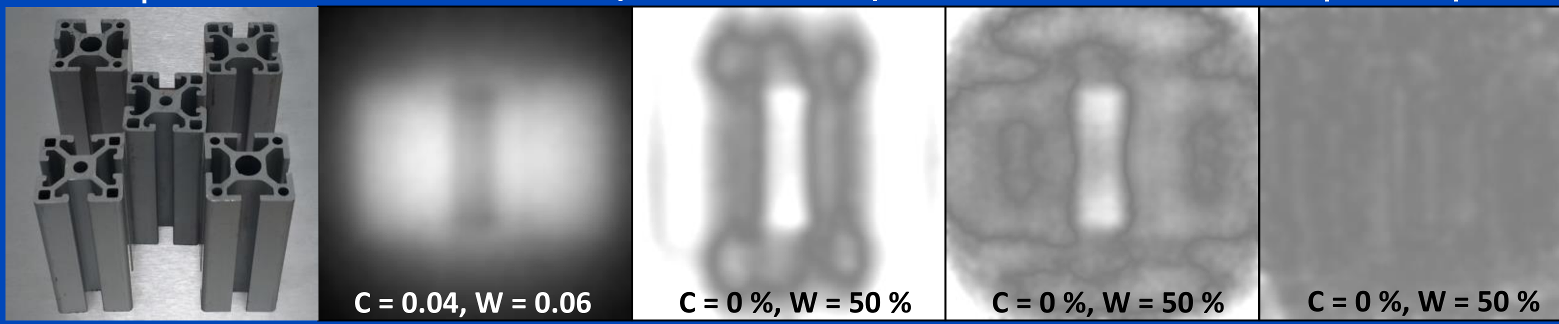
- **Measurement at DKFZ table-top CT**
- **Tomography of aluminum profile (720 projections / 360°)**
- **110 kV Hamamatsu micro-focus x-ray tube**
- **Varian flat detector**

	Training	Testing
Components		
Detector elements	768×768	768×768
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

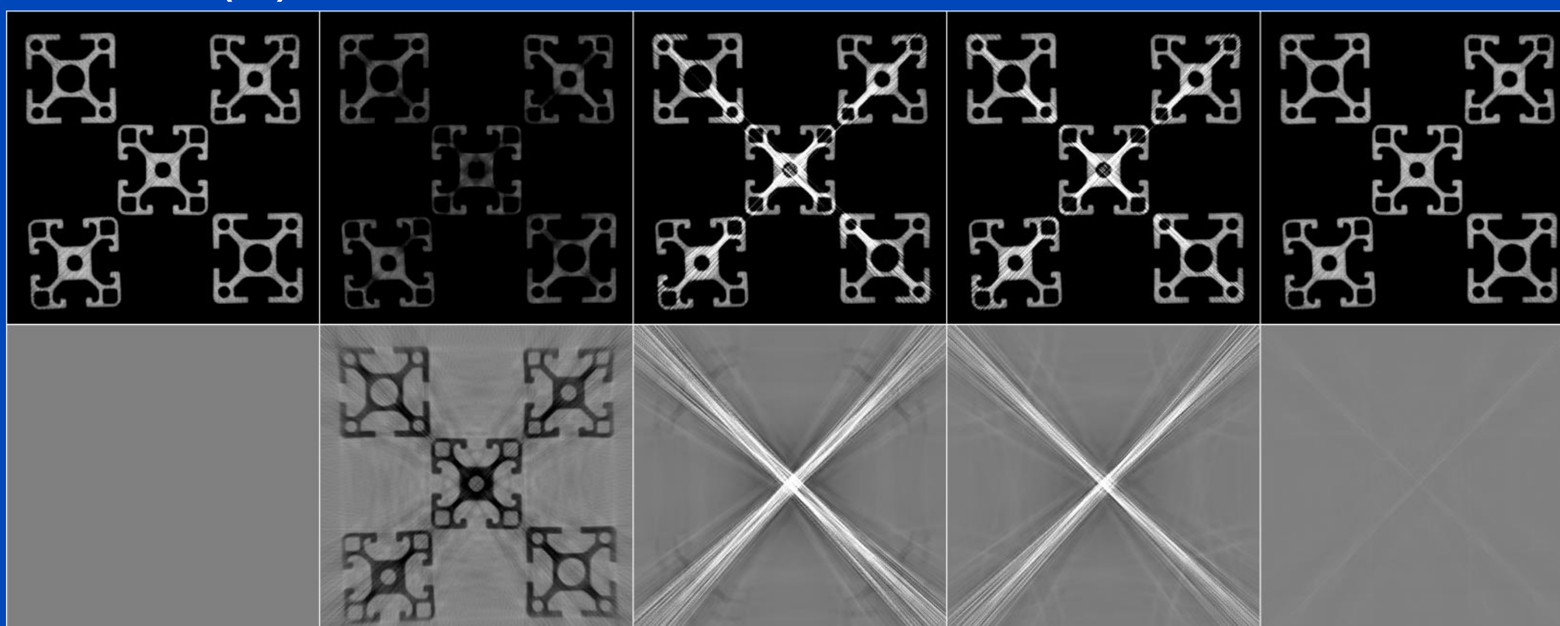
Results

Performance of DSE for measured data

Projection data



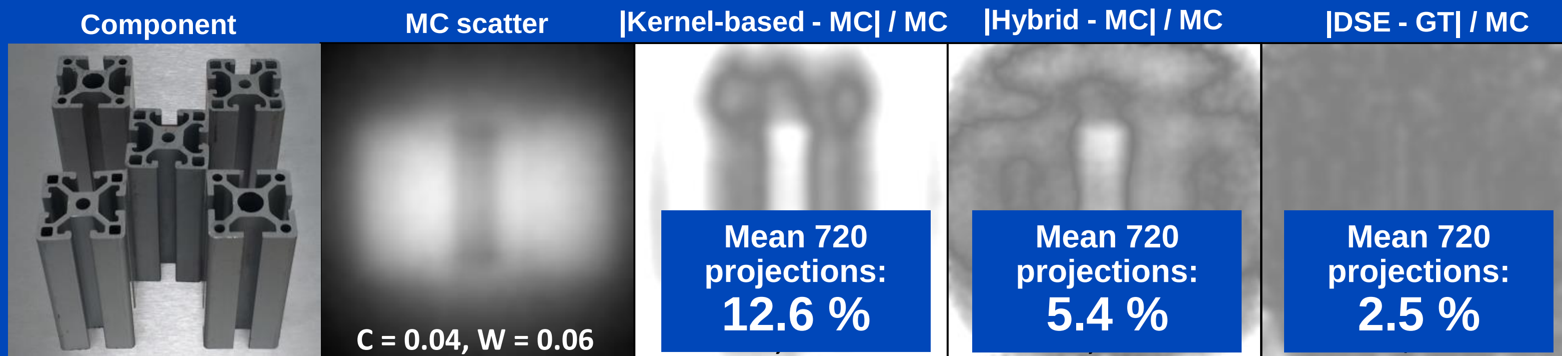
CT reconstructions



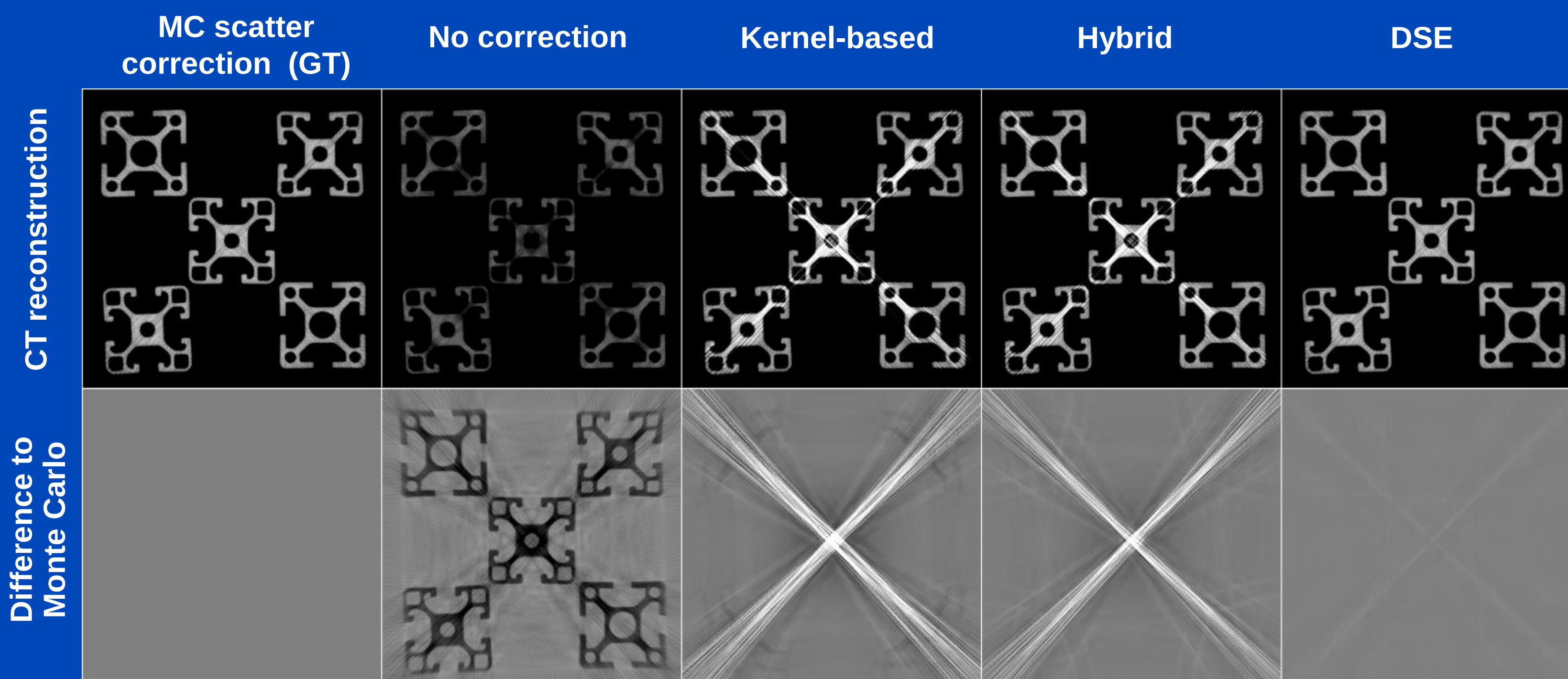
Results

Performance of DSE for measured data

Projection data



CT reconstructions



Conclusions

- DSE is a fast (~ 20 ms / projection) and accurate alternative to Monte Carlo simulation.
- DSE outperforms conventional kernel-based approaches in terms of accuracy.
- DSE is not restricted to reproduce only Monte Carlo scatter estimates but can be used with any other scatter estimate.

Thank You!

This presentation will soon be available at www.dkfz.de/ct

Job opportunities through DKFZ's international PhD or Postdoctoral Fellowship programs (www.dkfz.de), or directly through Prof. Dr. Marc Kachelrieß (marc.kachelriess@dkfz.de).

Parts of the reconstruction software were provided by RayConStruct® GmbH, Nürnberg, Germany.