Deep Scatter Estimation (DSE): Feasibility of using a Deep Convolutional Neural Network for Real-Time X-Ray Scatter Prediction in Cone-Beam CT

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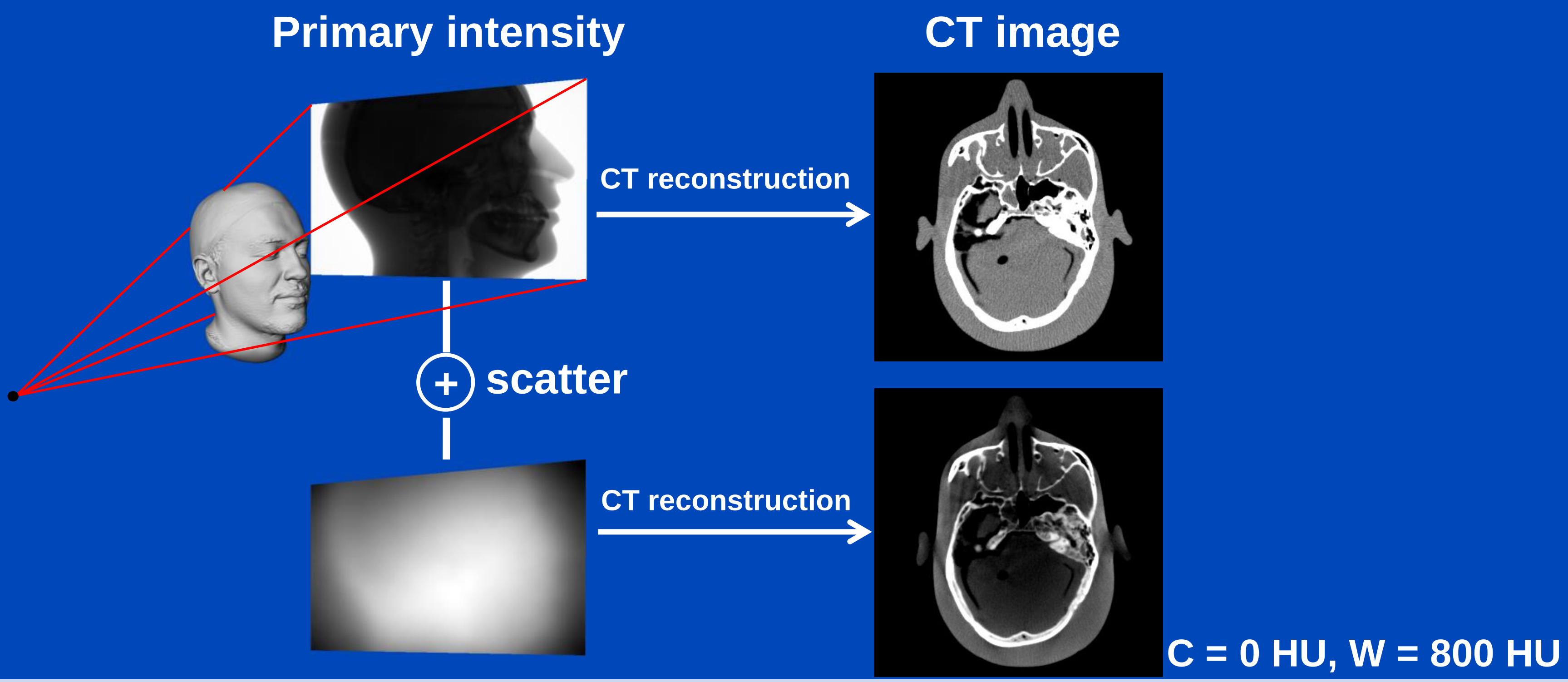
DEUTSCHES KREBSFORSCHUNGSZENTRUM IN DER HELMHOLTZ-GEMEINSCHAFT

Motivation

- X-ray scatter is a major cause of image quality degradation in CT and CBCT.
- Appropriate scatter correction is crucial to maintain the diagnostic value of the CT examination.



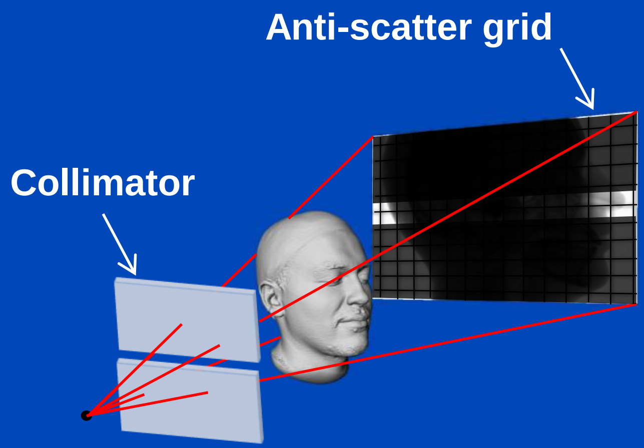
Scatter Correction

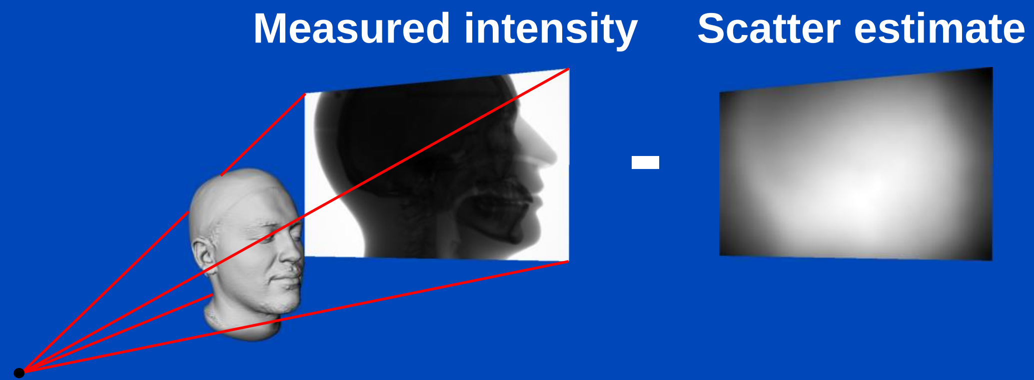
Scatter suppression

- Anti-scatter grids
- Collimators
- …

Scatter estimation

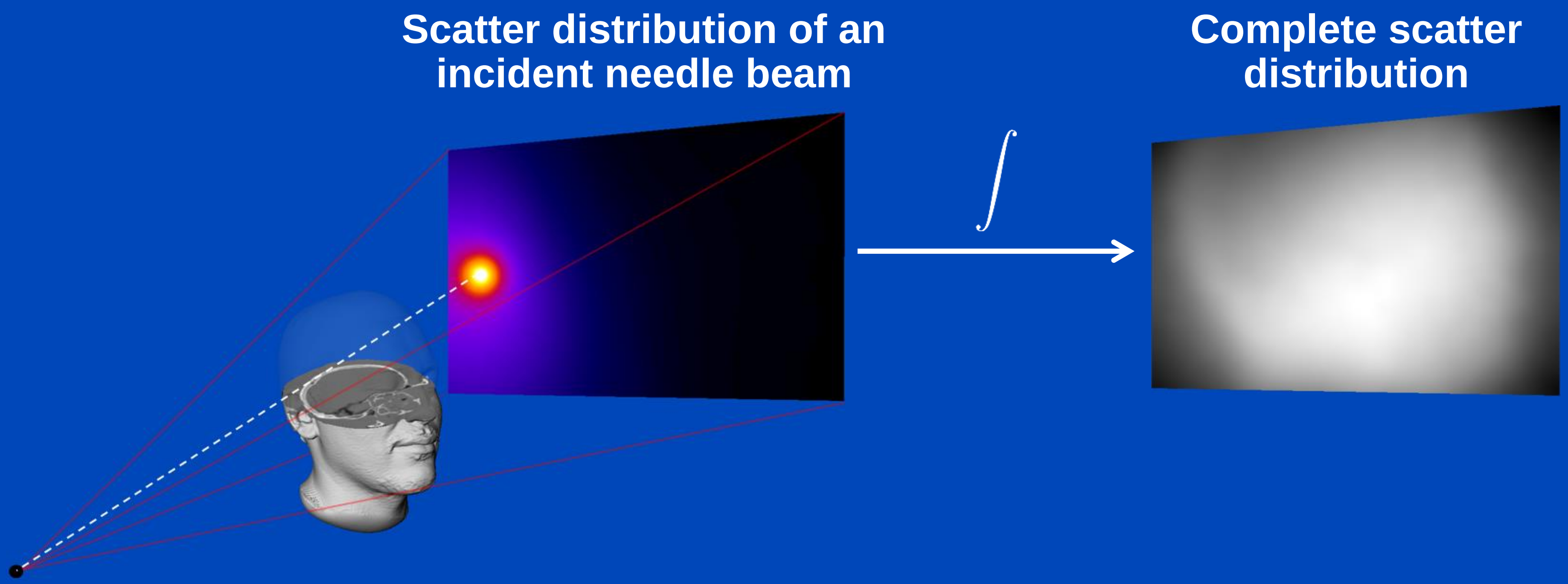
- Monte Carlo simulation
- Kernel-based approaches
- Boltzmann transport
- Primary modulation
- Beam blockers
- …





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.

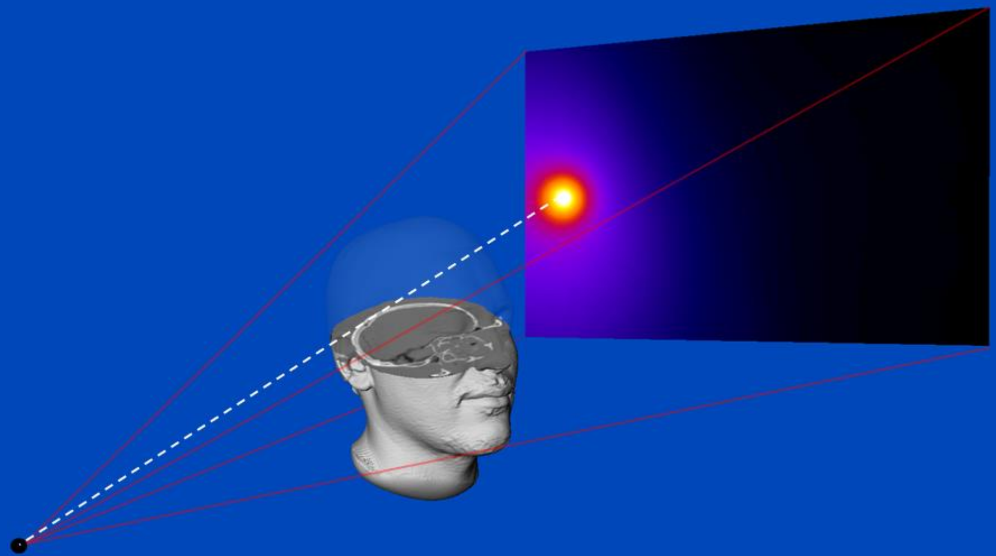


Kernel-Based Scatter Estimation

$T(p)$

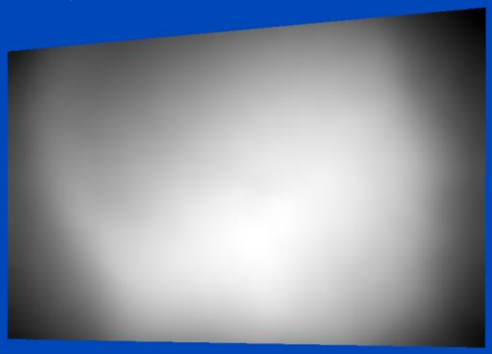
Estimate needle beam scatter kernels as a function of the projection data p

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



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

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

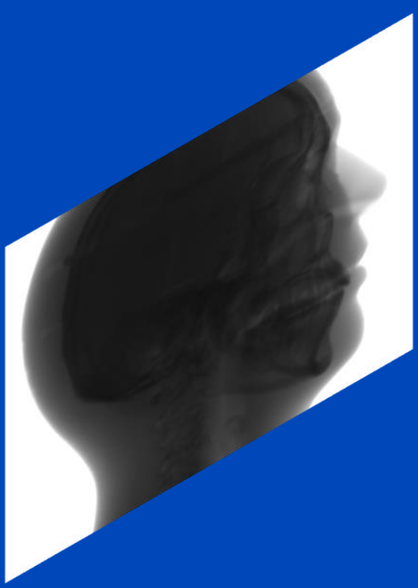


Deep Scatter Estimation (DSE)

Idea

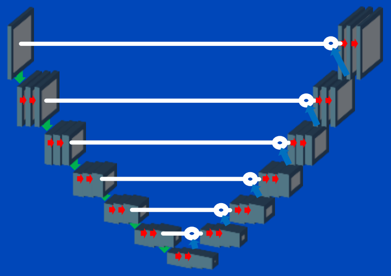
- **Train a deep convolutional neural network to estimate scatter using a function of the acquired projection data as input.**

Input: $T(p)$

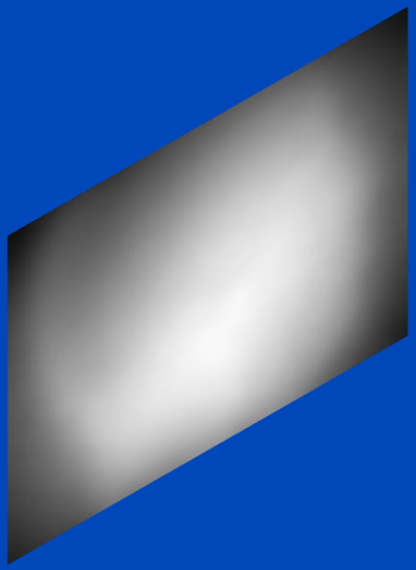


$$\int T(p)(\boldsymbol{u}')G(\boldsymbol{u},\boldsymbol{u}',\boldsymbol{c})d\boldsymbol{u}'$$

Convolutional neural network



Scatter estimate



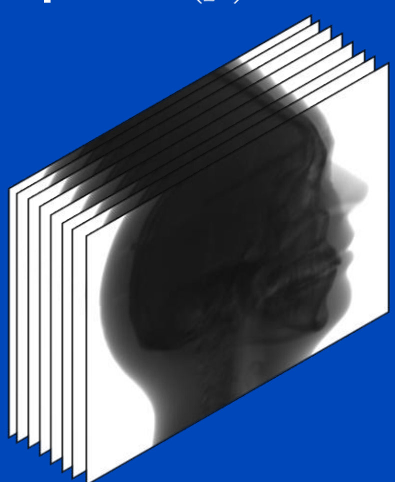
Deep Scatter Estimation (DSE)

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:**

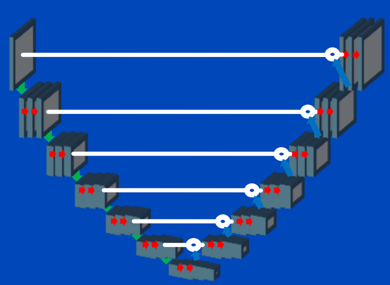
$$\{w, b\} = \operatorname{argmin} ||DSE(T(p)) - I_{\mathrm{MC}}||_2^2$$

Input: $T(p)$

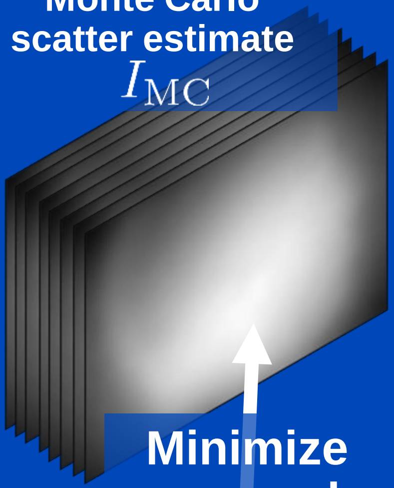


$$\int T(p)(\boldsymbol{u}')C(\boldsymbol{u}, \boldsymbol{u}', \boldsymbol{c})d\boldsymbol{u}'$$

Convolutional neural network

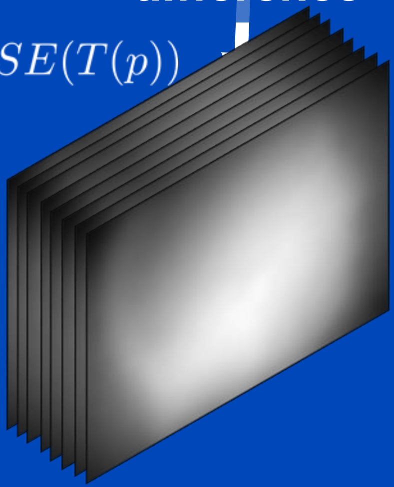


Monte Carlo scatter estimate I_{MC}



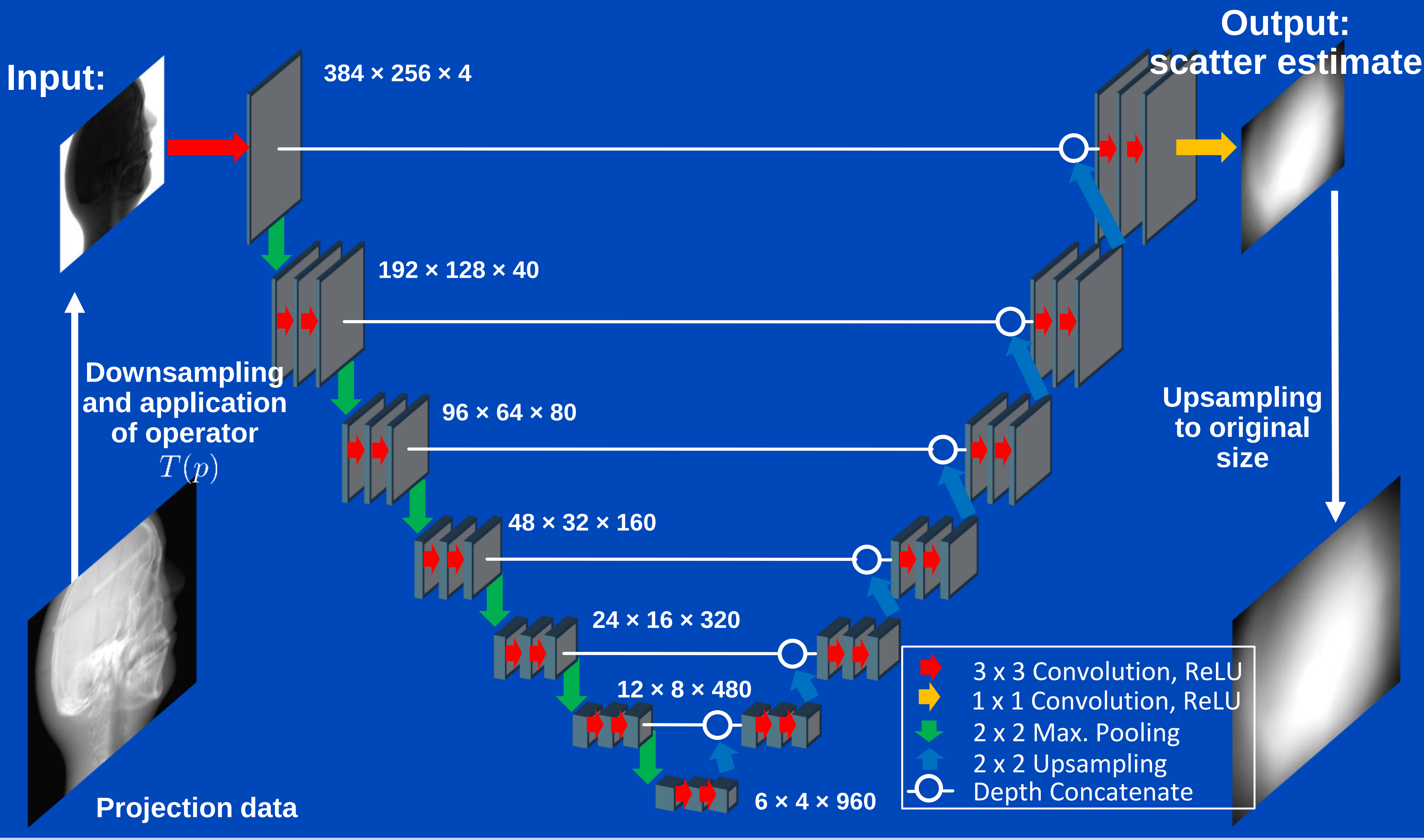
Minimize squared difference

$DSE(T(p))$

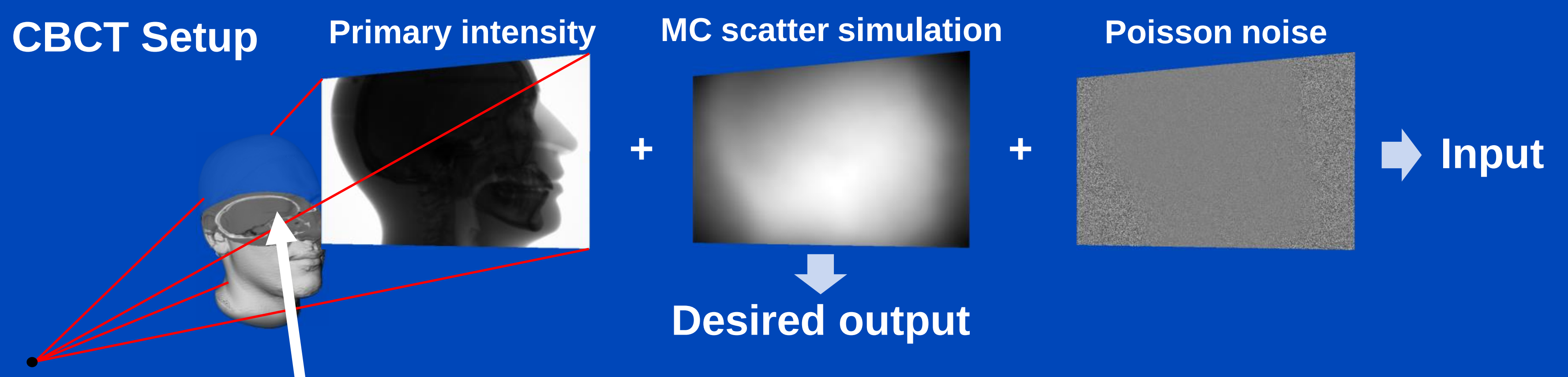


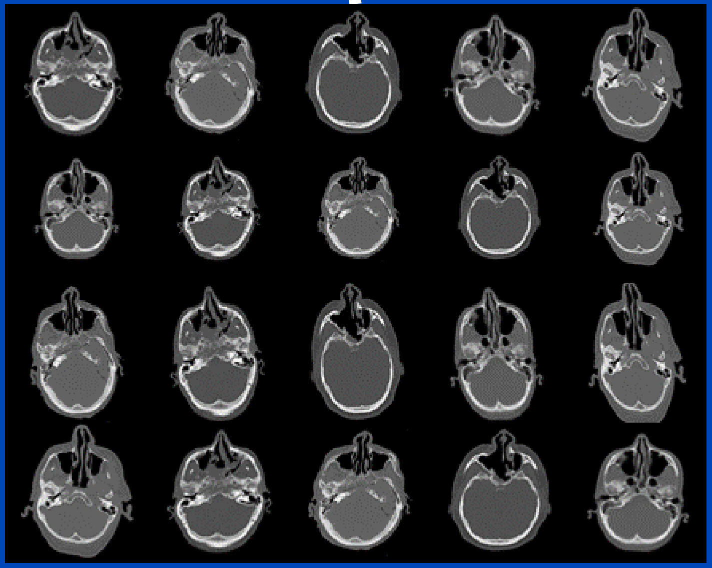
Deep Scatter Estimation

Network architecture & scatter estimation framework



Training of the DSE Network





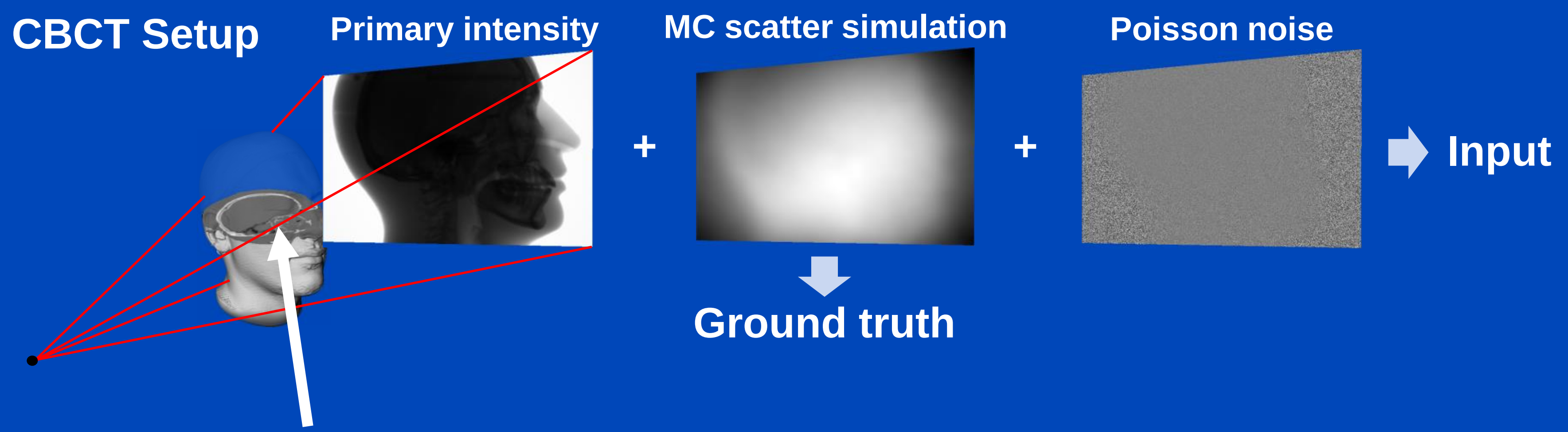
- Simulation of 12000 projection data using simulations of different heads and different acquisition parameters.
- Splitting into 80 % training and 20 % validation data.
- Optimize weights of convolutional network to reproduce Monte Carlo scatter estimates:

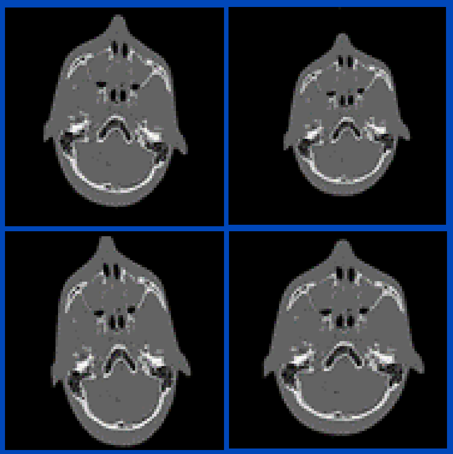
$$\{w, b\} = \operatorname{argmin} ||DSE(T(p)) - I_{\mathrm{MC}}||_2^2$$

- Training on a GeForce GTX 1080 for 80 epochs.

Testing of the DSE Network

Simulated Data



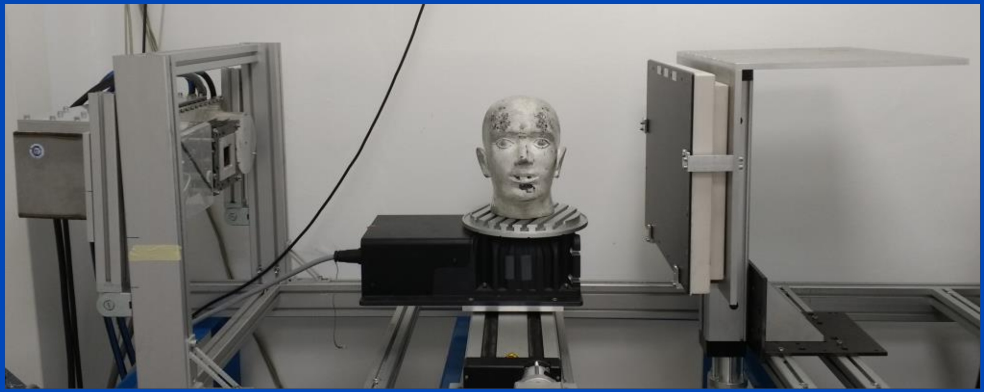


- Application of the DSE network to predict scatter for simulated data of a head (different from training data).

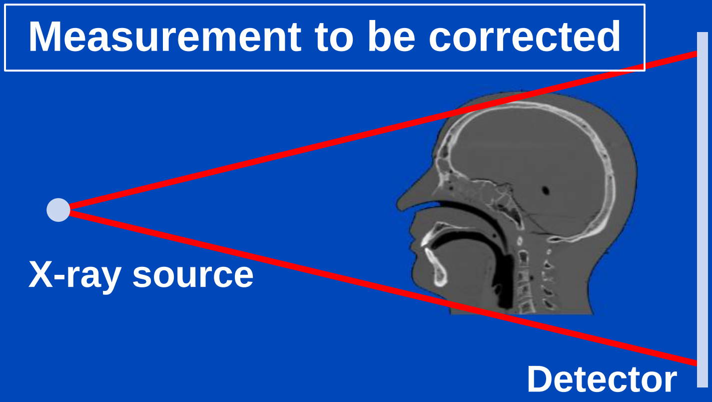
Testing of the DSE Network

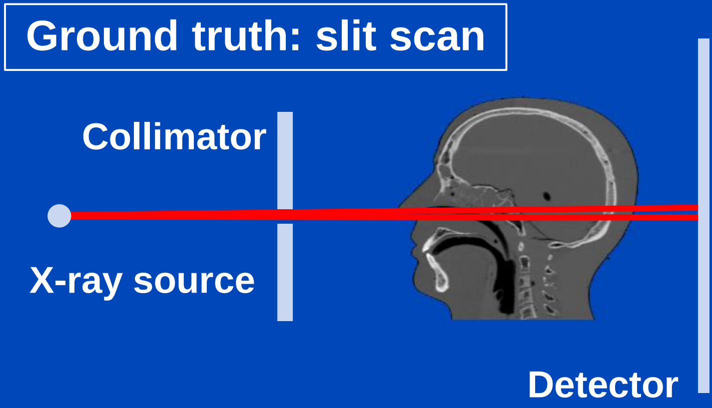
Measured Data

DKFZ table-top CT



- Measurement of a head phantom at our in-house table-top CT.
- Slit scan measurement serves as ground truth.





Reference 1

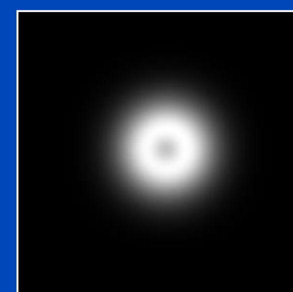
Kernel-based scatter estimation

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

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

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

Open parameters: c_0



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

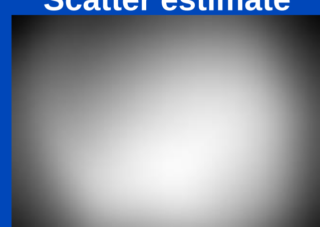
Open parameters: c_1, c_2, c_3, c_4

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

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).

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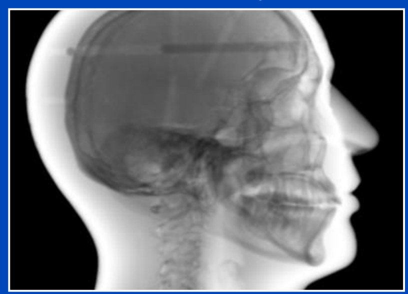
Reference 2

Hybrid scatter estimation

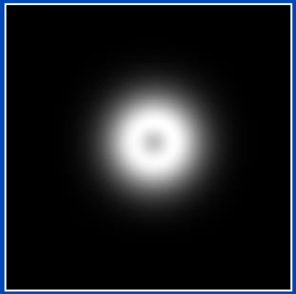
- **Hybrid scatter estimation[2] :**
  - **Estimation of scatter by a convolution of the scatter source term $T(p)$ with a scatter propagation kernel $G(\boldsymbol{u},\boldsymbol{c})$:**

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



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

Open parameters: c_0



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

Open parameters: c_1, c_2, c_3, c_4

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

Samples of the test data set

Detector coordinate

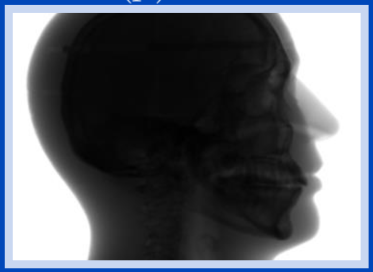
Scatter estimate

Coarse MC simulation

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

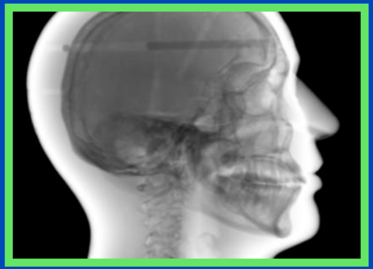
Performance on Validation Data for Different Inputs

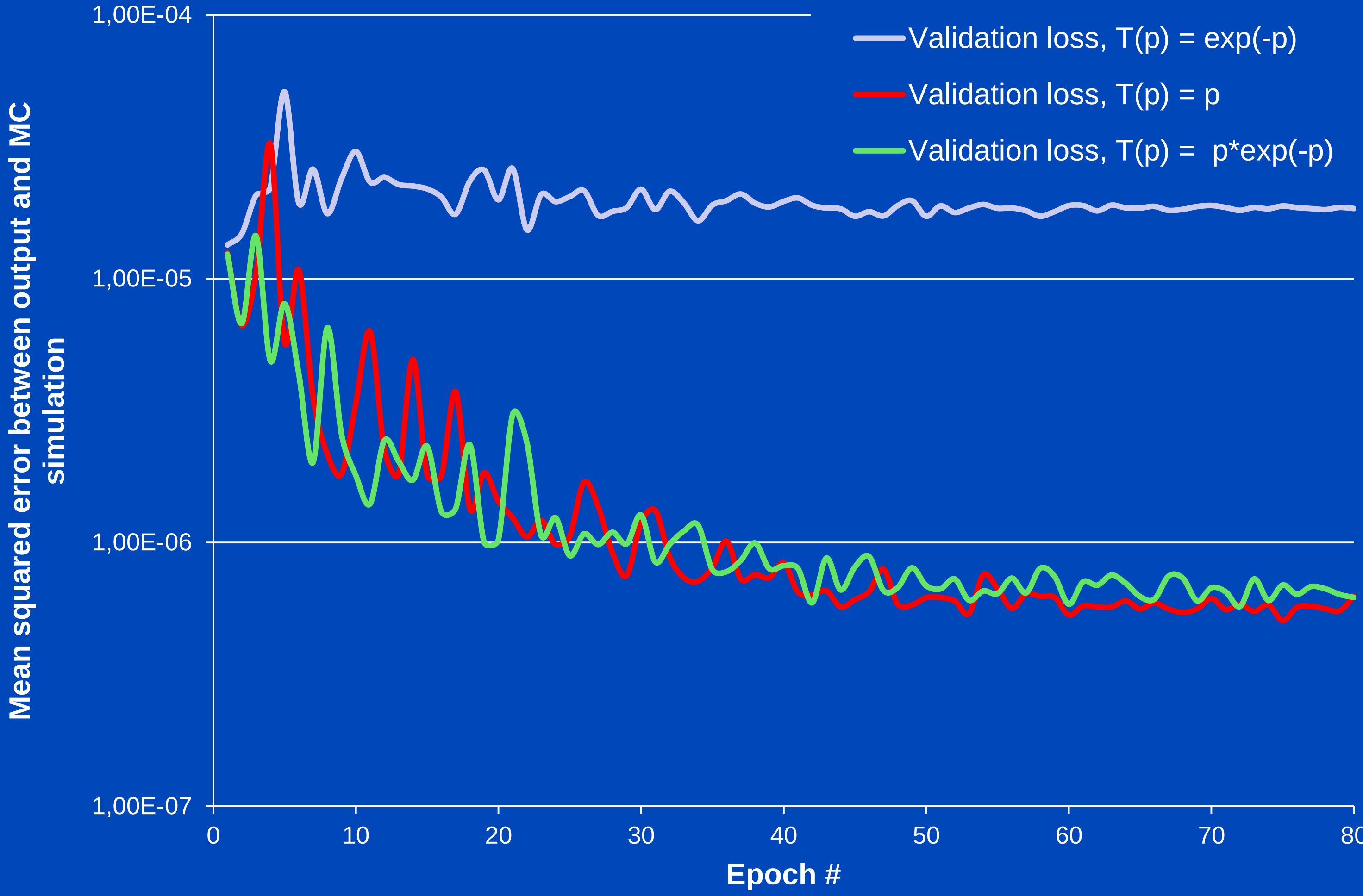
$T(p) = e^{-p}$



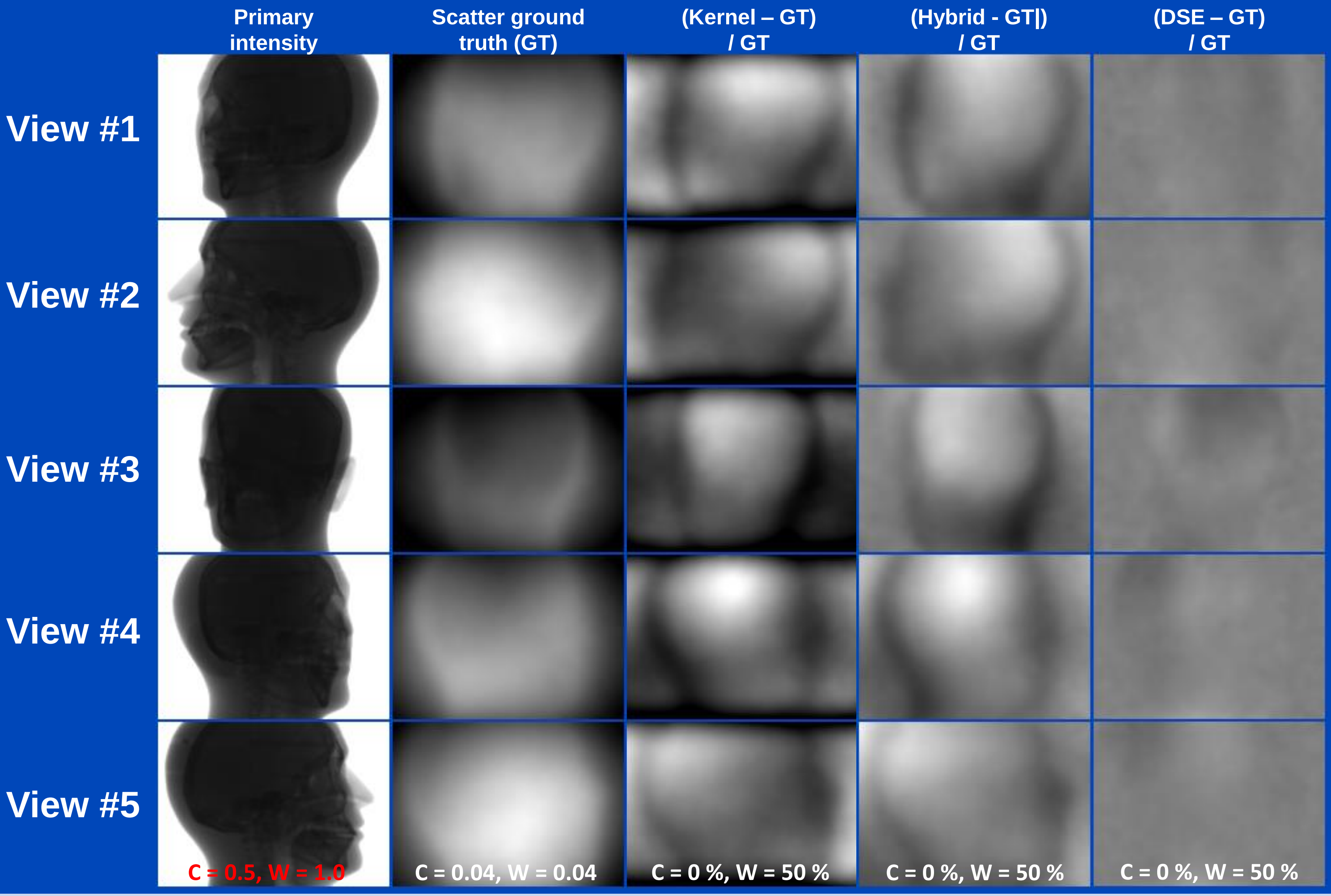
$T(p) = p$

$T(p) = p \cdot e^{-p}$

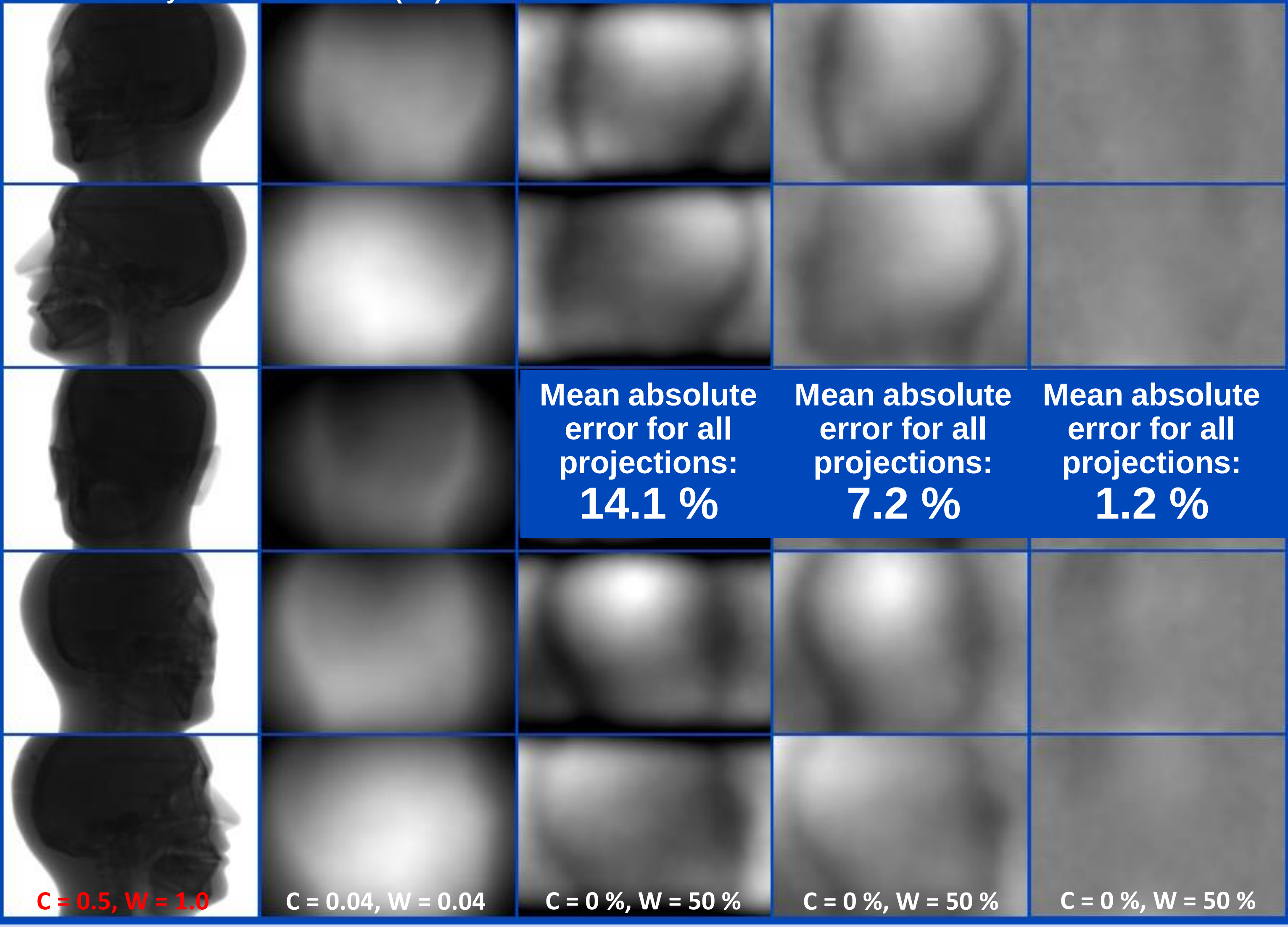




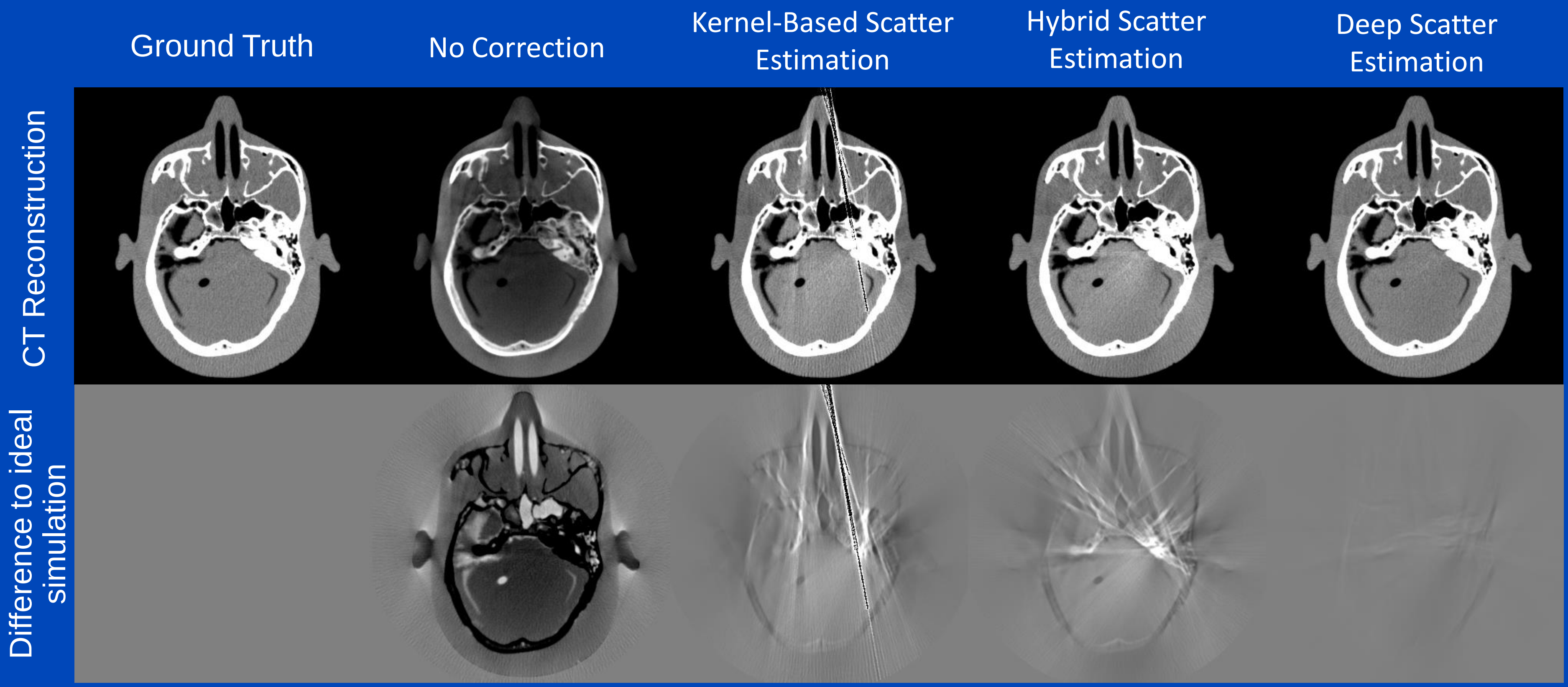
Results – Simulated Projection Data



Results – Simulated Projection Data

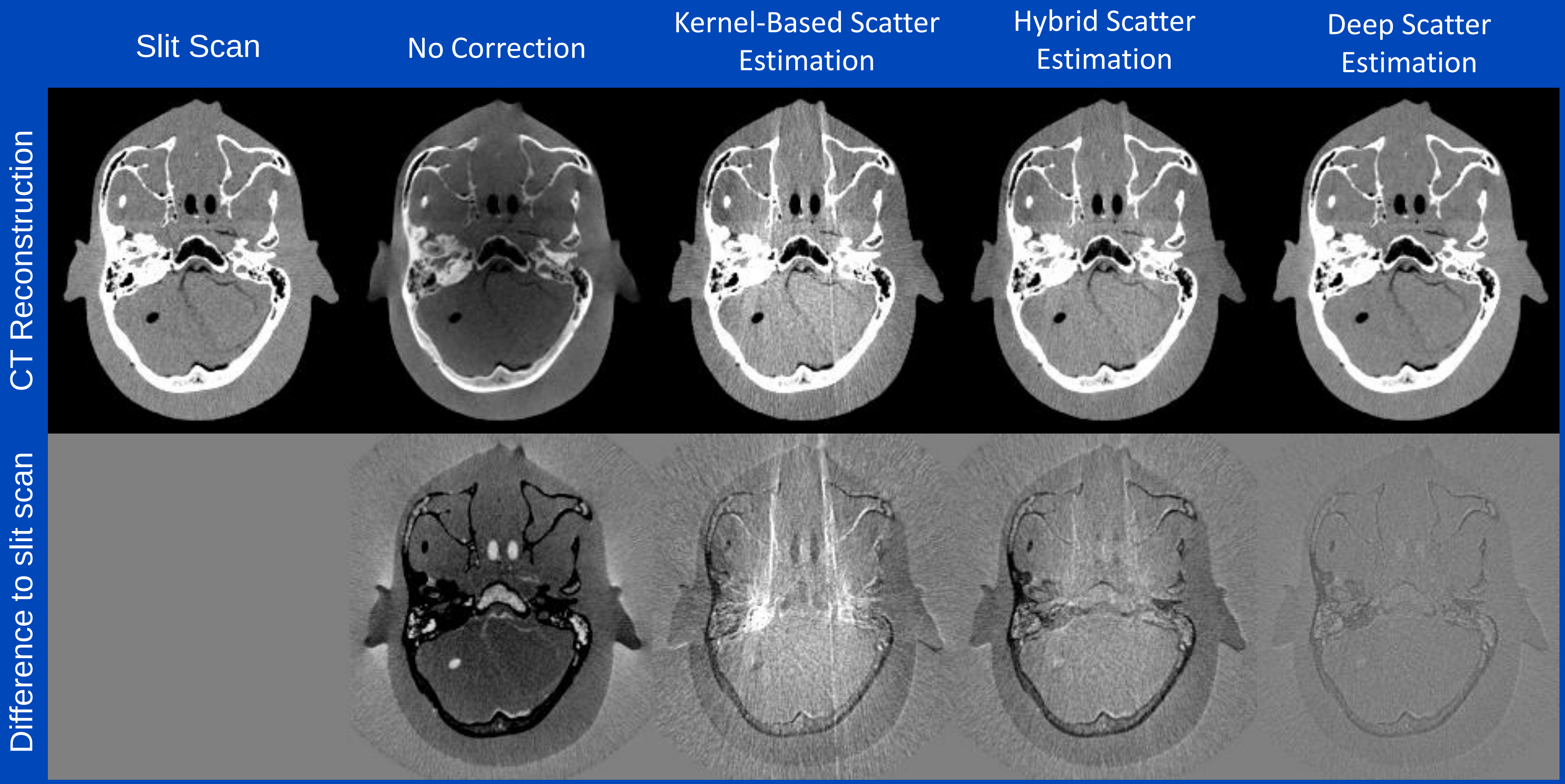


Results – CT Reconstructions of Simulated Data



C = 0 HU, W = 1000 HU

Results – CT Reconstructions of Measured Data



C = 0 HU, W = 1000 HU

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Conclusions

- DSE is a fast 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.