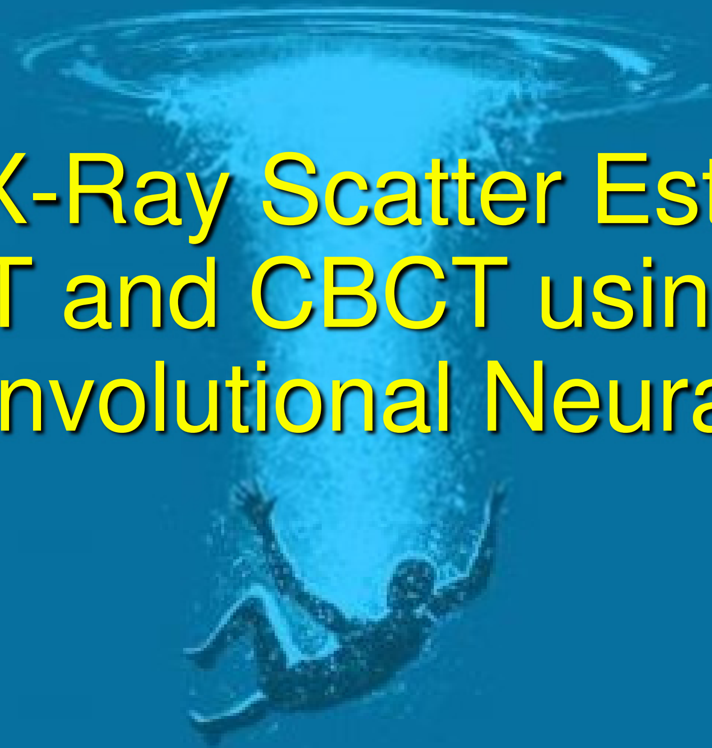
Real-Time X-Ray Scatter Estimation for CT and CBCT using a **Deep** Convolutional Neural Network



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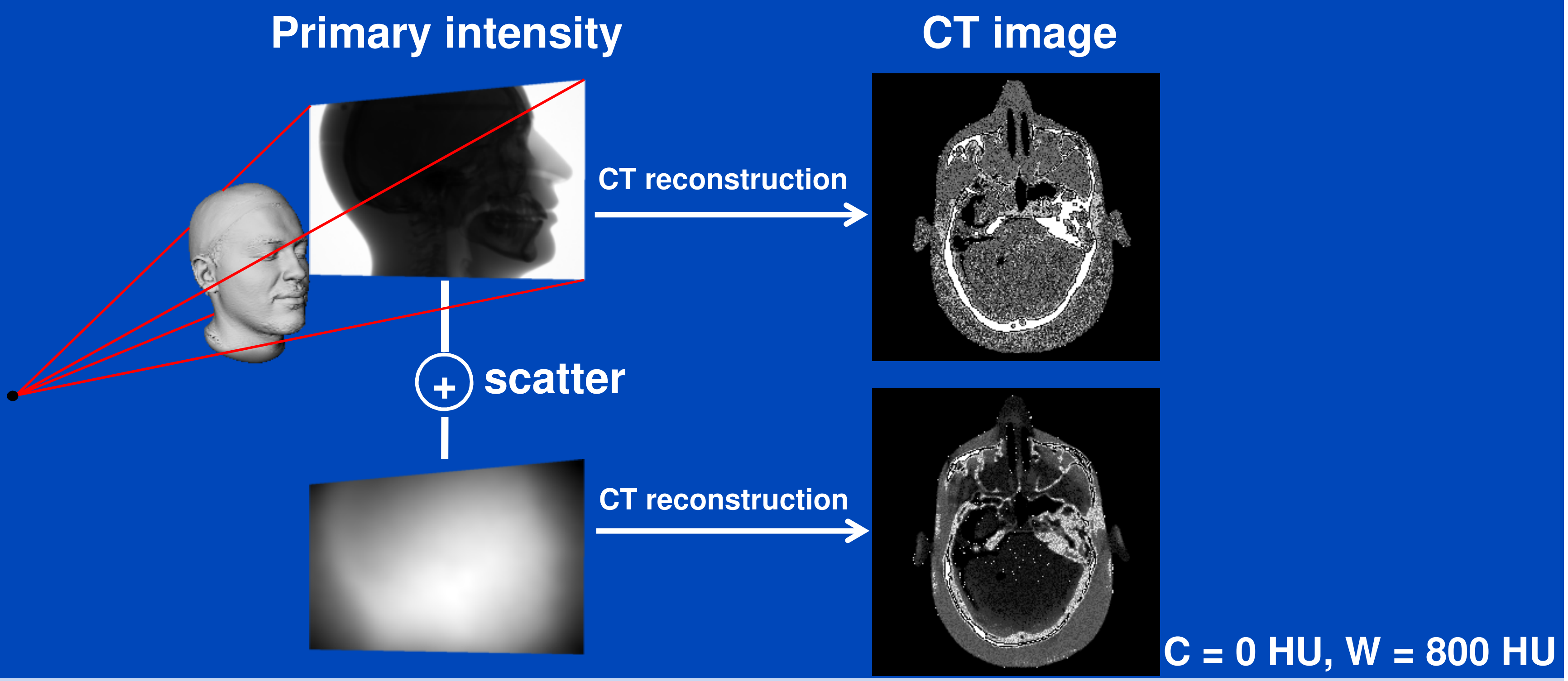
DEUTSCHES KREBSFORSCHUNGSZENTRUM IN DER HELMHOLTZ-GEMEINSCHAFT

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.



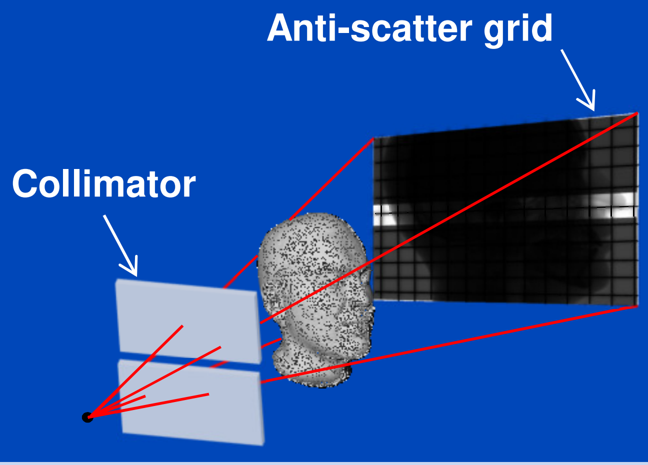
Scatter Correction

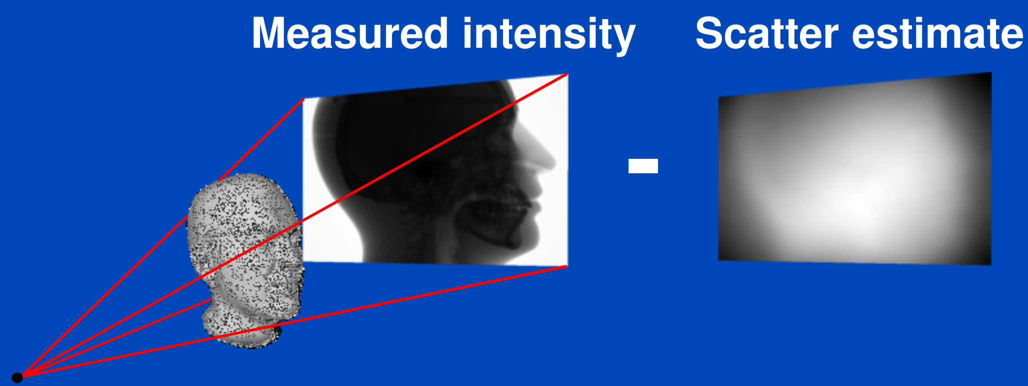
Scatter suppression

- Anti-scatter grids
- Collimators
- …

Scatter estimation

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

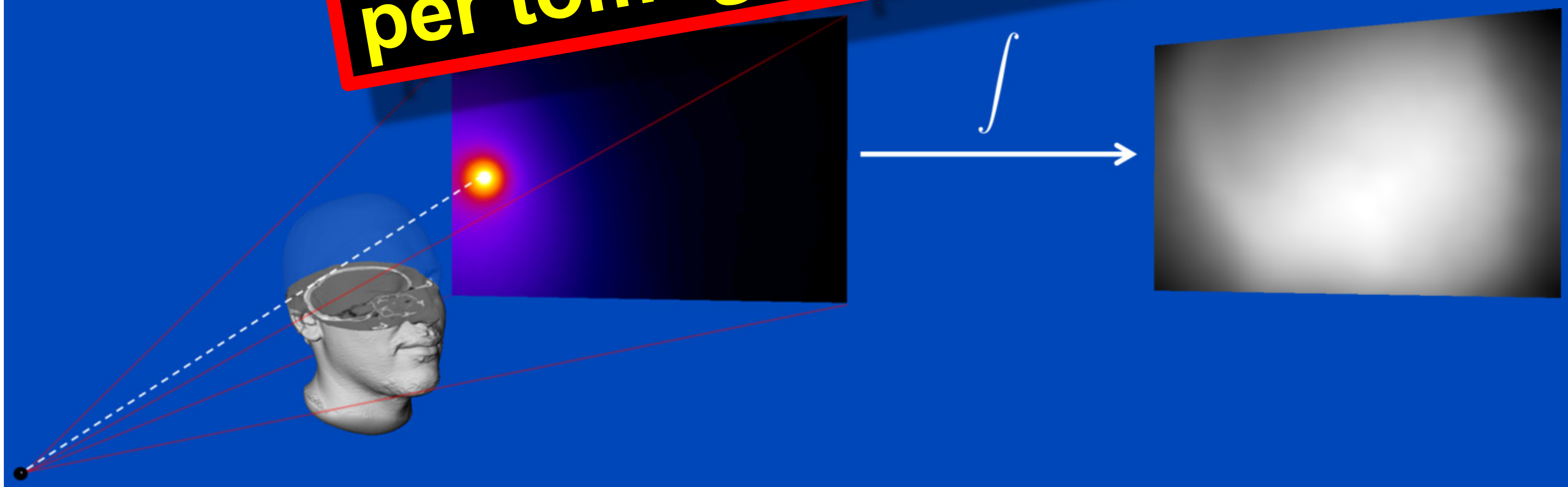




Monte Carlo Scatter Estimation

- Simulation of photon trajectories according to physical interaction probabilities.
- Simulating a large numb… …ries well approximat…

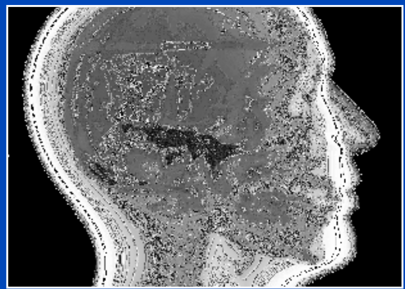
1 to 10 hours
per tomographic data set



Kernel-Based Scatter Estimation

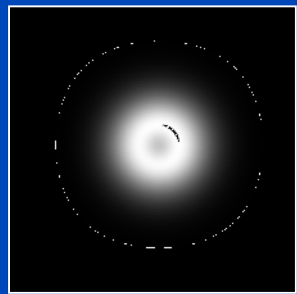
- **Kernel-based scatter estimation[1]:**
  - **Estimation of scatter by a convolution of the scatter source term $T(p)$ with a scatter propagation kernel $G(\boldsymbol{u}, \boldsymbol{c})$:**

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



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

Open parameters: c_0



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

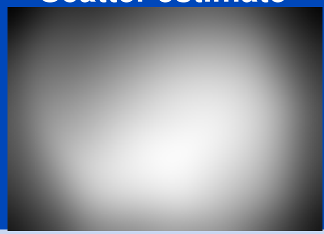
Open parameters: c_1, c_2, c_3, c_4

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

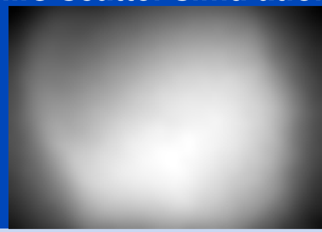
Samples of the training data set (n)

Detector coordinate ($\boldsymbol{u}$)

Scatter estimate



MC scatter simulation

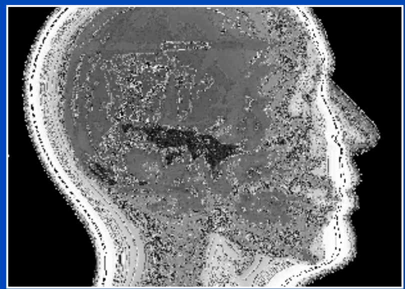


[1] B. Ohnesorge, T. Flohr, K. Klingenbeck-Regn: Efficient object scatter correction algorithm for third and fourth generation CT scanners. Eur. Radiol. 9, 563–569 (1999).

Hybrid Scatter Estimation

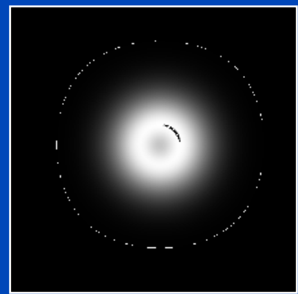
- **Hybrid scatter estimation[2] :**
  - Estimation of scatter by a convolution of the scatter source term $T(p)$ with a scatter propagation kernel $G(\boldsymbol{u}, \boldsymbol{c})$:

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



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

Open parameters: c_0



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

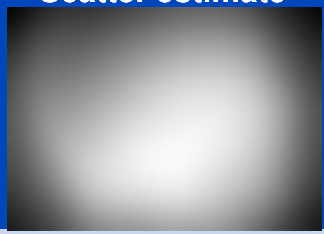
Open parameters: c_1, c_2, c_3, c_4

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

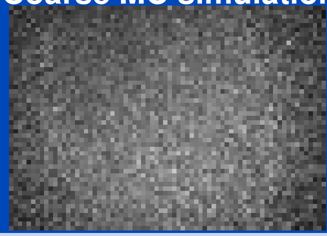
Samples of the test data set

Detector coordinate

Scatter estimate



Coarse MC simulation



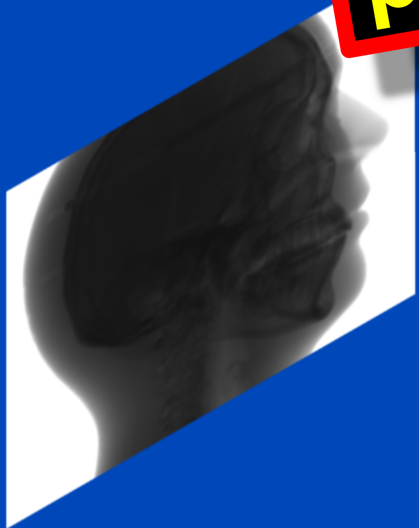
[2] M. Baer, M. Kachelrieß: Hybrid scatter correction for CT imaging. Phys. Med. Biol. 57, 6849–6867 (2012).

Deep Scatter Estimation (DSE)

Train a deep convolutional neural network (CNN) to estimate scatter using a function of ... d projection data as in...

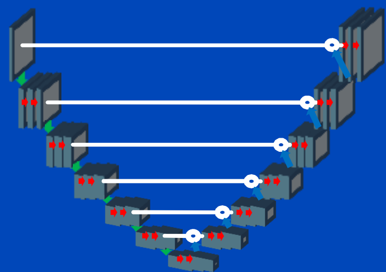
0.1 to 1 minute per tomographic data set

Input: $T(p)$

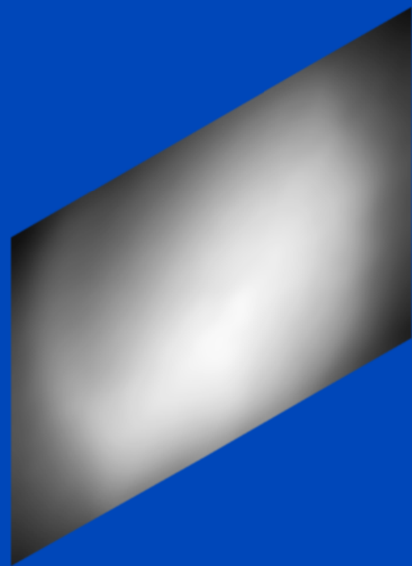


~~$\int T(p)(\boldsymbol{u}')C(\boldsymbol{u},\boldsymbol{u}',\boldsymbol{c})du'$~~

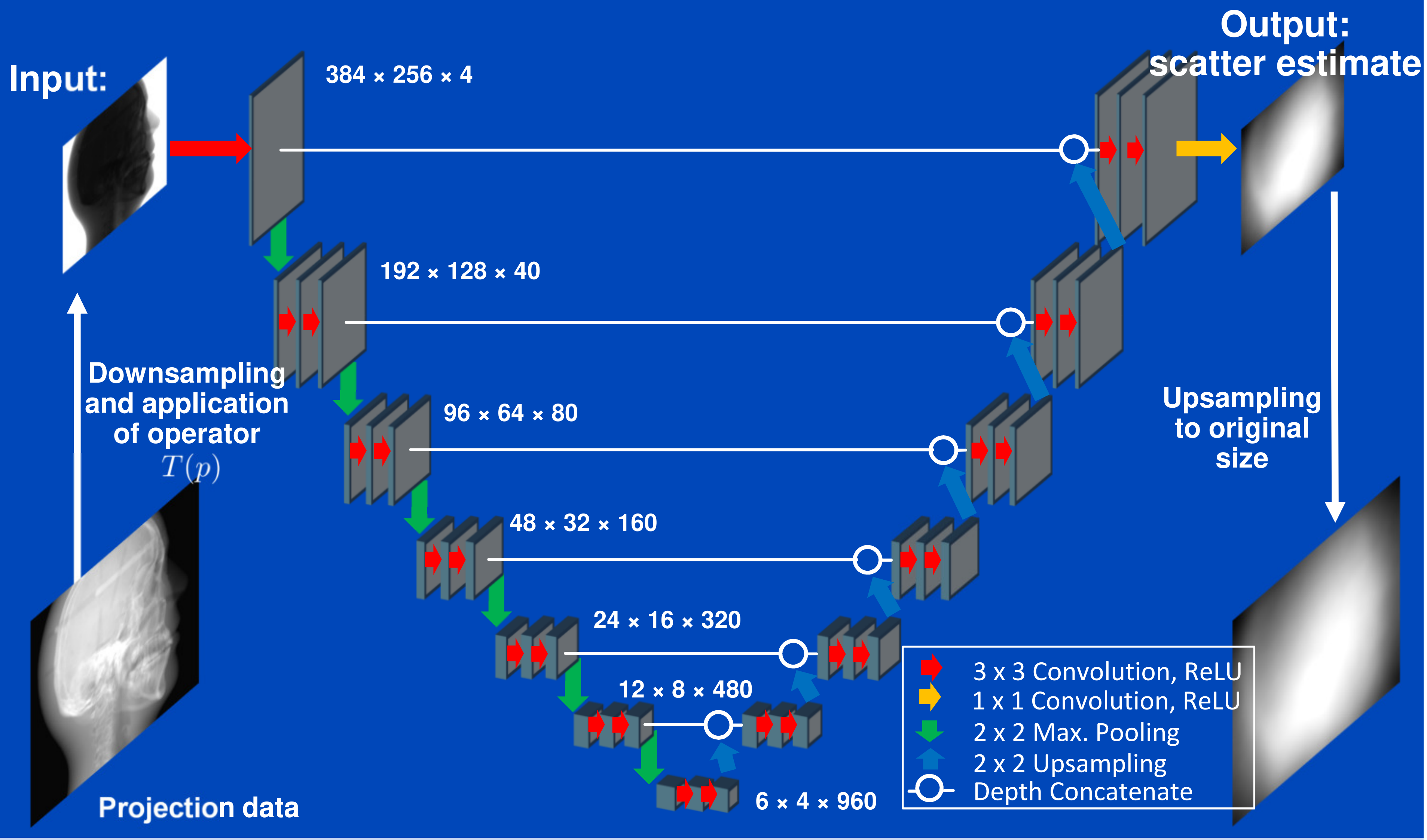
Convolutional neural network



Scatter estimate



DSE Network Architecture

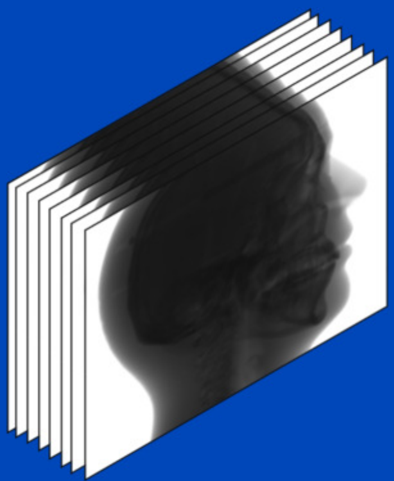


Training the DSE Network

Optimize weights and biases of our CNN to minimize the discrepancy between the DSE output and MC scatter simulations:

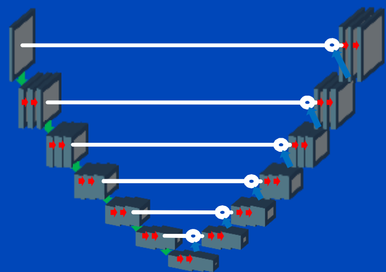
$$(\boldsymbol{w}, \boldsymbol{b}) = \arg\min_{\boldsymbol{w},\boldsymbol{b}} \|\mathrm{DSE}_{\boldsymbol{w},\boldsymbol{b}}(T(p)) - I_{\mathrm{MC}}\|_2^2$$

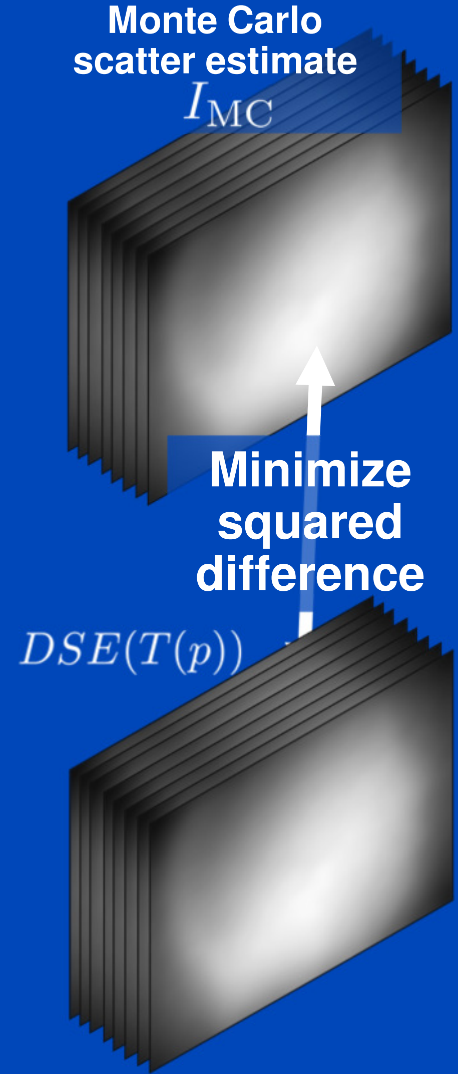
Input: $T(p)$



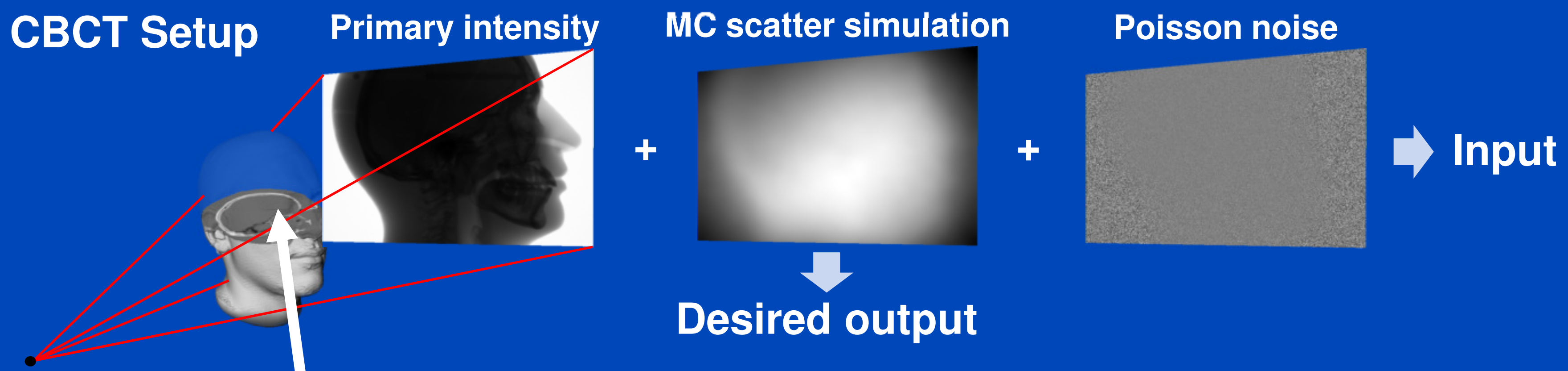
~~$\int T(p)(\boldsymbol{u}')G(\boldsymbol{u}, \boldsymbol{u}', \boldsymbol{c})d\boldsymbol{u}'$~~

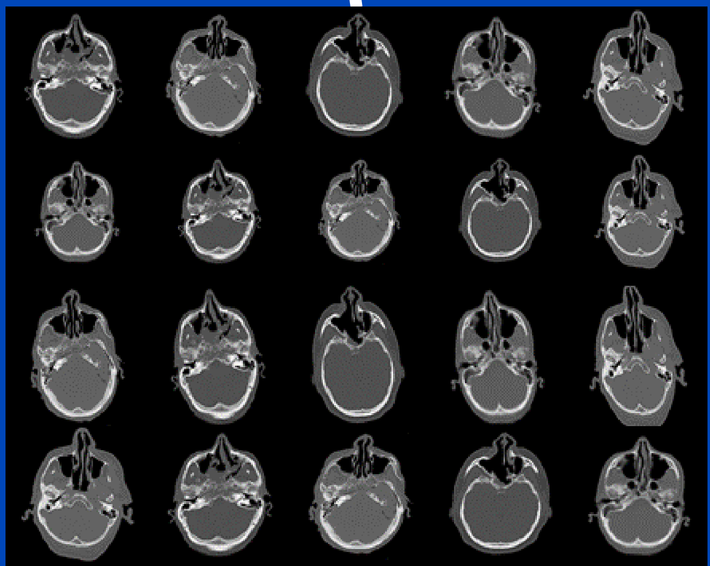
Convolutional neural network





Training the DSE Network



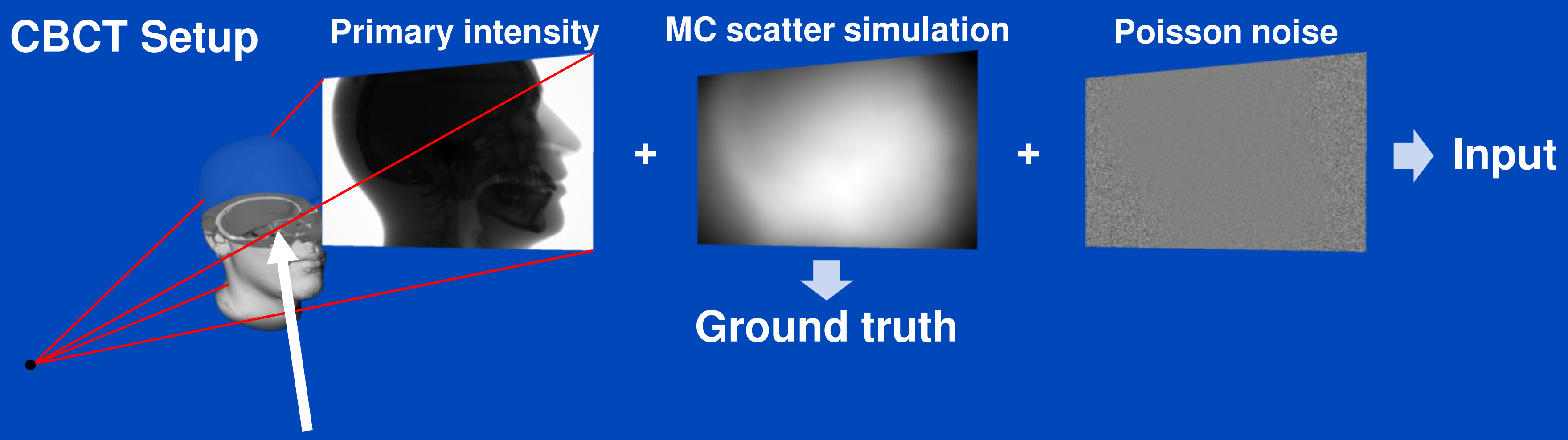


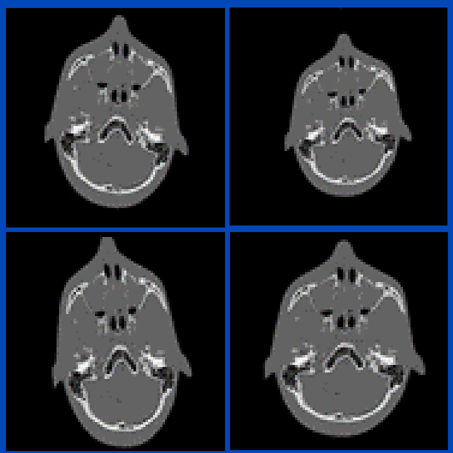
- **Simulation of 12000 flat detector projection using data of different heads.**
- **Simulate different acquisition parameters.**
- **Splitting into 80% training and 20% validation data.**
- **Optimize weights of the CNN to reproduce the Monte Carlo scatter estimates:**

$$(\boldsymbol{w}, \boldsymbol{b}) = \arg\min_{\boldsymbol{w},\boldsymbol{b}} \|\mathrm{DSE}_{\boldsymbol{w},\boldsymbol{b}}(T(p)) - I_{\mathrm{MC}}\|_2^2$$

- **Training on a GeForce GTX 1080 for 80 epochs.**

Testing DSE

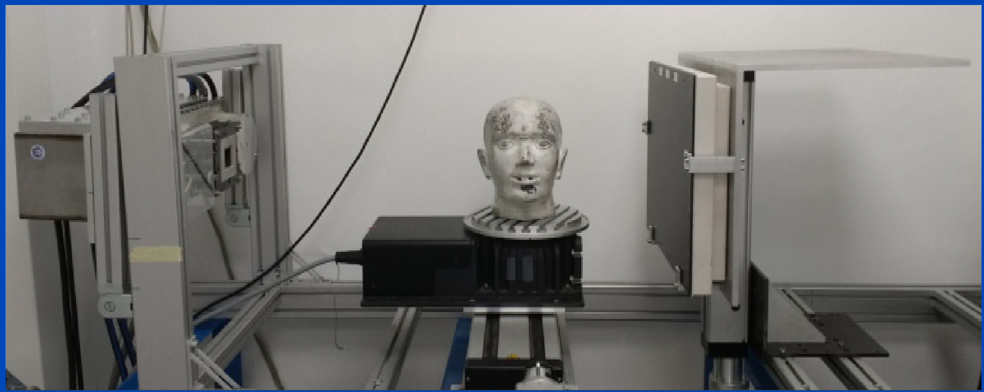




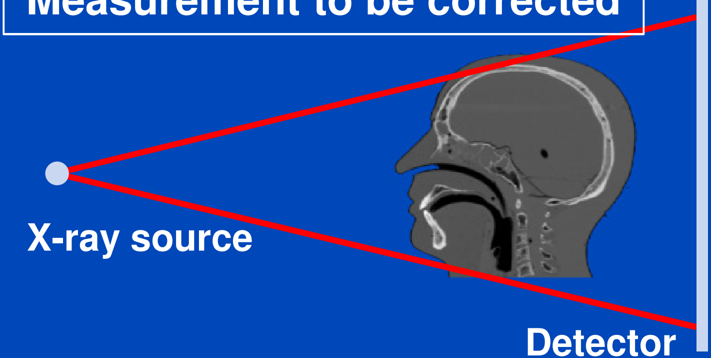
- **Application of the DSE network to predict scatter for simulated data of a head (different from training data).**

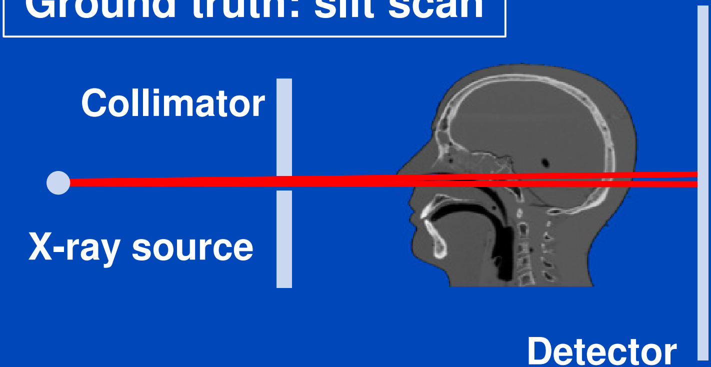
Testing DSE

DKFZ table-top CT

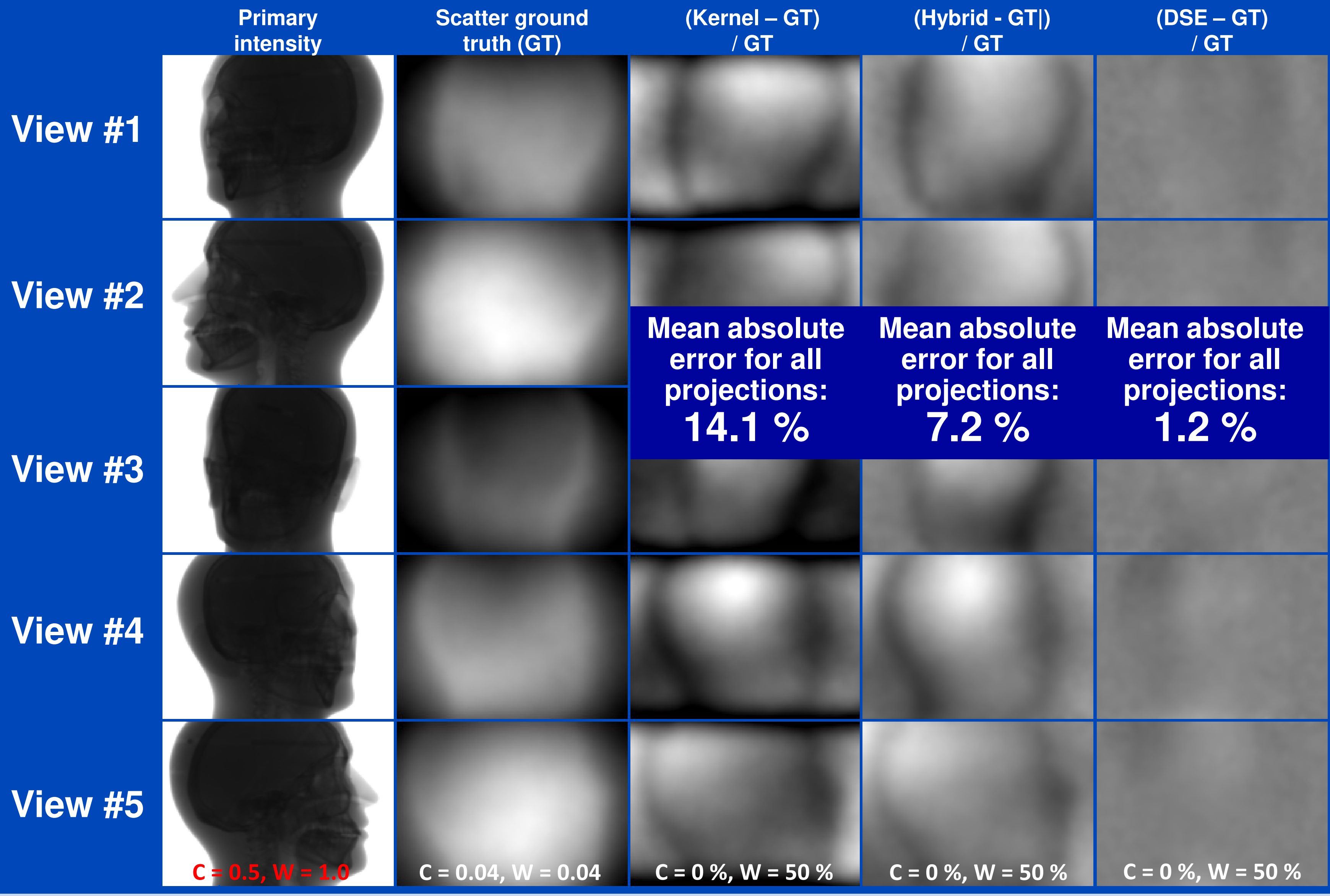


- Measurement of a head phantom at our in-house table-top CT.
- Slit scan measurement serves as ground truth.

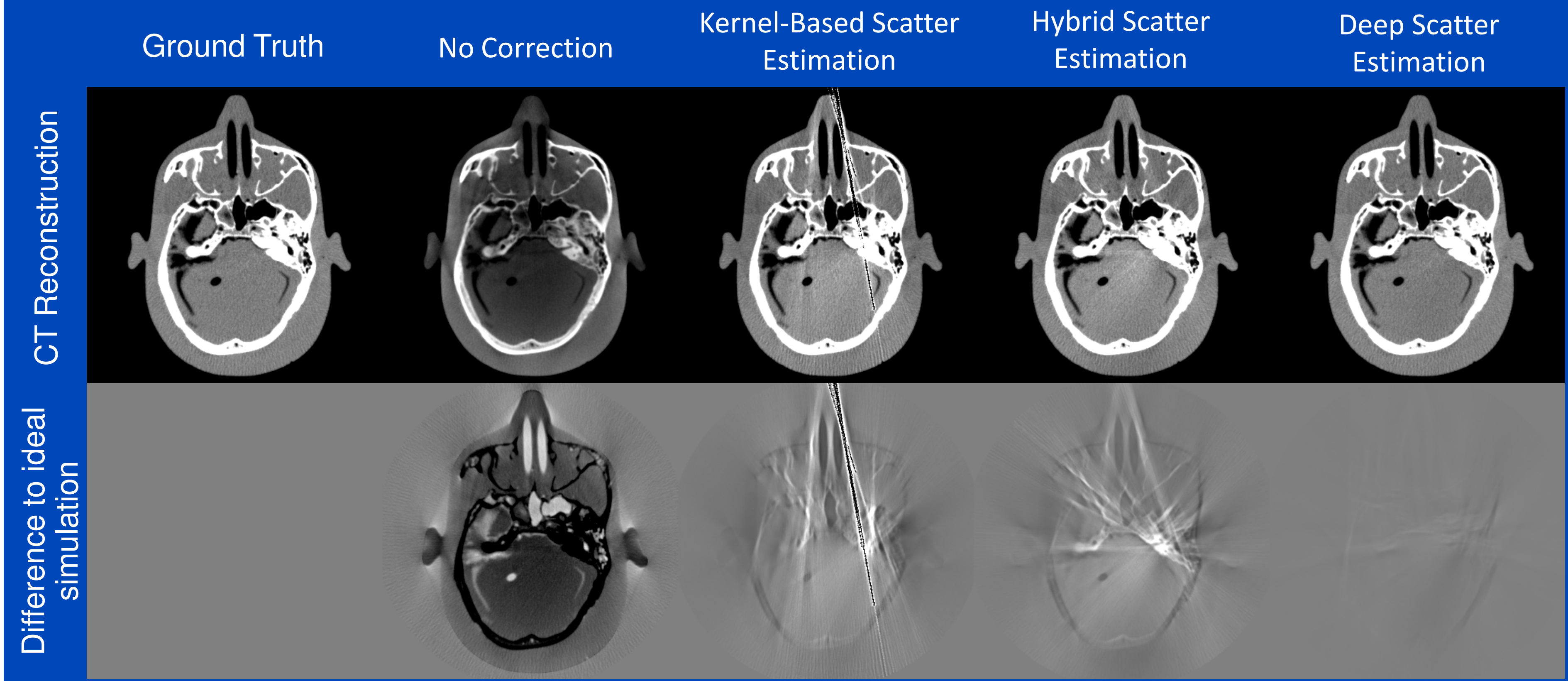




Results – Simulated Projection Data

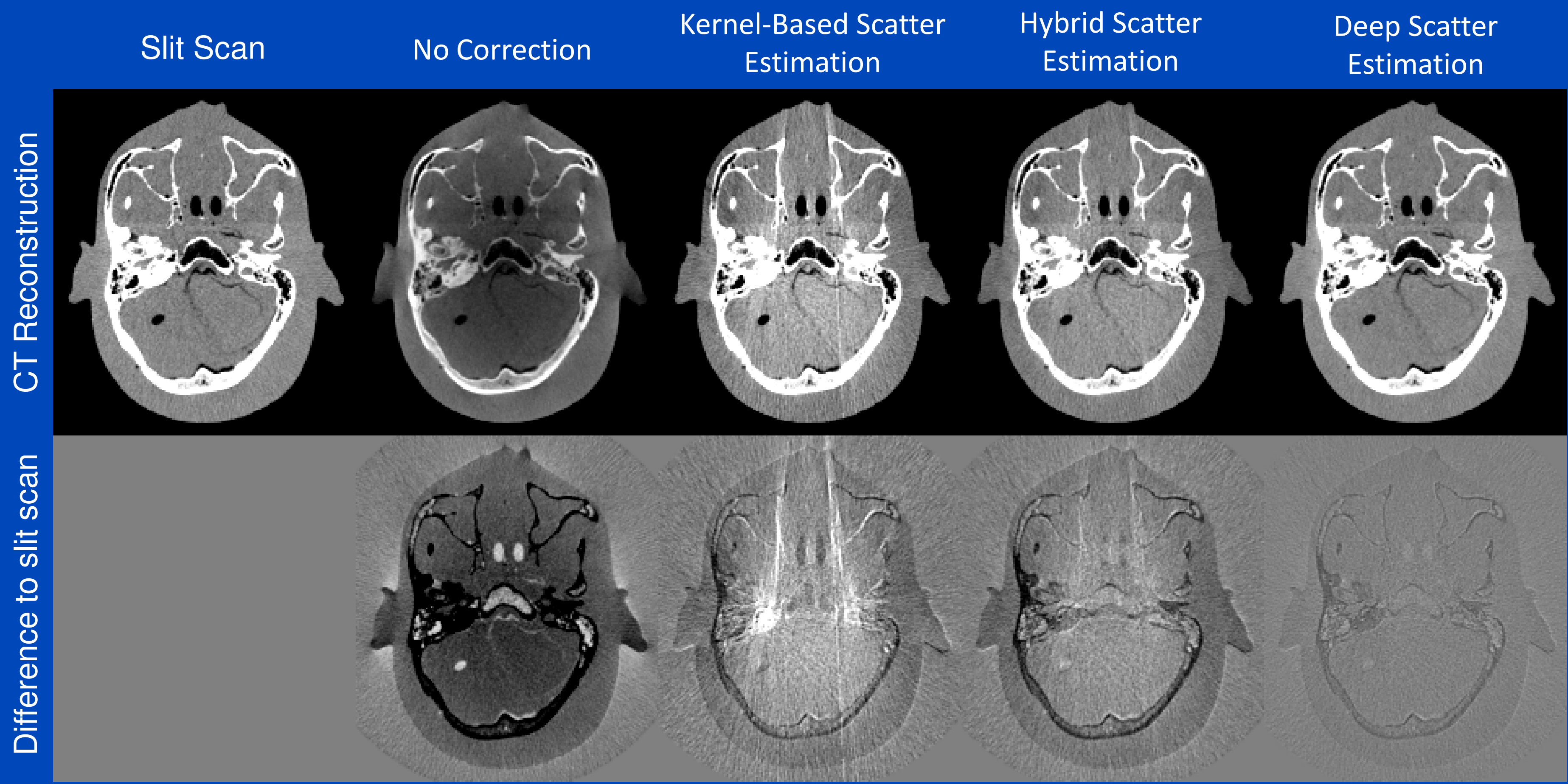


Results – CT Reconstructions of Simulated Data



C = 0 HU, W = 1000 HU

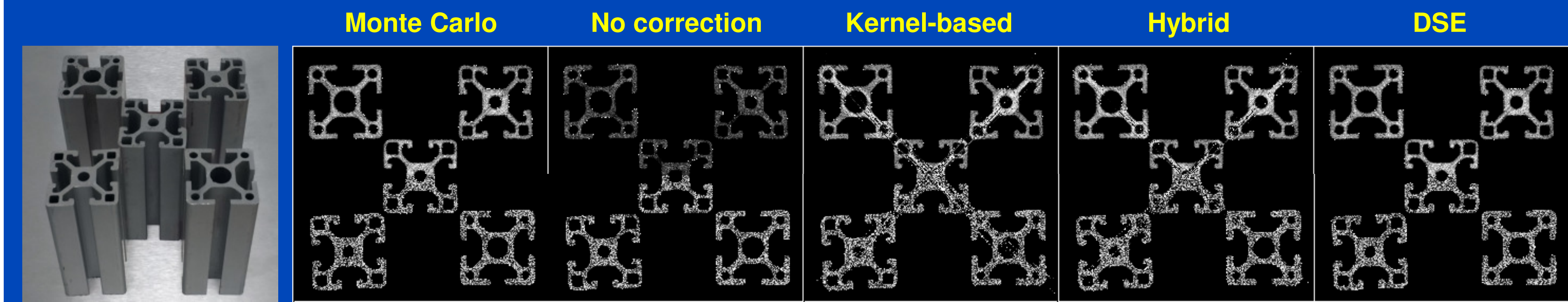
Results – CT Reconstructions of Measured Data



C = 0 HU, W = 1000 HU

Conclusions

- DSE is a fast and accurate alternative to Monte Carlo.
- DSE performs in real time.
- 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.
- DSE also works well for industrial applications:



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.