Deep Scatter Estimation (DSE) for Static CT

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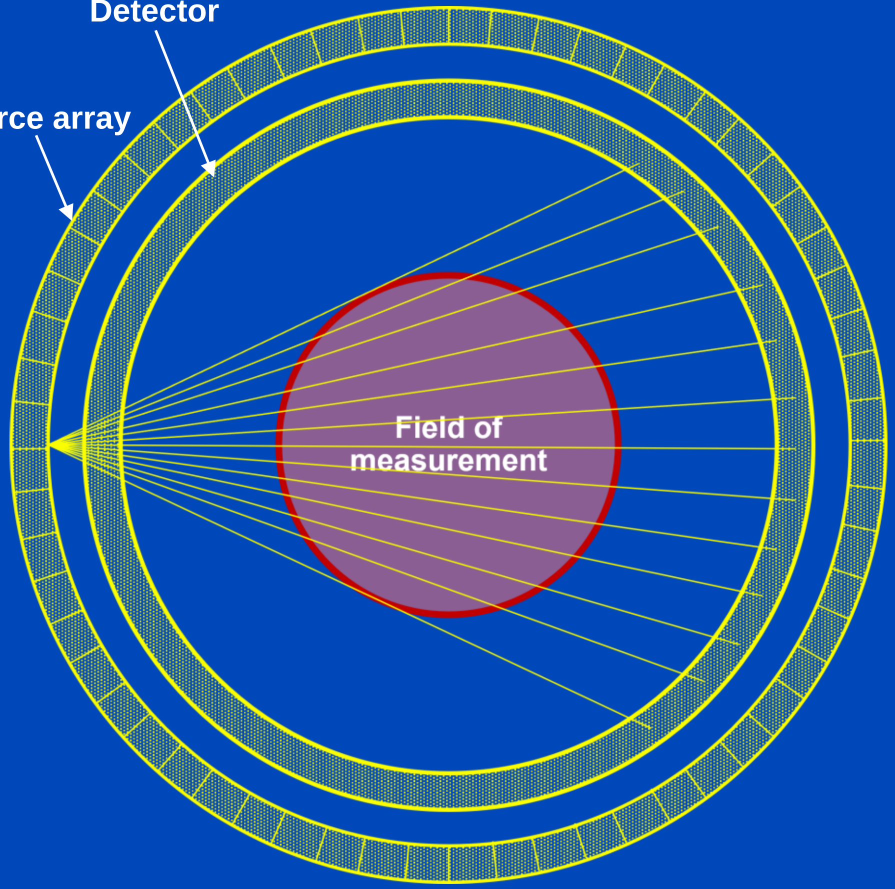
Static CT: Construction and Motivation

- 4^{th} generation CT scanner
- No rotating components
- Ring source array
  - Composed of many individual sources
  - Field emission technology → more efficient
  - Ability of acquisition with varying tube voltage
- Ring detector

→ Mechanical simplification
→ Acquisition time is not limited by rotation speed but rather by source power
→ Arbitrary acquisition patterns possible that may lead to dose reduction



Challenges in Static CT and Aim

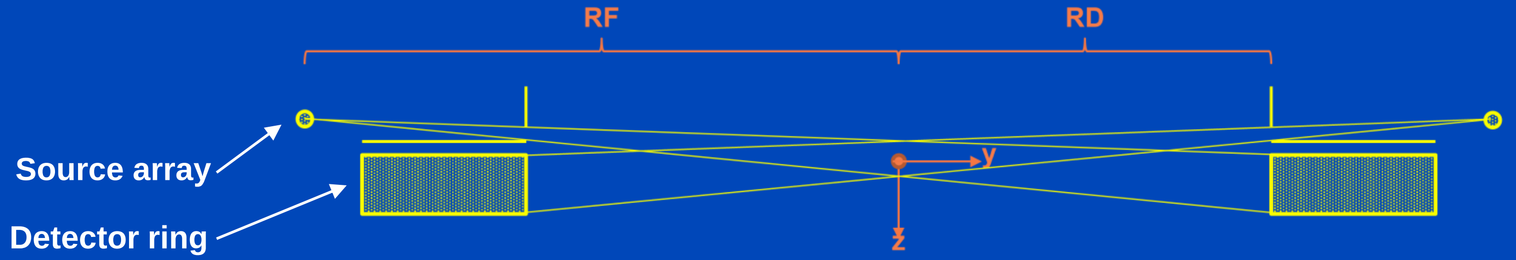
Challenges

- **No hardware-based scatter rejection possible**
  - → Impairment of image quality due to scatter artifacts
  - → Increased image noise due to scatter
- **Challenges in reconstruction**
  - → No loss-free reconstruction possible due to z-shift between source array and detector
- **Source and detector ring cause high expenses**

Software-based scatter correction is one of the central challenges in static CT

Aim

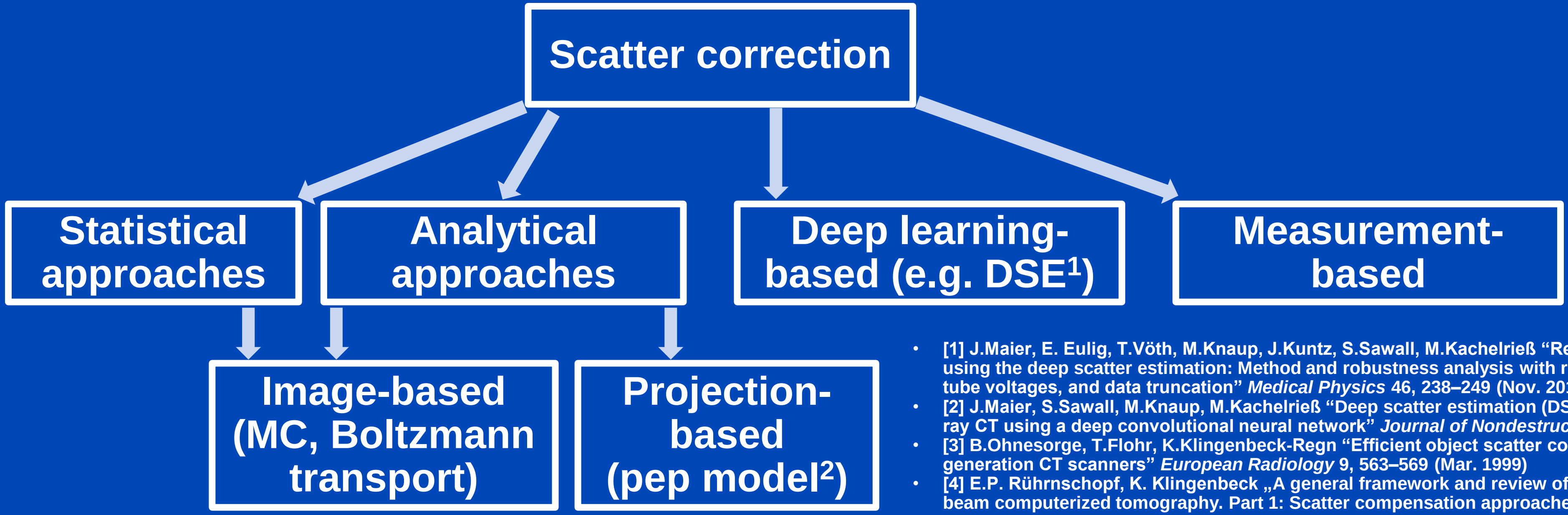
- **Development of a software-based scatter correction method to minimize scatter artifacts**



Z-shift between detector and source array

Software-based Scatter Correction Methods

- Gold standard to obtain scatter estimates is the Monte Carlo (MC) method
  - High accuracy but computationally expensive and therefore not suitable for clinical application
- In this work, we focus on DSE[1,2], a deep learning-based approach
  - DSE can predict MC scatter estimates
  - DSE maintains high accuracy while being computationally less expensive than MC by orders of magnitude
- We use an implementation of the pep model[3] as comparison method
- A summary of scatter correction methods is provided by Rührnschopf and Klingenbeck[4]



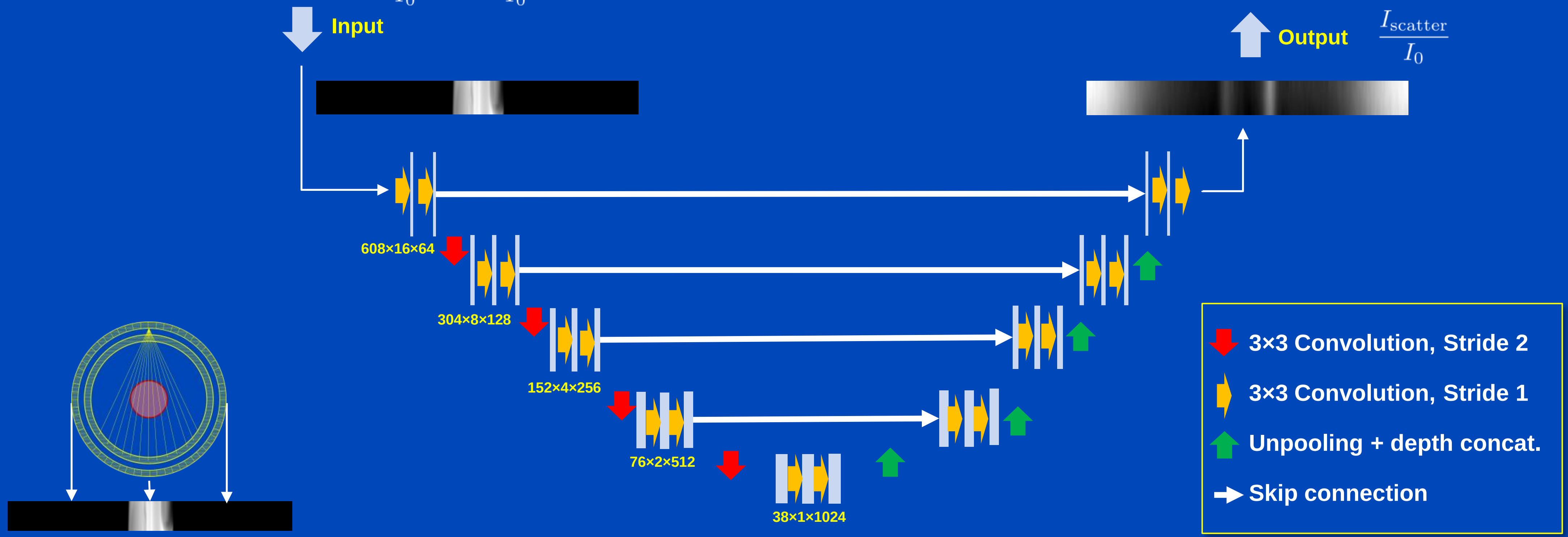
- [1] J.Maier, E. Eulig, T.Vöth, M.Knaup, J.Kuntz, S.Sawall, M.Kachelrieß “Real-time scatter estimation for medical CT using the deep scatter estimation: Method and robustness analysis with respect to different anatomies, dose levels, tube voltages, and data truncation” *Medical Physics* 46, 238–249 (Nov. 2018)
- [2] J.Maier, S.Sawall, M.Knaup, M.Kachelrieß “Deep scatter estimation (DSE): Accurate real-time scatter estimation for x-ray CT using a deep convolutional neural network” *Journal of Nondestructive Evaluation* 37 (July 2018)
- [3] B.Ohnesorge, T.Flohr, K.Klingenbeck-Regn “Efficient object scatter correction algorithm for third and fourth generation CT scanners” *European Radiology* 9, 563–569 (Mar. 1999)
- [4] E.P. Rührnschopf, K. Klingenbeck „A general framework and review of scatter correction methods in x-ray cone-beam computerized tomography. Part 1: Scatter compensation approaches“ *Medical Physics* 38, 4296–4311 (June 2011)

DSE (Deep Scatter Estimation) Architecture

- **Use a deep convolutional neural network to estimate scatter using the acquired projection data as input**
- **Train the network to predict Monte Carlo scatter estimates based on the acquired projection data**
- **DSE outperforms other scatter estimation techniques**
- **DSE is faster than Monte Carlo simulations by orders of magnitude**

Input dimension:
608×16
Input mapping:

$$p = -\ln\left(\frac{I_{\text{primary}}}{I_0} + \frac{I_{\text{scatter}}}{I_0}\right)$$



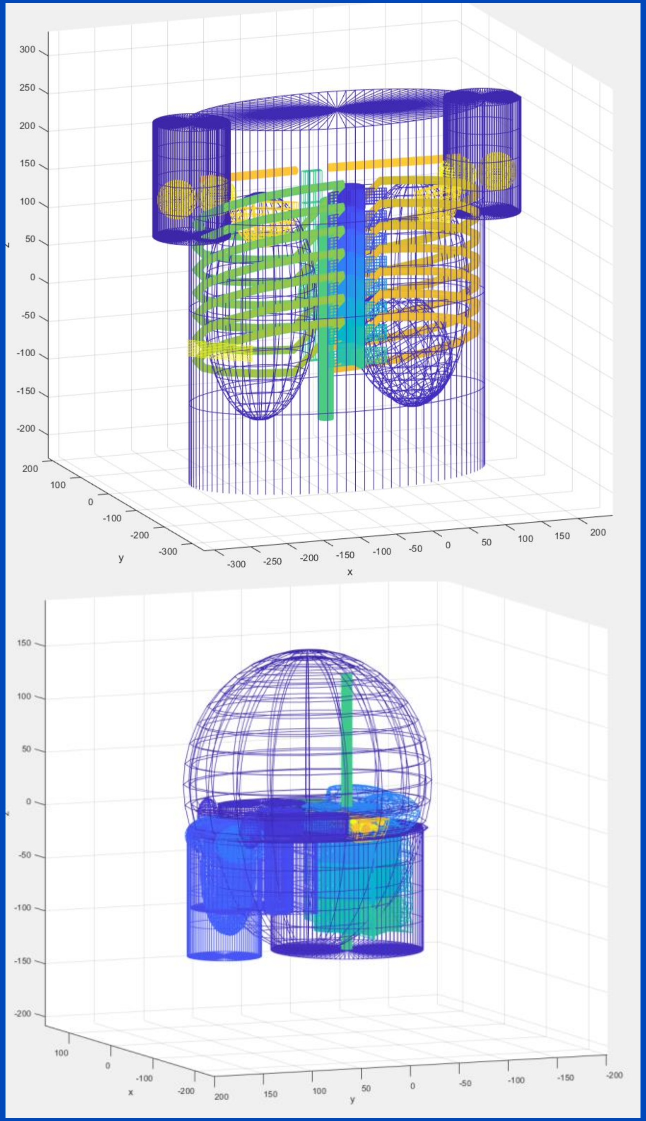
DSE Architecture

- Loss function only evaluates region within the primary fan beam
- Measured scatter outside of the primary fan can be provided to DSE as additional information
- Scatter-to-primary mean absolute percentage error (SPMAPE) is used as loss function as it correlates with the error in the image
- SPMAPE is limited to the primary fan by applying a primary mask to the detector array

$$\mathrm{SPMAPE} = \frac{1}{n_{\text{data points}}} \times \sum_{j=0}^{n_{\text{data points}}} \left| \frac{I_{\text{scatter,MC}} - I_{\text{scatter,DSE}}}{I_{\text{scatter,MC}}} \times \frac{I_{\text{scatter,MC}}}{I_{\text{prim}}} \right|$$

$$= \frac{1}{n_{\text{data points}}} \times \sum_{j=0}^{n_{\text{data points}}} \left| \frac{I_{\text{scatter,MC}} - I_{\text{scatter,DSE}}}{I_{\text{prim}}} \right|$$

Monte Carlo Simulations



- **Training dataset consists of:**
  - **Water phantom ×50**
  - **Ellipse phantom ×50**
  - **Thorax phantom ×100**
- **Angular steps of 5° simulated**
  - **72 projections per phantom**
- **Train validation split 90:10**

Phantoms differ from each other by simulating with:

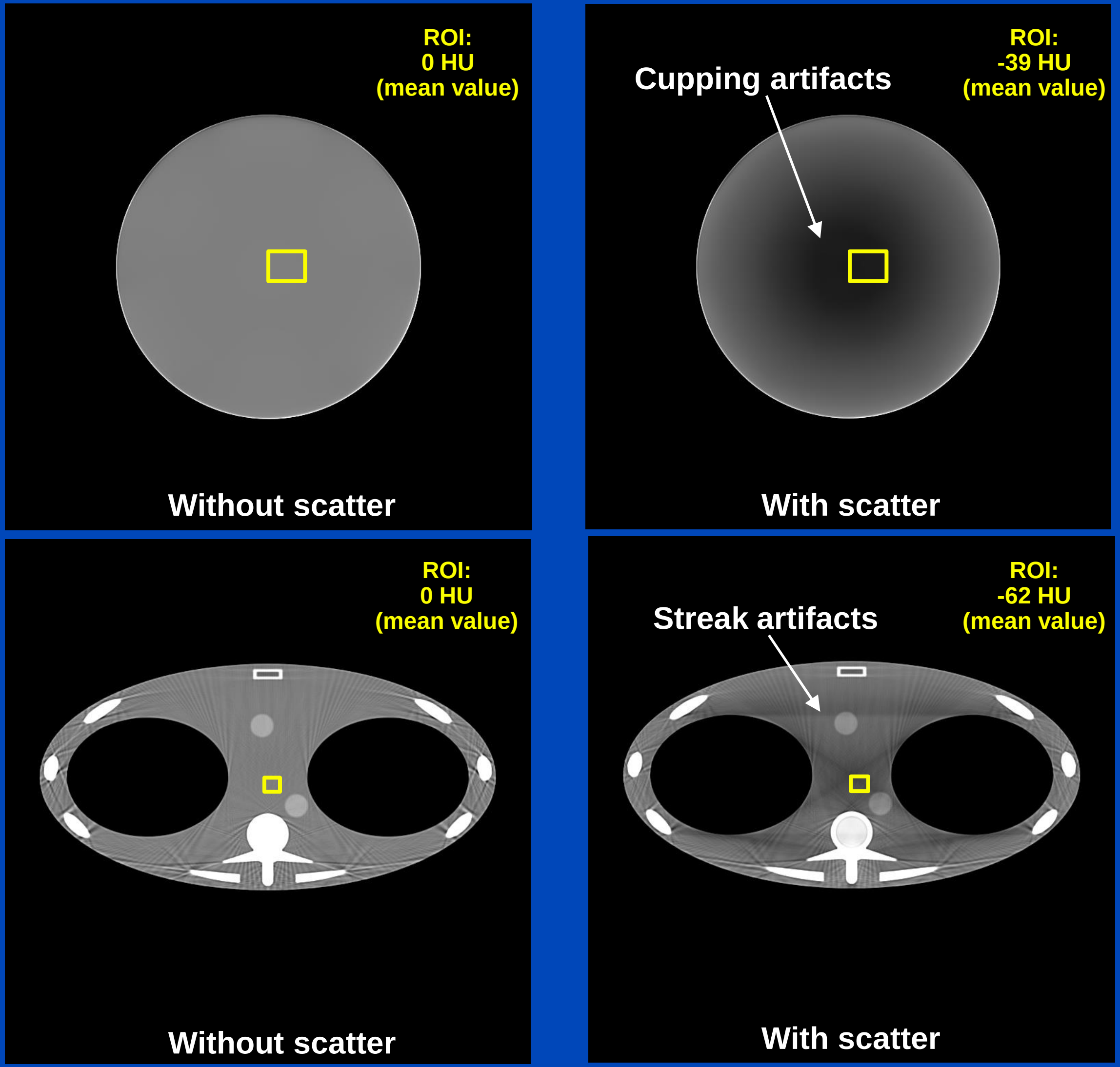
- **Random size**
- **Random lateral shift up to 8 cm in x and y direction**
- **Random longitudinal shift (thorax)**

→ A total of 200 phantoms simulated
→ 14400 projections
→ For testing, additional phantoms were simulated (thorax and head)

Artifacts in the Image Caused by Scatter

Water phantom, *d* = 32 cm
***C* = 0 HU, *W* = 100 HU**

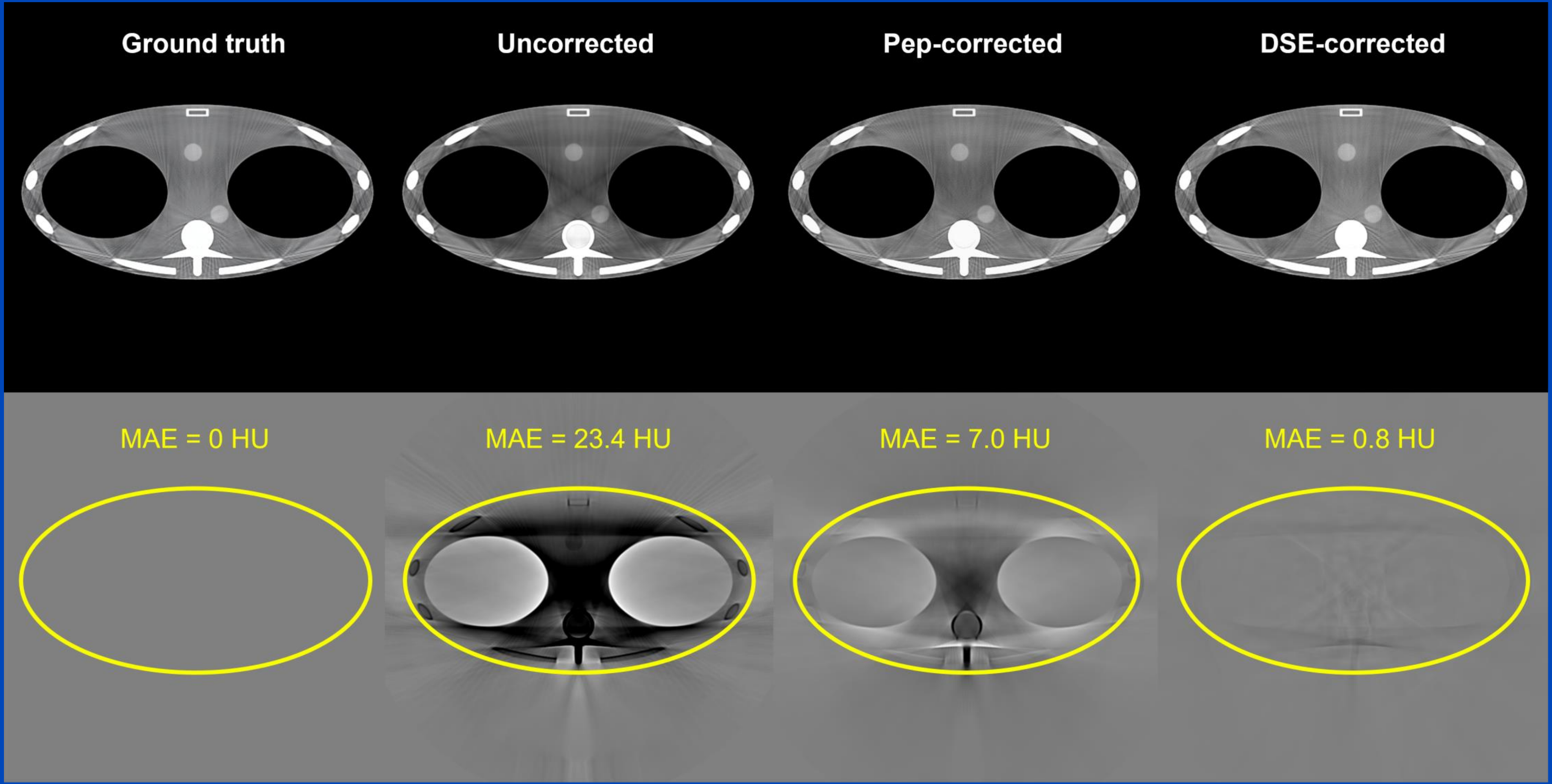
Forbild thorax phantom
***C* = 0 HU, *W* = 300 HU**



Evaluation

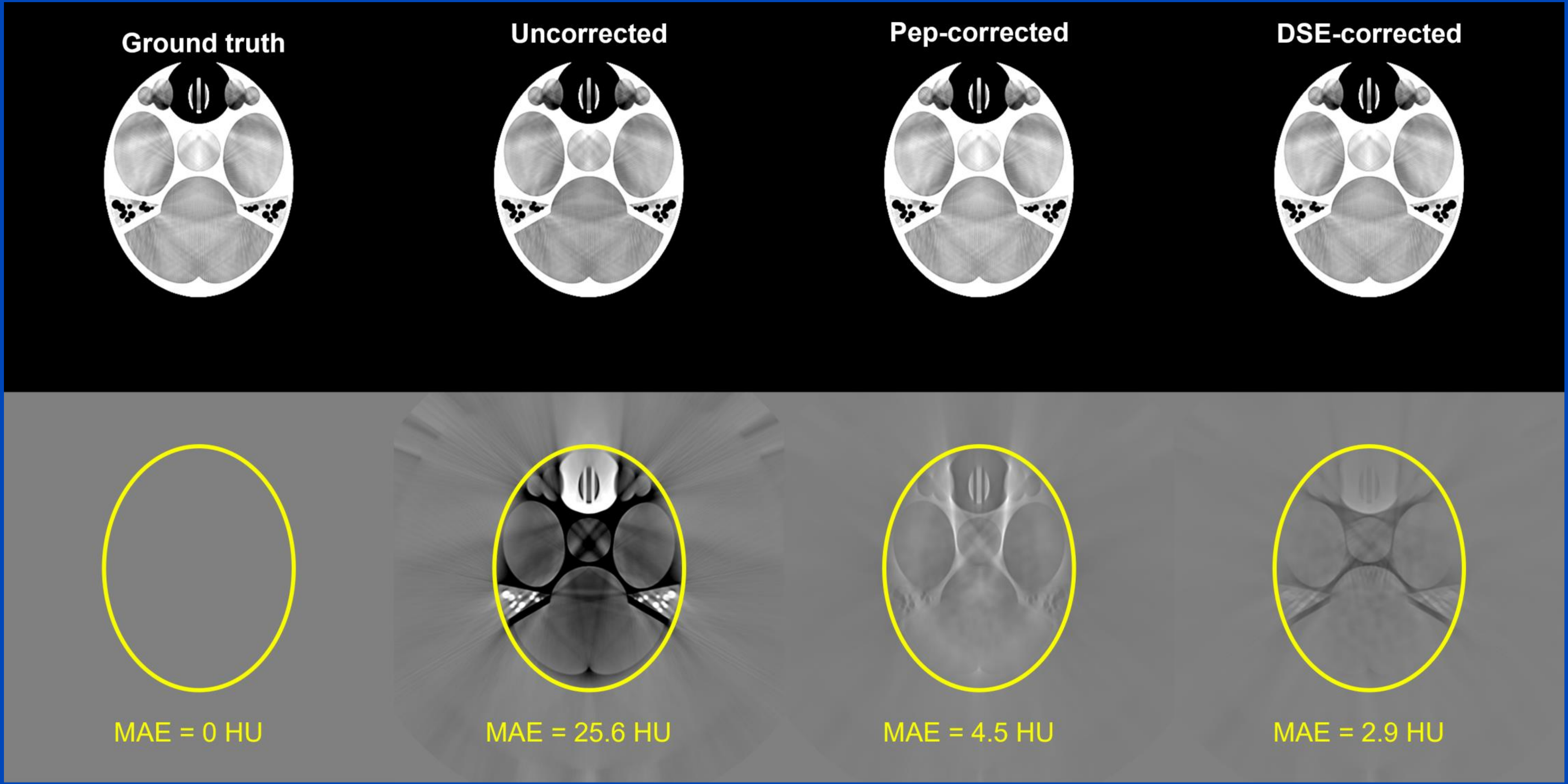
- Testing is done by evaluating the mean absolute error (MAE) in image domain within a mask over the phantom
- For evaluation, a thorax and a head phantom are used. While, among other, our training dataset contains thorax phantoms, DSE is not trained on any head phantom
- Performance of DSE is compared to a pep-model
- The primary signal for reconstruction was simulated monochromatically to avoid the occurrence of other artifacts such as beam hardening. Scatter was simulated polychromatically. The monochromatic tube voltage was matched to produce realistic results

Results Thorax Phantom



Upper row: Reconstructions, C = 0 HU, W = 300 HU. Bottom row: Difference images, C = 0 HU, W = 100 HU

Results Head Phantom



Upper row: Reconstructions, *C* = 0 HU, *W* = 300 HU. Bottom row: Difference images, *C* = 0 HU, *W* = 100 HU

Conclusions and Limitations

Conclusion

- DSE can effectively correct scatter artifacts in static CT reconstructions
- DSE generalizes to unseen phantoms such as the head phantom
- DSE outperforms the comparison method even for phantoms that it was not trained on such as the head phantom

Limitations

- This work is simulation-based, we did not correct any physical measurements
- Since there are no static CT scanners in clinical use, we could not try to correct any clinical data

Thank You!

- This study was supported by Siemens Healthineers AG.
- 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).