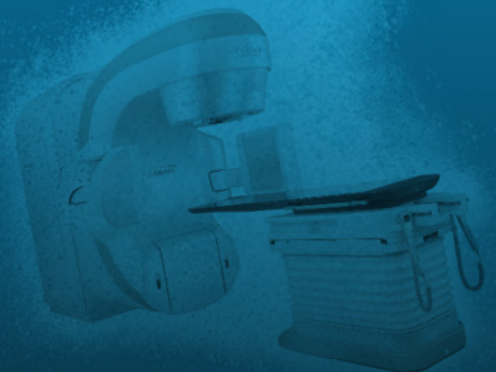
Deep Scatter Estimation (DSE) for Truncated Cone-Beam CT (CBCT)



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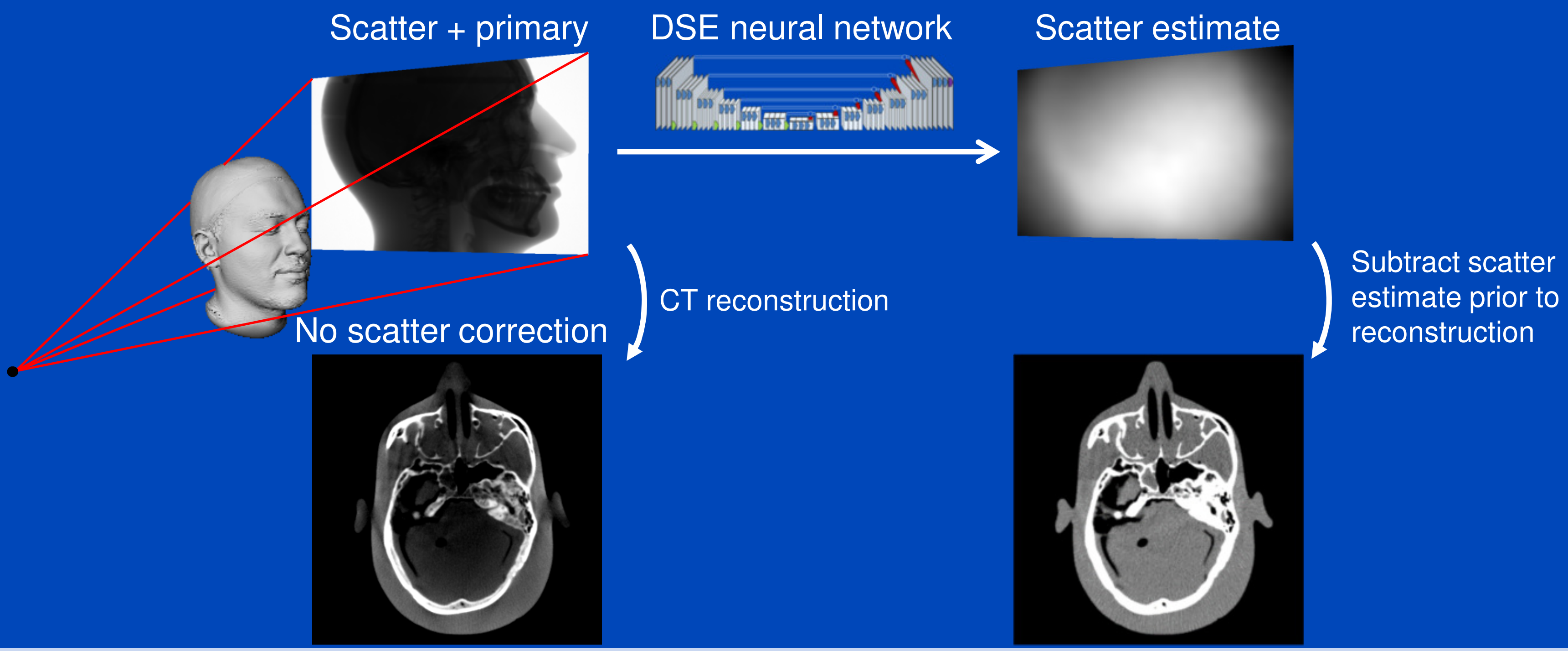
dkfz. DEUTSCHES KREBSFORSCHUNGSZENTRUM IN DER HELMHOLTZ-GEMEINSCHAFT

Motivation

- X-ray scatter leads to a degradation of image quality in CT.
- Appropriate scatter correction is crucial to maintain the diagnostic and quantitative value of the CT examination.
- Recently, we proposed the deep scatter estimation (DSE)[1,2] which has demonstrated great potential for scatter-correction of non-truncated CBCT simulations and measurements.

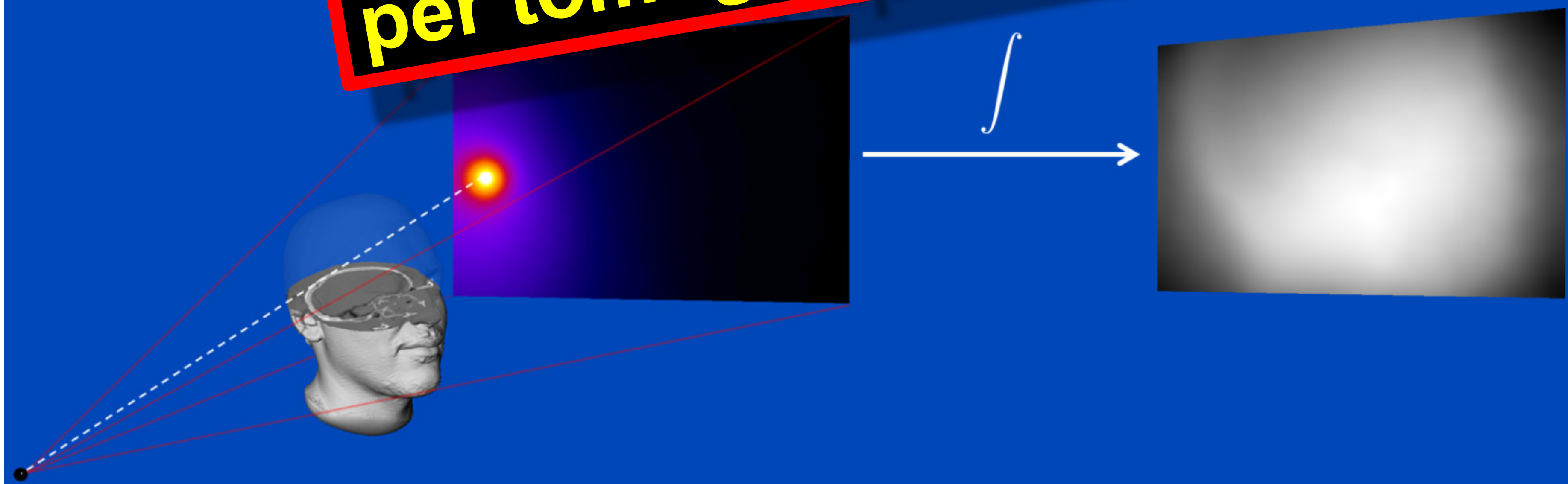


[1]J. Maier, Y. Berker, S. Sawall, M. Kachelrieß. SPIE Medical Imaging Conference Record 105731L:1-6, 2018.
[2]J. Maier, S. Sawall, M. Knaup, M. Kachelrieß. Journal of Nondestructive Evaluation 37:57, 2018.

Monte Carlo Scatter Estimation

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

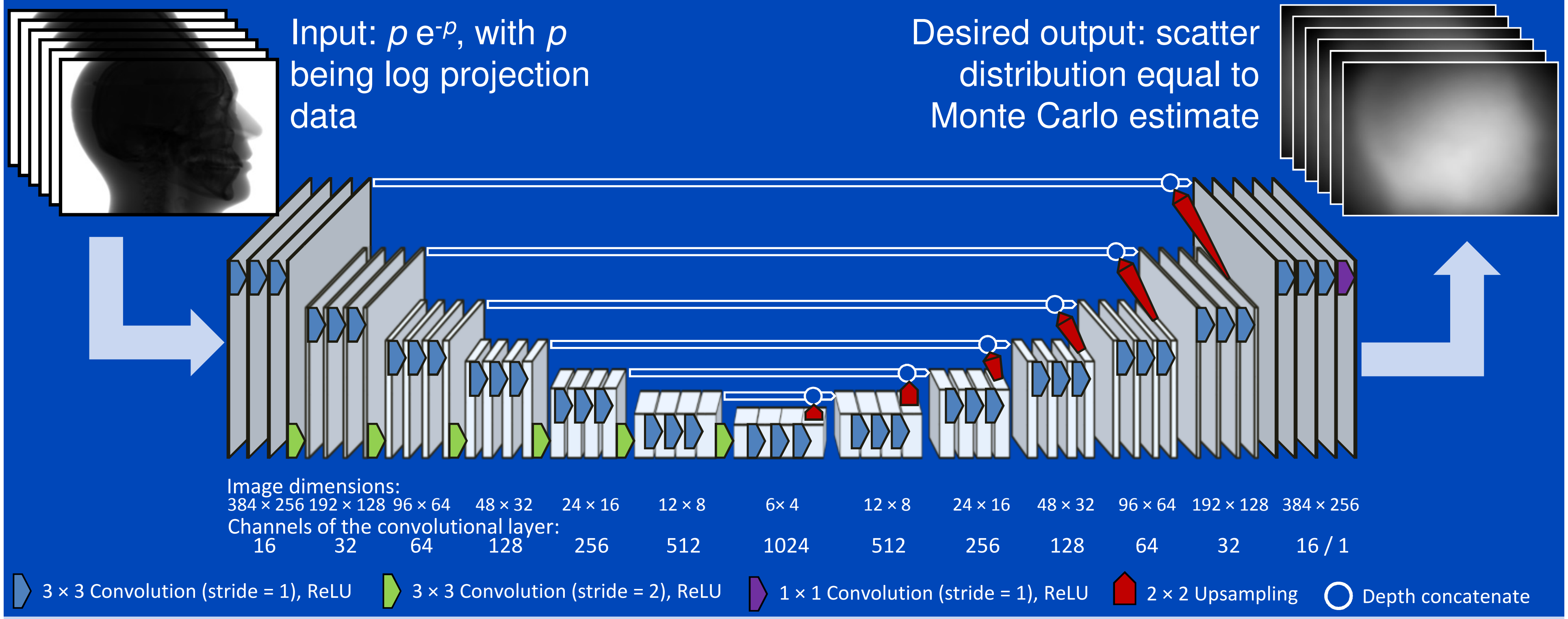
1 to 10 hours
per tomographic data set



Deep Scatter Estimation[1,2] (DSE)

Basic Principle

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



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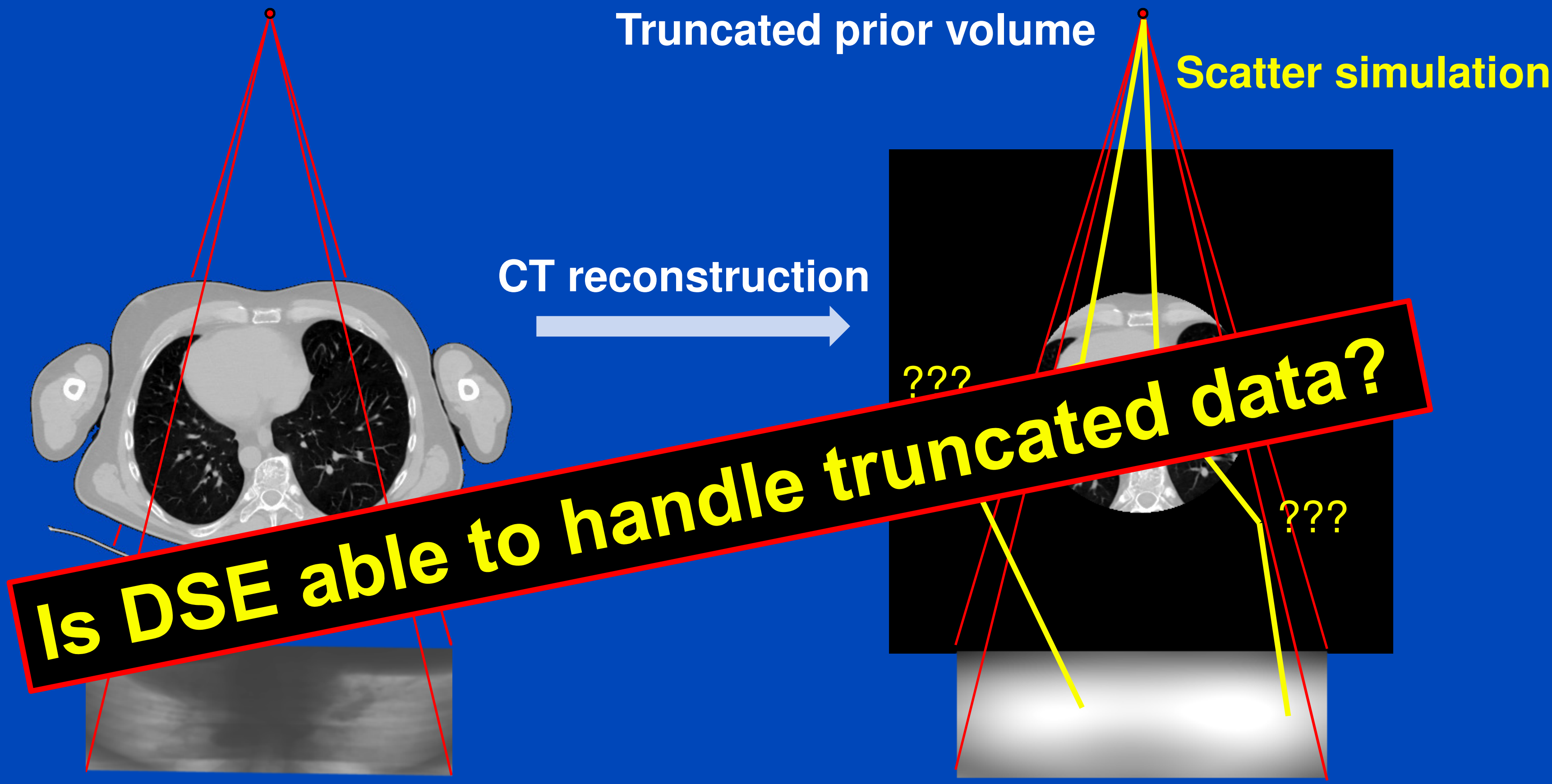
Data Truncation

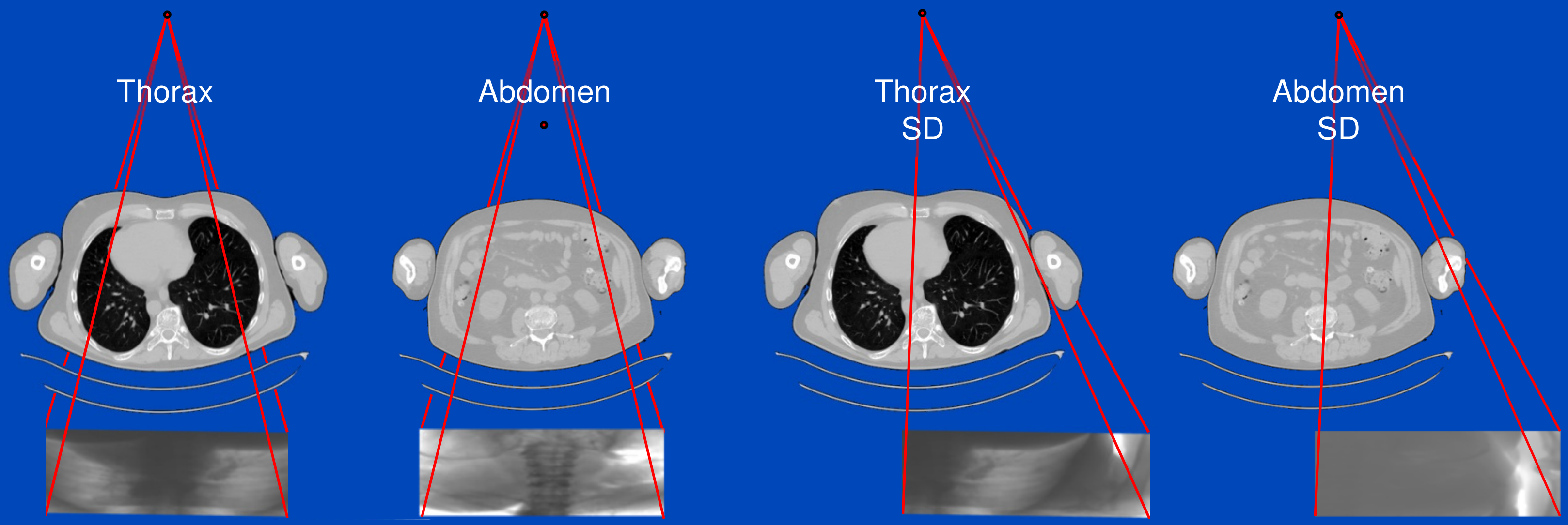
- CBCT often has to deal with truncation which.
- Truncation decreases the performance of scatter estimation approaches such as MC or Boltzmann transport[1].



[1]N. Waltrich, D. Sawall, J. Maier, J. Kuntz, K. Stannigel, K. Lindenberg, and M. Kachelrieß. Effect of detruncation on the accuracy of Monte Carlo-based scatter estimation in truncated CBCT. Med. Phys. 45(8):3574–3590, 2018.

Simulation Study

- Simulation of head, thorax and abdomen CBCT data using 14 clinical CT patient data sets as a starting point.
- Typical CBCT geometry and a 40 × 30 cm flat detector.
- Two different setups:
  - centered detector
  - shifted detector (SD)
- Simulation of scatter using our in house MC simulation[1].



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

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DSE Training & Testing

- Simulation of 30240 head, thorax and abdomen projections.
- Splitting into 80% training data and 20% test data.
- The DSE network was trained to learn the mapping:

$$M_{\mathrm{pep}} : p \cdot e^{-p} \to S_{\mathrm{MC}}$$

- The weights *w* and the biases *b* were determined by minimizing the mean absolute percentage error between the output and a MC scatter prediction S_{MC}:

$$\{\boldsymbol{w}, \boldsymbol{b}\} = \operatorname{argmin} \frac{100}{K} \sum_{n,\boldsymbol{u}} \left| \frac{\mathrm{DSE}(n, \boldsymbol{u}, \boldsymbol{w}, \boldsymbol{b}) - S_{\mathrm{MC}}(n, \boldsymbol{u})}{S_{\mathrm{MC}}(n, \boldsymbol{u})} \right|$$

- The training was performed on an NVIDIA Quadro P6000 for 80 epochs using an Adam optimizer and a batch size of 16.
- Training took about 15 h.
- Training on each anatomy separately or using all data together.

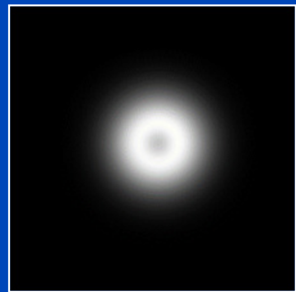
Kernel-based Scatter Estimation (KSE)
(Reference 1)

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

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

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

Open parameters: c_0



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

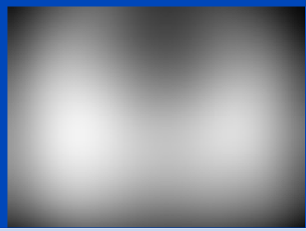
Open parameters: c_1, c_2, c_3, c_4

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

Samples of the training data set

Detector coordinate

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. Rad. 9:563–569, 1999.

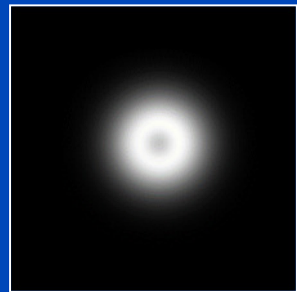
Hybrid Scatter Estimation (HSE)
(Reference 2)

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

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

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

Open parameters: c_0



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

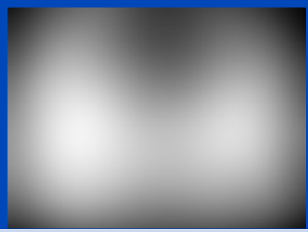
Open parameters: c_1, c_2, c_3, c_4

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

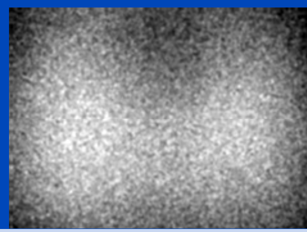
Samples of the test data set

Detector coordinate

Scatter estimate



Coarse MC scatter simulation



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

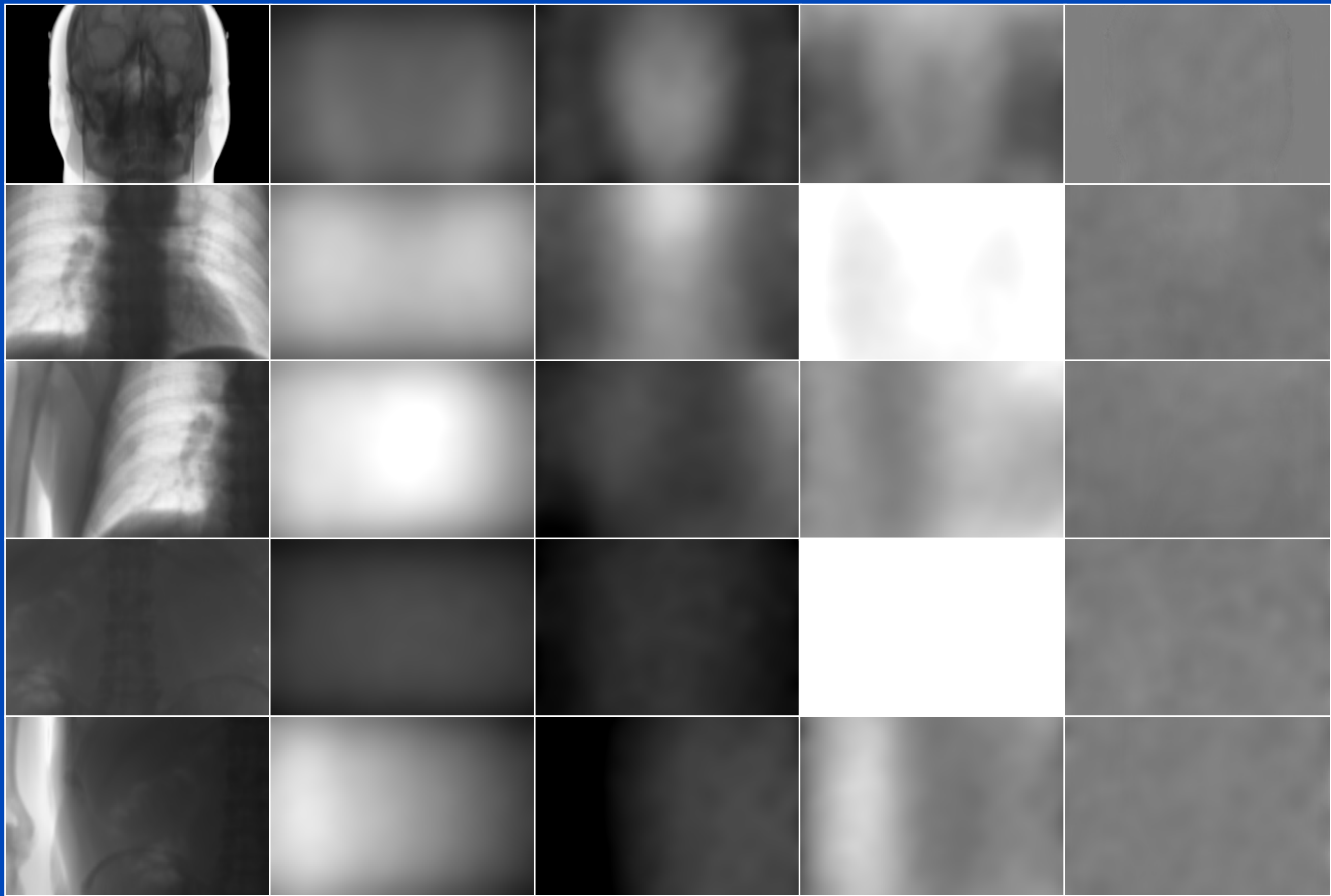
Results

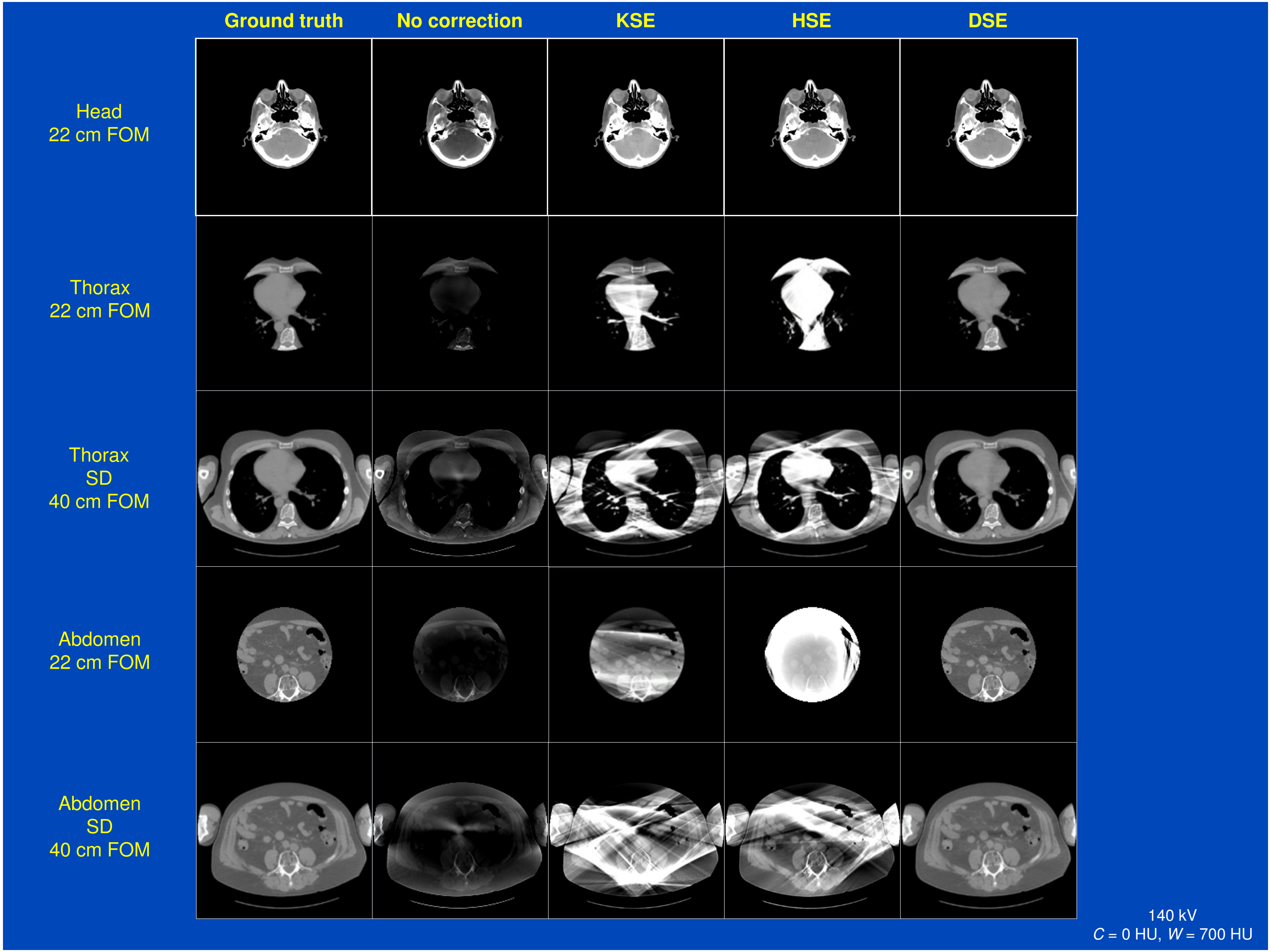
KSE	Head	Thorax	Abdomen
Head	14.5	26.8	32.5
Thorax	16.2	18.5	19.4
Abdomen	16.8	22.1	17.8
All data	14.9	20.5	19.3

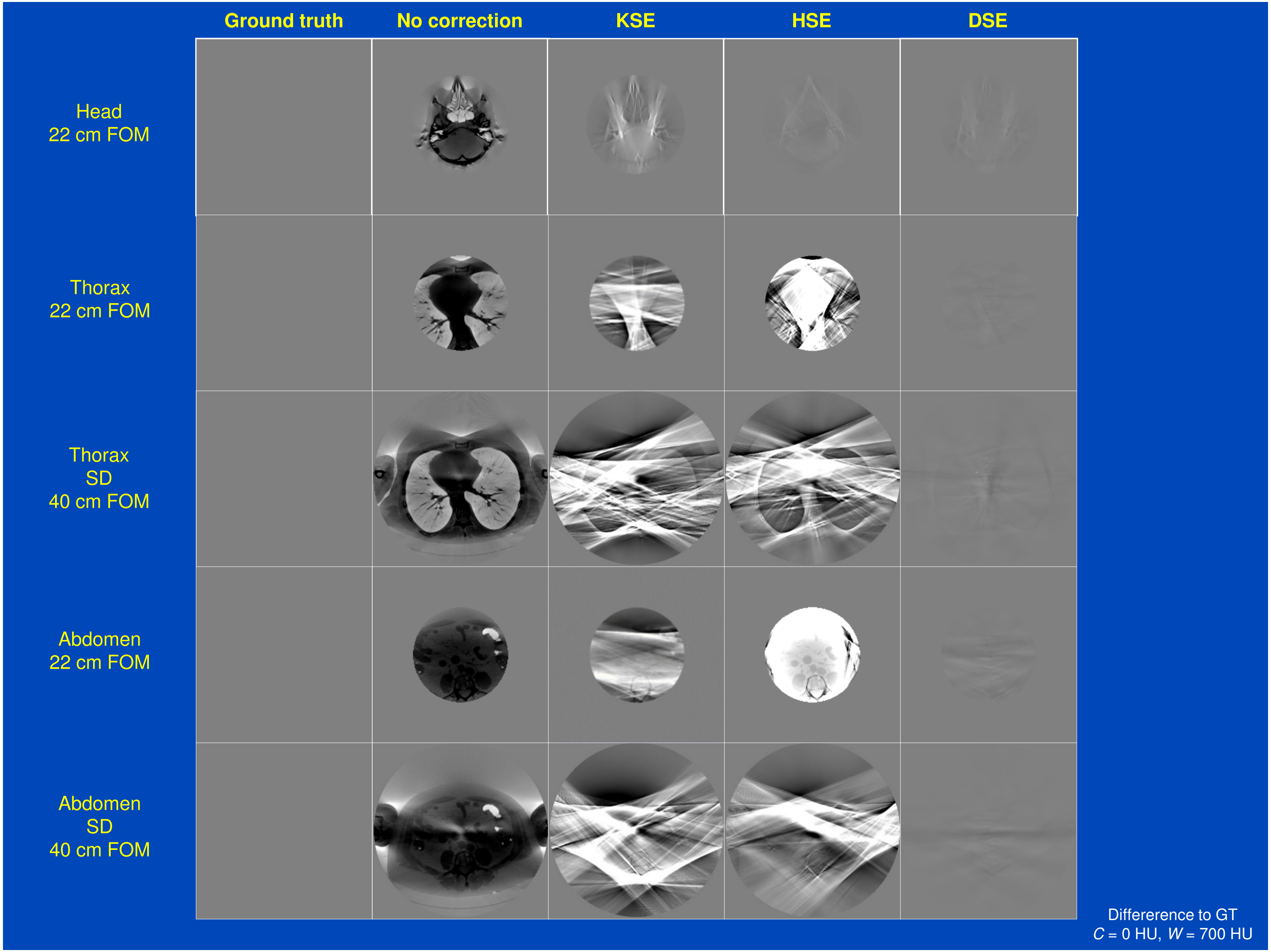
DSE	Head	Thorax	Abdomen
Head	1.2	21.1	32.7
Thorax	8.8	1.5	9.1
Abdomen	11.9	10.9	1.3
All data	1.8	1.4	1.4

Values shown are the mean absolute percentage errors (MAPEs) of the testing data.

Scatter Estimates




Ground truth
No correction
KSE
HSE
DSE
Head
22 cm FOM
Thorax
22 cm FOM
Thorax
SD
40 cm FOM
Abdomen
22 cm FOM
Abdomen
SD
40 cm FOM
140 kV
C = 0 HU, W = 700 HU


Ground truth
No correction
KSE
HSE
DSE
Head
22 cm FOM
Thorax
22 cm FOM
Thorax
SD
40 cm FOM
Abdomen
22 cm FOM
Abdomen
SD
40 cm FOM
Differerence to GT
C = 0 HU, W = 700 HU

Conclusions

- DSE yields scatter estimates that only differ by about 1.5% on average from the ground truth.
- DSE outperforms conventional kernel-based approaches in terms of accuracy and speed (DSE = 10 ms/projection)
- DSE generalizes well to varying anatomical regions. A single DSE network can correct for head, thorax and abdomen data.
- Interesting observations
  - DSE can estimate scatter from a single (!) x-ray image.
  - DSE can accurately estimate scatter from a primary+scatter image, but
  - DSE cannot accurately estimate scatter from a primary only image.
  - DSE may outperform MC even though DSE is trained with MC.
- DSE is not restricted to reproducing MC scatter estimates. It can obviously be used with any other scatter estimate.

Thank You!

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Image Formation in X-Ray Computed Tomography

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Conference Chair: **Marc Kachelrieß**, German Cancer Research Center (DKFZ), Heidelberg, Germany

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