Deep Learning-Based Scatter Correction for Dual Source CT Systems

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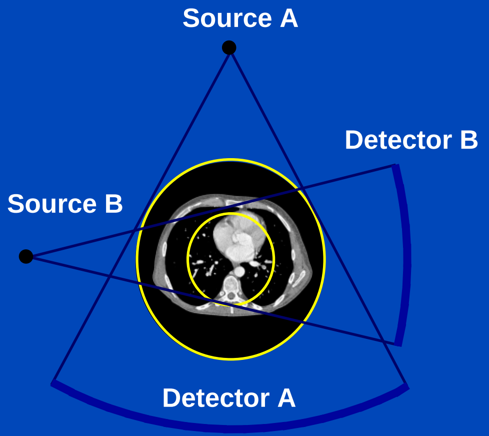
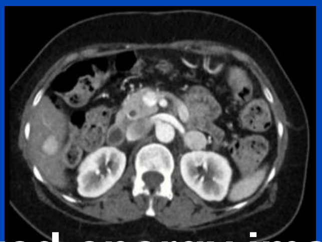
Introduction: Dual Source CT (DSCT)

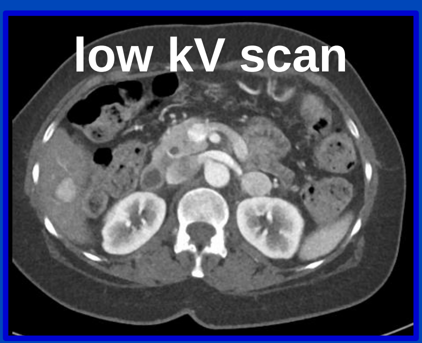


- **Utilizes two measurement systems A and B**
- **Increased temporal resolution (important for cardiac imaging)**
- **Dual Energy CT**
  - Different attenuation (HU) of materials at different energies enable material decomposition and characterization to create different image sets like Virtual Non Contrast (VNC), Iodine Maps or monoenergetic images with additional diagnostic information.

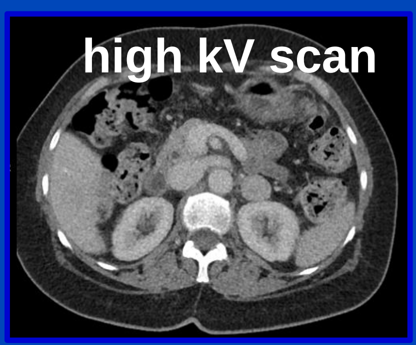


Mixed energy image

Acquisition of low and high energy image …



low kV scan



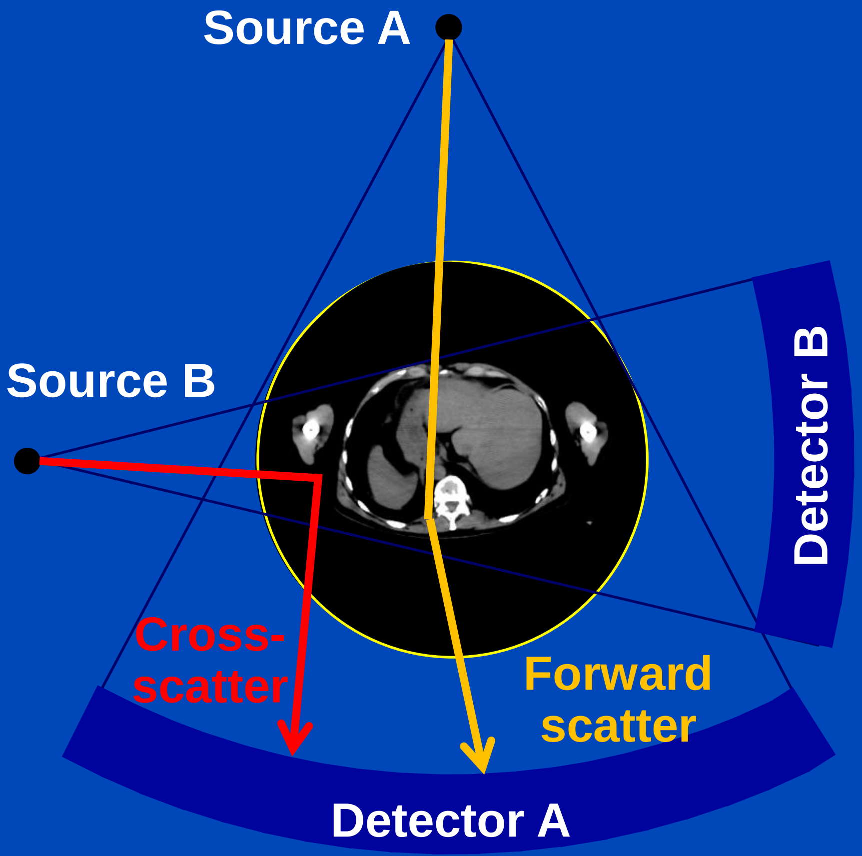
high kV scan

VNC

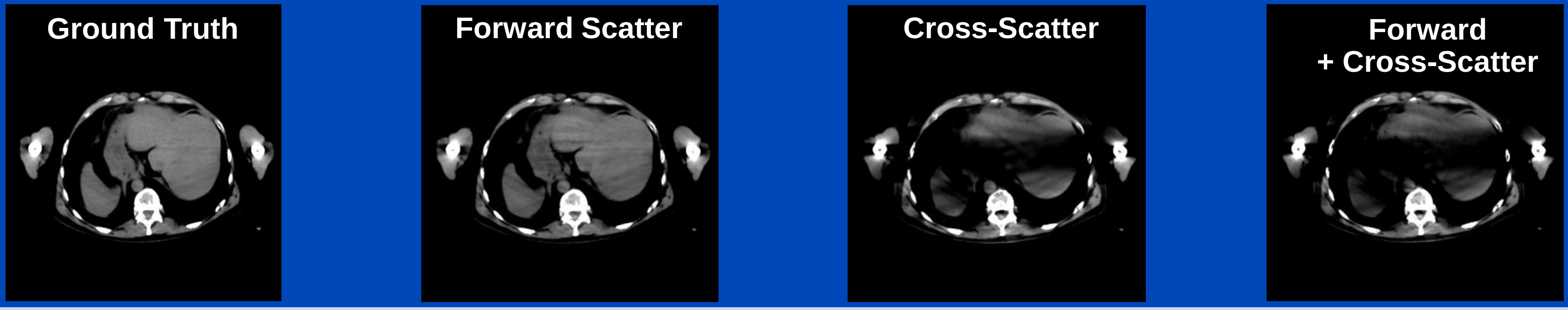
Iodine map overlay

… which can be reconstructed in different ways

Motivation: Scatter in DSCT

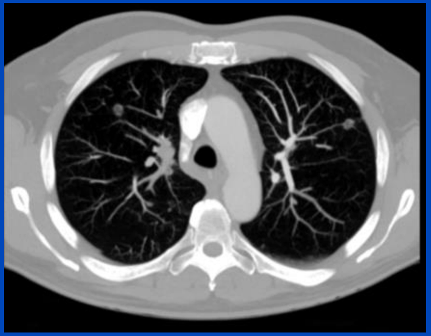


- Scatter in dual source CT: forward and cross-scatter
- Leads to cupping artifacts and dark streaks
- Reduces the contrast-to-noise ratio of the images
- Scatter correction is necessary to maintain the accuracy of CT-measurement



State of the Art: Scatter Correction in DSCT

- **Model-based scatter correction[1]:**
  - assuming that cross-scatter is mostly surface scatter
  - obtaining surface information using the raw data sinogram
  - correction with previously measured look-up table containing scatter information for a variety of objects with different surface characteristics
  - low accuracy
- **Measurement-based scatter correction[1]:**
  - additional detector elements to sensor scatter (but no primary) close to the detector
  - online measurement of scatter during the scan
  - expensive correction
- **First order scatter correction:**
  - accurate scatter estimation
  - high computational need



Dual Source CT images

[1] M. Petersilka, K. Stierstorfer, H. Bruder, T. Flohr „Strategies for scatter correction in dual source CT“ Med Phys. 2010 Nov; 37 (11), 5971-92.

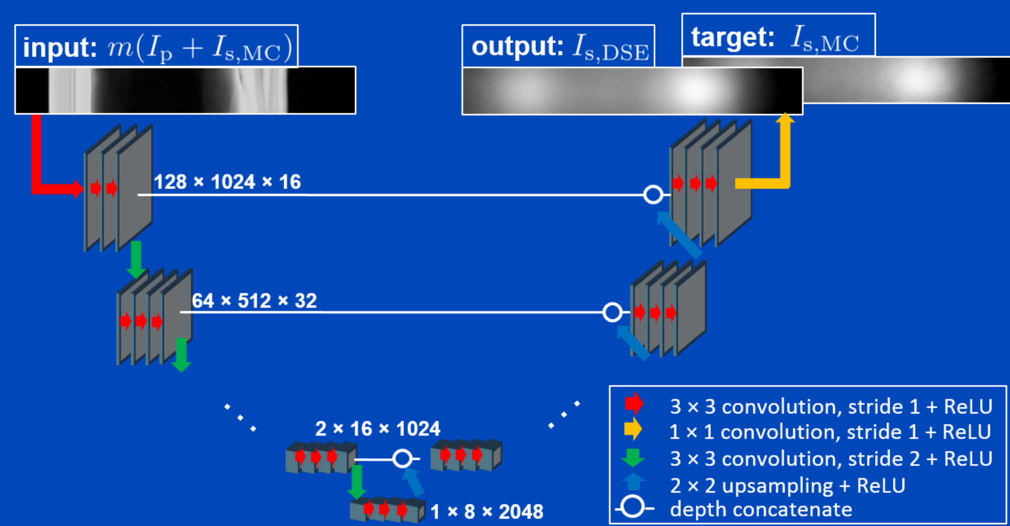
Deep Scatter Estimation (DSE)

- Use a deep convolutional neural network to estimate forward 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 much faster than the Monte Carlo simulation.

Scatter profile from Monte Carlo simulation

Scatter prediction from deep scatter estimation

| DSE - MC | MAPE = 2.5 %



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J. Maier, M. Kachelrieß et al. Deep scatter estimation (DSE). SPIE 2017 and J. of Nondest. Eval. 37:57, July 2018.
J. Maier, M. Kachelrieß et al. Robustness of DSE. Med. Phys. 46(1):238-249, January 2019.

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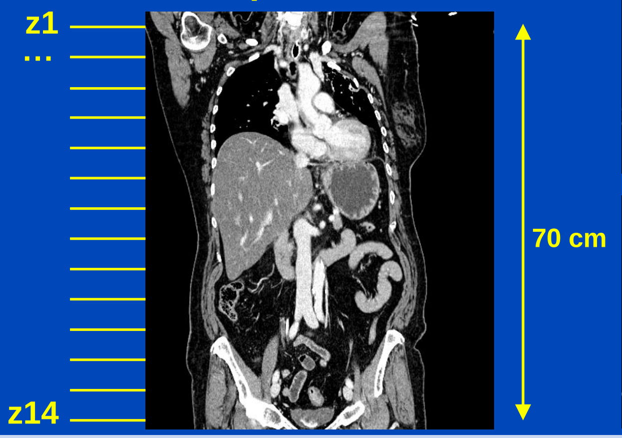
Overview Methods

- **Input of one projection:**
  - containing primary, forward scatter and cross-scatter
  - mapping: $p = -\ln\left(\frac{I_{\text{primary}}}{I_0} + \frac{I_{\text{forward-scatter}}}{I_0} + \frac{I_{\text{cross-scatter}}}{I_0}\right)$
- **Different networks with different inputs:**
  - one projection (DSE, 2D)
  - one projection + approximation of cross-scatter (DSE, 2D, xSSE)
  - several projections of defined range (e.g. 240°) (DSE, 3D)
- **Output possibilities:**
  - cross-scatter
  - forward scatter
  - total scatter (cross-scatter + forward scatter)
  - scatter for one projection or several scatter profiles for different angles

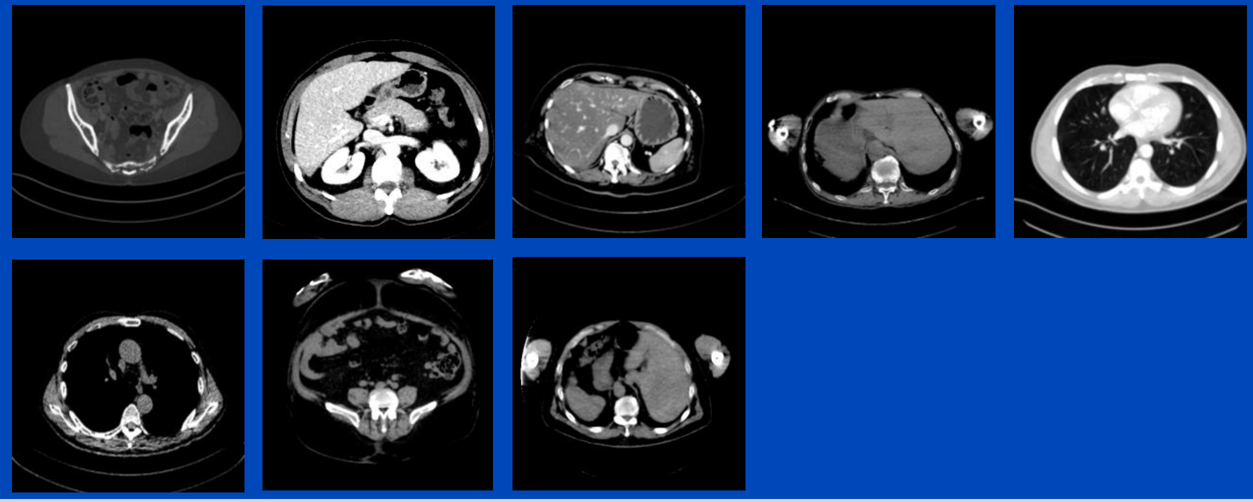
Training and Validation Data

- MC Simulation – 17 patients for training and 8 for validation
- Geometry is adapted to the Somatom Force Siemens Healthcare
- 14 z-positions per patient simulated, scatter simulation every 10°
- Validation patients with variety in external shapes and different clinical situations (contrast agent, arms above head)
- Training and evaluation separately at 80 kV and at 140 kV, can easily be transferred to other tube voltage

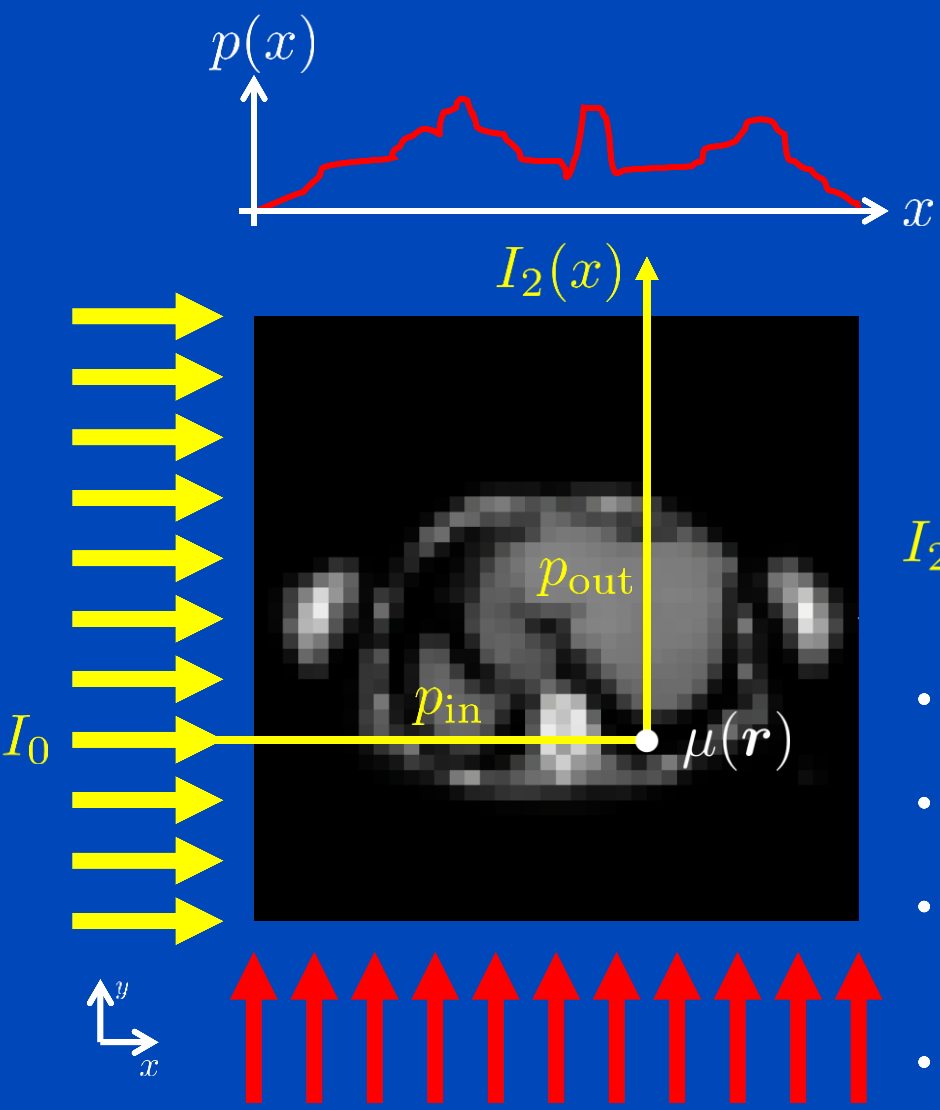
14 z positions



Validation patients:



xSSE – Cross-Scatter Approximation



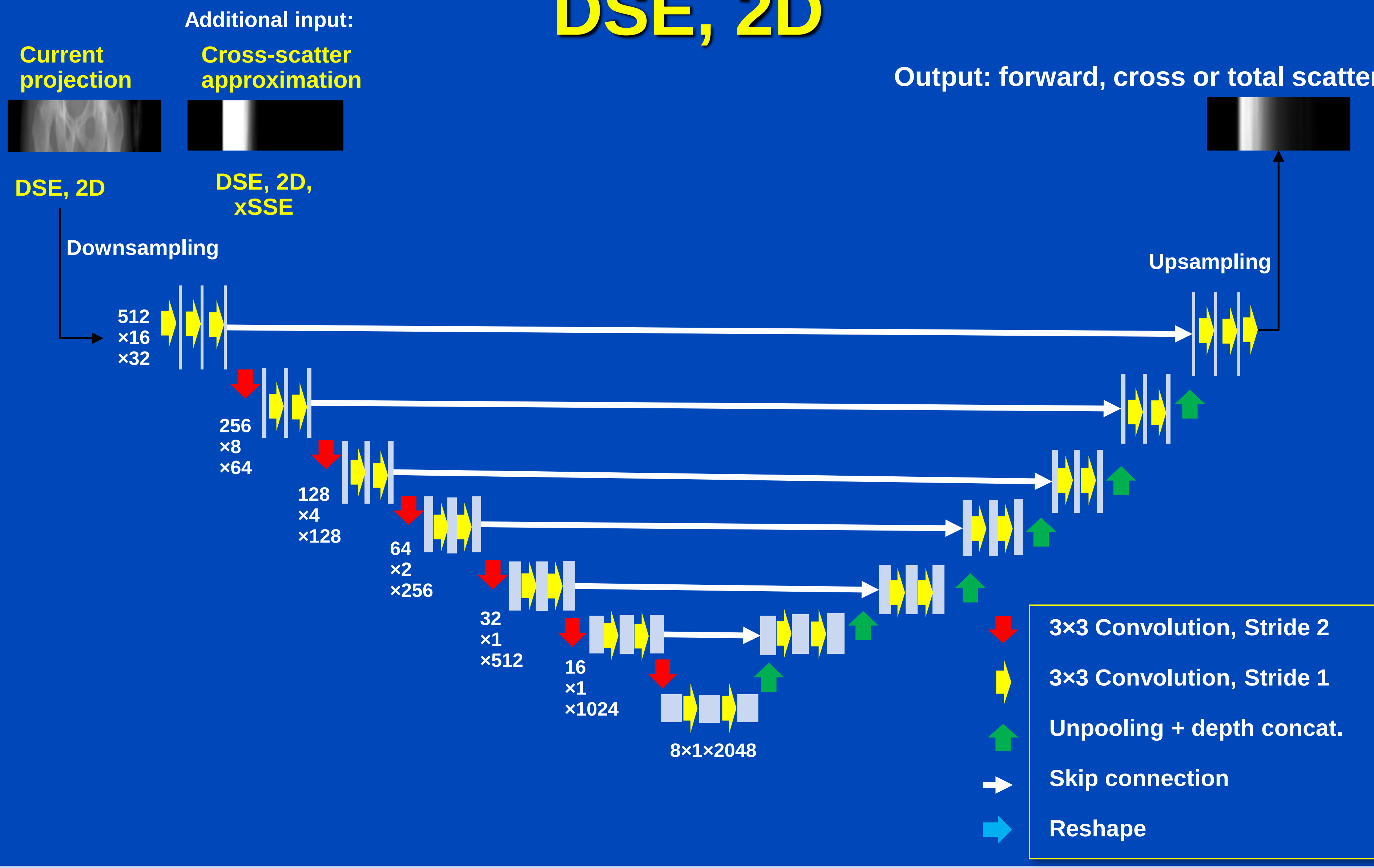
$$p_{\mathrm{in}}(\boldsymbol{r}) = \int_{-\infty}^{x} d\hat{x}\ \mu(\hat{x}, y)$$

$$p_{\mathrm{out}}(\boldsymbol{r}) = \int_{y}^{\infty} d\hat{y}\ \mu(x, \hat{y})$$

$$I_2(x) \propto \int_{-\infty}^{\infty} dy\ e^{-p_{\mathrm{in}}(\boldsymbol{r})}\ \mu(\boldsymbol{r})\ e^{-p_{\mathrm{out}}(\boldsymbol{r})}$$

- **First an initial non-scatter-corrected reconstruction is computed**
- **Than the algorithm models the interactions of X-rays with matter**
- **One simplifying assumption that cross-scatter only occurs along the primary rays**
- **Use this approximation (xSSE) as second input to the neural network**

Network Architectures
DSE, 2D



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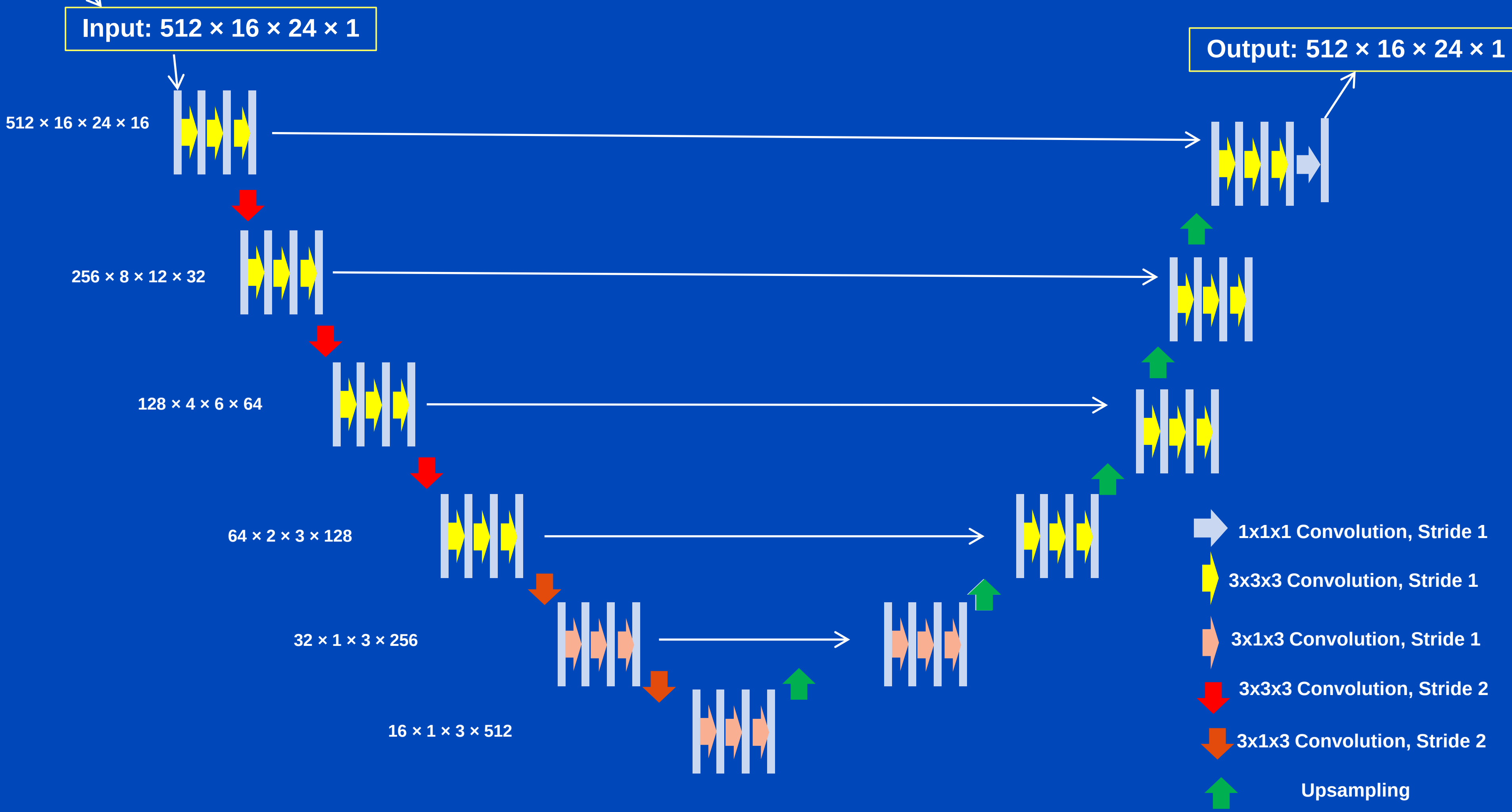
Network Architecture
DSE, 3D

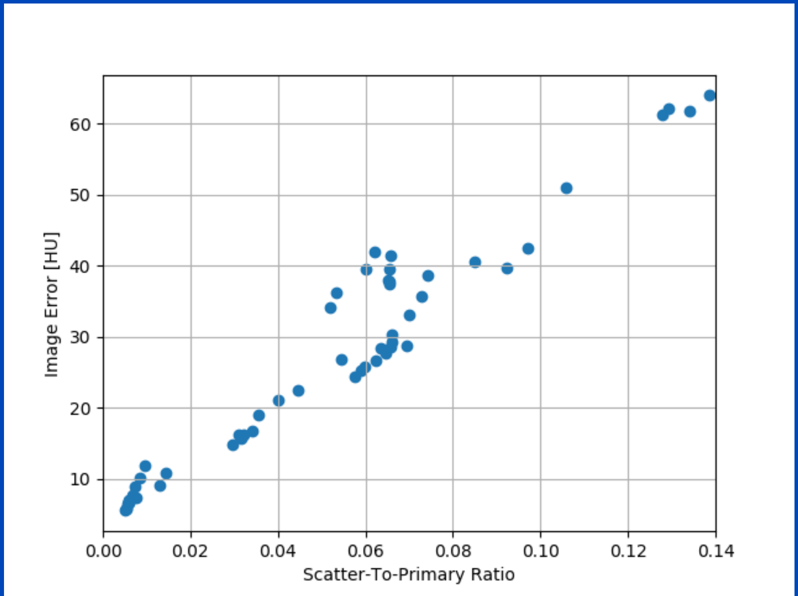
Input: 24 projections with offset of 10°

Output: 24 scatter profiles with offset of 10°



Importance of Scatter-to-Primary Ratio

Error in the uncorrected image in relation to the scatter-to-primary ratio



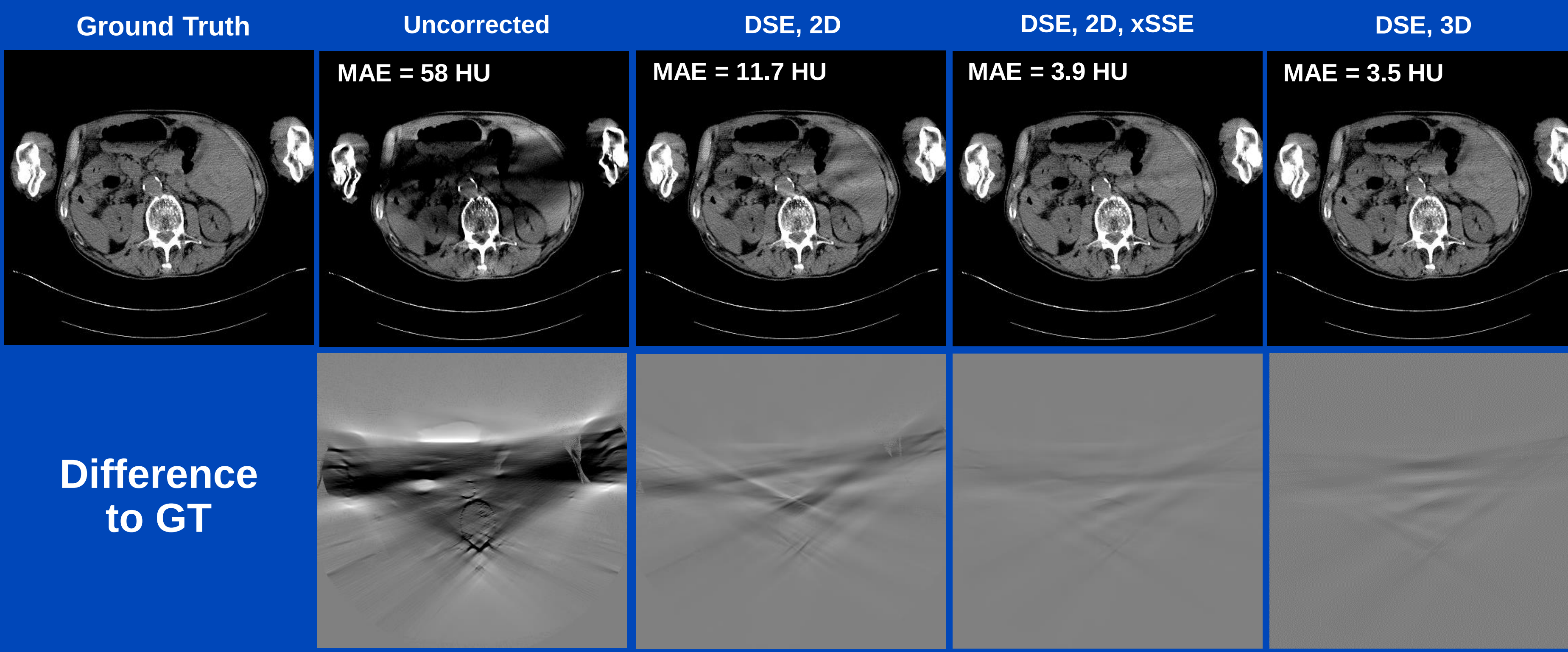
Loss-Function:

Scatter-to-primary weighted	mean absolute percentage error

$$\mathrm{SPMAPE} = \frac{1}{N}\sum \left| \frac{I_{\mathrm{scatter,MC}}}{I_{\mathrm{prim}}} \times \frac{I_{\mathrm{scatter,MC}} - I_{\mathrm{scatter,DSE}}}{I_{\mathrm{scatter,MC}}} \right| = \frac{1}{N}\sum \left| \frac{I_{\mathrm{scatter,MC}} - I_{\mathrm{scatter,DSE}}}{I_{\mathrm{prim}}} \right|.$$

- **The scatter-to-primary ratio correlates with the error in the reconstructed images.**
- **At detector pixels, where the primary signal is low, the scattered photons can lead to an high image error.**
- **The correction of scatter at positions with high scatter-to-primary ratio is particularly important.**
- **Use this knowledge to optimize our scatter estimation.**

Evaluation Cross-Scatter Correction



The accuracy of the algorithms is estimated by computing the mean absolute error (MAE) in the patient area of the image.

Tube Voltage: 80 kV

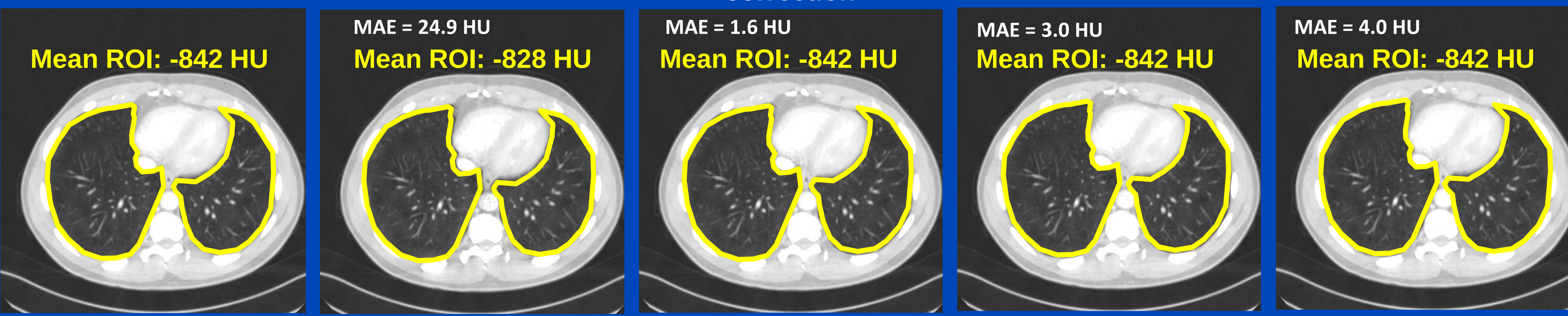
Reconstructed images C = 40 HU, W = 300 HU,
Difference to GT C = 0 HU, W = 300 HU

Comparison Method – Measurement-based Correction

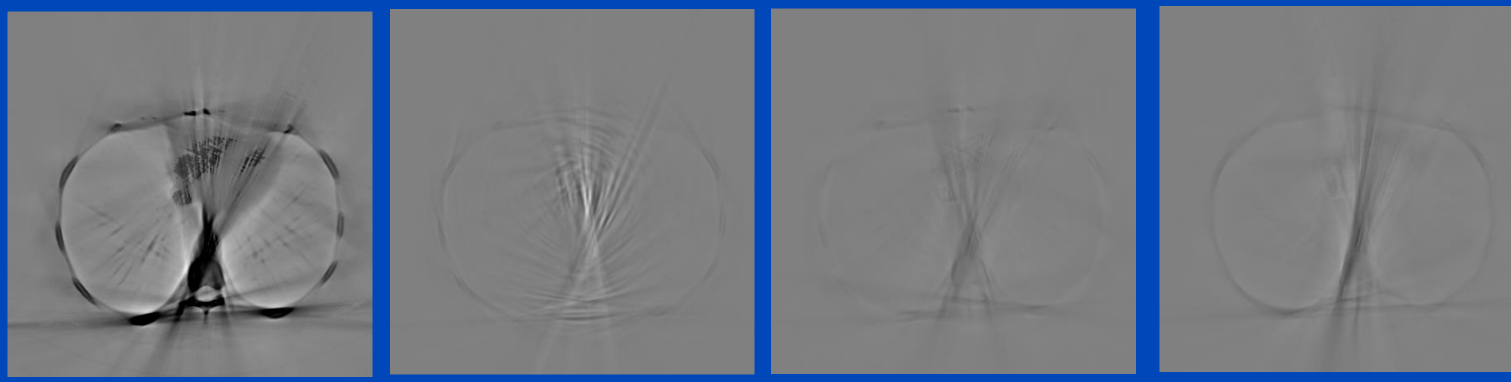
- Measurement-based correction: additional detector elements to sensor scatter close to the detector.
- To simulate this method the scatter data are interpolated between the first and last row of the detector.
- Simulated results with measurement-based correction will lead to slightly better results than in a real setting – since scatter is normally measured outside of the detector.

Evaluation Total Scatter Correction

Ground Truth	Uncorrected	Measurement-based correction	DSE, 2D, xSSE	DSE, 3D



Difference to GT

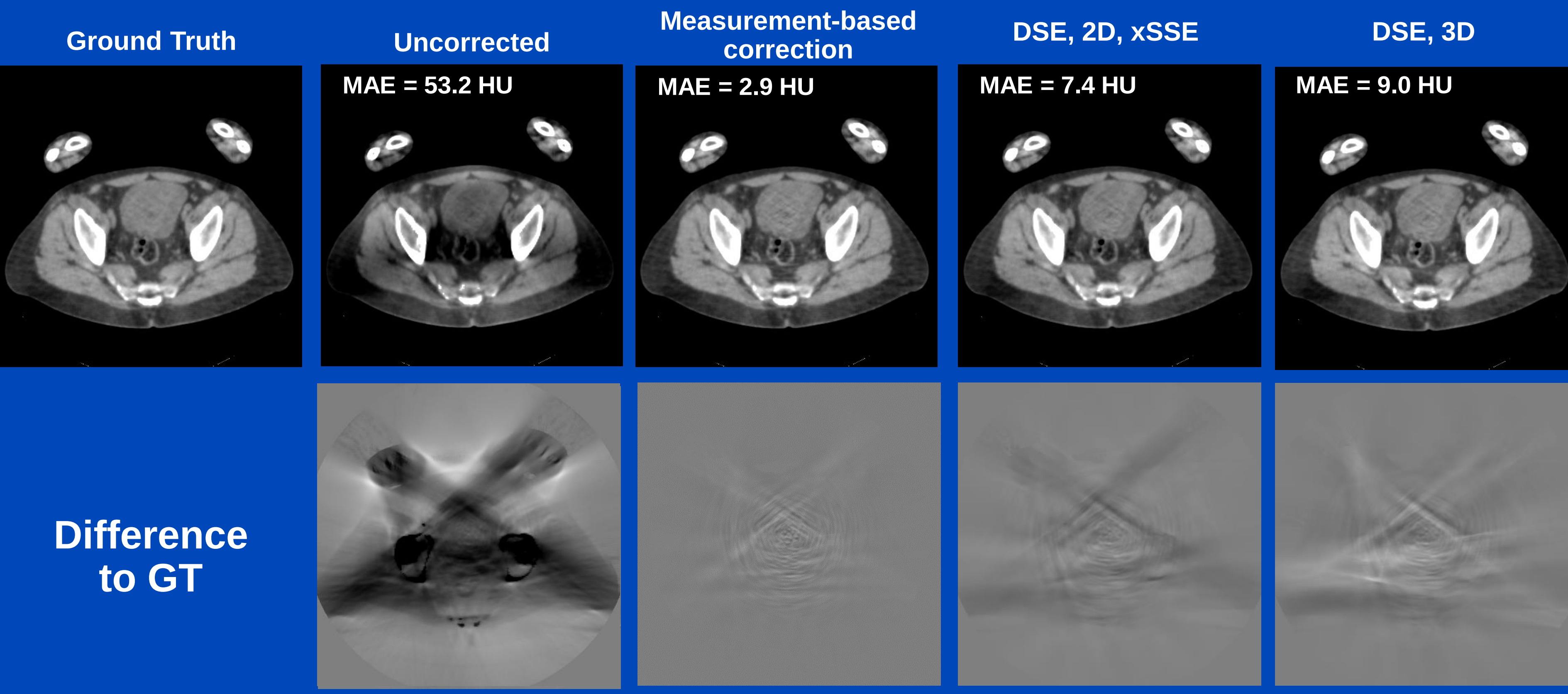


Tube voltage: 80 kV

Improving accuracy of air CT numbers is of great importance for quantitative lung imaging

Reconstruction, *C* = -500 HU, *W* = 1500 HU
Difference Reconstruction to Ground Truth
C = 0 HU, *W* = 300 HU

Evaluation Total Scatter Correction



Tube voltage: 140 kV

Reconstruction, *C* = 0 HU, *W* = 400 HU
Difference Reconstruction to Ground Truth
C = 0 HU, *W* = 300 HU

Overview Results

Method	Input	Output	MAE in image domain [HU]	Min / Max error in image domain [HU]	interference time / projection
Uncorrected			33.21 ± 18.34	11.2 / 88.2	
DSE, 2D	One projection	Scatter for this projection	9.31 ± 7.41	1.6 / 39.4	3.6 ms
DSE, 2D, xSSE	One projection + approximation	Scatter for this projection	6.92 ± 4.53	1.6 / 17.5	3.6 ms
DSE, 3D	Projections in a range of 240° every 10°	Scatter in a range of 240°	7.22 ± 5.83	2.3 / 22.5	5.4 ms
Measurement Based	First and last row of scatter	Scatter for this projection	3.42 ± 3.31	0.7 / 12.5	-
Monte Carlo simulation	Volume data of the patient	Scatter	-	-	65 s

7 validation patients, with each 14 different z-positions

Conclusion

- Our presented algorithms are able to correct most of the scatter artifacts in dual source CT.
- The methods do not need additional scatter sensors.
- The algorithms are much faster than high computational methods like the Monte Carlo simulation.
- The ability to leverage context about different angles leads to improved performance for cross-scatter estimation.
- The cross-scatter approximation (xSSE) as additional input improves the robustness of the algorithm.
- So far the results are based on simulations.
- Outlook:
  - apply and evaluate our algorithms with measurements.
  - scatter correction for photon-counting detector.

Thank You!

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Job opportunities through DKFZ's international Fellowship programs (marc.kachelriess@dkfz.de).
Parts of the reconstruction software were provided by RayConStruct® GmbH, Nürnberg, Germany.