

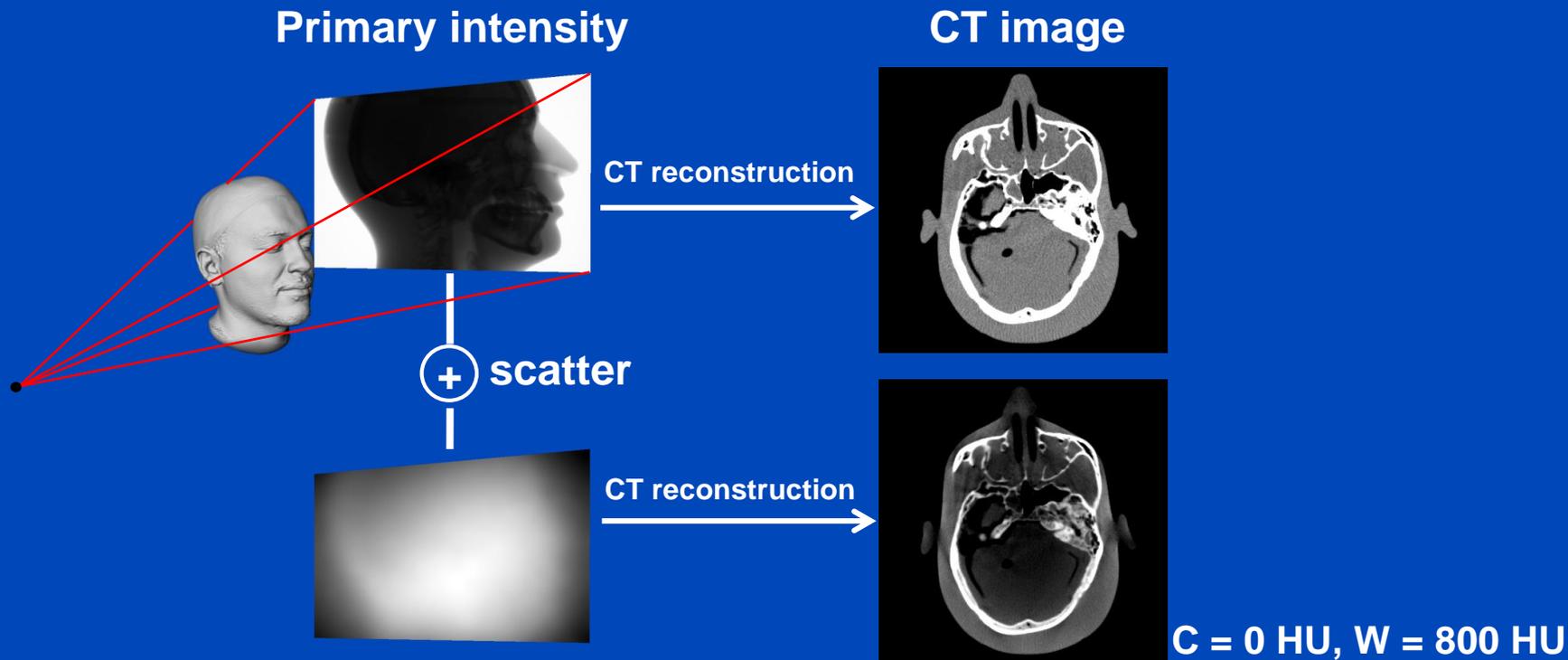
Real-Time Scatter Estimation for Medical CT using the Deep Scatter Estimation (DSE)

Joscha Maier, Elias Eulig, Tim Vöth, Michael Knaup,
Jan Kuntz, Stefan Sawall, and Marc Kachelrieß

German Cancer Research Center (DKFZ), Heidelberg, Germany

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.



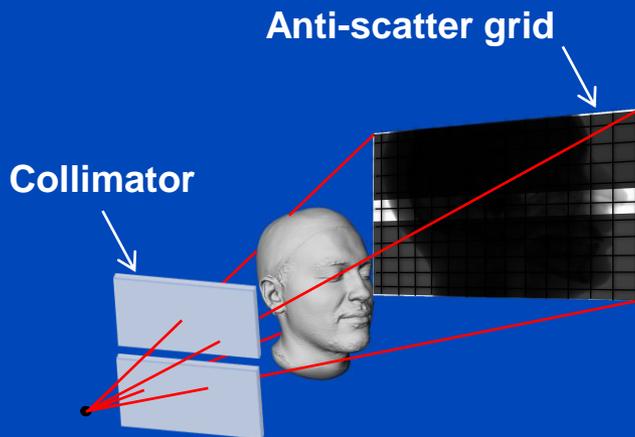
Scatter Correction

Scatter suppression

- Anti-scatter grids
- Collimators
- ...

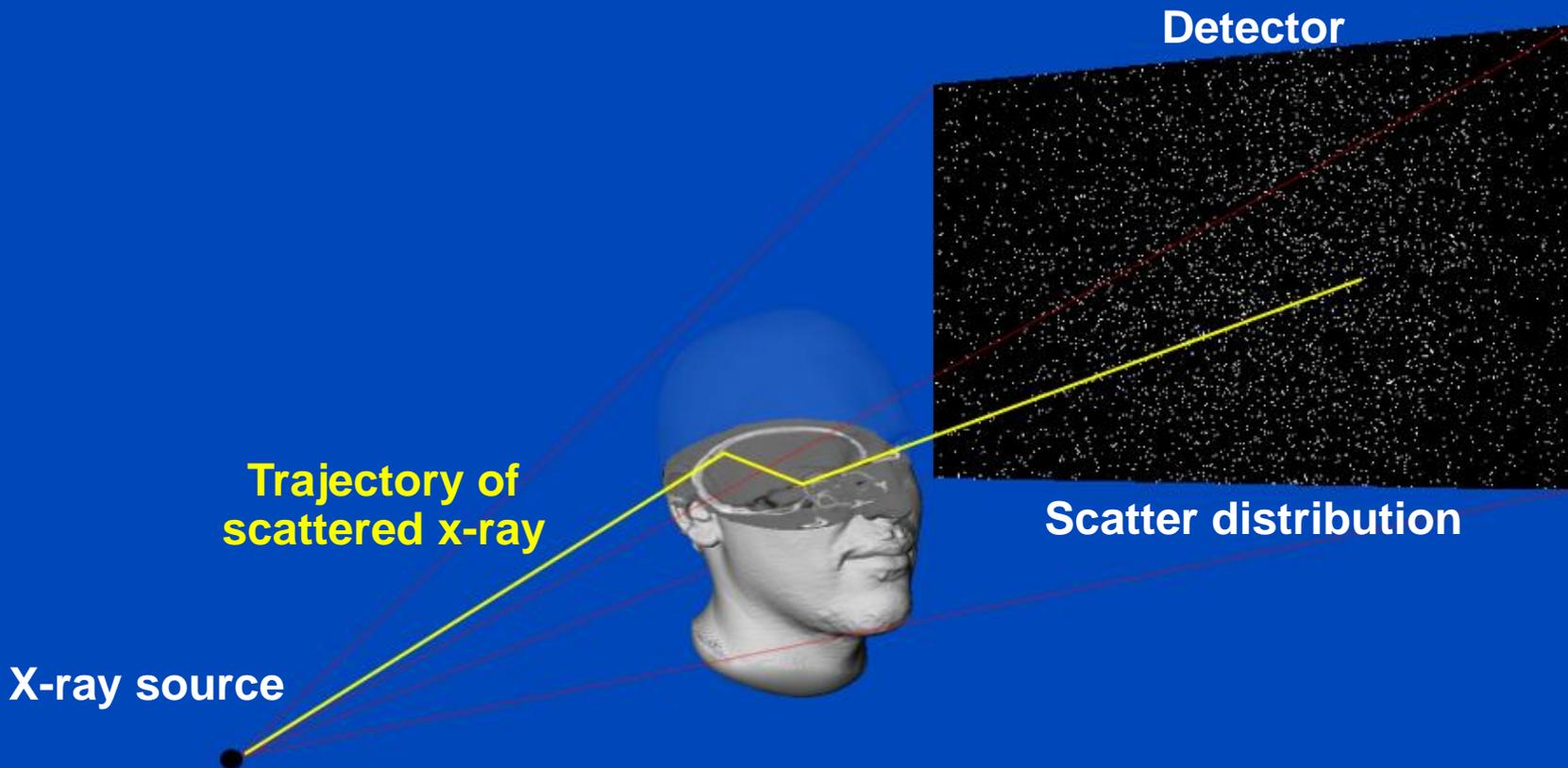
Scatter estimation

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



Monte Carlo Scatter Estimation

- Simulation of individual photon trajectories according to physical interaction probabilities.

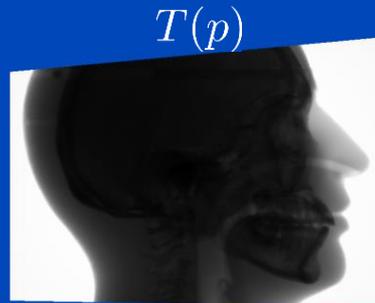


→ Typically too slow to be applied routinely.

Faster Alternative: Kernel-Based Scatter Estimation

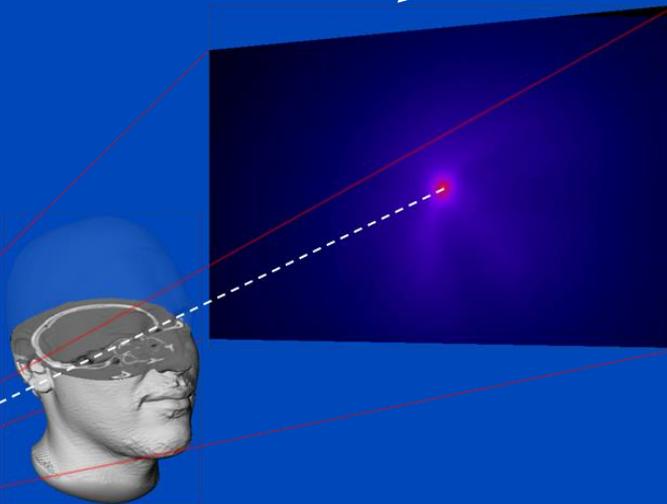
Estimate needle beam scatter kernels as a function of the projection data p

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



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

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

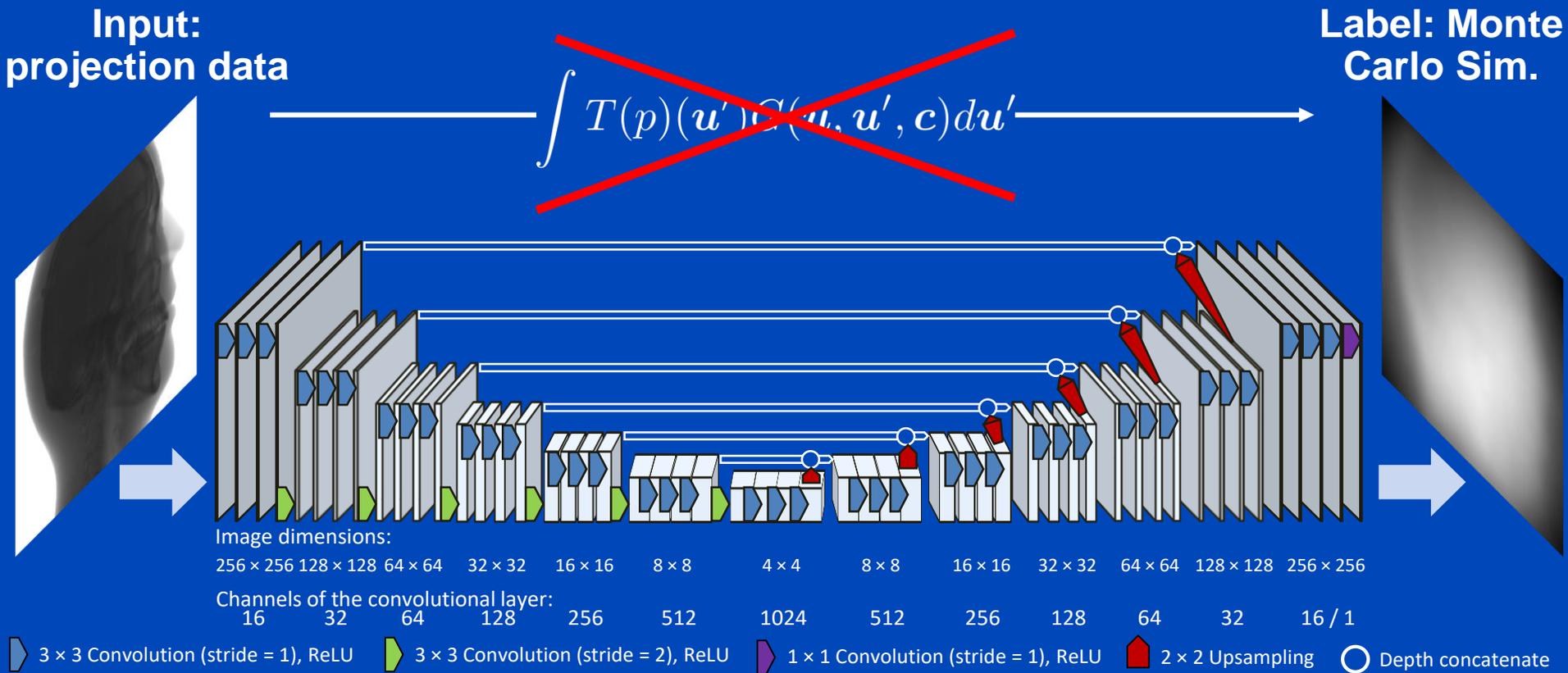


→ Typically far less accurate than Monte Carlo simulations.

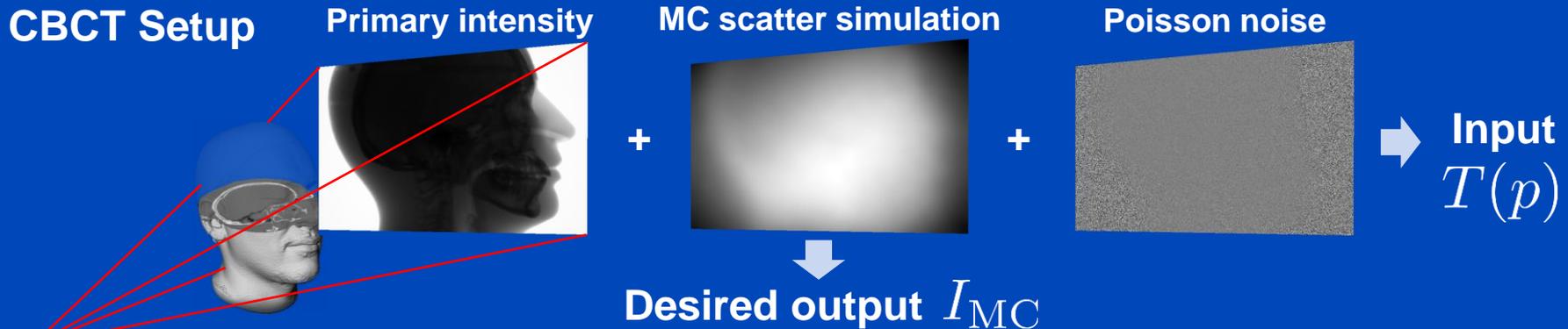
Deep Scatter Estimation (DSE)

Basic Principle

- Use a deep convolutional neural network to estimate scatter as a function of the acquired projection data.



Training / Testing of the DSE Network



- Training data: Simulated CBCT projection data (input) and Monte Carlo scatter simulation (label).
- Simulation of different anatomical regions, tube voltages and scan protocols.
- Optimization of the network's trainable parameters:
$$\{w, b\} = \operatorname{argmin} \|DSE(T(p)) - I_{MC}\|_2^2$$
- Testing on independent simulations of different patients.

Reference 1

Kernel-based scatter estimation (KSE)

- Kernel-based scatter estimation¹:

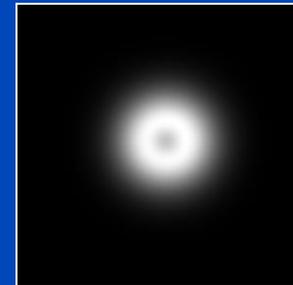
- Estimation of scatter by a convolution of the scatter source term $T(p)$ with a scatter propagation kernel $G(u, c)$:

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



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

Open
parameters:
 c_0



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

Open
parameters:
 c_1, c_2, c_3, c_4

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

Samples of the
training data set

Scatter estimate

MC scatter simulation

Detector
coordinate



Reference 2

Hybrid scatter estimation (HSE)

- Hybrid scatter estimation² :

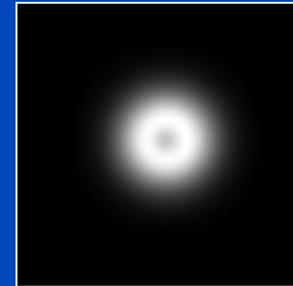
- Estimation of scatter by a convolution of the scatter source term $T(p)$ with a scatter propagation kernel $G(u, c)$:

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



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

Open
parameters:
 c_0



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

Open
parameters:
 c_1, c_2, c_3, c_4

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

Samples of the test
data set

Detector
coordinate

Scatter estimate



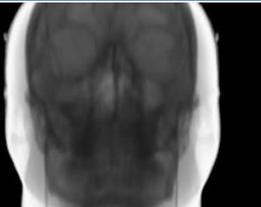
Coarse MC simulation



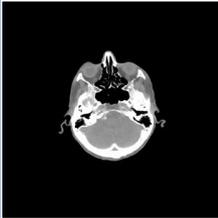
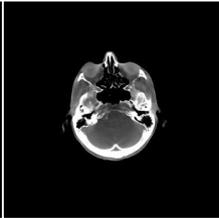
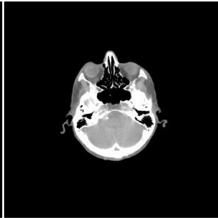
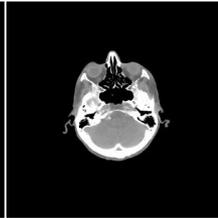
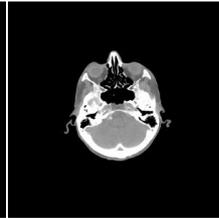
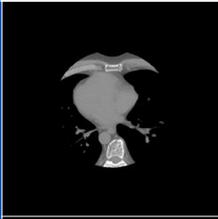
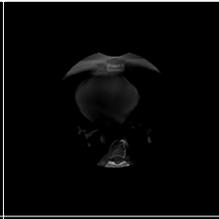
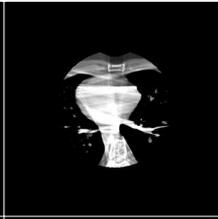
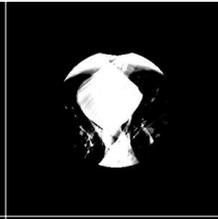
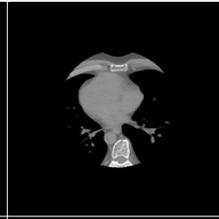
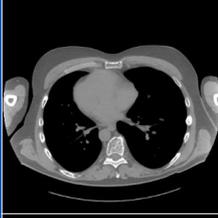
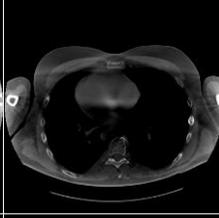
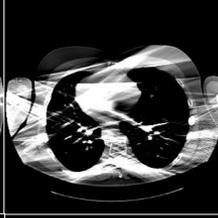
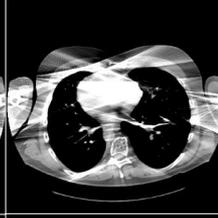
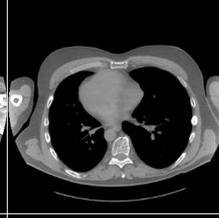
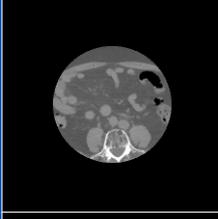
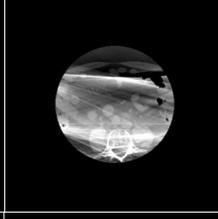
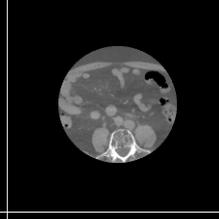
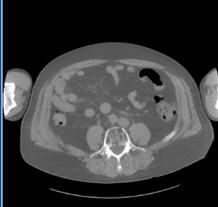
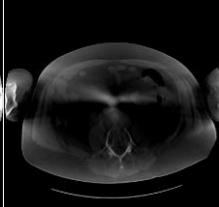
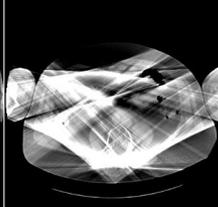
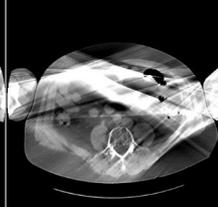
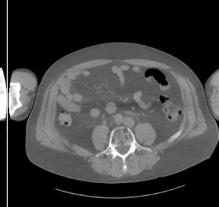
Results – Scatter Estimates

	Input	Scatter ground truth (GT)	(KSE - GT) / GT	(HSE - GT) / GT	(DSE - GT) / GT
Head					
Thorax					
Thorax, shifted detector					
Abdomen					
Abdomen, shifted detector					
	C = 0.2, W = 0.35	C = 0.015, W = 0.02	C = 0 %, W = 50 %	C = 0 %, W = 50 %	C = 0 %, W = 50 %

Results – Scatter Estimates

	Input	Scatter ground truth (GT)	(KSE - GT) / GT	(HSE - GT) / GT	(DSE - GT) / GT
Head			Mean absolute error 14.9 %	Mean absolute error 6.2 %	Mean absolute error 1.8 %
Thorax			Mean absolute error 20.5 %	Mean absolute error 22.9 %	Mean absolute error 1.4 %
Thorax, shifted detector			Mean absolute error 19.3 %	Mean absolute error 26.5 %	Mean absolute error 1.4 %
Abdomen			Mean absolute error 19.3 %	Mean absolute error 26.5 %	Mean absolute error 1.4 %
Abdomen, shifted detector			Mean absolute error 19.3 %	Mean absolute error 26.5 %	Mean absolute error 1.4 %
	C = 0.2, W = 0.35	C = 0.015, W = 0.02	C = 0 %, W = 50 %	C = 0 %, W = 50 %	C = 0 %, W = 50 %

Results – CT Reconstructions

	Ground truth (GT)	No scatter correction	KSE	HSE	DSE
Head					
Thorax					
Thorax, shifted detector					
Abdomen					
Abdomen, shifted detector					

C = 0 HU, W = 700 HU

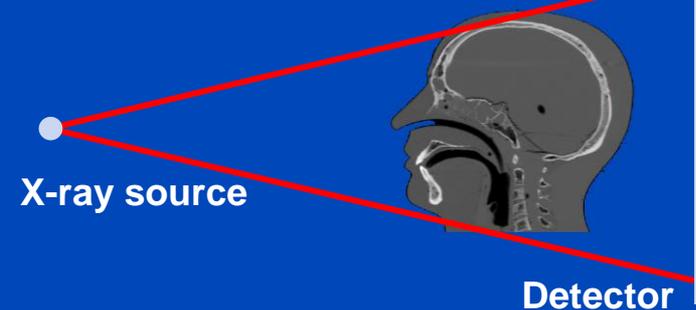
Application to Measured Data

DKFZ table-top CT

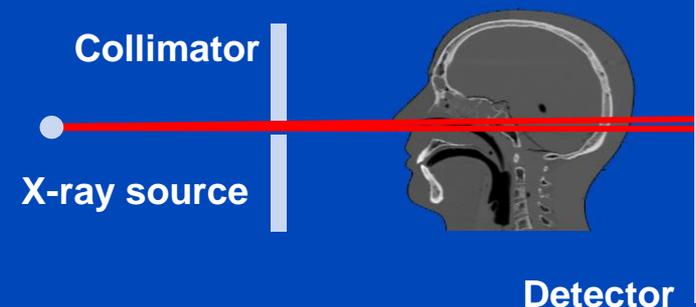


- Measurement of a head phantom at our in-house table-top CT.
- Slit scan measurement serves as ground truth.

Measurement to be corrected



Ground truth: slit scan



CT Reconstructions of Measured Data

Slit Scan

No Correction

Kernel-Based Scatter Estimation

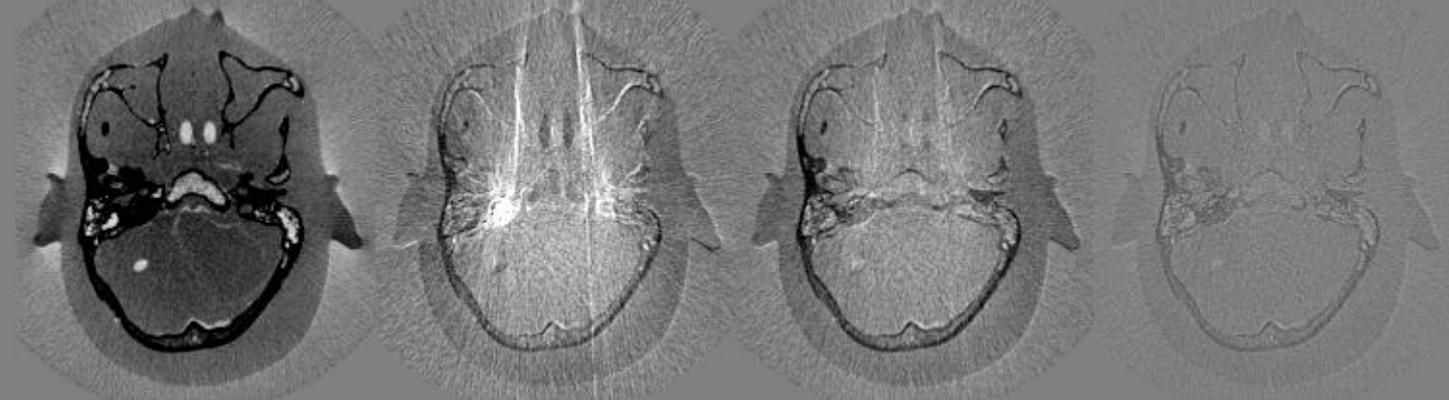
Hybrid Scatter Estimation

Deep Scatter Estimation

CT Reconstruction



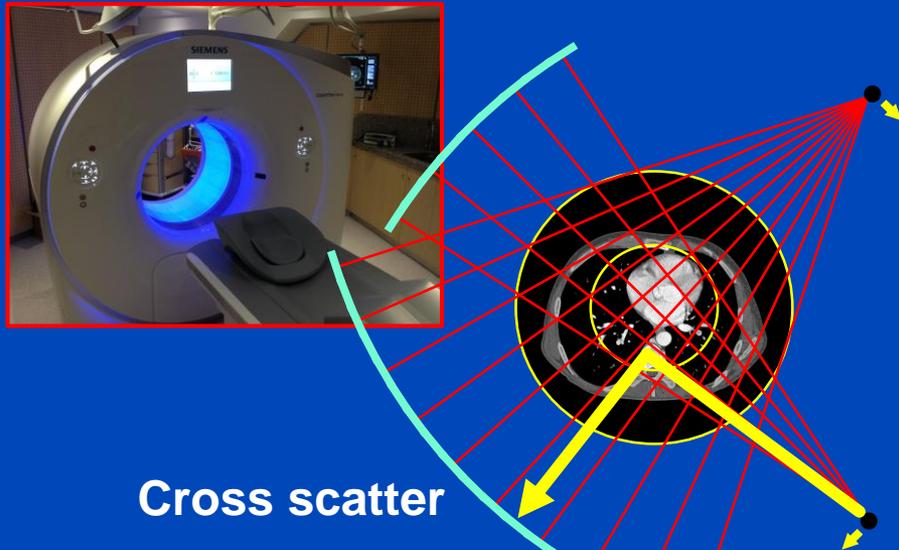
Difference to slit scan



$C = 0 \text{ HU}$, $W = 1000 \text{ HU}$

Further DSE Applications

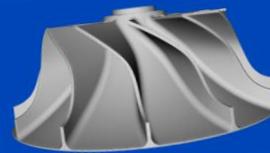
Single- and dual-source CT



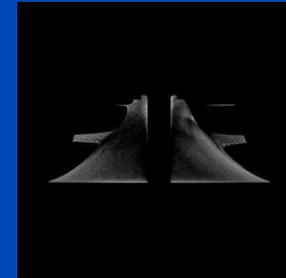
Industrial CT



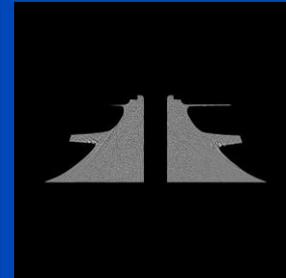
Sample: turbo charger



Uncorrected

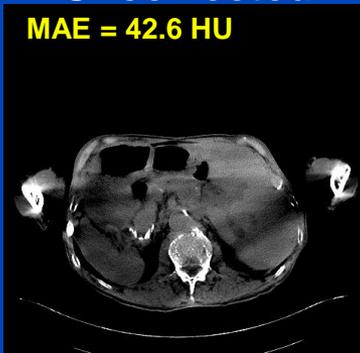


DSE



Uncorrected

MAE = 42.6 HU

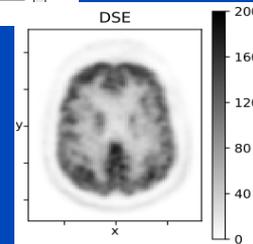
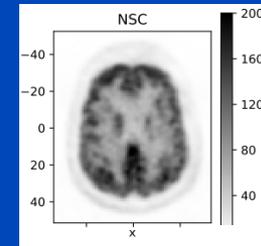


xDSE

MAE = 4.9 HU



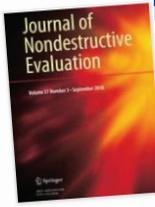
PET Imaging



DSE Publications

DOI: 10.1109/NSSMIC.2018.8824594 • Corpus ID: 201848248
Deep Scatter Estimation in PET: Fast Scatter Correction Using a Convolutional Neural Network
Yannick Berker, J. Maier, M. Kachelrieß • Published 2018 • Mathematics •
2018 IEEE Nuclear Science Symposium and Medical Imaging Conference Proceedings (NSS/MIC)

01-09-2018 | Issue 3/2018 **OPEN ACCESS**
Deep Scatter Estimation (DSE): Accurate Real-Time Scatter Estimation for X-Ray CT Using a Deep Convolutional Neural Network



Journal: [Journal of Nondestructive Evaluation](#) > Issue 3/2018
Authors: Joscha Maier, Stefan Sawall, Michael Knaup, Marc Kachelrieß

MEDICAL PHYSICS

The International Journal of Medical Physics Research and Practice

Research Article

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

Joscha Maier ✉, Elias Eulig, Tim Vöth, Michael Knaup, Jan K...

RESEARCH ARTICLE | Open Access |
Deep learning-based forward and cross-scatter correction in dual-source CT
Julien Erath ✉, Tim Vöth, Joscha Maier, Eric Fournié, Martin Petersilka, Karl Stierstorfer

1 March 2019
Forward and cross-scatter estimation in dual source CT using the deep scatter estimation (DSE)
Tim Vöth, Joscha Maier, Julien Erath, Marc Kachelrieß

9 March 2018
Deep scatter estimation (DSE): feasibility of using a deep convolutional neural network for real-time x-ray scatter prediction in cone-beam CT
Joscha Maier, Yannick Berker, Stefan Sawall, Marc Kachelrieß

Deep Learning-Based Cross-Scatter Correction for Clinical CT
Julien Erath, Tim Vöth, Joscha Maier, Eric Fournié, Karl Stierstorfer, Martin Petersilka, and Marc Kachelrieß

10573, [Medical Imaging 2018: Physics of Medical Imaging](#); 105731L (2018)
12.2292919
[Imaging](#), 2018, Houston, Texas, United States

Citations (as of 09/13/2021): 107



Conclusions

- DSE needs about 3 ms per CT and 10 ms per CBCT projection.
- DSE is a fast and accurate alternative to MC simulations.
- DSE outperforms kernel-based approaches in terms of accuracy and speed.
- **Facts:**
 - DSE can estimate scatter from a single (!) x-ray image.
 - DSE generalizes to all anatomical regions.
 - DSE works for geometries and beam qualities differing from training.
 - DSE may outperform MC even though DSE is trained with MC.
- DSE is not restricted to reproducing MC scatter estimates.
- DSE can rather be trained with any other scatter estimate, including those based on measurements.

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.