Real-Time Patient-Specific CT Dose Estimation for Single- and Dual-Source CT using a Deep Convolutional Neural Network

Joscha Maier[1,2], Sabrina Dorn[1,2], Elias Eulig[1,2], Stefan Sawall[1,2] and Marc Kachelrieß[1,2]

[1]German Cancer Research Center (DKFZ), Heidelberg, Germany

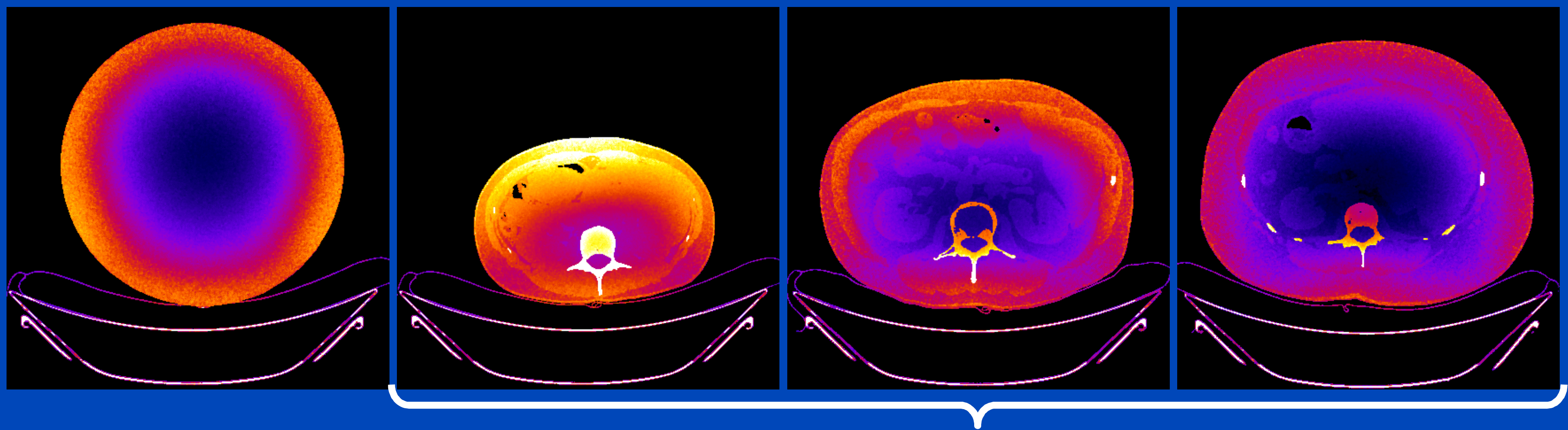
[2]Ruprecht-Karls-Universität, Heidelberg, Germany

DEUTSCHES KREBSFORSCHUNGSZENTRUM IN DER HELMHOLTZ-GEMEINSCHAFT

Motivation

- The potential risk of ionizing radiation makes dose assessment an important issue in CT imaging.
- Limitation of common metrics (e.g. $CTDI_w$, $CTDI_{vol}$, DLP, k-factor, SSDE, …) to provide information on organ or patient dose.

CTDI phantom | Small patient | Medium patient | Large patient



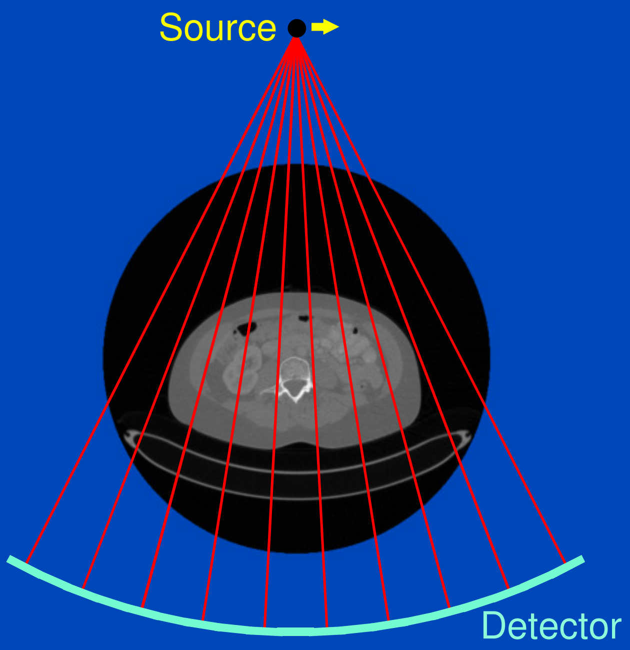
Same CTDI, but different dose distribution

Dose values in air voxels are set to zero (black) in this presentation.

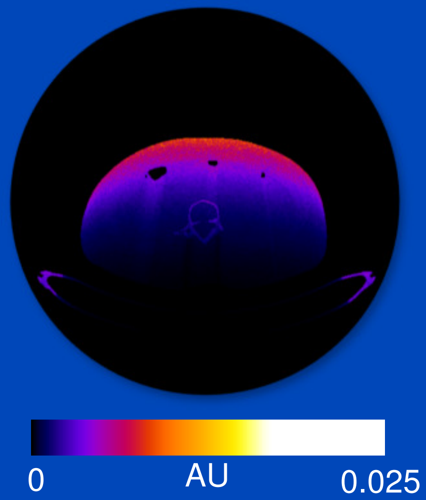
Patient-Specific Dose Estimation

- Gold standard: Monte Carlo (MC) simulation of the CT acquisition[1,2].

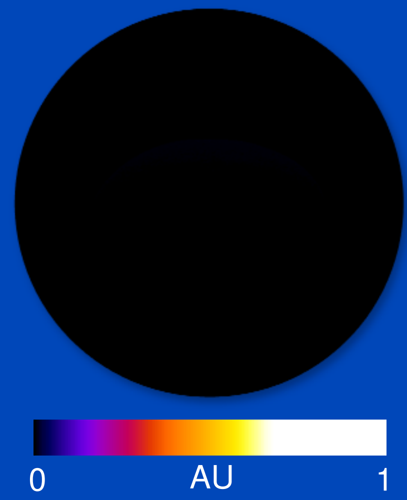
→ Accurate but computationally expensive



Prior model



Dose per view



Cumulative Dose

[1] G. Jarry et al., "A Monte Carlo-based method to estimate radiation dose from spiral CT", Phys. Med. Biol. 48, 2003.
[2] W. Chen et al., "Fast on-site Monte Carlo tool for dose calculations in CT applications", Med. Phys. 39, 2012.

Patient-Specific Dose Estimation

- **Accurate solutions:**
  - Monte Carlo (MC) simulation[1], gold standard, stochastic LBTE solver
  - Analytic linear Boltzmann transport equation (LBTE) solver[2]

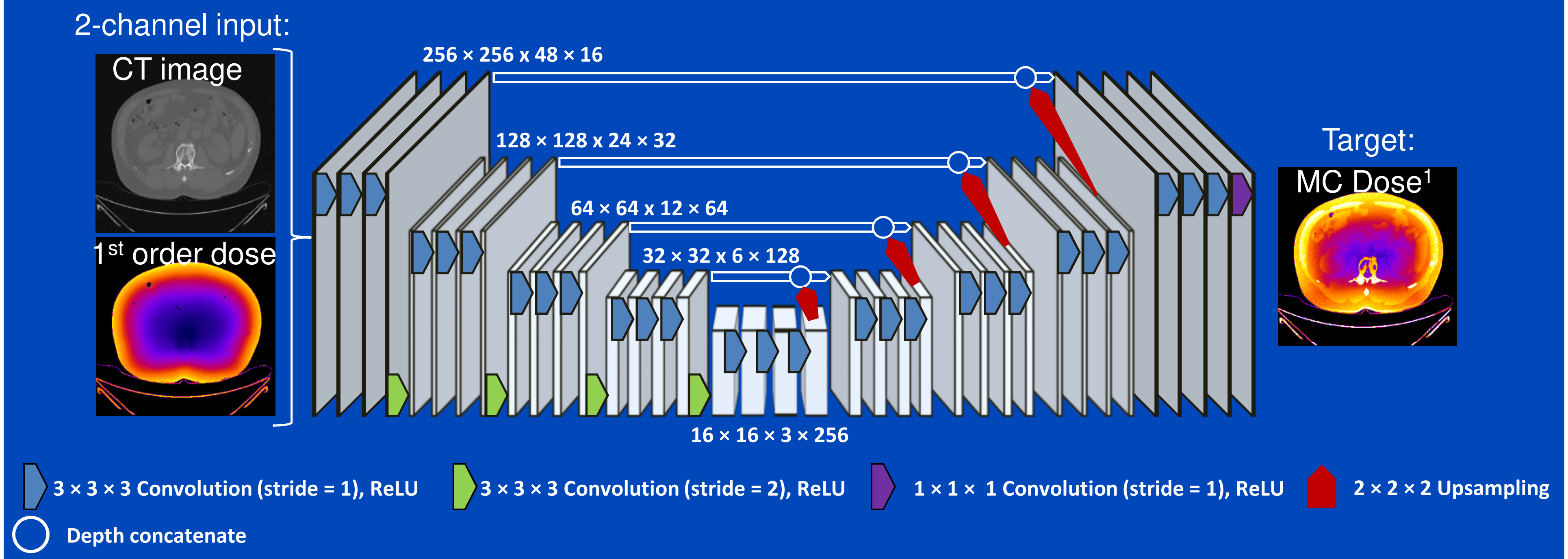
  → **Accurate but computationally expensive**
- **Fast alternatives:**
  - Application of patient-specific conversion factors to the DLP[3].
  - Application of look-up tables using MC simulations of phantoms[4].
  - Analytic approximation of CT dose deposition[5].

  → **Fast but less accurate**

[1]G. Jarry et al., "A Monte Carlo-based method to estimate radiation dose from spiral CT", Phys. Med. Biol. 48, 2003.
[2]A. Wang et al., "A fast, linear Boltzmann transport equation solver for computed tomography dose calculation (Acuros CTD)". Med. Phys. 46(2), 2019.
[3]B. Moore et al., "Size-specific dose estimate (SSDE) provides a simple method to calculate organ dose for pediatric CT examinations", Med. Phys. 41, 2014.
[4]A. Ding et al., "VirtualDose: a software for reporting organ doses from CT for adult and pediatric patients", Phys. Med. Biol. 60, 2015.
[5]B. De Man, "Dose reconstruction for real-time patient-specific dose estimation in CT", Med. Phys. 42, 2015.

Deep Dose Estimation (DDE)

- Combine fast and accurate CT dose estimation using a deep convolutional neural network.
- Train the network to reproduce MC dose estimates given the CT image and a first-order dose estimate.



[1] M. Baer, M. Kachelrieß. Phys. Med. Biol. 57, 6849–6867, 2012.

First-Order Dose Estimate

- **DDE network needs information about the tube current, the tube voltage, shaped filters etc., which is encoded in the first-order dose estimate.**
- **First order dose-estimate in a voxel with volume V and mass *m* at position *r* :**

$$D_{1^{\text{st}}}(\boldsymbol{r}) = \frac{V}{m}\int \frac{d^2N}{d\Omega dE}\sum_{i=\text{PE, CS}} P_{\text{int},i}(\boldsymbol{r},E)E_{\text{dep},i}(E)\,dE$$

Emission characteristic of the x-ray source (including shaped filters)

Interaction probability for photo effect (i = PE) and Compton scattering (i = CS)

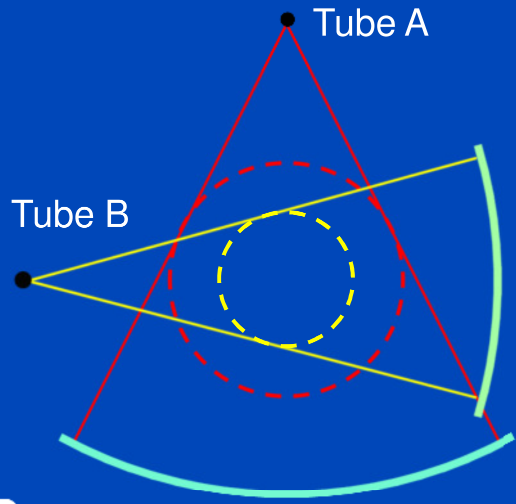
Energy deposition by photo effect (i = PE) and Compton scattering (i = CS)

$$P_{\text{int, PE}}(\boldsymbol{r},E) = \mu_{\text{PE}}(\boldsymbol{r},E)\cdot e^{-\int_0^r \mu(r',E)dr'} \qquad E_{\text{dep, PE}}(E) = E$$

$$P_{\text{int, CS}}(\boldsymbol{r},E) = \mu_{\text{CS}}(\boldsymbol{r},E)\cdot e^{-\int_0^r \mu(r',E)dr'} \qquad E_{\text{dep, CS}}(E) = \int \frac{d\sigma}{d\Omega}(E)\Delta E_{\text{CS}}(\vartheta)d\Omega$$

J. Maier, E. Eulig, S. Dorn, S. Sawall, and M. Kachelrieß. Real-time patient-specific CT dose estimation using a deep convolutional neural network. Proc. IEEE MIC 2018.

Training and Validation

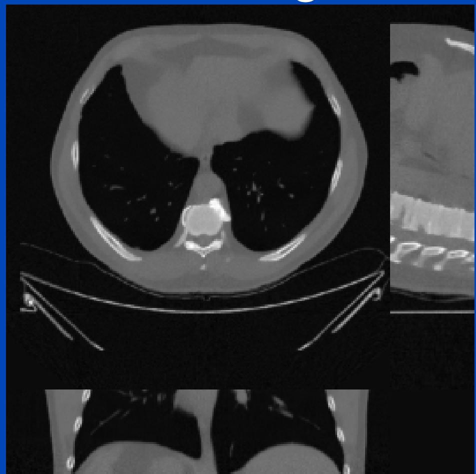


- Simulation of 1440 circular dual-source CT scans (64×0.6 mm, FOM_A = 50 cm, FOM_B = 32 cm) of thorax, abdomen, and pelvis using 12 different patients.
- Simulation with and without bowtie.
- No data augmentation
- Reconstruction on a 512×512×96 grid with 1 mm voxel size, followed by 2×2×2 binning for dose estimation.
- 9 patients were used for training and 3 for testing.
- DDE was trained for 300 epochs on an Nvidia Quadro P6000 GPU using a mean absolute error pixel-wise loss, the Adam optimizer, and a batch size of 4.
- The same weights and biases were used for all cases.

Results

Thorax, tube A, 120 kV, with bowtie

CT image



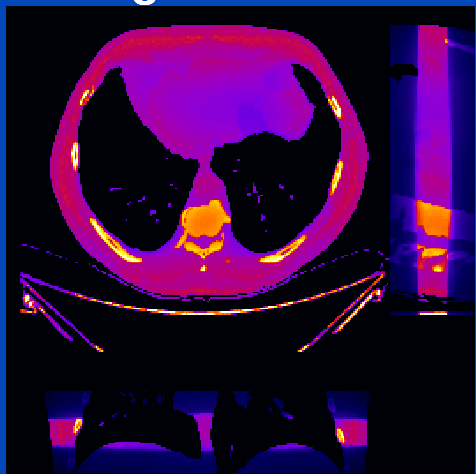
First order dose

	MC	DDE
48 slices	1 h	0.25 s
whole body	20 h	5 s

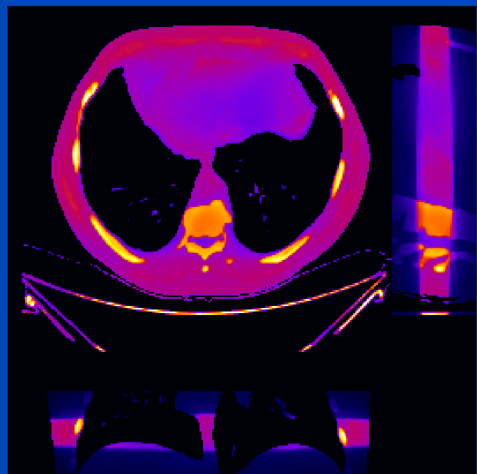
MC uses 16 CPU kernels
DDE uses one Nvidia Quadro P600 GPU

DDE training took 74 h for 300 epochs, 1440 samples, 48 slices per sample

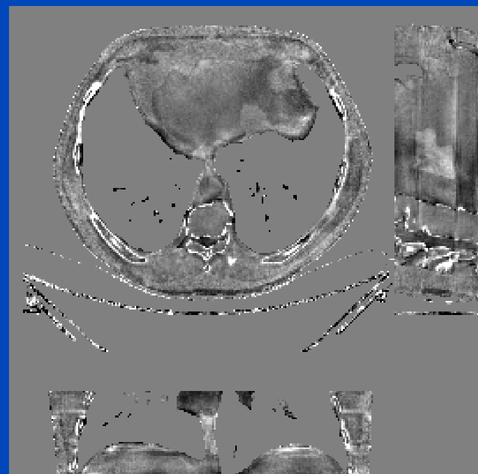
MC ground truth[1]



DDE



Relative error



C = 0%
W = 40%

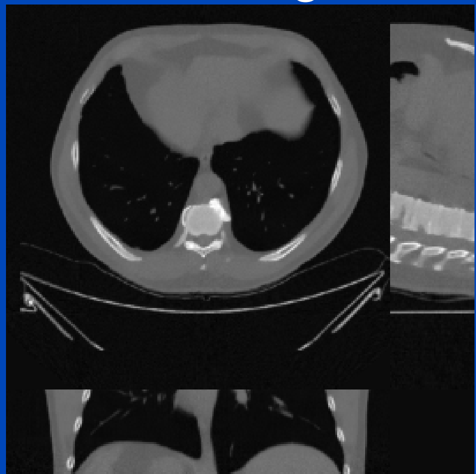
[1]M. Baer, M. Kachelrieß. Phys. Med. Biol. 57, 6849–6867, 2012.

dkfz.

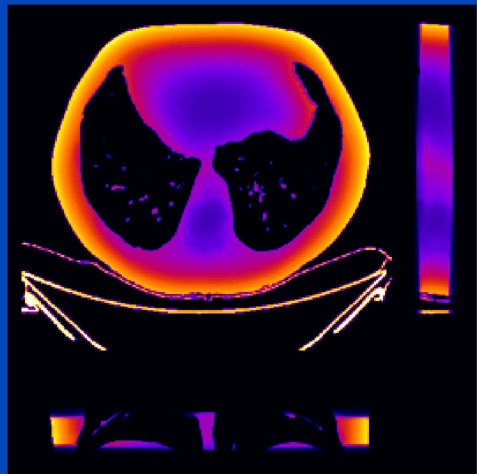
Results

Thorax, tube A, 120 kV, no bowtie

CT image



First order dose

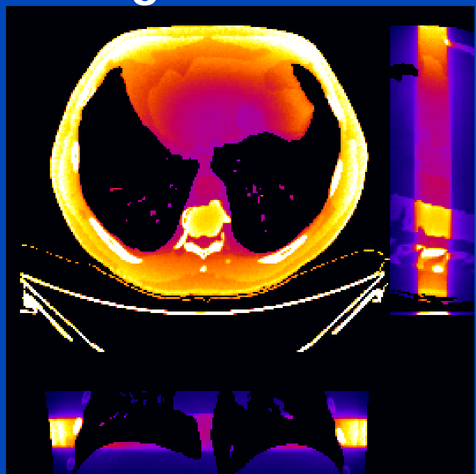


	MC	DDE
48 slices	1 h	0.25 s
whole body	20 h	5 s

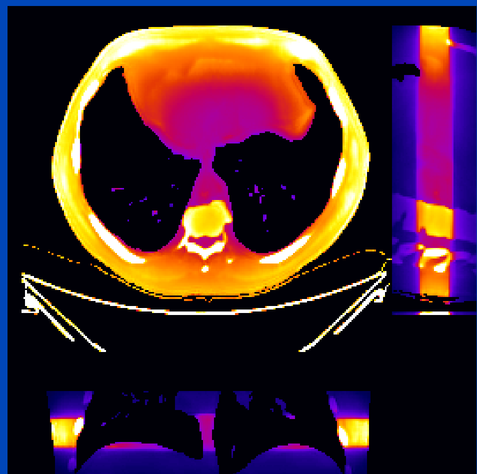
MC uses 16 CPU kernels
DDE uses one Nvidia Quadro P600 GPU

DDE training took 74 h for 300 epochs, 1440 samples, 48 slices per sample

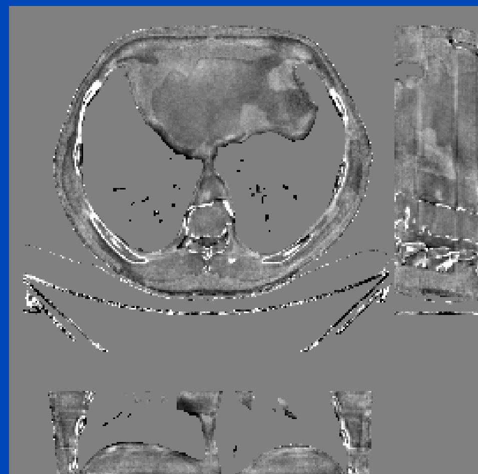
MC ground truth[1]



DDE



Relative error



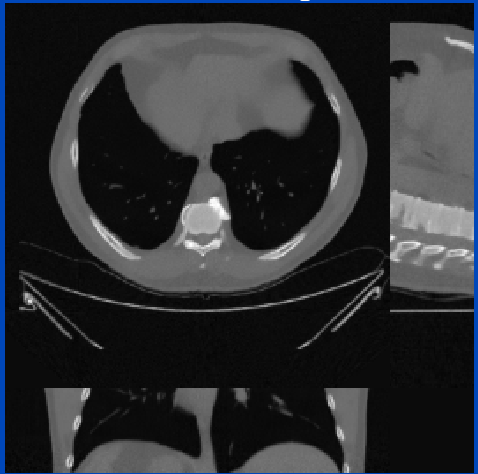
C = 0%
W = 40%

[1]M. Baer, M. Kachelrieß. Phys. Med. Biol. 57, 6849–6867, 2012.

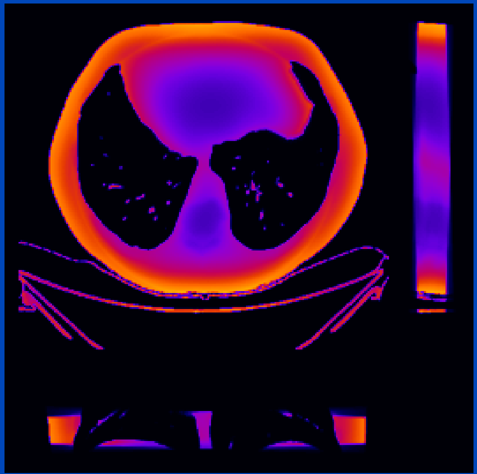
Results

Thorax, tube B, 120 kV, no bowtie

CT image



First order dose

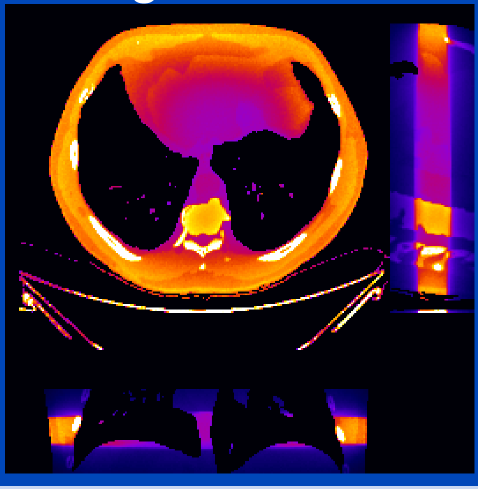


	MC	DDE
48 slices	1 h	0.25 s
whole body	20 h	5 s

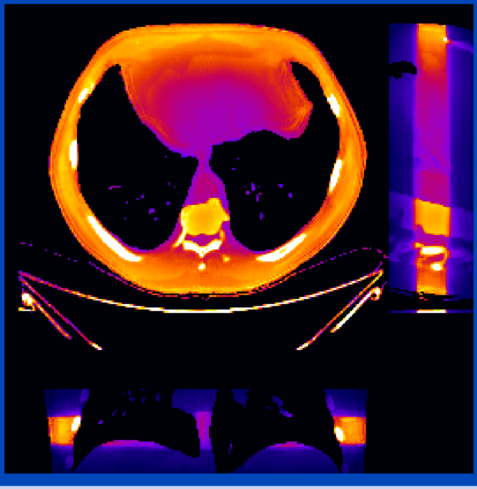
MC uses 16 CPU kernels
DDE uses one Nvidia Quadro P600 GPU

DDE training took 74 h for 300 epochs, 1440 samples, 48 slices per sample

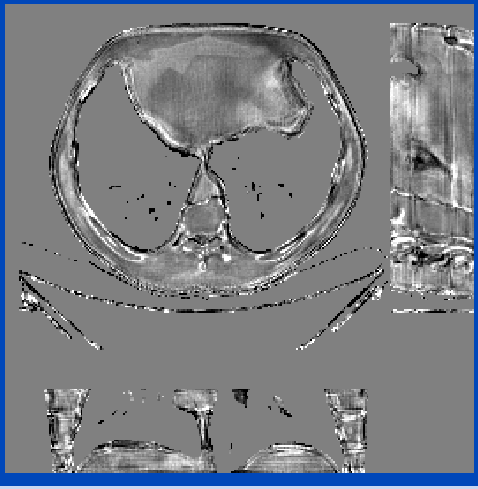
MC ground truth[1]



DDE



Relative error



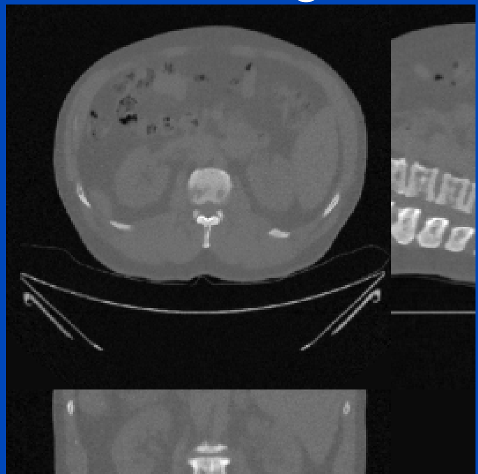
C = 0%
W = 40%

[1]M. Baer, M. Kachelrieß. Phys. Med. Biol. 57, 6849–6867, 2012.

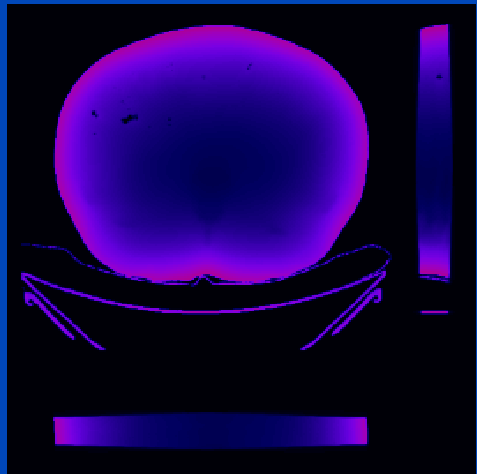
Results

Abdomen, tube A, 120 kV, with bowtie

CT image



First order dose

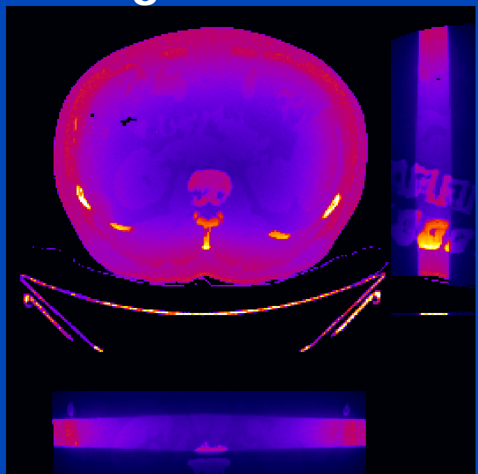


	MC	DDE
48 slices	1 h	0.25 s
whole body	20 h	5 s

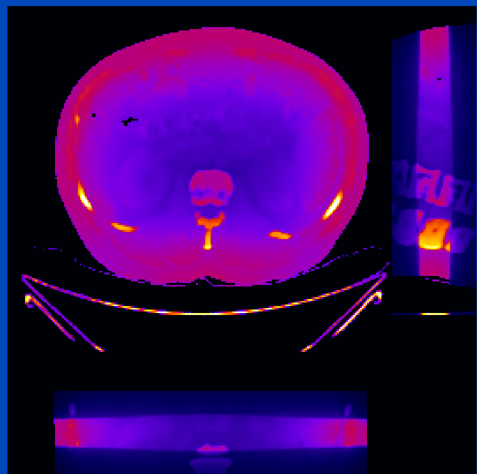
MC uses 16 CPU kernels
DDE uses one Nvidia Quadro P600 GPU

DDE training took 74 h for 300 epochs,
1440 samples, 48 slices per sample

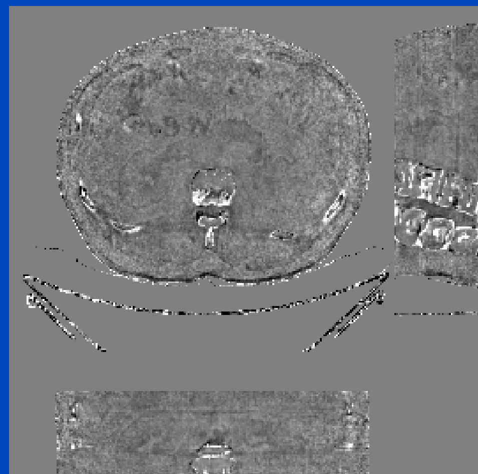
MC ground truth[1]



DDE



Relative error



C = 0%
W = 40%

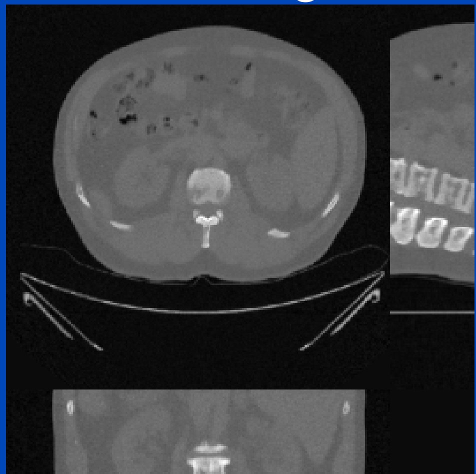
[1]M. Baer, M. Kachelrieß. Phys. Med. Biol. 57, 6849–6867, 2012.

dkfz.

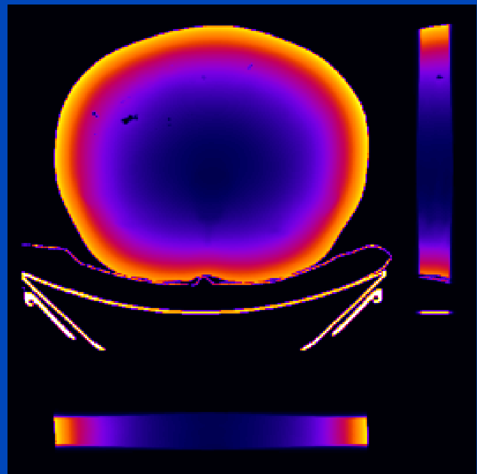
Results

Abdomen, tube A, 120 kV, no bowtie

CT image



First order dose

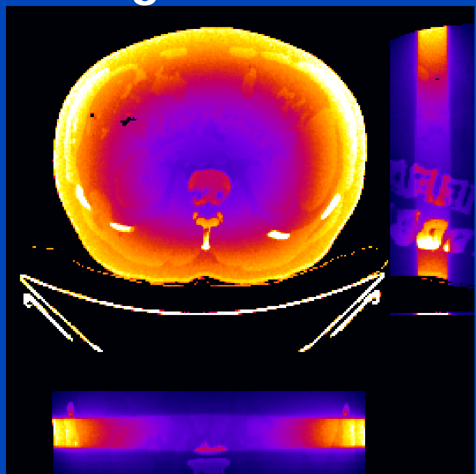


	MC	DDE
48 slices	1 h	0.25 s
whole body	20 h	5 s

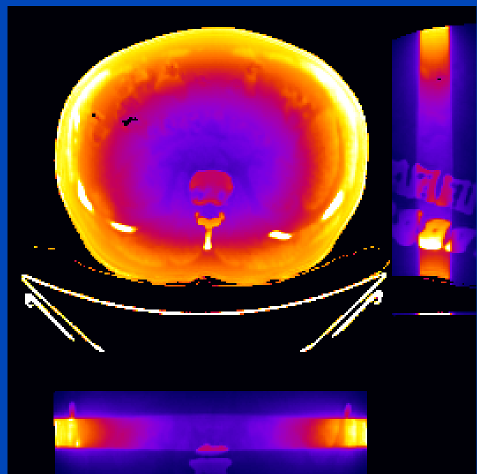
MC uses 16 CPU kernels
DDE uses one Nvidia Quadro P600 GPU

DDE training took 74 h for 300 epochs, 1440 samples, 48 slices per sample

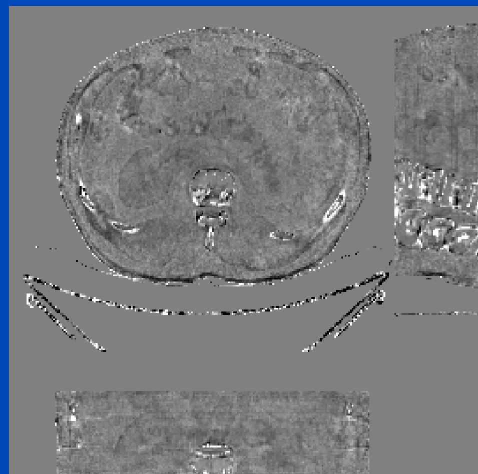
MC ground truth[1]



DDE



Relative error



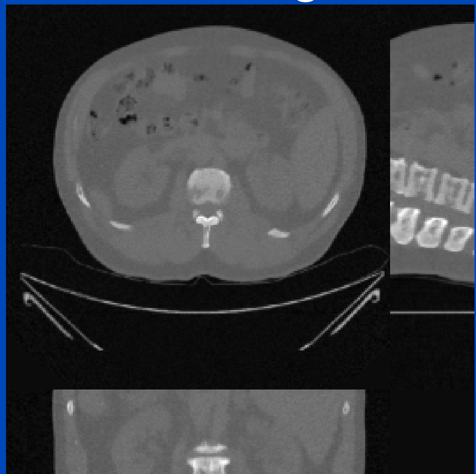
C = 0%
W = 40%

[1]M. Baer, M. Kachelrieß. Phys. Med. Biol. 57, 6849–6867, 2012.

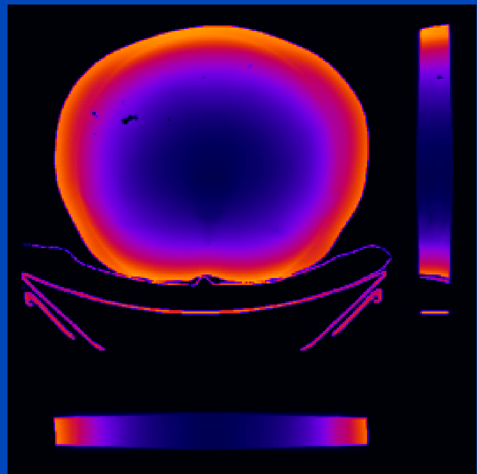
Results

Abdomen, tube B, 120 kV, no bowtie

CT image



First order dose

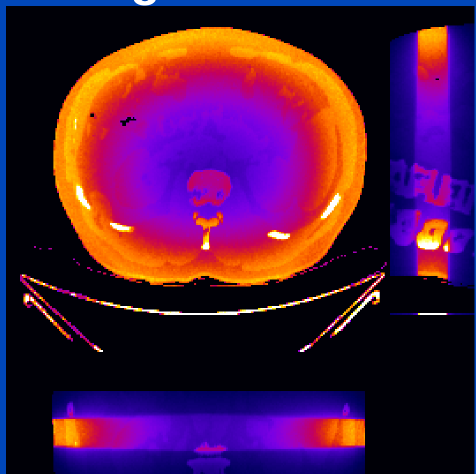


	MC	DDE
48 slices	1 h	0.25 s
whole body	20 h	5 s

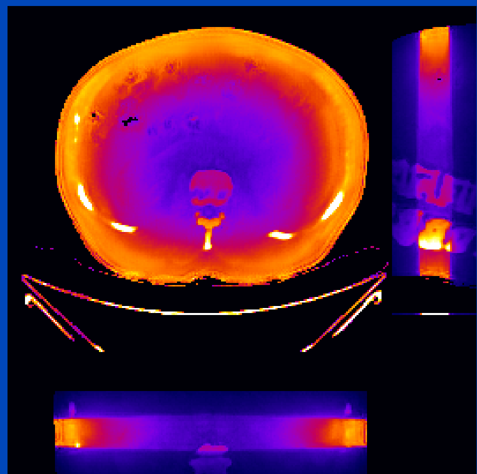
MC uses 16 CPU kernels
DDE uses one Nvidia Quadro P600 GPU

DDE training took 74 h for 300 epochs, 1440 samples, 48 slices per sample

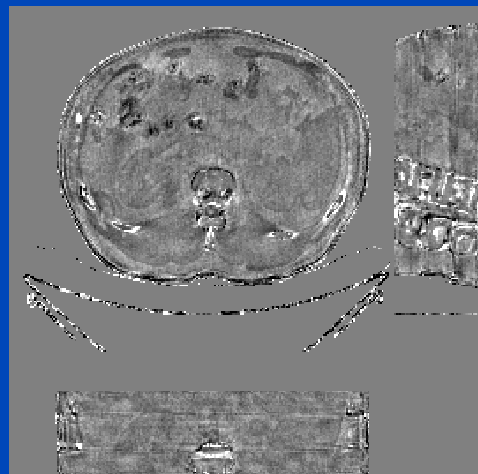
MC ground truth[1]



DDE



Relative error



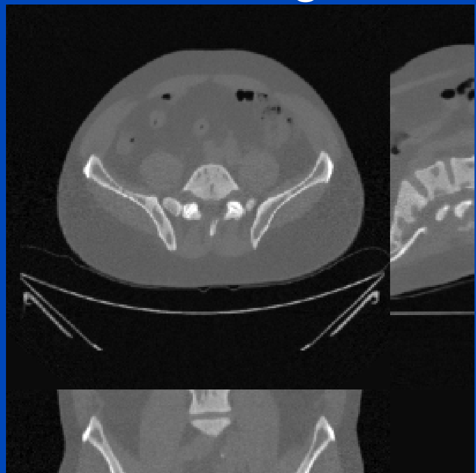
C = 0%
W = 40%

[1]M. Baer, M. Kachelrieß. Phys. Med. Biol. 57, 6849–6867, 2012.

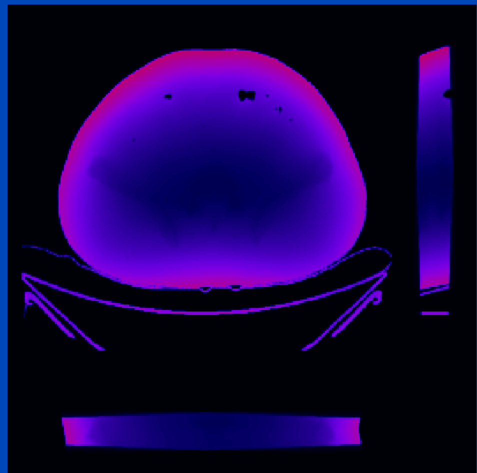
Results

Pelvis, tube A, 120 kV, with bowtie

CT image



First order dose

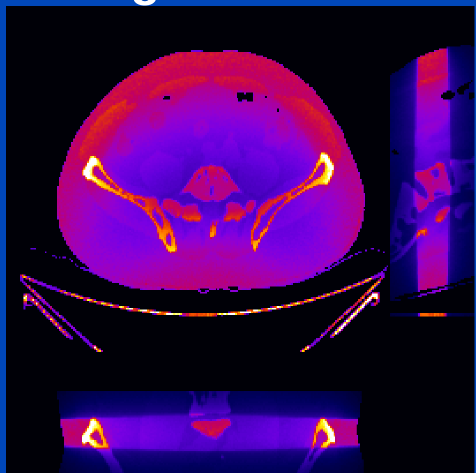


	MC	DDE
48 slices	1 h	0.25 s
whole body	20 h	5 s

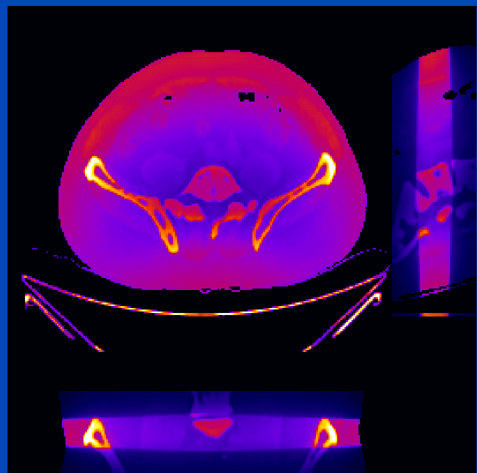
MC uses 16 CPU kernels
DDE uses one Nvidia Quadro P600 GPU

DDE training took 74 h for 300 epochs,
1440 samples, 48 slices per sample

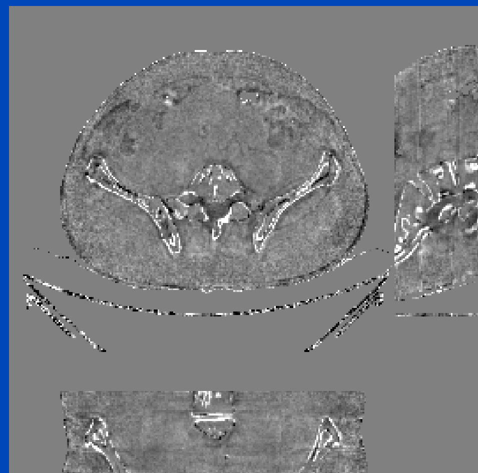
MC ground truth[1]



DDE



Relative error



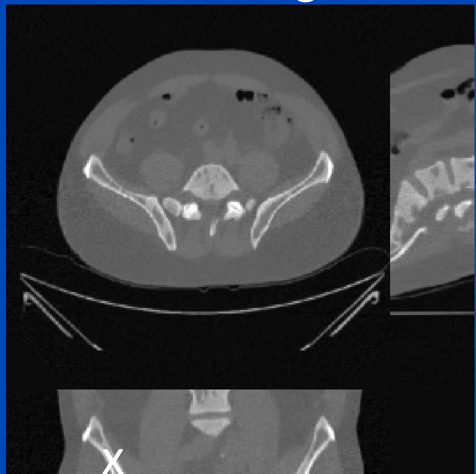
$C = 0\%$
$W = 40\%$

[1]M. Baer, M. Kachelrieß. Phys. Med. Biol. 57, 6849–6867, 2012.

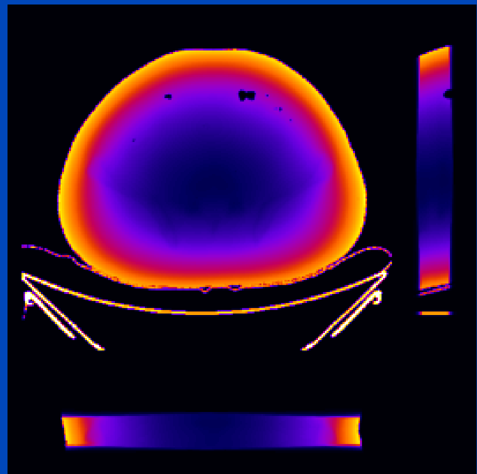
Results

Pelvis, tube A, 120 kV, no bowtie

CT image



First order dose

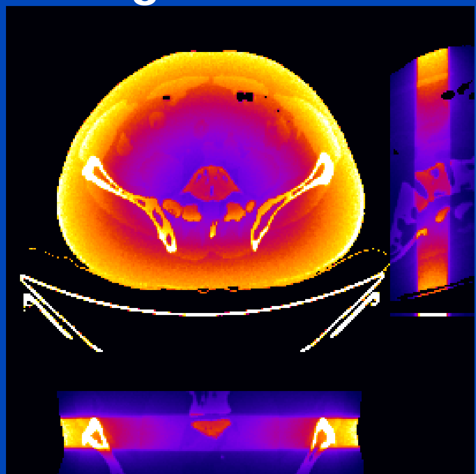


	MC	DDE
48 slices	1 h	0.25 s
whole body	20 h	5 s

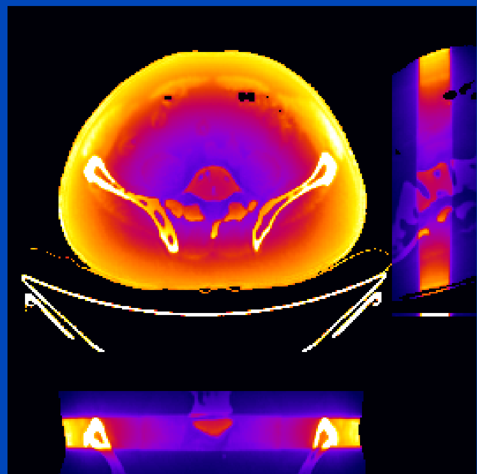
MC uses 16 CPU kernels
DDE uses one Nvidia Quadro P600 GPU

DDE training took 74 h for 300 epochs, 1440 samples, 48 slices per sample

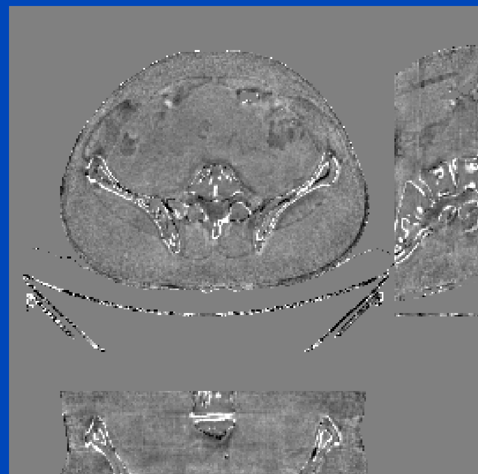
MC ground truth[1]



DDE



Relative error



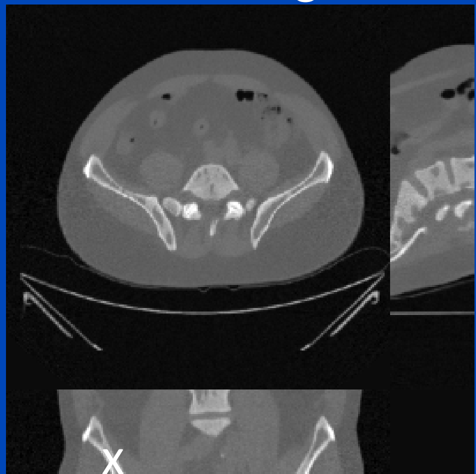
C = 0%
W = 40%

[1]M. Baer, M. Kachelrieß. Phys. Med. Biol. 57, 6849–6867, 2012.

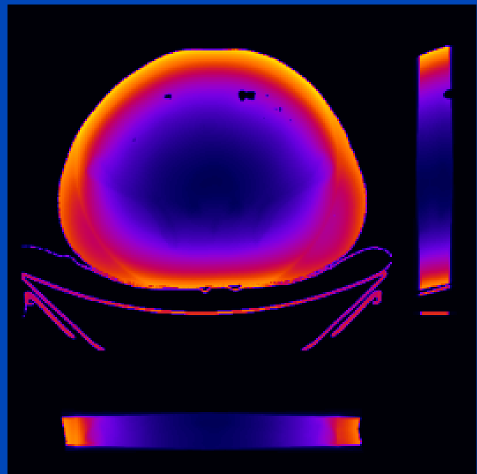
Results

Pelvis, tube B, 120 kV, no bowtie

CT image



First order dose

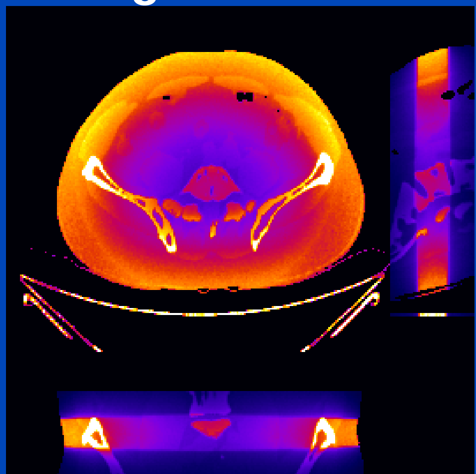


	MC	DDE
48 slices	1 h	0.25 s
whole body	20 h	5 s

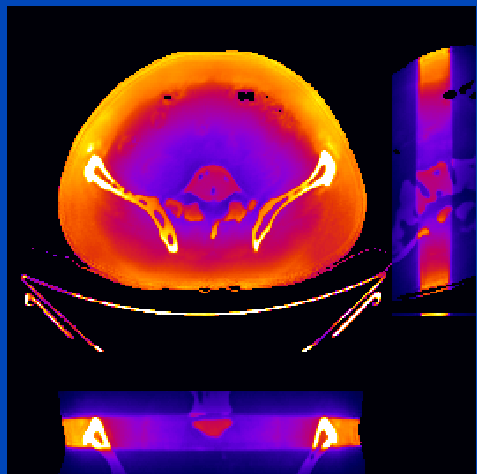
MC uses 16 CPU kernels
DDE uses one Nvidia Quadro P600 GPU

DDE training took 74 h for 300 epochs, 1440 samples, 48 slices per sample

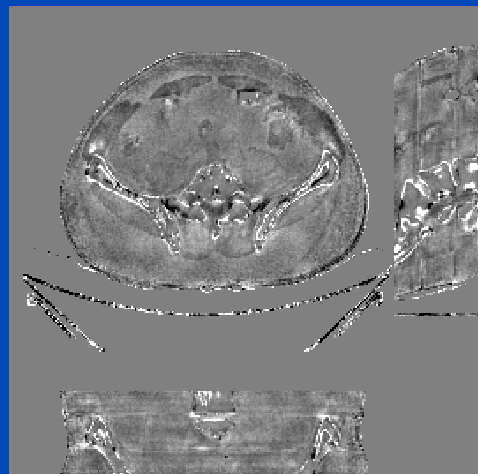
MC ground truth[1]



DDE



Relative error



C = 0%
W = 40%

[1]M. Baer, M. Kachelrieß. Phys. Med. Biol. 57, 6849–6867, 2012.

dkfz.

Conclusions on DDE

- DDE is able to derive dose estimates with almost similar accuracy as MC (average deviation: 4.6 %).
- Pixel-wise loss is responsible for blurring at edges.
- DDE generalizes to different anatomical regions and is able to handle different fluence fields.
- A 256×256×48 voxel volume with 2 mm voxel size can be processed in 250 ms. Approximately 5 s are required for a whole body scan.
- This study was restricted to training data with a z-axis coverage of about 10 cm (≈ 2.5 × collimation). For practical use, it might be necessary to extend the z-axis coverage to account for all dose contributions.

Interested in more deep learning applications for CT optimization?
Come and find out tomorrow 10:30-12:00, EFOMP workshop, room G!

Thank You!

The 6th International Conference on

Image Formation in X-Ray Computed Tomography

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.