AI-Based Real-Time Estimation of Patient Dose Distributions

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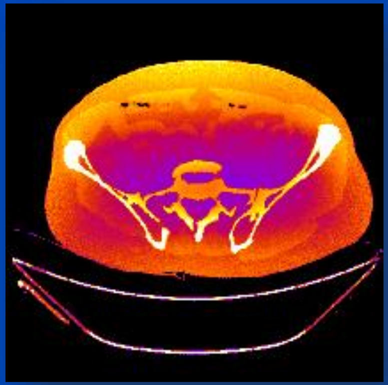
Deep Dose Estimation

???

In real time?



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RESEARCH ARTICLE

MEDICAL PHYSICS

Real-time estimation of patient-specific dose distributions for medical CT using the deep dose estimation

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Abstract

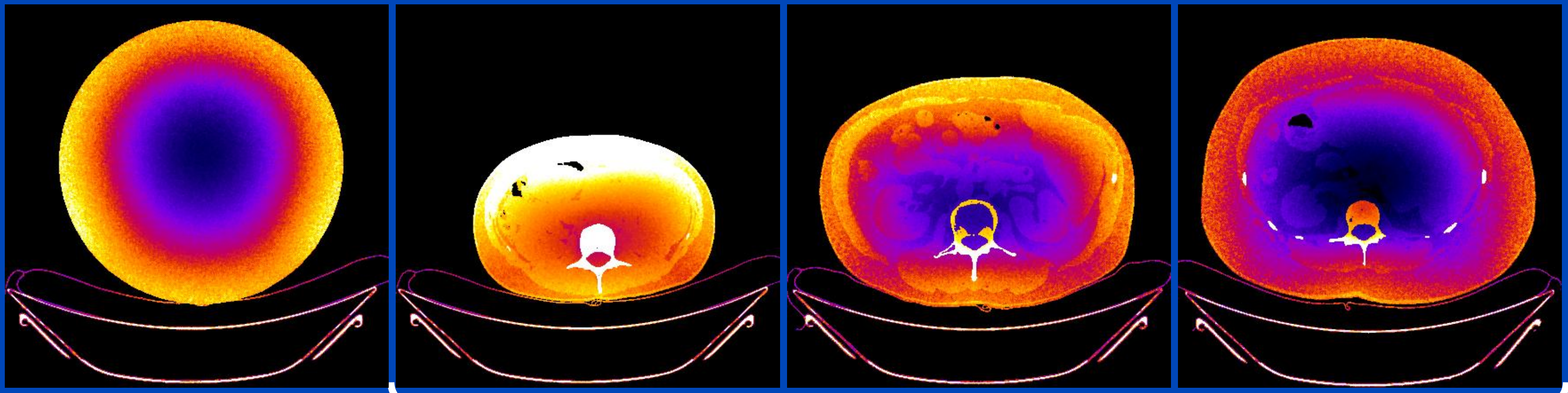
Purpose: With the rising number of computed tomography (CT) examinations and the trend toward personalized medicine, patient-specific dose estimates are becoming more and more important in CT imaging. However, current approaches are often too slow or too inaccurate to be applied routinely. Therefore, we propose the so-called deep dose estimation (DDE) to provide highly accurate patient dose distributions in real time

Methods: To combine accuracy and computational performance, the DDE algorithm uses a deep convolutional neural network to predict patient dose distributions. To do so, a U-net like architecture is trained to reproduce Monte Carlo simulations from a two-channel input consisting of a CT reconstruction and a

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.

Why Dose Distributions?

- **Useful to study dose reduction techniques**
  - Tube current modulation
  - Prefiltration and shaped filtration
  - Tube voltage settings
  - …
- **Useful to estimate patient dose**
  - Risk assessment requires segmentation of the organs
  - Often semiantropomorphic patient models take over
  - The infamous k-factors that convert DLP into D_{eff} are derived this way, e.g. k_{chest} = 0.014 mSv/mGy/cm
  - …
- **Useful for patient-specific CT scan protocol optimization**
- **However: Dose estimation is often said not to work in real time.**

J. Maier, L. Klein, E. Eulig, S. Sawall, and M. Kachelrieß. Real-time estimation of patient-specific dose distributions for medical CT using the deep dose estimation. Med. Phys. 49(4):2259-2269, April 2022. *Best Paper within Machine Learning at ECR 2019!*

Classical Patient-Specific Dose Estimation

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

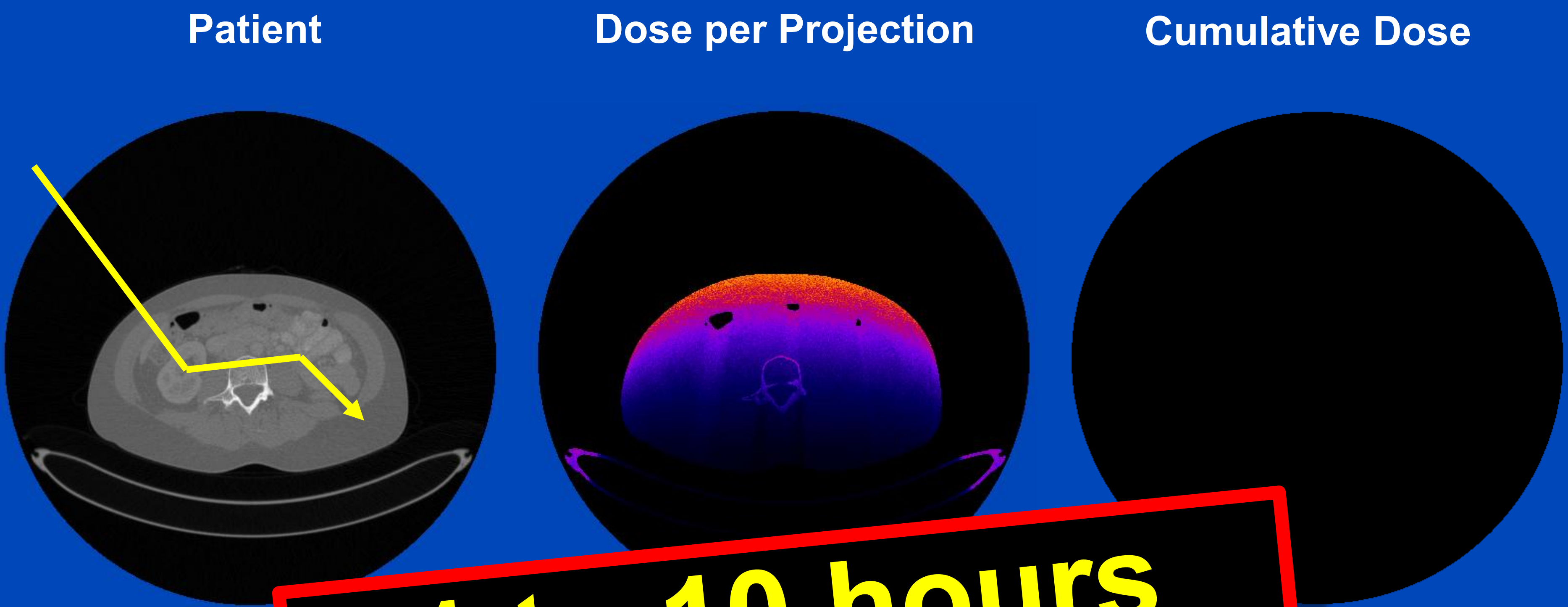
  → Accurate but computationally expensive

- 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.

MC Dose Simulation for a 360° Scan



1 to 10 hours
per tomographic data set

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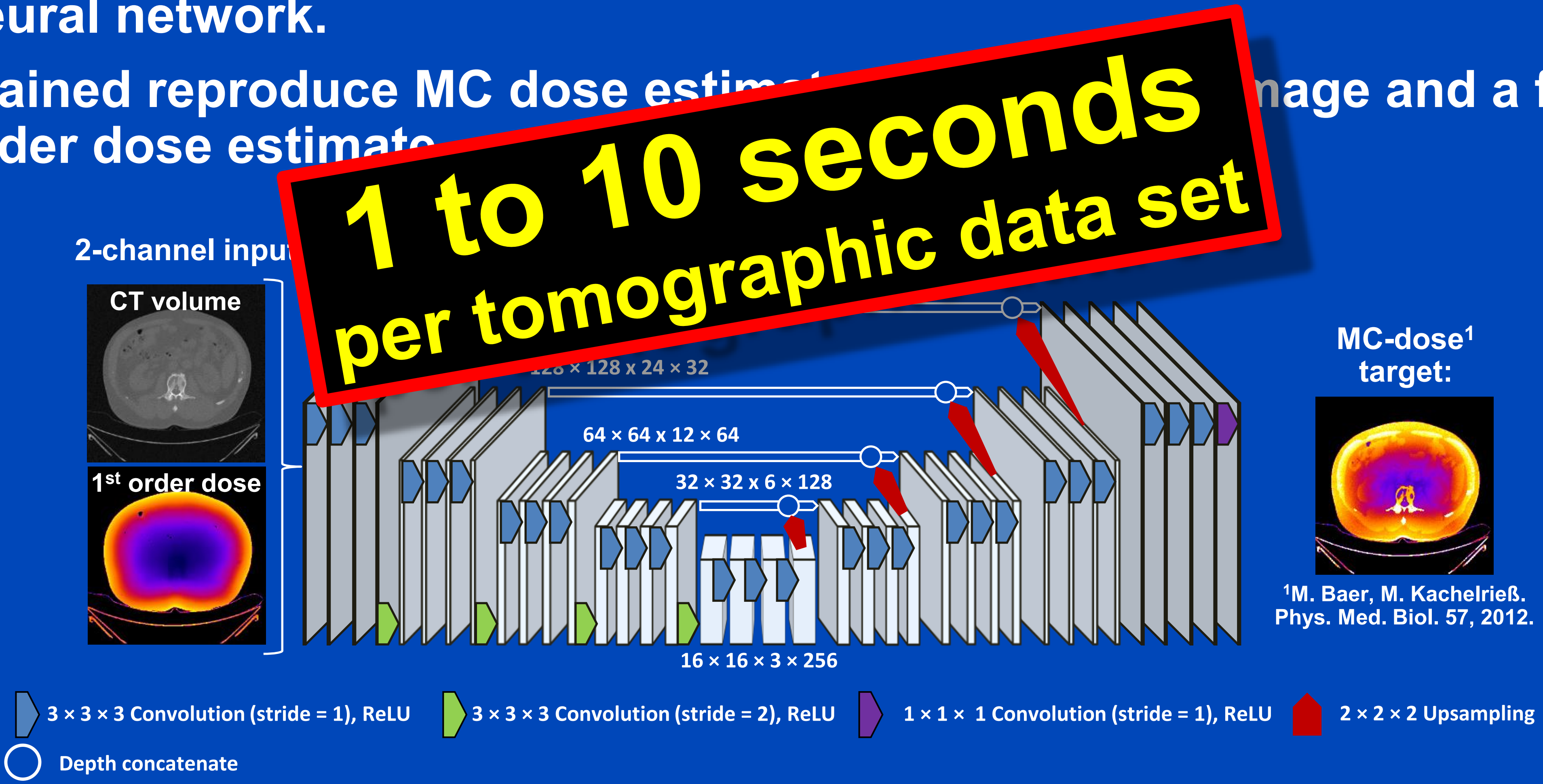
Deep Dose Estimation (DDE)

- Fast and accurate CT dose estimation using a deep convolutional neural network.
- Trained reproduce MC dose estim... ...mage and a first-order dose estimate.



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

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First-Order Dose Estimate

- DDE needs information about the tube position, tube current, tube voltage, shaped filters, collimation, scan trajectory etc.
- This information is encoded in the first-order dose estimate.
- First order dose-estimate in a voxel at position *r* with mass *m*:

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

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)

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

$$E_{\text{int,PE}} = E$$

$$P_{\text{int,CS}}(\boldsymbol{r},E,\alpha) = \mu_{\text{CS}}(\boldsymbol{r},E)\cdot e^{-\int_0^r \mu(r',E)dr'}$$

$$E_{\text{int,CS}} = \int \frac{d\sigma}{d\Omega}(E)\Delta E_{\text{CS}}(\theta)d\Omega$$

- Our first order dose estimate assumes the object to be water-equivalent (because it turned out to work this way).

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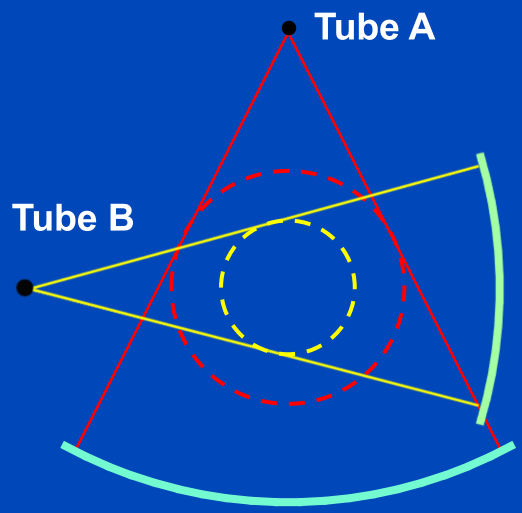
Training and Validation



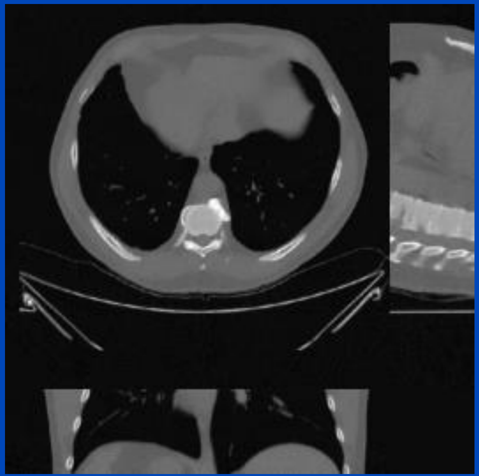
- Simulation of 6480 circular and spiral dual-source CT scans (64×0.6 mm, FOM_A = 50 cm, FOM_B = 32 cm) of head, thorax, abdomen, and pelvis of 45 patients.
- Simulation of six z-positions, three tube voltages, with and without bowtie and TCM.
- No data augmentation
- Reconstruction on a 512×512×128 grid with 1 mm voxel size, followed by 2×2×2 binning for dose estimation.
- 40 patients were used for training and 5 for testing.
- DDE was trained for 200 epochs on an Nvidia GeForce RTX 3090 GPU using a mean absolute error pixel-wise loss (with 25-fold weight on the bone voxels), the Adam optimizer, and a batch size of 8.
- The same weights and biases were used for all cases.

6480 = 45 patients × 6 z-positions × 3 voltages × 2 trajectories × 2 bowties × 2 TCM modes

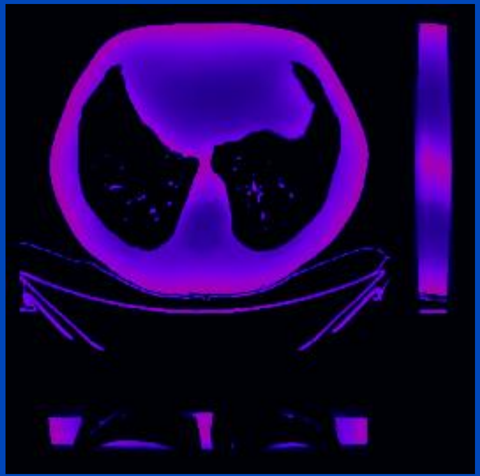
Results

Thorax, tube A, 120 kV, with bowtie

CT image



First order dose

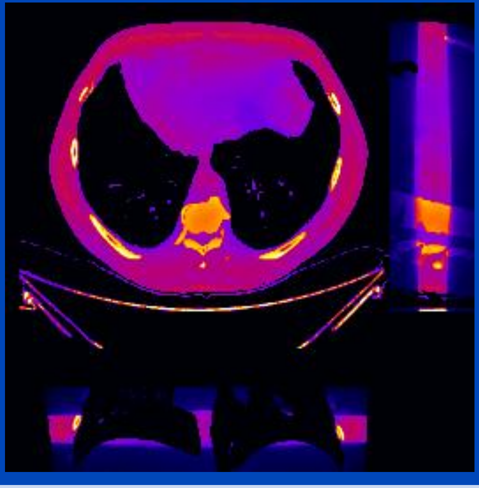


	MC	DDE
48 slices	1 h	0.25 s
whole body	20 h	5 s

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



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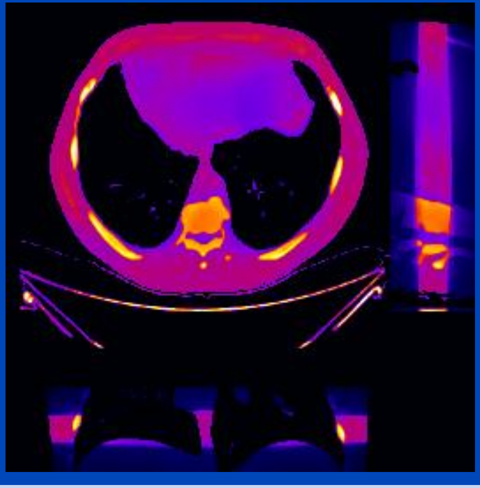
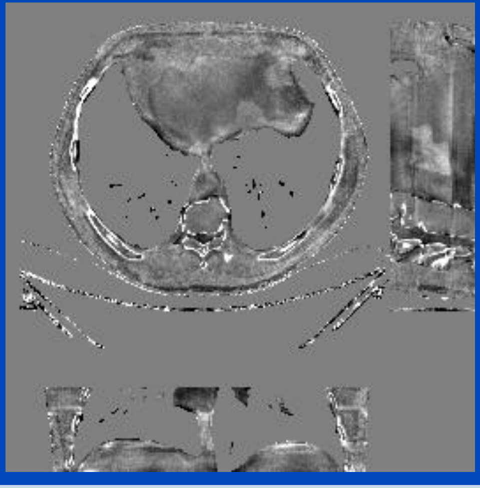


Relative error



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W = 40%

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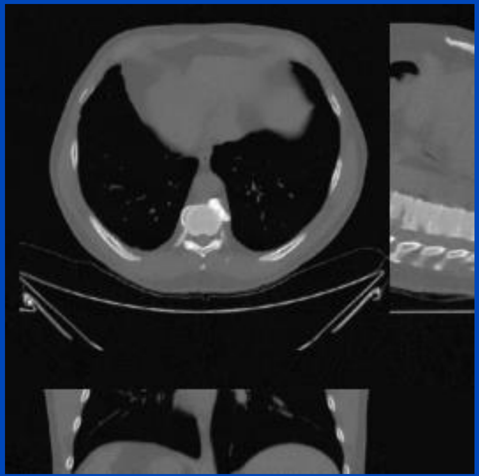

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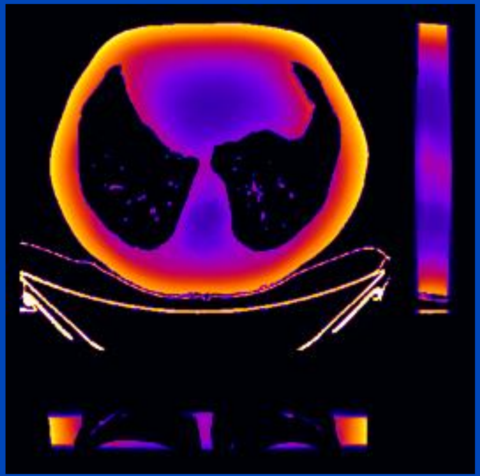

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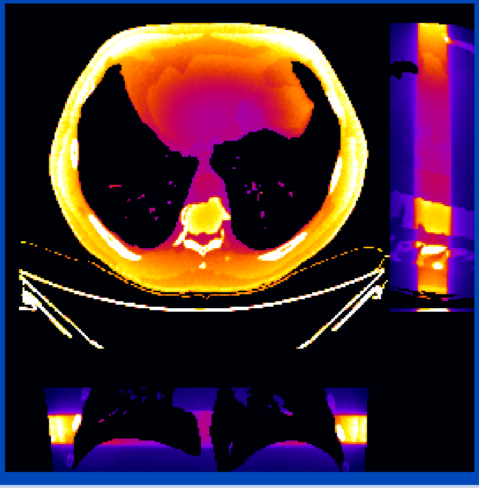

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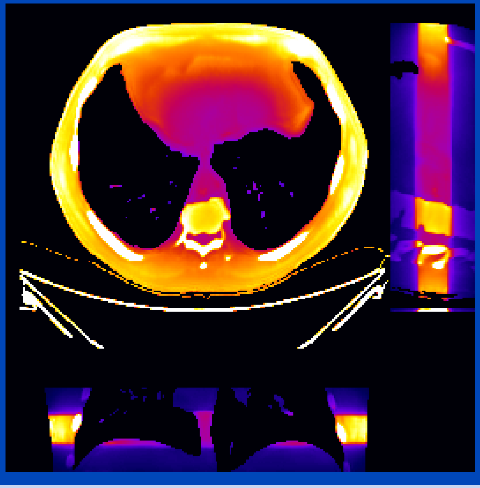

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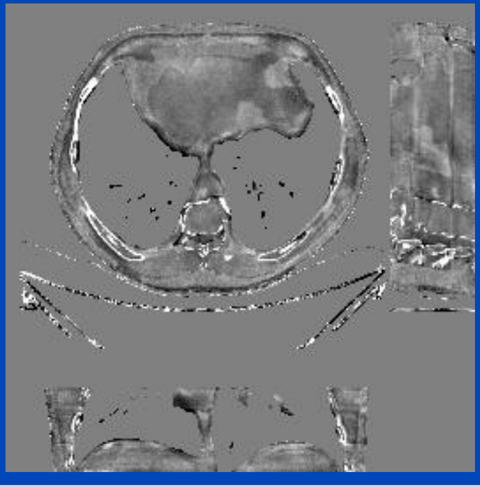

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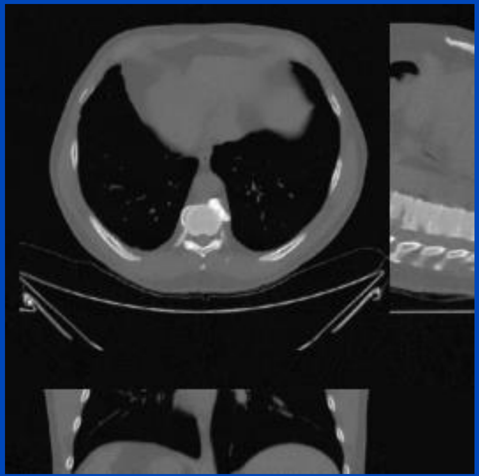
Results

Thorax, tube B, 120 kV, no bowtie

CT image



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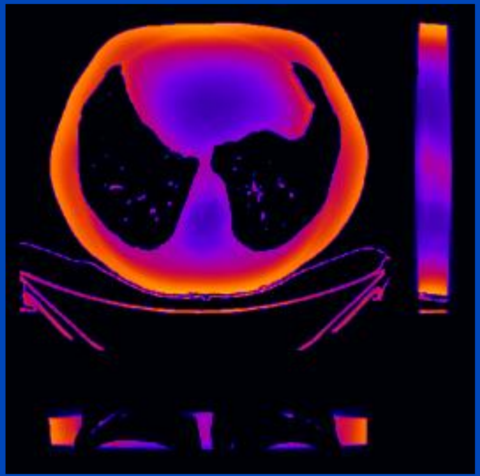

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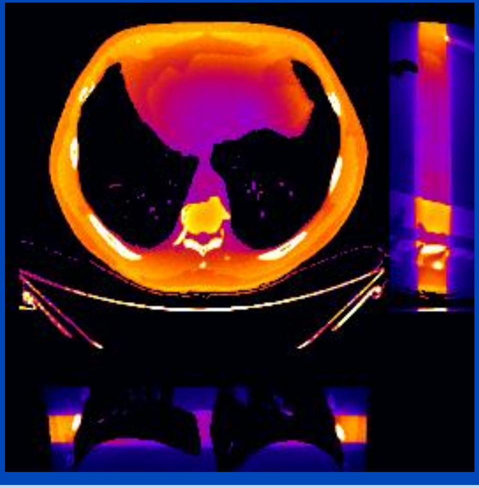

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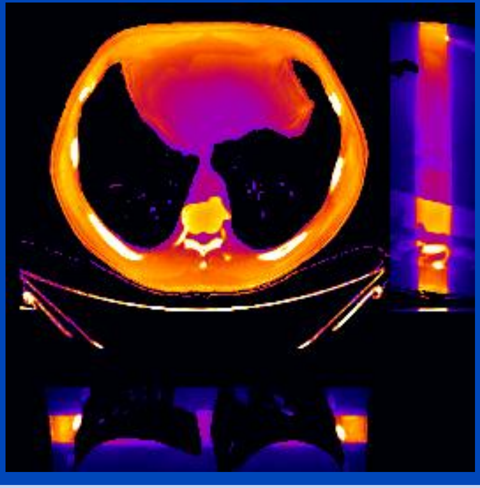

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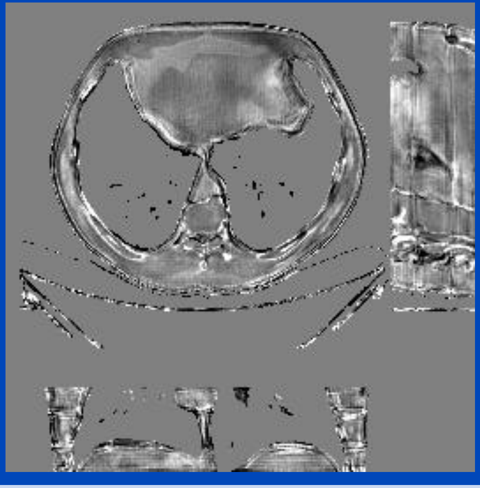

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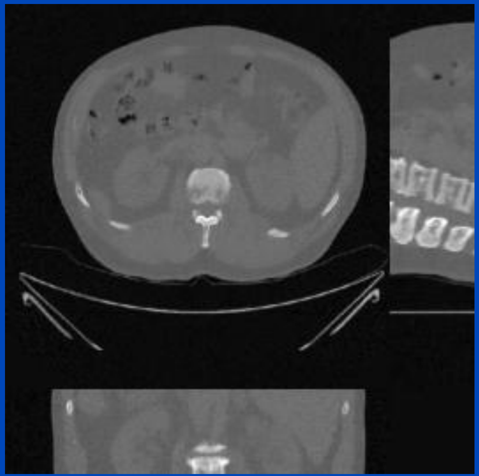
Results

Abdomen, tube A, 120 kV, with bowtie

CT image



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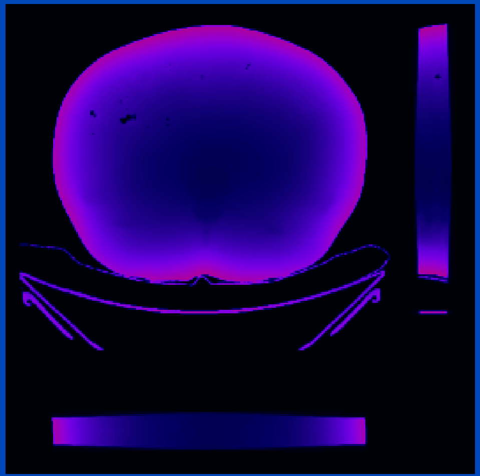

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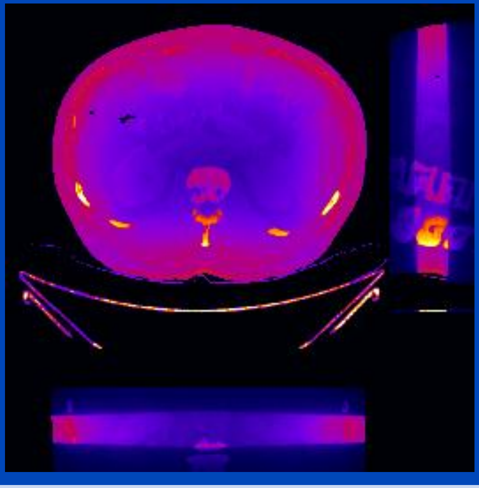

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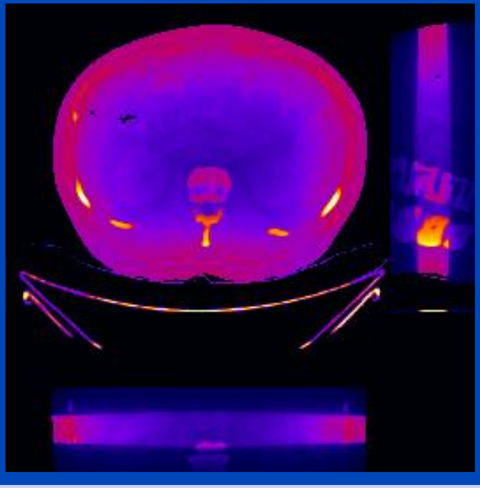

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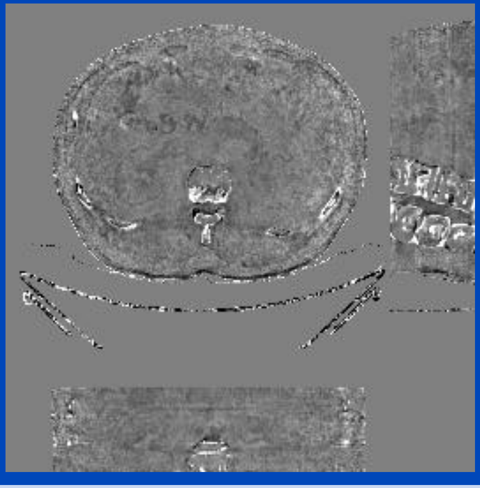

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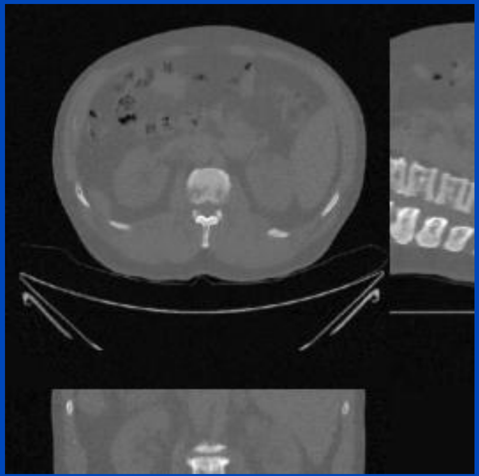

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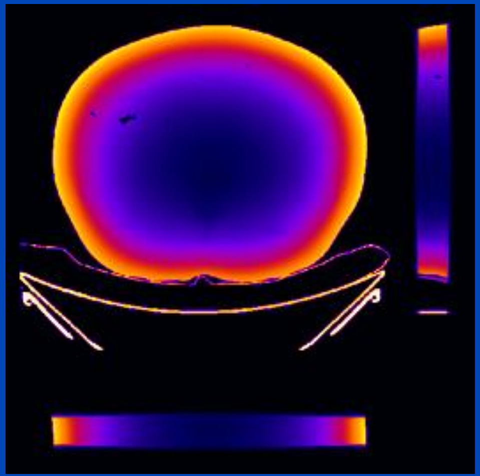

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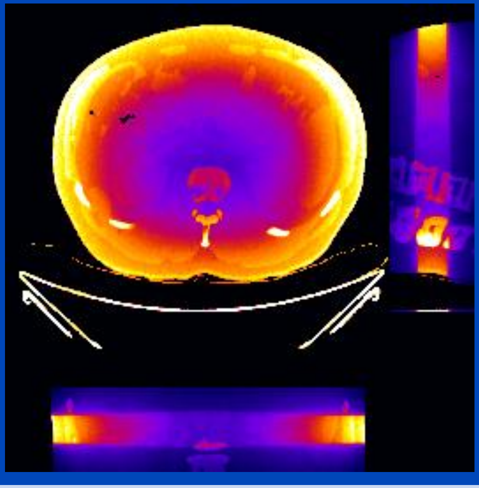

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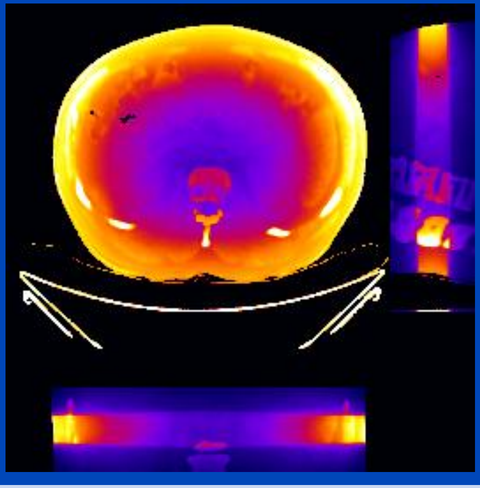

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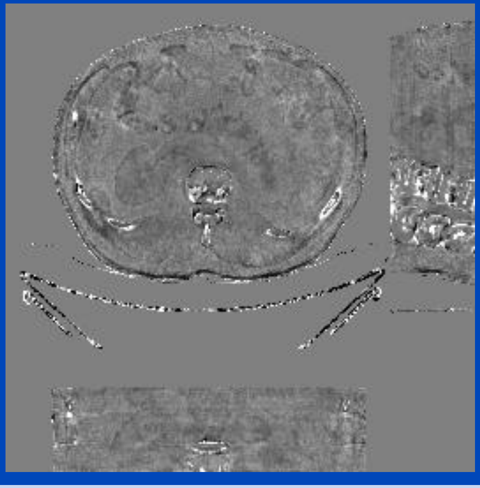

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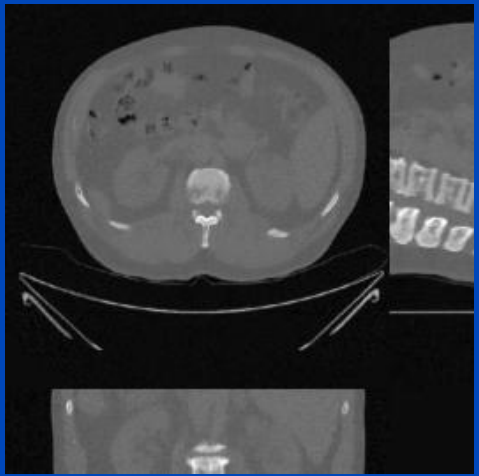

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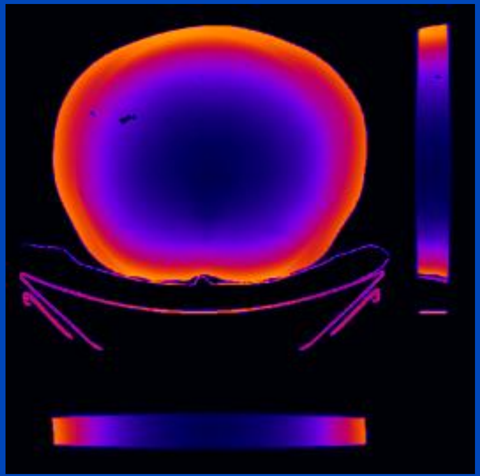

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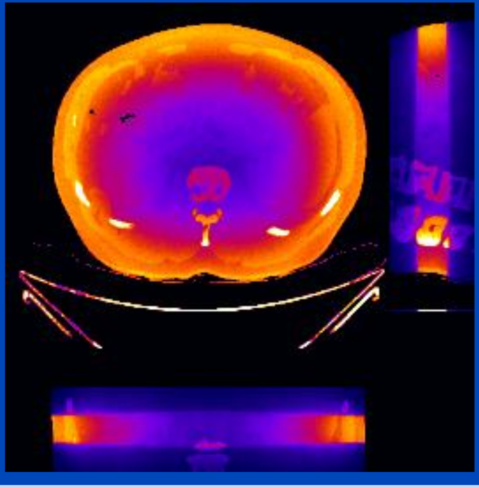

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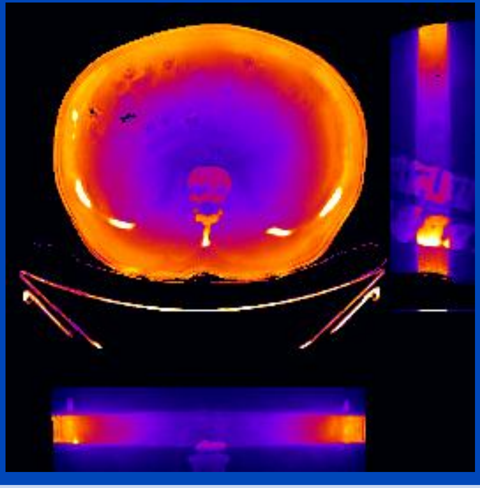

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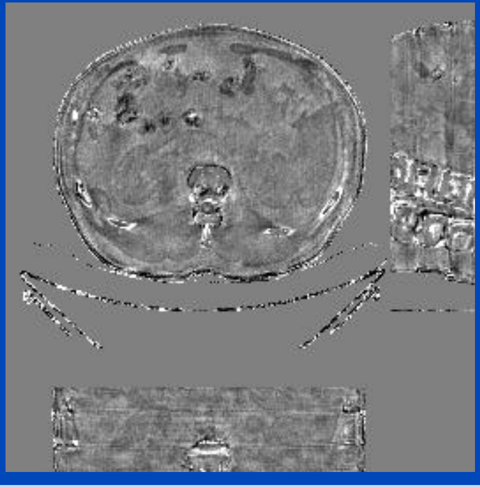

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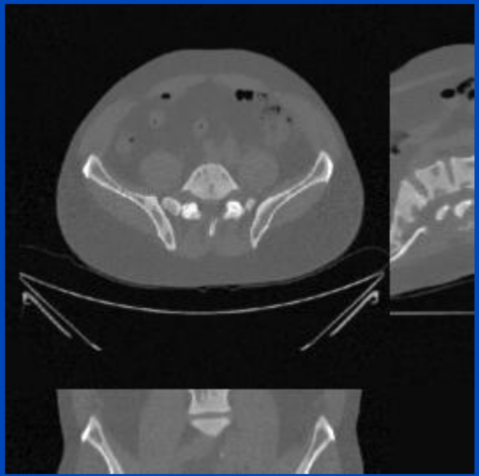
Results

Pelvis, tube A, 120 kV, with bowtie

CT image



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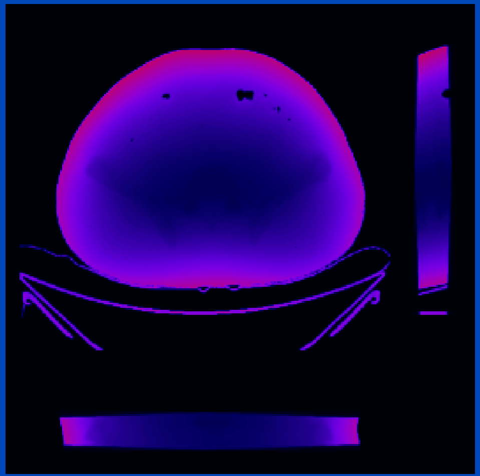

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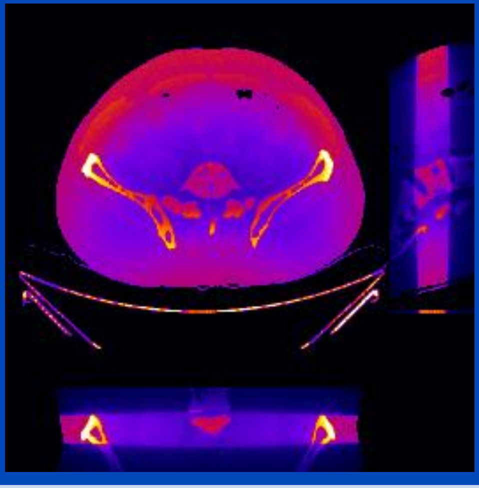

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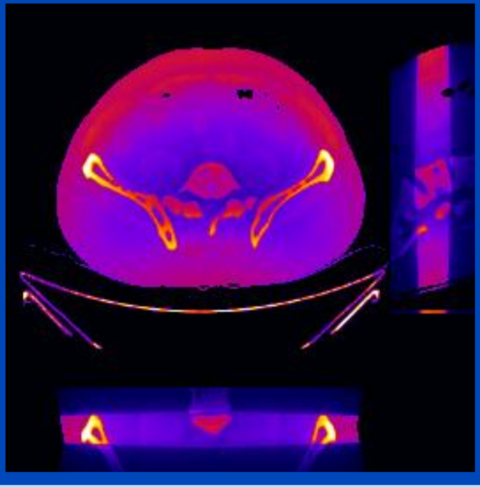

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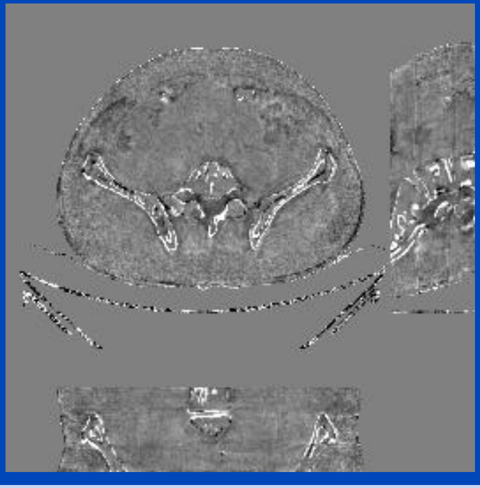

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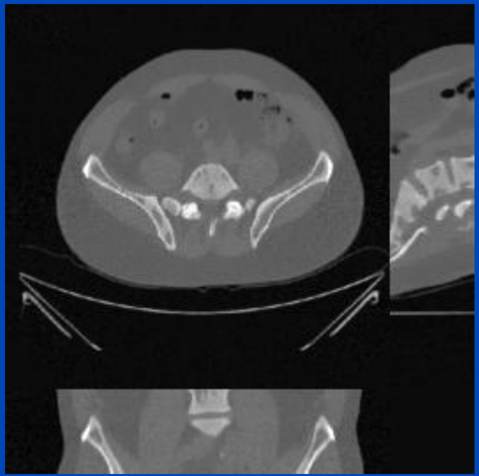

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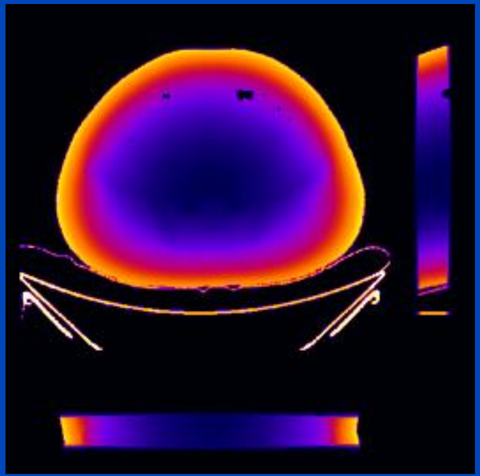

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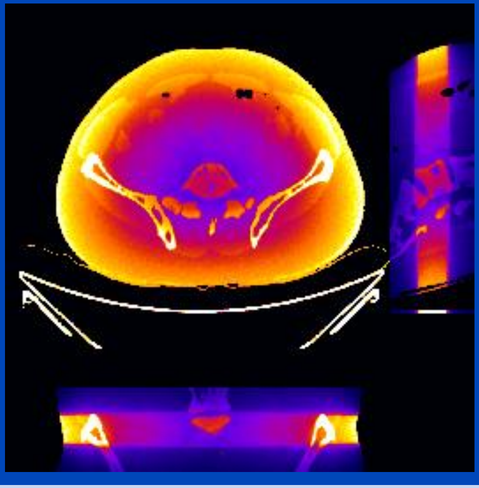

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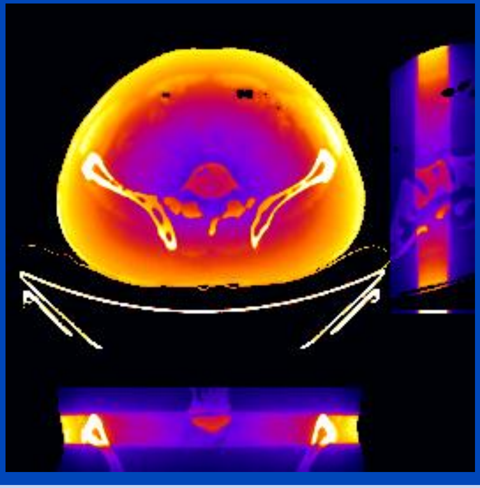
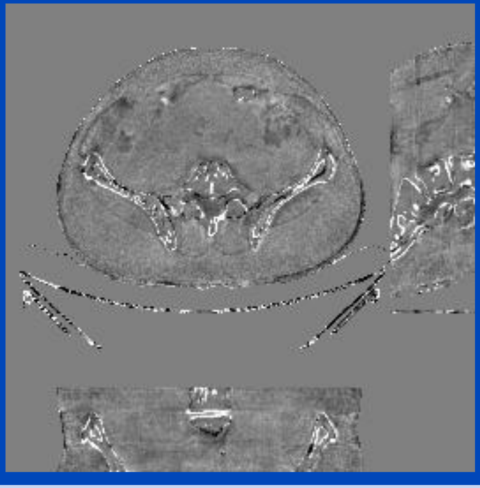


Relative error



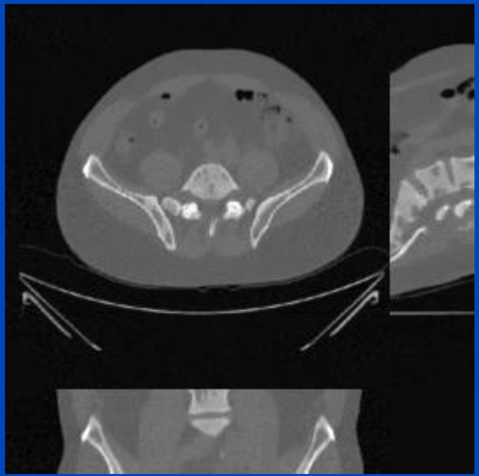
C = 0%
W = 40%

J. Maier, L. Klein, E. Eulig, S. Sawall, and M. Kachelrieß. Real-time estimation of patient-specific dose distributions for medical CT using the deep dose estimation. Med. Phys. 49(4):2259-2269, April 2022. *Best Paper within Machine Learning at ECR 2019!*

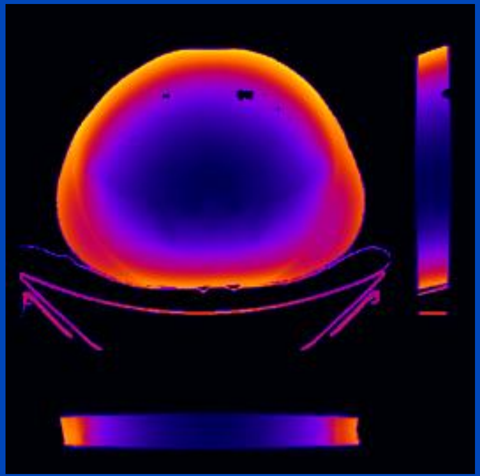
Results

Pelvis, tube B, 120 kV, no bowtie

CT image



First order dose

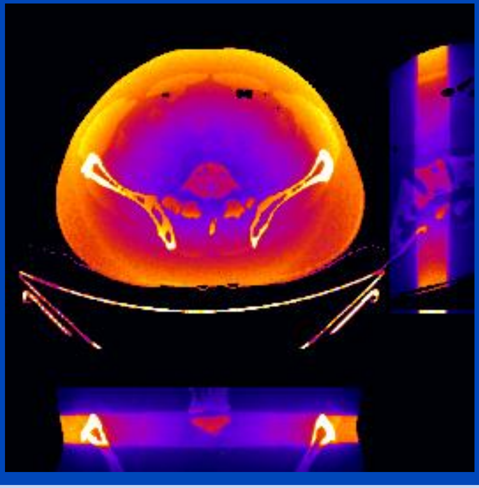


	MC	DDE
48 slices	1 h	0.25 s
whole body	20 h	5 s

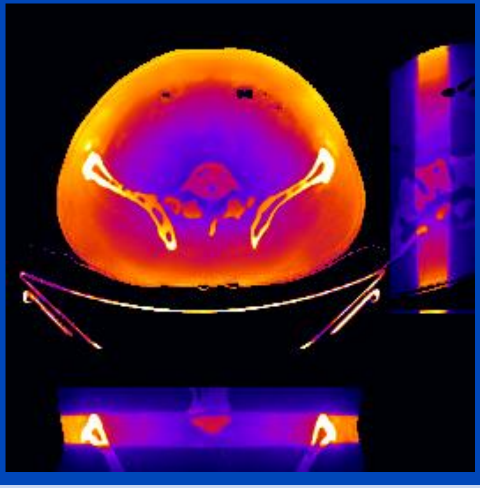
MC uses 16 CPU kernels
DDE uses one Nvidia Quadro P600 GPU

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

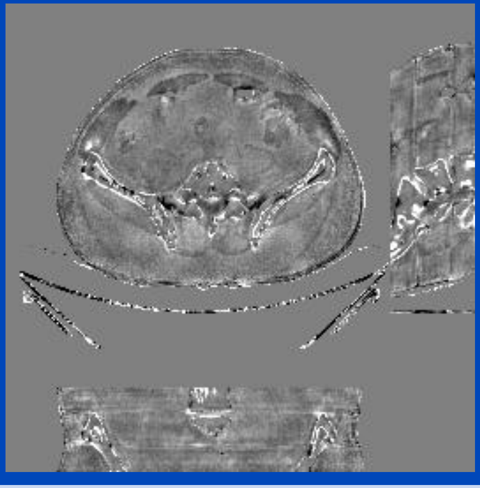
MC ground truth



DDE



Relative error



C = 0%
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DDE's Organ Dose and D_{eff} MAPEs

Organ and ICRP weight		80 kV	100 kV	120 kV
Bone marrow	0.12	5.2%	6.7%	7.1%
Bone surface	0.01	5.7%	7.0%	7.2%
Brain	0.01	5.1%	4.9%	5.3%
Breast	0.12	1.0%	1.4%	2.1%
Colon	0.12	0.9%	1.7%	1.9%
Esophagus	0.04	1.3%	2.4%	2.3%
Gonads	0.08	3.2%	2.7%	2.2%
Liver	0.04	2.9%	1.1%	0.8%
Lung	0.12	1.7%	3.5%	4.0%
Remainder	0.12	0.9%	1.9%	2.3%
Salivary glands	0.01	4.9%	5.1%	5.3%
Skin	0.01	2.8%	3.3%	4.2%
Stomach	0.12	2.3%	1.1%	0.8%
Thyroid gland	0.04	3.1%	3.0%	2.3%
Urinary bladder	0.04	1.7%	1.7%	1.3%
Effective dose		**1.2%**	**2.5%**	**2.7%**

Weighting factors and mean absolute percentage error of the DDE organ dose values with respect to the ground truth Monte Carlo organ dose values.

Conclusions on DDE

- DDE provides accurate dose predictions
  - for circle scans
  - for sequence scans
  - for partial scans (less than 360°)
  - for limited angle scans (less than 180°)
  - for spiral scans
  - for different tube voltages
  - for scans with and without bowtie filtration
  - for scans with tube current modulation
  - for DSCT scanners, i.e. with large (A) and small (B) detector
- In practice it may therefore be not necessary to perform separate training runs for these cases.
- Thus, accurate real-time patient dose estimation is feasible with DDE or related AI-based approaches.

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Comments for Practical Use

- DDE needs to use the actual
  - x-ray spectrum (not available in DICOM)
  - scan trajectory (not available in DICOM)
- The patient volume
  - must laterally show the full patient cross-section
  - should longitudinally show the scanned range plus, say, 10 cm at each end.

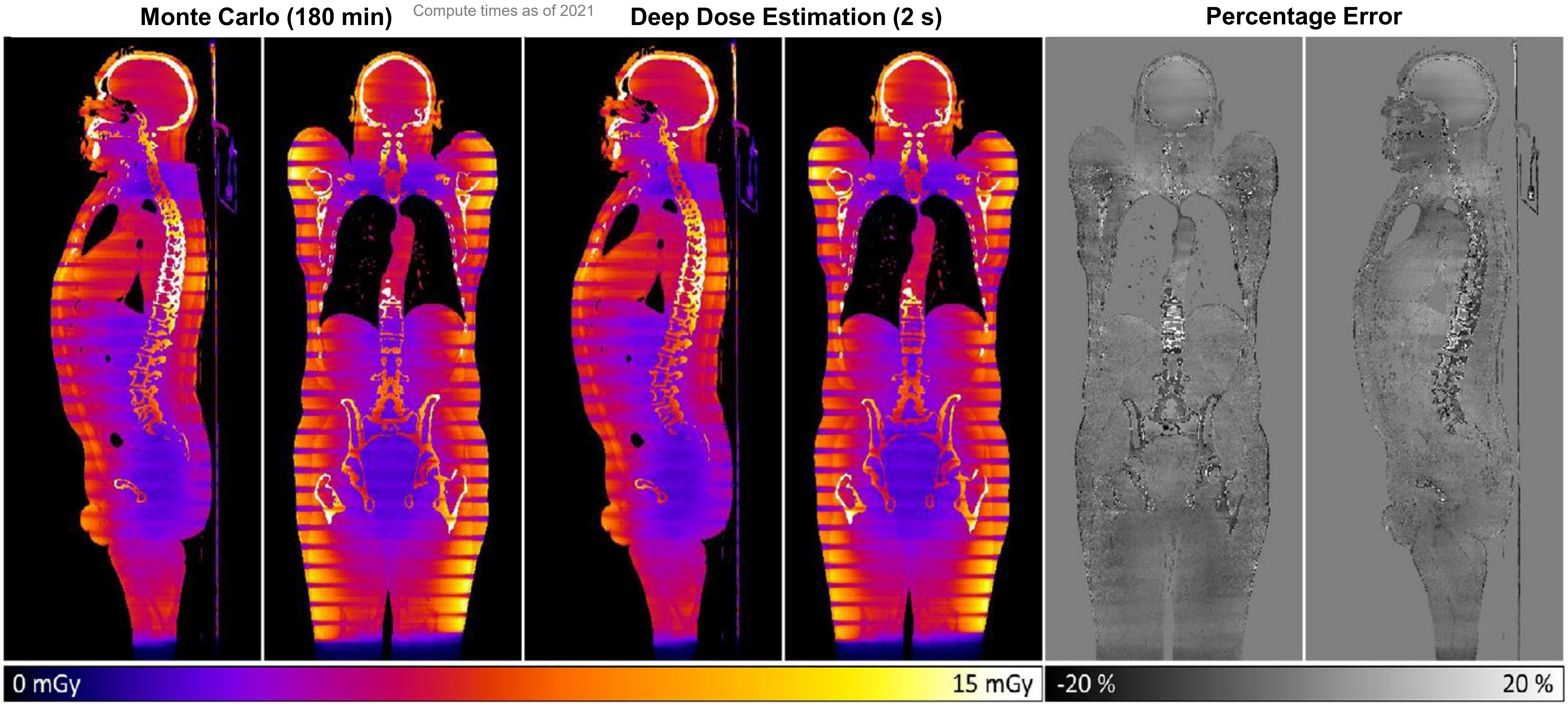

FIGURE 5 Sagittal and coronal view of the dose distribution of a 100 kV whole-body spiral computed tomography (CT) scan including a bowtie filter and an angular tube current modulation. Here, the two left columns show the ground truth, the middle columns show the deep dose estimation (DDE) prediction and the two right columns the corresponding percentage error. Note that dose to air is neglected for computational reasons, and therefore, displayed as zero

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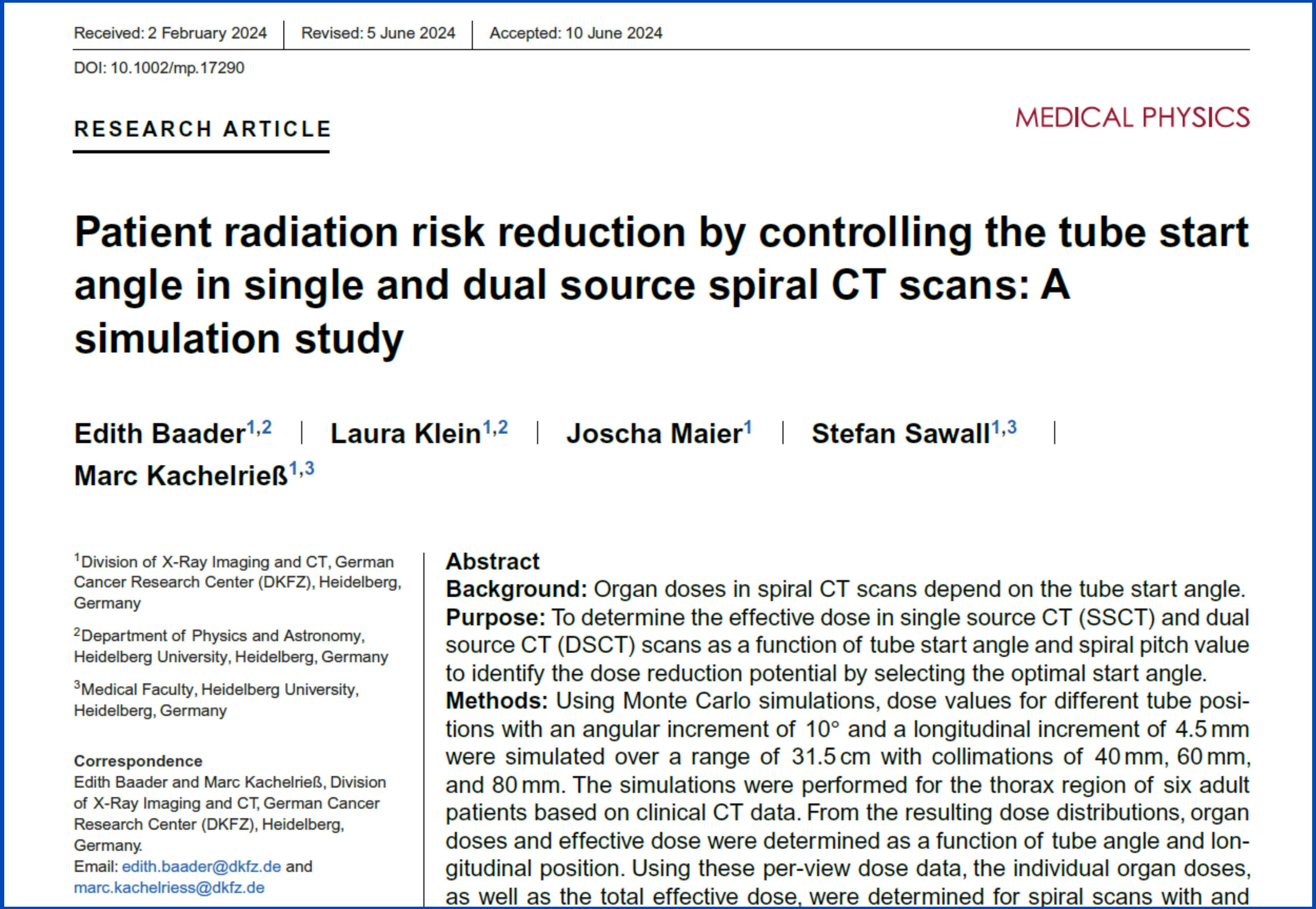

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RESEARCH ARTICLE

MEDICAL PHYSICS

Patient radiation risk reduction by controlling the tube start angle in single and dual source spiral CT scans: A simulation study

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Abstract

Background: Organ doses in spiral CT scans depend on the tube start angle.
Purpose: To determine the effective dose in single source CT (SSCT) and dual source CT (DSCT) scans as a function of tube start angle and spiral pitch value to identify the dose reduction potential by selecting the optimal start angle.
Methods: Using Monte Carlo simulations, dose values for different tube positions with an angular increment of 10° and a longitudinal increment of 4.5 mm were simulated over a range of 31.5 cm with collimations of 40 mm, 60 mm, and 80 mm. The simulations were performed for the thorax region of six adult patients based on clinical CT data. From the resulting dose distributions, organ doses and effective dose were determined as a function of tube angle and longitudinal position. Using these per-view dose data, the individual organ doses, as well as the total effective dose, were determined for spiral scans with and

E. Baader, M. Kachelrieß et al. Patient radiation risk reduction by controlling the tube start angle in single and dual source spiral CT scans: A simulation study. Med. Phys. 51:7080-7092

Calculation of Dose of Spiral Scans

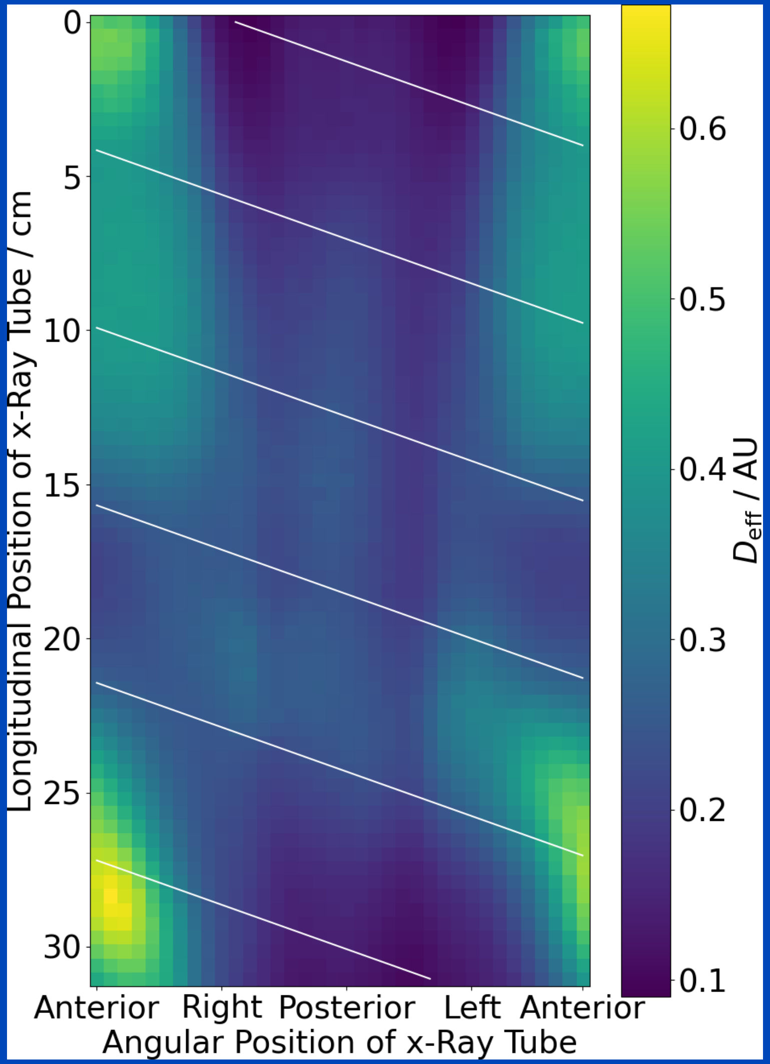
- **Sum of dose values along spiral trajectory for different tube start angles α_0 (and α_0 + 90° for DSCT)**
- **Pitch values $p = d/C$:**
  - **SSCT: 0.5 … 1.5**
  - **DSCT: 0.5 … 3.0**
- **Best and worst dose-minimizing tube start angle:**

$$\alpha_{\text{best}} = \min_{\alpha_0} D(p, \alpha_0)$$

$$\alpha_{\text{worst}} = \max_{\alpha_0} D(p, \alpha_0)$$

- **Maximum possible dose reduction for given pitch :**

$$\text{MaxDoseReduction}(p) = 1 - \frac{D(p, \alpha_{\text{best}})}{D(p, \alpha_{\text{worst}})}$$



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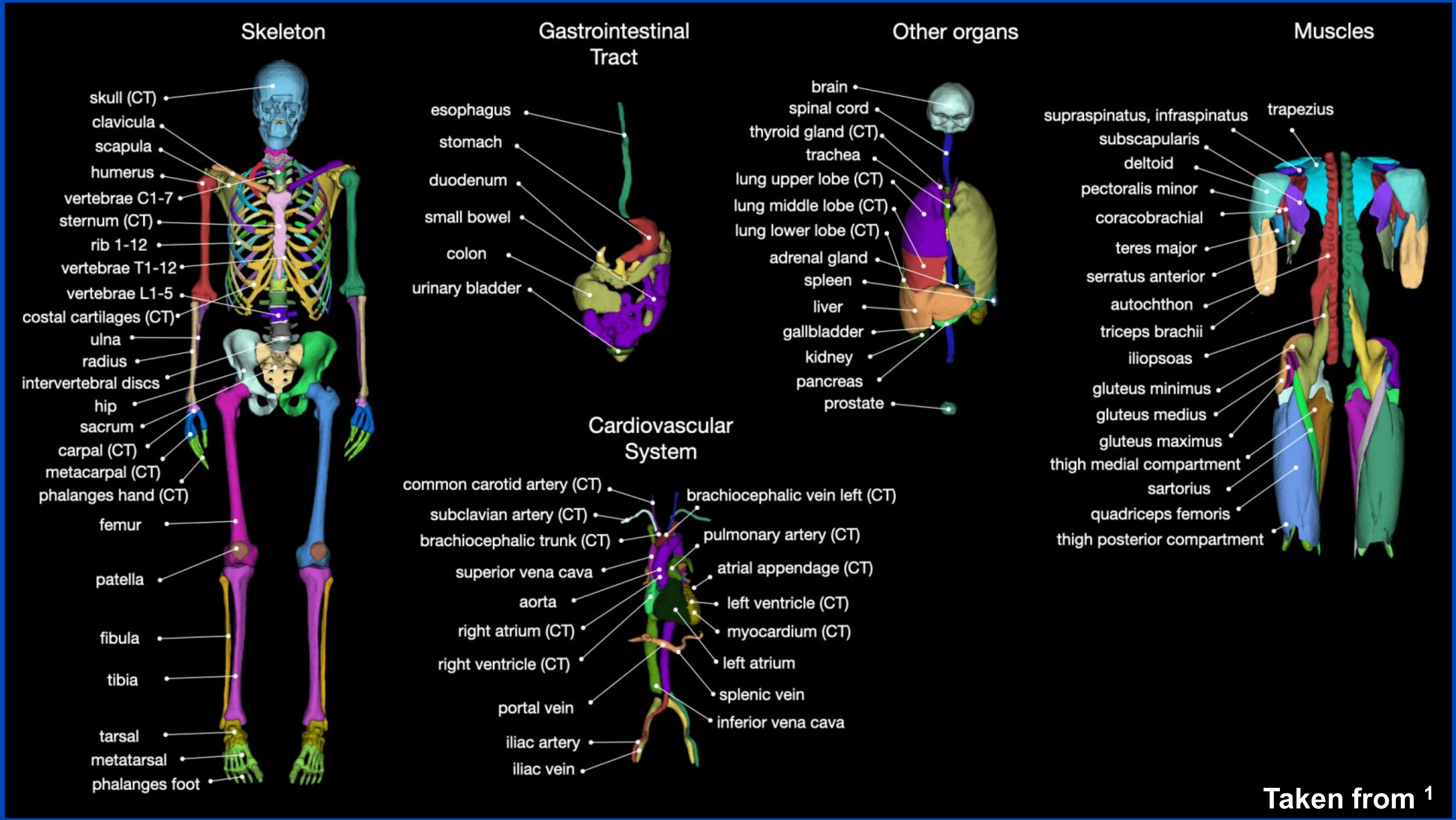
Summary on Start Angle Dependency

- Dose reductions for single organs are highly organ-specific.
- While the tube start angle affects the lung dose less than 5%, higher variations occur e.g. for the dose to the thyroid gland and the stomach.
- For the effective dose, dose reductions of up to 7% for SCCT and up to 20% for DSCT can be achieved in particular for high pitch values when selecting the optimal start angle for the simulated patients.

Risk Measures

- Risk measures typically require organ segmentation.
  - Vendors often have a variety of proprietory segmentation software, e.g. for radiation therapy planning.
  - Open source segmentation is available, too.
  - Segmentation does not have to be highly accurate
- Problem:
  - Organs may only partially be within the scan field of measurement.
  - Organ mass must be known for organ dose calculation.

TotalSegmentator



- **Neural network based fully automated segmentation of up to 104 anatomic structures in CT images**
- **Two models to choose from: 1.5 mm and 3 mm**
- **1.5 mm higher resolution model**
- **3 mm fast model with lower resolution**

[1]Wasserthal, Jakob et al. (2023). "TotalSegmentator: Robust segmentation of 104 anatomic structures in CT images". In: *Radiology: Artificial Intelligence* 5.5, e230024.

Color Map for Organ Segmentation

Remainder 0.12	*Red bone marrow 0.12	*Skin 0.01
*Bone surface 0.01	Salivary glands 0.01	Stomach 0.12
Brain 0.01	Esophagus 0.04	*Gonads 0.08
Breast 0.12	Liver 0.04	Thyroid 0.04
Colon 0.12	Lung 0.12	Bladder 0.04

Organs used for the dose calculation according to ICRP 103. Asterisks indicate organs that cannot be segmented with TotalSegmentator. For the skin and bone surface morphological erosion is used. The red bone marrow is found by subtraction of the bone surface from the whole segmented bone. Gonads are missing for both male and female patients.

Conclusions

- Patient dose distributions are useful for
  - calculating risk measures (this session)
  - driving tube current curves (e.g. riskTCM)
  - optimizing scan start angles and pitch values
  - optimizing scan protocols
- It is possible to estimate in real time
  - patient dose distributions
  - organ segmentations
  - and therefore patient-specific risk
- Longitudinal extension of the CT volume should be addressed
- Vendor should help by providing information on
  - x-ray spectra
  - scan trajectories

Thank You!

This presentation will soon be available at www.dkfz.de/ct.

Job opportunities through marc.kachelriess@dkfz.de or through DKFZ's international PhD or Postdoctoral Fellowship programs.

Parts of the reconstruction software were provided by RayConStruct® GmbH, Nürnberg, Germany.