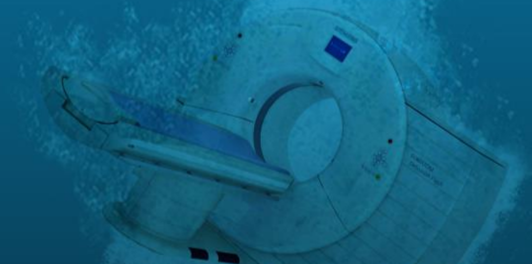
RöKo 2021: Physik und IT: Welche Anwendungsbereiche gibt es noch?

KI in der CT-Rekonstruktion

AI in CT Image Formation



Marc Kachelrieß

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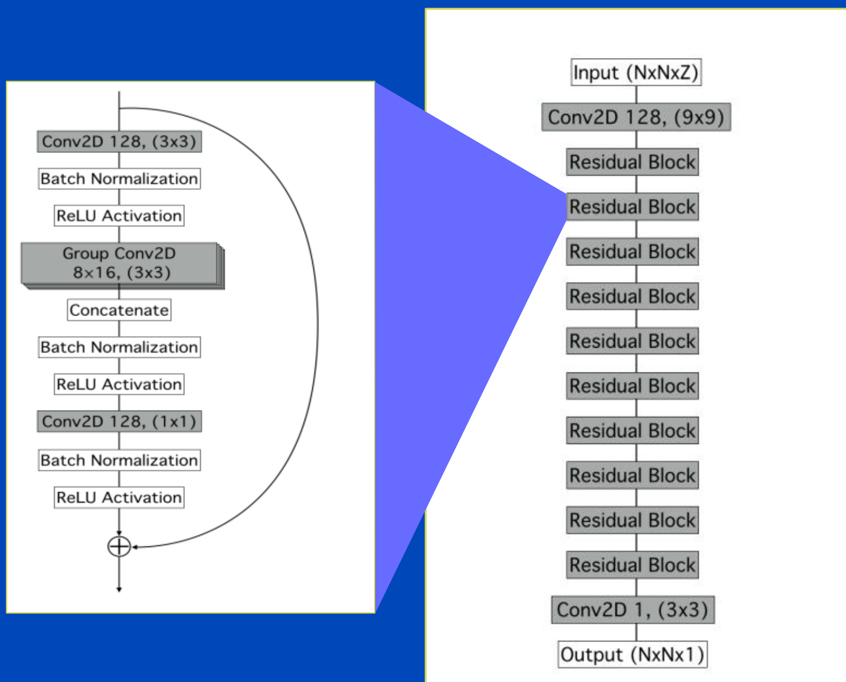
Heidelberg, Germany
www.dkfz.de/ct

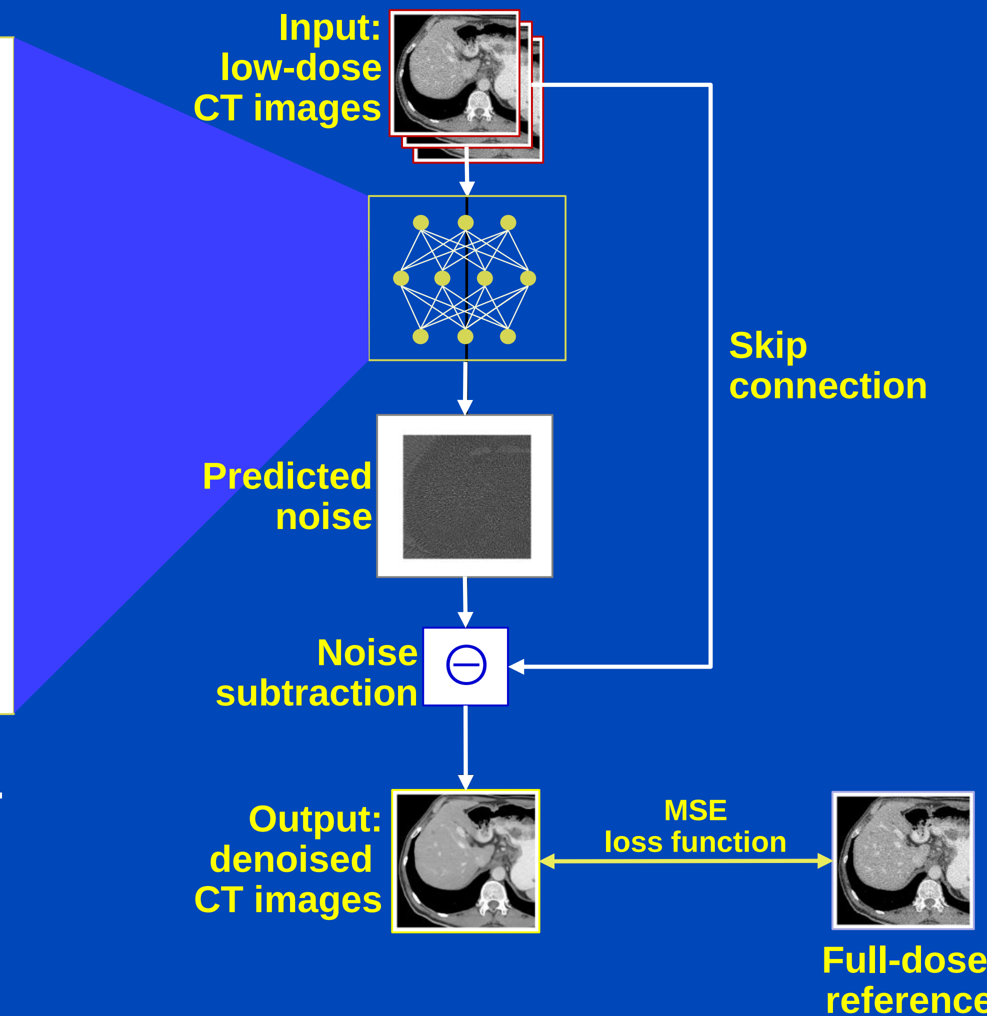
DEUTSCHES KREBSFORSCHUNGSZENTRUM IN DER HELMHOLTZ-GEMEINSCHAFT

Part 1:

Noise/Dose Reduction

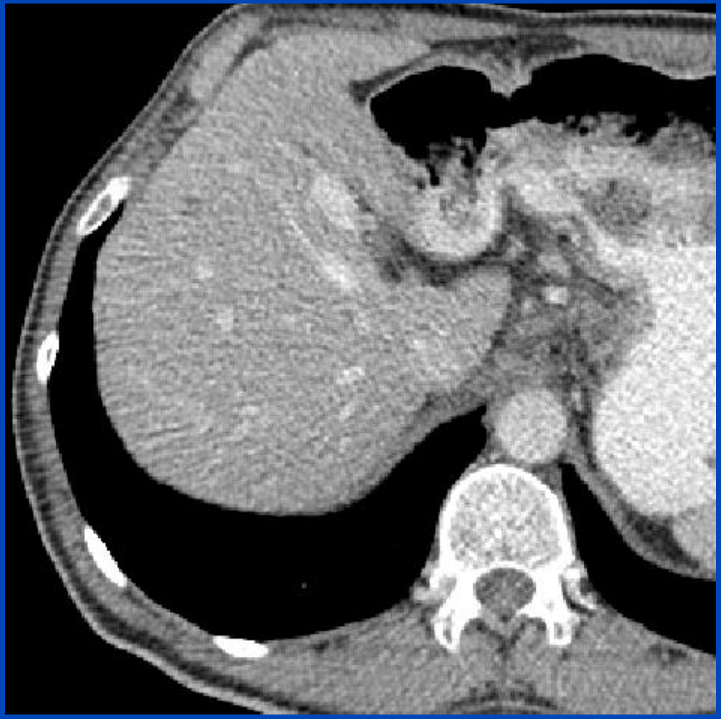
Noise Removal

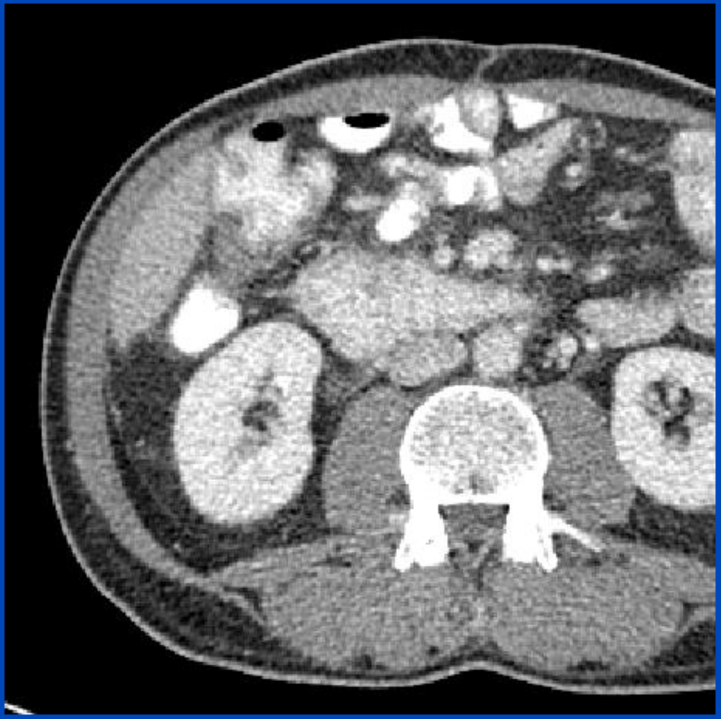




- Architecture based on state-of-the-art networks for image classification (ResNet).
- 32 conv layers with skip connections
- About 2 million tunable parameters in total
- Input is arbitrarily-size stack of images, with a fixed number of adjacent slices in the channel/feature dimension.

Noise Removal





Low dose images (1/4 of full dose)

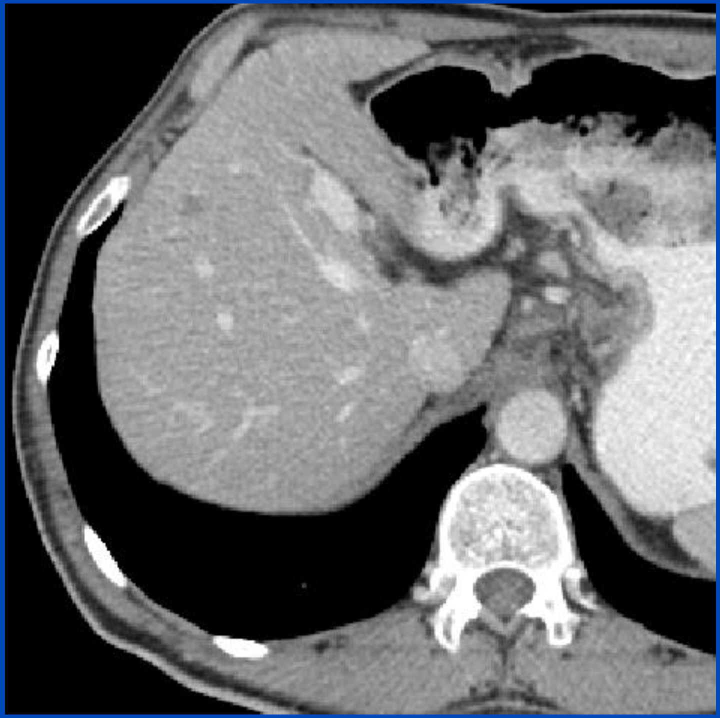
Andrew D. Missert, Shuai Leng, Lifeng Yu, and Cynthia H. McCollough. Noise Subtraction for Low-Dose CT Images Using a Deep Convolutional Neural Network. Proceedings of the 5th CT-Meeting: 399-402, 2018.

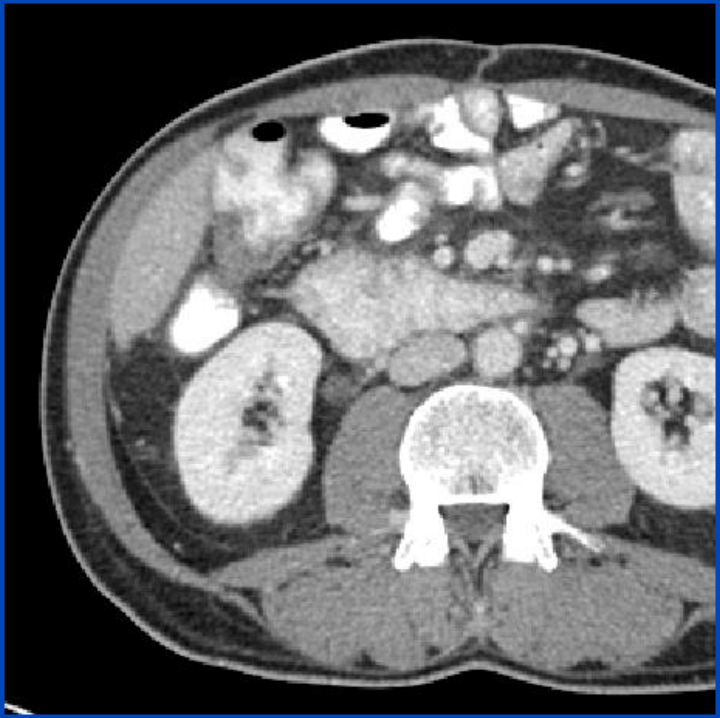
Noise Removal

Denoised low dose

Andrew D. Missert, Shuai Leng, Lifeng Yu, and Cynthia H. McCollough. Noise Subtraction for Low-Dose CT Images Using a Deep Convolutional Neural Network. Proceedings of the 5th CT-Meeting: 399-402, 2018.

Noise Removal





Full dose

Andrew D. Missert, Shuai Leng, Lifeng Yu, and Cynthia H. McCollough. Noise Subtraction for Low-Dose CT Images Using a Deep Convolutional Neural Network. Proceedings of the 5th CT-Meeting: 399-402, 2018.

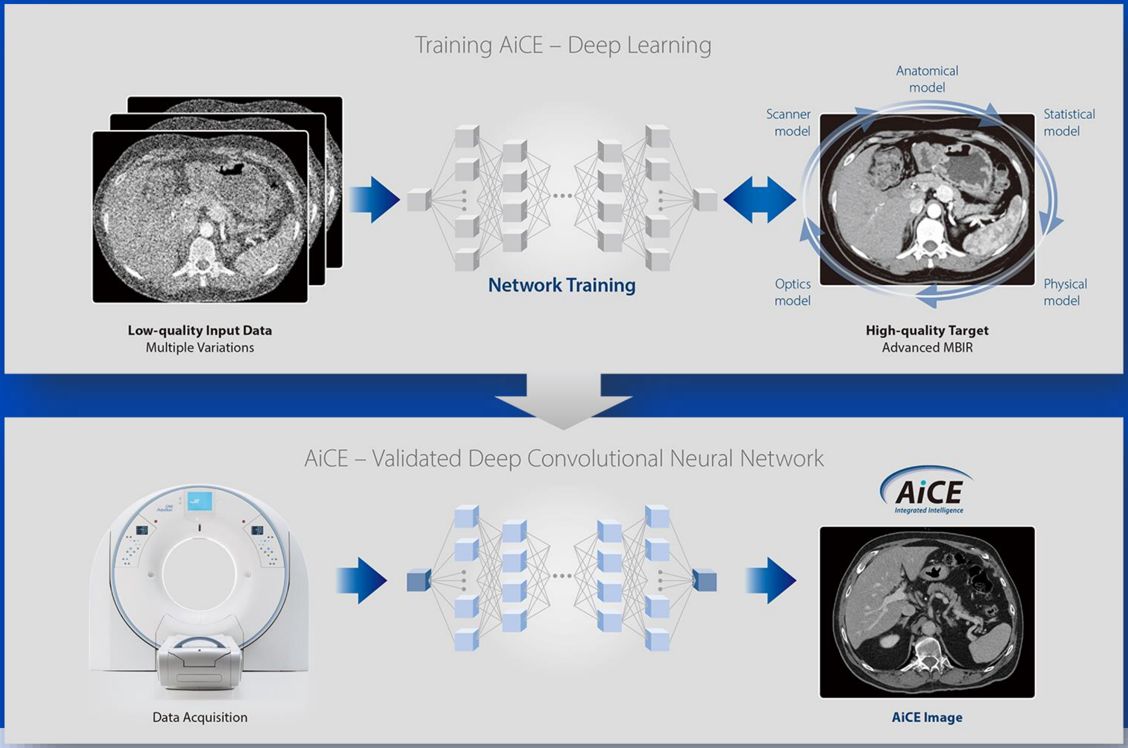
Noise Removal

Denoised full dose

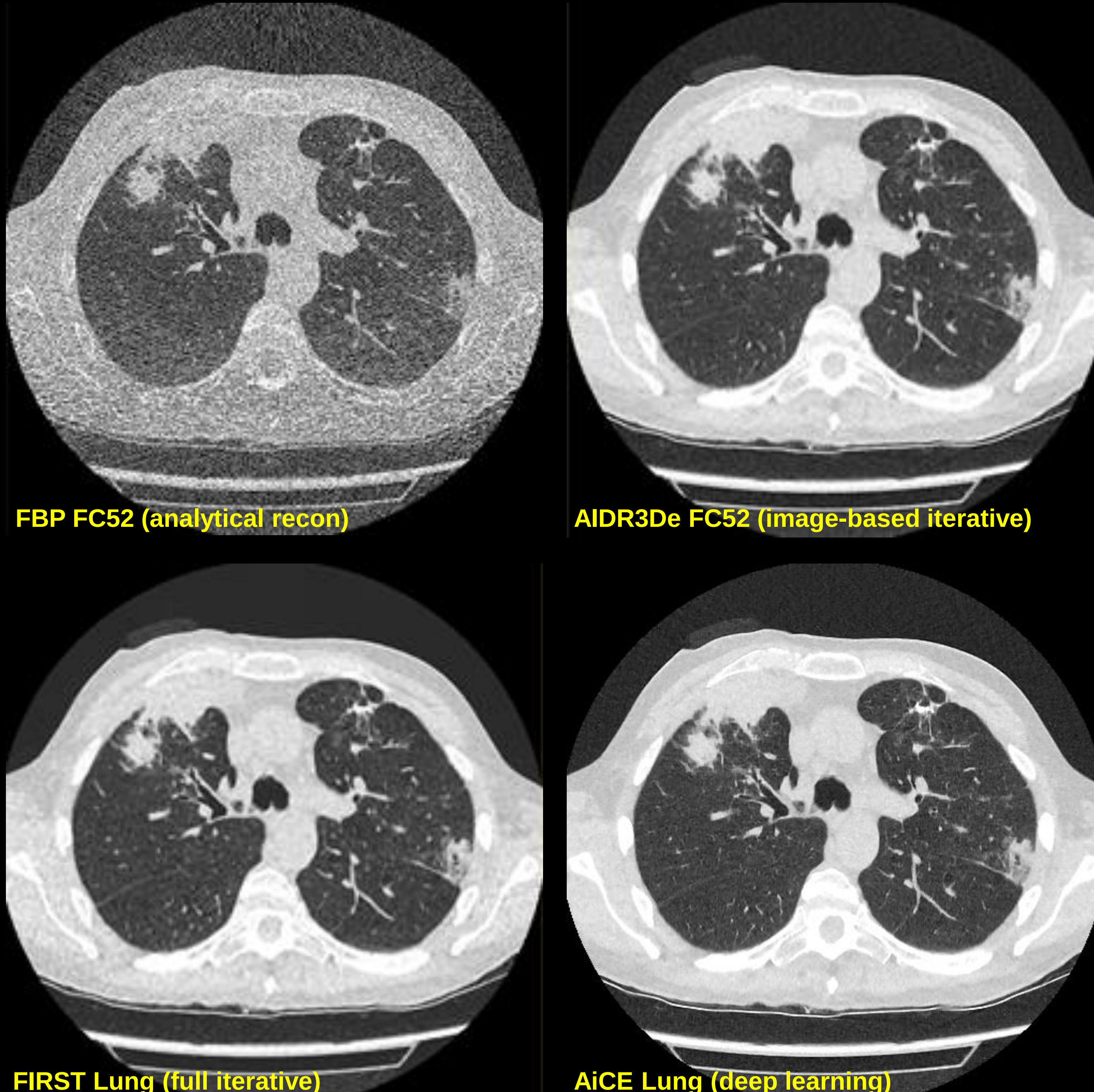
Andrew D. Missert, Shuai Leng, Lifeng Yu, and Cynthia H. McCollough. Noise Subtraction for Low-Dose CT Images Using a Deep Convolutional Neural Network. Proceedings of the 5th CT-Meeting: 399-402, 2018.

Canon's AiCE

- Advanced intelligent Clear-IQ Engine (AiCE)
- Trained to restore low-dose CT data to match the properties of FIRST, the model-based IR of Canon.
- FIRST is applied to high-dose CT images to obtain a high fidelity training target



U = 100 kV
CTDI = 0.6 mGy
DLP = 24.7 mGy·cm
D_{eff} = 0.35 mSv

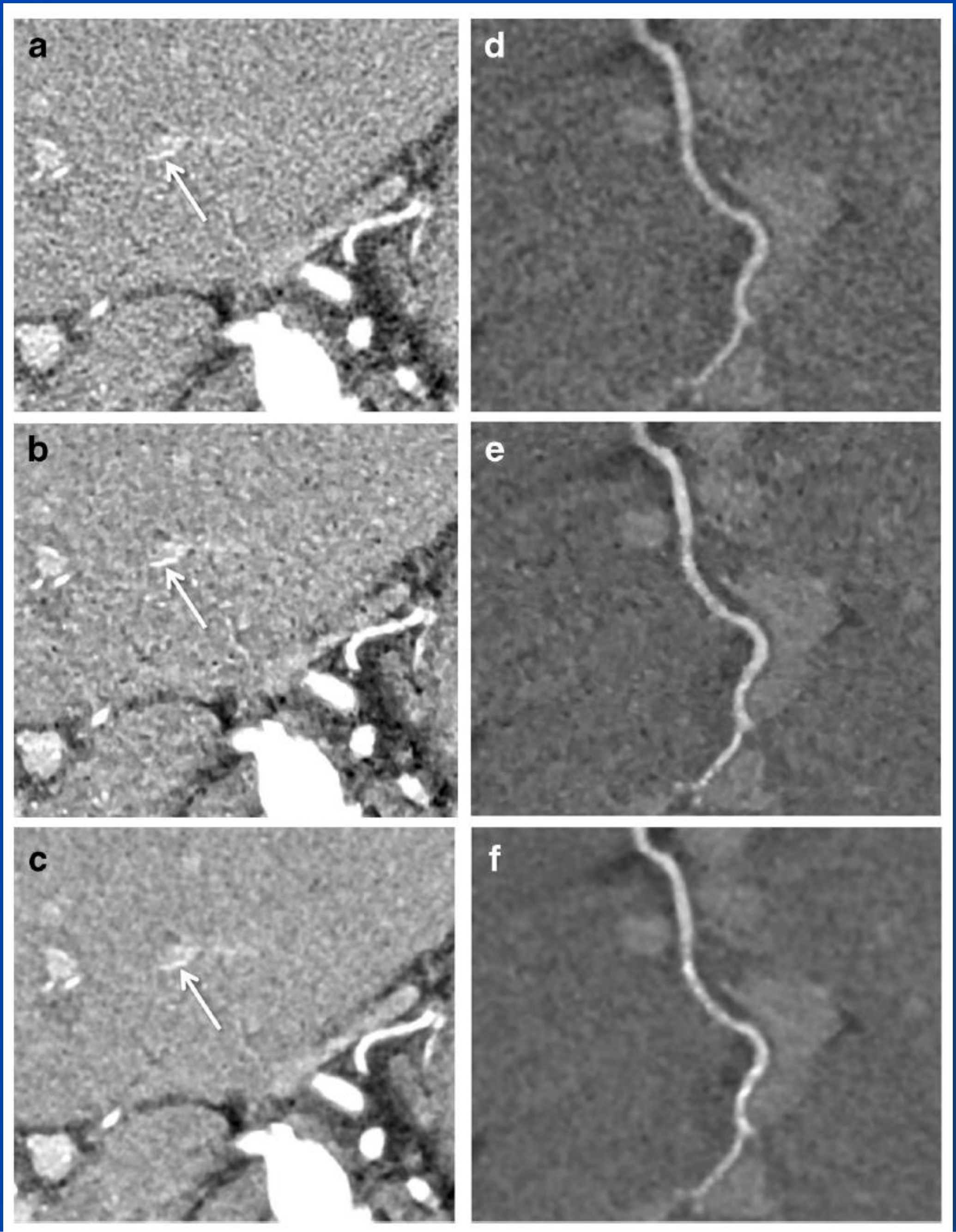


Courtesy of
Radboudumc,
the Netherlands

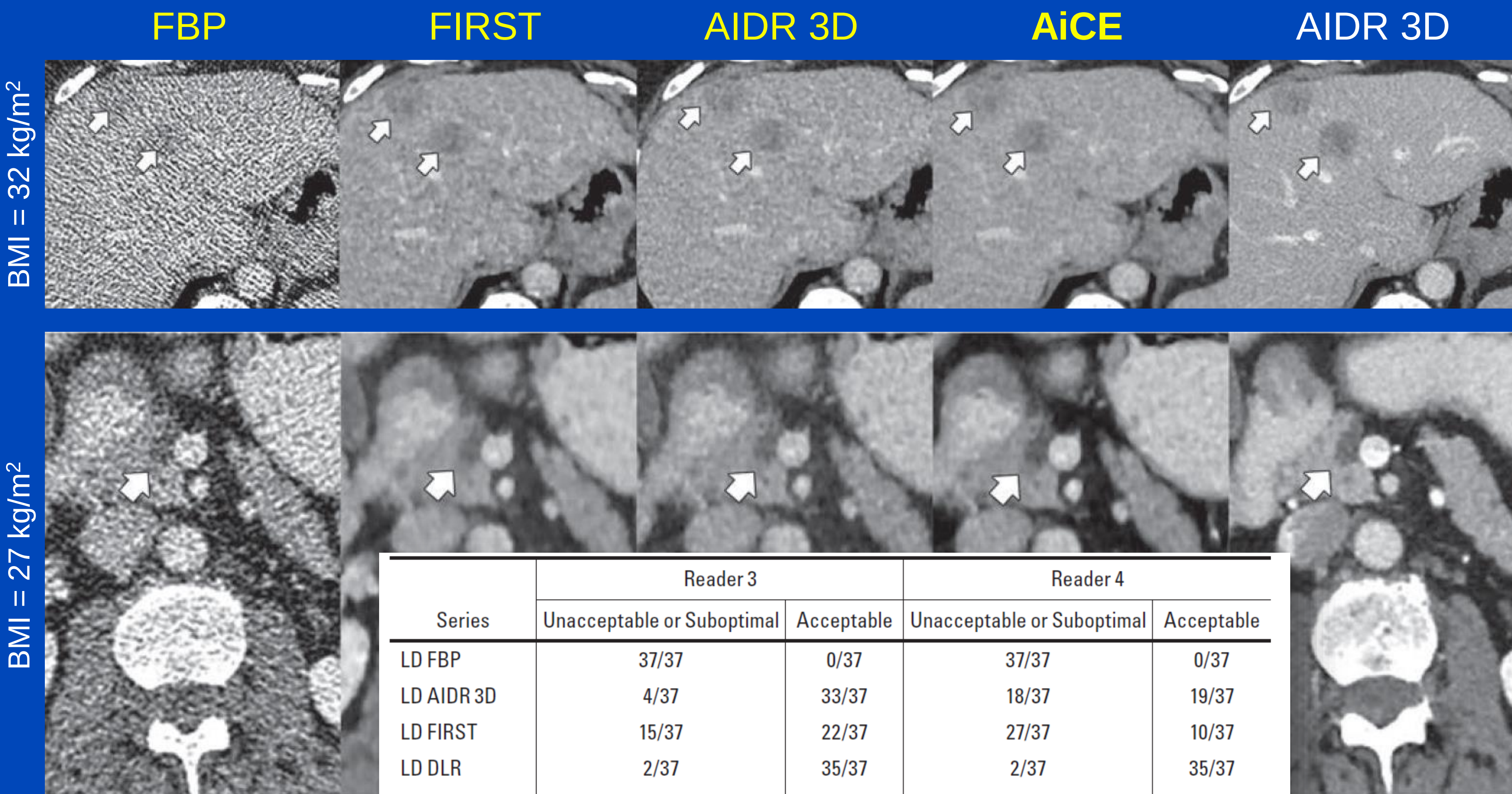
AIDR 3D

First

AiCE



Akagi et al., Deep learning reconstruction improves image quality of abdominal ultra-high-resolution CT, Eur. Radiol. 2019



Series	Reader 3		Reader 4	
	Unacceptable or Suboptimal	Acceptable	Unacceptable or Suboptimal	Acceptable
LD FBP	37/37	0/37	37/37	0/37
LD AIDR 3D	4/37	33/37	18/37	19/37
LD FIRST	15/37	22/37	27/37	10/37
LD DLR	2/37	35/37	2/37	35/37
SD AIDR 3D	0/37	37/37	0/37	37/37

Low Dose CT
2 mGy CTDI (top)
3 mGy CTDI (bottom)

Standard Dose CT
19 mGy CTDI (top)
18 mGy CTDI (bottom)

Singh et al., Image Quality and Lesion Detection on Deep Learning Reconstruction and Iterative Reconstruction of Submillisievert Chest and Abdominal CT. AJR 214:566-573, March 2020

GE‘s True Fidelity

- Based on a deep CNN
- Trained to restore low-dose CT data to match the properties of Veo, the model-based IR of GE.
- No information can be obtained in how the training is conducted for the product implementation.

2.5D DEEP LEARNING FOR CT IMAGE RECONSTRUCTION USING A MULTI-GPU IMPLEMENTATION

Amirkoushyar Ziabari[⋆], *Dong Hye Ye*[⋆ †], *Somesh Srivastava*[‡], *Ken D. Sauer*[⊕]
Jean-Baptiste Thibault[‡], *Charles A. Bouman*[⋆]

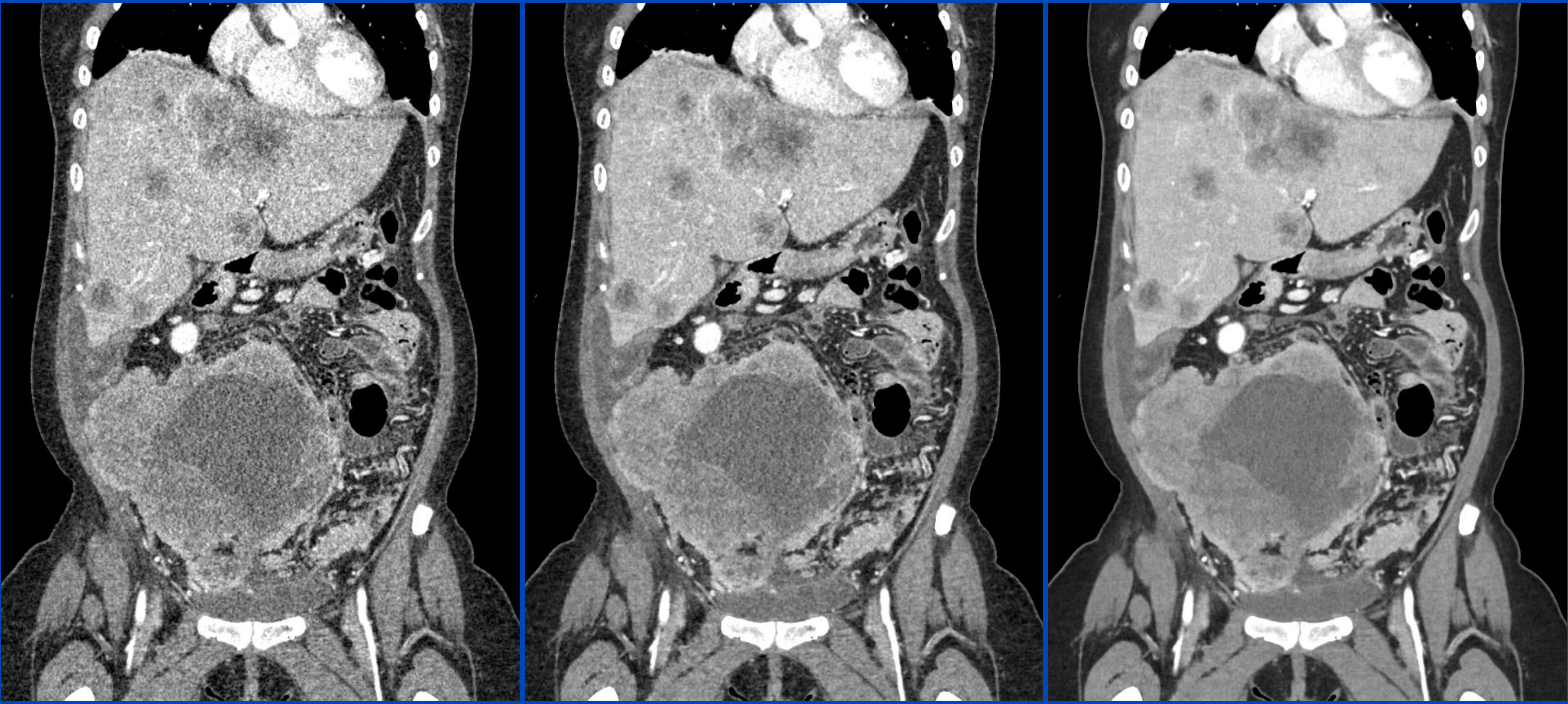
[⋆] Electrical and Computer Engineering at Purdue University
[†] Electrical and Computer Engineering at Marquett University
[‡] GE Healthcare
[⊕] Electrical Engineering at University of Notre Dame

ABSTRACT

While Model Based Iterative Reconstruction (MBIR) of CT scans has been shown to have better image quality than Filtered Back Projection (FBP), its use has been limited by its high computational cost. More recently, deep convolutional neural networks (CNN) have shown great promise in both denoising and reconstruction applications. In this research, we propose a fast reconstruction algorithm, which we call Deep

streaking artifacts caused by sparse projection views in CT images [8]. More recently, Ye, et al. [9] developed method for incorporating CNN denoisers into MBIR reconstruction as advanced prior models using the Plug-and-Play framework [10, 11].

In this paper, we propose a fast reconstruction algorithm, which we call Deep Learning MBIR (DL-MBIR), for approximately achieving the improved quality of MBIR using a deep residual neural network. The DL-MBIR method is trained to



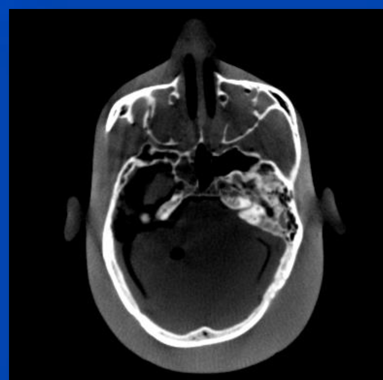
FBP | ASIR V 50% | True Fidelity

Courtesy of GE Healthcare

Part 2:

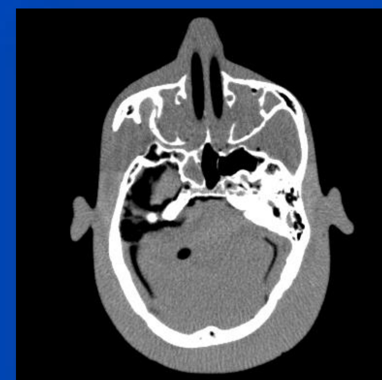
Fast Physics

Deep Scatter Estimation



???

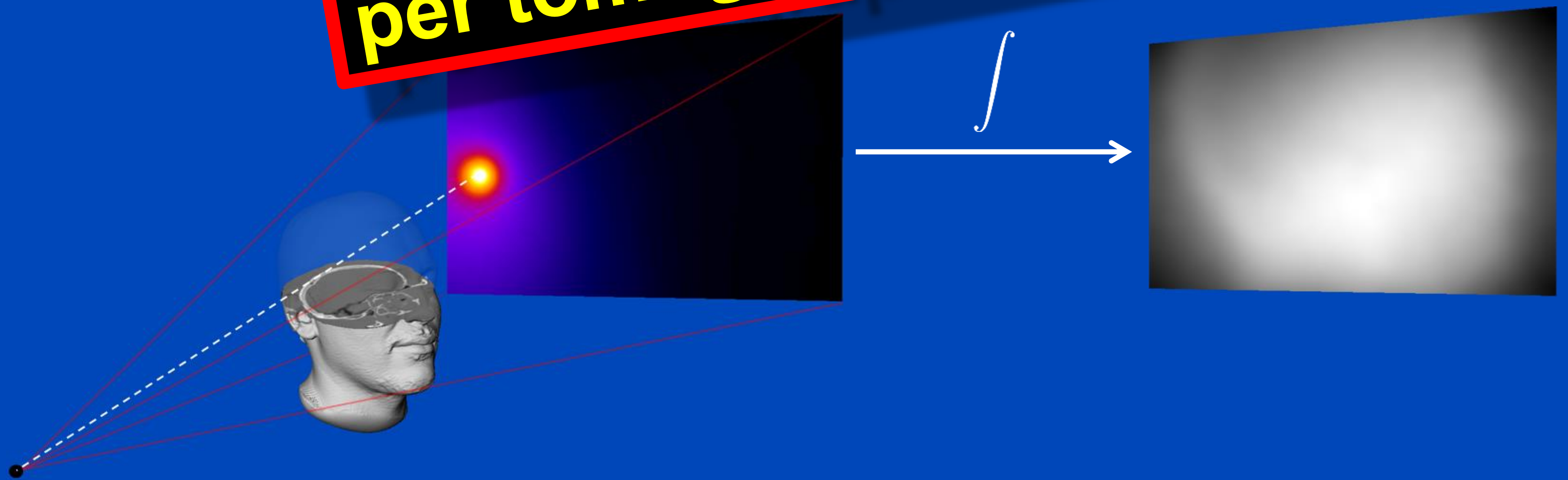
In real time?



Monte Carlo Scatter Estimation

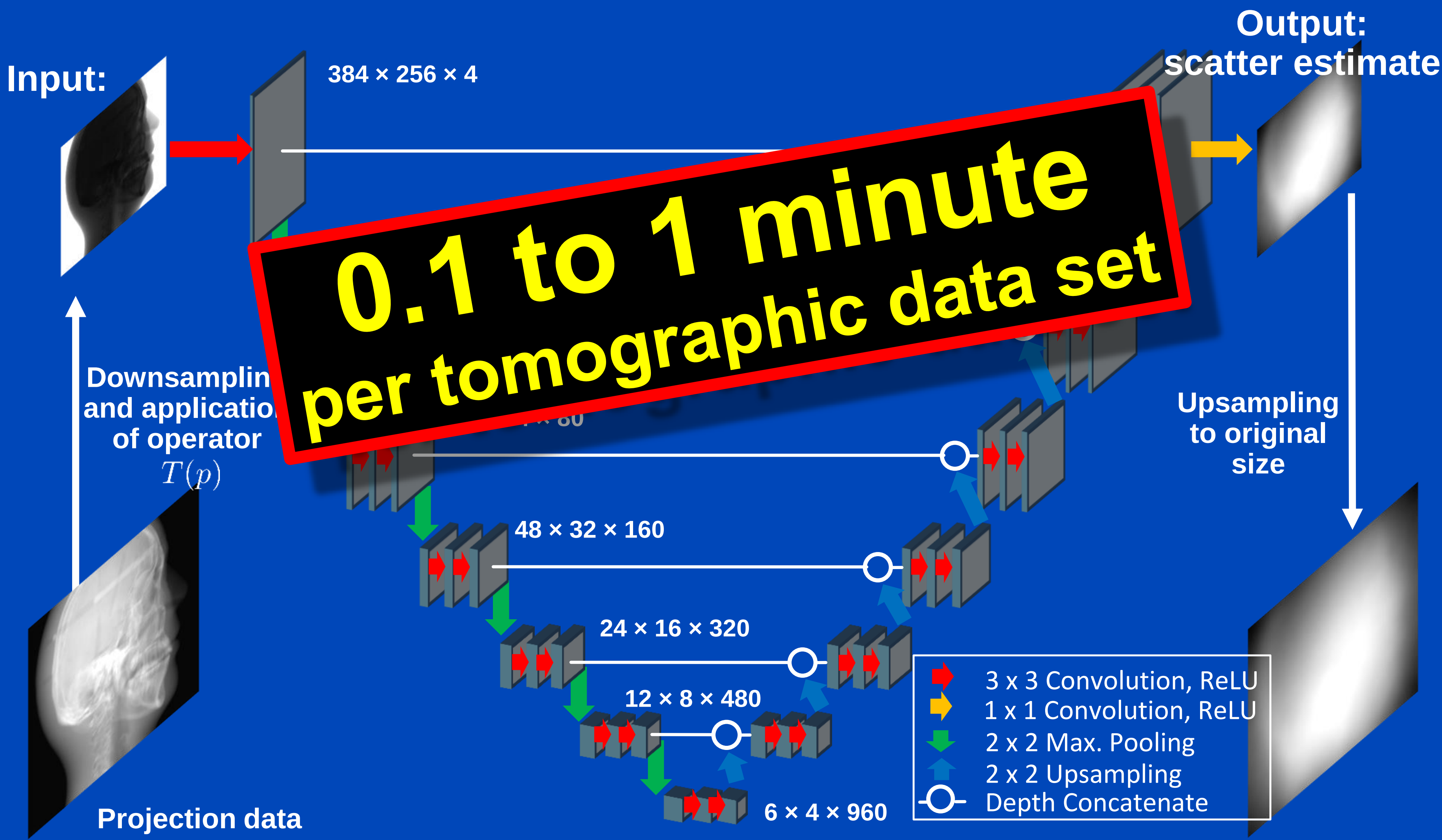
- Simulation of photon trajectories according to physical interaction probabilities.
- Simulating a large num… …ories well approxima…

1 to 10 hours
per tomographic data set

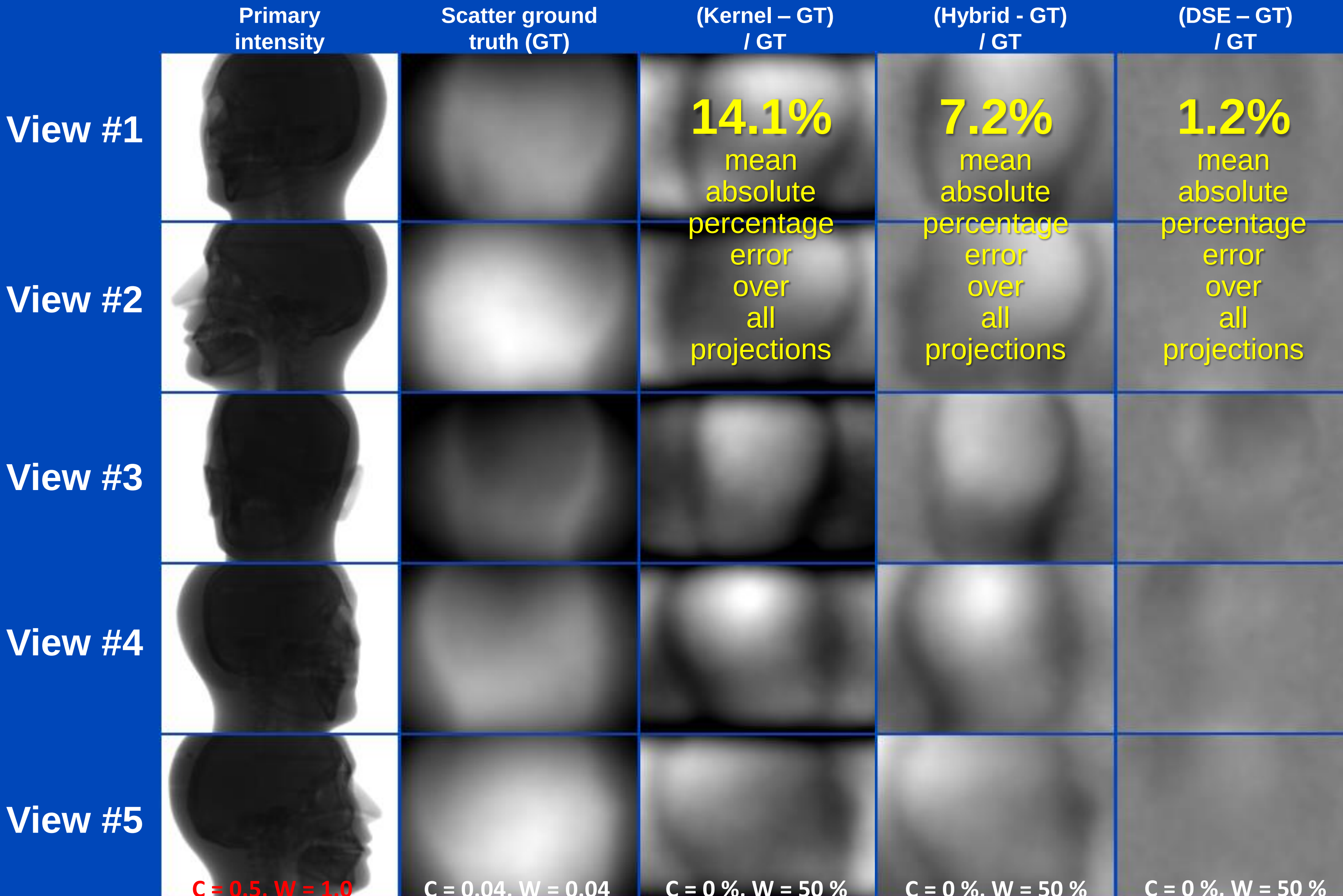


Deep Scatter Estimation

Network architecture & scatter estimation framework

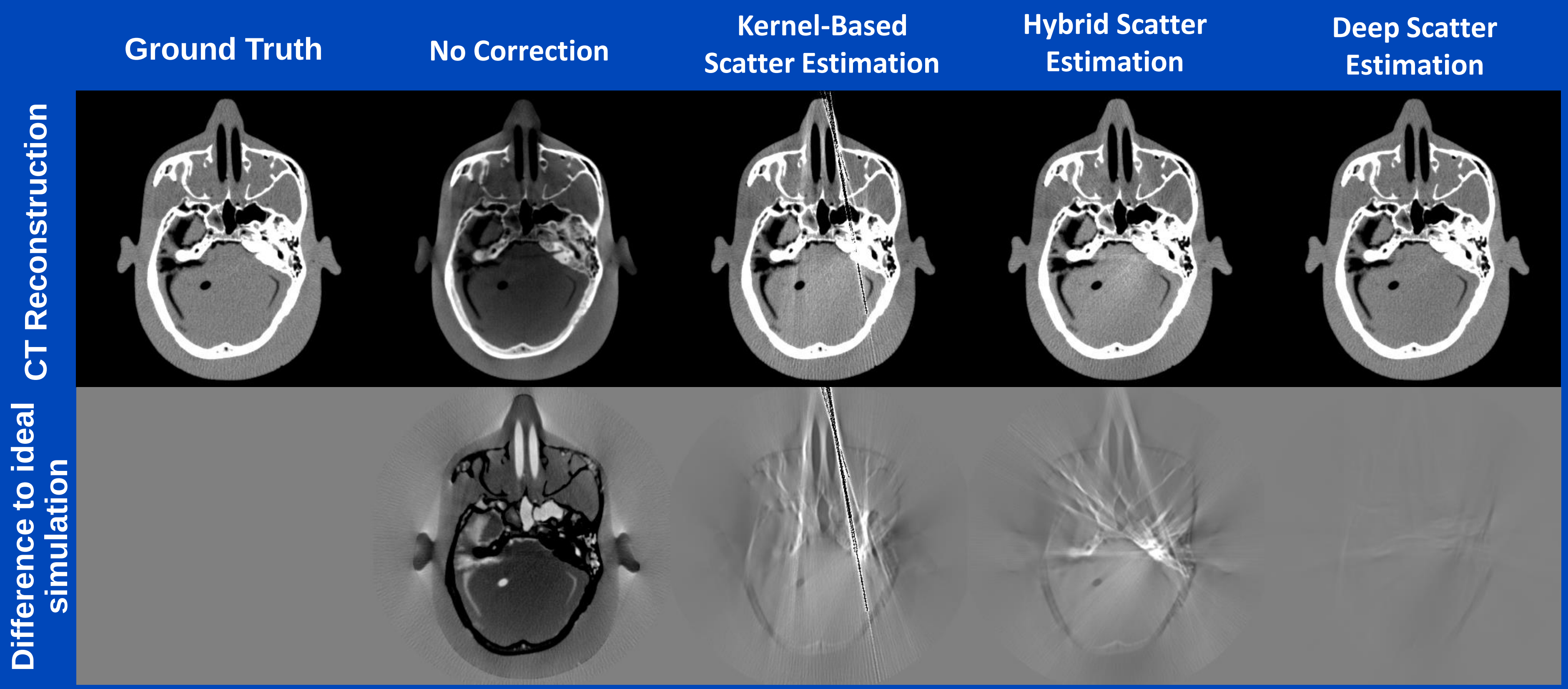


Results on Simulated Projection Data



DSE trained to estimate scatter from **primary plus scatter**: High accuracy

Reconstructions of Simulated Data

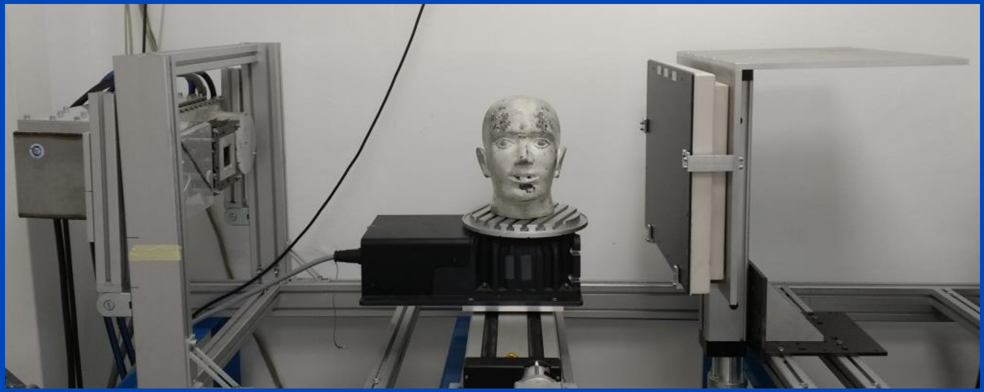


C = 0 HU, W = 1000 HU

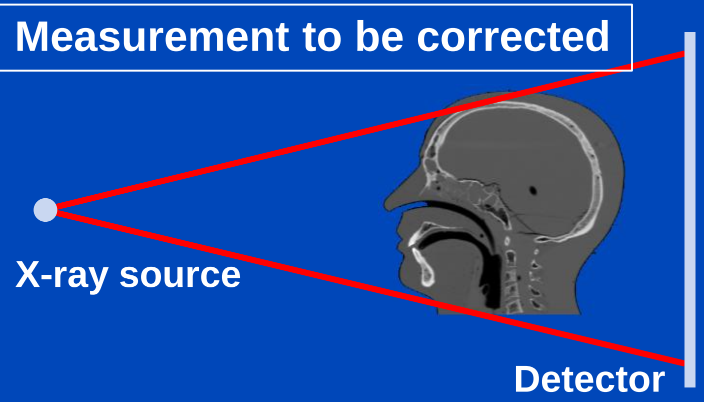
J. Maier, M. Kachelrieß et al. Deep scatter estimation (DSE). SPIE 2017 and Journal of Nondestructive Evaluation 37:57, July 2018.
J. Maier, M. Kachelrieß et al. Robustness of DSE. Med. Phys. 46(1):238-249, January 2019.

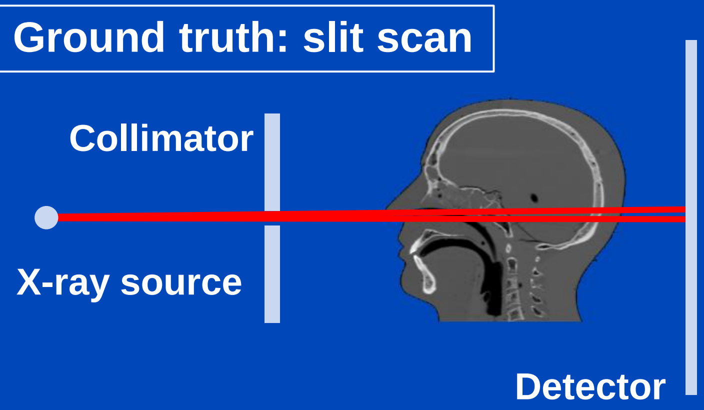
Testing of the DSE Network for Measured Data (120 kV)

DKFZ table-top CT

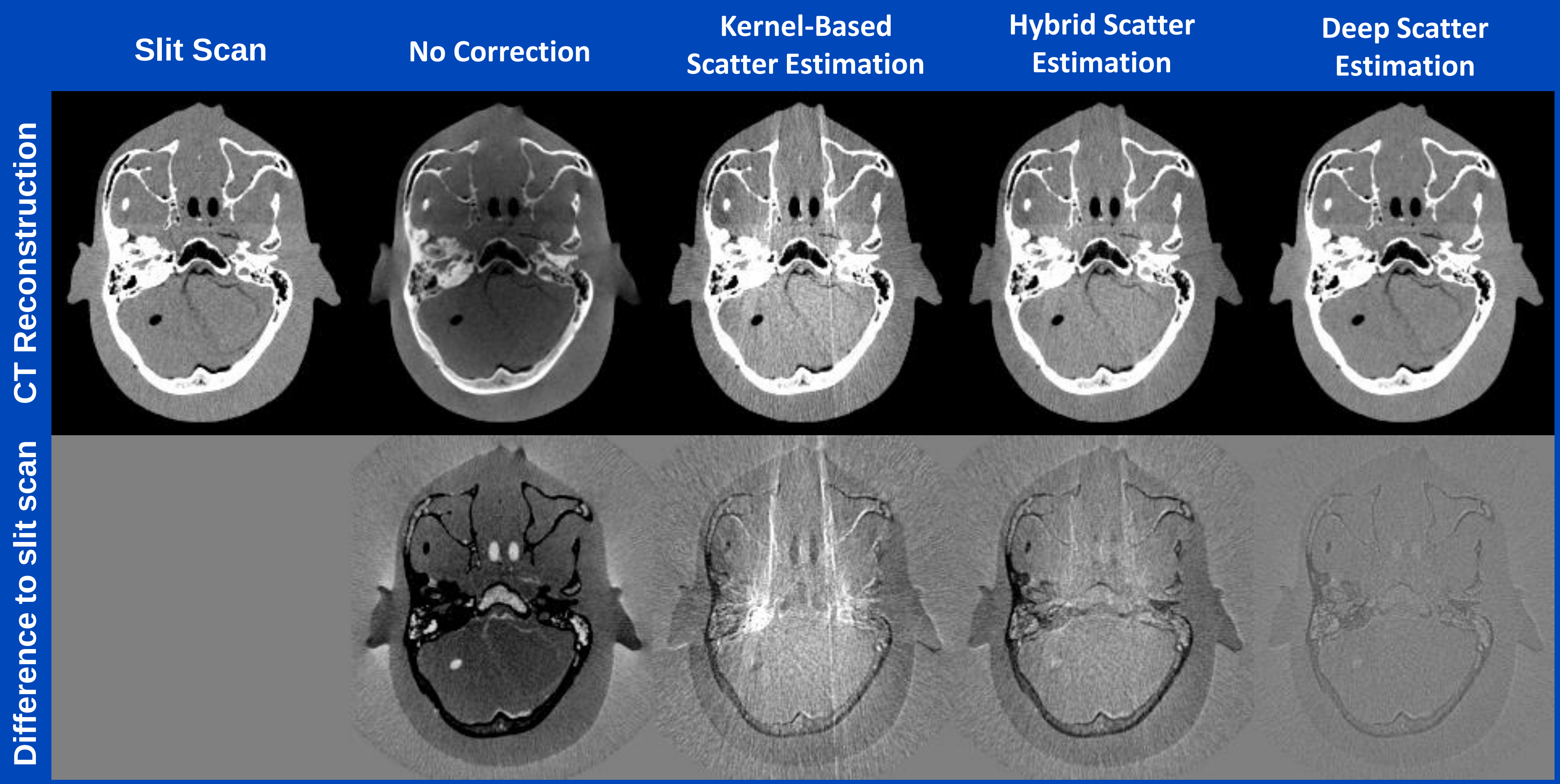


- Measurement of a head phantom at our in-house table-top CT.
- Slit scan measurement serves as ground truth.





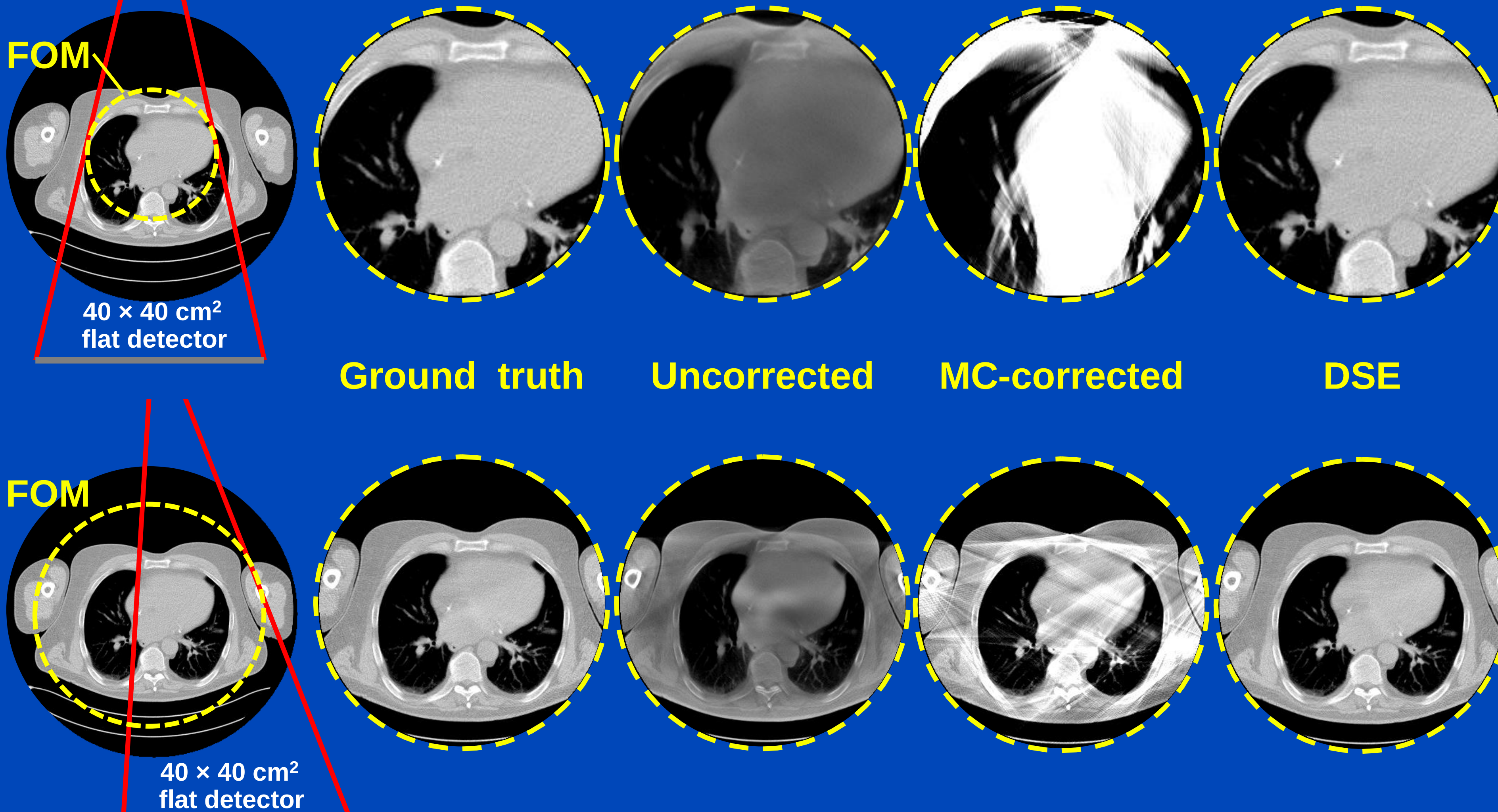
Reconstructions of Measured Data



C = 0 HU, W = 1000 HU

A simple detruncation was applied to the rawdata before reconstruction. Images were clipped to the FOM before display. C = -200 HU, W = 1000 HU.

Truncated DSE[1,2]



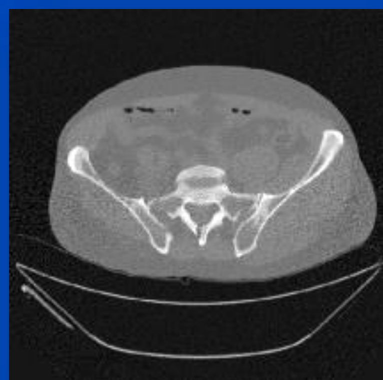
To learn why MC fails at truncated data and what significant efforts are necessary to cope with that situation see [Kachelrieß et al. Effect of detruncation on the accuracy of MC-based scatter estimation in truncated CBCT. Med. Phys. 45(8):3574-3590, August 2018].

[1] J. Maier, M. Kachelrieß et al. Deep scatter estimation (DSE) for truncated cone-beam CT (CBCT). RSNA 2018.
[2] J. Maier, M. Kachelrieß et al. Robustness of DSE. Med. Phys. 46(1):238-249, January 2019.

Conclusions on DSE

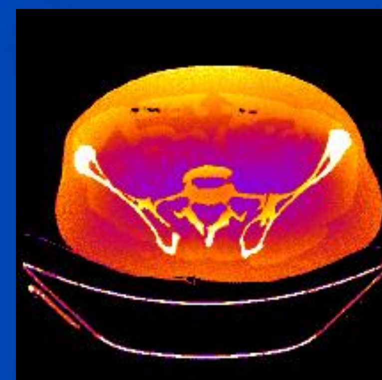
- DSE needs about 3 ms per CT and 10 ms per CBCT projection (as of 2020).
- DSE is a fast and accurate alternative to MC simulations.
- DSE outperforms kernel-based approaches in terms of accuracy and speed.
- Facts:
  - DSE can estimate scatter from a single (!) x-ray image.
  - DSE can accurately estimate scatter from a primary+scatter 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.

Deep Dose Estimation



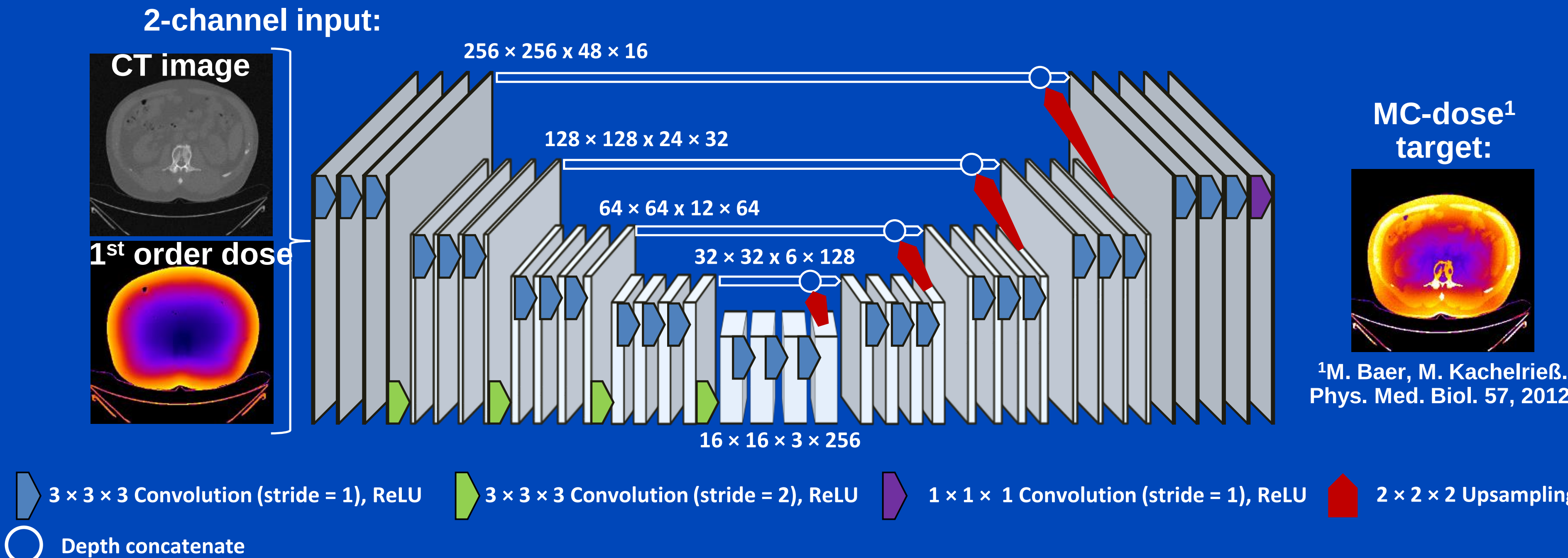
???

In real time?



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.

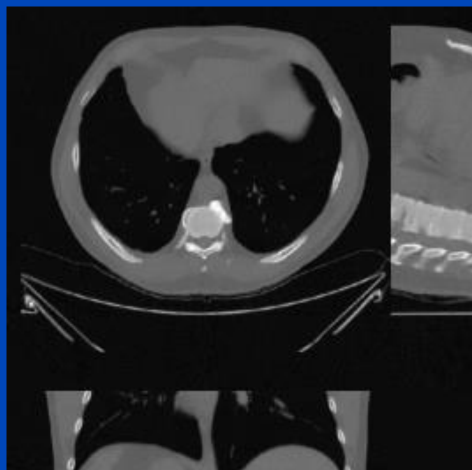


J. Maier, E. Eulig, S. Sawall, and M. Kachelrieß. Real-time patient-specific CT dose estimation using a deep convolutional neural network, Proc. IEEE MIC 2018 and ECR Book of Abstracts 2019. *Best Paper within Machine Learning at ECR 2019!*

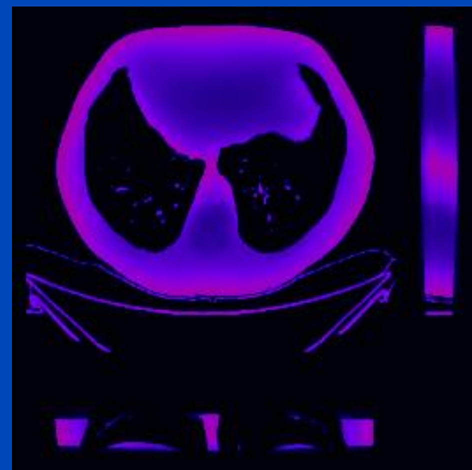
Results

Thorax, tube A, 120 kV, with bowtie

CT image



First order dose

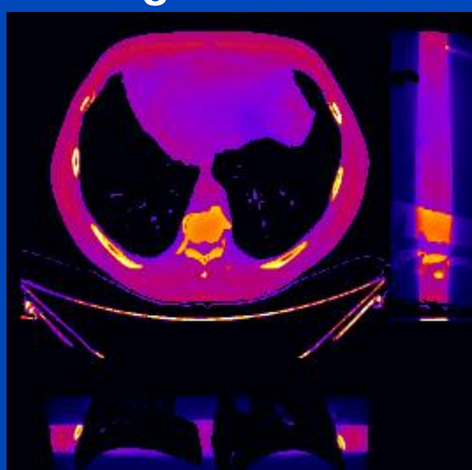


	MC	DDE
48 slices	1 h	0.25 s
whole body	20 h	5 s

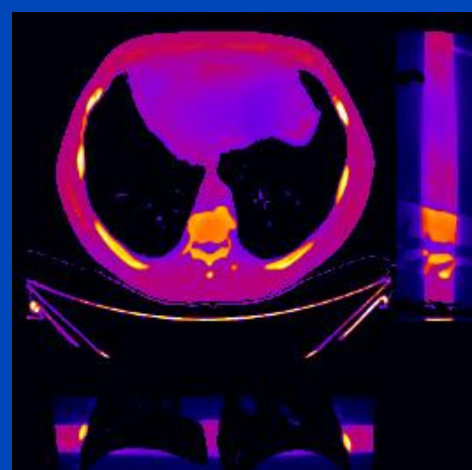
MC uses 16 CPU kernels
DDE uses one Nvidia Quadro P600 GPU

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

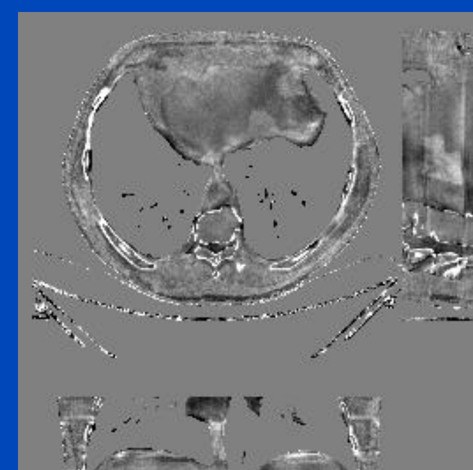
MC ground truth



DDE



Relative error



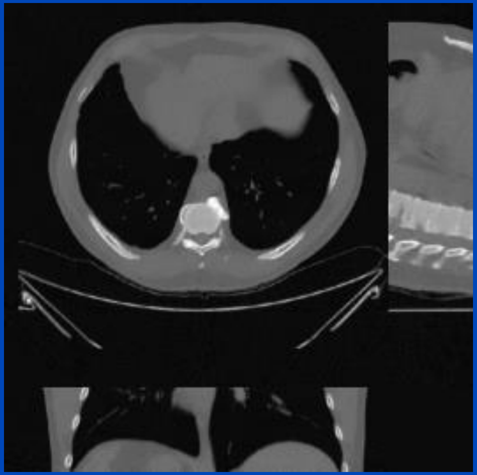
C = 0%
W = 40%

J. Maier, E. Eulig, S. Sawall, and M. Kachelrieß. Real-time patient-specific CT dose estimation using a deep convolutional neural network, Proc. IEEE MIC 2018 and ECR Book of Abstracts 2019. *Best Paper within Machine Learning at ECR 2019!*

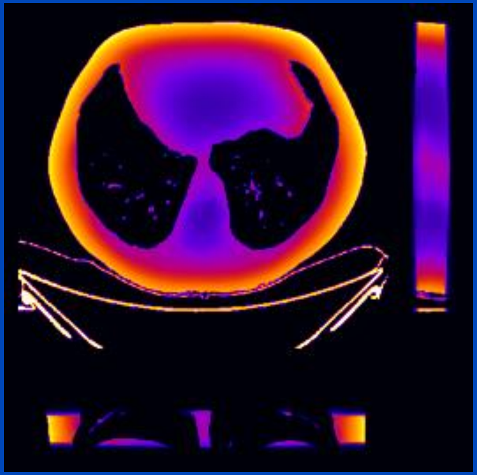
Results

Thorax, tube A, 120 kV, no bowtie

CT image



First order dose



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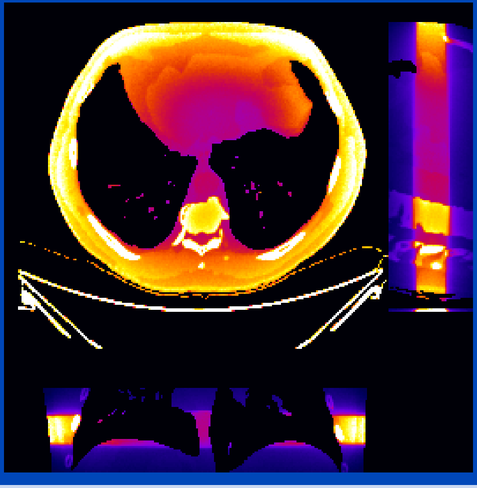
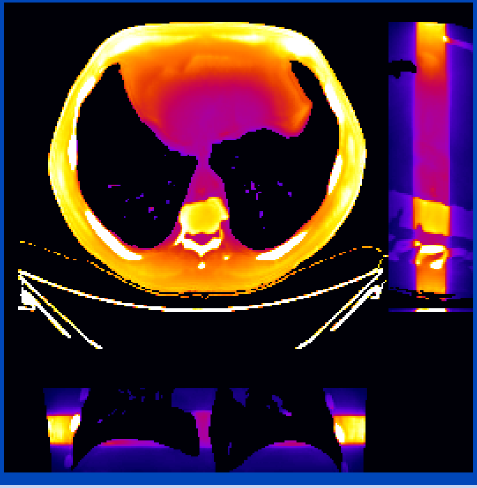
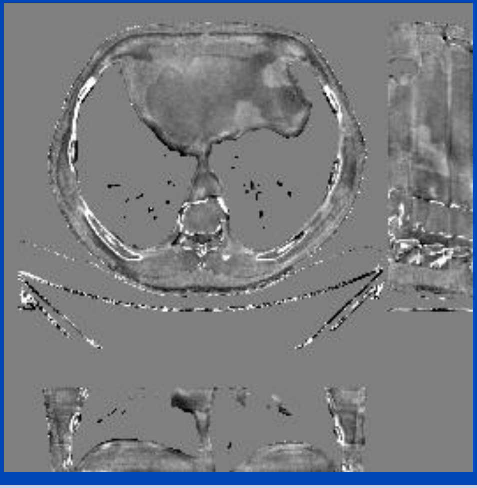


DDE



Relative error



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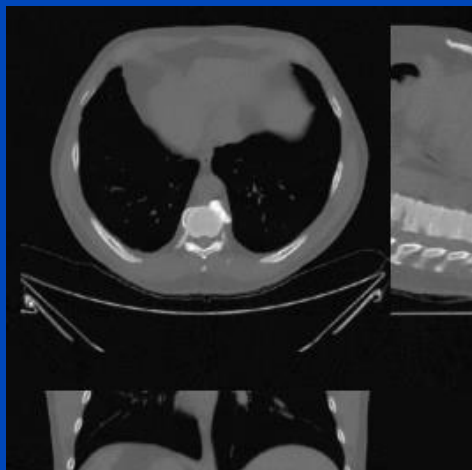
dkfz.

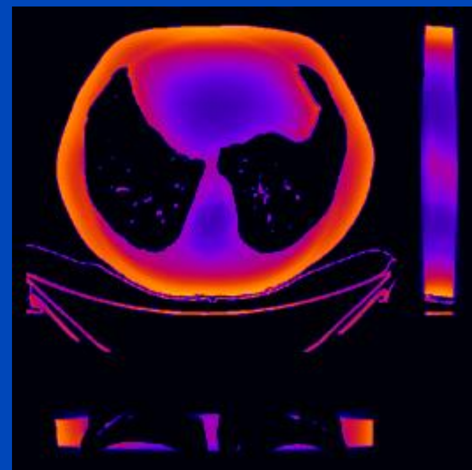
Results

Thorax, tube B, 120 kV, no bowtie

CT image



First order dose



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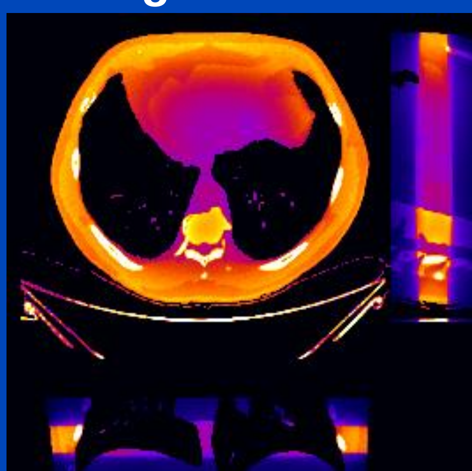
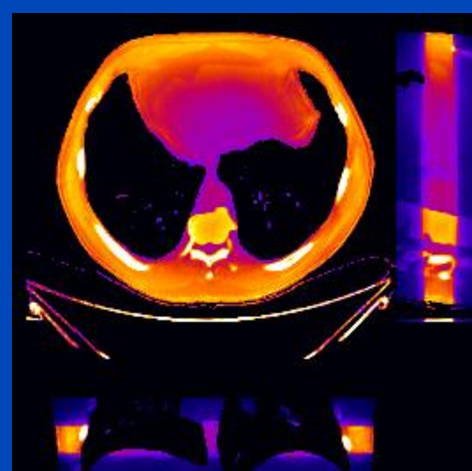
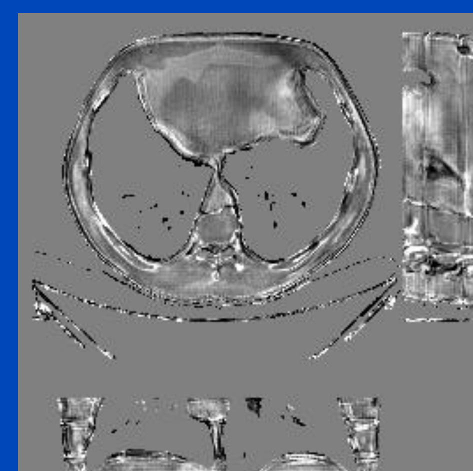
MC ground truth



DDE



Relative error



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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
- In practice it may therefore be not necessary to perform separate training runs for these cases.
- Thus, accurate real-time patient dose estimation may become feasible with DDE.

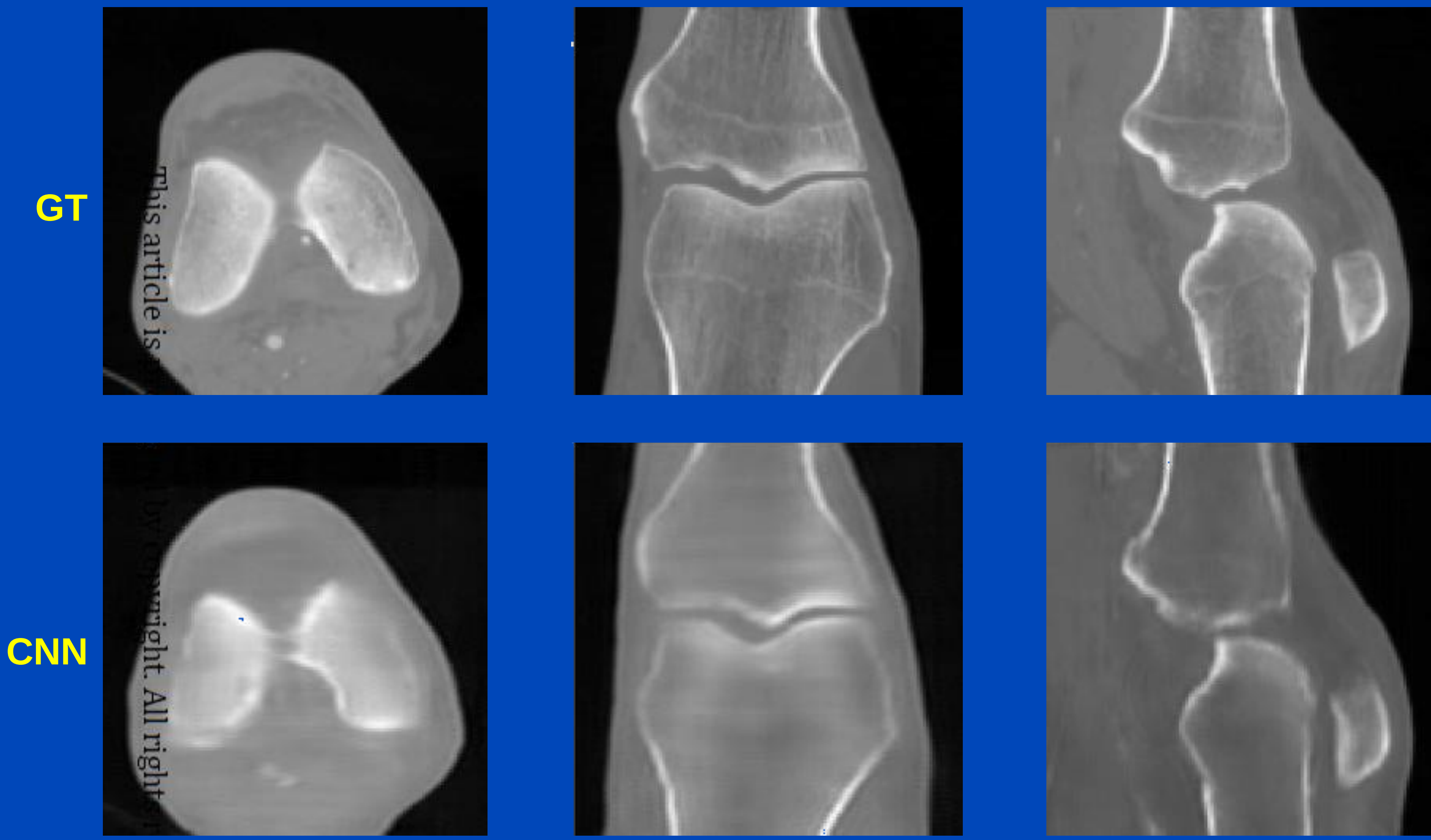
J. Maier, E. Eulig, S. Sawall, and M. Kachelrieß. Real-time patient-specific CT dose estimation using a deep convolutional neural network, Proc. IEEE MIC 2018 and ECR Book of Abstracts 2019. *Best Paper within Machine Learning at ECR 2019!*

Part 3:

Very Few Projections

Reconstruct from 1 or 2 Projections

- P. Henzler, V. Rasche, T. Ropinski, and T. Ritschel. Single-image Tomography: 3D Volumes from 2D X-Rays: 3D Volumes from 2D Cranial X-Rays. Computer Graphics Forum. 37(2):377-388, 2018.
  - *N*=1, mainly sculls in air but also mouse with soft tissue
  - modified U-Net without reducing the number of features in the decoder (2D -> 3D)
- Li Jiang, Shaoshuai Shi, Xiaojuan Qi, and Jiaya Jia. GAL: Geometric Adversarial Loss for Single-View 3D-Object Reconstruction. In: ECCV 2018 Lecture Notes in Computer Science 11212:820-834, 2018.
  - *N*=1, object shapes from photography
  - GAN-type network
- Yuan Xu, Hao Yan, Luo Ouyang, Jing Wang, Linghong Zhou, Laura Cervino, Steve B. Jiang, and Xun Jia. A Method for Volumetric Imaging in Radiotherapy using Single X-Ray Projection. Med. Phys. 42(5):2498-2509, 2015
  - *N*=1. Derives MVFs from an x-ray projection that are then applied to a 3D CBCT volume
  - Sparse learning
- Liyue Shen, Wei Zhao, and Lei Xing. Patient-Specific Reconstruction of Volumetric Computed Tomography Images from a Single Projection View via Deep Learning. Nat. Biomed. Eng. 3:880–888, 2019.
  - *N*=1. Training and validation in the same patient. Example 1: train on 6 phases of 4D CT and test on the remaining 4 phases. Example 2: train on 4D CT of day 1 and test on 4D CT of day 2.
2D encoder CNN, 2D->3D FCN, 3D decoder CNN.
- Xingde Ying, Heng Guo, Kai Ma, Jian Wu, Zhengxin Weng, and Yefeng Zheng. X2CT-GAN: Reconstructing CT from Biplanar X-Rays with Generative Adversarial Networks. arXiv:1905.06902v1, May 2019
  - *N*=2. Thorax cases
  - GAN with U-Net-type generator whose skips are backprojections.
- Diogo F. Almeida, Patricio Astudillo, and Dirk Vandermeulen. 3D Image Volumes From 2D Digitally Reconstructed X-Rays: A Deep Learning Approach In Lower Limb CT-Scans. Med. Phys. 48:published online, 2021.
  - *N*=2. Lower limb DRRs.
  - Based on Henzler et al. (see above).



Almeida, Astudillo, and Vandermeulen. 3D Image Volumes From 2D Digitally Reconstructed X-Rays: A Deep Learning Approach In Lower Limb CT-Scans. Med. Phys. 48:published online, 2021.

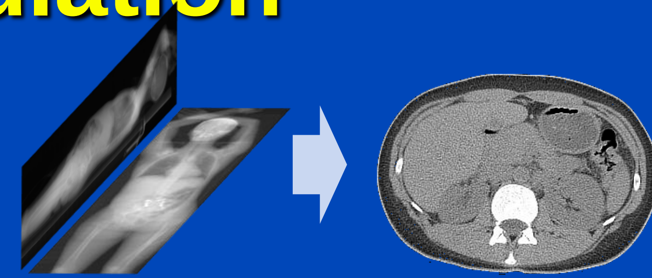
dkfz.

What for?

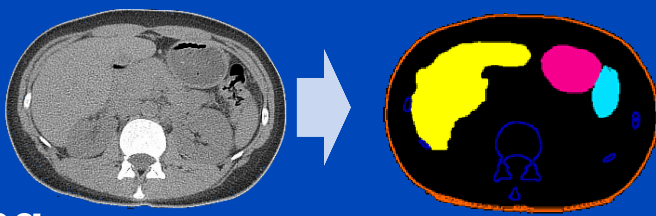
- Avoid CT scans if only coarse 3D information is required.
- Real-time guidance in RT or in intervention: Generate 4D volumes from fluoroscopy (a series of x-ray CT image)
- Niche applications
  - Assess location and size of organs from just one or two x-ray images
  - Patient position verification
  - …
- Perform patient-specific tube current modulation (next slides).

Patient Risk-Minimizing Tube Current Modulation

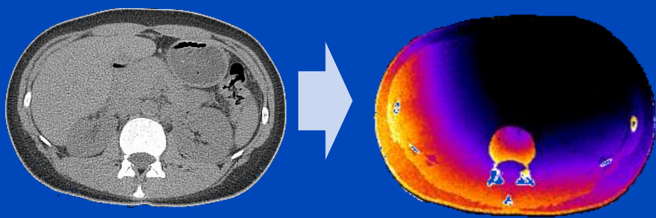
1. **Coarse reconstruction from two scout views**
   – E.g. X. Ying, et al. X2CT-GAN: Reconstructing CT from biplanar x-rays with generative adversarial networks. CVPR 2019.



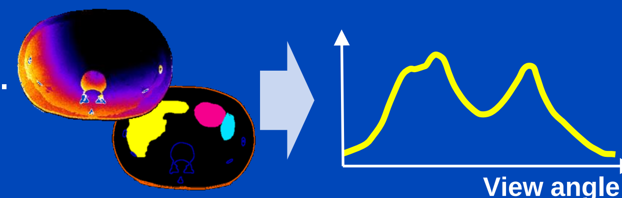
2. **Segmentation of radiation-sensitive organs**
   – E.g. S. Chen, M. Kachelrieß et al., Automatic multi-organ segmentation in dual-energy CT (DECT) with dedicated 3D fully convolutional DECT networks. Med. Phys. 2019.



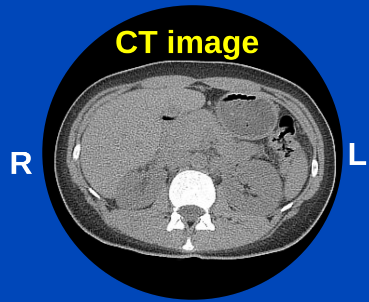
3. **Calculation of the effective dose per view using the deep dose estimation (DDE)**
   – J. Maier, E. Eulig, S. Dorn, S. Sawall and M. Kachelrieß. Real-time patient-specific CT dose estimation using a deep convolutional neural network. IEEE Medical Imaging Conference Record, M-03-178: 3 pages, Nov. 2018.

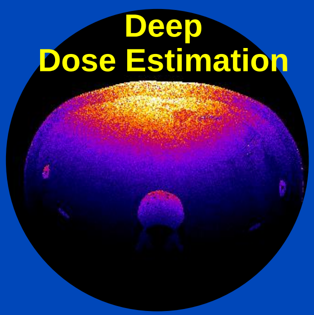


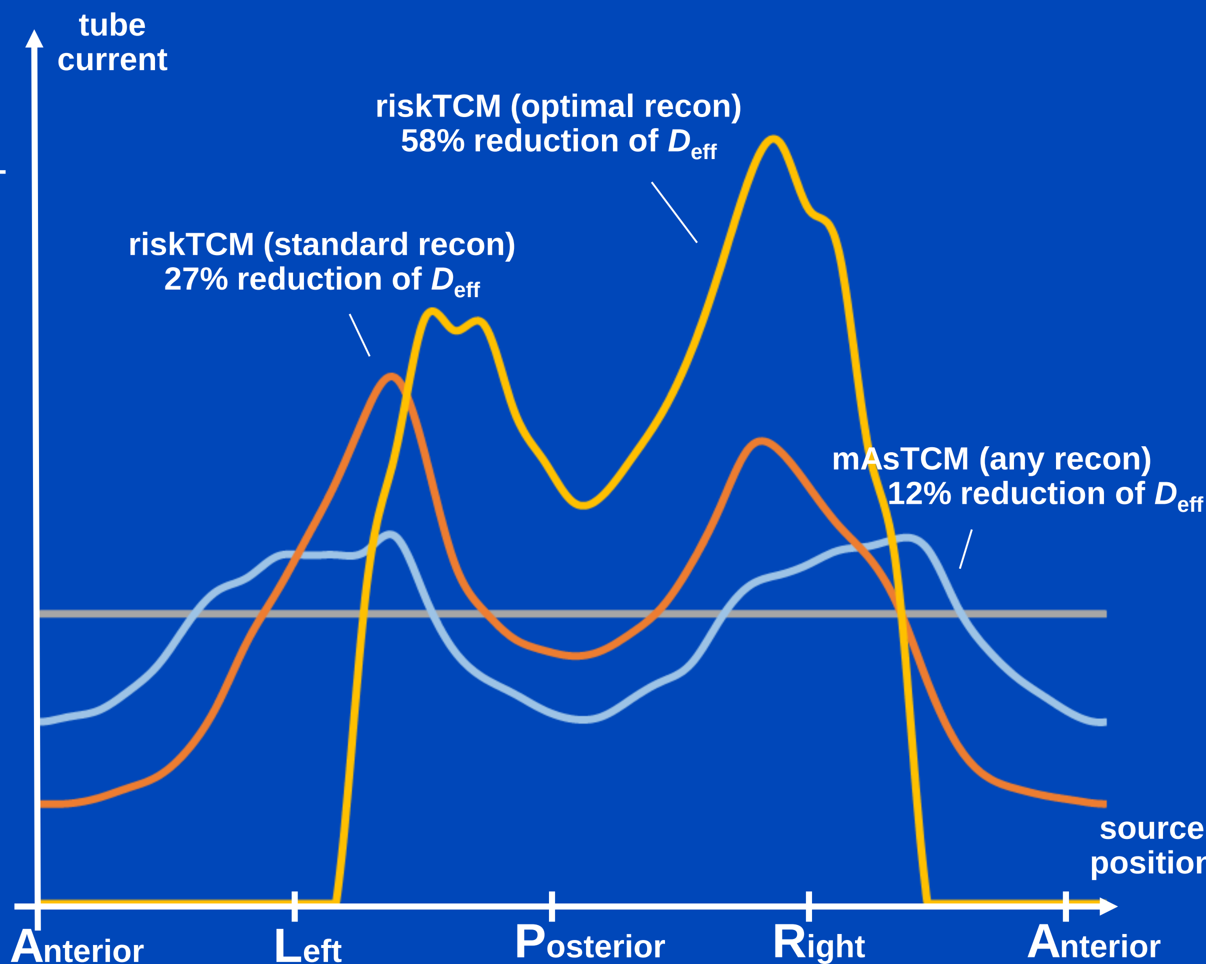
4. **Determination of the tube current modulation curve that minimizes the radiation risk**
   – L. Klein, J. Maier, C. Liu, A. Maier, M. Lell, and M. Kachelrieß. Patient radiation risk–minimizing tube current modulation for diagnostic CT. Submitted to Med. Phys., 2021.



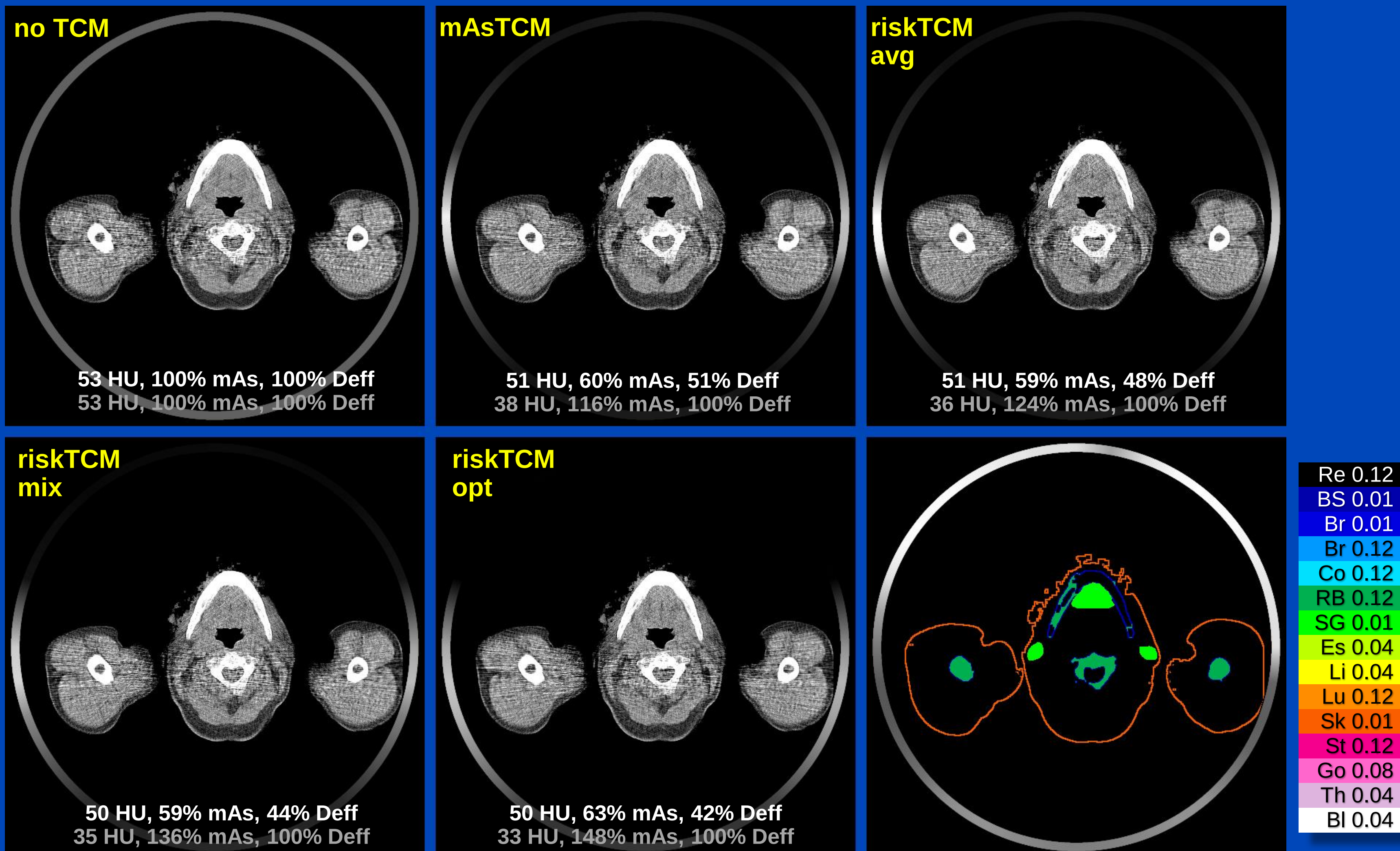
Remainder 0.12
Bone surface 0.01
Brain 0.01
Breast 0.12
Colon 0.12
Red Bone Marrow 0.12
Salivary glands 0.01
Esophagus 0.04
Liver 0.04
Lung 0.12
Skin 0.01
Stomach 0.12
Gonads 0.08
Thyroid 0.04
Bladder 0.04





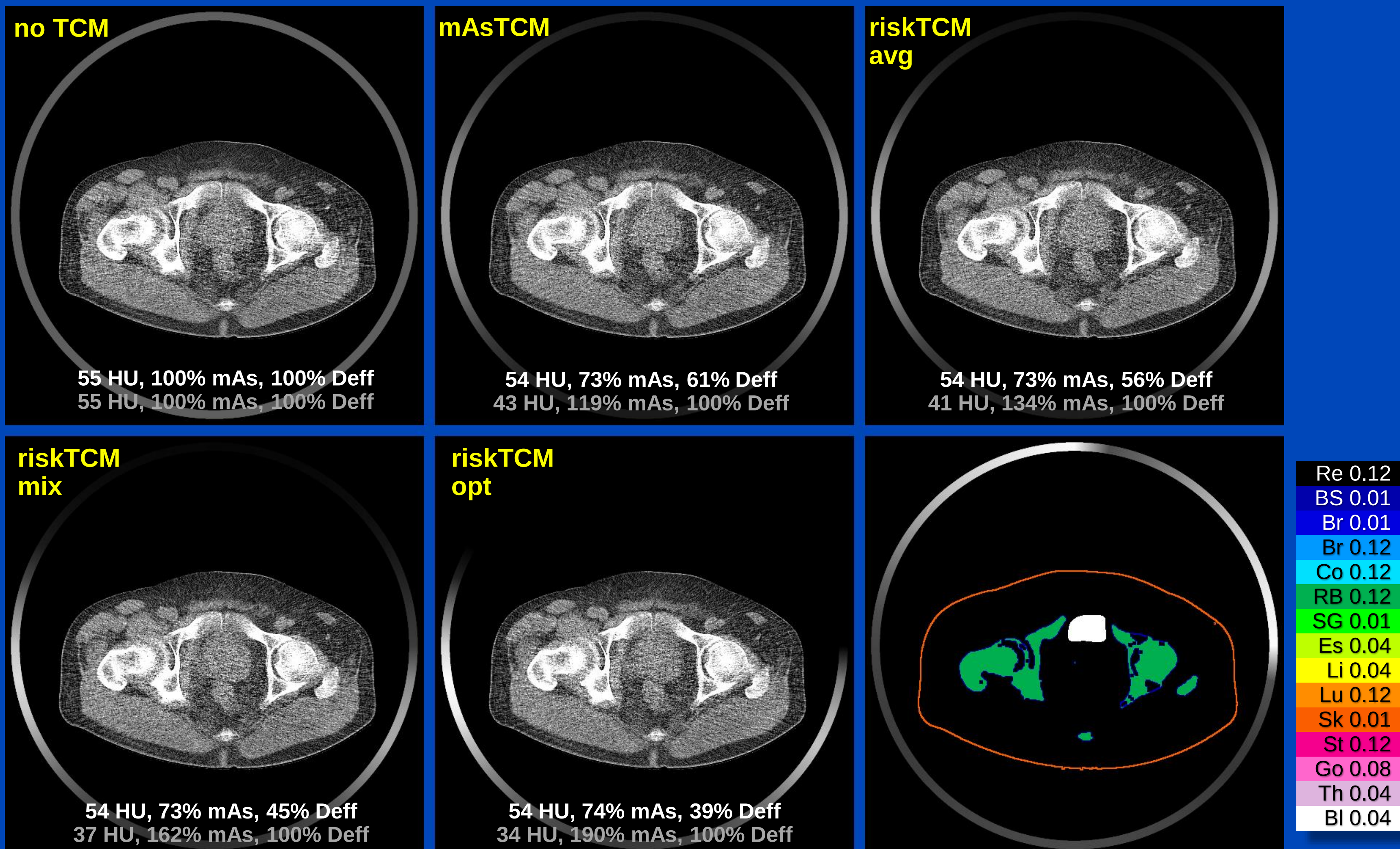


Patient 03 - Neck



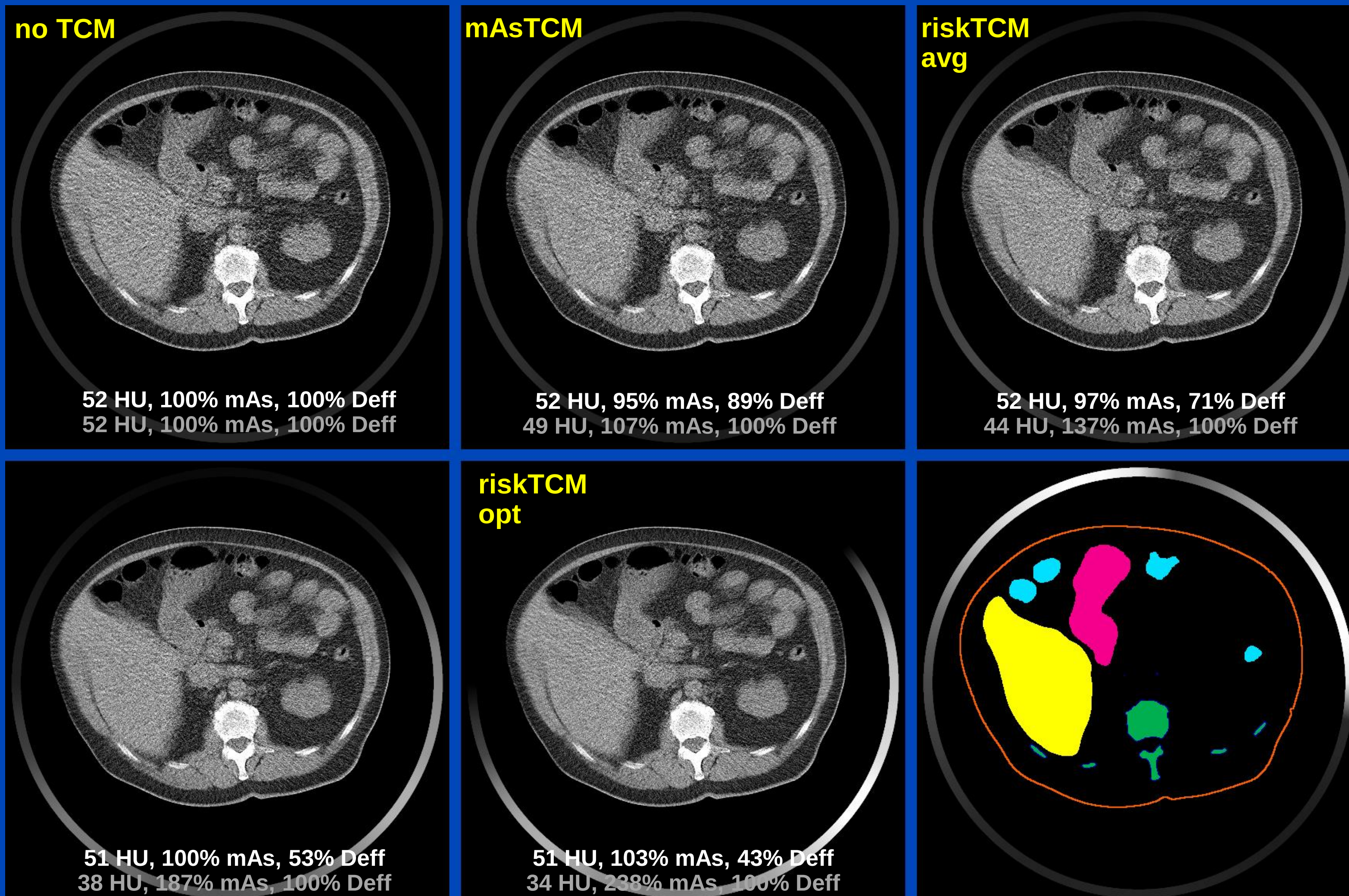
C = 25 HU, *W* = 400 HU

Patient 03 - Pelvis



C = 25 HU, *W* = 400 HU

Patient 04 - Abdomen



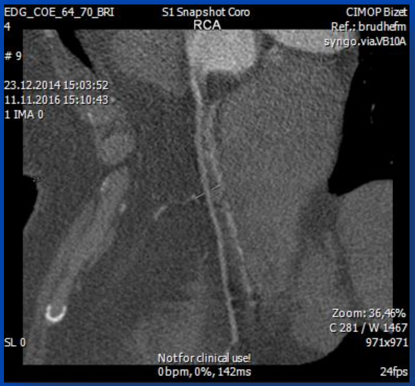
Re 0.12
BS 0.01
Br 0.01
Br 0.12
Co 0.12
RB 0.12
SG 0.01
Es 0.04
Li 0.04
Lu 0.12
Sk 0.01
St 0.12
Go 0.08
Th 0.04
Bl 0.04

C = 25 HU, *W* = 400 HU

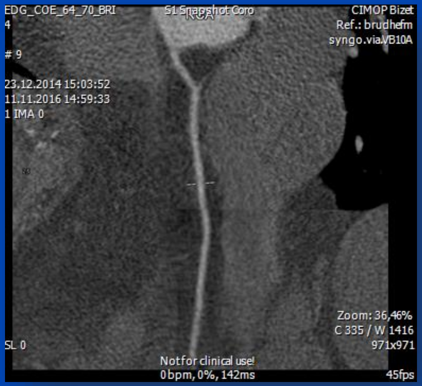
Part 5:

Motion Compensation (MoCo)

Deep Cardiac Motion Compensation



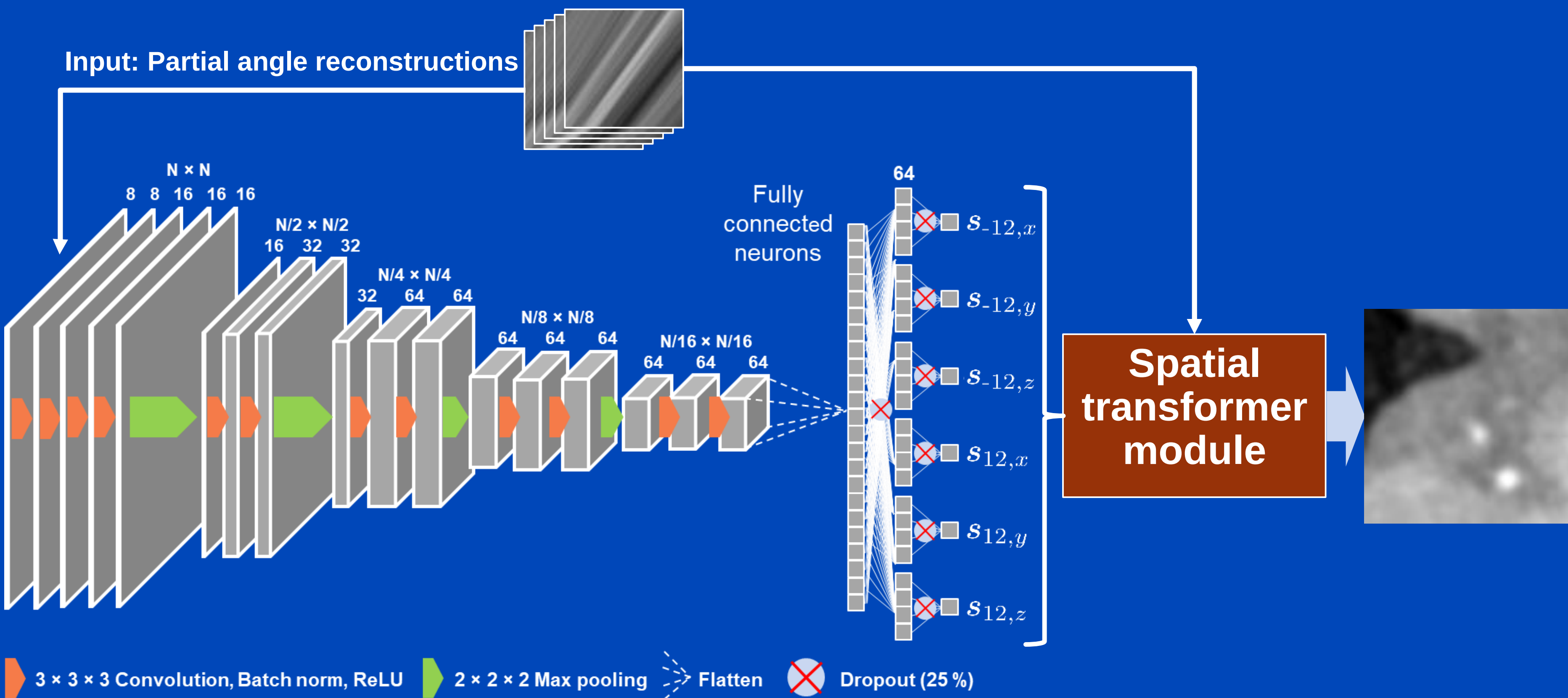
???



dkfz.

Deep PAMoCo

Network architecture

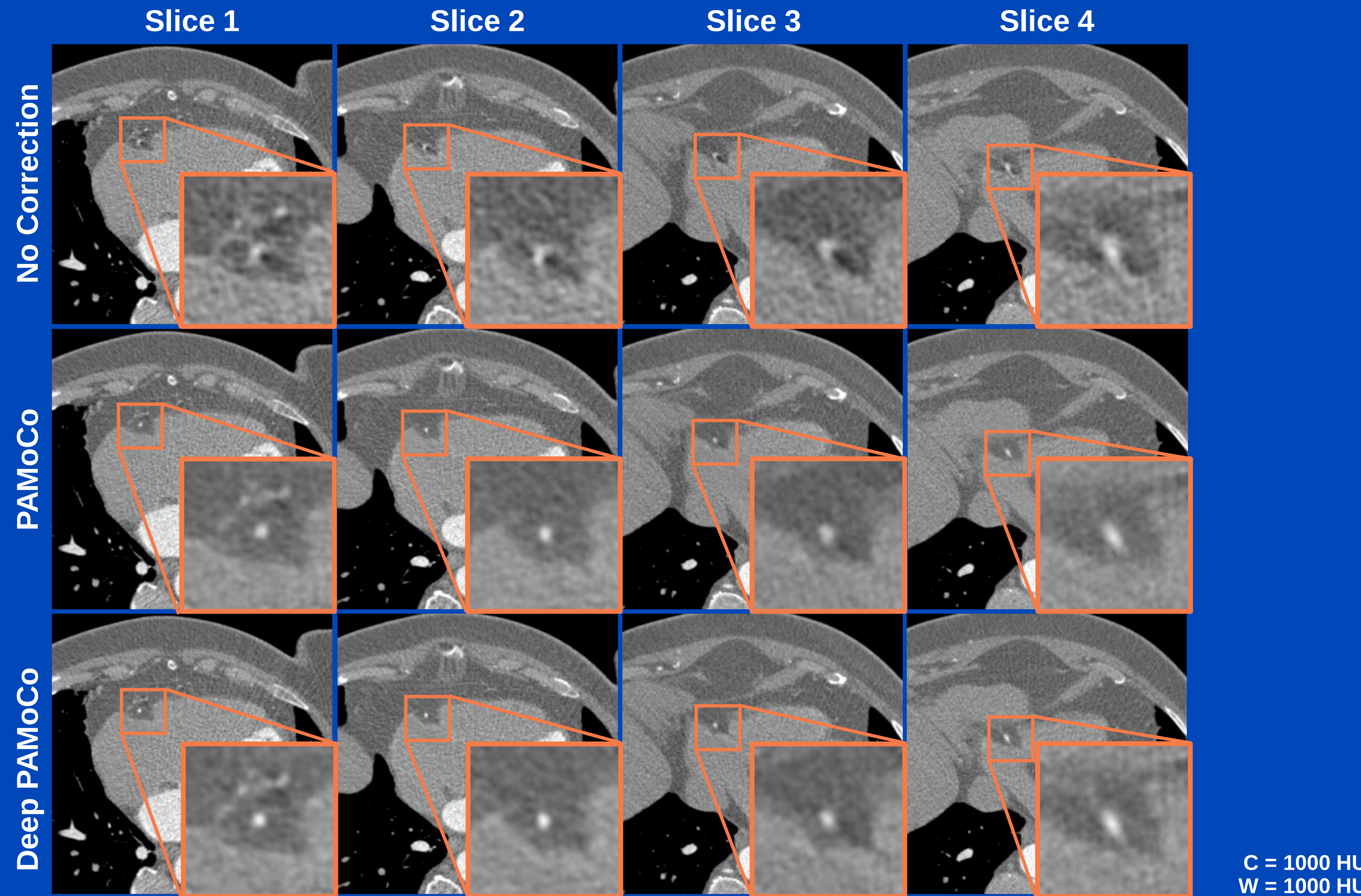


J. Maier, S. Lebedev, E. Eulig, S. Sawall, E. Fournié, K. Stierstorfer, and M. Kachelrieß. Coronary artery motion compensation for short-scan cardiac CT using a spatial transformer network. Conference Program of the 6th International CT-Meeting, August 2020.

J. Maier, S. Lebedev, J. Erath, E. Eulig, S. Sawall, E. Fournié, K. Stierstorfer, M. Lell, and M. Kachelrieß. Deep learning-based coronary artery motion estimation and compensation for short-scan cardiac CT. Med. Phys. 48, in press, 2021.

Results

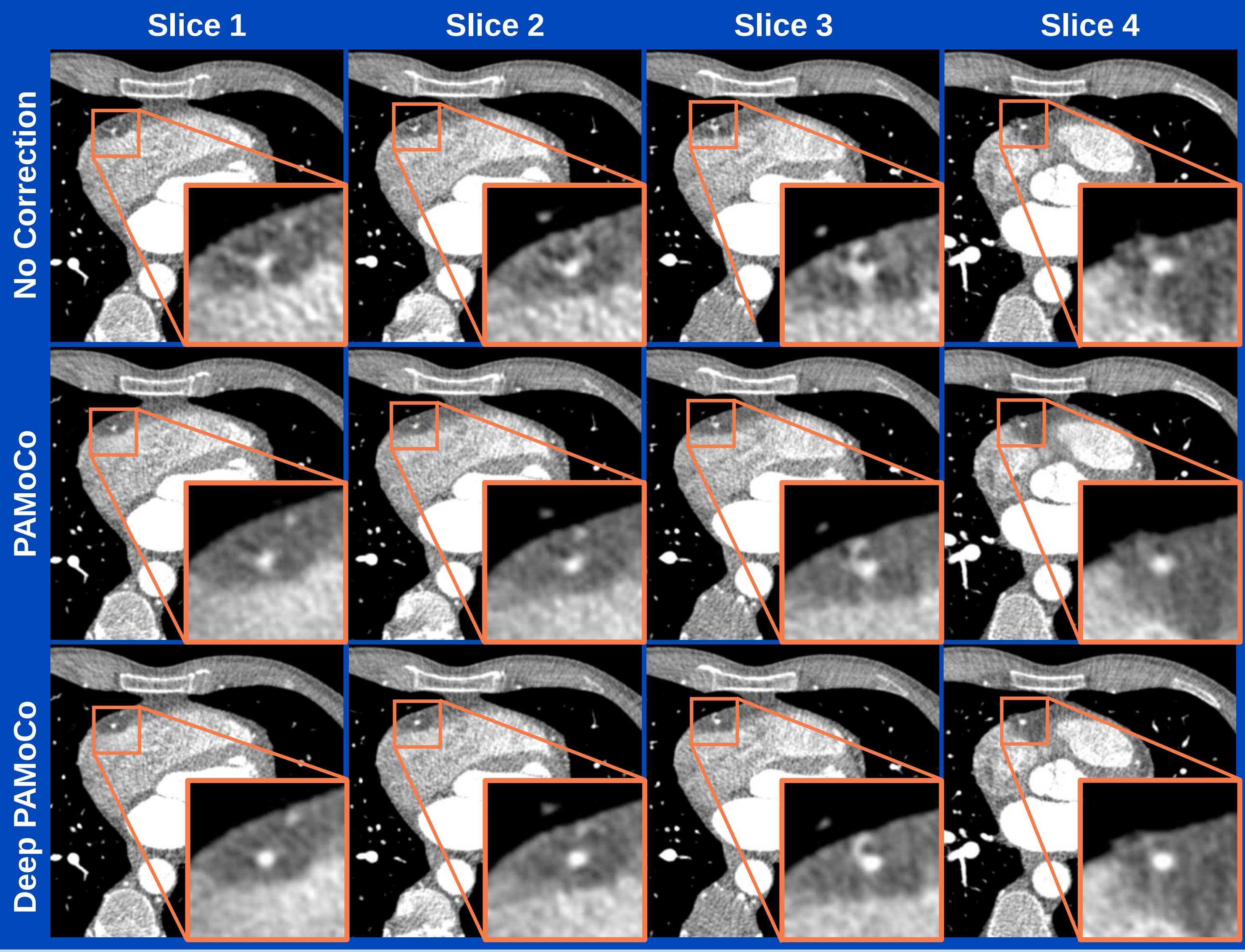
Measurements, patient 1



J. Maier, S. Lebedev, J. Erath, E. Eulig, S. Sawall, E. Fournié, K. Stierstorfer, M. Lell, and M. Kachelrieß. Deep learning-based coronary artery motion estimation and compensation for short-scan cardiac CT. Med. Phys. 48, in press, 2021.

Results

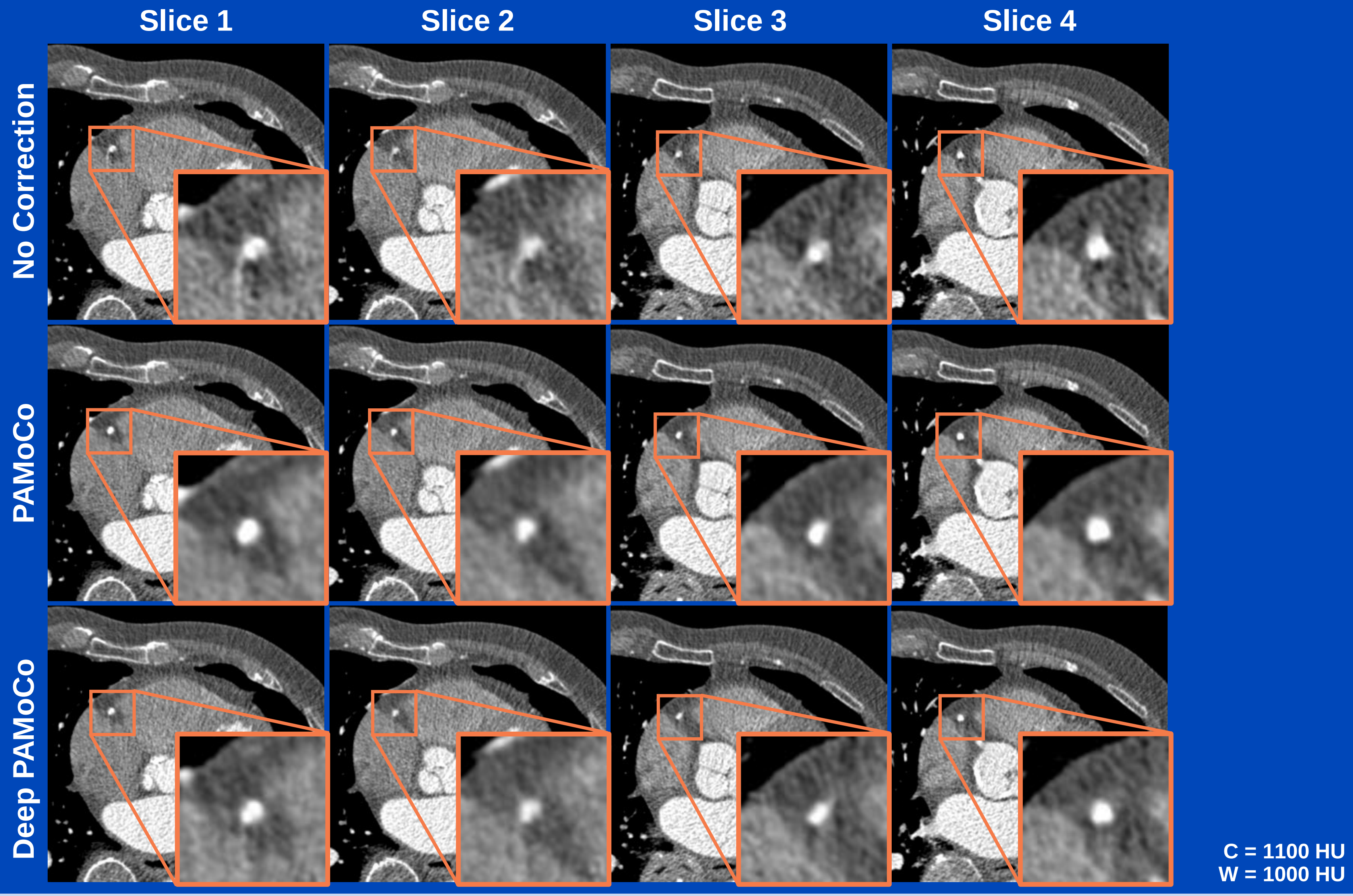
Measurements, patient 2



C = 1000 HU
W = 1000 HU

Results

Measurements, patient 3



J. Maier, S. Lebedev, J. Erath, E. Eulig, S. Sawall, E. Fournié, K. Stierstorfer, M. Lell, and M. Kachelrieß. Deep learning-based coronary artery motion estimation and compensation for short-scan cardiac CT. Med. Phys. 48, in press, 2021.

Thank You!

This presentation is available at www.dkfz.de/ct.

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

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