Deep Learning
in CT Image Formation

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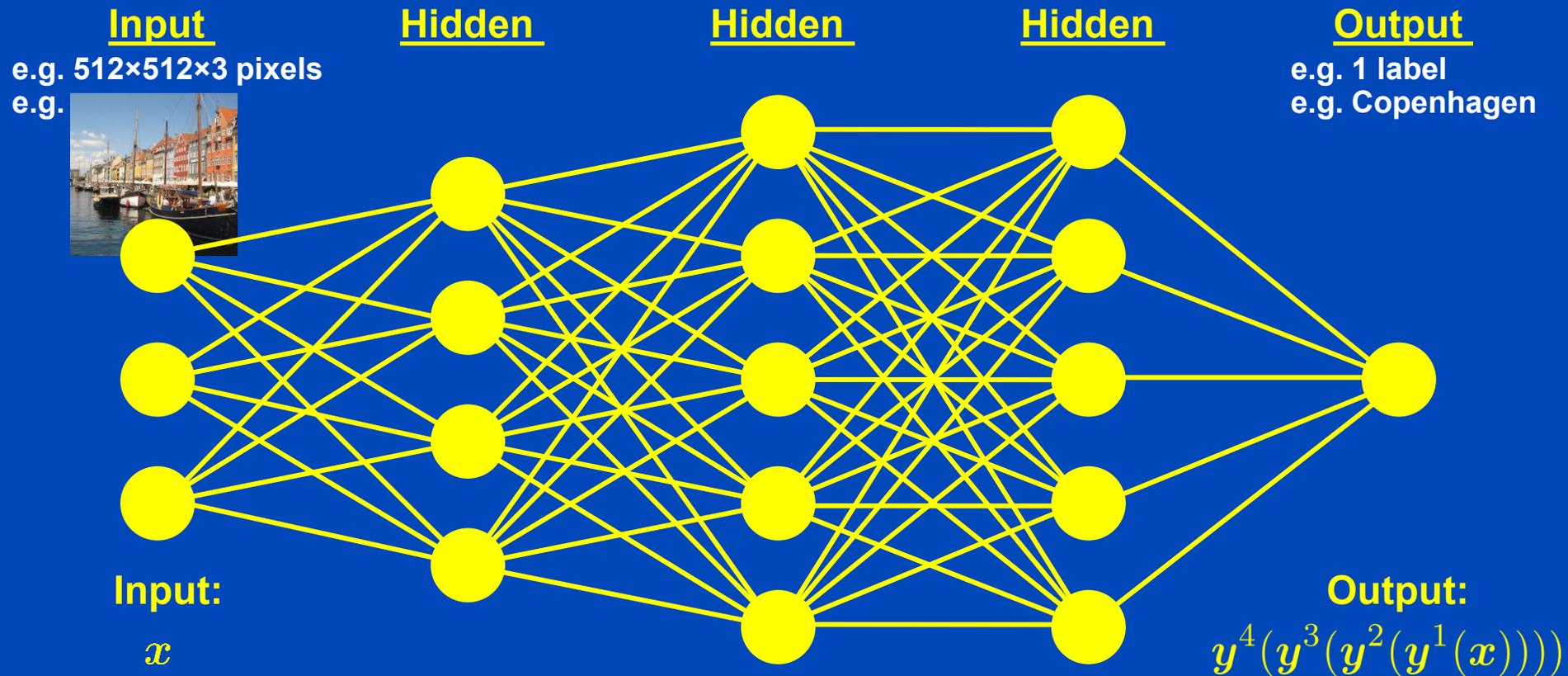
www.dkfz.de/ct

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DEUTSCHES
KREBSFORSCHUNGSZENTRUM
IN DER HELMHOLTZ-GEMEINSCHAFT

REALLY SHORT BASICS

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Fully-Connected Neural Network

- **Each layer fully connects to previous layer**
- **Difficult to train (many parameters in *W* and *b*)**
- **Spatial relations not necessarily preserved**

Input
e.g. 512×512×3 pixels
e.g.

Hidden

Hidden

Hidden

Output
e.g. 1 label
e.g. Copenhagen

Input:

x

Output:

$y^4(y^3(y^2(y^1(x))))$

$y(x) = f(W \cdot x + b)$ with $f(x) = (f(x_1), f(x_2), \ldots)$ point-wise scalar, e.g. $f(x) = x \vee 0 = \mathrm{ReLU}$

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Universal Approximation Theorem[1]

- **A fully-connected network with at least three layers is also called a multi layer perceptron (MLP).**

If σ is continuous, bounded and nonconstant, then $\Re_M(\sigma)$ is dense in the subset C of continuous and compact functions of $\mathbb{R}^M$.

$$\Re_M(\sigma) = \bigcup_N \Re_M^{(N)}(\sigma)$$

3-layer MLP with final activation linear and N hidden neurons

$$= \bigcup_N \left\{ g : \mathbb{R}^M \to \mathbb{R} \ \middle| \ g(x) = \sum_{j=0}^{N} w_{k,j}^{(3)} \, \sigma \left(\textstyle\sum_{i=0}^{M} w_{j,i}^{(2)} x_i \right) \right\}$$

- **For any function $h(x) \in C \in \mathbb{R}^M$ we can find a function $g(x) \in \mathcal{R}_M(\sigma)$ for which $\|h(x) - g(x)\|_p < \epsilon$.**

- **Any 3-layer MLP with appropriately chosen layer sizes and activation function, e.g. the sigmoid function, is a universal function approximator.**

- **This theorem does not provide any insight into how to find the unknowns!**

[1]Hornik, Kurt; Stinchcombe, Maxwell; White, Halbert (1989). Multilayer Feedforward Networks are Universal Approximators. Neural Networks. Vol. 2. Pergamon Press. pp. 359–366; Theorem 2

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Convolutional Neural Network (CNN)

- **Replace dense *W* in** $y(x) = f(W \cdot x + b)$ **by a sparse matrix *W* with sparsity being of convolutional type (band diagonal of Toeplitz type).**

- **CNNs consist (mainly) of convolutional layers.**

- **Convolutional layers are not fully connected.**

- **Convolutional layers are small, say 3×3, convolution kernels whose entries need to be found by training.**

- **CNNs preserve spatial relations to some extent.**

$$W_{1D} = \begin{pmatrix} 1 & 8 & 0 & 0 & 0 & 0 \\ 2 & 1 & 8 & 0 & 0 & 0 \\ 0 & 2 & 1 & 8 & 0 & 0 \\ 0 & 0 & 2 & 1 & 8 & 0 \\ 0 & 0 & 0 & 2 & 1 & 8 \\ 0 & 0 & 0 & 0 & 2 & 1 \end{pmatrix}$$

Only three unknowns!

Src
512×512×*F*

Dst
512×512×*G*

**G kernels
3×3×*F***
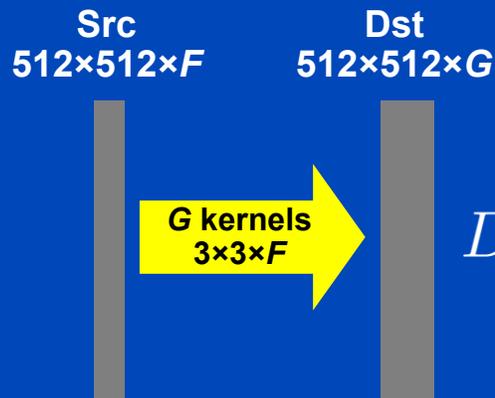
$$D_{i,j,g} = \sum_f S_{i,j,f} * K_{i,j,f}^g = \sum_{a,b,f} S_{i-a,j-b,f} K_{a,b,f}^g$$

= 3×3×*F*×*I*×*J*×*G* madd operations

Attention: No convolution in depth direction!

Here, a 2D example is shown. Conv layers also exist in 3D and higher dimensions.

Convolution Layers

- ## Input layer *S*
  - *vector of size I with F features: I×F*
  - **image of size *I* by *J* with *F* features: *I×J×F***
  - *volume of size I by J by K with F features: I×J×K×F*
  - *…*

- ## Convolution kernel *K*
  - **G kernels of size (2*A*+1)×(2*B*+1)×*F* with or without padding***

- ## Output layer *D*
  - **same spatial dimensions as input layer***
  - ***G* features (depth *G*)**

Src
512×512×*F*

Dst
512×512×*G*

G kernels
3×3×*F*
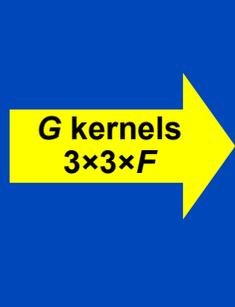
$$D_{i,j,g} = \sum_{f} S_{i,j,f} * K_{i,j,f}^{g} = \sum_{a,b,f} S_{i-a,j-b,f} K_{a,b,f}^{g}$$

Attention: No convolution in depth direction!

*Convolution may include a stride (step size) > 1. Similar to convolution with stride 1 follwed by pooling.

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Convolution Layers

- **Convolution in spatial domain (1D, 2D, 3D, …)**
- **Full connectivity in depth**
- **Filter size, number of filters, receptive field**
- **Learns filter kernels**
- **Far less parameters than fully connected layers**
- **Respects properties of many imaging systems**

Src
512×512×F

Dst
512×512×G

G kernels 3×3×F

$$D_{i,j,g} = \sum_f S_{i,j,f} * K_{i,j,f}^g = \sum_{a,b,f} S_{i-a,j-b,f} K_{a,b,f}^g$$

Attention: No convolution in depth direction!

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U-Net[1]

Input:

Output:

384 × 256 × 4

Concatenative skip connection

192 × 128 × 40

96 × 64 × 80

48 × 32 × 160

24 × 16 × 320

12 × 8 × 480

6 × 4 × 960

- → 3 x 3 Convolution, ReLU
- → 1 x 1 Convolution, ReLU
- ↓ 2 x 2 Max. Pooling
- ↑ 2 x 2 Upsampling
- ○ Depth Concatenate
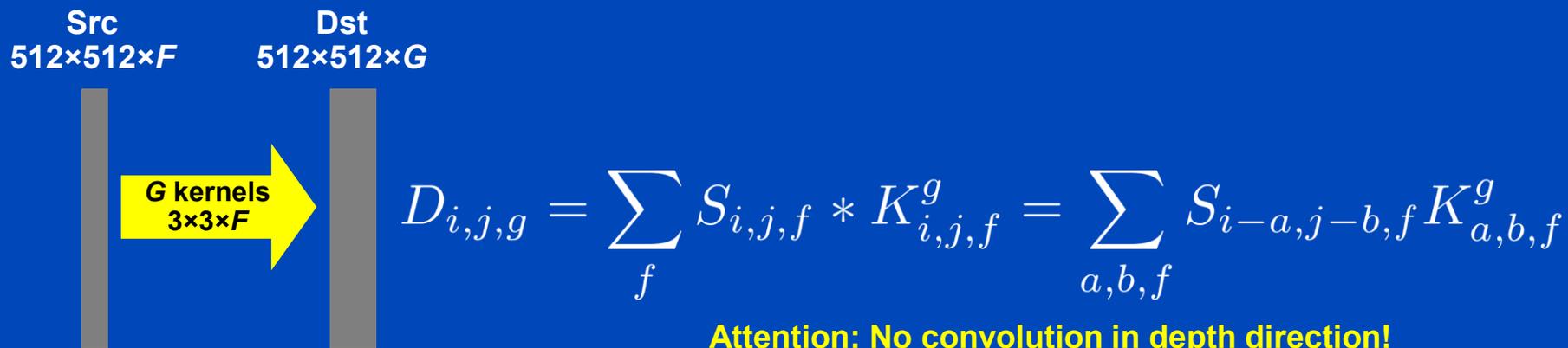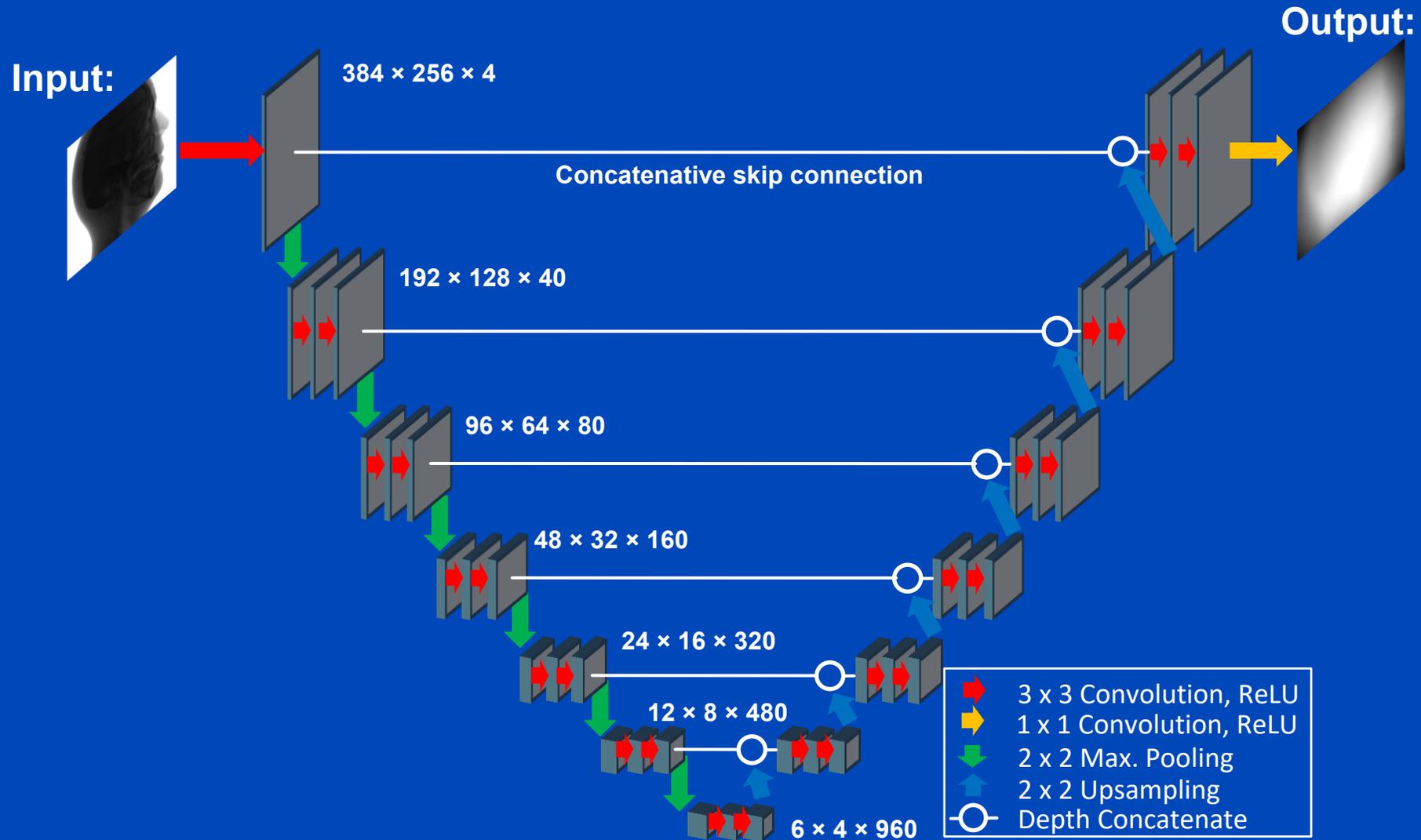
[1]O. Ronneberger, P. Fischer, and T. Brox. U-net: Convolutional networks for biomedical image segmentation. Proc. MICCAI:234-241, 2015.

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Loss Function

- **The neural network coefficients (weights and biases) *c* are chosen by minimizing a loss function (cost function)**

$$c = \arg\min_{c} \sum_{n=1}^{N} L(c, x_n, y_n)$$

  with x_n being the training data input, $y(c, x_n)$ being the network output, and y_n being the so-called labels, i.e. the training target, and *N* being the number of training samples.

- **An example for such a loss function is the MSE loss**

$$L(c, x_n, y_n) = \left(y(c, x_n) - y_n) \right)^2$$

Toy Example

Nested scalar functions $f(c, x)$ with unknown coefficients c

Loss Function

$$L(c_3, c_2, c_1, x) = \left(f_3(c_3, f_2(c_2, f_1(c_1, x))) - y \right)^2$$

(labels over the equation): last layer output, 2nd layer output, 1st layer output, input, training target

Intermediate Values

$$L_3 = \frac{dL}{df_3} = 2(f_3 - y)$$

$$L_2 = \frac{dL}{df_2} = \frac{dL}{df_3}\frac{df_3}{df_2} = L_3\frac{df_3}{df_2}$$

$$\ldots$$

$$L_n = \frac{dL}{df_n} = L_{n+1}\frac{df_{n+1}}{df_n}$$

Desired Gradients

$$\frac{dL}{dc_3} = \frac{dL}{df_3}\frac{df_3}{dc_3} = L_3\frac{df_3}{dc_3}$$

$$\frac{dL}{dc_2} = \frac{dL}{df_3}\frac{df_3}{df_2}\frac{df_2}{dc_2} = L_2\frac{df_2}{dc_2}$$

$$\ldots$$

$$\frac{dL}{dc_n} = L_n\frac{df_n}{dc_n}$$

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MAKING UP DATA

Limited Angle Example

GT   FBP (150°)   CNN

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Deep MAR Examples

Deep MAR Examples

Metal artifacts are

beam hardening

+ scatter

+ directed noise

+ increased susceptibility to sampling artifacts and motion.

MAR without Machine Learning is a Good Alternative: Frequency Split Normalized MAR[1,2]

Uncorrected   FSLIMAR   FSNMAR
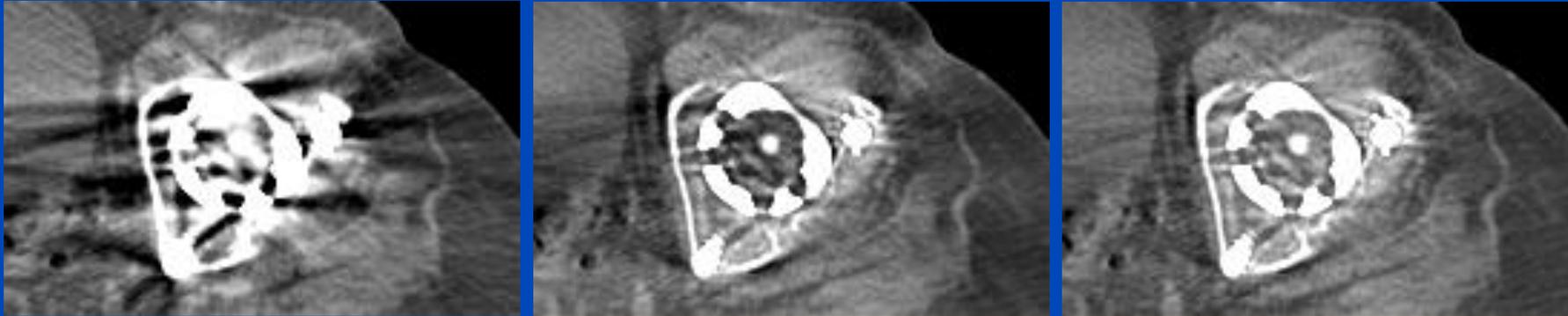
Patient with bilateral hip prosthesis, Somatom Definition Flash, (C=40/W=500).

[1]E. Meyer, M. Kachelrieß et al. Normalized metal artifact reduction (NMAR) in computed tomography. Med. Phys. 37(10):5482-5493, Oct. 2010.
[2]E. Meyer, M. Kachelrieß et al. Frequency split metal artifact reduction (FSMAR) in CT. Med. Phys. 39(4):1904-1916, April 2012.
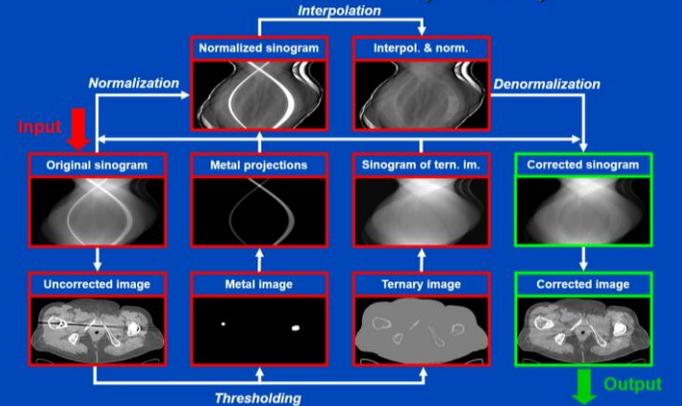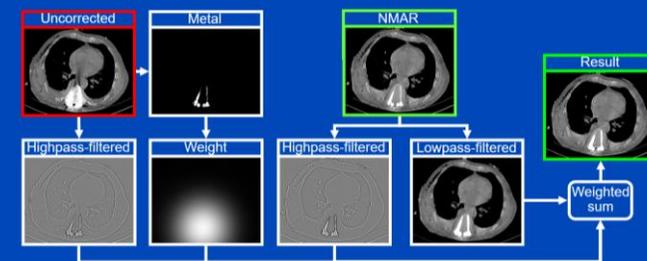
MAR Example

- **Deep CNN-driven patch-based combination of the advantages of several MAR methods trained on simulated artifacts**
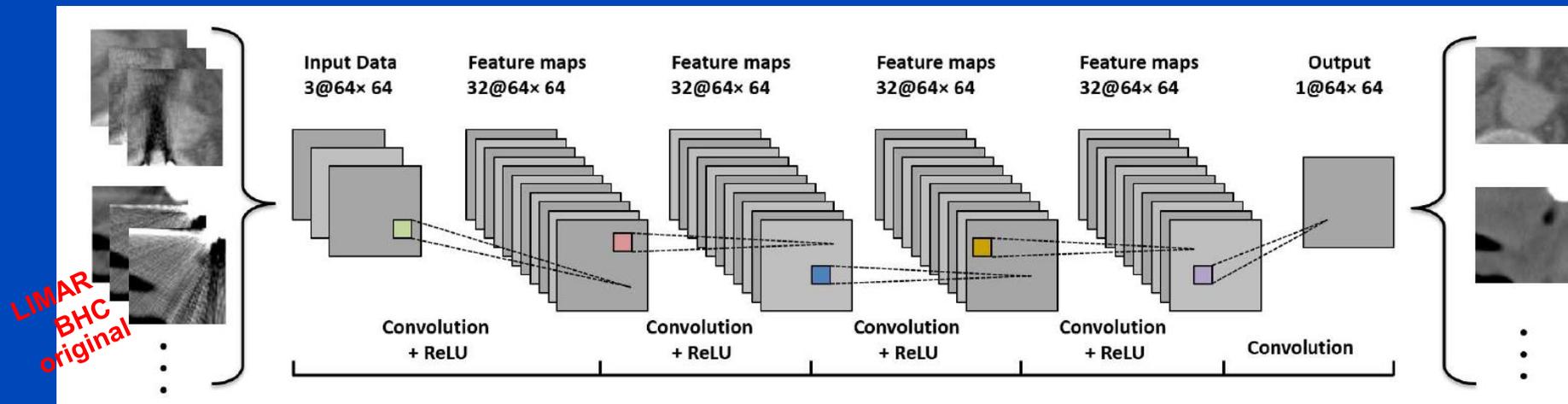
- **followed by segmentation into tissue classes**

- **followed by forward projection of the CNN prior and replacement of metal areas of the original sinogram**

- **followed by reconstruction**

Yanbo Zhang and Hengyong Yu. Convolutional Neural Network Based Metal Artifact Reduction in X-Ray Computed Tomography. TMI 37(6):1370-1381, June 2018.

Left panel:

(a) Reference Image

(b) Original Image
= input feature 1

(c) BHC
= input feature 2

(d) LI
= input feature 3

(e) NMAR1

(f) NMAR2

(g) CNN Image

(h) CNN-MAR
= proposed method

Right panel:

(a) NMAR1 Prior

(b) NMAR2 Prior

(c) CNN Prior
= output

Evaluation of novel AI-based extended field-of-view CT reconstructions

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Network Input Image | Network Output Image | HDeepFoV Result Image

Original

Truncated

ADT-corrected

ADT-corrected (clipped)

C = 0 HU, W = 1000 HU

K. Sourbelle, M. Kachelrieß, and W.A. Kalender. Reconstruction from truncated projections in CT using adaptive detruncation (ADT). Eur Rad 15:1008–1014, 2005.

Original

Truncated

ADT-corrected

ADT-corrected (clipped)

$C = 0$ HU, $W = 1000$ HU

K. Sourbelle, M. Kachelrieß, and W.A. Kalender. Reconstruction from truncated projections in CT using adaptive detruncation (ADT). Eur Rad 15:1008–1014, 2005.
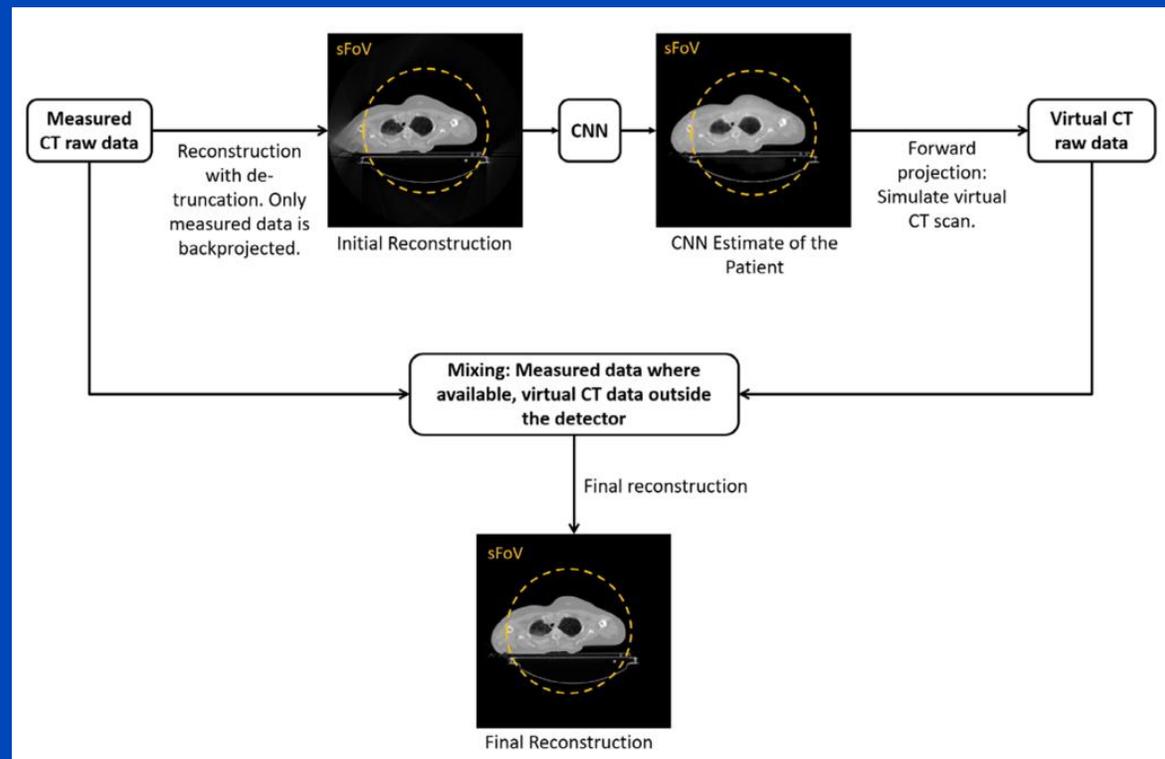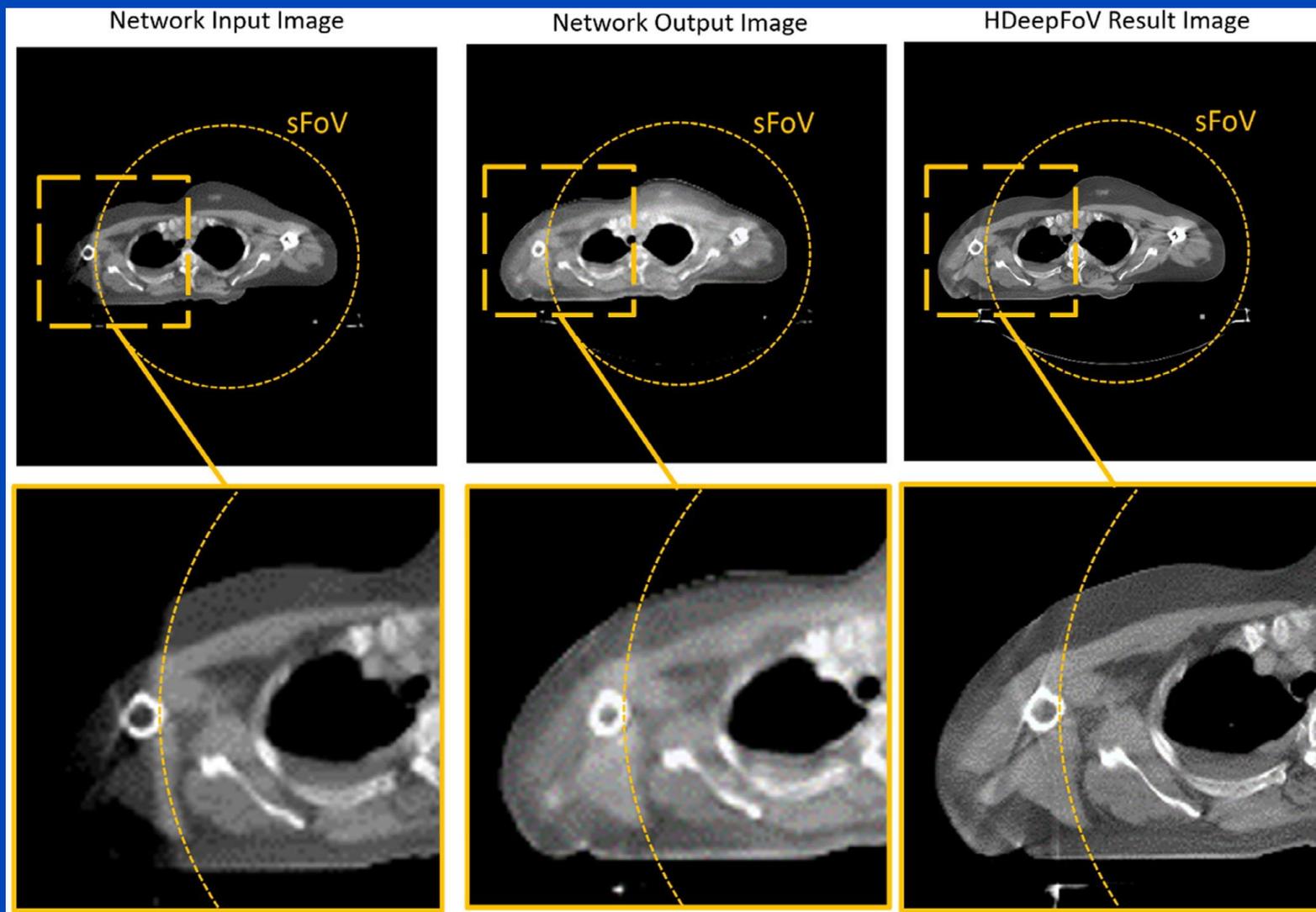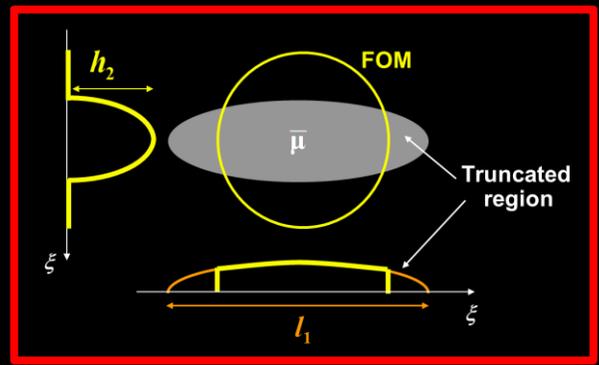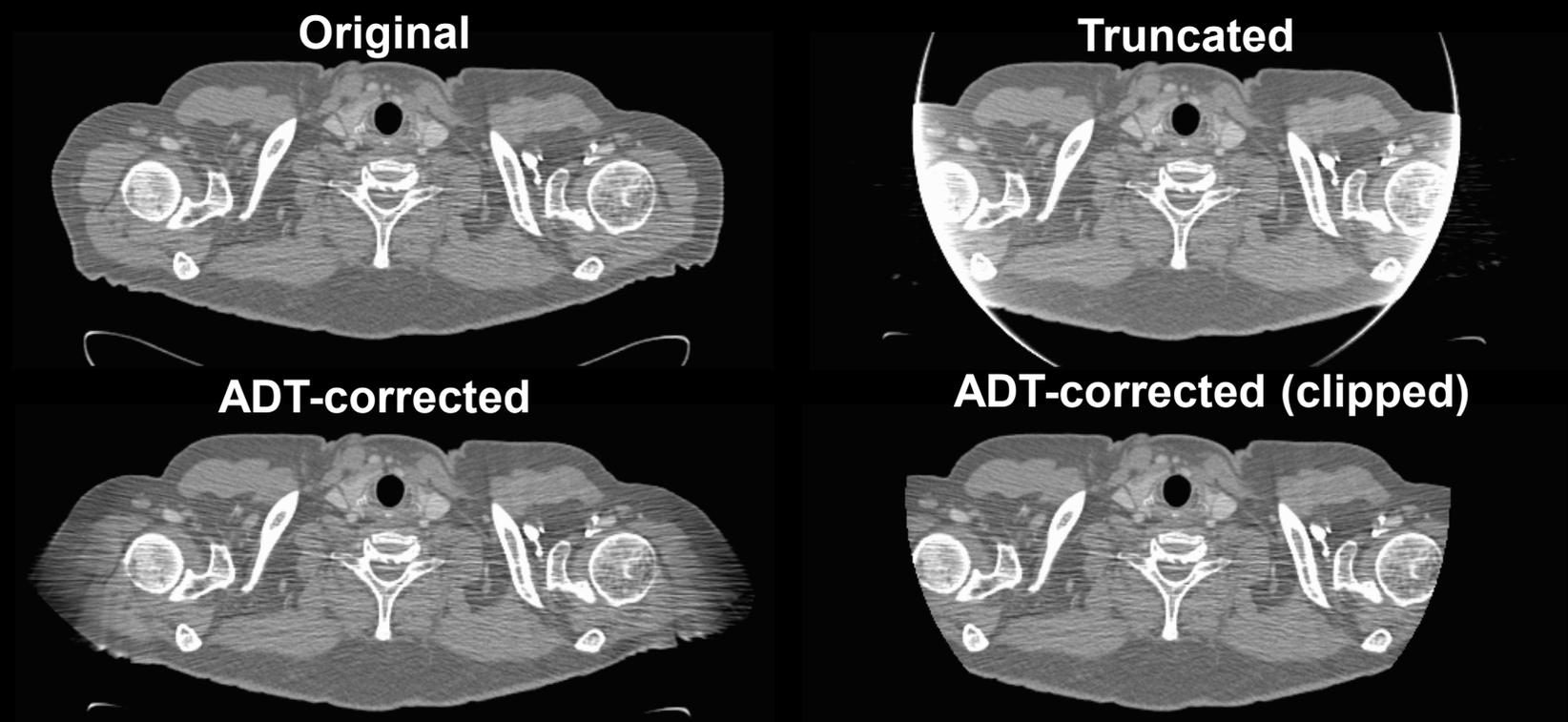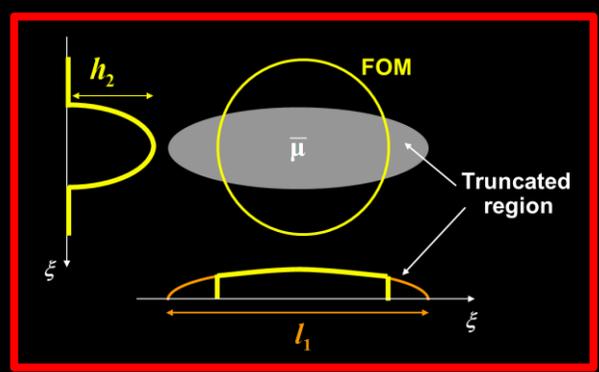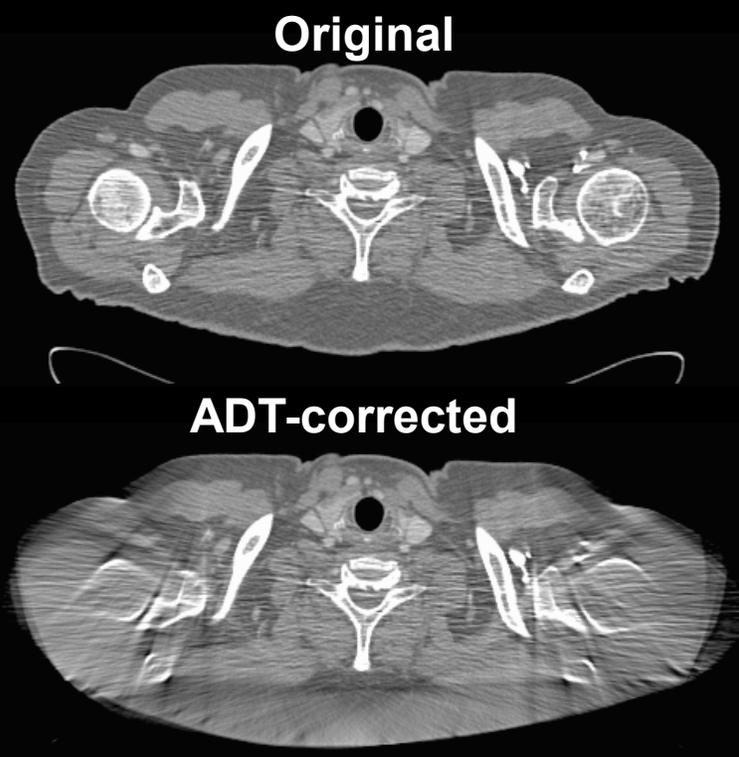
RESEARCH ARTICLE

Latent space reconstruction for missing data problems in CT **e.g. for metal inpainting, <u>detruncation</u>, limited angle extrapolation, ...**

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Email: anton.kabelac@dkfz.de

Abstract

Background: The reconstruction of a computed tomography (CT) image can be compromised by artifacts, which, in many cases, reduce the diagnostic value of the image. These artifacts often result from missing or corrupt regions in the projection data, for example, by truncation, metal, or limited angle acquisitions.

Purpose: In this work, we introduce a novel deep learning-based framework, latent space reconstruction (LSR), which enables correction of various types of artifacts arising from missing or corrupted data.

Methods: First, we train a generative neural network on uncorrupted CT images. After training, we iteratively search for the point in the latent space of this network that best matches the compromised projection data we measured. Once an optimal point is found, forward-projection of the generated CT image can be used to inpaint the corrupted or incomplete regions of the measured raw data.

A. Kabelac, E. Eulig, J. Maier, M. Hammermann, M. Knaup and M. Kachelrieß. Latent space reconstruction for missing data problems in CT. Med. Phys. 52(7):e17910, July 2025.

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Image Domain Experiment

- **Purely image domain**

- **Hand-crafted mask**

- **Minimizing**

$$z = \arg\min_{z} \|D(z) - M(\boldsymbol{r})f(\boldsymbol{r})\|$$

- **Results see rhs.**
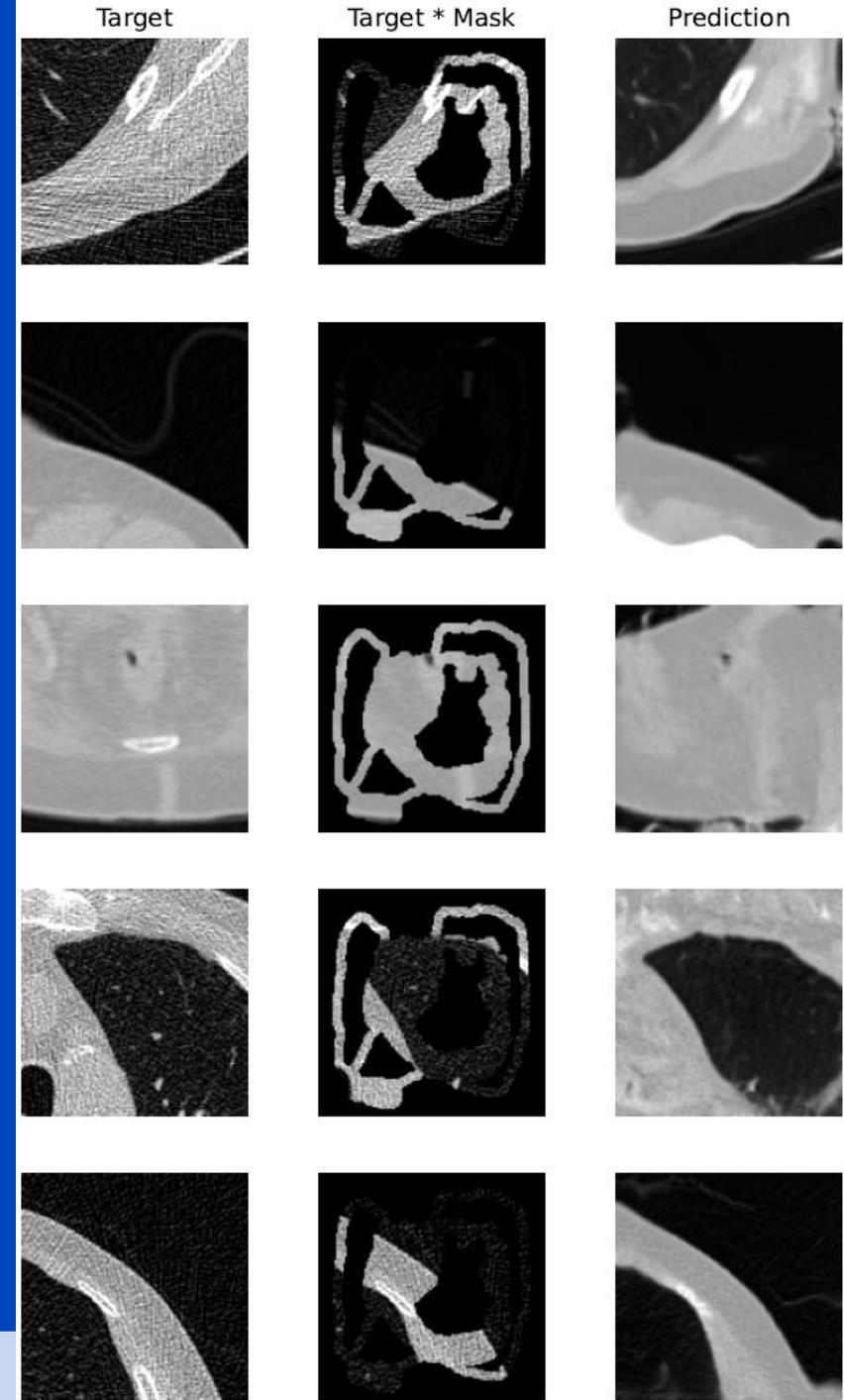
Search in Latent Space

- **Optimization of latent space vector in projection domain**

$$z = \arg\min_{z} \lVert XD(z) - p \rVert_{15\ \text{cm}}$$

- **Video showing intermediate images of selected iteration steps.**

Target Image — Target Sinogram — Masked (15 cm) Target Sinogram

Generated Image — Generated Sinogram — Masked (15 cm) Generated Sinogram — Difference to Target Sinogram

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Results

Ground Truth	ADT (classical)	U-Net (Ketola et al.)	LSR (ours)
MAEs: 0 HU, 0 HU	MAEs: 127 HU, 272 HU	MAEs: 31 HU, 121 HU	MAEs: 10 HU, 69 HU
MAEs: 0 HU, 0 HU	MAEs: 24 HU, 260 HU	MAEs: 60 HU, 218 HU	MAEs: 6 HU, 95 HU

C = 50 HU, W = 1200 HU

dkfz.
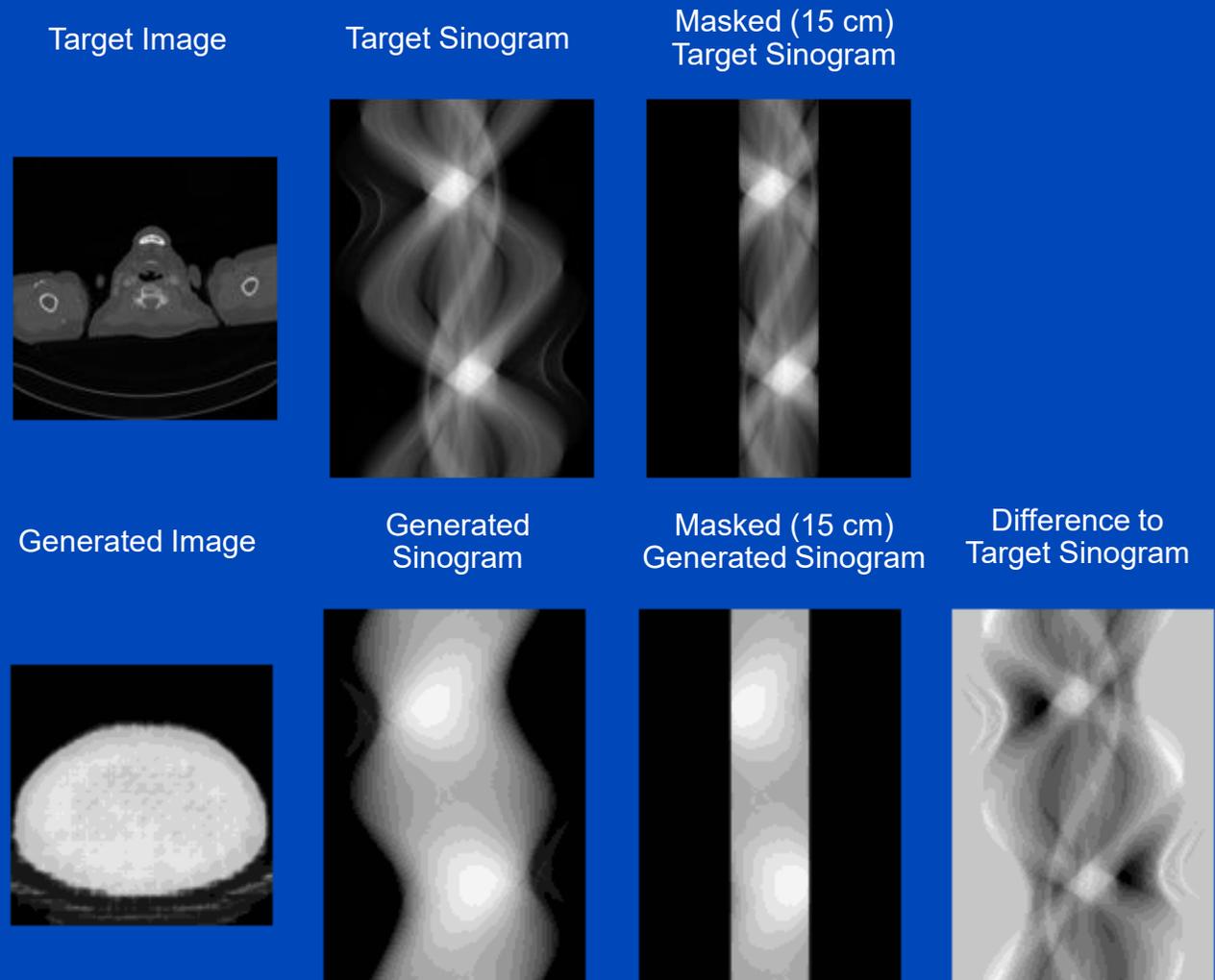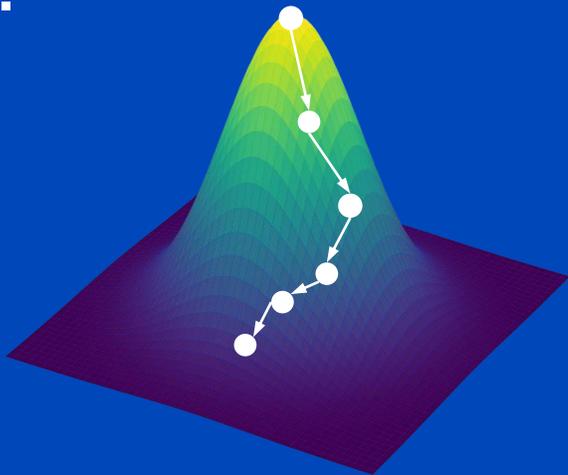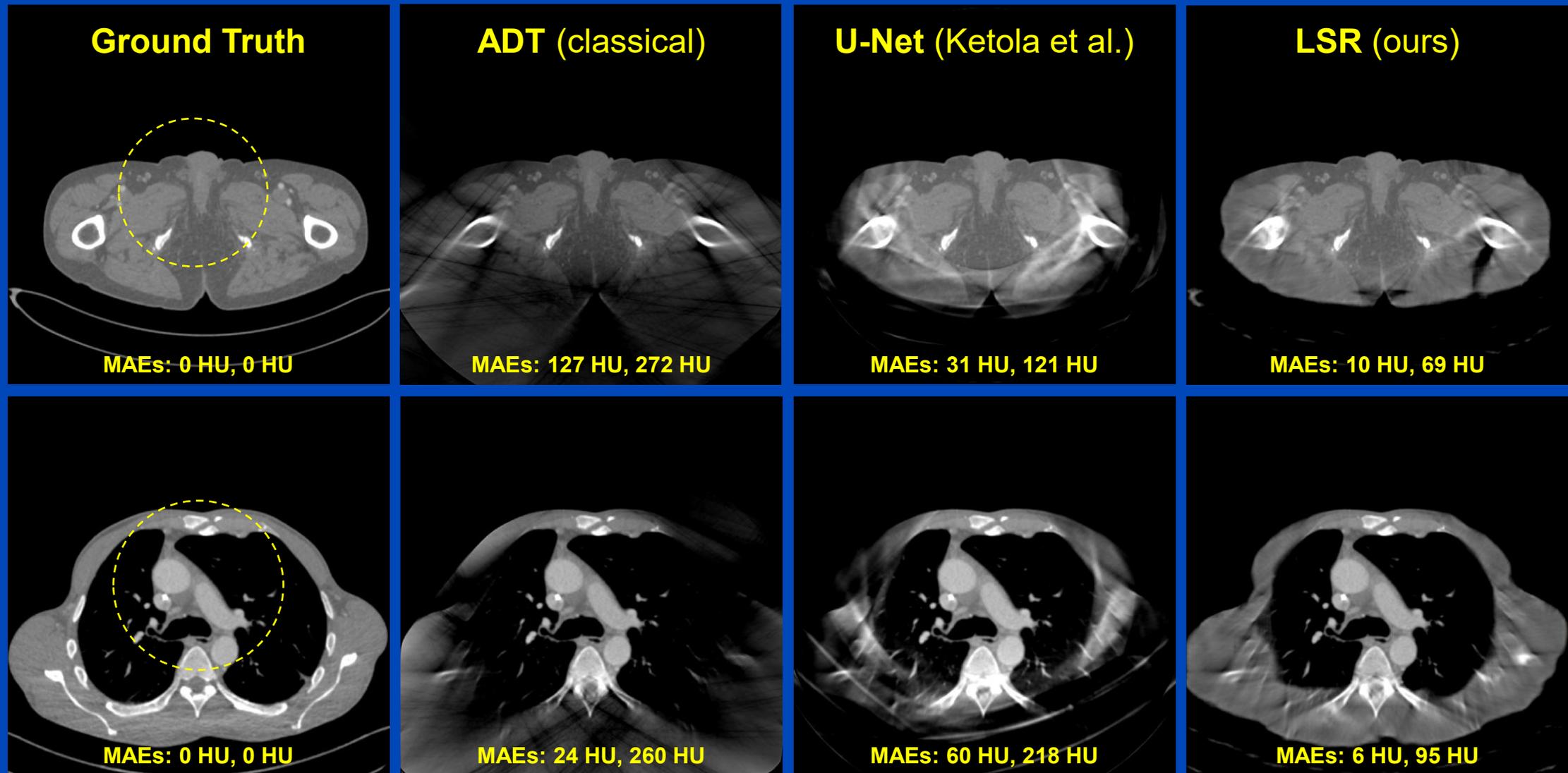
Super resolution does not add new information.

SPATIAL RESOLUTION IMPROVEMENT

Resolution Improvement Example

- **2D U-net to converts 5 mm thick images into 1 mm ones.**
- **E.g. to "replace a scanning protocol for a 1 mm slice with a 5 mm protocol".**
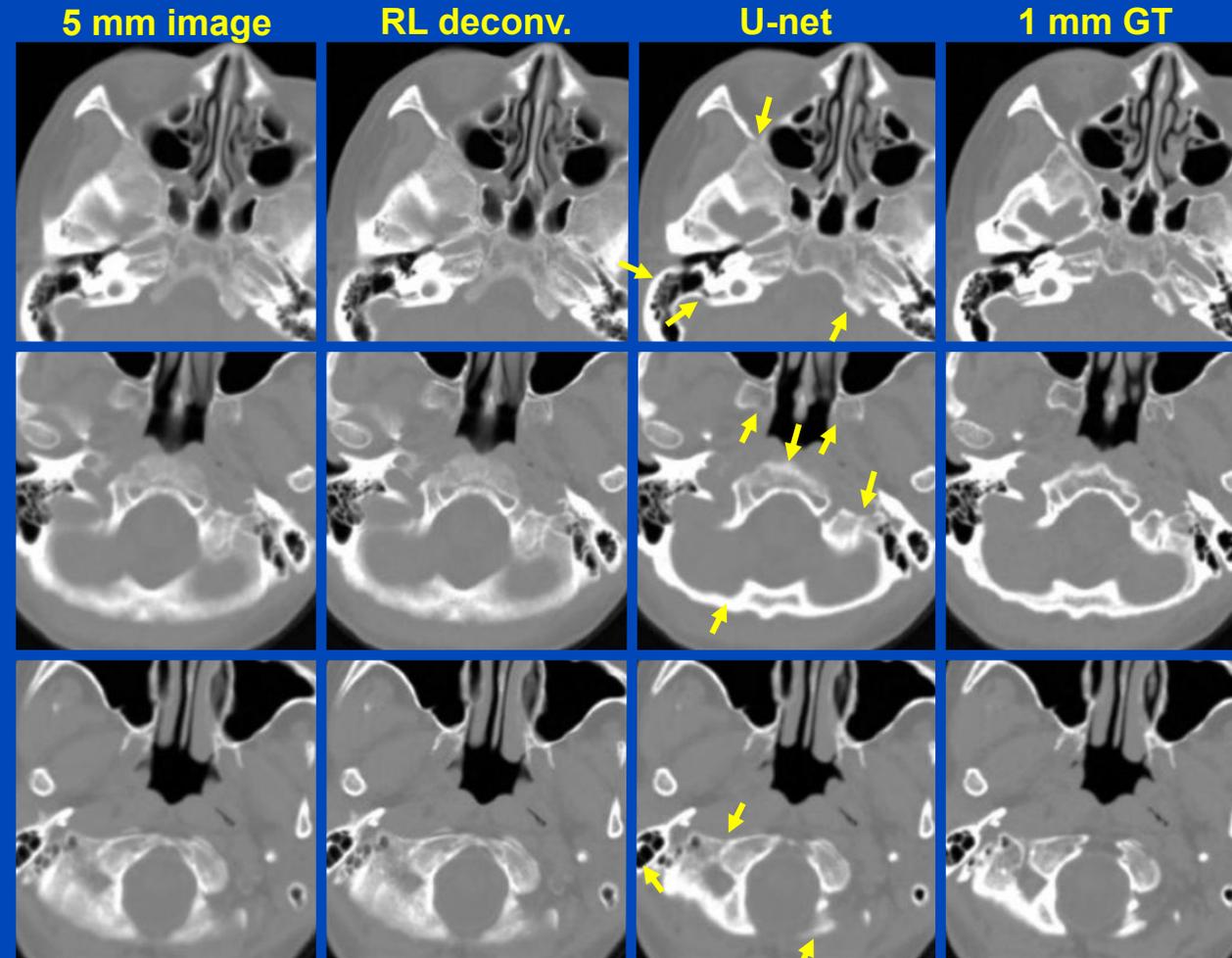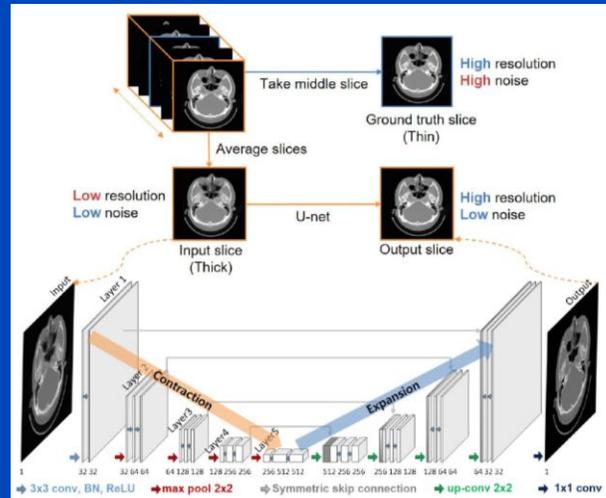
Canon PIQE

- **Precise IQ Engine (PIQE).**

- **Trained on data from Canon's Precision high spatial resolution CT**

- **Converts images from Canon's standard spatial resolution scanners (e.g. Aquilion ONE / PRISM edition) to look like high spatial resolution images.**
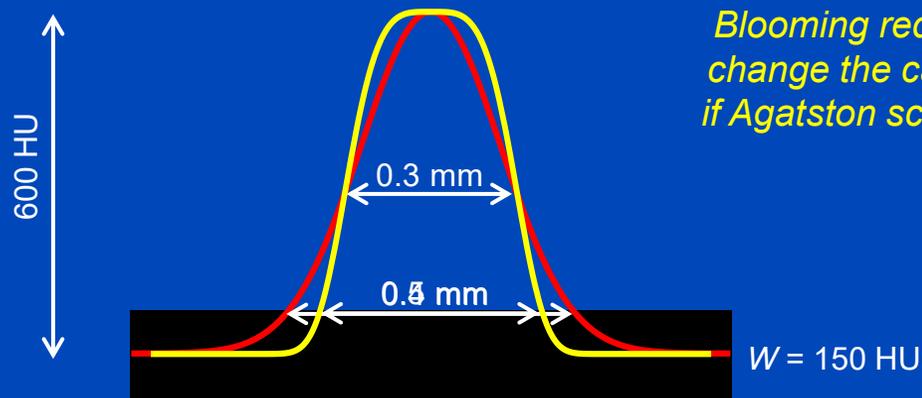
Warning:
Blooming reduction might change the calcium score, if Agatston scoring is used.

600 HU

0.3 mm

0.5 mm

W = 150 HU

AIDR 3D

PIQE

Image courtesy of Canon Medical Systems

dkfz.
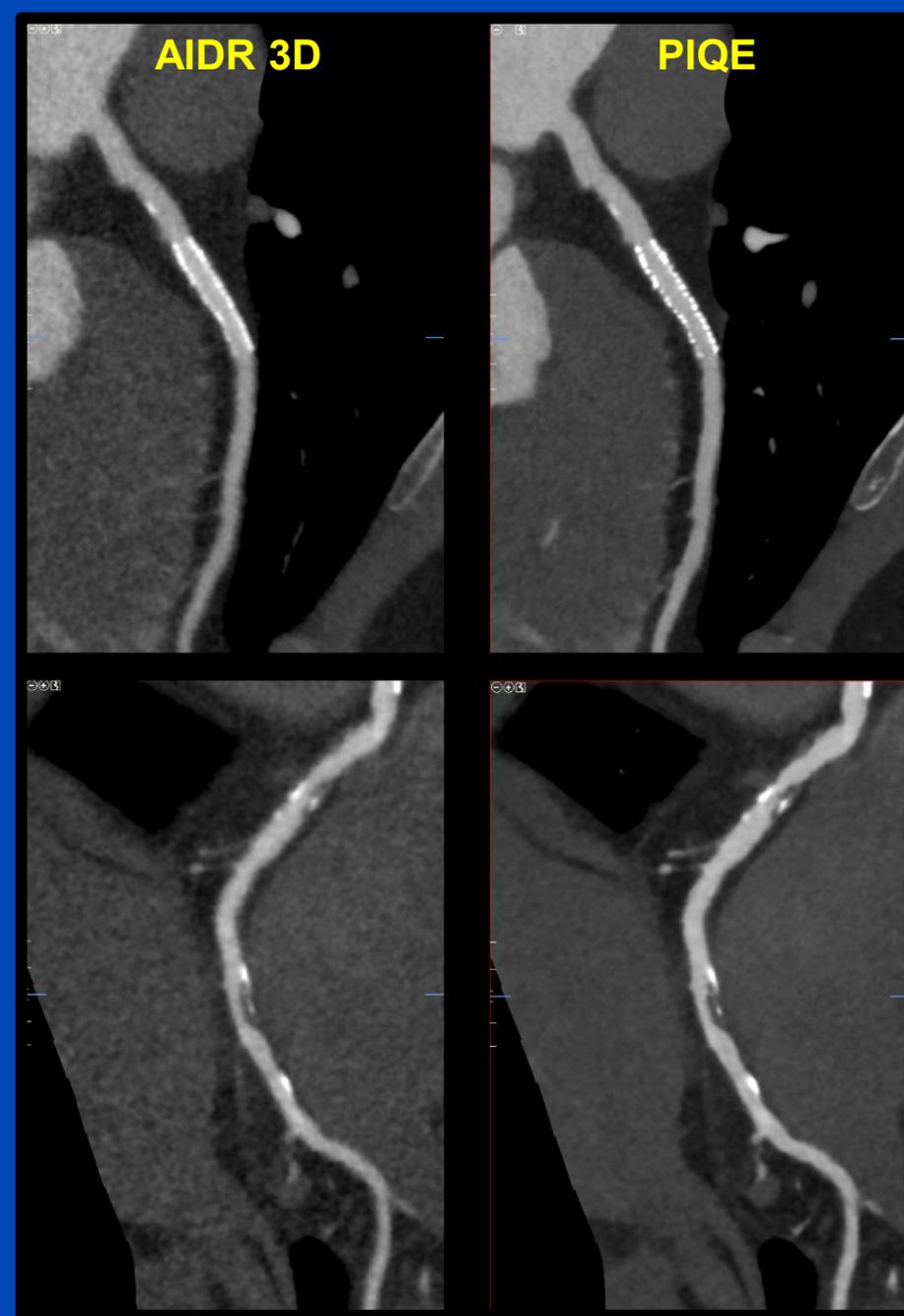
Fake Contrast Enhancement

[1] G. Santini, L. M. Zumbo, N. Martini, G. Valvano, A. Leo, A. Ripoli, F. Avogliero, D. Chiappino, D. D. Latta, "Synthetic contrast enhancement in cardiac CT with deep learning," arXiv 1807:01779, 2018.

[2] J. Liu, Y. Tian, A. M. Ağıldere, K. M. Haberal, M. Coşkun, C. Duzgol, and O. Akin, "DyeFreeNet: Deep virtual contrast CT synthesis," Lecture Notes in Computer Science. Springer International Publishing, pp. 80–89, 2020.

[3] A. Chandrashekar, A. Handa, N. Shivakumar, P. Lapolla, V. Grau, R. Lee, "A deep learning approach to generate contrast-enhanced computerised tomography Angiography without the use of intravenous contrast agents," arXiv 2003.01223, 2020.

[4] J. W. Choi, Y. J. Cho, J. Y. Ha, S. B. Lee, S. Lee, Y. H. Choi, J.-E. Cheon, and W. S. Kim, "Generating synthetic contrast enhancement from non-contrast chest computed tomography using a generative adversarial network," Scientific Reports, vol. 11, no. 1, 2021.

[5] S. W. Kim, J. H. Kim, S. Kwak, M. Seo, C. Ryoo, C.-I. Shin, S. Jang, J. Cho, Y.-H. Kim, and K. Jeon, "The feasibility of deep learning-based synthetic contrast-enhanced CT from non-enhanced CT in emergency department patients with acute abdominal pain," Scientific Reports, vol. 11, 2021.

[6] J. Chun, J. S. Chang, C. Oh, I. Park, M. S. Choi, C.-S. Hong, H. Kim, G. Yang, J. Y. Moon, S. Y. Chung, Y. J. Suh, and J. S. Kim, "Synthetic contrast-enhanced computed tomography generation using a deep convolutional neural network for cardiac substructure delineation in breast cancer radiation therapy: a feasibility study," Radiation Oncology, vol. 17, no. 1, 2022.

[7] Y. Gao, H. Xie, C. Chang, J. Peng, S. Pan, R. L. J. Qiu, T. Wang, B. Ghavidel, J. Roper, J. Zhou, and X. Yang, "CT-based synthetic iodine map generation using conditional denoising diffusion probabilistic model," Medical Physics, vol. 51, no. 9, pp. 6246–6258, 2024.

[8] S. Han, J.-M. Kim, J. Park, S. W. Kim, S. Park, J. Cho, S.-J. Park, H.-J. Chung, S.-M. Ham, S. J. Park, and J. H. Kim, "Clinical feasibility of deep learning based synthetic contrast-enhanced abdominal CT in patients undergoing non-enhanced CT scans," Scientific Reports, vol. 14, no. 1, 2024.

(a) NCT slice #1

(b) SCECT slice #1

(c) CECT slice #1
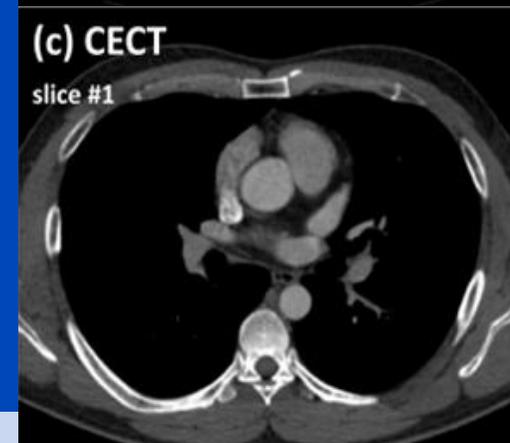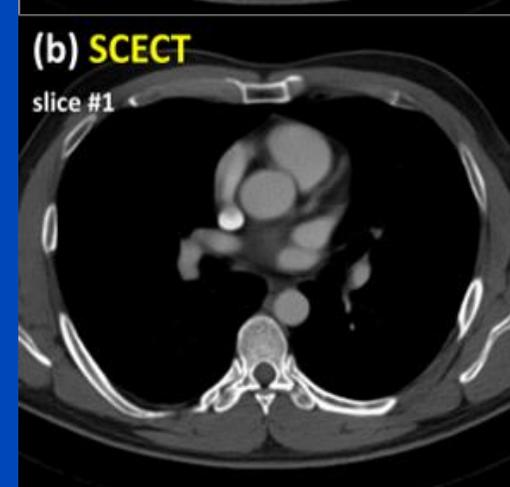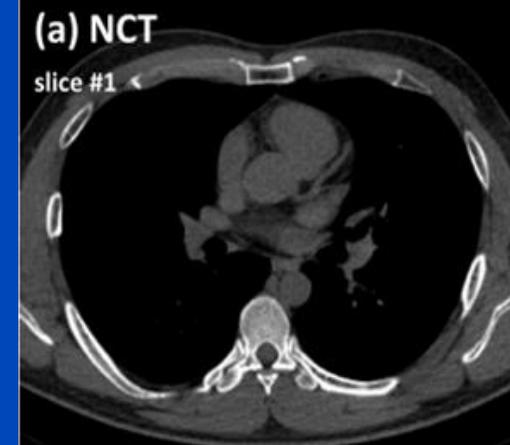
From [4]

NOISE REDUCTION

Noise Removal Example 2

Input (NxNxZ)
Conv2D 128, (9x9)
Residual Block
Residual Block
Residual Block
Residual Block
Residual Block
Residual Block
Residual Block
Residual Block
Residual Block
Residual Block
Residual Block
Conv2D 1, (3x3)
Output (NxNx1)

Conv2D 128, (3x3)
Batch Normalization
ReLU Activation
Group Conv2D 8×16, (3x3)
Concatenate
Batch Normalization
ReLU Activation
Conv2D 128, (1x1)
Batch Normalization
ReLU Activation

Input: low-dose CT images

Skip connection

Predicted noise

Noise subtraction

Output: denoised CT images

MSE loss function

Full-dose reference

- 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.

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Noise Removal Example 2
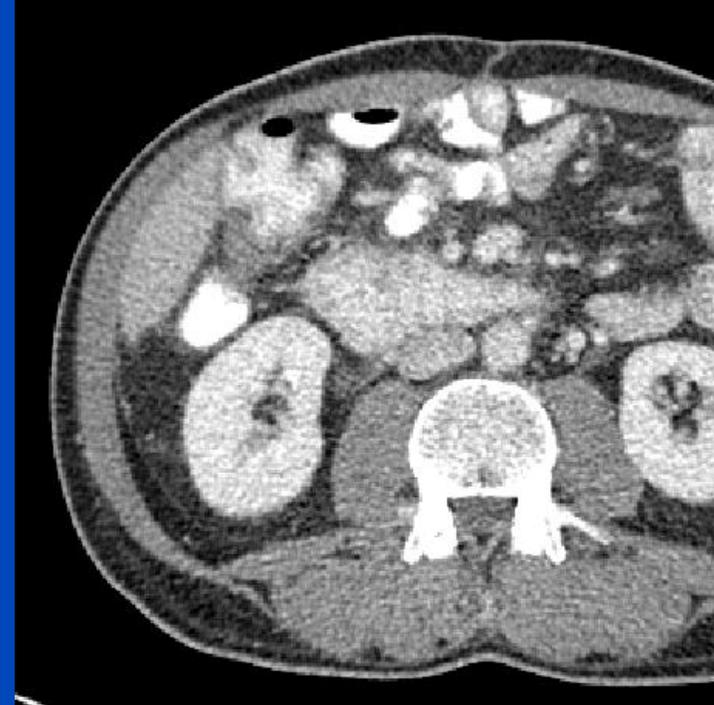
Low dose images (1/4 of full dose)

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Noise Removal Example 2

Denoised low dose

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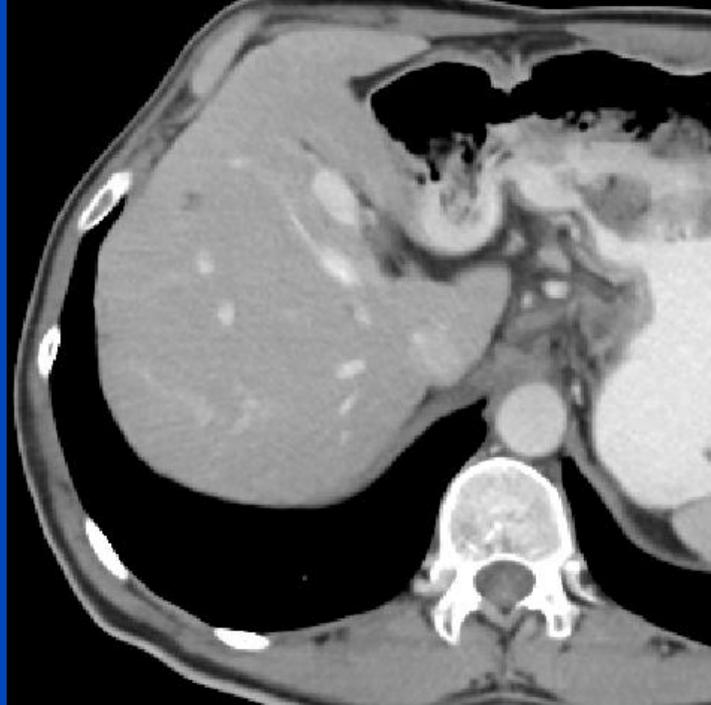
Noise Removal Example 2

Full dose

dkfz.

Noise Removal Example 2

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.

dkfz.
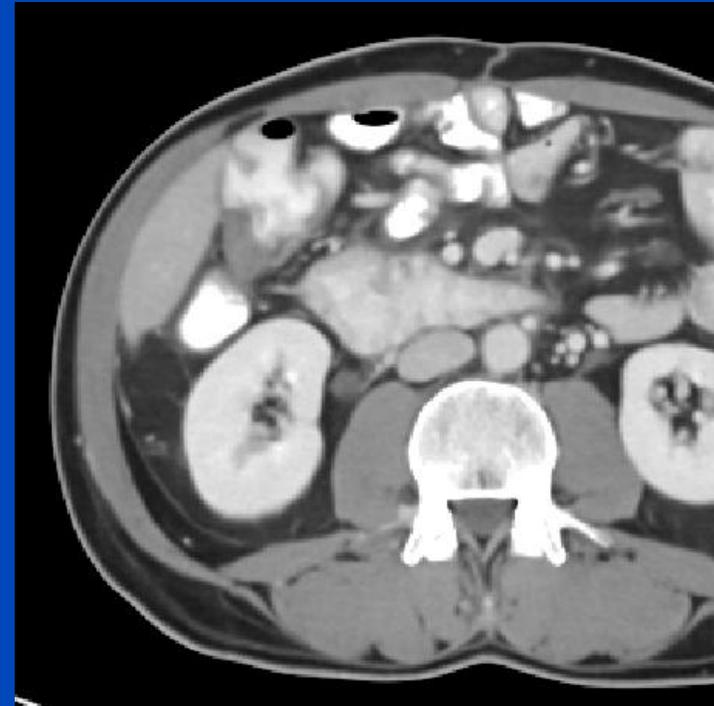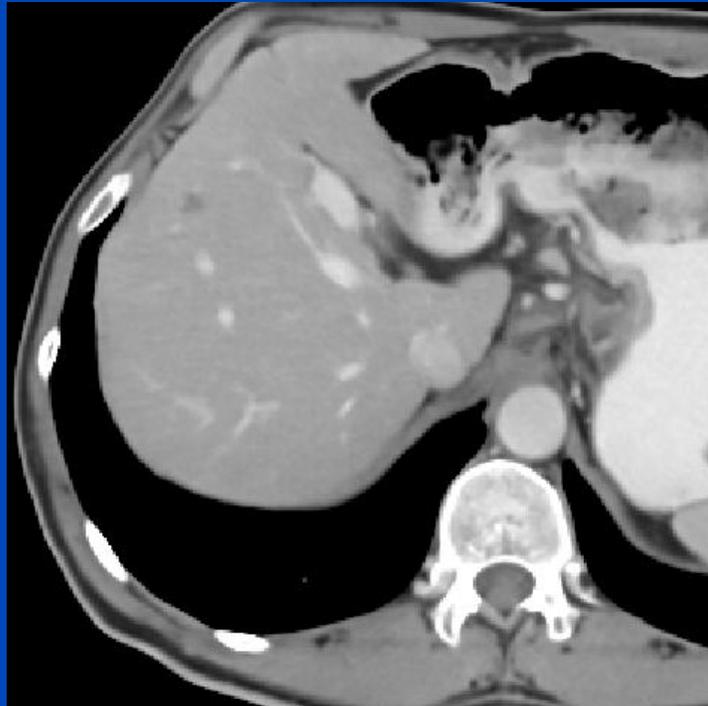
Noise Removal: Canon's AiCE

- **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**

K. Boedeker. AiCE Deep Learning Reconstruction: Bringing the Power of Ultra High Resolution CT to Routine Imaging. Whitepaper, Canon, 2019.
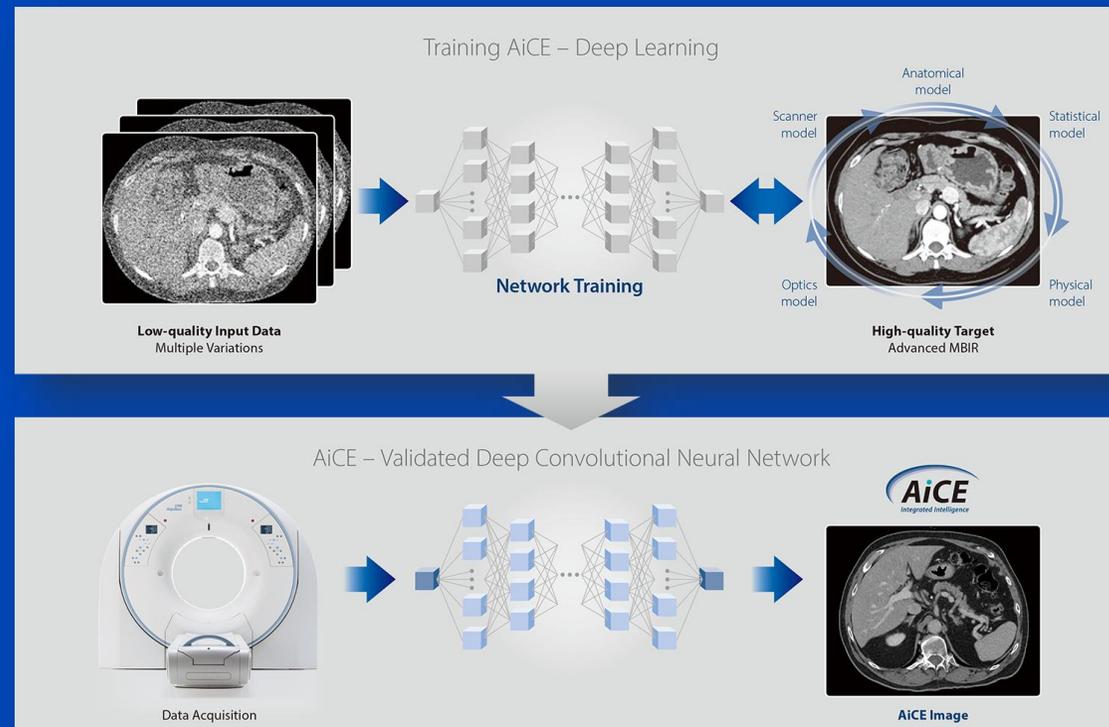
U = 100 kV
CTDI = 0.6 mGy
DLP = 24.7 mGy·cm
D_{eff} = 0.35 mSv
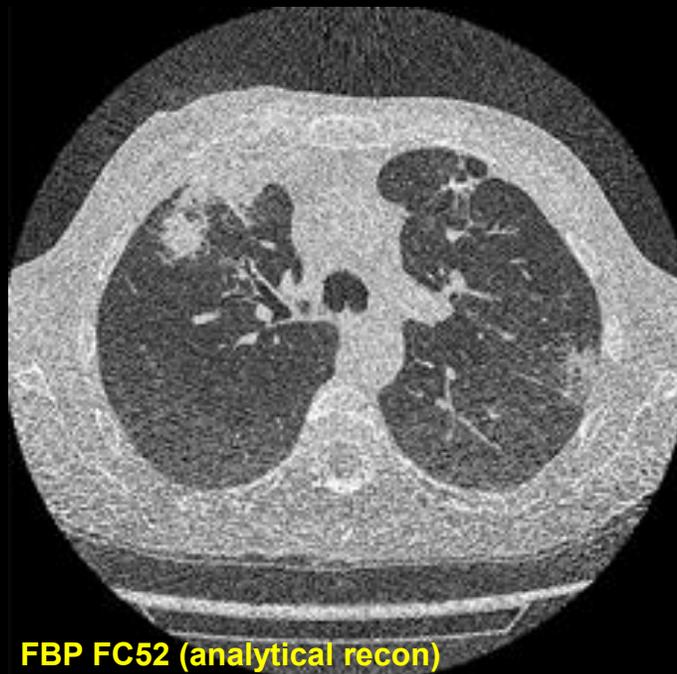
FBP FC52 (analytical recon)
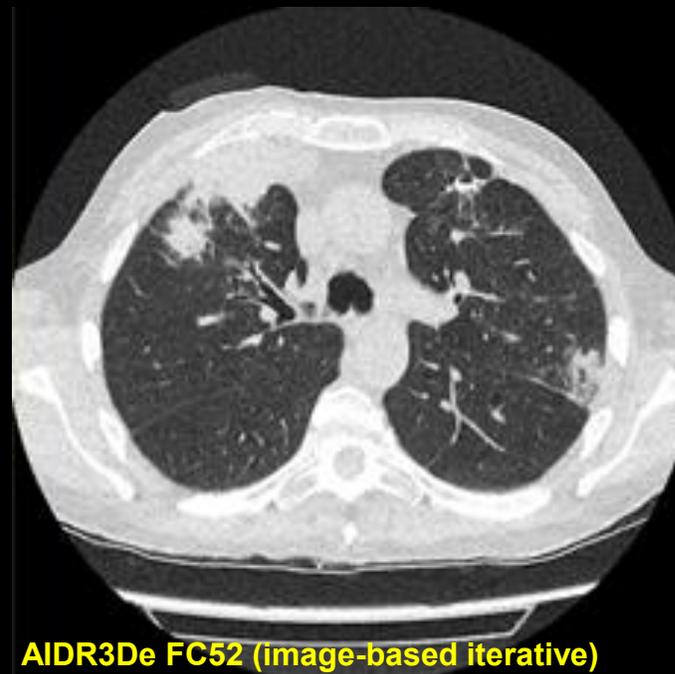
AIDR3De FC52 (image-based iterative)
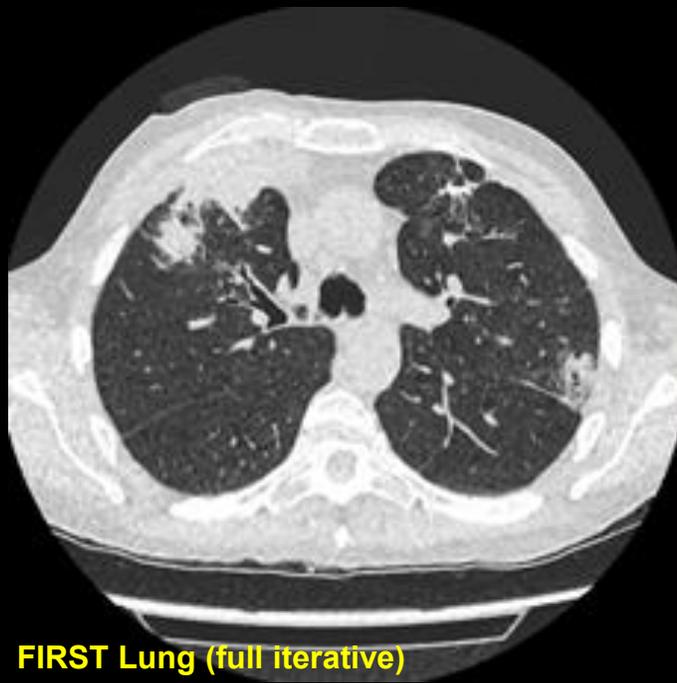
FIRST Lung (full iterative)
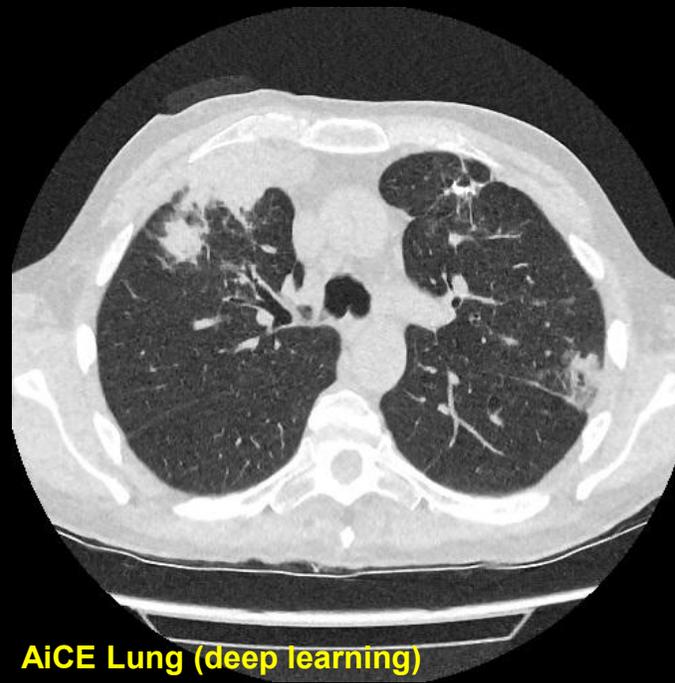
AiCE Lung (deep learning)

Courtesy of Radboudumc, the Netherlands

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Noise Reduction: GE's True Fidelity

- **Based on a deep CNN**
- **Trained to restore low-dose CT data to match the properties of high quality FBP datasets.**
- **Said to preserve noise texture and NPS**

The 20 cm water phantom (GE Healthcare, WI, US) was scanned on Revolution CT with two CTDIvol levels: 4.9mGy and 15.1mGy, and 2.5 mm thick images were reconstructed using FBP, ASiR-V 100% and DLIR-H (Fig. 11a). ASiR-V 100% and DLIR-H were selected for the highest potential visible change in image texture relative to the FBP reference at higher dose, for a challenging setup to compare the impact of the iterative reconstruction and deep-learning technologies on image appearance. The normalized NPS curves (Fig. 11b) show that images of low-dose DLIR have the same NPS characteristics as the images of high-dose FBP, whereas iterative reconstruction produces results that are clearly different.

FBP, 15.1 mGy   ASiR-V 100%, 4.9 mGy   DLIR-H, 4.9 mGy

Normalized NPS Curves

- DLIR-H, 4.9 mGy
- ASiR-V 100%, 4.9 mGy
- FBP, 15.1 mGy

nNPS (mm²)

Spatial Frequency (lp/cm)

dkfz.
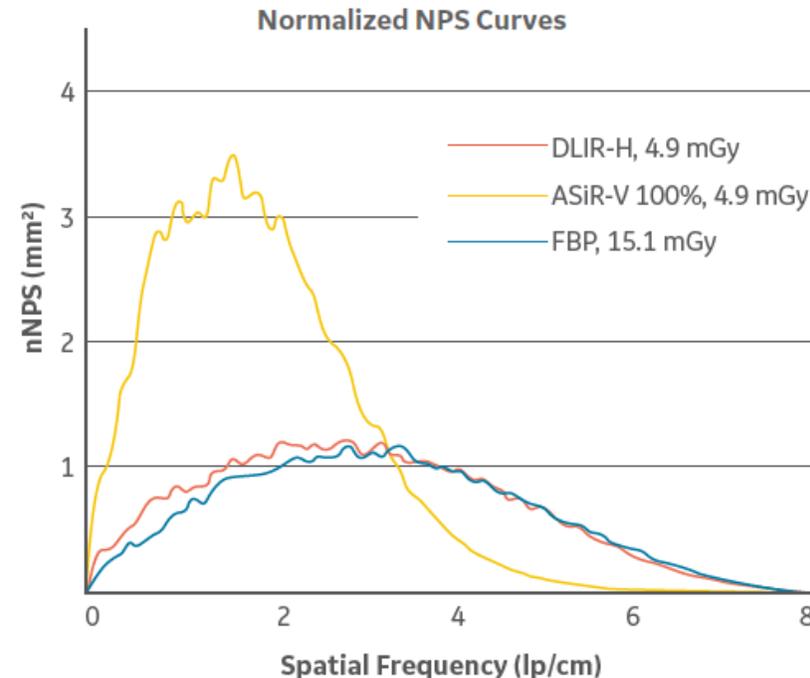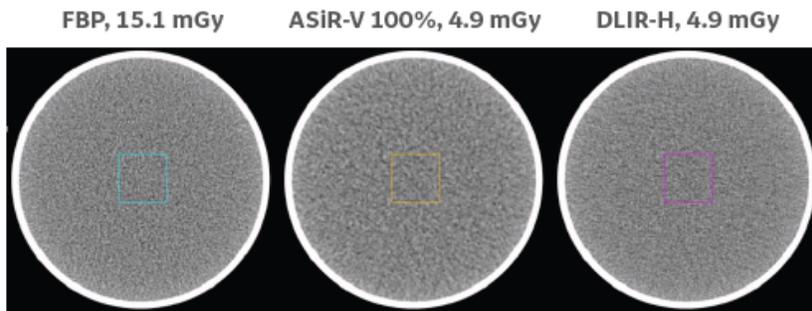
FBP **ASIR V 50%** **True Fidelity**

Courtesy of GE Healthcare
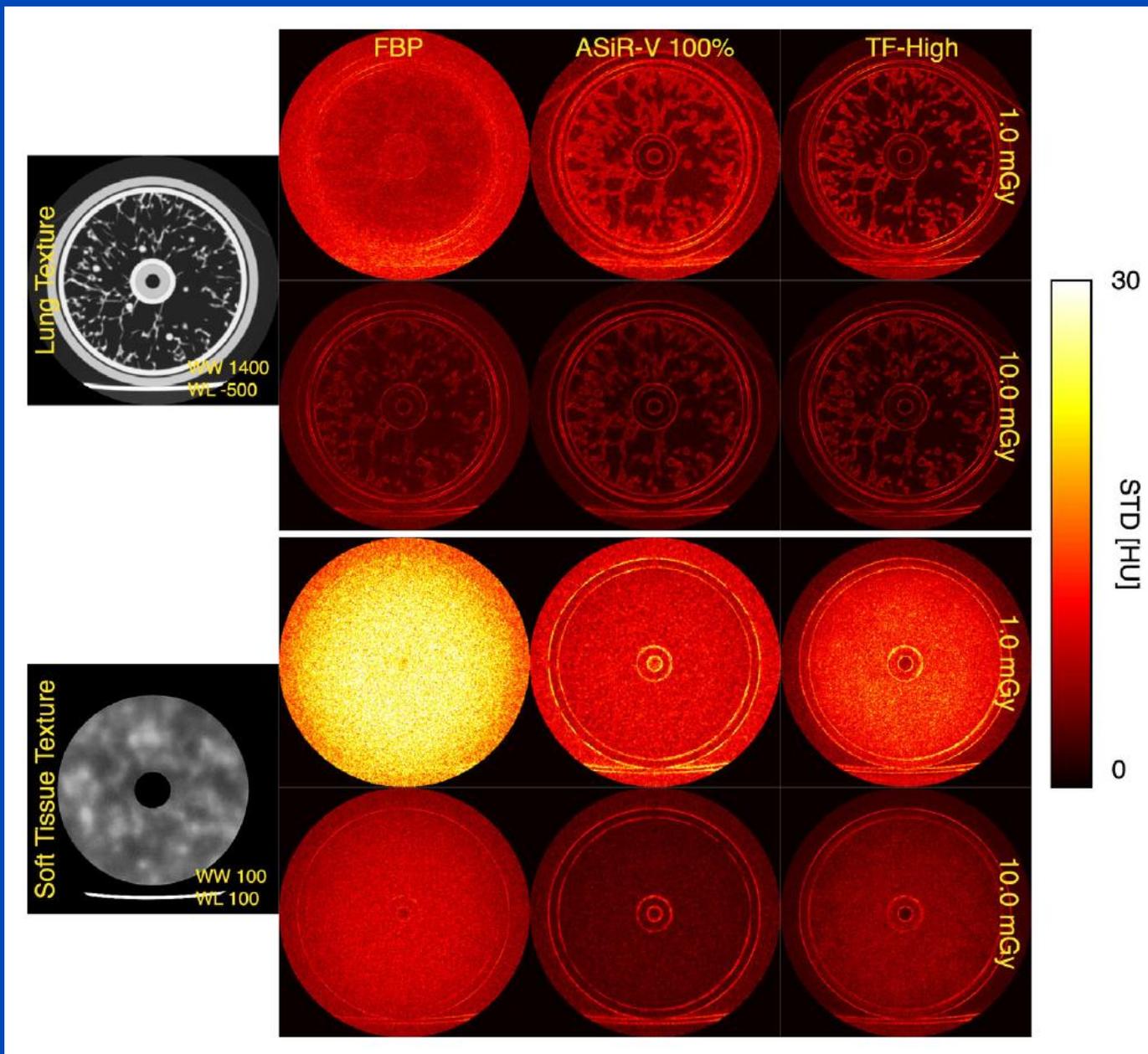
Noise Removal: Philips' Precise Image

- **Noise-injected data serve as low dose examples while their original reconstructions are the labels. A CNN learns how to denoise the low dose images.**
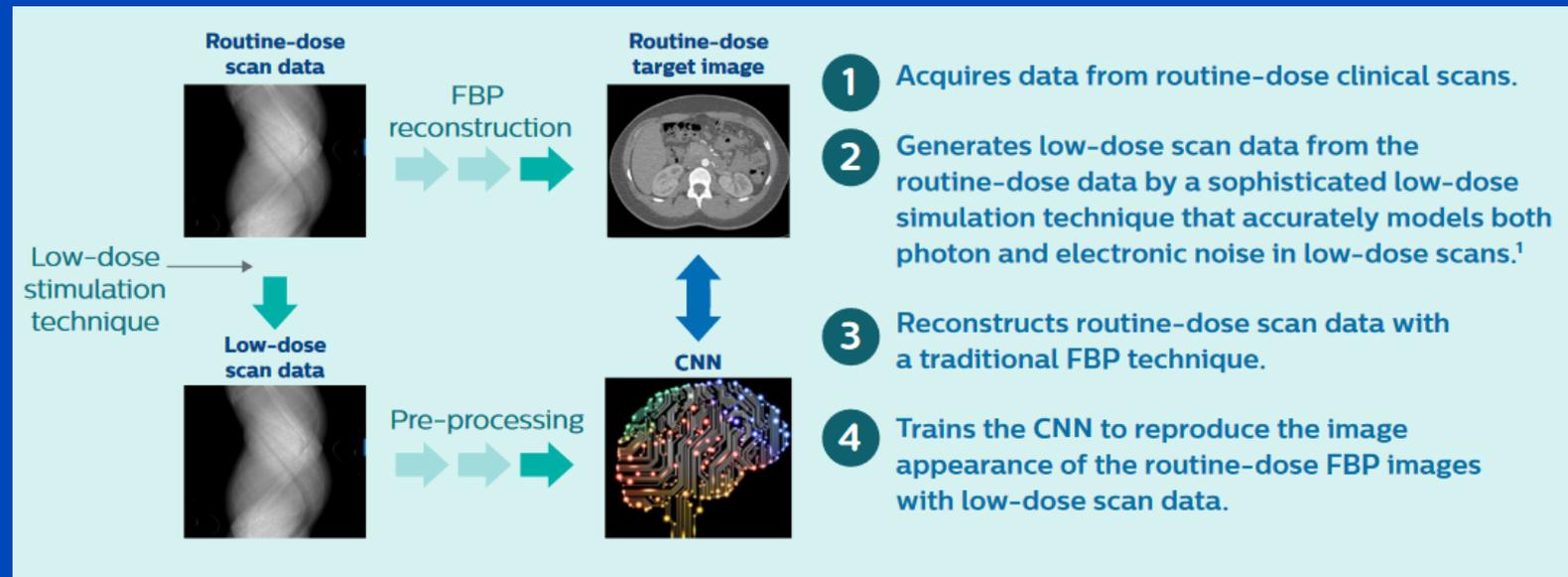
iDose⁴ 1.4 mSv   Precise Image 0.7 mSv   iDose⁴ 5.1 mSv   Precise Image 2.6 mSv
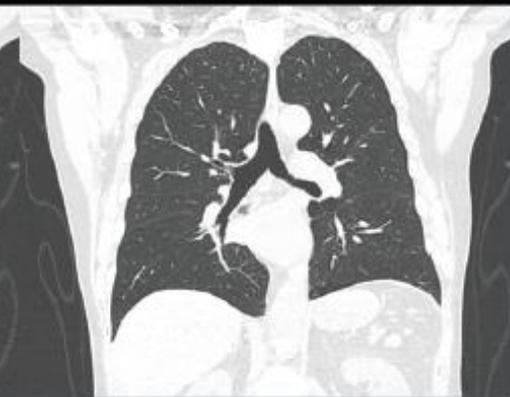
iDose⁴ 1.5 mSv   Precise Image 0.75 mSv   iDose⁴ 5.4 mSv   Precise Image 2.6 mSv
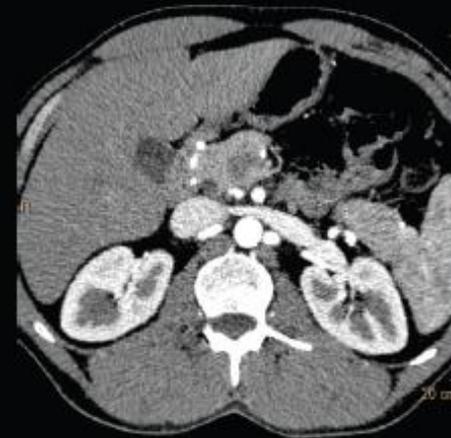
Taken from https://www.philips.com/c-dam/b2bhc/master/resource-catalog/landing/precise-suite/incisive_precise_image.pdf

dkfz.
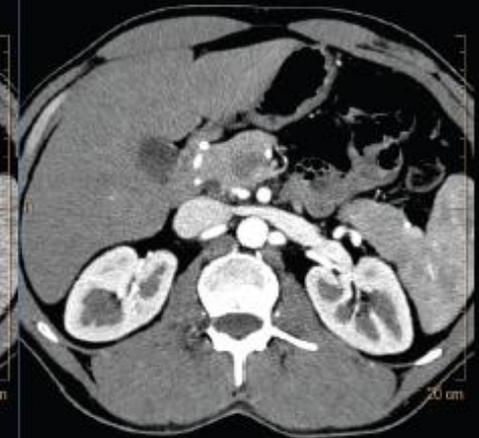
Study	Topic	Dose Reduction	Assessment	Reconstruction	Vendor
Beregi et al., 2022	low-dose abdomen phantom	79%	objective	AiCE	Canon
Hirai et al., 2022a	low-dose multiphase hepatic	52%	objective, subjective	AiCE	Canon
Hirai et al., 2022b	low-dose pediatric 80 kV	54%	objective, subjective	AiCE	Canon
Jin et al., 2022	low-dose interstitial lung disease	62%	objective, subjective	AiCE	Canon
Loffroy et al., 2022	low-dose head & neck	43%	objective, subjective	AiCE	Canon
Sun et al., 2022	ultra-low-dose urolithiasis	75%	objective, subjective	AiCE	Canon
Yoshioka et al., 2022	low-dose contrast abdomen	40%	objective, subjective	AiCE	Canon
Awai et al., 2021	low-dose abdominal UHR	30%	objective, subjective	AiCE	Canon
Dillman et al., 2021	pediatric detectability	52%	objective, subjective	AiCE	Canon
Loffroy et al., 2021	cardiac CTA stroke	40%	objective, subjective	AiCE	Canon
Kalra et al., 2020	low-dose lesion detection	83%	subjective	AiCE	Canon
Song et al., 2024	low-dose chest, lung parenchyma	86%	objective, subjective	AiCE	Canon
Othmann et al., 2023	ultra-high-resolution Head and Neck	30%	objective, subjective	AiCE	Canon
Willemink et al., 2023	principles & prospects	71%	mixed	meta	many
Strigari et al., 2023	image quality phantom	96%	objective	Precise Image	Philips
Noel et al., 2024	lung phantom	25%-67%	objective	Precise Image	Philips
Deng et al., 2022	ultra-low-dose pulmonary nodules phantom	72%	objective, subjective	TrueFidelity	GE
Lee et al., 2021	pediatric chest & abdomen	63%	objective, subjective	TrueFidelity	GE
Funama et al., 2024	preoperative transcatheter aortic valve implantation	30%	objective, subjective	TrueFidelity	GE
Xi et al., 2024	colorectal cancer	75%	objective, subjective	AIIR	United

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REPLACEMENT OF LENGTHY COMPUTATIONS, FAST PHYSICS

Deep Scatter Estimation (DSE)

TOP DOWNLOADED PAPER 2018-2019

CONGRATULATIONS TO
Marc Kachelriess
whose paper has been recognized as
one of the most read in

Medical...

WILEY

MEDICAL PHYSICS
The International Journal of Medical Physics Research and Practice

Congratulations — your work was one of the top downloaded in recent publication history!

Dear MARC,

We are excited to share that your research, published in *Medical Physics*, is among the top 10% most downloaded papers!

- **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**

This work received the
Behnken-Berger Award
at the DGMP annual meeting 2021

BEHNKEN-BERGER STIFTUNG

OP DOWNLOADED PAPER 2018-2019

CONGRATULATIONS TO
Joscha Maier
whose paper has been recognized as
one of the most read in

Medical Physics

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.

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Motivation

- **X-ray scatter is a major cause of artifacts in CT and CBCT.**

- **Appropriate scatter correction is crucial to maintain the diagnostic value of the CT examination.**

Primary intensity

CT image

CT reconstruction

(+) scatter

CT reconstruction

C = 0 HU, *W* = 800 HU

dkfz.
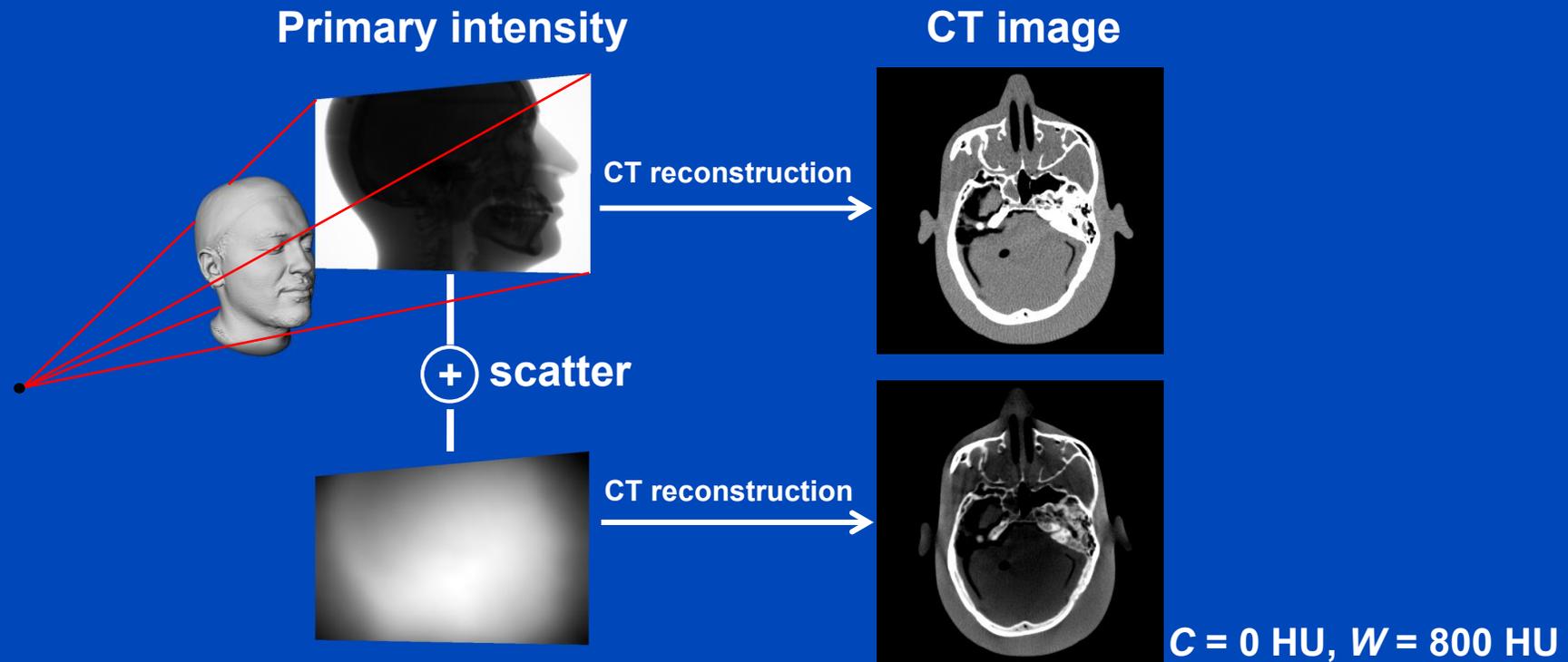
Monte Carlo Scatter Estimation

- Simulation of photon trajectories according to physical interaction probabilities.

- Simulating a large number of photon t~~~~~~~~~~~~ approximates the actual scatter distrib~~~~~

1 to 10 hours per tomographic data set

Complete scatter distribution

$$\int$$
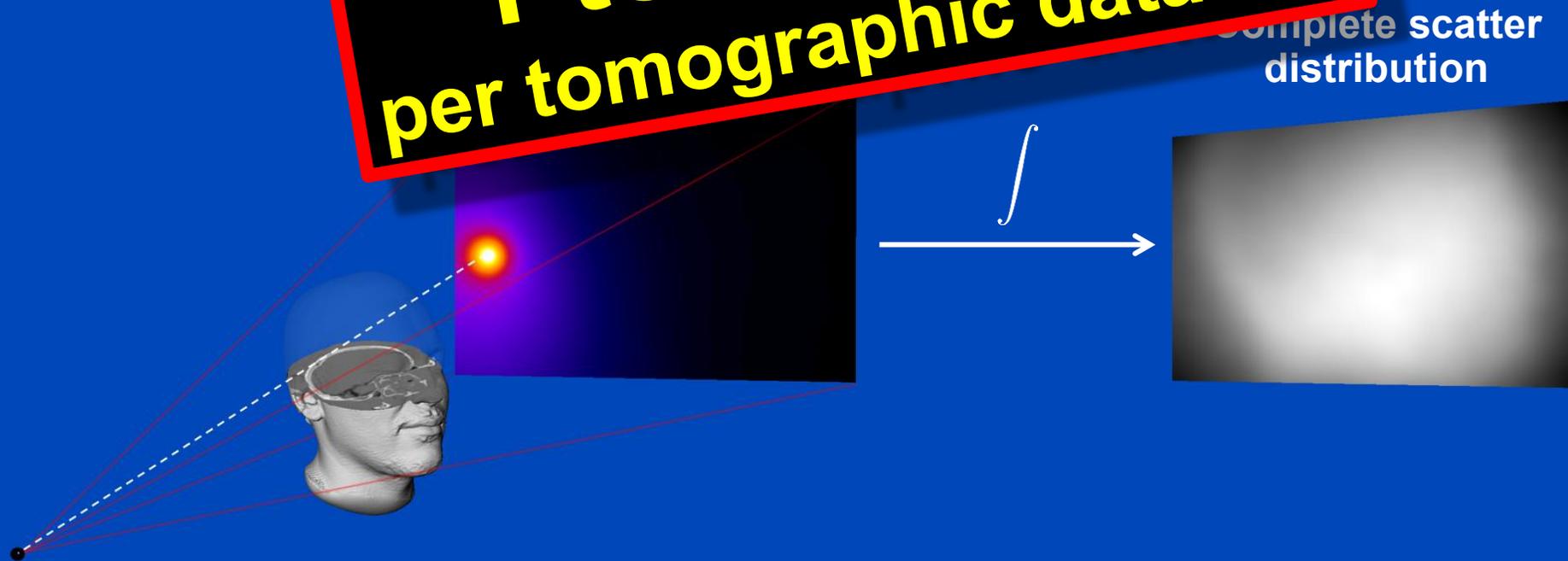
Deep Scatter Estimation
Network architecture & scatter estimation framework

Input:

384 × 256 × 4

**Output:
scatter estimate**

**1 to 10 seconds
per tomographic data set**

**Downsampling
and application
of operator**

$$T(p) = p\,e^{-p}$$

**Upsampling
to original
size**

48 × 32 × 160

24 × 16 × 320

12 × 8 × 480

6 × 4 × 960

Projection data

→ 3 x 3 Convolution, ReLU
→ 1 x 1 Convolution, ReLU
↓ 2 x 2 Max. Pooling
↑ 2 x 2 Upsampling
○ Depth Concatenate

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.

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Training the DSE Network

CBCT Setup

Primary intensity

MC scatter simulation

Poisson noise

\+ \+ → **Input**

Desired output
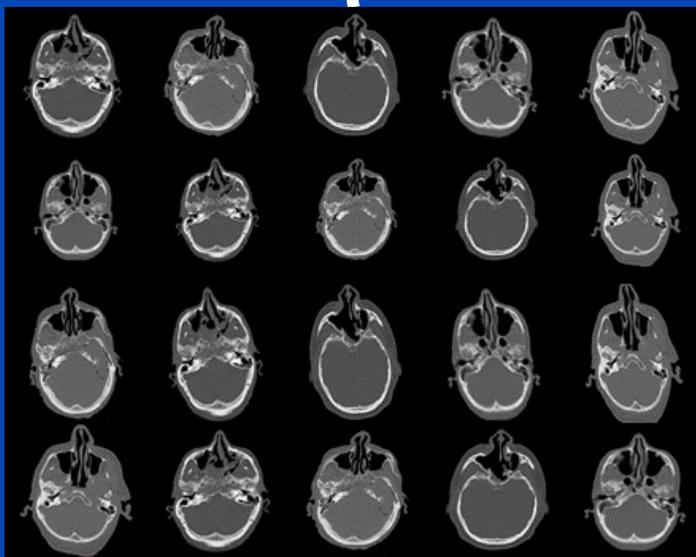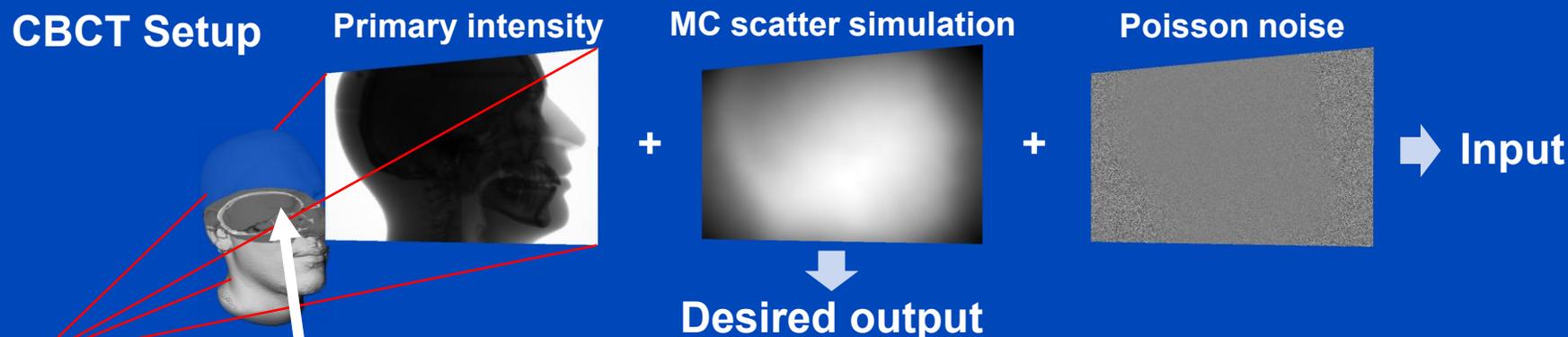
- **Simulation of 6000 projections using different heads and acquisition parameters (80 kV, …, 140 kV in steps of 20 kV).**
- **Splitting into 80% training and 20% validation data.**
- **Mean S/P = 0.9**
- **90th percentile S/P = 1.32**
- **Training minimizes MSE pixel-wise loss on a GeForce GTX 1080 for 80 epochs.**

dkfz.

Testing of the DSE Network for Simulated Data (at 120 kV)

CBCT Setup

Primary intensity

MC scatter simulation

Poisson noise

+ + → **Input**
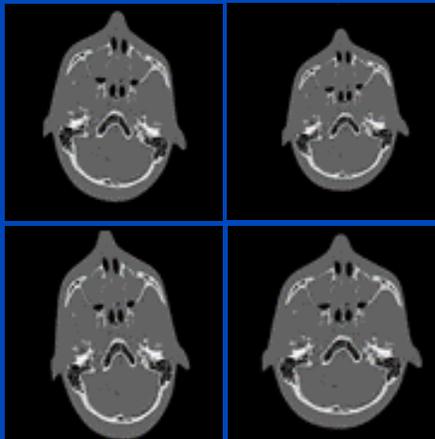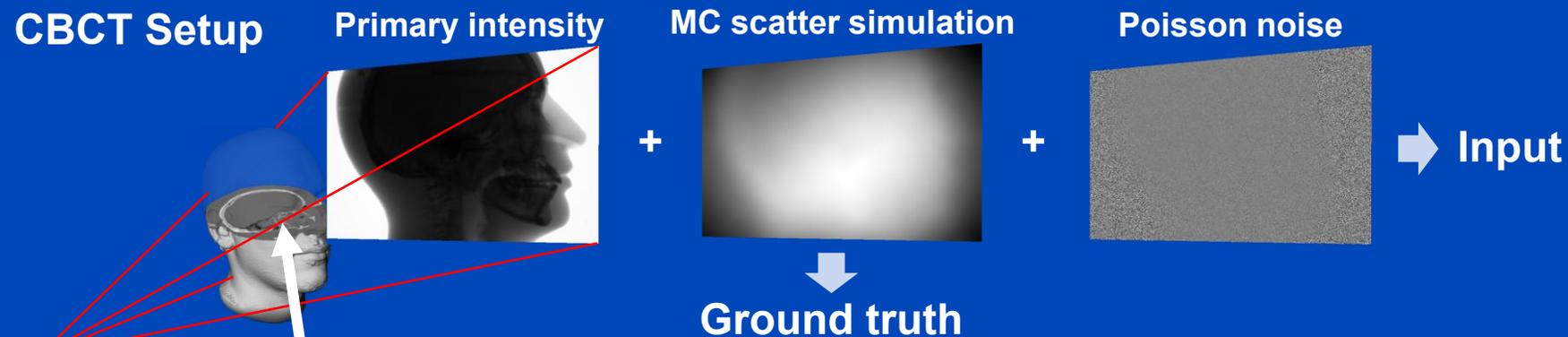
Ground truth

- Application of the DSE network to predict scatter for simulated data of a head (different from training data).

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.

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Results on Simulated Projection Data

	Primary intensity	Scatter ground truth (GT)	(Kernel – GT) / GT	(Hybrid - GT) / GT	(DSE – GT) / GT
View #1			**14.1%** mean absolute percentage error over all projections	**7.2%** mean absolute percentage error over all projections	**1.2%** mean absolute percentage error over all projections
View #2					
View #3					
View #4					
View #5	C = 0.5, W = 1.0	C = 0.04, W = 0.04	C = 0%, W = 50%	C = 0%, W = 50%	C = 0%, W = 50%

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

Results on Simulated Projection Data

	Primary intensity	Scatter ground truth (GT)	(Kernel – GT) / GT	(Hybrid - GT) / GT	(DSE – GT) / GT
View #1			**14.1%** mean absolute percentage error over all projections	**7.2%** mean absolute percentage error over all projections	**6.4%** mean absolute percentage error over all projections
View #2					
View #3					
View #4					
View #5					
	C = 0.5, W = 1.0	C = 0.04, W = 0.04	C = 0%, W = 50%	C = 0%, W = 50%	C = 0%, W = 50%

DSE, in its present form, needs to see scatter in its input data!

DSE trained to estimate scatter from **primary only**: Low accuracy

Results on Simulated Projection Data

	Primary intensity	Scatter ground truth (GT)	(Kernel – GT) / GT	(Hybrid - GT) / GT	(DSE – GT) / GT
View #1			**14.1%** mean absolute percentage error over all projections	**7.2%** mean absolute percentage error over all projections	**1.2%** mean absolute percentage error over all projections
View #2					
View #3					
View #4					
View #5	C = 0.5, W = 1.0	C = 0.04, W = 0.04	C = 0%, W = 50%	C = 0%, W = 50%	C = 0%, W = 50%

DSE, in its present form, needs to see scatter in its input data!

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

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Reconstructions of Simulated Data

Ground Truth | No Correction | Kernel-Based Scatter Estimation | Hybrid Scatter Estimation | Deep Scatter Estimation

CT Reconstruction / Difference to ideal simulation

$C = 0$ 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.
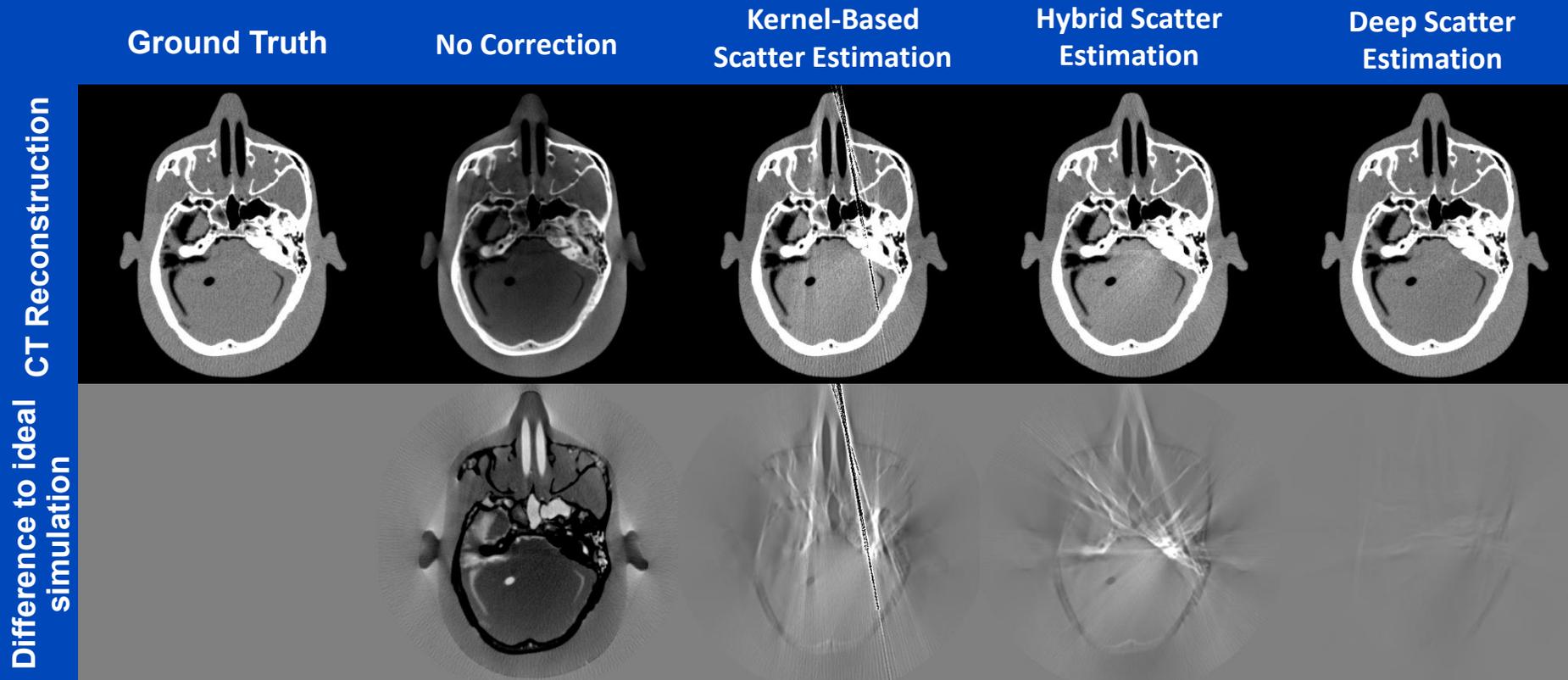
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Testing of the DSE Network for Measured Data (120 kV)

DKFZ table-top CT

Measurement to be corrected

X-ray source

Detector

Ground truth: slit scan

Collimator

X-ray source

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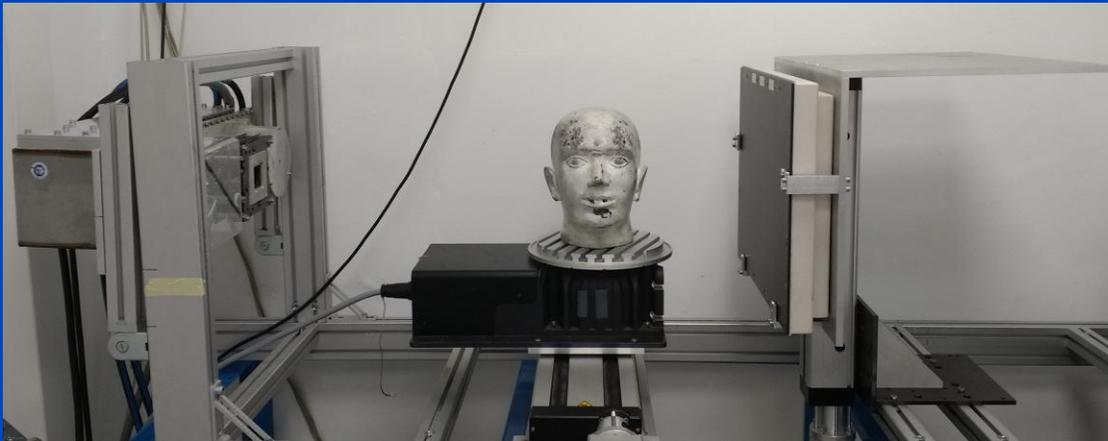
- **Measurement of a head phantom at our in-house table-top CT.**
- **Slit scan measurement serves as ground truth.**

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.

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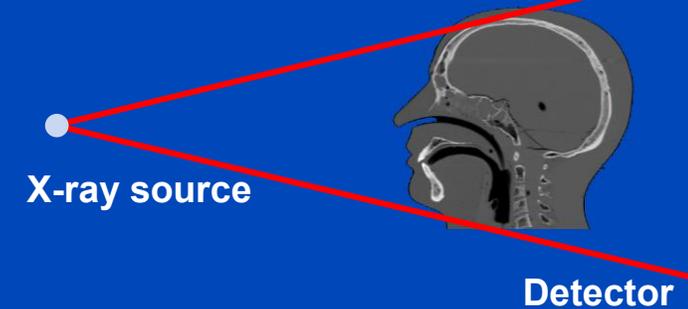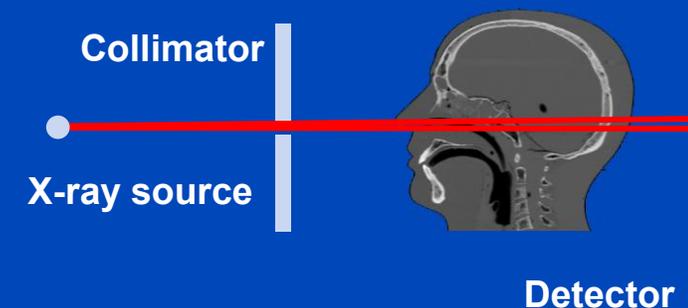
Reconstructions of Measured Data

Parameters of the two comparison methods trained in the same way as those of DSE: same data, same loss function, same optimization algorithm.

Slit Scan | No Correction | Kernel-Based Scatter Estimation | Hybrid Scatter Estimation | DSE Deep Scatter Estimation

CT Reconstruction

Difference to slit scan

$C = 0$ 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.

dkfz.
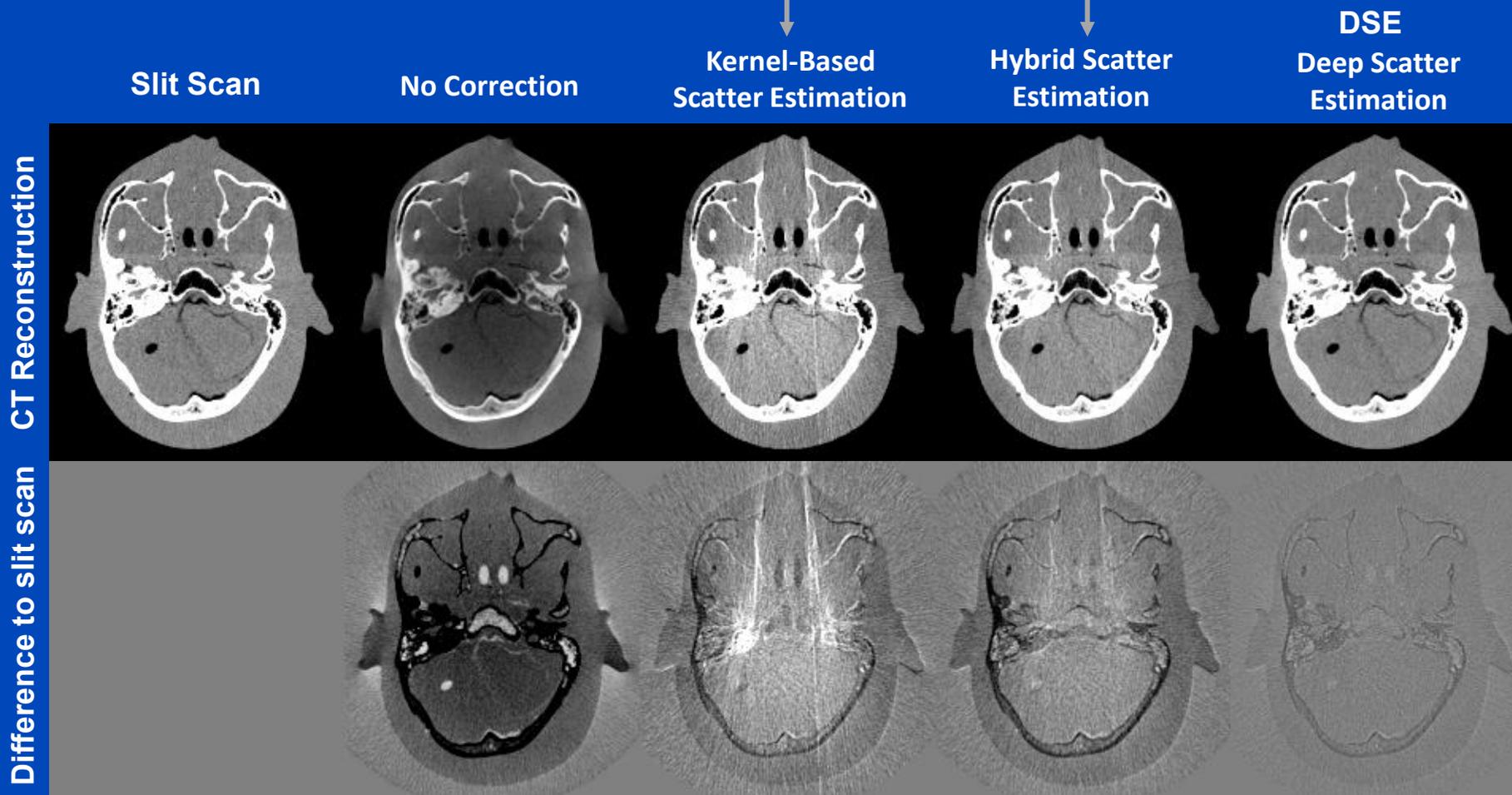
Truncated DSE

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

FOM

40 × 40 cm² flat detector
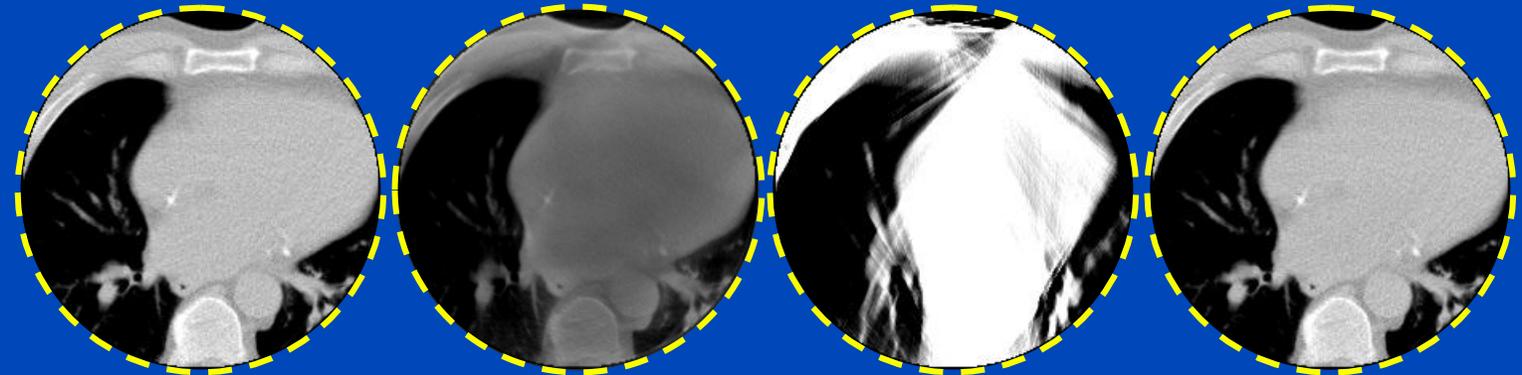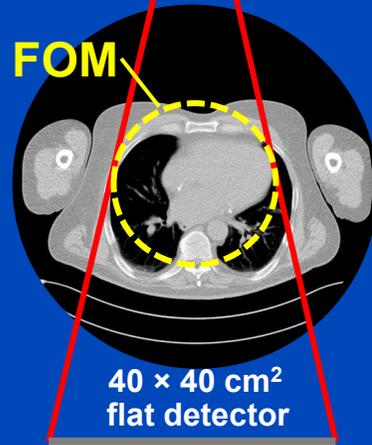
Ground truth **Uncorrected** **MC-corrected** **DSE**

FOM

40 × 40 cm² flat detector
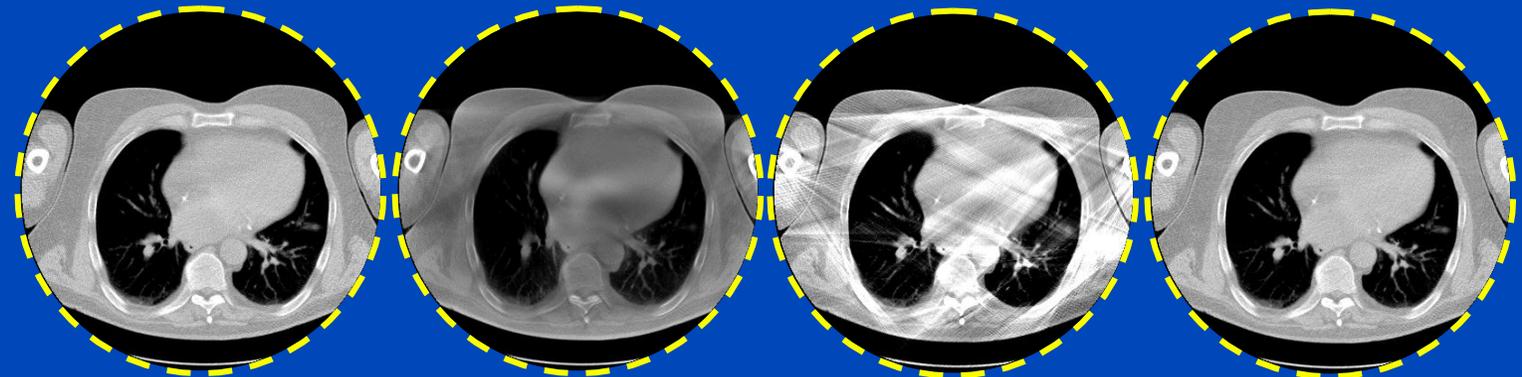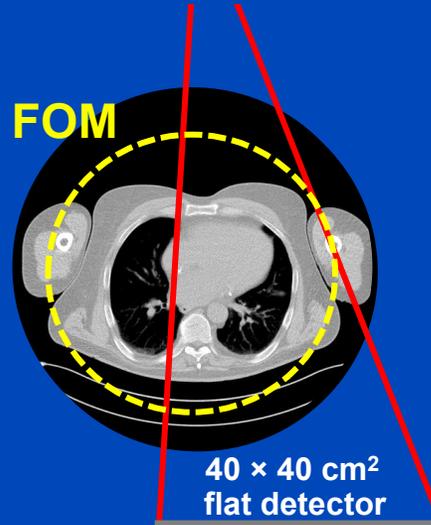
To learn why MC fails at truncated data and what significant efforts are necessary to cope with that situation see [Kachelrieß et al. Effect of detruncation on the accuracy of MC-based scatter estimation in truncated CBCT. Med. Phys. 45(8):3574-3590, August 2018].

Does DSE Generalize to Different Anatomical Regions?

- **DSE:**

DSE	Head	Thorax	Abdomen
Head	1.2	21.1	32.7
Thorax	8.8	1.5	9.1
Abdomen	11.9	10.9	1.3
All data	1.8	1.4	1.4

Values shown are the mean absolute percentage errors (MAPEs) of the testing data.
Note that thorax and head suffer from truncation due to the small size of the 40×30 cm flat detector.

- **KSE** ("trained" using the same data)**:**

KSE	Head	Thorax	Abdomen
Head	14.5	26.8	32.5
Thorax	16.2	18.5	19.4
Abdomen	16.8	22.1	17.8
All data	14.9	20.5	19.3

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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.

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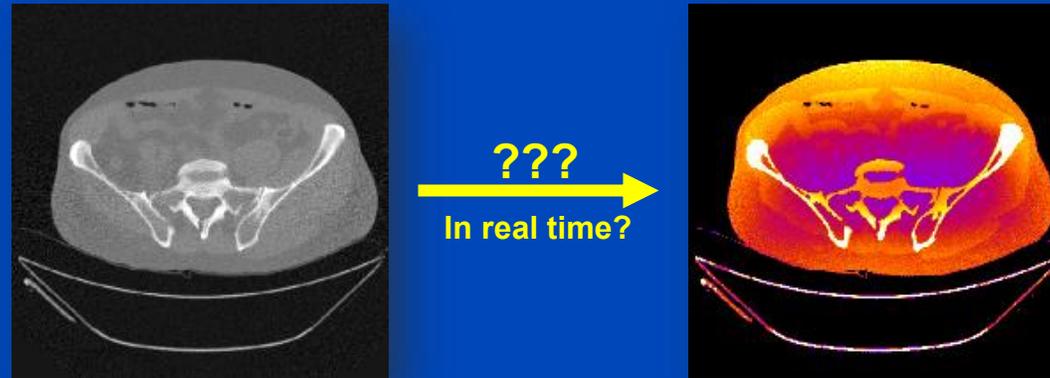
Deep Dose Estimation

MEDICAL PHYSICS

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

Joscha Maier[1] | Laura Klein[1,2] | Elias Eulig[1,2] | Stefan Sawall[1,2] |
Marc Kachelrieß[1,2]

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

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

Correspondence
Joscha Maier, German Cancer Research Center (DKFZ), Heidelberg, Germany.
Email: joscha.maier@dkfz.de

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

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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.**

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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.

dkfz.

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 |
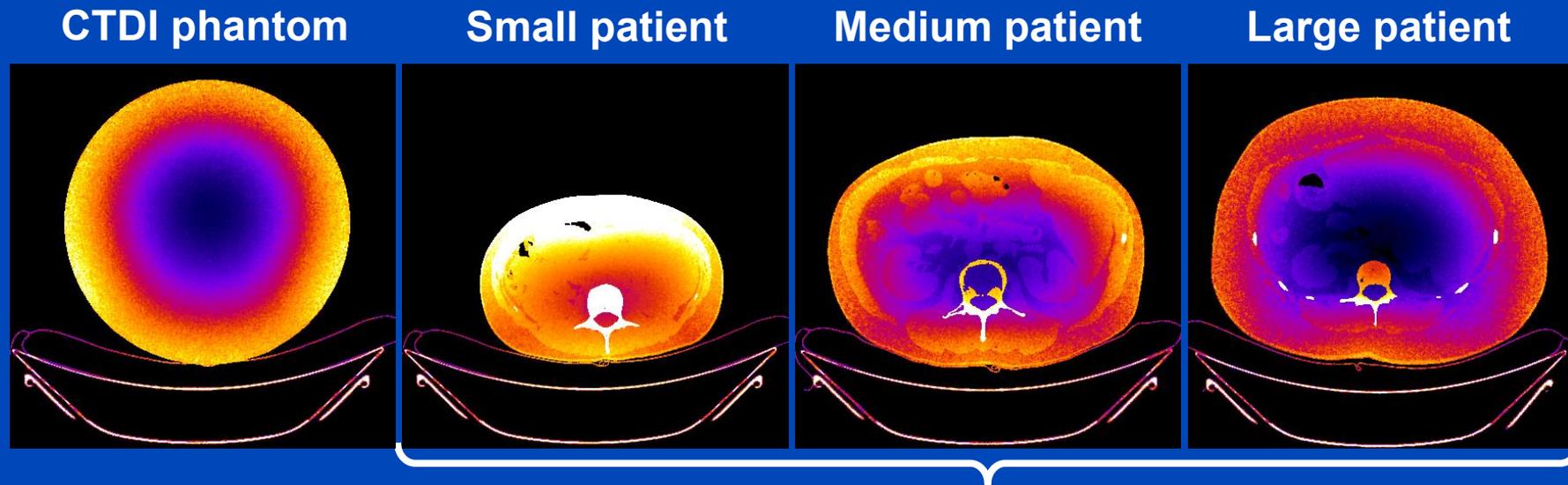
Same CTDI, but different dose distribution

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

MC Dose Simulation for a 360° Scan
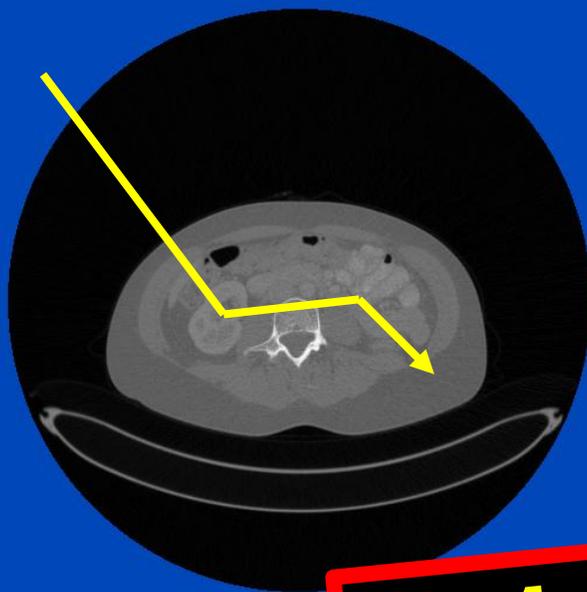
Patient **Dose per Projection** **Cumulative Dose**
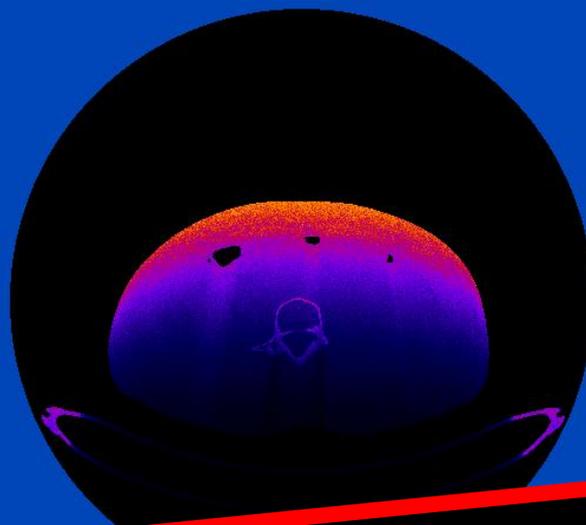
1 to 10 hours
per tomographic data set

dkfz.
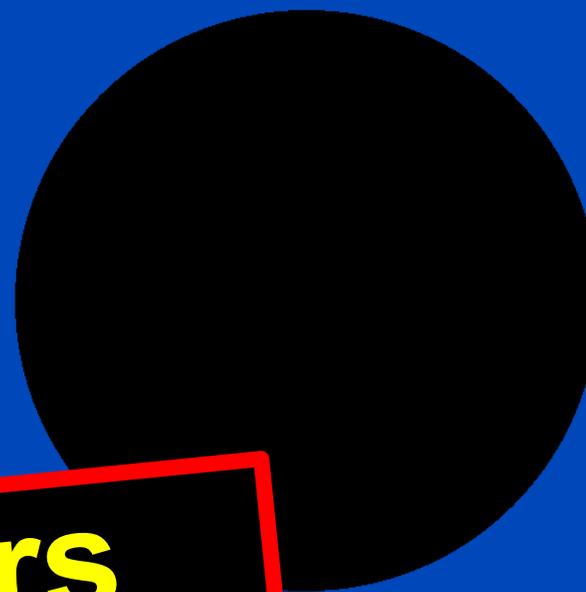
Deep Dose Estimation (DDE)

- **Combine fast and accurate CT dose estimation using a deep convolutional neural network.**

- **Train the network to reproduce MC ~~...~~ ven the CT image and a first-orde~~...~~**

1 to 10 seconds per tomographic data set

2-channel

CT image

1st order dose

$128 \times 128 \times 24 \times 32$

$64 \times 64 \times 12 \times 64$

$32 \times 32 \times 6 \times 128$

$16 \times 16 \times 3 \times 256$

MC-dose[1] target:

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

▷ $3 \times 3 \times 3$ Convolution (stride = 1), ReLU   ▷ $3 \times 3 \times 3$ Convolution (stride = 2), ReLU   ▷ $1 \times 1 \times 1$ Convolution (stride = 1), ReLU   ▮ $2 \times 2 \times 2$ Upsampling

○ Depth concatenate

dkfz.
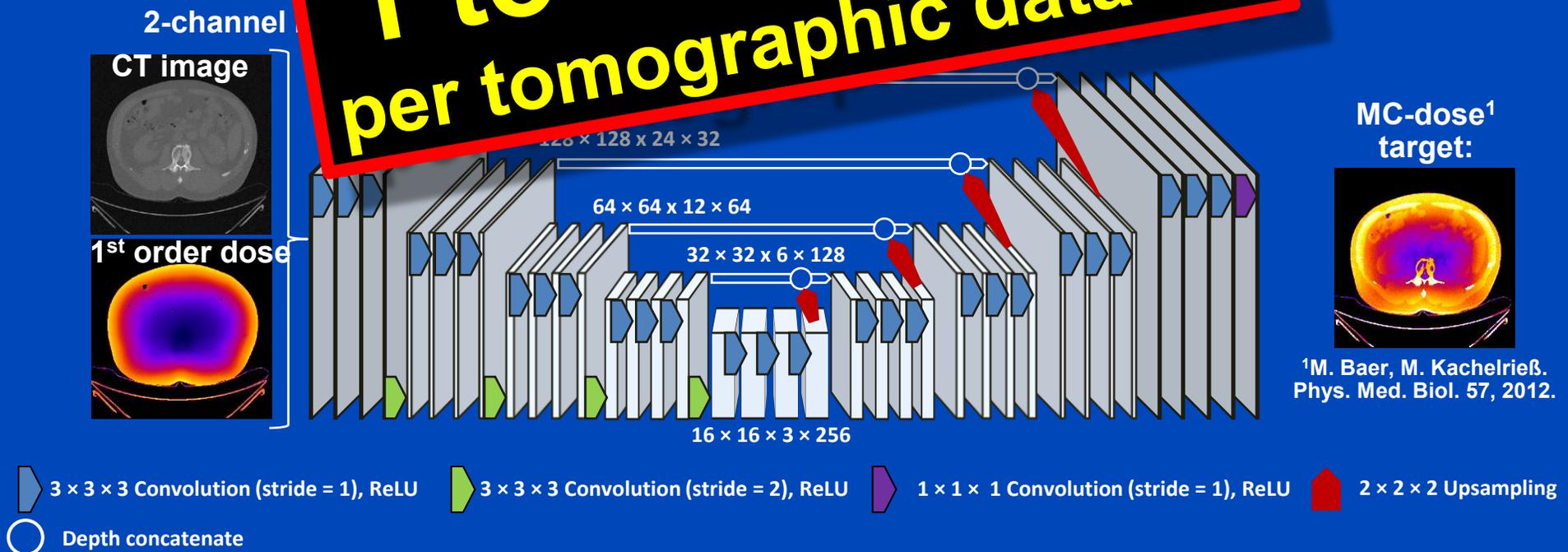
Results
Thorax, tube A, 120 kV, no bowtie

CT image
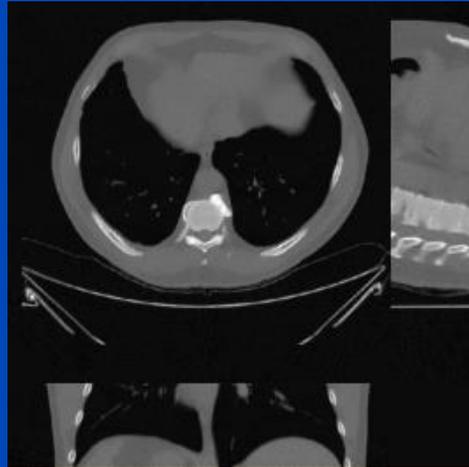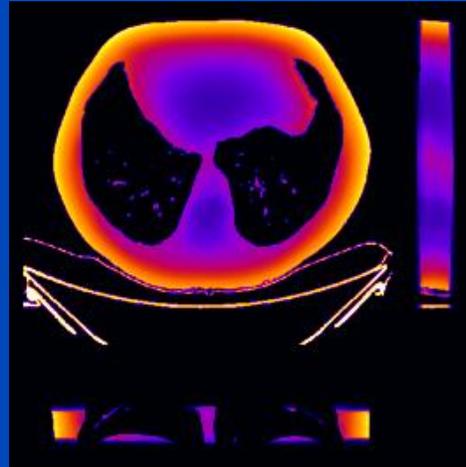
First order dose

	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
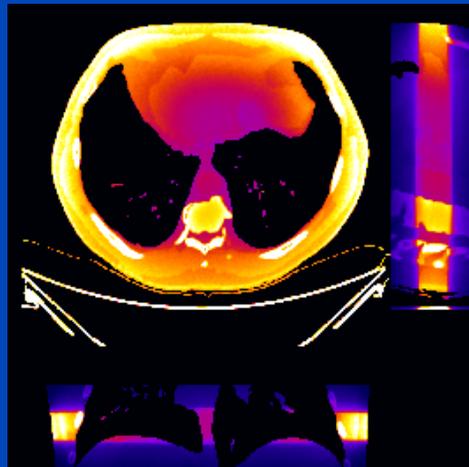
DDE
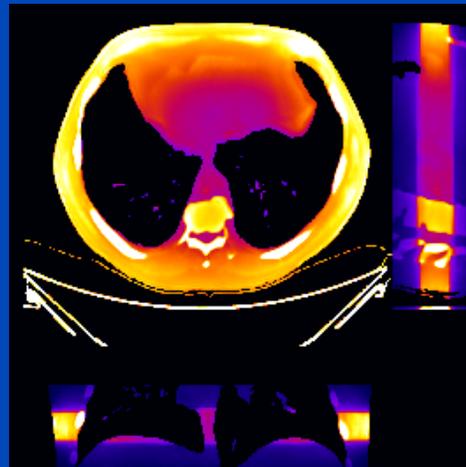
Relative error

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

dkfz.
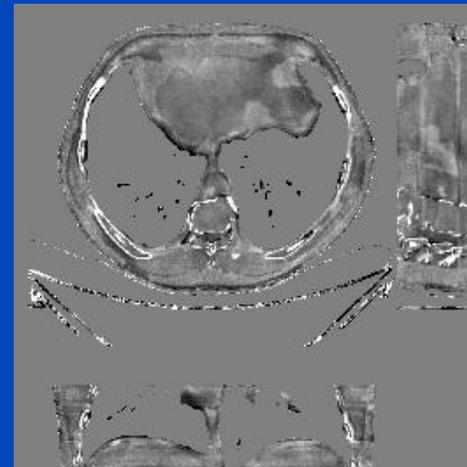
Results
Thorax, tube B, 120 kV, no bowtie

CT image

First order dose

MC ground truth

DDE

Relative error

	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

C = 0%
W = 40%

dkfz.
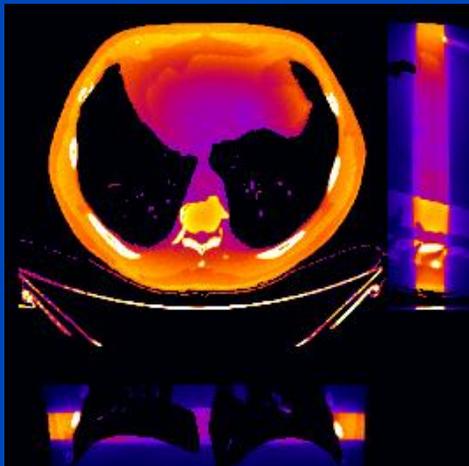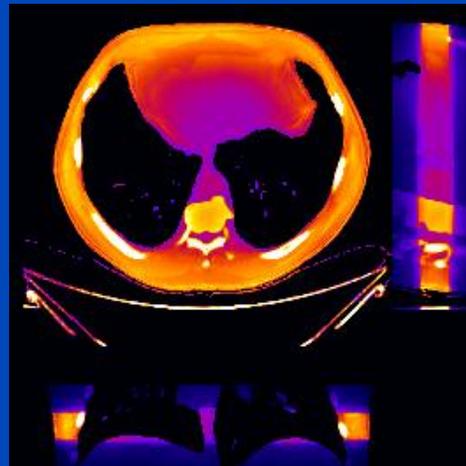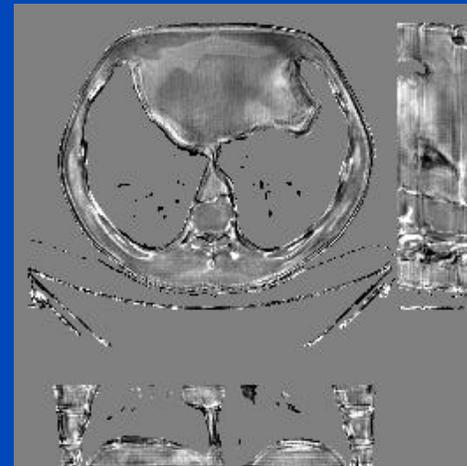
Comments for Practical Use

- **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.**

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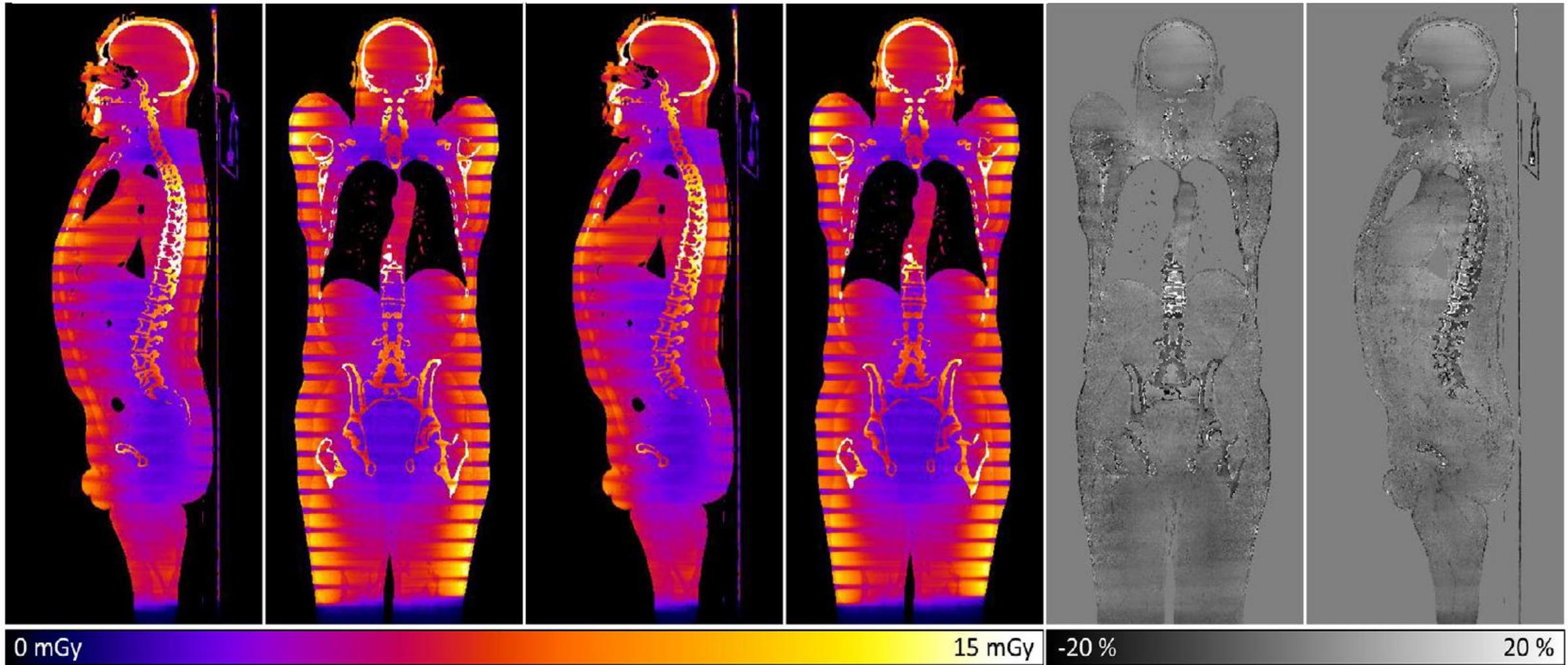
FIGURE 5 Sagittal and coronal view of the dose distribution of a 100 kV whole-body spiral computed tomography (CT) scan including a bowtie filter and an angular tube current modulation. Here, the two left columns show the ground truth, the middle columns show the deep dose estimation (DDE) prediction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

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 may become feasible with DDE.**

dkfz.

OTHER APPLICATIONS

dkfz.

Patient Risk-Minimizing Tube Current Modulation (riskTCM)

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, C. Liu, J. Steidel, L. Enzmann, M. Knaup, S. Sawall, A. Maier, M. Lell, J. Maier, and M. Kachelrieß. Patient-specific radiation risk-based tube current modulation for diagnostic CT. Med. Phys. 49(7):4391-4403, July 2022.

$D_{\text{eff}}(\alpha)$

View angle

dkfz.
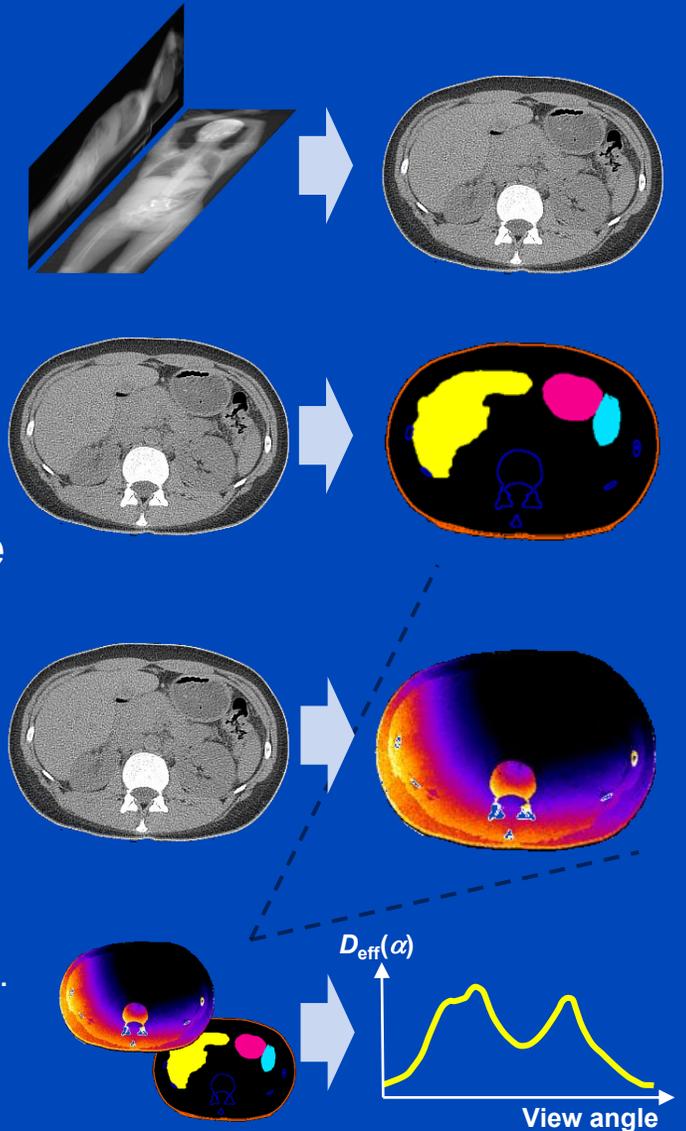
riskTCM Recognition

- Editor's Choice in Medical Physics 2022
- Best Research Presentation Award within Physics in Medical Imaging at the European Congress of Radiology (ECR) 2022
- Moses&Sylvia Greenfield Award 2023 for the best scientific paper on imaging in Medical Physics in 2022 (AAPM)
- Behnken-Berger-Award 2023 of the Behnken-Berger Society
- Dr. Franz Holeczke Award 2023 of the Association for Medical Radiation Protection in Austria (VMSÖ)

no TCM — $I(\alpha)$
21 HU, 133% mAs, 152% D_{eff}

mAsTCM — $I(\alpha)$
21 HU, 100% mAs, 100% D_{eff}

riskTCM — $I(\alpha)$
21 HU, 105% mAs, 95% D_{eff}

$D_{eff}(\alpha)$

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

dkfz.
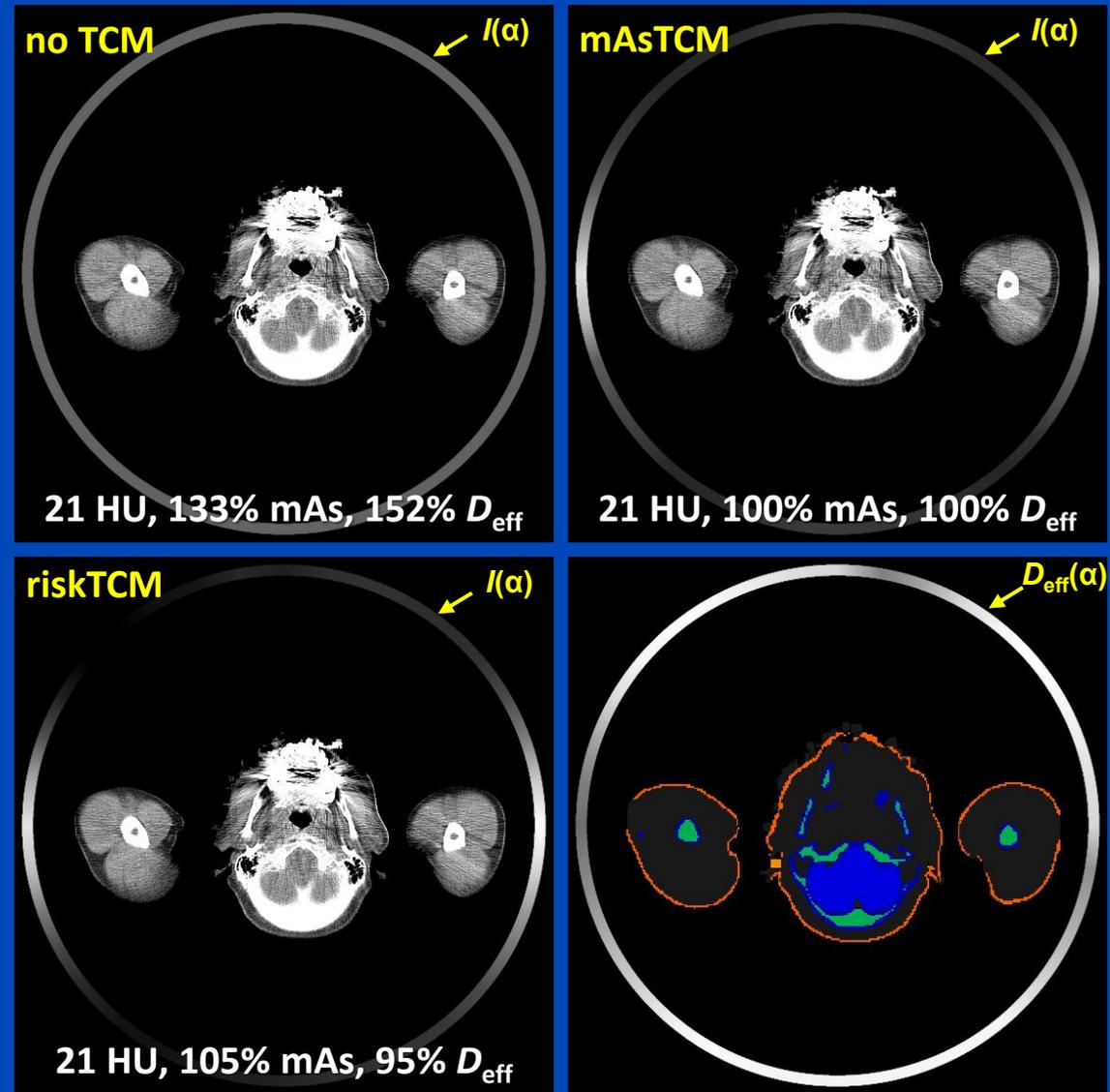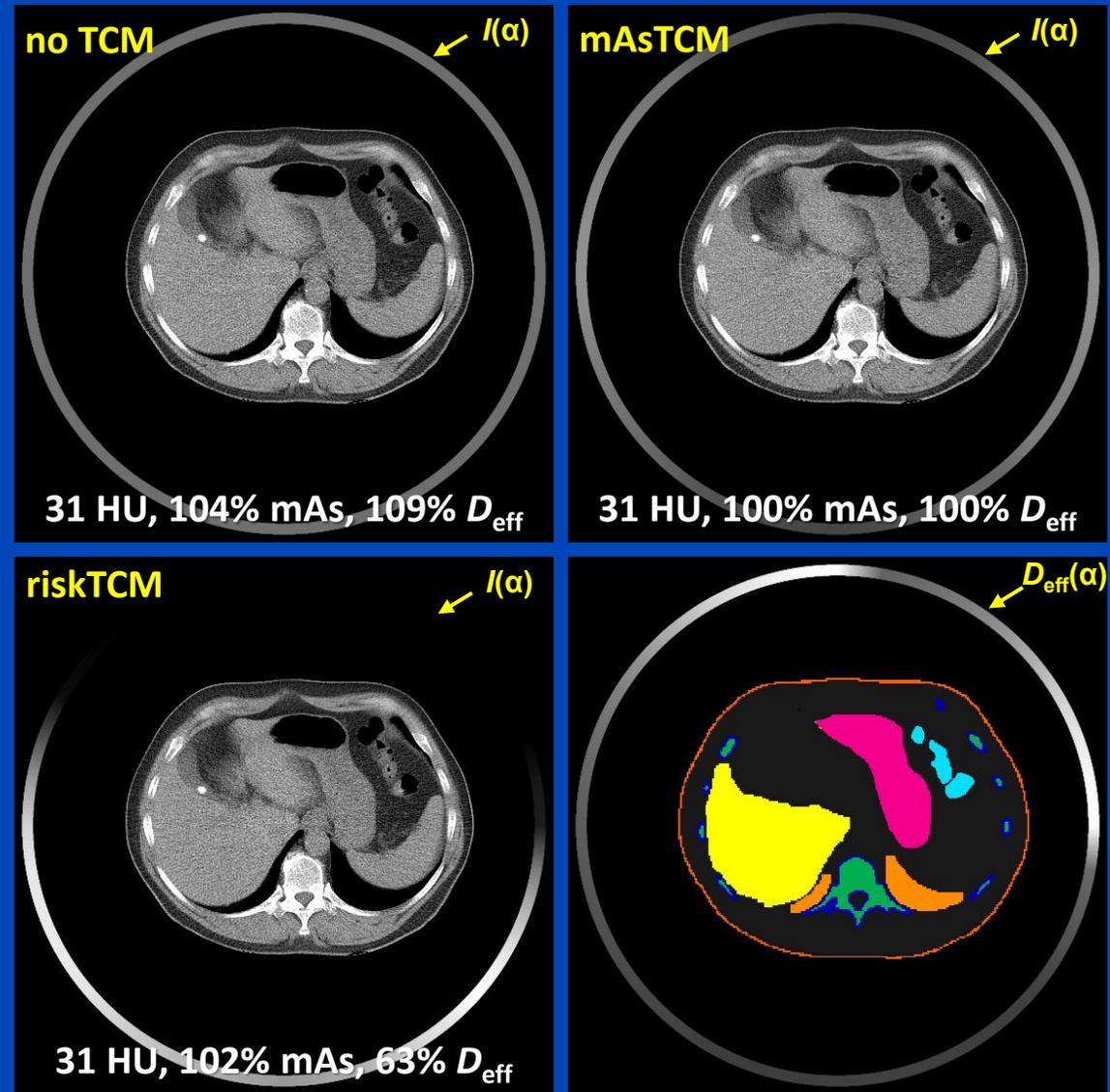
Effective Dose Values Relative to mAsTCM
Average over all patients and across all tube voltages (70 to 150 kV)

	noTCM	mAsTCM	riskTCM
Head	110%	100%	92%
Head+Arms	162%	100%	88%
Neck	223%	100%	76%
Thorax	113%	100%	81%
Abdomen	114%	100%	71%
Pelvis	152%	100%	79%

dkfz.

Conclusions on riskTCM

- **Risk-specific TCM minimizes the patient risk.**

- **With D_{eff} as a risk model riskTCM can reduce risk by up to 30%, compared with the gold standard.**

- **Other risk models, weight- and sex-specific models, can be used with riskTCM as well.**

- **Note:**
  - **mAsTCM = good for the x-ray tube**
  - **riskTCM = good for the patient**
  - detector flux equalizing TCM = good for the detector

It is up to the vendors to take action!

BEHNKEN-BERGER STIFTUNG
URKUNDE

For the scientific contributions to the reduction of radiation exposure in computed tomography through patient-specific tube current modulation oriented to the radiation risk of the organs
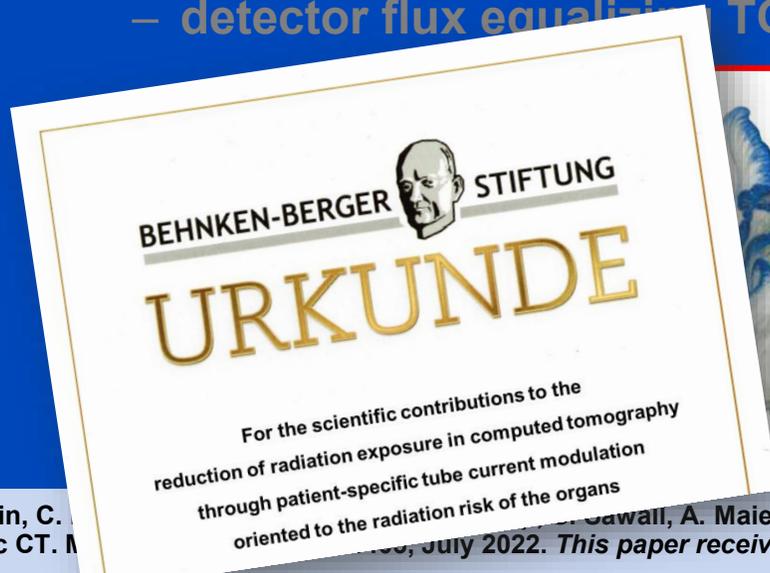
ECR 2022 – Best Research Presentation Abstract

within the topic Physics in Medical Imaging with the presentation:

Risk-minimising tube current modulation (riskTCM) for CT – potential dose reduction across different tube voltages (16765)

L. Klein1, C. Liu2, J. Steidel1, L. Enzmann1, S. Sawall1, J. Maier1, A. Maier2, M. Lell3, M. Kachelrieß1; 1Heidelberg/DE, 2Erlangen/DE, 3Nuremberg/DE

AMERICAN ASSOCIATION of PHYSICISTS IN MEDICINE

Congratulations

This paper received the Sylvia&Moses Greenfield Award for the best scientific paper on imaging in Medical Physics in 2022.

dkfz.

riskTCM vs. Breast-Specific TCM

- osTCM mimics X-Care (Siemens Healthineers)
- Reduces the tube current to 25% for the anterior 120°
- Higher tube current for the remaining 240°
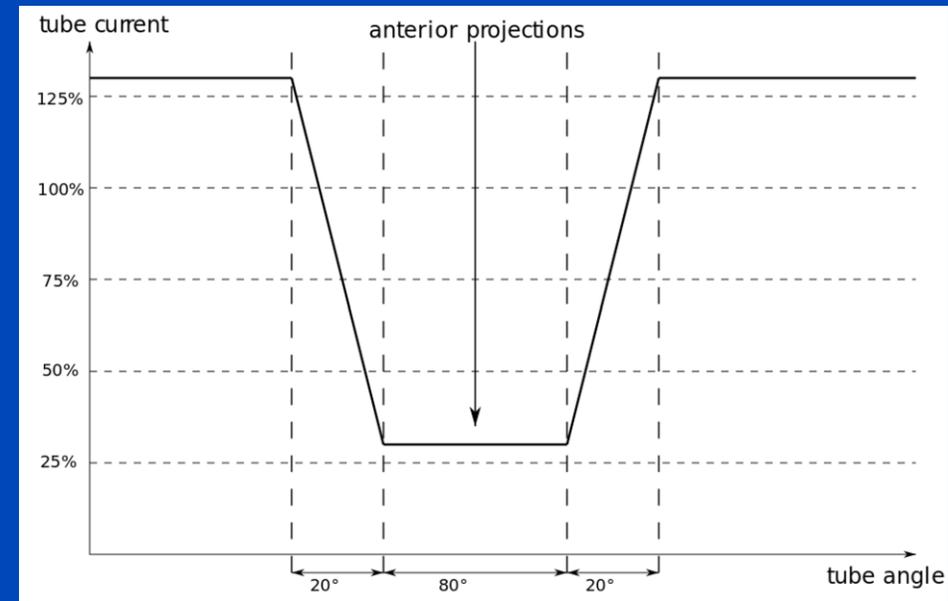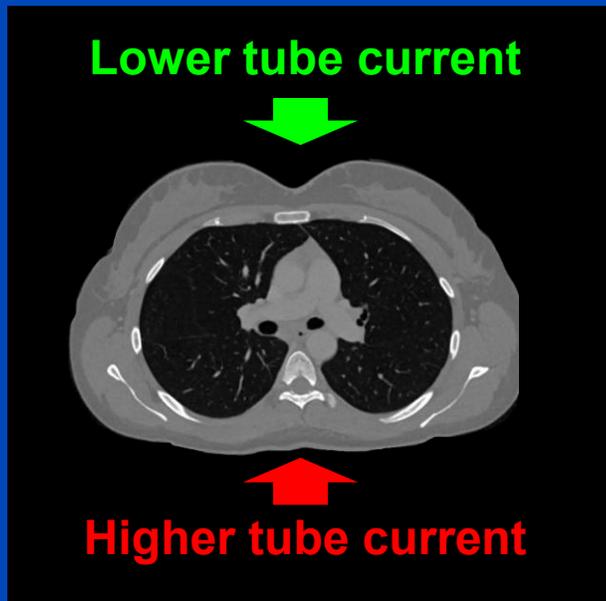
D. Ketelsen et al. Automated computed tomography dosesaving algorithm to protect radiosensitive tissues: estimation of radiation exposure and image quality considerations. Invest Radiol, 47(2):148–52, 2012

L. Klein, L. Enzmann, A. Byl, C. Liu, S. Sawall, A. Maier, J. Maier, M. Lell, and M. Kachelrieß.
Organ- vs. patient risk-specific TCM in thorax CT scans covering the female breast. CT Meeting 2022.

dkfz.

Results

noTCM

50 HU, 100% mAs, 100% D_{eff}
50 HU, 100% mAs, 100% D_{eff}
50 HU, 100% mAs, 100% D_{breast}

mAsTCM

50 HU, 90% mAs, 86% D_{eff}
47 HU, 104% mAs, 100% D_{eff}
50 HU, 90% mAs, 87% D_{breast}

osTCM$_{0\%}$

50 HU, 90% mAs, 71% D_{eff}
42 HU, 127% mAs, 100% D_{eff}
50 HU, 90% mAs, 56% D_{breast}

osTCM$_{25\%}$ (mimics X-Care)

50 HU, 90% mAs, 76% D_{eff}
44 HU, 119% mAs, 100% D_{eff}
50 HU, 91% mAs, 65% D_{breast}

riskTCM

50 HU, 89% mAs, 62% D_{eff}
39 HU, 145% mAs, 100% D_{eff}
50 HU, 92% mAs, 39% D_{breast}

Data courtesy of Prof. Lell, Nürnberg. C = 25 HU, W = 400 HU

L. Klein, L. Enzmann, A. Byl, C. Liu, S. Sawall, A. Maier, J. Maier, M. Lell, and M. Kachelrieß.
Organ- vs. patient risk-specific TCM in thorax CT scans covering the female breast. CT Meeting 2022.

dkfz.

Dose Values for the Thorax at Same Image Noise for 70 kV
Average over all patients

TCM Method	Effective Dose D_{eff}	Dose to the Breast D_{Breast}
noTCM	**116%** from 111% to 132%	**108%** from 102% to 125%
mAsTCM	**100%**	**100%**
osTCM$_{25\%}$	**95%** from 91% to 100%	**77%** from 74% to 90%
osTCM$_{0\%}$	**91%** from 83% to 98%	**70%** from 65% to 87%
riskTCM	**77%** from 67% to 81%	**49%** from 40% to 66%

dkfz.

REGISTRATION AND MOCO

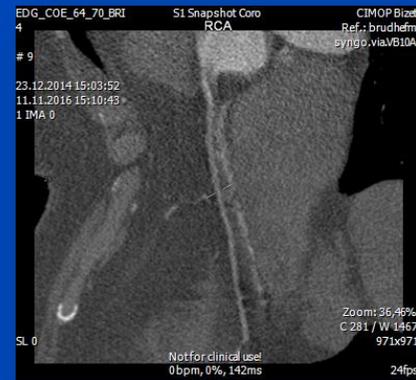# Deep Cosmetic Motion Artifact Reduction

- **Image-based correction
  = cosmetic correction
  = similar to pic beauty and others**

- **May not be the most ~~confi~~**

Don't do that! It's not physical!

**Stick to estimating motion vector fields!**

-affected

on generative adversarial networks. EuRad 33:43-53, 2023.

dkfz.

Deep Cardiac CT MoCo

???

Motivation

- **Cardiac CT imaging is routinely used for the diagnosis of cardiovascular diseases, especially those related to coronary arteries.**

- **Imaging of coronary arteries places high demands on the spatial and temporal resolution of the CT reconstruction.**

- **Motion artifacts and image noise may impair the diagnostic value of the CT examination.**

CTCA image of the right coronary artery[1]

Significant stenosis

CTCA image of the left coronary artery[2]

Nonsignificant stenosis
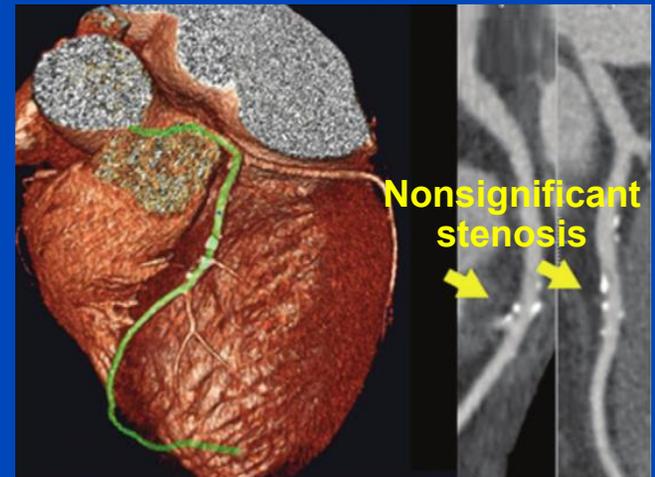
[1]W. B. Meijboom et al., "64-Slice Computed Tomography Coronary Angiography in Patients With High, Intermediate, or Low Pretest Probability of Significant Coronary Artery Disease", J. Am. Coll. Cardiol. 50 (15): 1469–1475 (2007).
[2]R. Leta et al., "Ruling Out Coronary Artery Disease with Noninvasive Coronary Multidetector CT Angiography before Noncoronary Cardiovascular Surgery", Heart 258 (2) (2011).
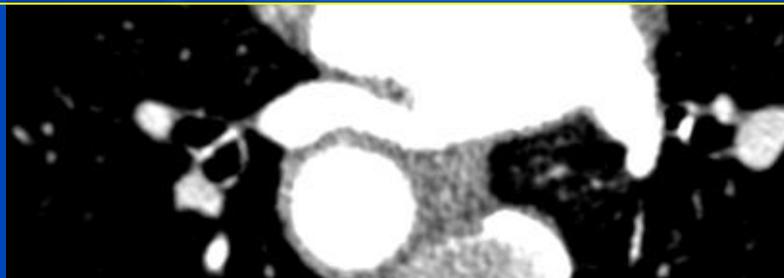
dkfz.

Motivation

Motion artifacts

High noise

C = 0 HU, W = 1200 HU

→Deep learning-based motion compensation to remove motion artifacts.
→Iterative reconstruction (Siemens ADMIRE) to reduce noise.

Table 3: Reason for FFR_CT Rejection in the ADVANCE Registry and Clinical Cohort

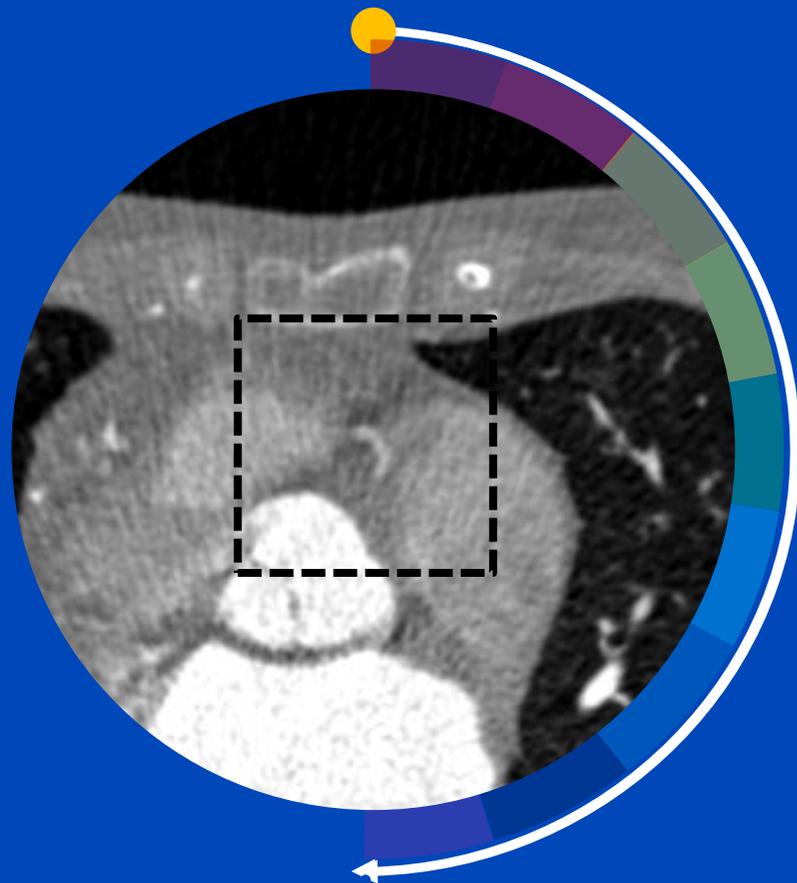|	FFR_CT Rejected*	
	ADVANCE (n = 80)	Clinical Cohort (n = 892)
Inadequate image quality		
Blooming	4 (5.0)	29 (3.0)
Clipped structure	4 (5.0)	39 (4.3)
Motion artifacts	63 (78.0)	729 (81.4)
Image noise	2 (2.5)	198 (22.1)
Inappropriate submission		
Stent or previous coronary artery bypass graft present	5 (6.2)	116 (13.0)
Cardiac hardware present	2 (2.5)	29 (3.2)

The rejection rate was 892 of 10 416 cases submitted

dkfz.

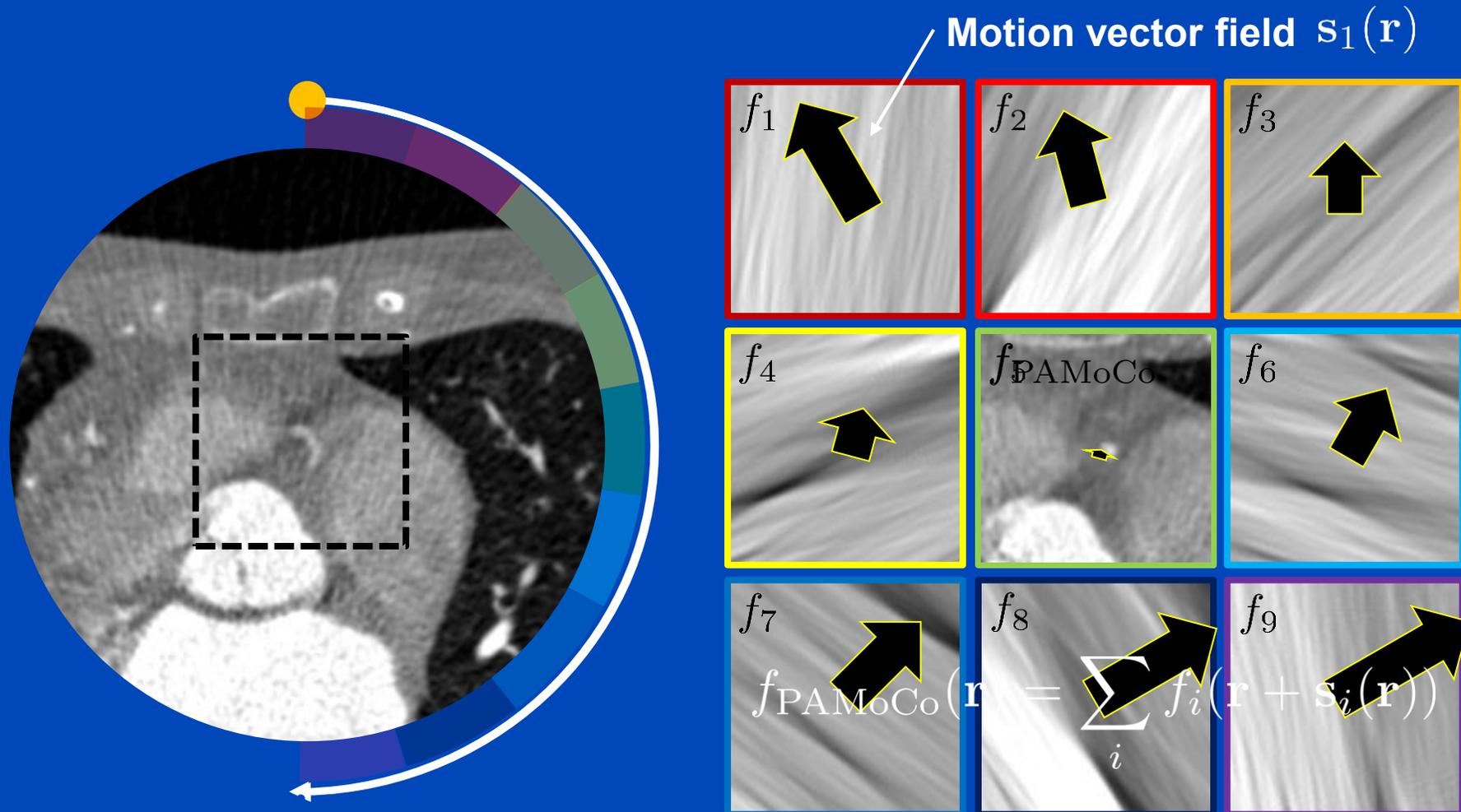# Partial Angle-Based Motion Compensation (PAMoCo)
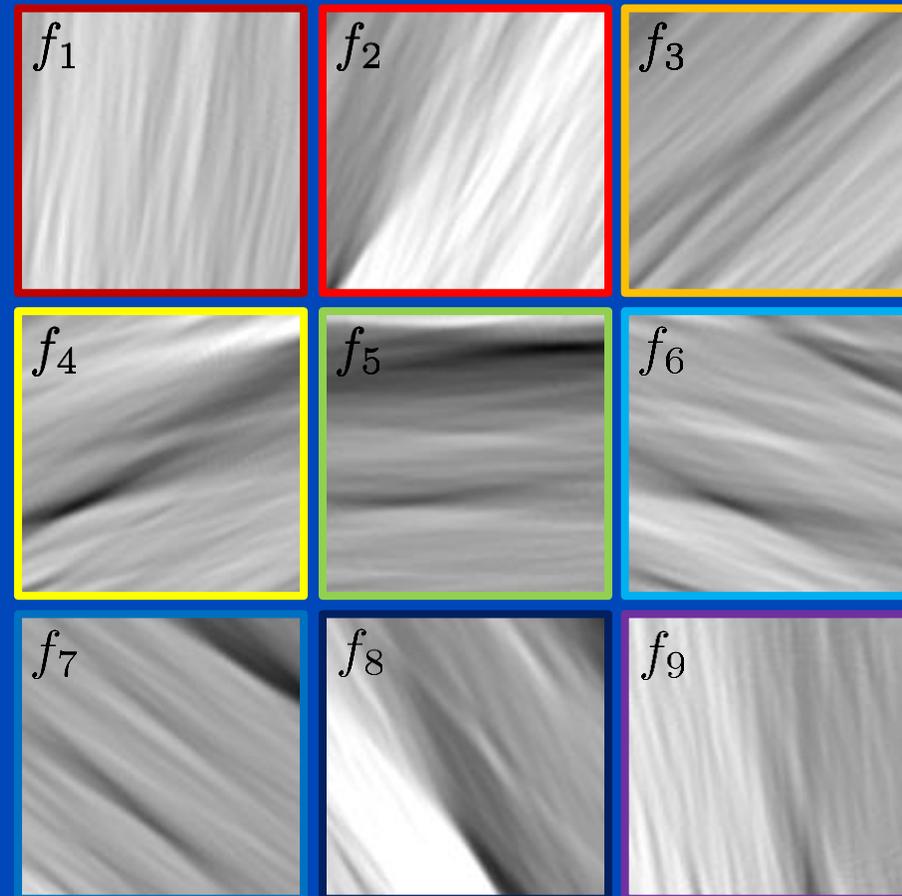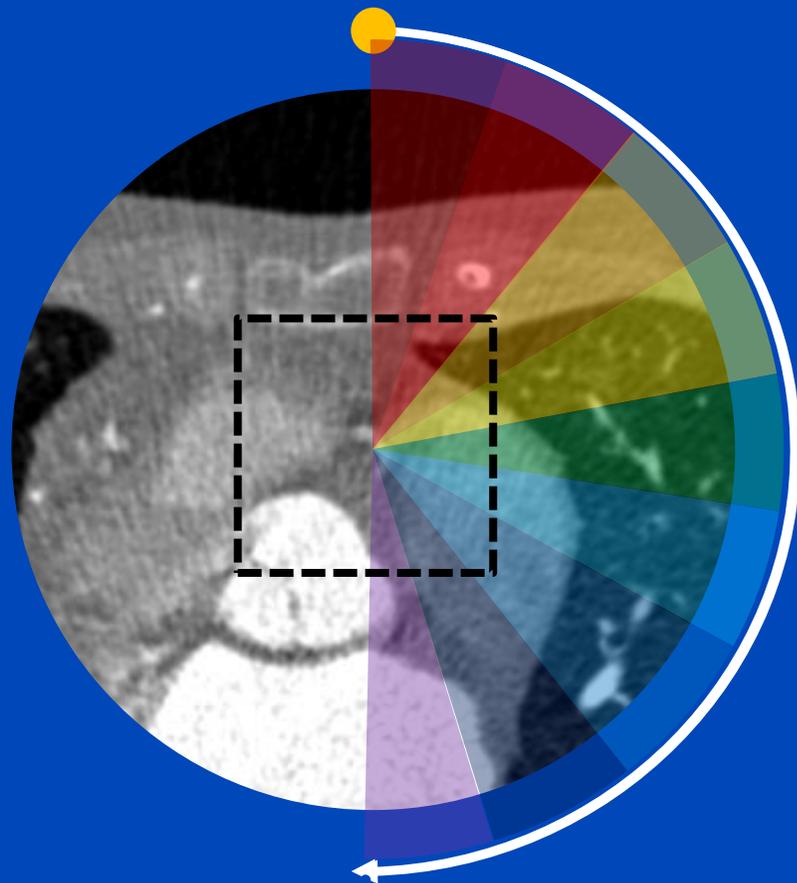
Animated rotation time = 100 × real rotation time
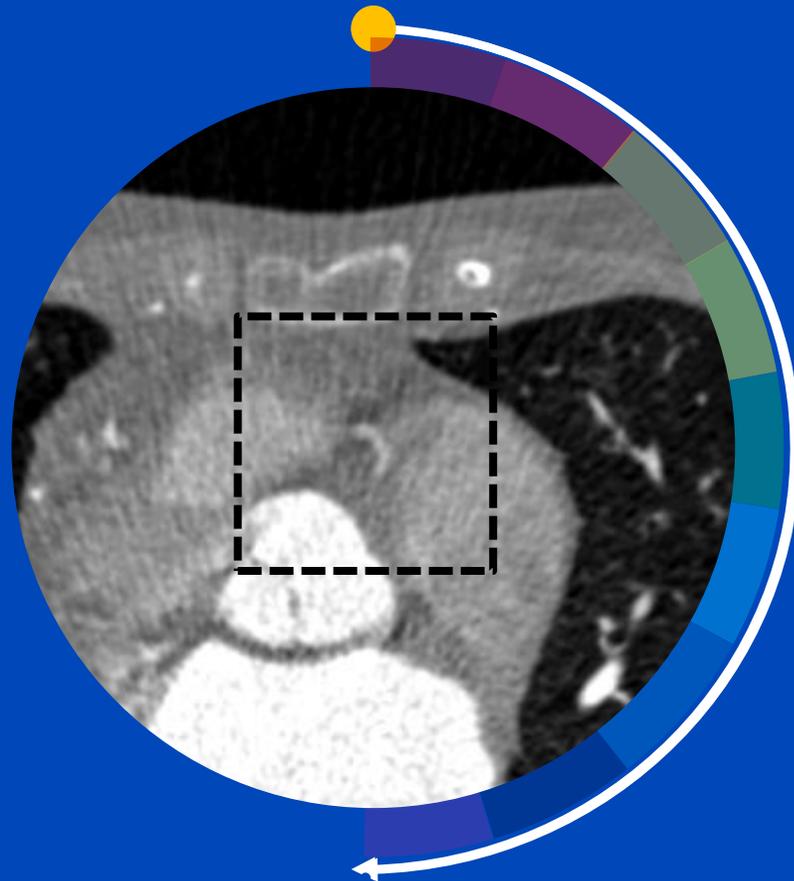
Partial Angle-Based Motion Compensation (PAMoCo)

$$f(\mathbf{r}) = \sum_i f_i(\mathbf{r})$$

Partial Angle-Based Motion Compensation (PAMoCo)

Motion vector field $\mathbf{s}_1(\mathbf{r})$

f_1 f_2 f_3

f_4 f_{PAMoCo} f_6

f_7 f_8 f_9

$$f_{\mathrm{PAMoCo}}(\mathbf{r}) = \sum_i f_i(\mathbf{r} + \mathbf{s}_i(\mathbf{r}))$$
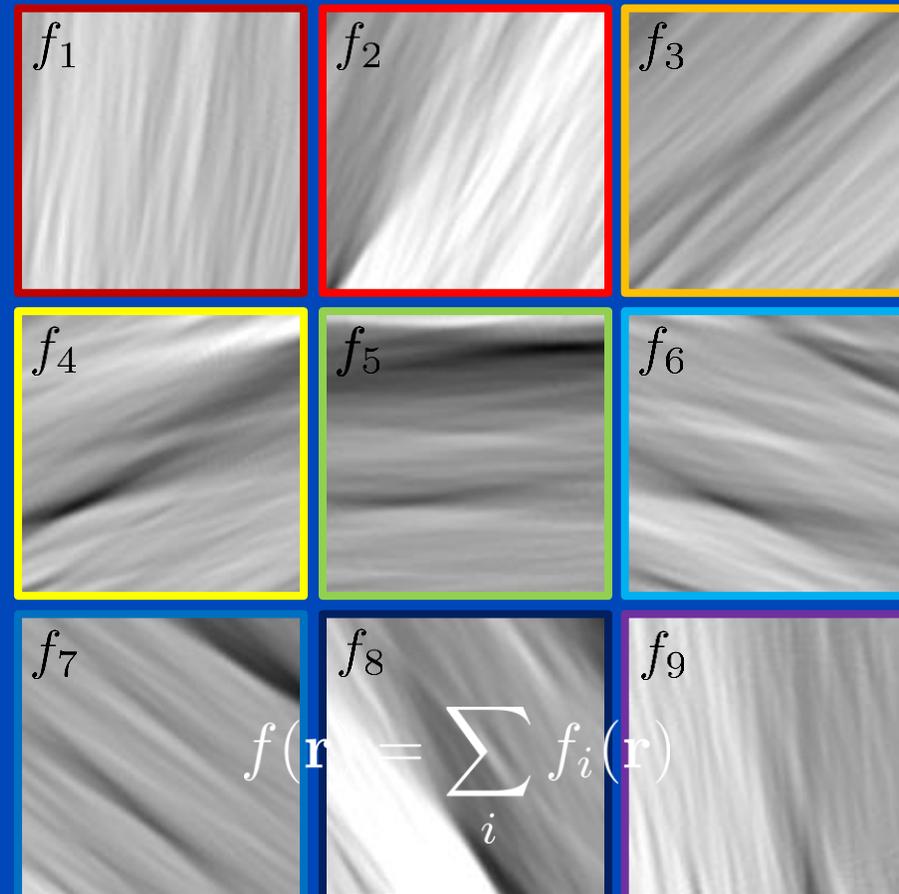
Apply motion vector fields (MVFs) to partial angle reconstructions

dkfz.

Partial Angle-Based Motion Compensation (PAMoCo)

Prior work:

[1] S. Kim et al., "Cardiac motion correction based on partial angle reconstructed images in x-ray CT", Med. Phys. 42 (5): 2560–2571 (2015).

[2] J. Hahn, M. Kachelrieß et al., "Motion compensation in the region of the coronary arteries based on partial angle reconstructions from short-scan CT data", Med. Phys. 44 (11): 5795–5813 (2017).

[3] S. Kim et al., "Cardiac motion correction for helical CT scan with an ordinary pitch", IEEE TMI 37 (7): 1587–1596 (2018).

→ **Limitation: Challenging / time-consuming optimization**

Deep PAMoCo
with fully connected final layers

PARs centered around coronary artery

Neural network to predict parameters of a motion model

Reinsertion of patch into initial reconstruction

Spatial transformer

**Application of the motion model to the PARs via a spatial transformer**

dkfz.
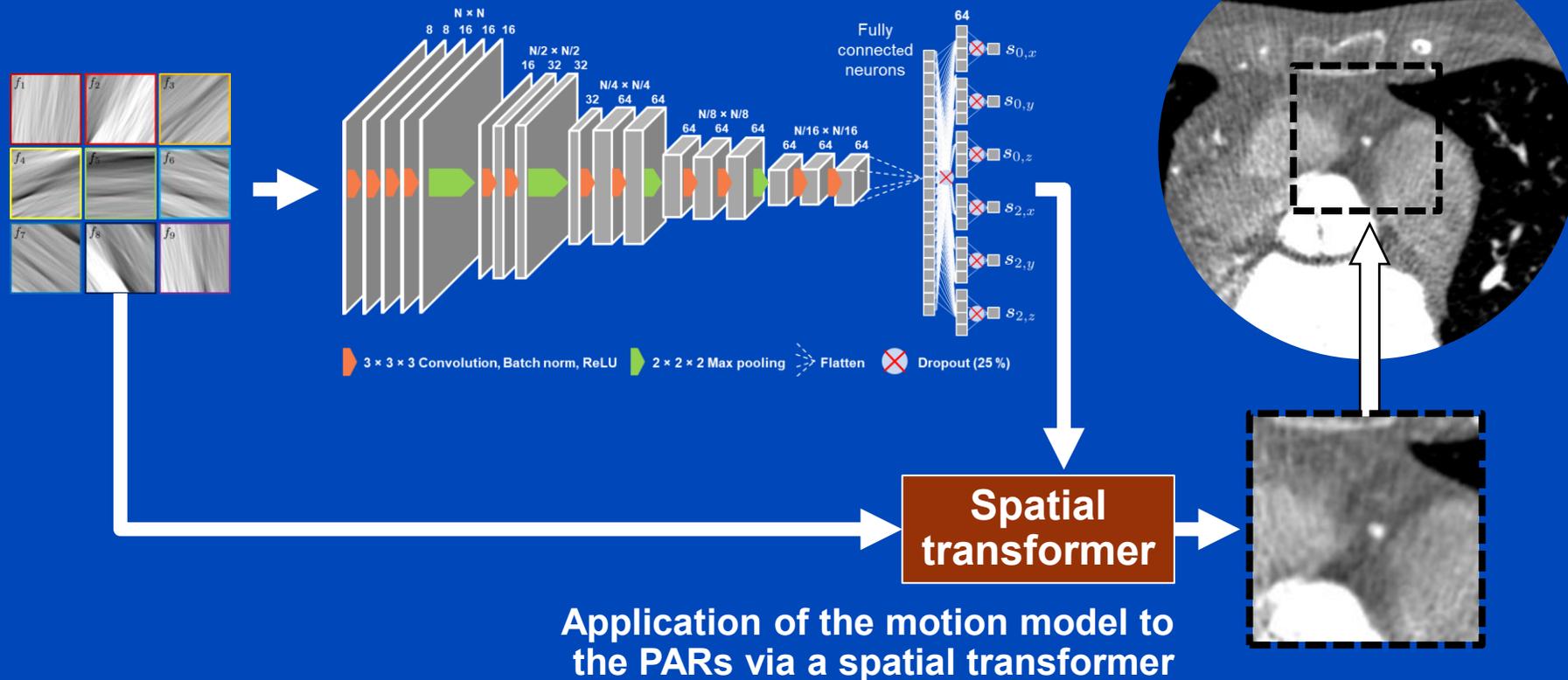
Deep Partial Angle-Based Motion Compensation (Deep PAMoCo)
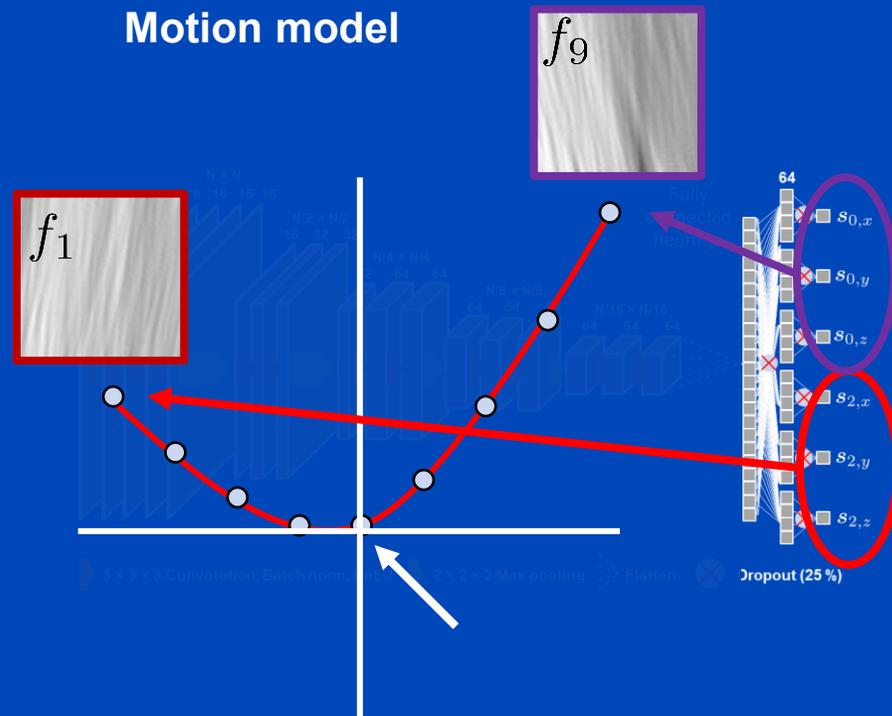
Deep PAMoCo
with fully connected final layers
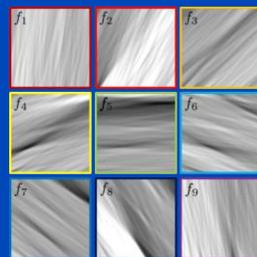
PARs centered around coronary artery

Neural network to predict parameters of a motion model
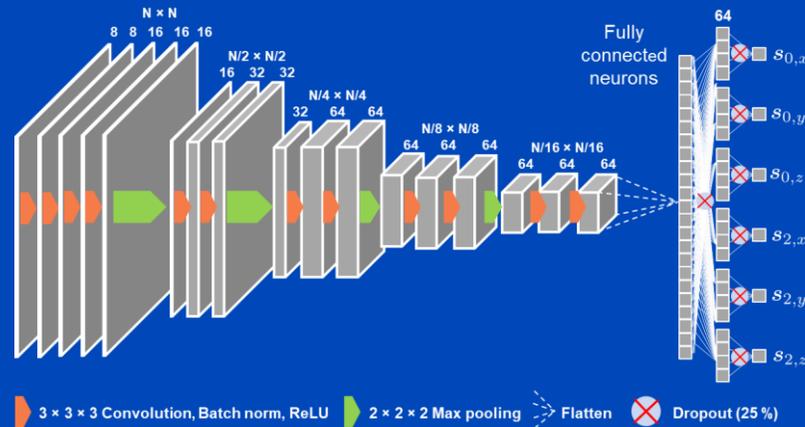
Reinsertion of patch into initial reconstruction

Spatial transformer

Application of the motion model to the PARs via a spatial transformer
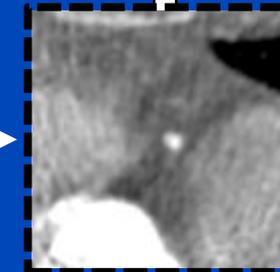
Training Data Generation

- **Removal of coronary arteries from real CT reconstructions.**
- **Insertion of artificial coronary arteries with different shape, size, and contrast.**
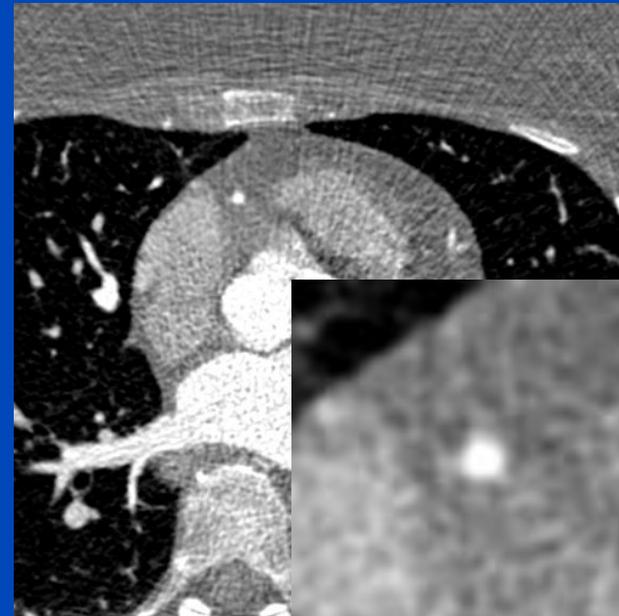- **Simulation of CT scans with coronary artery motion.**

Motion simulation

Patch extraction

Forward projection
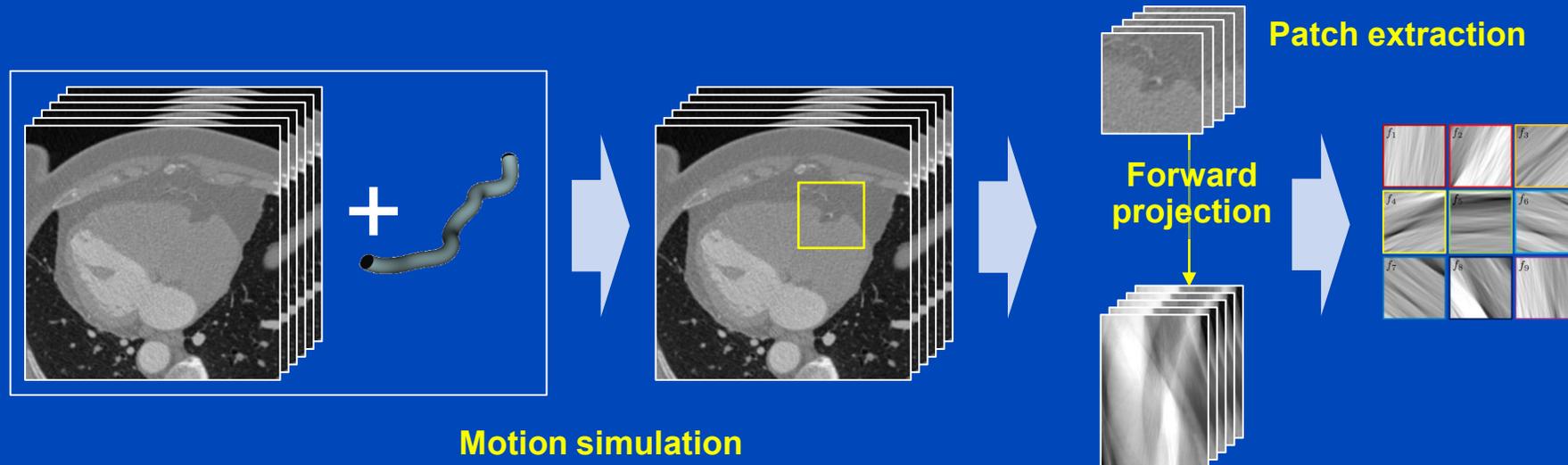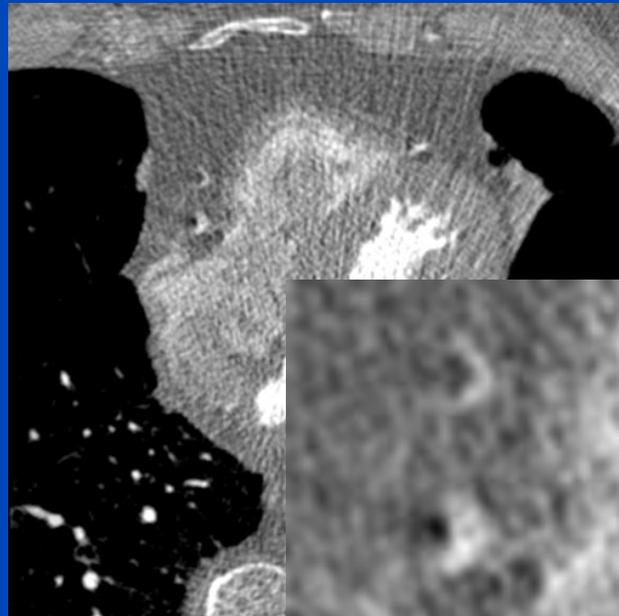
Patient 6

Original

Deep PAMoCo

C = 0 HU, W = 1400 HU

dkfz.
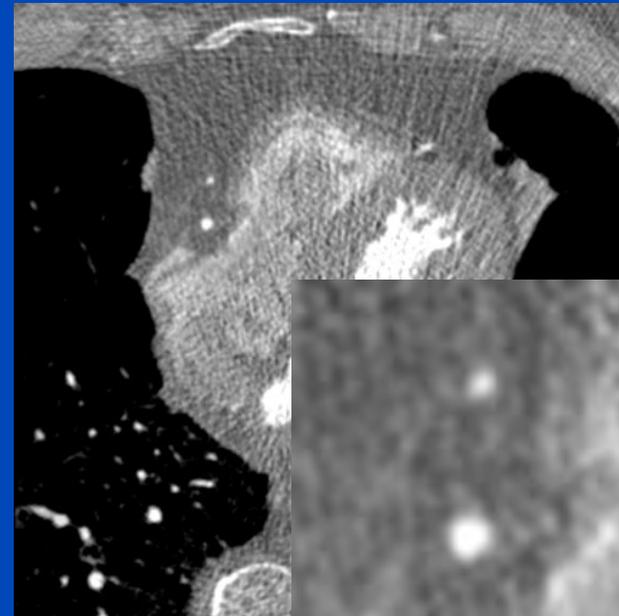
Patient 7

Original
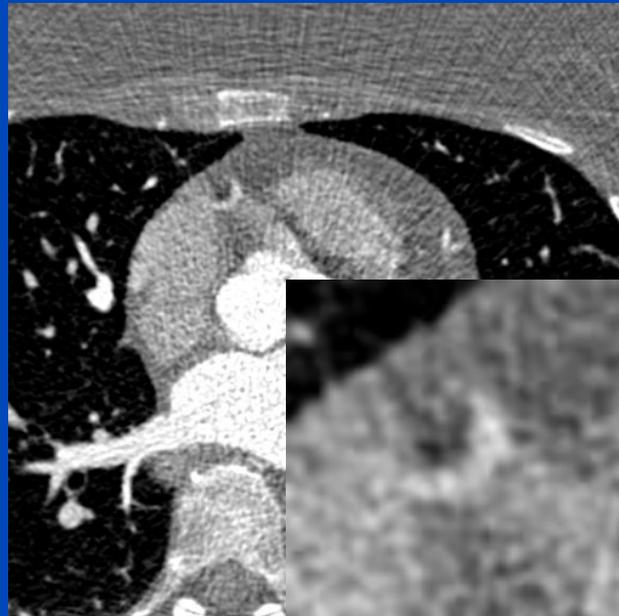
Deep PAMoCo

C = 0 HU, W = 1600 HU

dkfz.

Results
Measurements at a Siemens Somatom AS, patient 1

Slice 1 | Slice 2 | Slice 3 | Slice 4
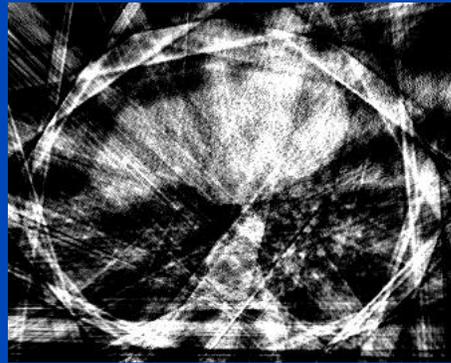
FBP reconstruction | ADMIRE | Deep PAMoCo

C = 0 HU, W = 1200 HU

dkfz.
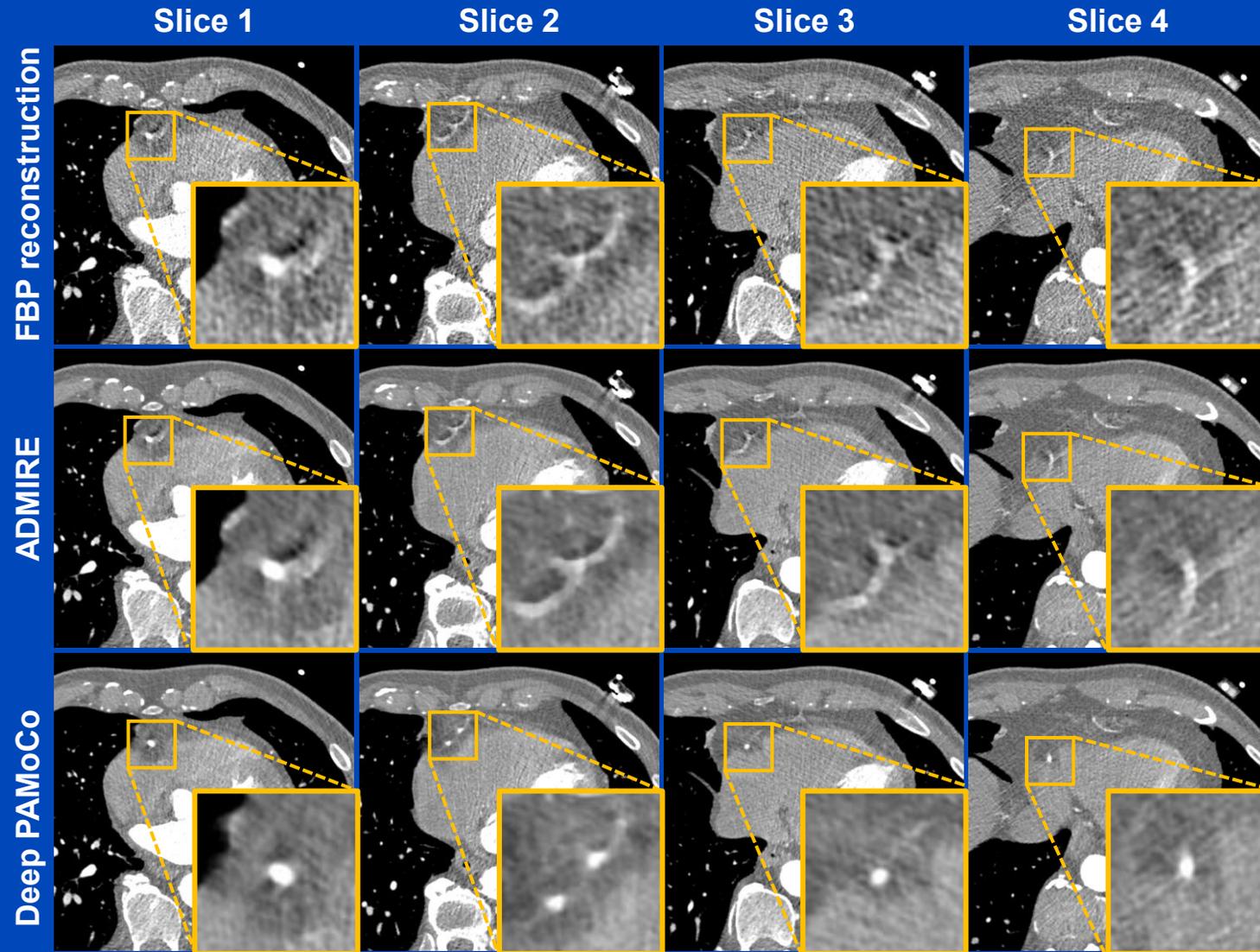
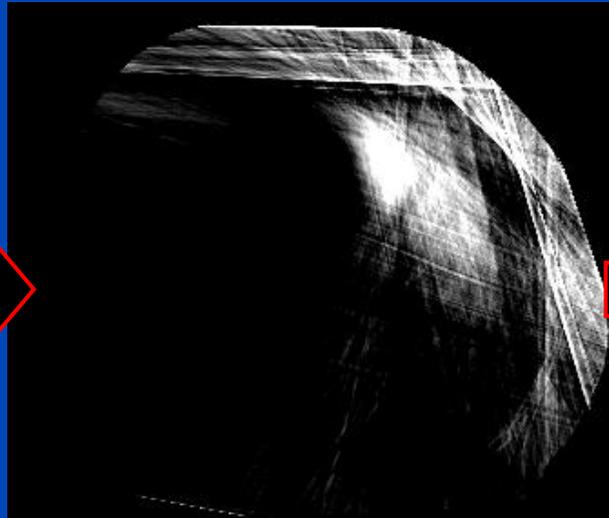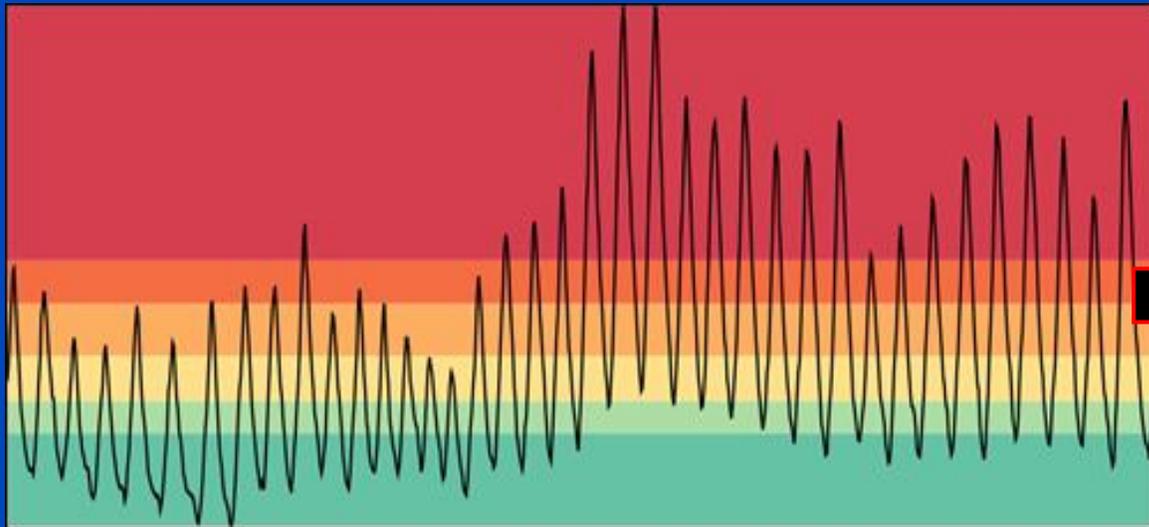# Results
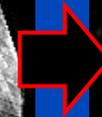## Measurements at a Siemens Somatom AS, patient 2
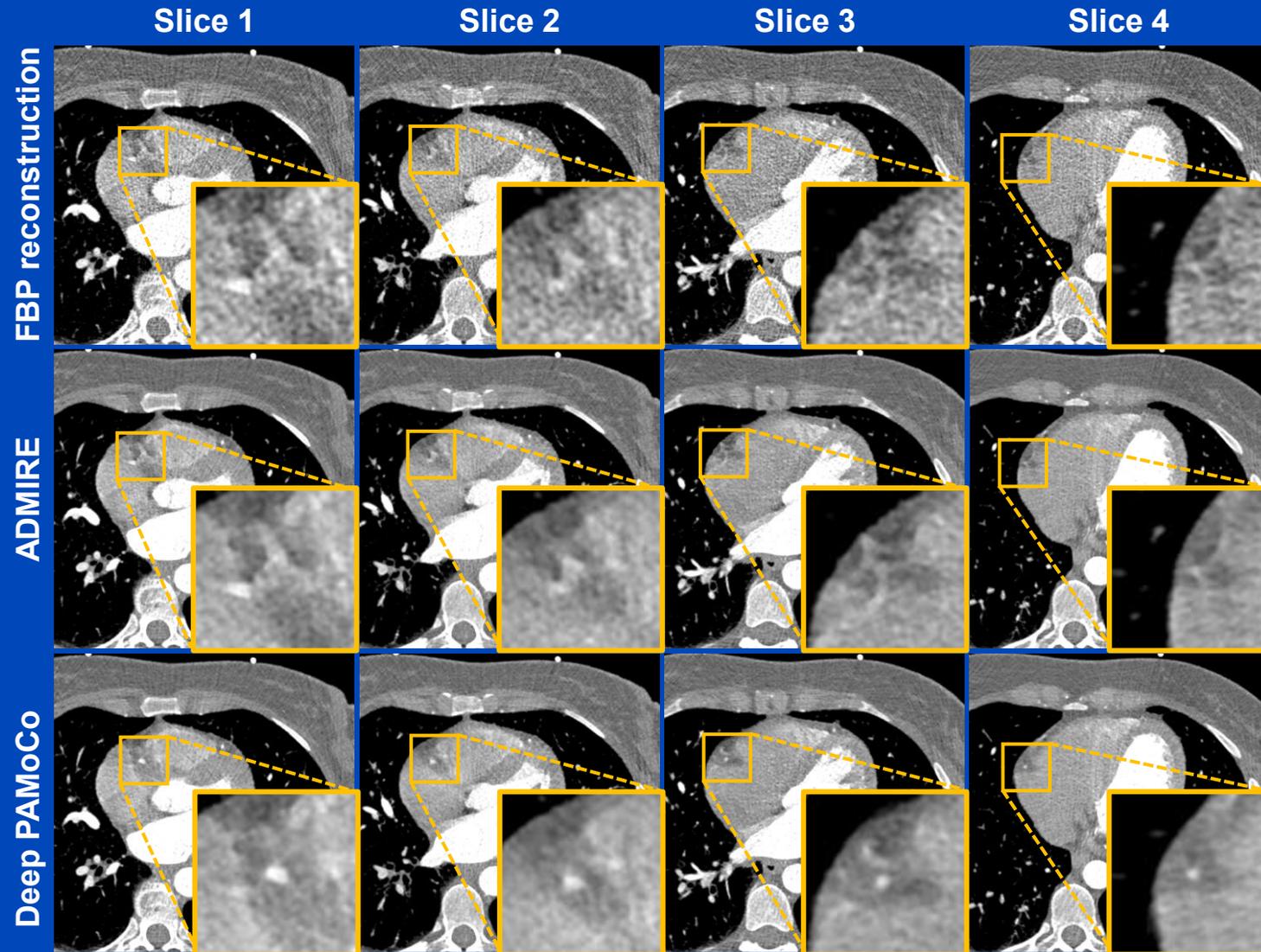
Deep Respiratory CBCT MoCo

Yet Unsolved Problems

Gating and gating-based motion compensation (MoCo)

- require gating signal,

- assume periodic motion,

- have low temporal resolution,

- fail on irregular breathing:

Gating = bad

Gating + MoCo = still bad

dkfz.

PAMoCo Adaptions for CBCT

- **Consideration of the entire FOM**
  - Estimation of a dense vector field for every voxel within the FOM.

- **Slow rotation speed**
  - Projections can only be grouped into tiny groups (here, no grouping is performed at all)
  - Partial angle reconstruction (PAR)

- **4D output**
  - Estimation of MVF from two arbitrary PARs
  - Similar to Voxelmorph but with PARs

- **Modification of PARs to add morphological context.**

RESEARCH ARTICLE

Deep learning-based cone-beam CT motion compensation with single-view temporal resolution

Joscha Maier[1] | Stefan Sawall[1,2] | Marcel Arheit[3] | Pascal Paysan[3] |
Marc Kachelrieß[1,2]

[1]Division of X-Ray Imaging and Computed Tomography, German Cancer Research Center (DKFZ), Heidelberg, Germany

[2]Medical Faculty Heidelberg, Heidelberg University, Heidelberg, Germany

[3]Varian Medical Systems Imaging Laboratory, GmbH, Baden-Daettwil, Switzerland

Correspondence
Marc Kachelrieß, Division of X-Ray Imaging and Computed Tomography, German Cancer Research Center (DKFZ), Heidelberg, Germany.
Email: marc.kachelriess@dkfz.de

Abstract

Background: Cone-beam CT (CBCT) scans that are affected by motion often require motion compensation to reduce artifacts or to reconstruct 4D (3D+time) representations of the patient. To do so, most existing strategies rely on some sort of gating strategy that sorts the acquired projections into motion bins. Subsequently, these bins can be reconstructed individually before further post-processing may be applied to improve image quality. While this concept is useful for periodic motion patterns, it fails in case of non-periodic motion as observed, for example, in irregularly breathing patients.

Purpose: To address this issue and to increase temporal resolution, we propose the deep single angle-based motion compensation (SAMoCo).

Methods: To avoid gating, and therefore its downsides, the deep SAMoCo trains
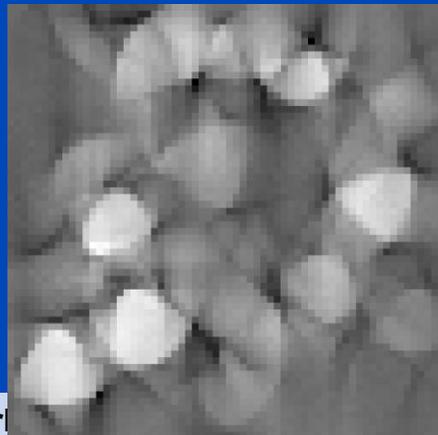
dkfz.

Bouncing Spheres

- **Spheres with random velocity and random density in a box.**

- **Elastic collisions with other spheres and walls are elastic.**

- **180° scan (180 projections) using a pseudo parallel-beam geometry.**

- **FDK reconstruction (64×64×32) of single views → 180 PARs.**

Parallel beam

Detector
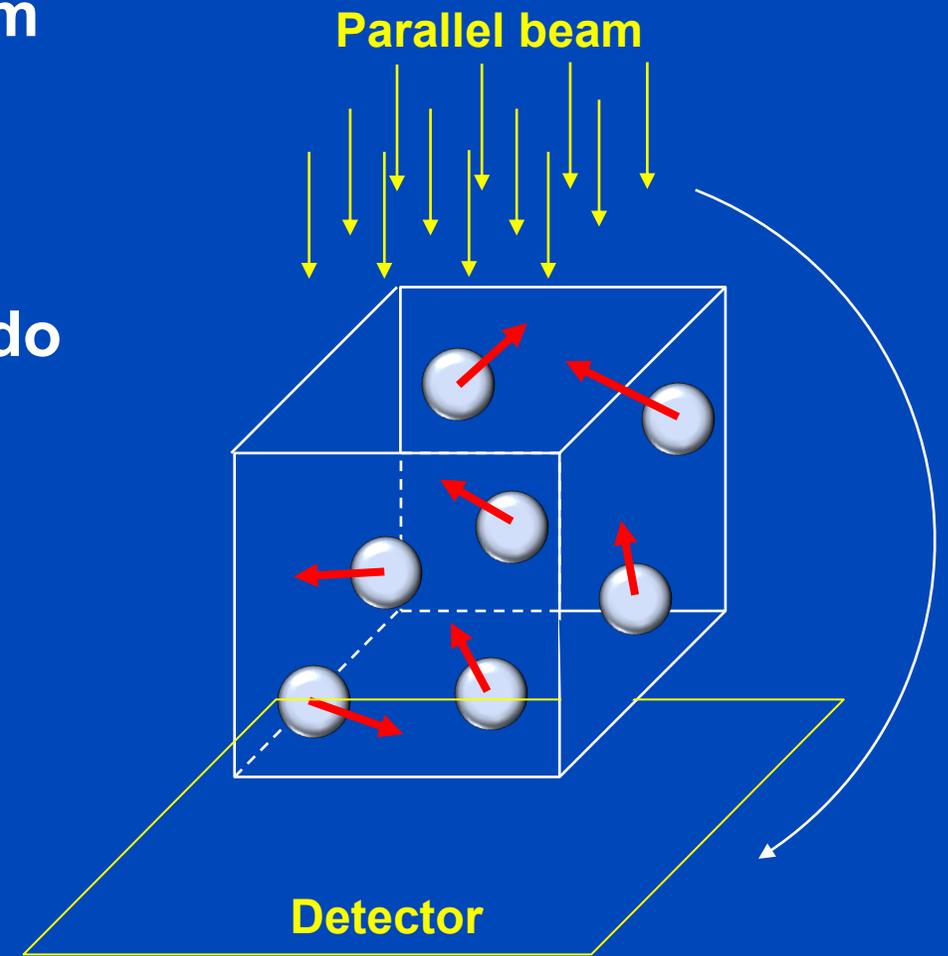
Slice of prior volume

3D reconstruction

dkfz.
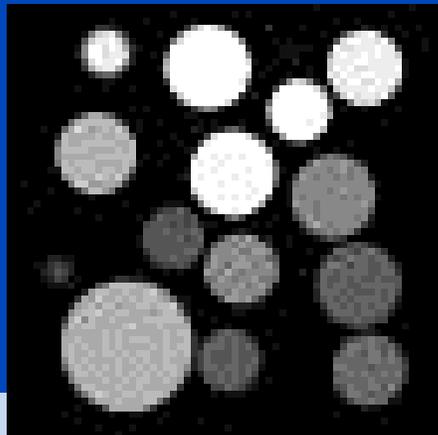
Results
Spheres

Prediction   **Ground truth**   **Difference**

dkfz.
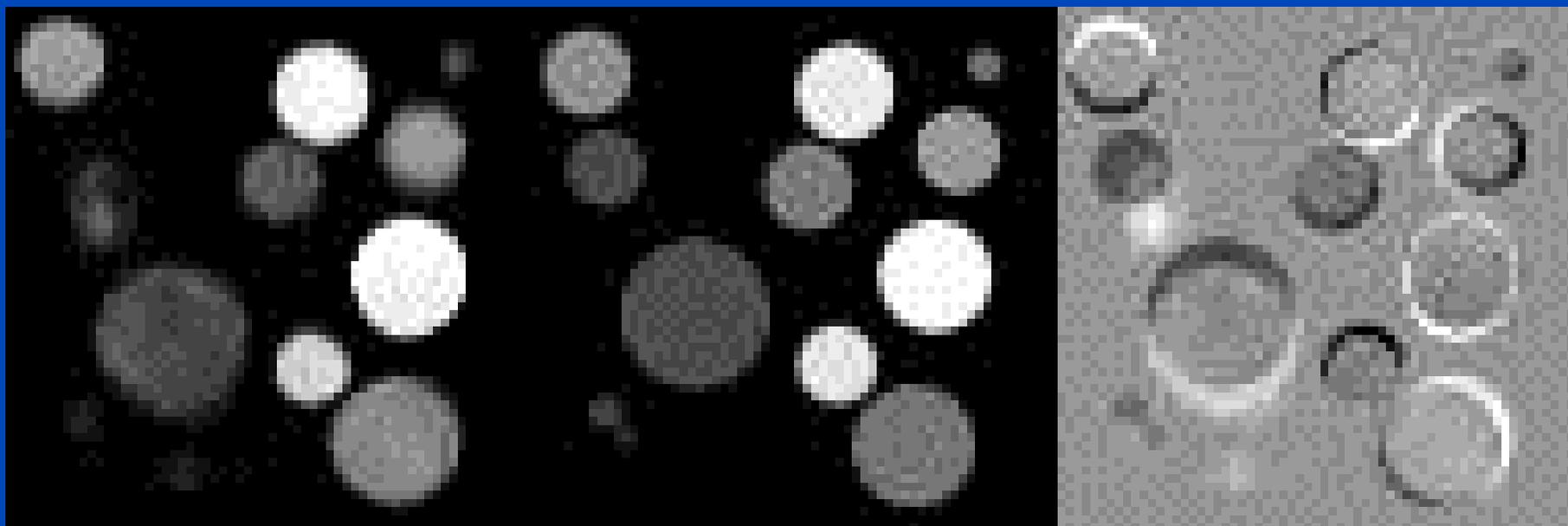
Single Angle Reconstructions (SARs)

WashU   SARs   Modified SARs

Axial

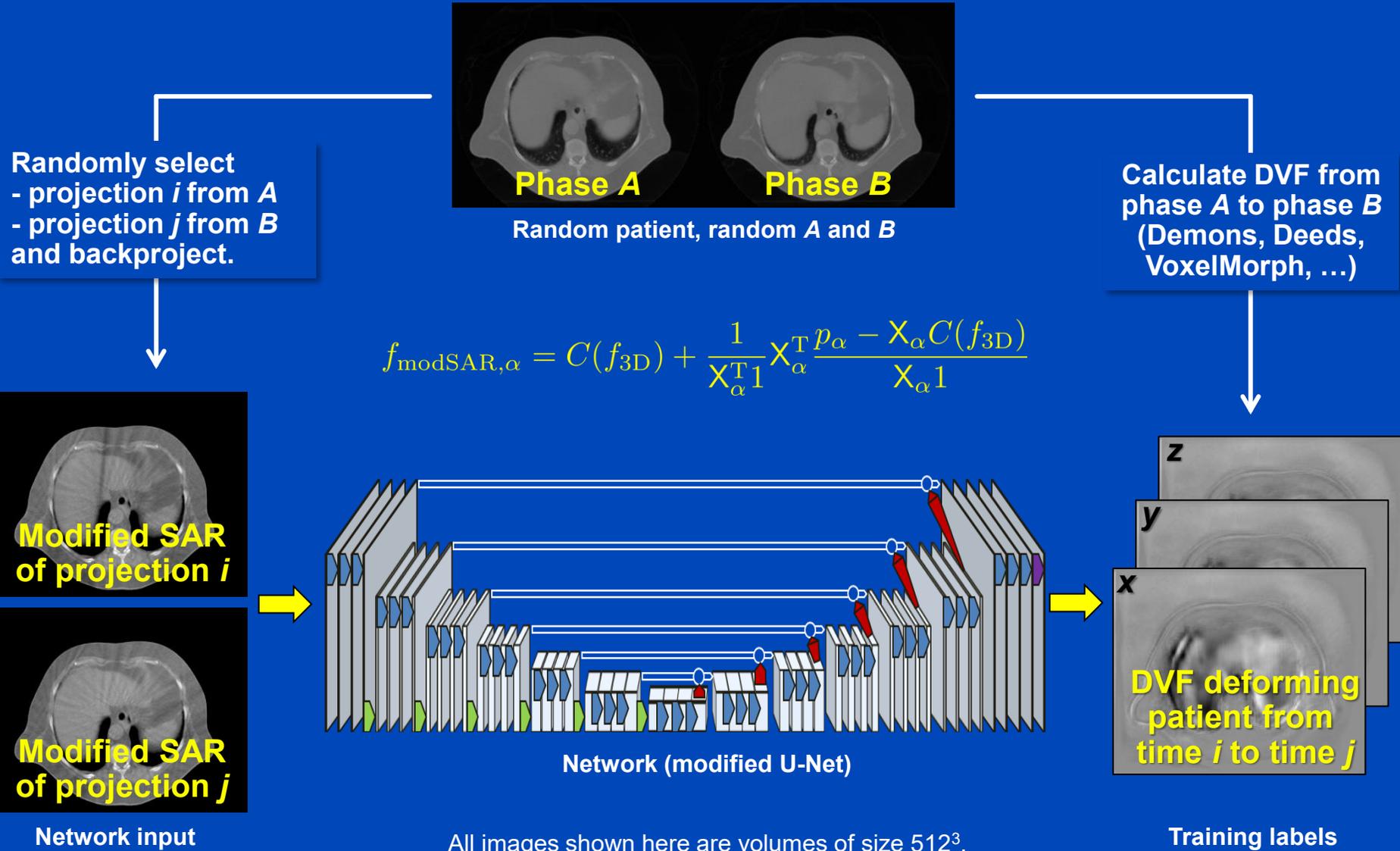**84 4D CT scans (no artifacts, high temporal resolution)**

- **10 respiratory phases each (WashU/Colorado dataset)**
- **10·10 combinations of phase *A* and *B* possible (including *A=B*)**
- **84·10·10 displacement vector fields (DVFs) known**
- **720 CBCT projections[1] simulated for each CT scan (each phase)**
- **84·10·720·10·720 projection pairs with known DVF**

[1]The actual projection numbers are between 420 and 900 and depend on the scan mode.

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Training Workflow of Deep SAMoCo

Training Workflow of Deep SAMoCo

Phase A   **Phase B**

Random patient, random A and B

Randomly select
- projection *i* from *A*
- projection *j* from *B*
and backproject.

Calculate DVF from
phase *A* to phase *B*
(Demons, Deeds,
VoxelMorph, …)

$$f_{\mathrm{modSAR},\alpha} = C(f_{3\mathrm{D}}) + \frac{1}{X_\alpha^{\mathrm{T}}1} X_\alpha^{\mathrm{T}} \frac{p_\alpha - X_\alpha C(f_{3\mathrm{D}})}{X_\alpha 1}$$

Modified SAR
of projection *i*

Modified SAR
of projection *j*

Network (modified U-Net)

DVF deforming
patient from
time *i* to time *j*

z   *y*   *x*

Network input

All images shown here are volumes of size 512^3.

Training labels

varian   dkfz.

Inference Workflow of Deep SAMoCo

- **For a new patient**
  - decide for the desired time point j, e.g. the one from 1 millisecond ago
  - for all $i \neq j$ get the DVFs pointing from i to j from the neural network
  - deform SARs for all $i \neq j$ into time point j
 - add all the volumes

For all $i \neq j$ do

SAR of projection i

SAR of projection j

Network input

Network (modified U-Net)

z

y

x

DVF deforming SAR i (from time i) to time j

Network output

For the videos shown in the following, we did this for all 720 time points j

varian

dkfz.

Inference Workflow of Deep SAMoCo

- ## For a new patient
    - decide for the desired time point j, e.g. the one from 1 millisecond ago
    - for all $i \neq j$ get the DVFs pointing from i to j from the neural network
    - deform SARs for all $i \neq j$ into time point j
    - add all the volumes

For all $i \neq j$ do

Modified SAR of projection i

Modified SAR of projection j

Network input

Network (modified U-Net)

DVF deforming SAR i (from time i) to time j

z

y

x

Network output

For the videos shown in the following, we did this for all 720 time points j

varian

dkfz.
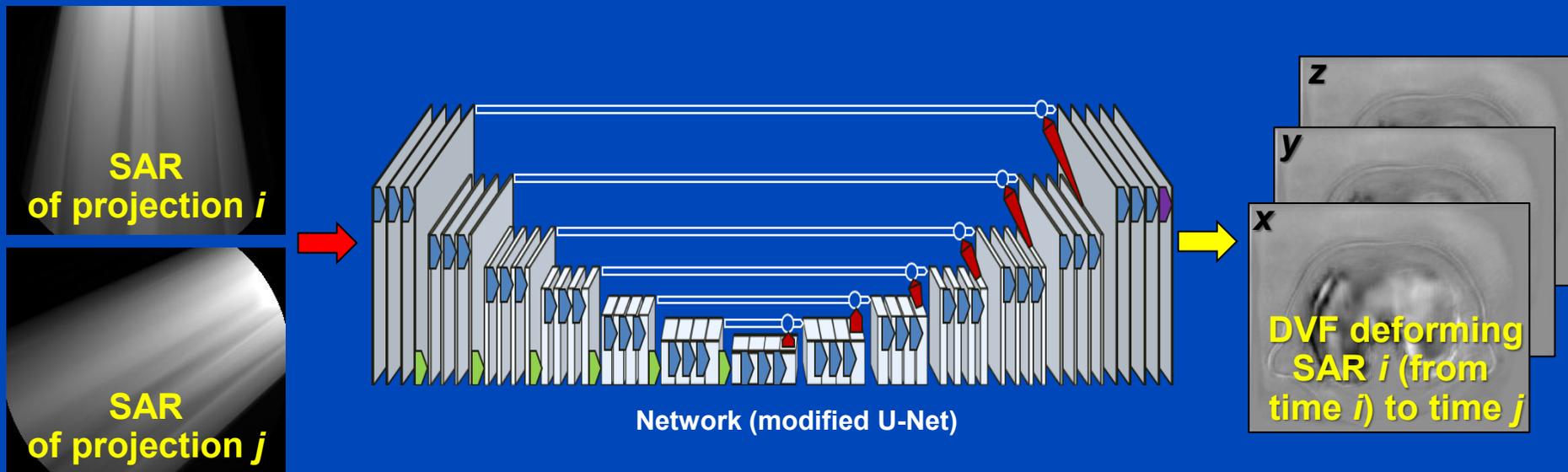
VUMC_4DThorax

Red: RPM signal (external signal – not used for recon)
Yellow: Diaphragm motion (intrinsic signal – from PAMoCo recon)

MSK 7
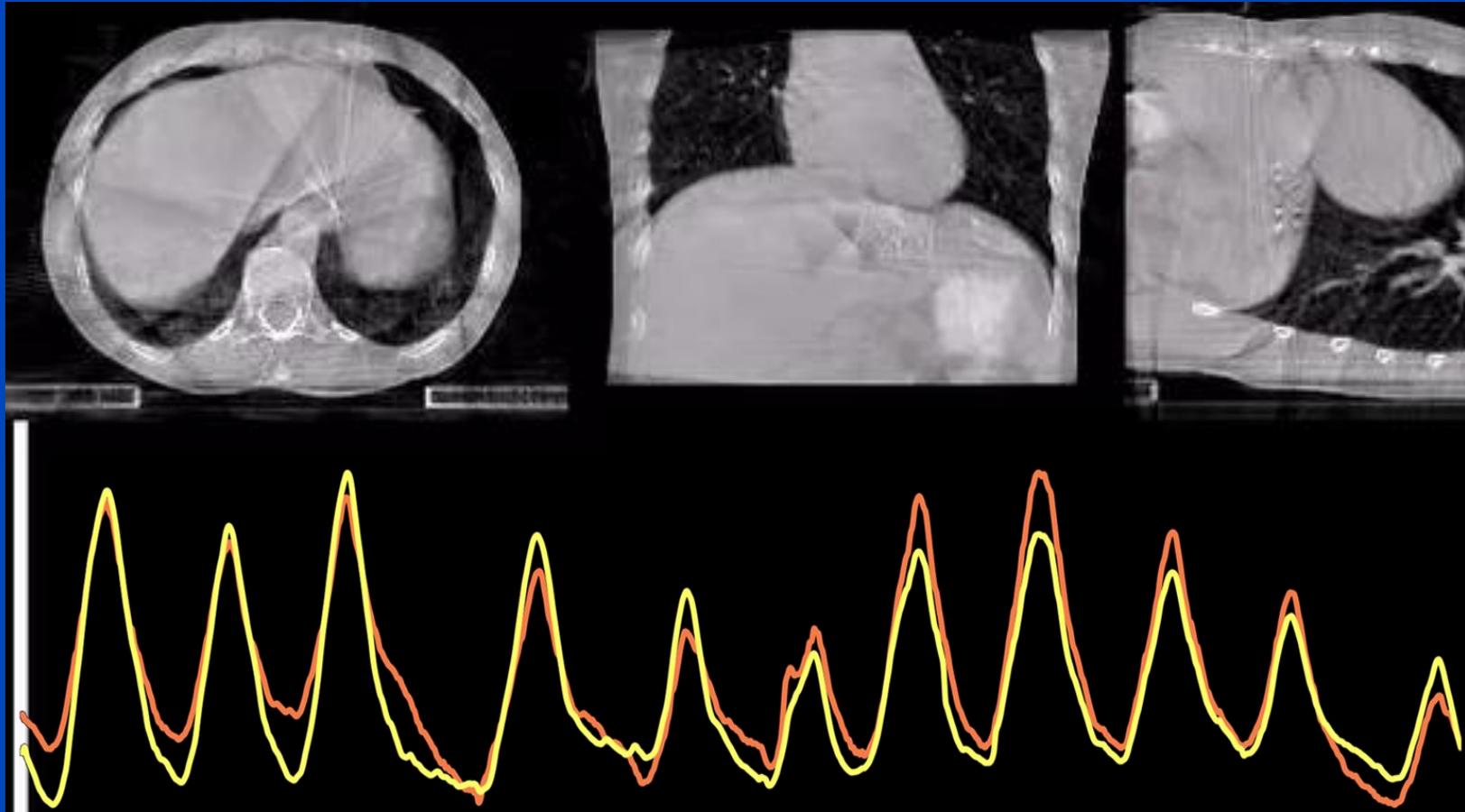
Red: RPM signal (external signal – not used for recon)
Yellow: Diaphragm motion (intrinsic signal – from PAMoCo recon)

MSK 1
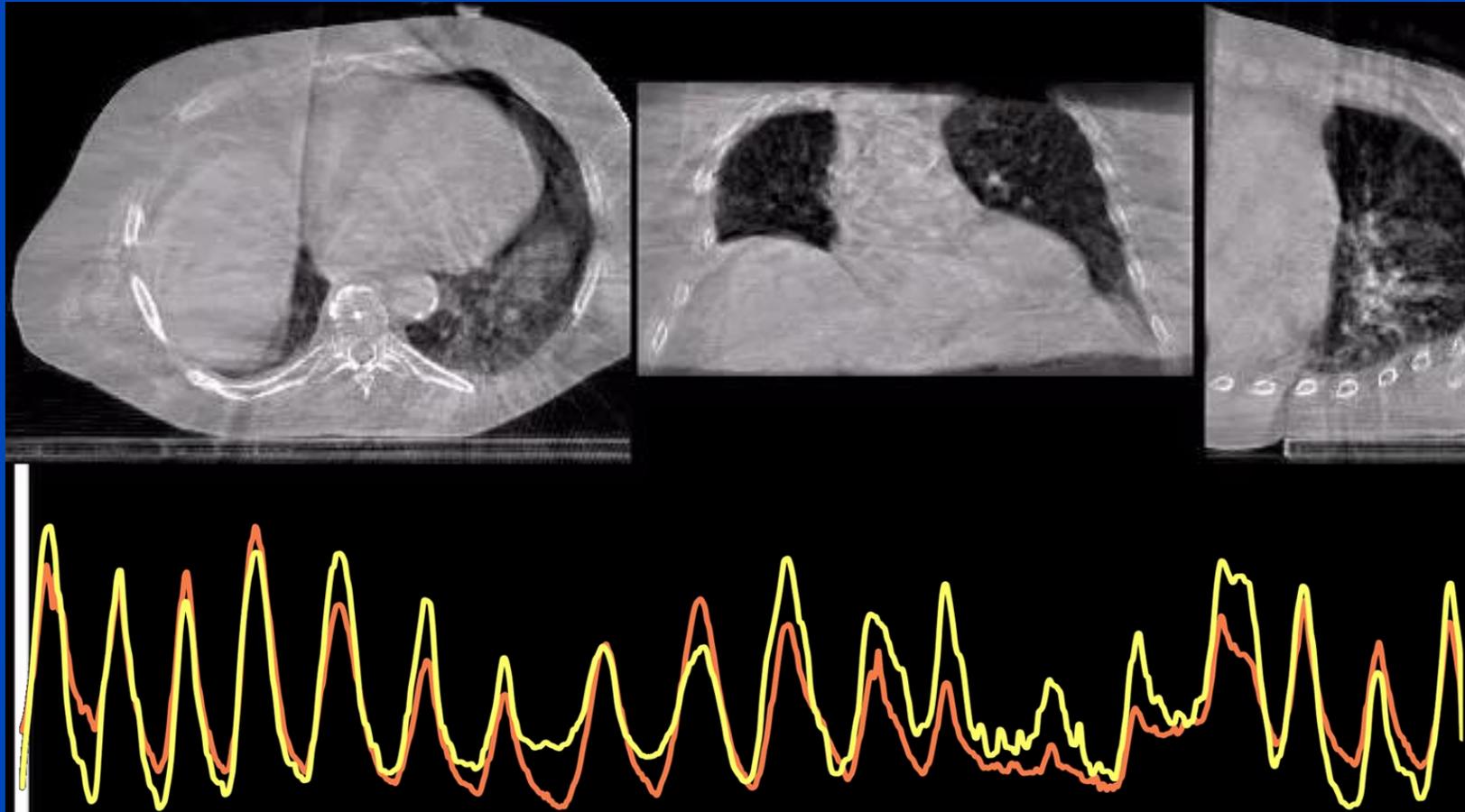
Red: RPM signal (external signal – not used for recon)
Yellow: Diaphragm motion (intrinsic signal – from PAMoCo recon)
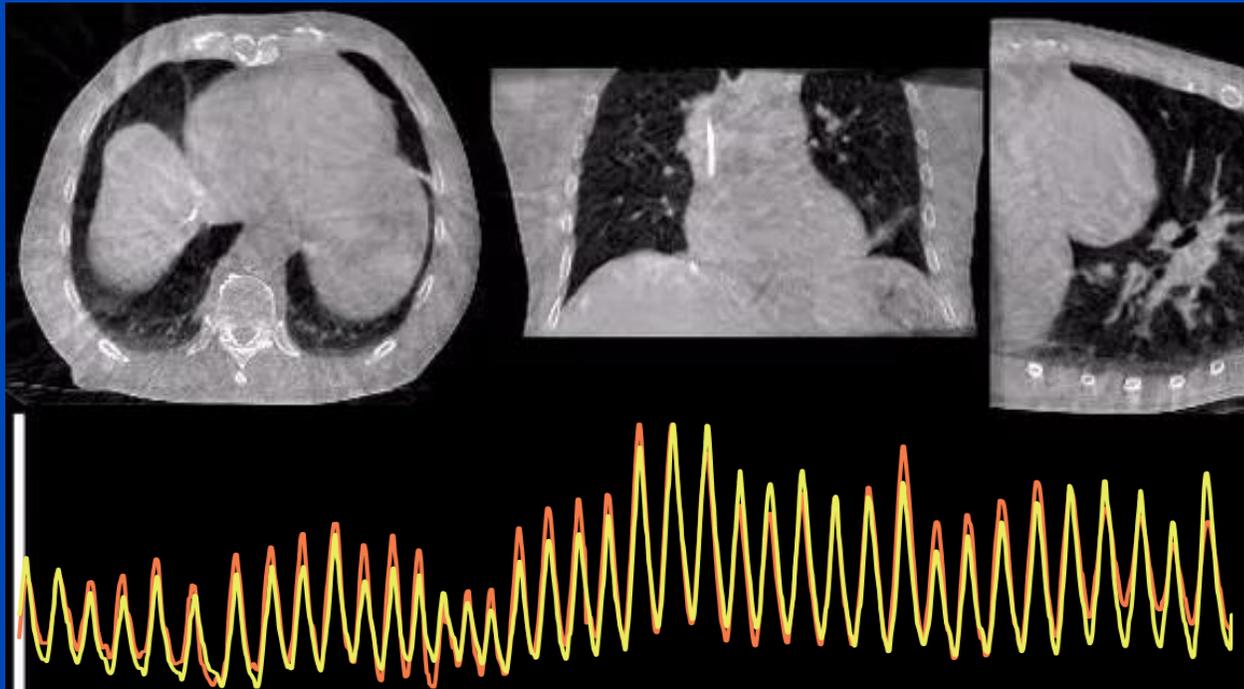
Upcoming in 2026 (yet to be developed)

Imaging ($t < 0$) Treatment ($t > 0$)

Hypersight Patient Example

60 s Scan

6 s Scan

FDK recon (3D) **SAMoCo recon (true 4D)** **FDK recon (3D)** **SAMoCo recon (true 4D)**
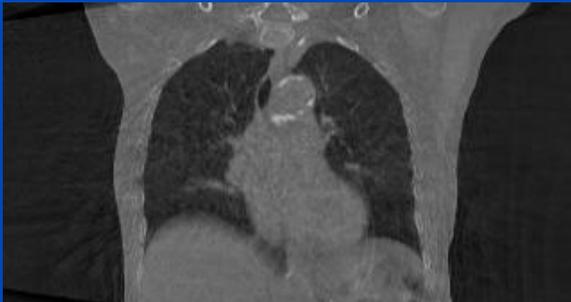
60 s, 200° short scan, 867 projections, MA_53_Lung_60s.
Displayed are 434 time points with 0.14 s increment at 10 fps.

6 s, 200° short scan, 406 projections, MA_53_Lung_BH_6s
Displayed are 41 time points with 0.14 s increment at 10 fps.

Numbers show frame numbers and not projection numbers

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INTERVENTIONAL IMAGING
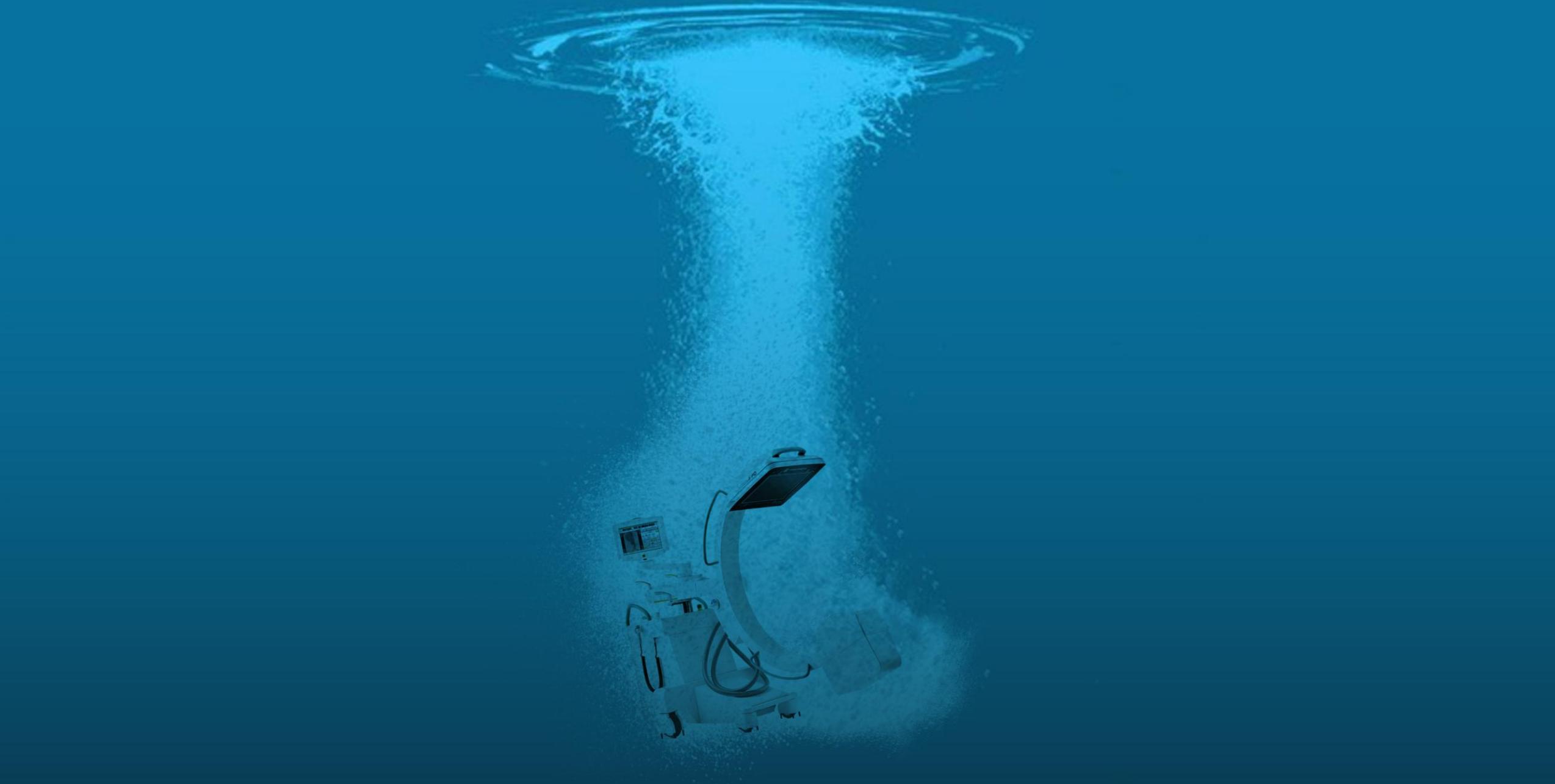
Intervention goes Deep!

Deep Vessel Extraction
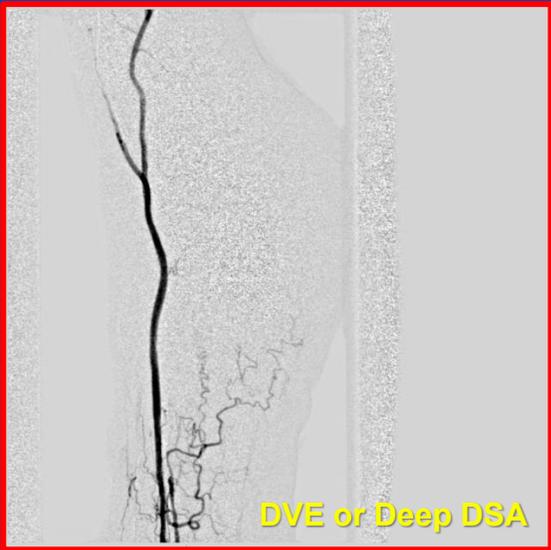
Deep Tool Extraction
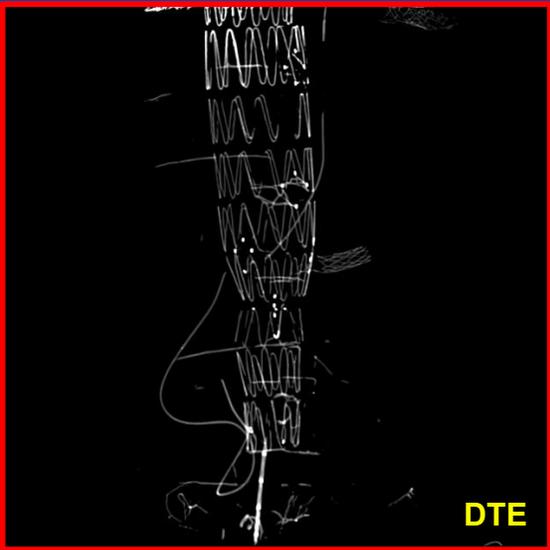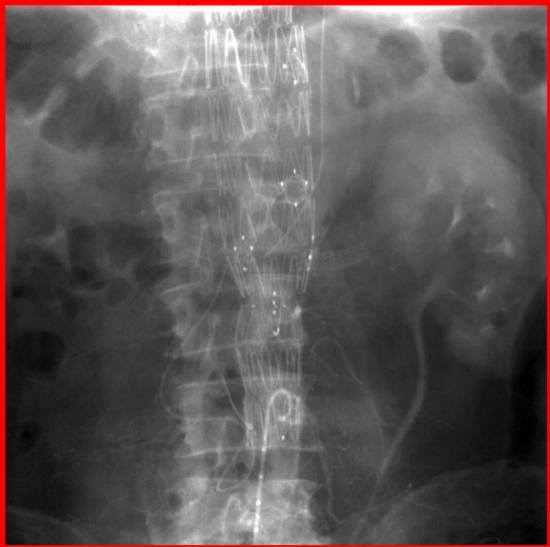
Deep Bone Extraction
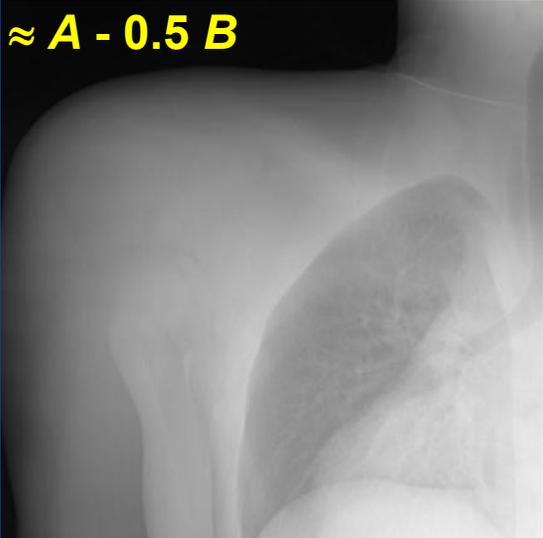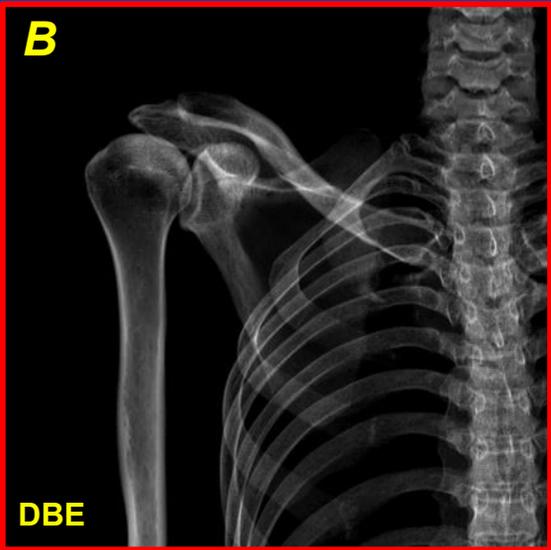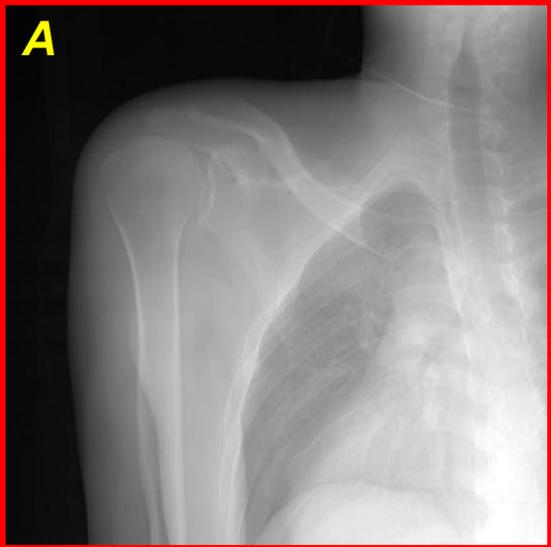
DVE or Deep DSA

DTE

DBE

A

B

$\approx A - 0.5\ B$

Deep DSA

???

Without mask?

RESEARCH ARTICLE MEDICAL PHYSICS

Training of a deep learning based digital subtraction angiography method using synthetic data

Lizhen Duan[1,2,3] | Elias Eulig[1,4] | Michael Knaup[1] | Ralf Adamus[5] |
Michael Lell[5] | Marc Kachelrieß[1,6]

dkfz.

Digital Subtraction Angiography (DSA)

- ## DSA principle:
  - Before contrast injection acquire a mask image.
  - When injecting contrast, perform fluoroscopy.
  - Display each fluoroscopic image minus the mask image

- ## For decades, DSA is used world-wide with great success in many clinical angiographic exams.

- ## Downsides:
  - Need to start acquisition before injecting the contrast medium
  - Works for only static situations.

- ## Future[1,2]:
  - Use AI to compute DSA without needing the mask image.
  - Do this in real-time (e.g. 5 ms per x-ray image).

Fluoro **DSA**

Motion! DSA does not work.

[1]E. Eulig, M. Kachelrieß et al. "Learned digital subtraction angiography (Deep DSA): method and application to lower extremities". Fully 3D, May 2019.
[2]L. Duan, M. Kachelrieß et al. "Training of a deep learning based digital subtraction angiography method using synthetic data". Med Phys. 51:4793–4810, July 2024.

dkfz.

General Principle

- **Conventional DSA**

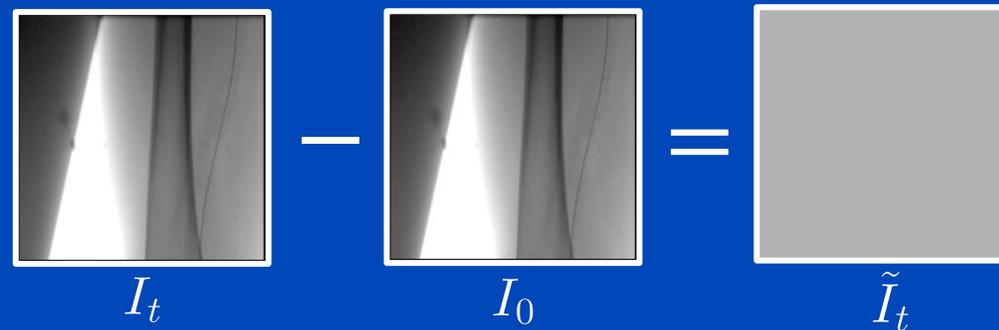$$I_t - I_0 = \tilde{I}_t$$
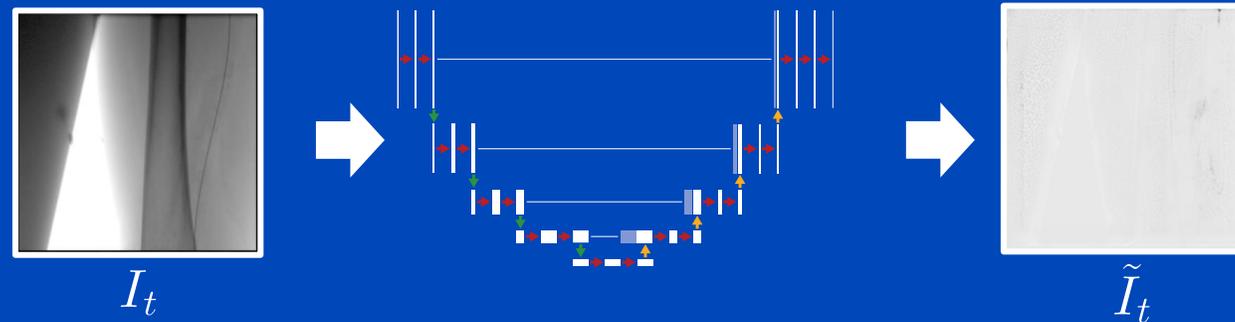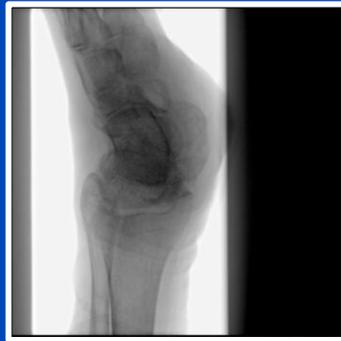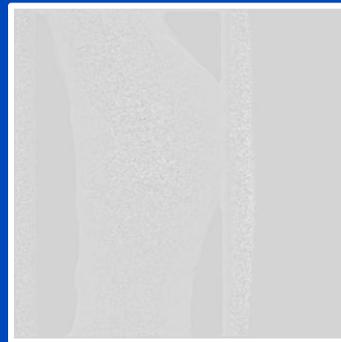
- **Deep DSA**

$$I_t \rightarrow \tilde{I}_t$$

- **Train on static cases where ground truth is conventional DSA**
- During inference CNN can be applied to both static and dynamic cases

E. Eulig, M. Kachelrieß et al. "Learned digital subtraction angiography (Deep DSA): method and application to lower extremities". Fully 3D, May 2019.
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dkfz.

General Principle

- **Conventional DSA**

$$I_t \quad - \quad I_0 \quad = \quad \tilde{I}_t$$

- **Deep DSA**

$$I_t \qquad\qquad\qquad\qquad \tilde{I}_t$$

- **Train on static cases where ground truth is conventional DSA**
- **During inference CNN can be applied to both static and dynamic cases**

E. Eulig, M. Kachelrieß et al. "Learned digital subtraction angiography (Deep DSA): method and application to lower extremities". Fully 3D, May 2019.
L. Duan, M. Kachelrieß et al. "Training of a deep learning based digital subtraction angiography method using synthetic data". Med Phys. 51:4793–4810, July 2024.

dkfz.
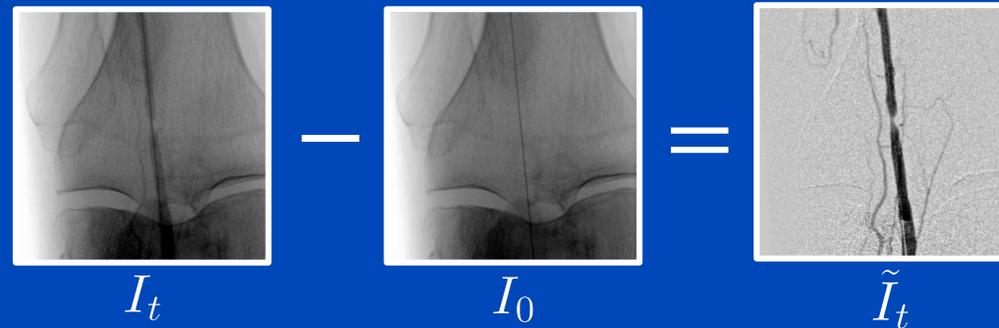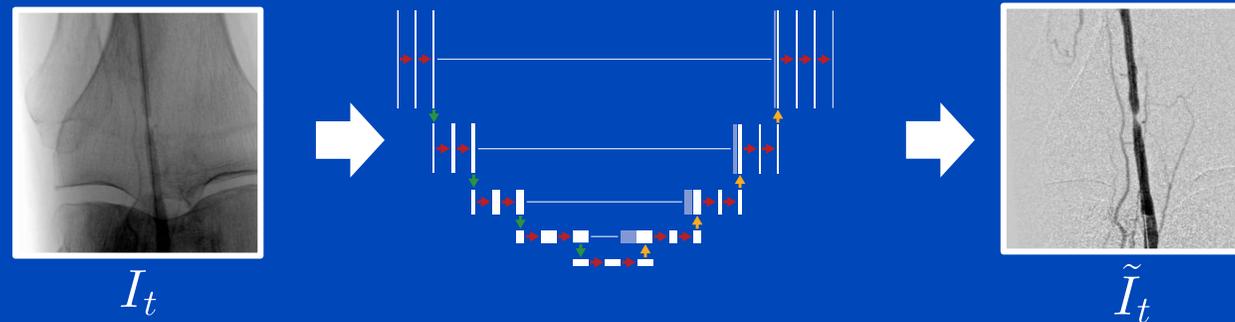
Results

Original x-ray sequence

Ground truth DSA
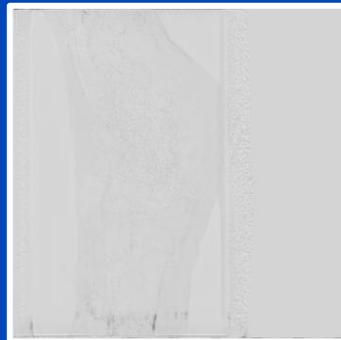
CNN output
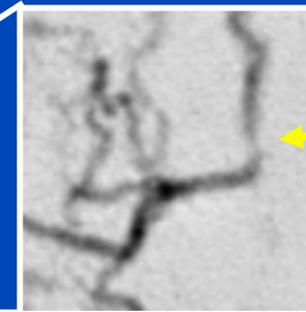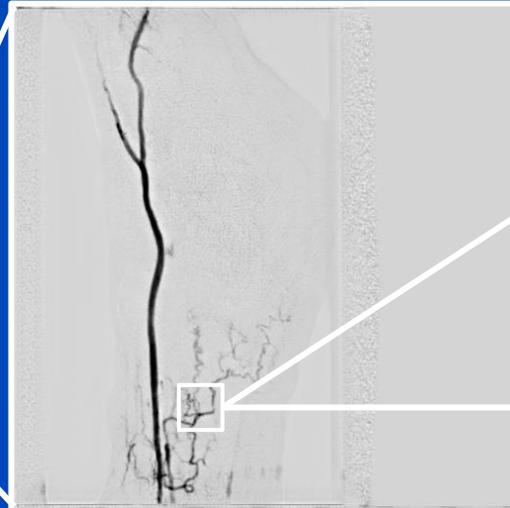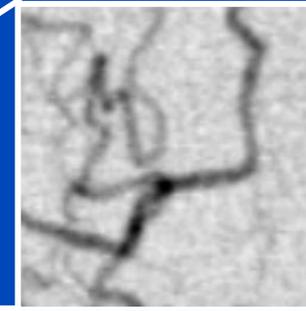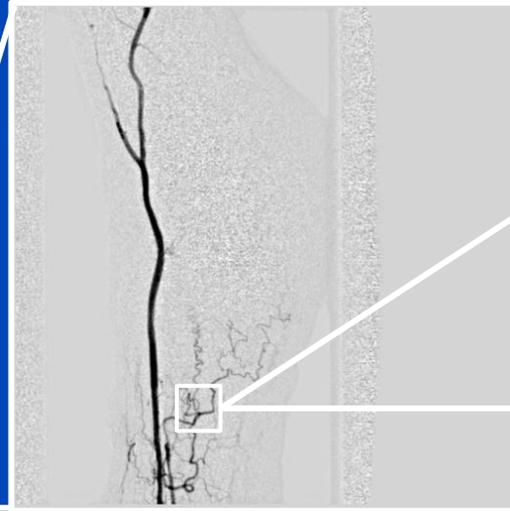
Artificially introduced stenosis?

Due to a low amount of training data and a low variability of the training data available to us the results shown on this slide are not optimal, yet.
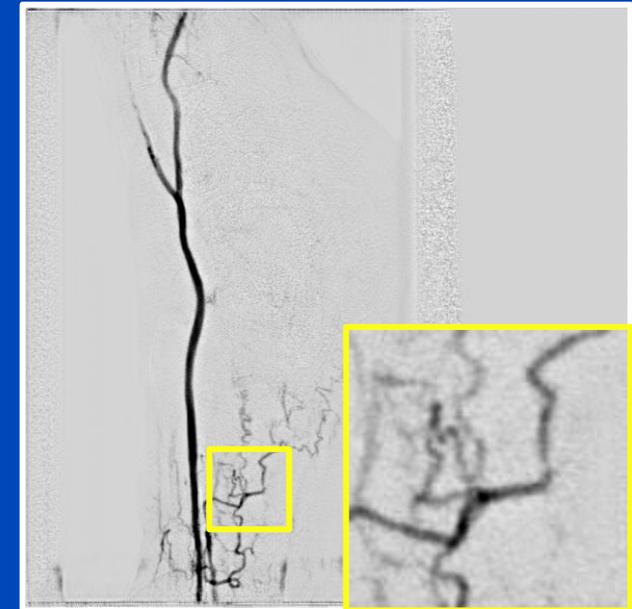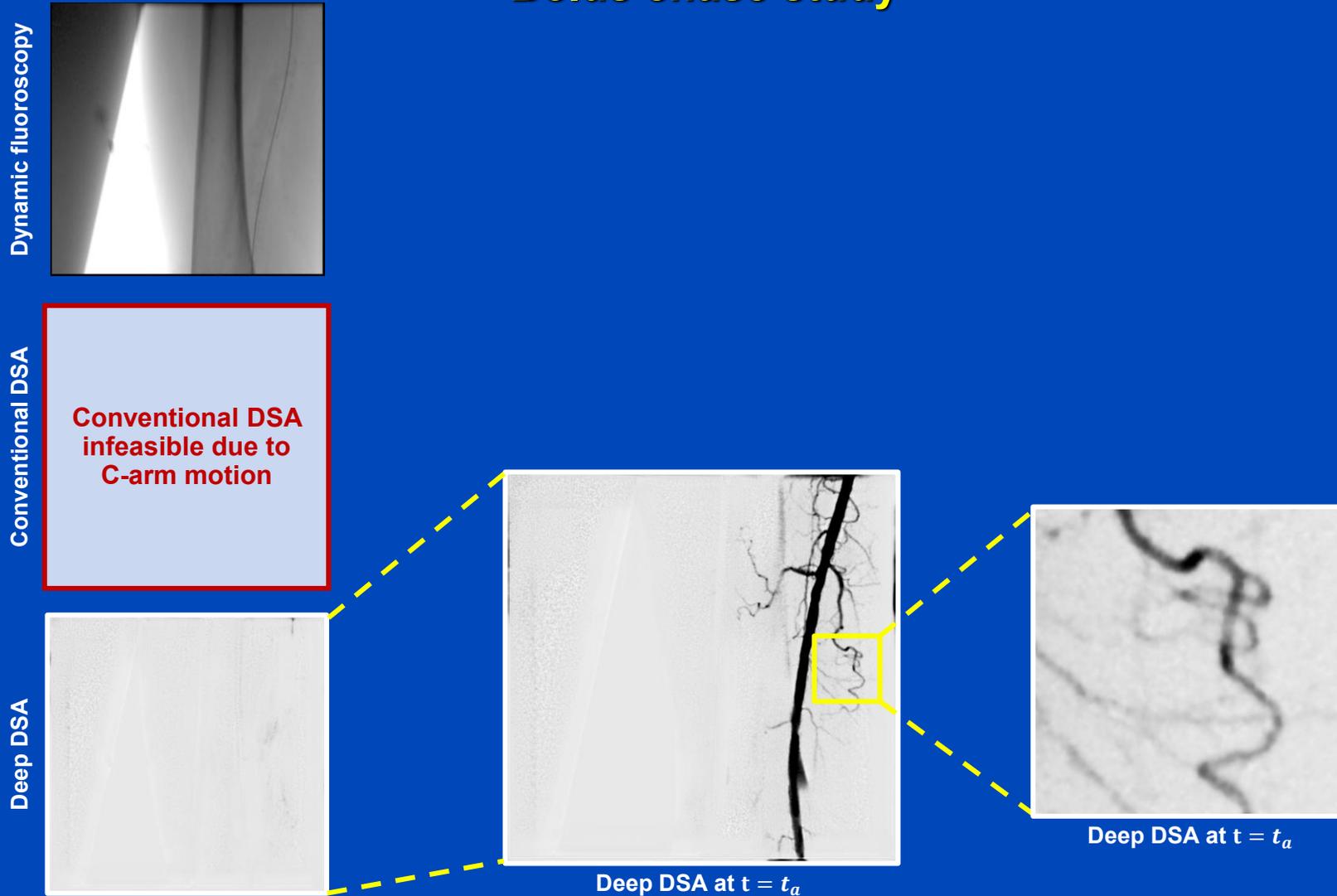
E. Eulig, M. Kachelrieß et al. "Learned digital subtraction angiography (Deep DSA): method and application to lower extremities". Fully 3D, May 2019.
L. Duan, M. Kachelrieß et al. "Training of a deep learning based digital subtraction angiography method using synthetic data". Med Phys. 51:4793–4810, July 2024.

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Deep DSA
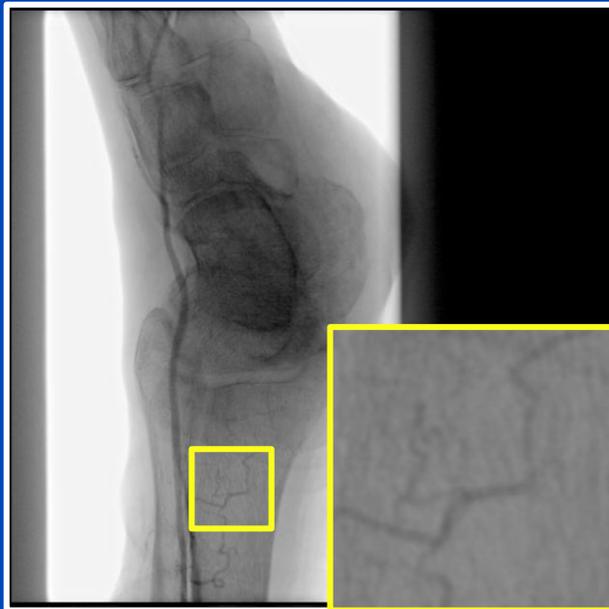
Fluoroscopy **DSA (fluoro minus mask)** **Deep DSA (from fluoro only)**

Due to a low amount of training data and a low variability of the training data available to us the results shown on this slide are not optimal, yet.

E. Eulig, M. Kachelrieß et al. "Learned digital subtraction angiography (Deep DSA): method and application to lower extremities". Fully 3D, May 2019.
L. Duan, M. Kachelrieß et al. "Training of a deep learning based digital subtraction angiography method using synthetic data". Med Phys. 51:4793–4810, July 2024.

Results
Bolus chase study

Dynamic fluoroscopy

Conventional DSA

Conventional DSA infeasible due to C-arm motion

Deep DSA

Deep DSA at $t = t_a$

Deep DSA at $t = t_a$

E. Eulig, M. Kachelrieß et al. "Learned digital subtraction angiography (Deep DSA): method and application to lower extremities". Fully 3D, May 2019.
L. Duan, M. Kachelrieß et al. "Training of a deep learning based digital subtraction angiography method using synthetic data". Med Phys. 51:4793–4810, July 2024.

dkfz.

Lessons Learned

- **Background frames with vessels sneaked into our training data.**

- **Mismatch in simulated PSF vs. measurement PSF may cause the network to fail**

	Epoch 5	Epoch 15	Epoch 30
Corrupted training data (here: not all background images were free of vessels)			
Forgot PSF augmentation (here: random $k{\times}k$ filter)			
Final good result			

dkfz.

Deep 3D+T Fluoroscopy

??? At 2D+T dose?

dkfz.
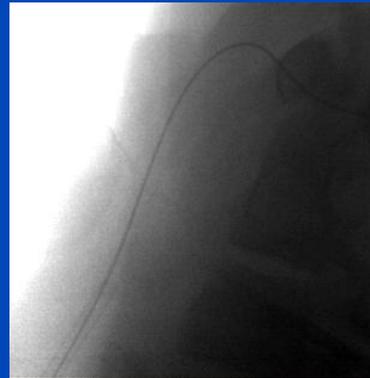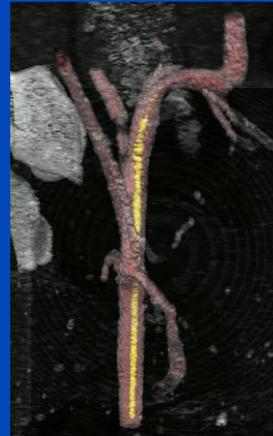
Deep 3D+T Tomographic Fluoroscopy
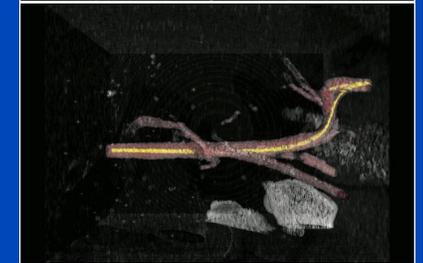
How to Realize 3D+T Fluoroscopy

- **Low dose by:**
  - Low tube current
  - Very few projections (pulsed mode)

- **Advantages of intervention guidance:**
  - Repetitive scanning of the same body region: changes are **sparse**.
  - Interventional materials are fine structures (few voxels) of high contrast (metal).

Prior scan
400 projections

Intervention scan
16 projections

Experimental setup

Pig in-vivo

B. Flach, J. Kuntz, M. Brehm, R. Kueres, S. Bartling, and M. Kachelrieß. "Low dose tomographic fluoroscopy: 4D intervention guidance with running prior.", Med. Phys. 40:101909, 11 pages, October 2013.

dkfz.
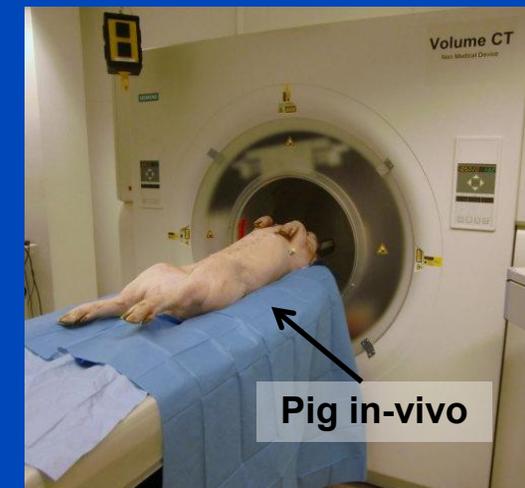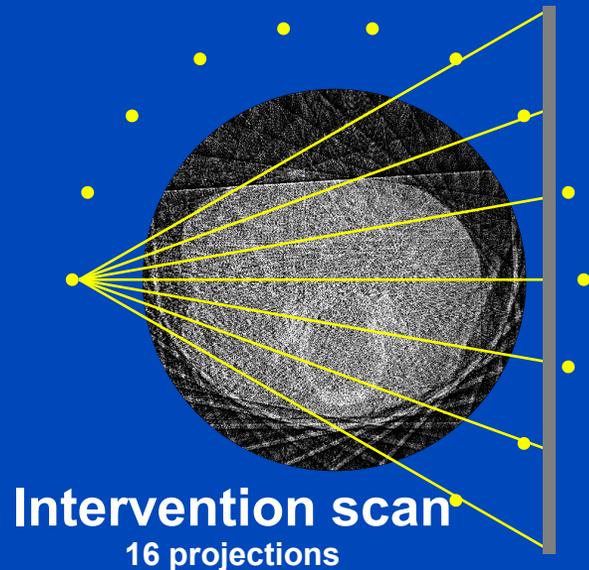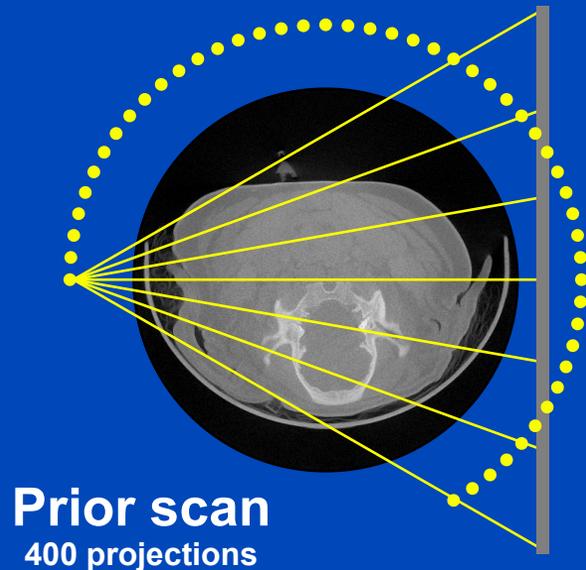
3D+T Image Guidance at 2D+T Dose
Stent Expansion in the Carotis of a Pig with Angio Roadmap Overlay

Iterative reconstruction using prior knowledge inside!
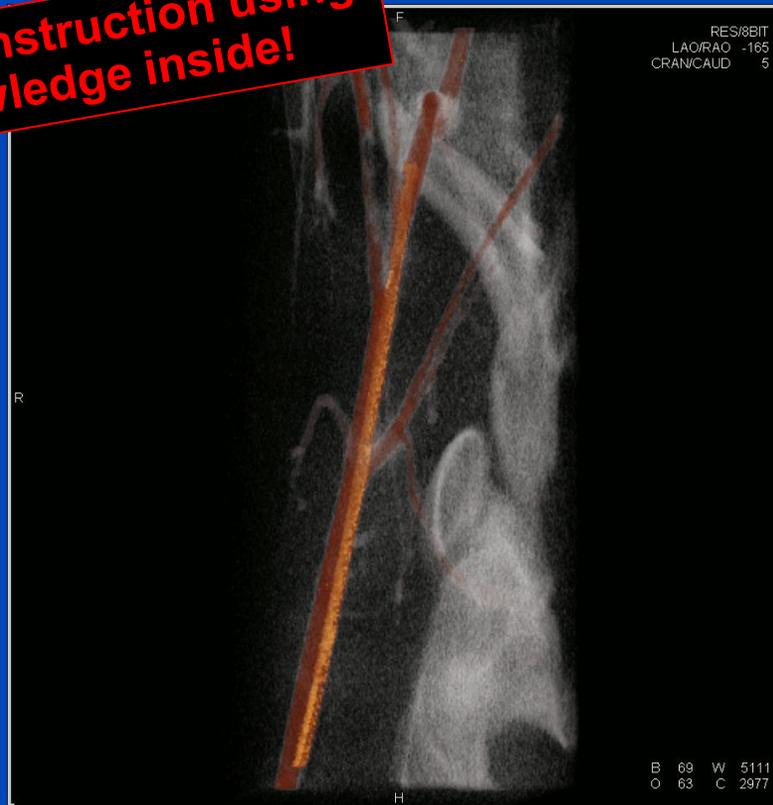
Dose of the yet unoptimized approach: 20 to 50 µGy/s.

This work was awarded the intervention award 2013 of the German Society of Neuroradiology (DGNR).
This work was further selected as the Editor's Pick for the Medical Physics Scitation site.

dkfz.

3D+T Fluoroscopy at 2D+T Dose
Guide Wire in the Carotis of a Pig with Angio Roadmap Overlay
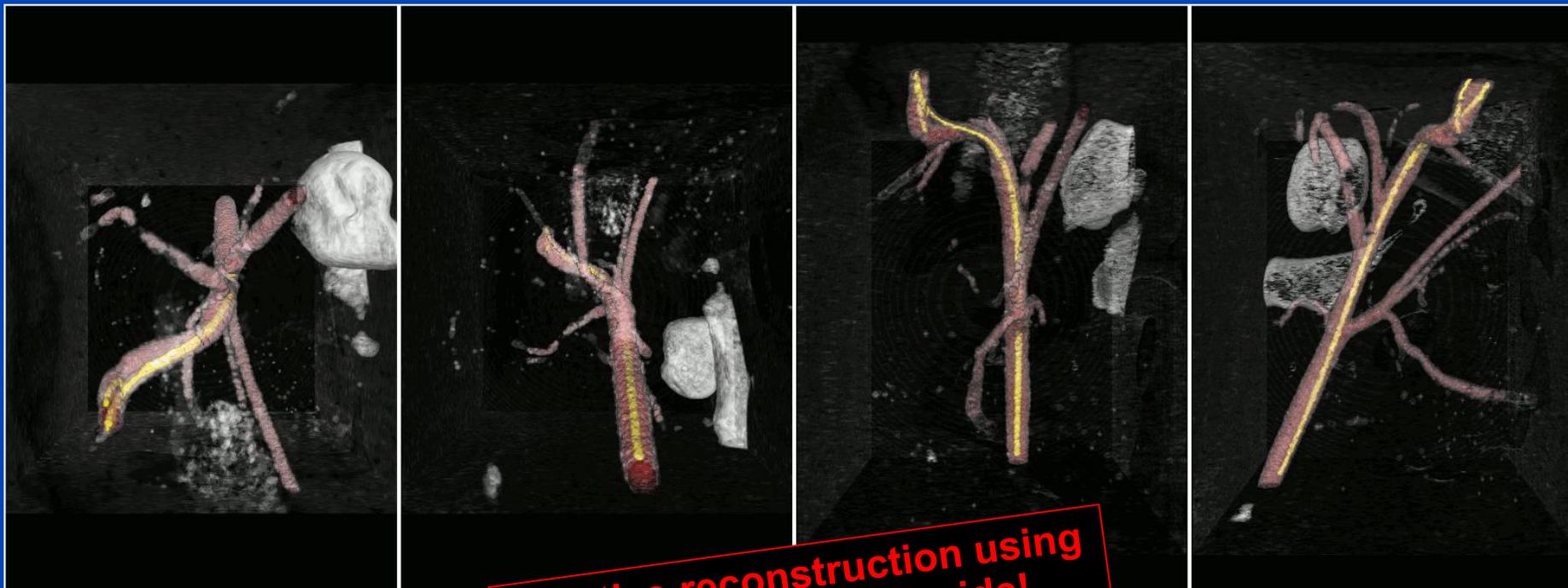
Iterative reconstruction using prior knowledge inside!

Dose of the yet unoptimized approach: 20 to 50 µGy/s.
Obviously, 16 projections are still too much.
Deep learning will help (5 years later)!

dkfz.

Deep Learning-Based 3D+T Fluoroscopy
Deep Tool Extraction (DTE) + Feldkamp Recon (FDK) + Deep Tool Reconstruction (DTR)
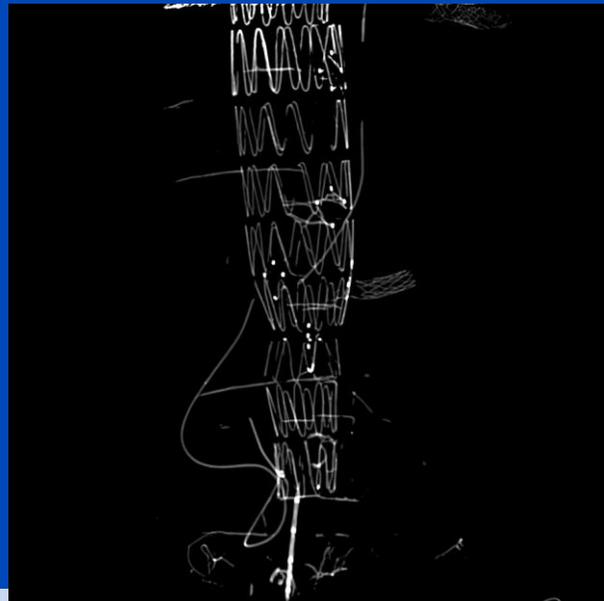
DTE Example 1

DTE Example 2

DTE

DTE

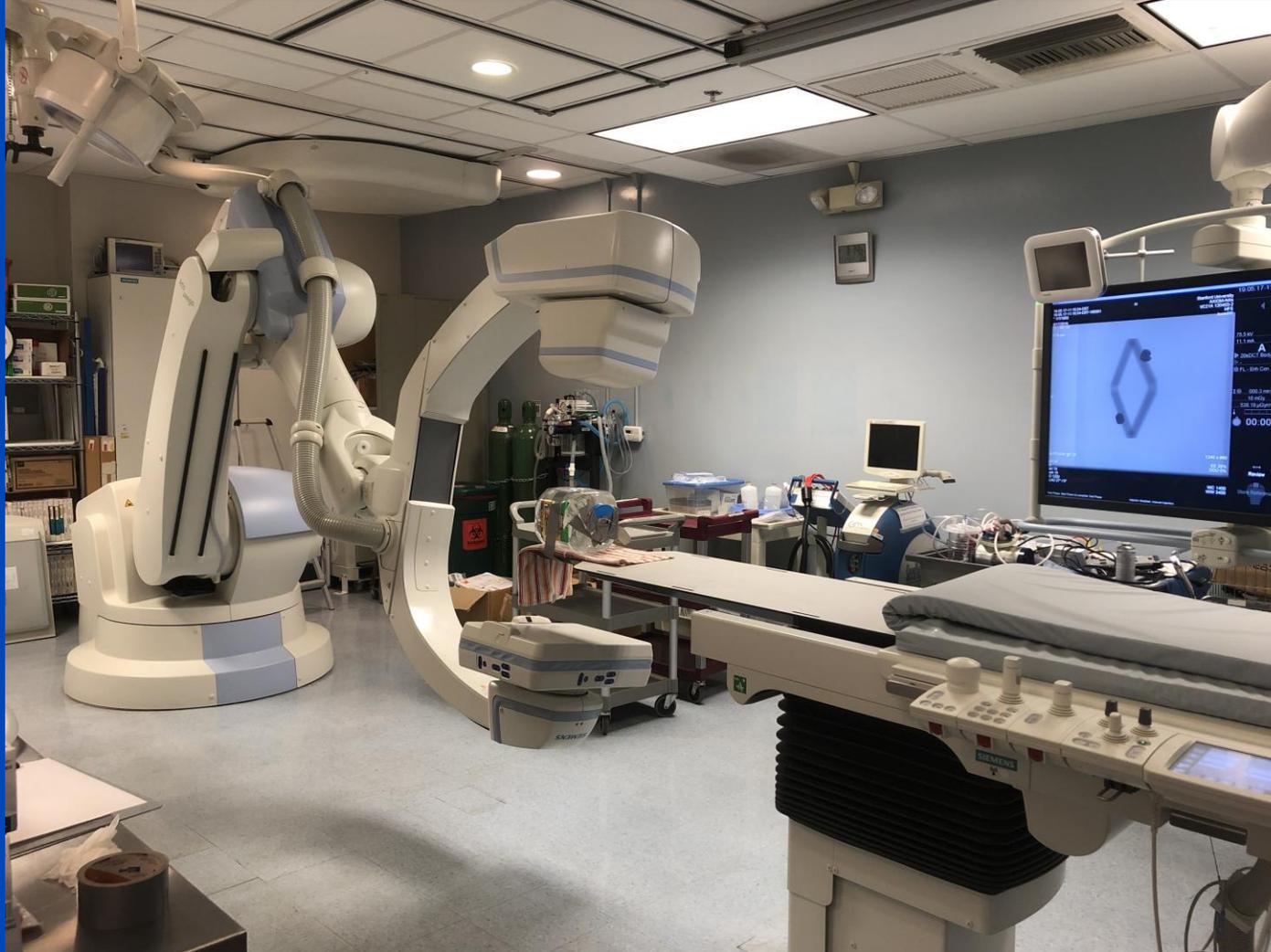dkfz.

More DTE Results

Evaluate DTE on

- **Fluoroscopy scans (top)**

- **Measurements of interventional tools and devices superimposed with patient CBCT (bottom)**

- **Good qualitative results on fluoroscopy data even though it differs from training data**

- **Good qualitative & quantitative results on superimposed data**

Tool	MAPE [%]
Guide wires	6.0 ± 0.1
Stents	13.4 ± 2.1
Coils	13.2 ± 1.6
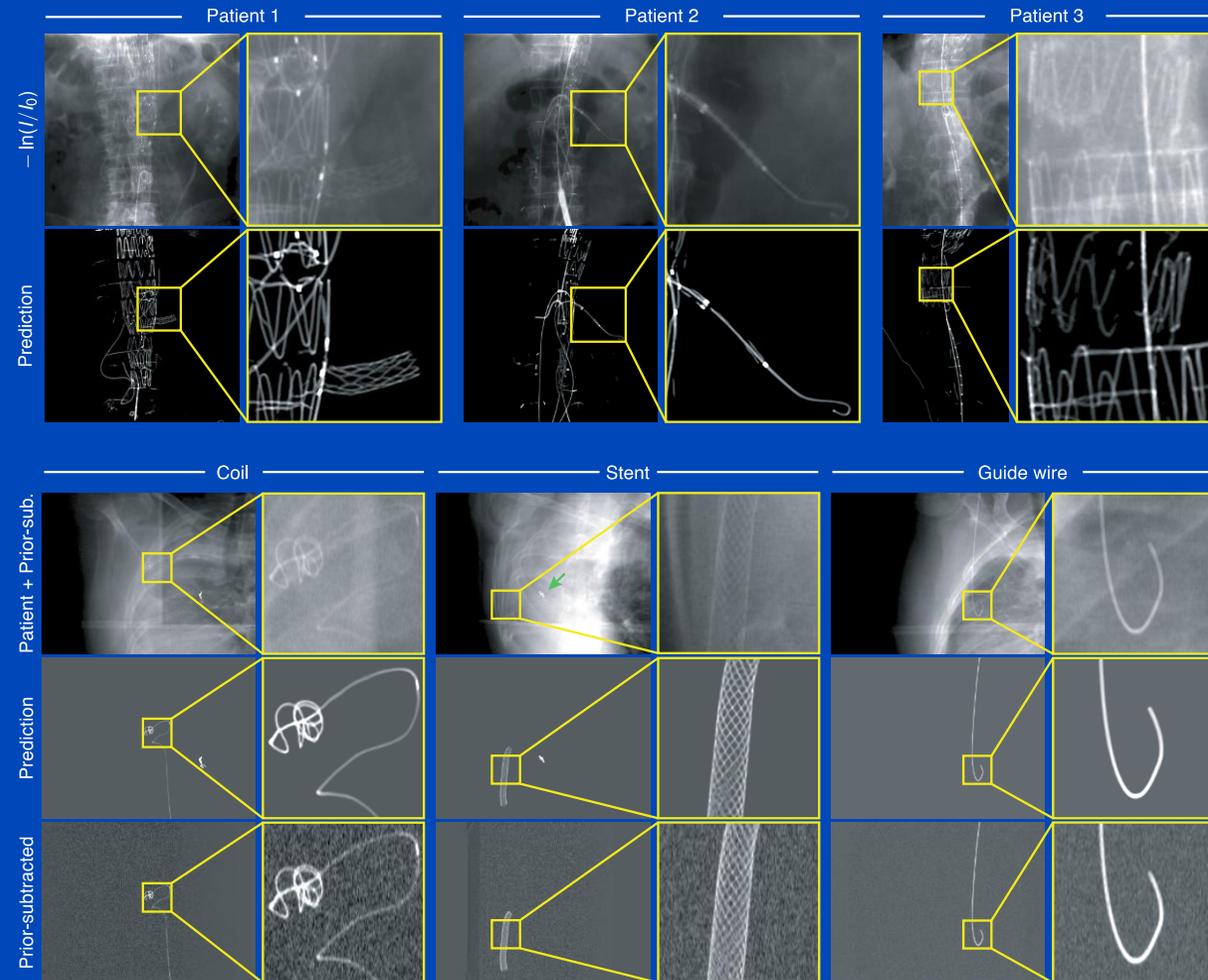
Zeego @ Stanford University

dkfz.

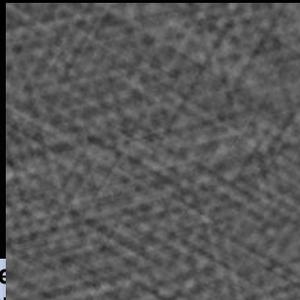# Zeego Measurements with Just 4 Projections

Ground truth (measurements from 400 projections)
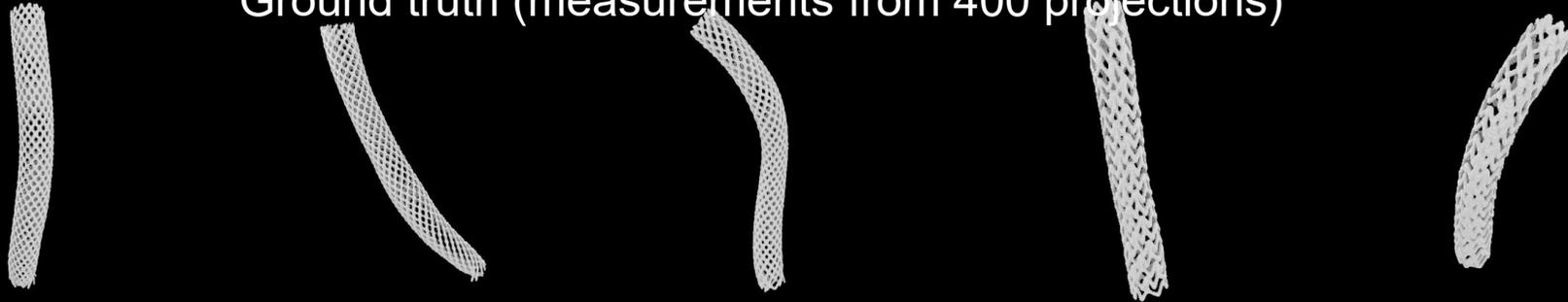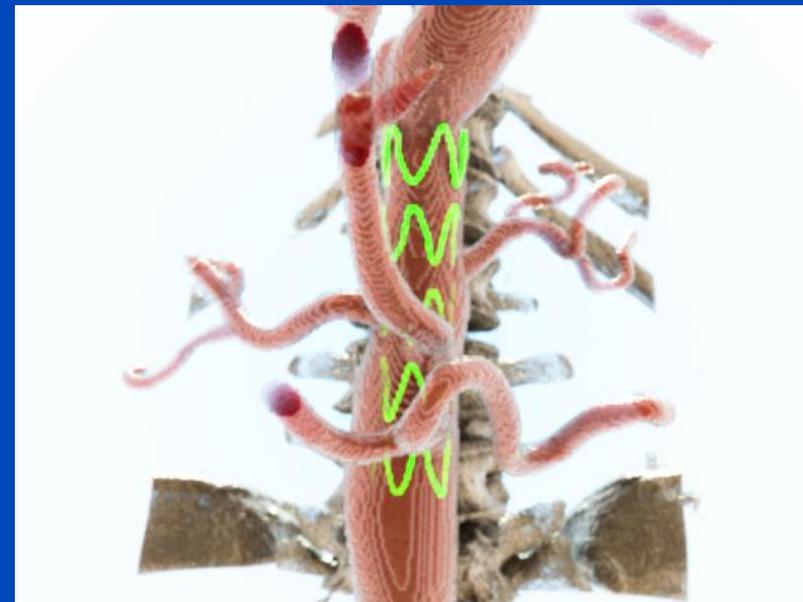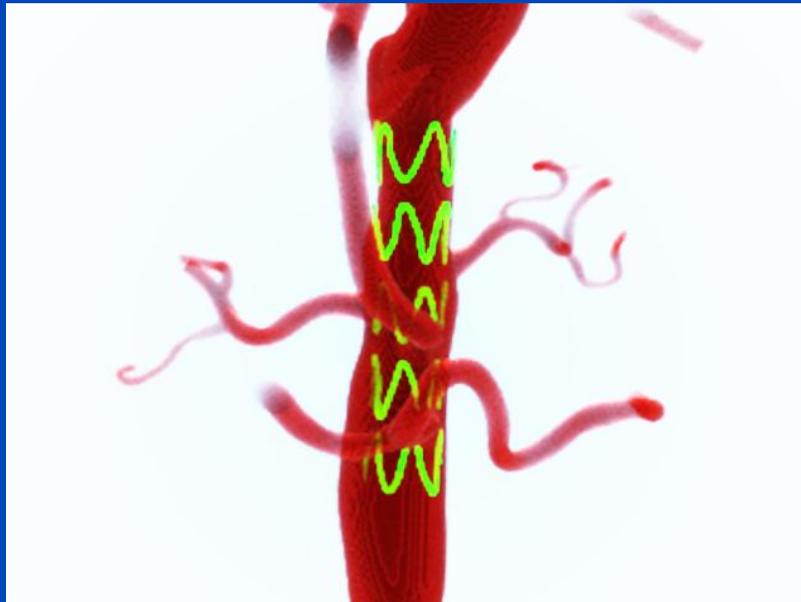

Neural network output (from just 4 projections)
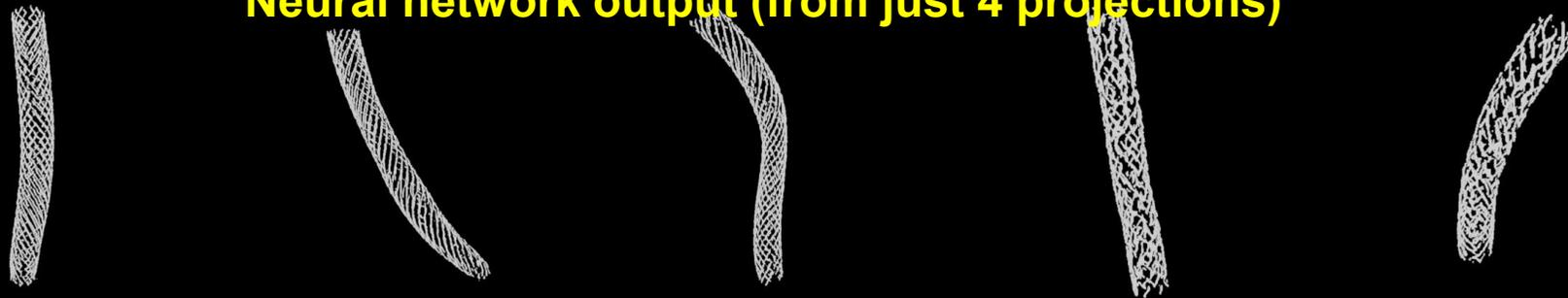
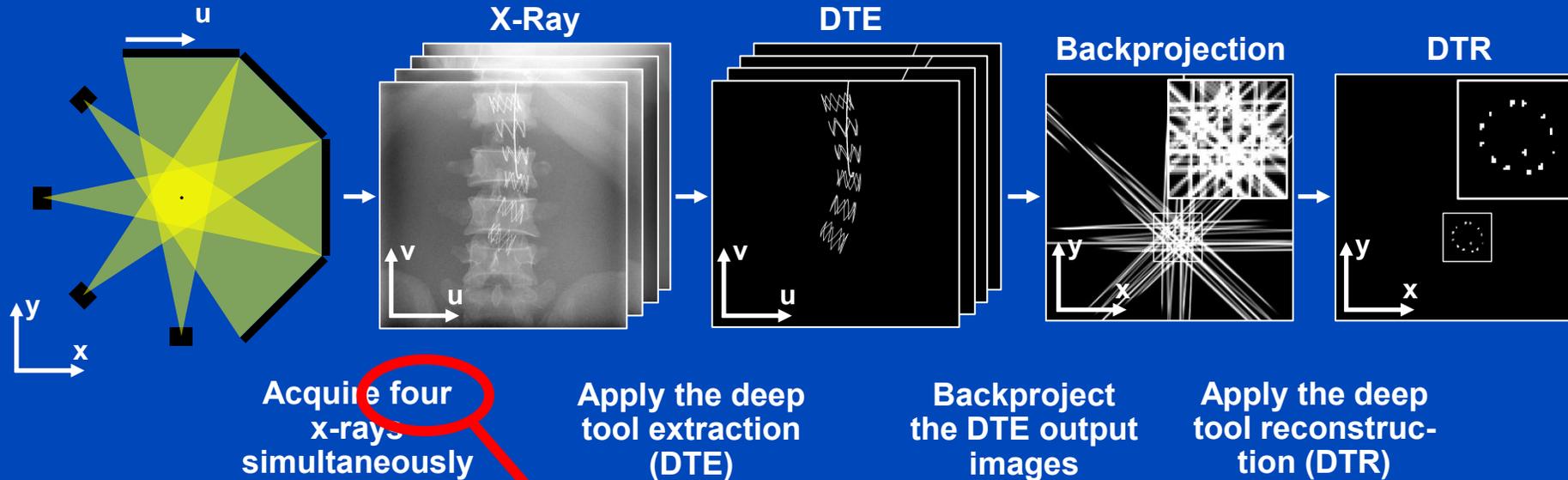**Loop through slices reconstructed from just 4 projections without AI:**

Stent examples:

dkfz.

So Far: Four-View Pipeline

Challenge

New Two-View Pipeline

$BP_{guidewire}(t-3)$, $ST_3(BP_{stent}(t-3))$,
$BP_{guidewire}(t-2)$, $ST_2(BP_{stent}(t-2))$,
$BP_{guidewire}(t-1)$ $ST_1(BP_{stent}(t-1))$

$DTEs_{stent}(t)$ $BP_{stent}(t)$ $DTR_{stent}(t)$

Projections(t)

$DTEs_{guidewire}(t)$ $BP_{guidewire}(t)$ $DTR_{guidewire}(t)$

Top Viewed Article

Congratulations to:
Marc Kachelriess

Whose work has been recognized as a top viewed article* in:

Medical Physics

Real-time 3D reconstruction of guidewires and stents using two update X-ray projections in a rotating imaging setup

*Among work published in *Medical Physics* between January 1, 2023 - December 31, 2023, up to 12 months after publication.

...ads

...d guidewire channels)

...spatial transformers (STs)

T. Voth, T. Kolig, E. Lang, M. Knaup, V. Wiesmann, K. Hörndler, and M. Kachelrieß. Real-time 3D reconstruction of guidewires and stents using two update x-ray projections in a rotating imaging setup. Med. Phys. 50(9):5312-5330, September 2023.

Semantic DTE

X-Ray Projection · DTE · Stent Output · Guidewire Output · 1024^2
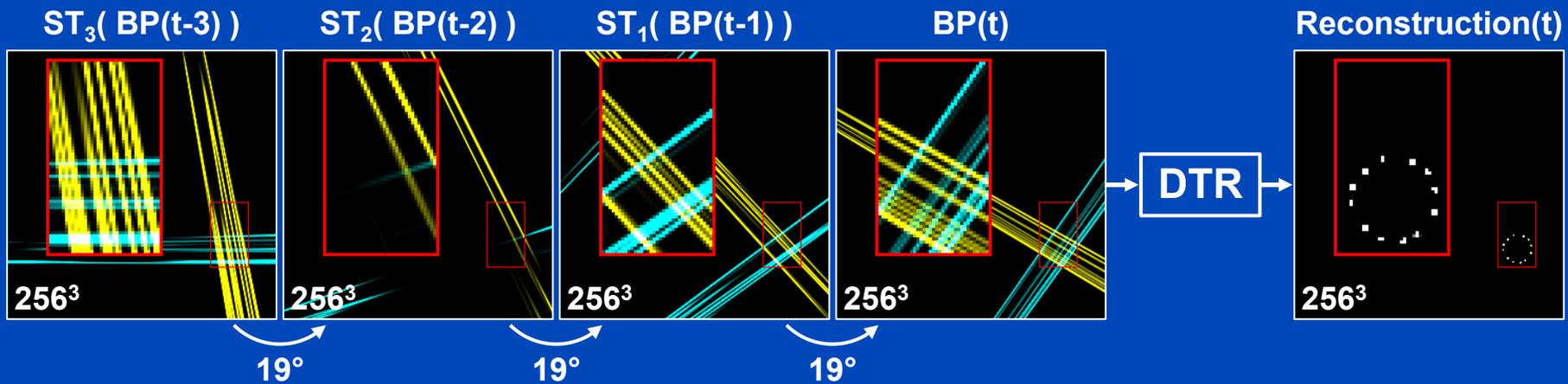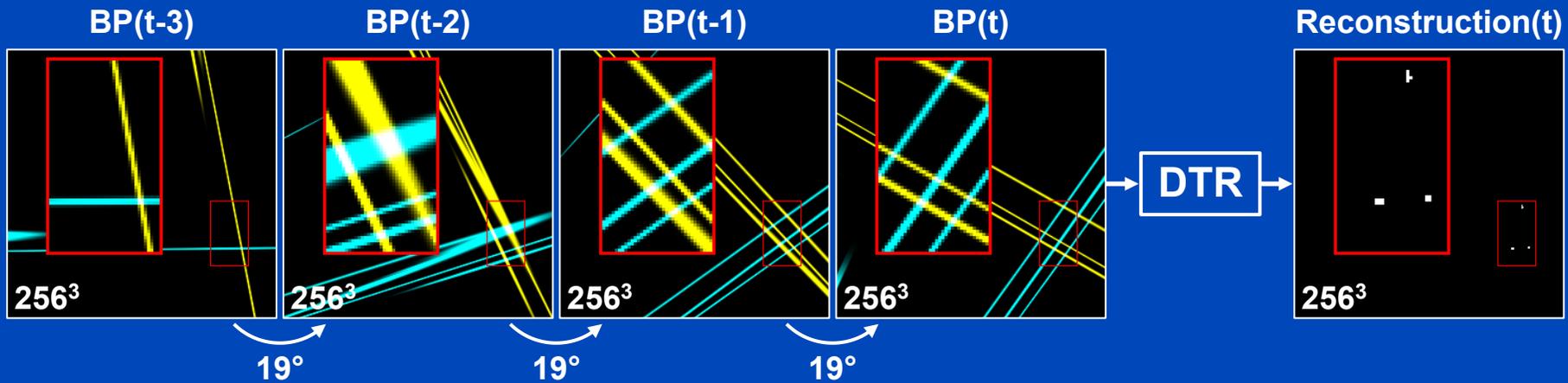
Guidewire and Stent DTR
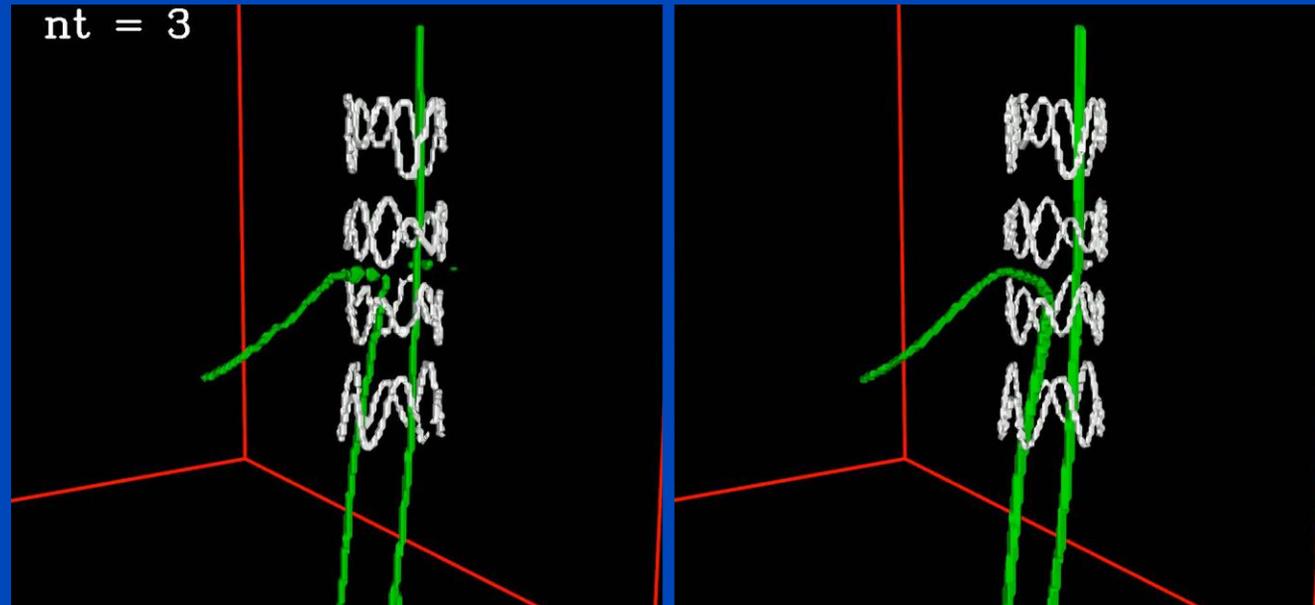
Stop Motion Measurements

- **Training: simulated data**

- **Results: stop motion measurements**

- **Flat detector**

- **For each time step t: 3D scan with fine angular sampling**

- **Choose two orthogonal projections from each 3D scan:**
    - » t = 1: 0°, 90°
    - » t = 2: 19°, 109°
    - » …

- **Objects: anthropomorphic trunk phantom + extension + interventional material placed between phantom and extension**

- **Motion: sinusoidal motion of phantom in superior-inferior direction (mimicking respiratory motion) + pulling of guidewire**

- **Parameters used during stop-motion measurement:**
  U = 100 kV, I = 30 mA, T_{rot} = 25 s, T_{pulse} = 20 ms

- **Simulated parameters:**
  U = 100 kV, I = 197 mA, T_{rot} = 3.8 s, T_{pulse} = 3 ms, Δt = 200 ms
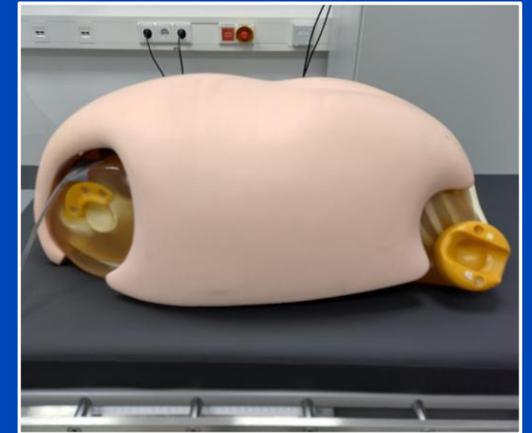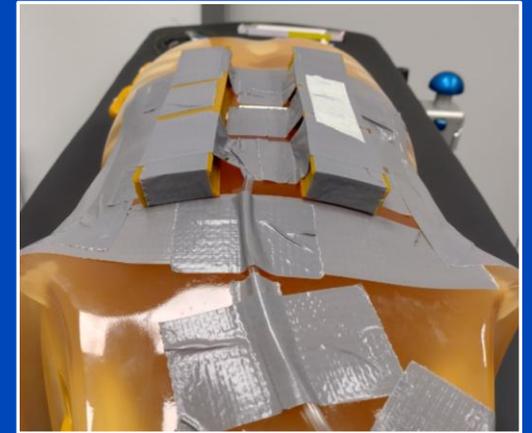
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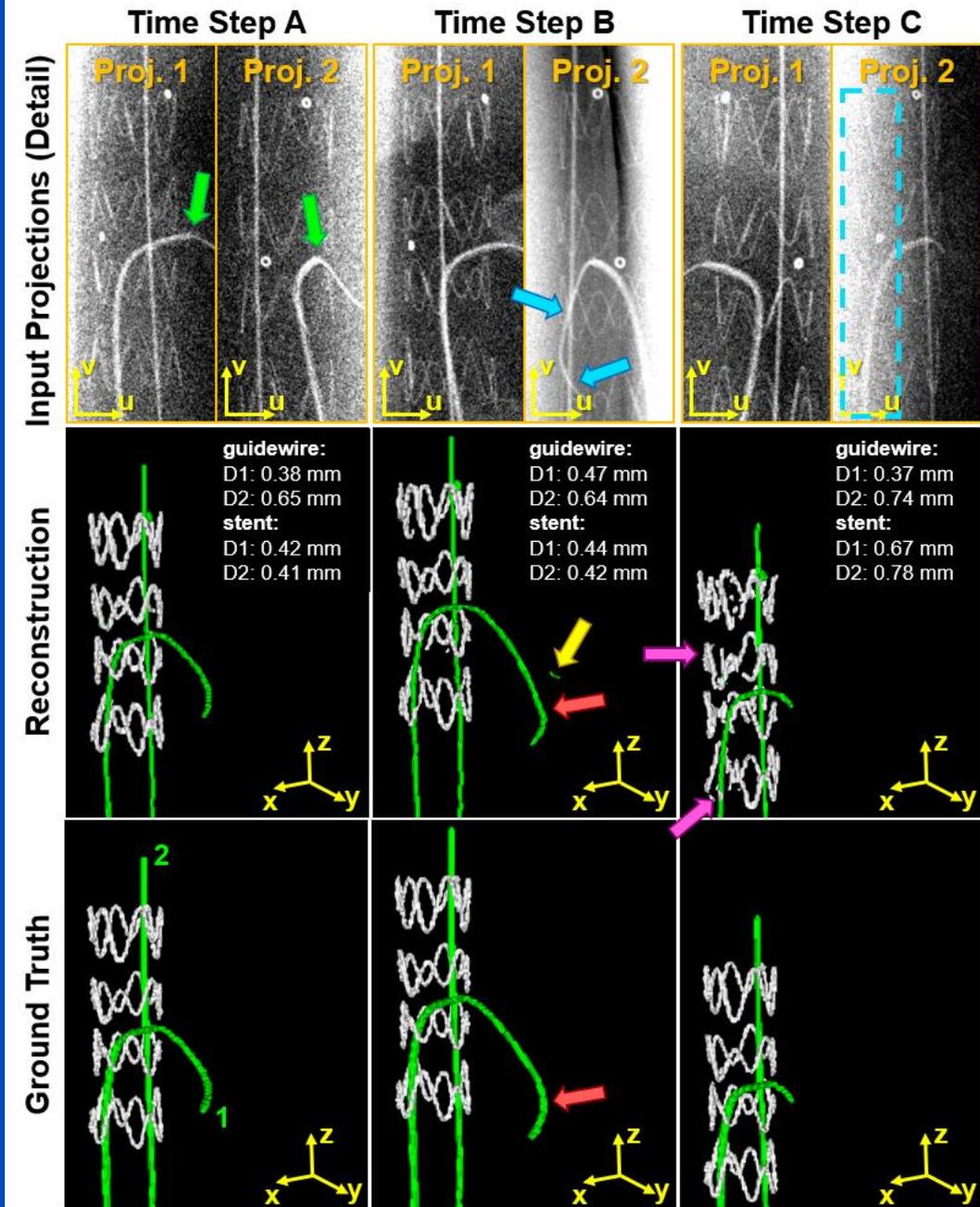
dkfz.
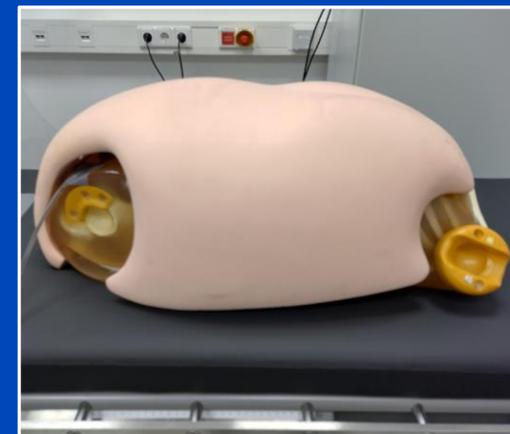
Results

Reconstruction | Ground Truth

5 fps video of stop motion scan with 57 time steps.
Sinusoidal 15 rpm motion of whole phantom with 11 mm amplitude.

Trunc phantom (with fat extension and interventional material) used for stop motion measurements.
U = 100 kV, I = 30 mA, T_{rot} = 25 s, T_{pulse} = 20 ms

T. Vöth, T. König, E. Eulig, M. Knaup, V. Wiesmann, K. Hörndler, and M. Kachelrieß. Real-time 3D reconstruction of guidewires and stents using two update x-ray projections in a rotating imaging setup. Med. Phys. 50(9):5312-5330, September 2023.

Results

- **Figures of merit:**
  - D_1: average distance between a skeleton of the ground truth and a skeleton of the reconstruction
  - D_2: average distance between a skeleton of the reconstruction and a skeleton of the ground truth

- **Median over 57 time steps:**
  - **Guidewire:**
    D_1 = 0.37 mm
    D_2 = 0.62 mm
  - **Stent:**
    D_1 = 0.44 mm
    D_2 = 0.44 mm

Thank You!

This presentation will soon be 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.