

Data-Driven Methods for Image Reconstruction and Artifact Correction in CBCT

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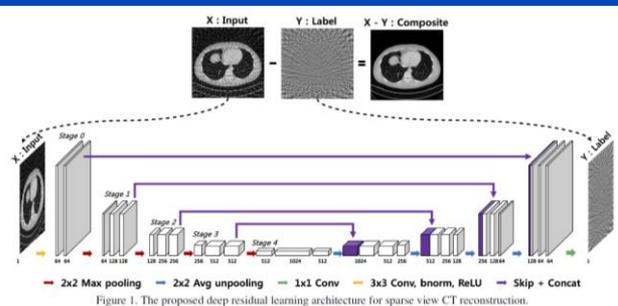
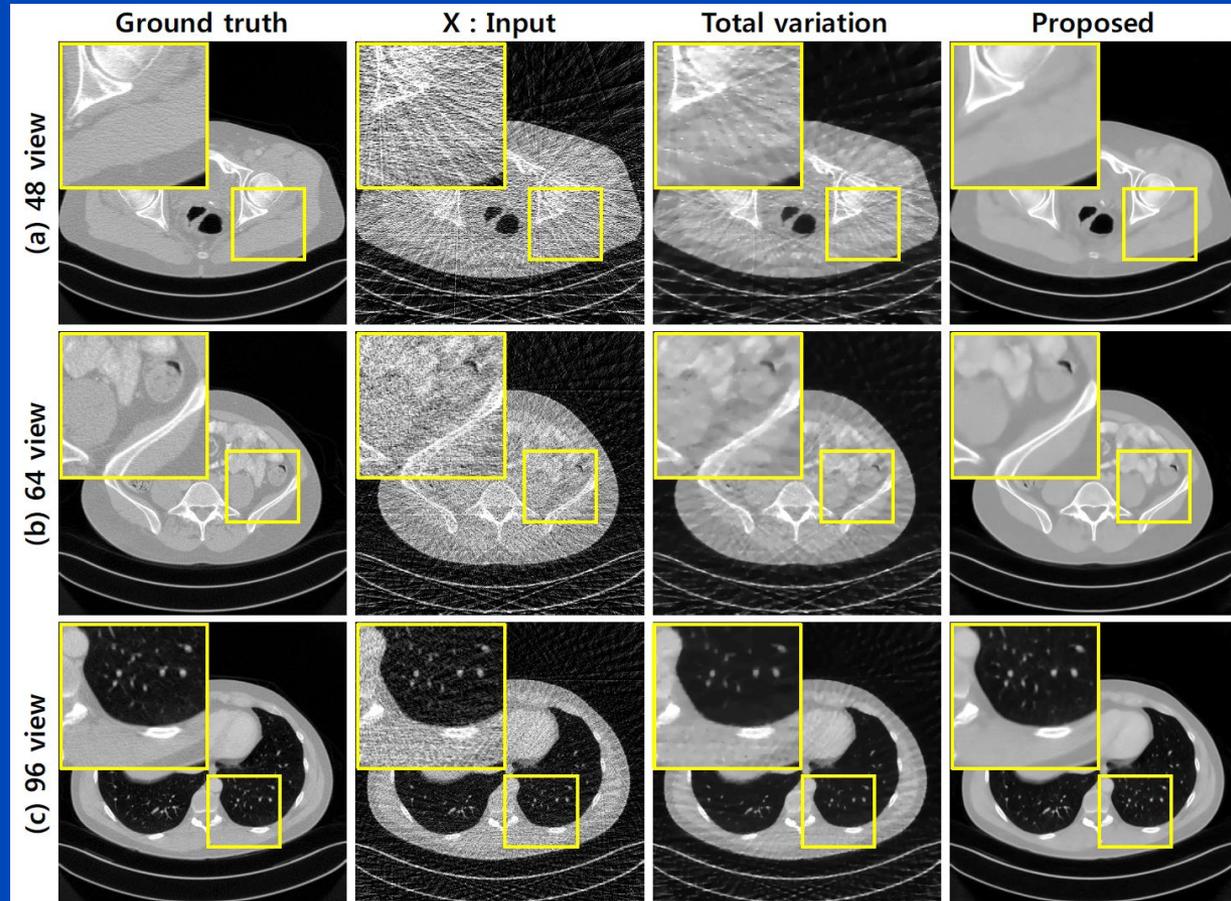
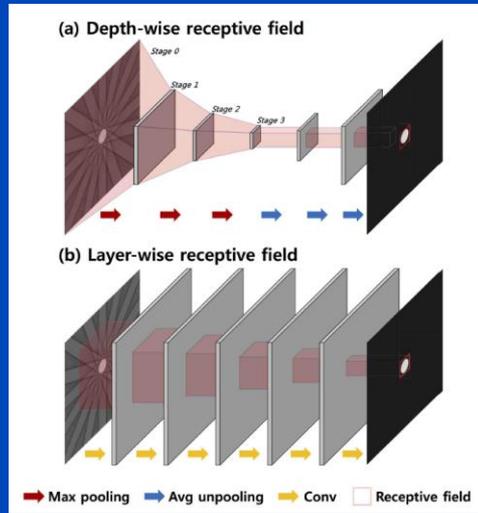


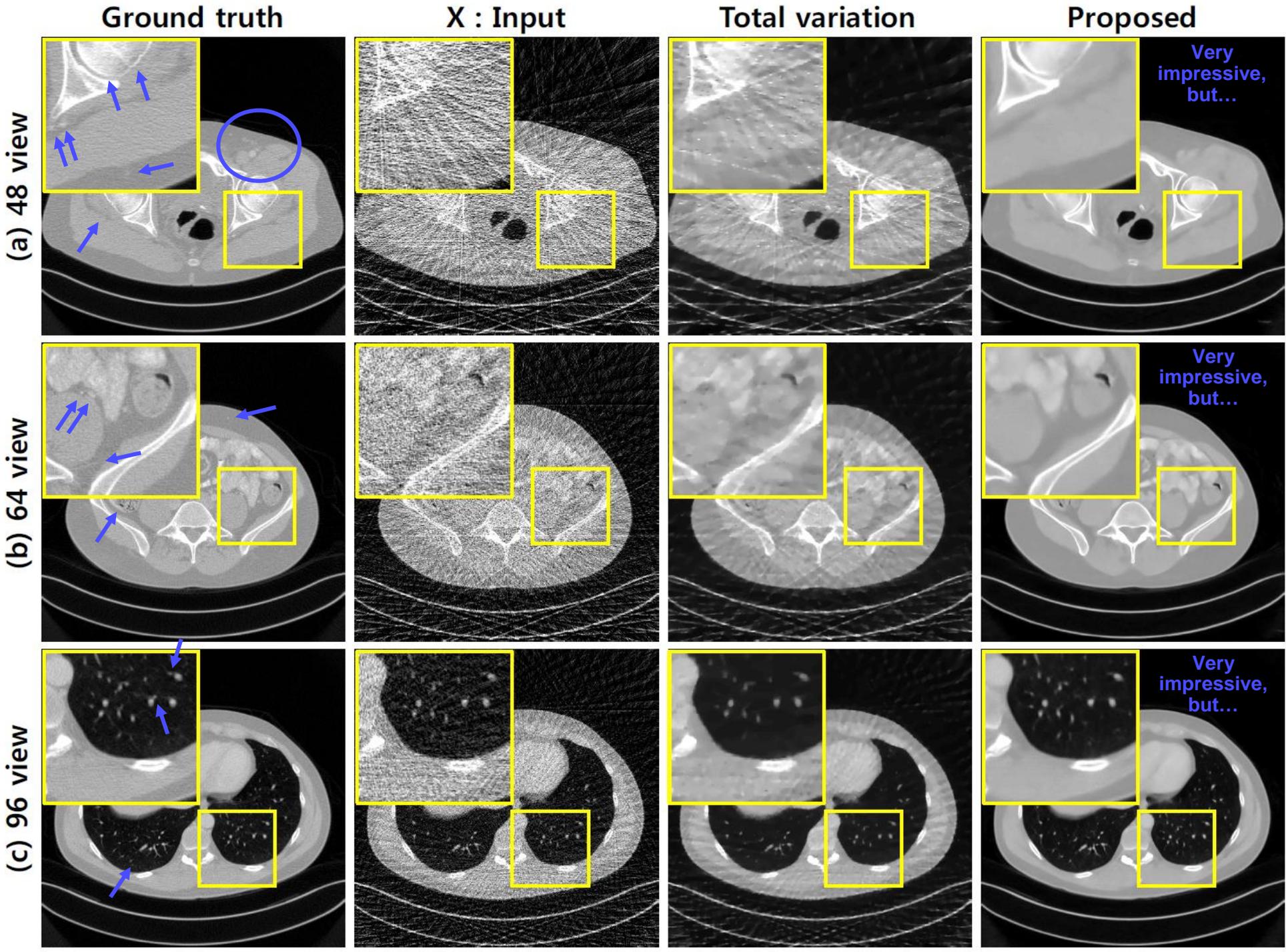
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KREBSFORSCHUNGSZENTRUM
IN DER HELMHOLTZ-GEMEINSCHAFT

Outline

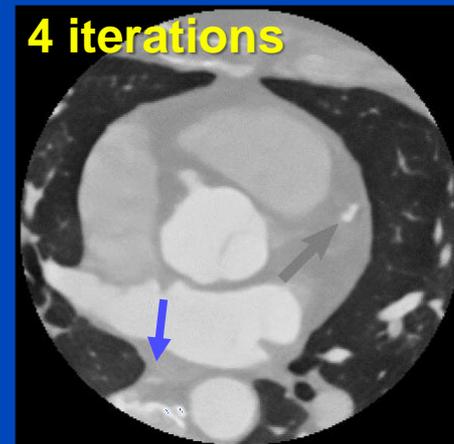
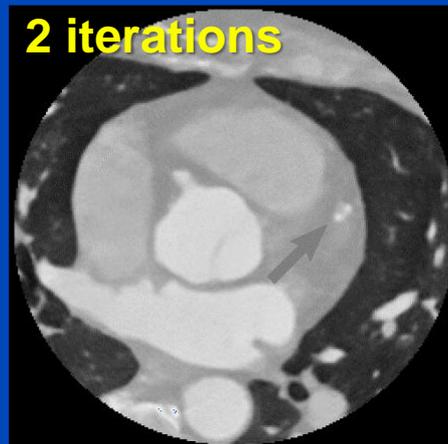
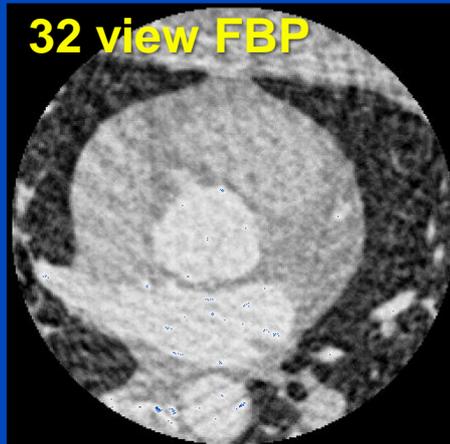
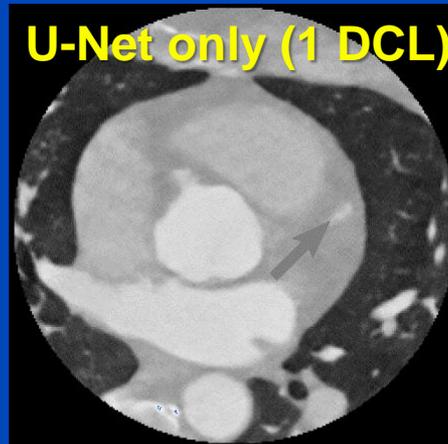
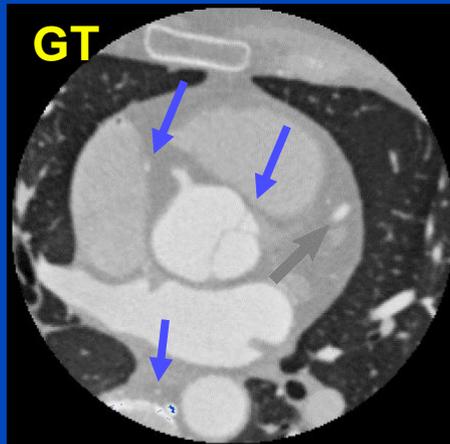
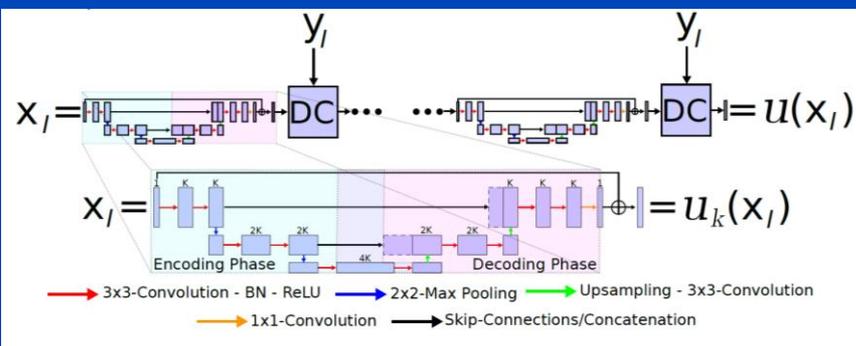
- Sparse view
- Ring artifacts
- Metal artifacts
- Scatter estimation
- Motion compensation
- 3D fluoroscopy (3D + time)

Sparse View Restoration Example





Sparse CT Recon with Data Consistency Layers (DCLs)



Ring Artifact Reduction: Literature

- Correction in sinogram/rawdata domain:
 - Nauwynck et al., *Ring Artifact Reduction in Sinogram Space Using Deep Learning*, Proc. CT Meeting 2020:486–489, 2020
- Correction in image domain:
 - Chang et al., *A Hybrid Ring Artifact Reduction Algorithm Based on CNN in CT Images*, Fully 3D 11072:1107226, 2019
 - Chao et al., *Removal of Computed Tomography Ring Artifacts via Radial Basis Function Artificial Neural Networks*, Phys. Med. Biol. 64(23):235015, 2019
 - Kornilov et al., *Deep Neural Networks for Ring Artifacts Segmentation and Corrections in Fragments of CT Images*, 28th FRUCT conference:181-193, 2021
 - Wang et al., *Removing Ring Artifacts in CBCT via GAN with Unidirectional Relative Total Variation Loss*, Neural Computing and Applications 31(9):5147-5158, 2019
 - Lv et al., *Image Denoising and Ring Artifacts Removal for Spectral CT via Deep Neural Network*, IEEE Access 8:225594-225601, 2020
- Correction in both, sinogram/raw-data and image domain:
 - Fang et al., *Comparison of Ring Artifacts Removal by Using Neural Network in Different Domains*, MIC, 2019
 - Fang et al., *Removing Ring Artefacts for Photon-Counting Detectors Using Neural Networks in Different Domains*, IEEE Access 8:42447-42457, 2020

Ring Artifact Reduction: Comments

- Correction in sinogram/rawdata domain:
 - Nauwynck et al. (2020) – Results are ok. The method can, however, not correct low-frequency ring artifacts.
- Correction in image domain:
 - Chang et al. (2019) – Strange mixture of CNN and classical method. New artifacts are introduced.
 - Chao et al. (2019) – It remains unclear how the artifact areas are segmented. Only zoom-ins show some improvements.
 - Kornilov et al. (2021) – Theoretically sound, however, no reasonable images are presented.
 - Wang et al. (2019) – The results of all correction methods look the same (suboptimal gray scale windowing).
 - Lv et al. (2020) – The question arises why the method to generate the ground-truth data is not directly used for correction.
- Correction in both, sinogram/raw-data and image domain:
 - Fang et al. (2019) – The results shown are interesting. However, there are no measured data processed.
 - Fang et al. (2020) – The results are good. Probably it is the best method of this slide's list.

Removing Ring Artefacts for Photon-Counting Detectors Using Neural Networks in Different Domains

WEI FANG^{ID}, LIANG LI^{ID}, (Senior Member, IEEE), AND ZHIQIANG CHEN

- Clean data from the AAPM Low Dose CT Grand Challenge.
- Ring artifacts are simulated by adding stripes in the sinogram data.
 - Slope and offset model in log domain
- The data were split into training (4800 images), validation (600 images) and testing datasets (526 images) and an MSE loss function is used.
- Simulate ring artifacts
 - slope and offset model in log domain

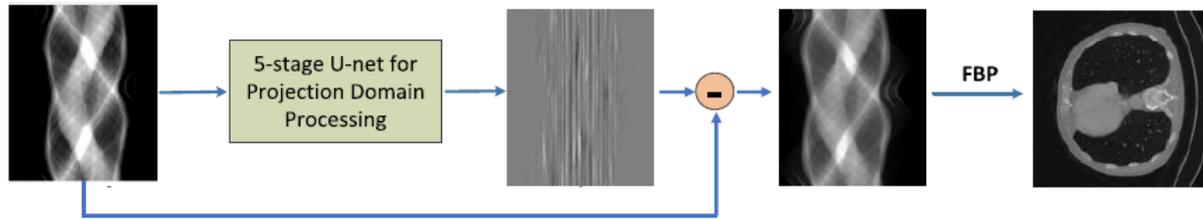


FIGURE 3. The diagram of ring artefacts removal in projection domain.

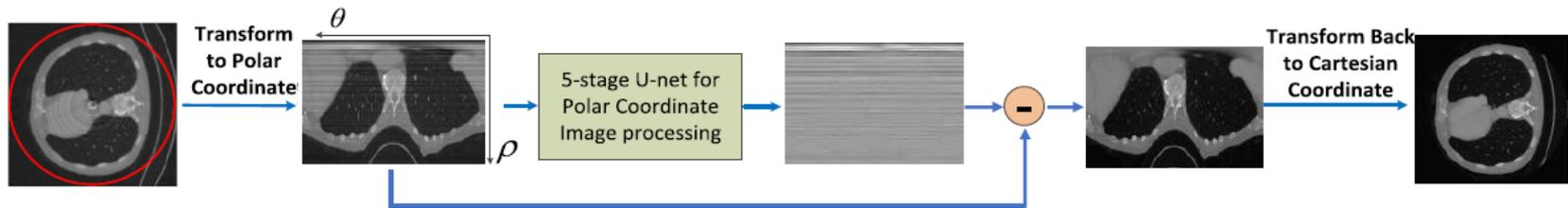


FIGURE 4. The diagram of ring artefacts removal in polar coordinate system.

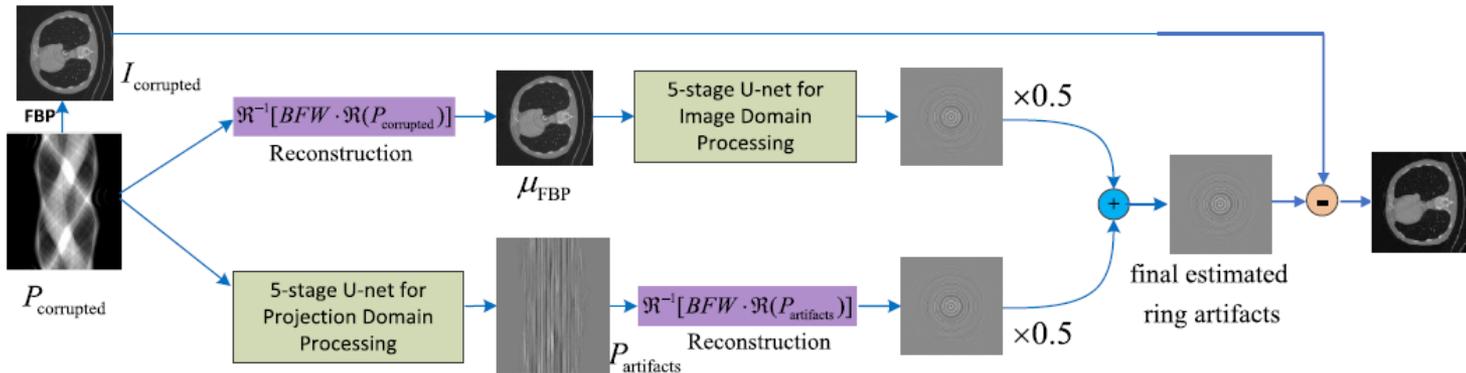
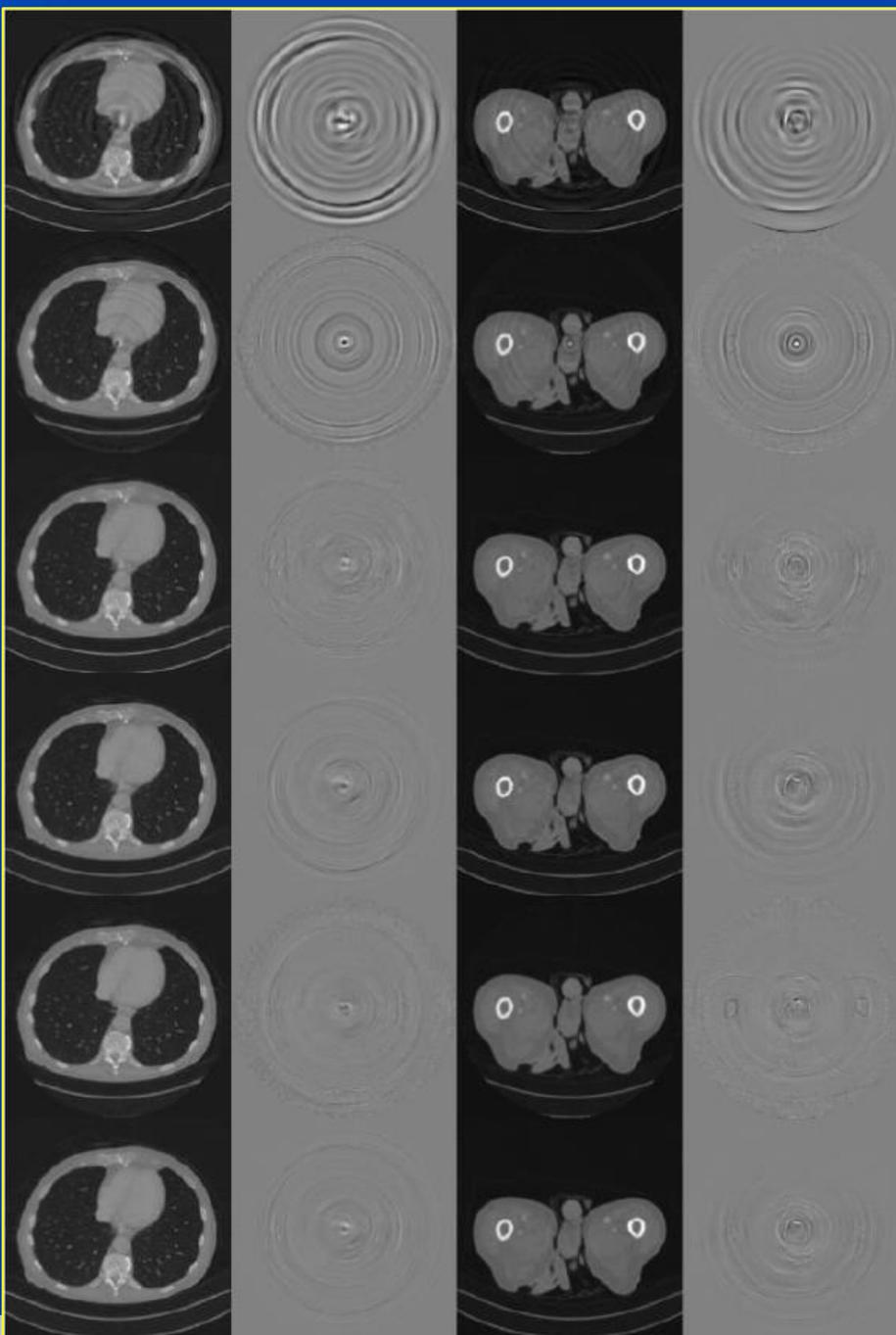


FIGURE 5. The diagram of ring artefacts removal using a comprehensive model.

Wavelet projection domain



Wavelet polar image domain

U-net image domain

U-net projection domain

U-net polar image domain

U-net in both domains

MAR Examples

Reducing Metal Streak Artifacts in CT Images via Deep Learning: Pilot Results

Lei Gengyi, Qingyan Tang, Tao Yu, Baohua Chen, Xiaohu Fu, Baojun Ma, Guo Yong

- Takes 32x32 input patch from NMAR image and produces 20x20 output patch
- Very basic CNN

Gjesteby, 2017

- Same network as in previous work
- Detail image is the high-pass filtered original image
- Detail image and NMAR image are both put as inputs in 2 streams that converge later in the CNN
- Network uses residual error and cost function is a combination of MSE and perceptual loss

Deep Neural Network for CT Metal Artifact Reduction with a Perceptual Loss Function

Lei Gengyi, Qingyan Tang, Tao Yu, Baohua Chen, Xiaohu Fu, Baojun Ma, Guo Yong

Gjesteby, 2018

- Inputs for the network are the NMAR image and the high-pass filtered original image
- Corrects streaks after NMAR
- Loss function is MSE or perceptual loss (from VGG network)
- MSE shows over-smoothing
- Trained on simulated data
- Each residual unit learns residual error

Gjesteby, 2018

A dual-stream deep convolutional network for reducing metal streak artifacts in CT images

Lei Gengyi, Qingyan Tang, Qingyan Tang, Tao Yu, Baohua Chen, Xiaohu Fu, Baojun Ma, Guo Yong

Xing, 2019

- Perform initial LIMAR to obtain images with interpolation artifacts
- Apply U-Net to pre-corrected images to reduce artifacts
- Network minimizes L2-norm loss outside of the metal regions

Gjesteby, 2019

Gjesteby, 2019

Gjesteby, 2019

- Same network as in previous work
- Detail image is the high-pass filtered original image
- Detail image and NMAR image are both put as inputs in 2 streams that converge later in the CNN
- Network uses residual error and cost function is a combination of MSE and perceptual loss

Metal artifact reduction for practical dental computed tomography by improving interpolation-based reconstruction with deep learning

Kunlun Liang, Li Zhang, and Hongyi Yang

Xing, 2019

Xing, 2019

- Perform initial LIMAR to obtain images with interpolation artifacts
- Apply U-Net to pre-corrected images to reduce artifacts
- Network minimizes L2-norm loss outside of the metal regions

Metal artifact reduction on cervical CT images by deep residual learning

Qi Huang¹, Jian Wang¹, Fan Tang¹, Tao Zhang¹ and Yu Zhang¹

Zhang, 2018

Zhang, 2018

- Metal is placed in real CT images. Artifacts are created by forward and back-projecting soft tissue, bone, and metal
- Network input is patch of artifact image I and output is the residual, i.e. $R = I - GT$
- Loss function is MSE of the residual
- Learning the residual is found to be better than learning the artifact-free image (no images)

Convolutional Neural Network Based Metal Artifact Reduction in X-Ray Computed Tomography

Nanli Zhang¹, Senjie Menze¹, and Hongyi Yang¹

Yu, 2018

Yu, 2018

- Training data are generated from clinical data with metal artifacts added afterwards through polychromatic forward- & back-projection
- Cost function is MSE
- CNN gets patches from the artifact BTC corrected, and LI corrected image as input, produces corrected patches
- Prior image is generated from CNN result by segmenting water and setting it to the average value of all water pixels and leaving bones intact
- Metal trace in the uncorrected sinogram is replaced with values from the prior image
- Having different types of MAR as input improves results

Metal-Artifact Reduction Using Deep-Learning Based Sinogram Completion: Initial Results

Richard E. Cole, Yuesha Li, Lei Gengyi, Guo Yong, Baojun Ma

Claus, 2017

- Trained and evaluated on simulated data with metal circle in the center (no other positions tested)
- Data are heavily simplified (random ellipses)
- Inputs are 2 81x21 sized patches from the sinogram next to metal patch. Won't work for complex metals
- Relatively small network (4 layers)

Deep Learning Based Metal inpainting in the Projection Domain: Initial Results

Shihua M. Gutschalk^{1,2}, Bijan W. Kruger¹, Balder Koenig¹, and Andrew Mauer^{1,2}

Gottschalk, 2019

- Corrects C-Arm projection data
- Data were obtained by placing metal on top of human knee cadavers
- Loss function is MSE
- Networks are based on U-Net with additional skip connection from original image to output
- Basic network can be used to implicitly segment the metal for the Mask-MAR-Net
- Providing a metal mask significantly improves results
- Results are blurred slightly

Gottschalk, 2019

Gottschalk, 2019

Deep Learning based Metal Inpainting in the Projection Domain using additional Neighboring Projection Information

Shihua M. Gutschalk, Bijan W. Kruger, and Andrew Mauer

Gottschalk, 2020

Gottschalk, 2020

- U-Net corrects CBCT projections
- Has metal mask and 10 neighbouring projections as additional input channels

Fast Enhanced CT Metal Artifact Reduction using Data Domain Deep Learning

Muhammad Usman Ghani, W. Chen, Karl, Felton, 2022

Ghani, 2019

- Metal trace is replaced via a CGAN
- Uses transfer learning from training data to real data; not described in depth
- Not applied to medical images

Ghani, 2019

Generative Mask Pyramid Network for CT/CBCT Metal Artifact Reduction with Joint Projection-Sinogram Correction

Huili Liao¹, Wei An Liao¹, Zhiliang Han¹, Lixun Yin^{1,2}, William J. Sekerac¹, Si Kevin Zhou¹, and Jiebo Luo¹

Liao, 2019

Liao, 2019

- First replaces metal trace in the projections (i.e. fixed angle but varying ϕ and z)
- Then transforms the projections into sinograms and uses a second network to improve those
- Both networks are GANs with a U-Net generator and CNN discriminator
- Uses a Mask Pyramid to ensure the metal mask is seen by all stages of the U-Net
- Data are regular CT scans with metal traces from other patients imposed on them

DuoNet: Dual Domain Network for CT Metal Artifact Reduction

Wei An Liao¹, Huili Liao¹, Cheng Ding¹, Xiaohua Guo¹, Jiebo Luo¹, Jiebo Luo¹, Rana Chellappa¹, Shaohua Kevin Zhuo¹

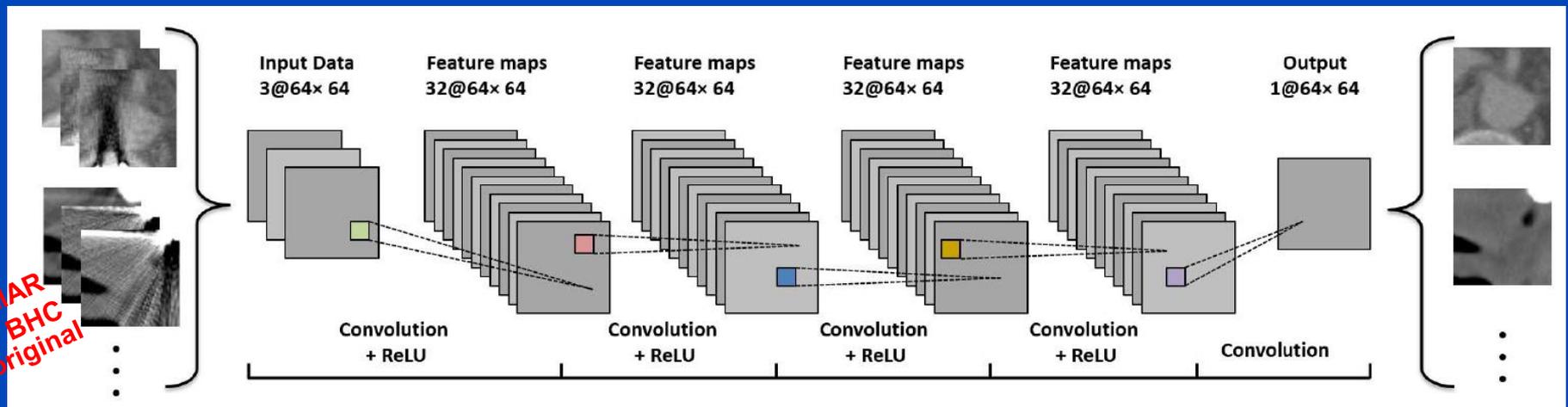
Lin, 2019

Lin, 2019

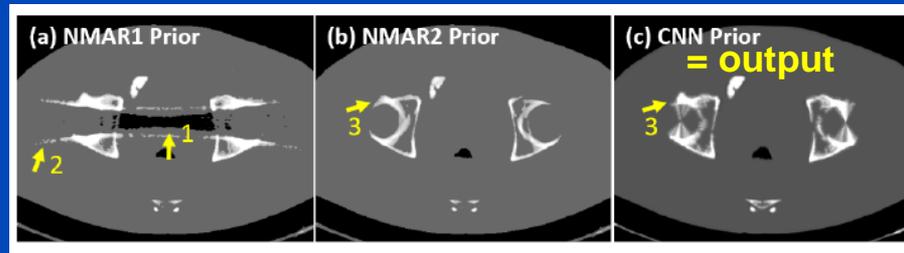
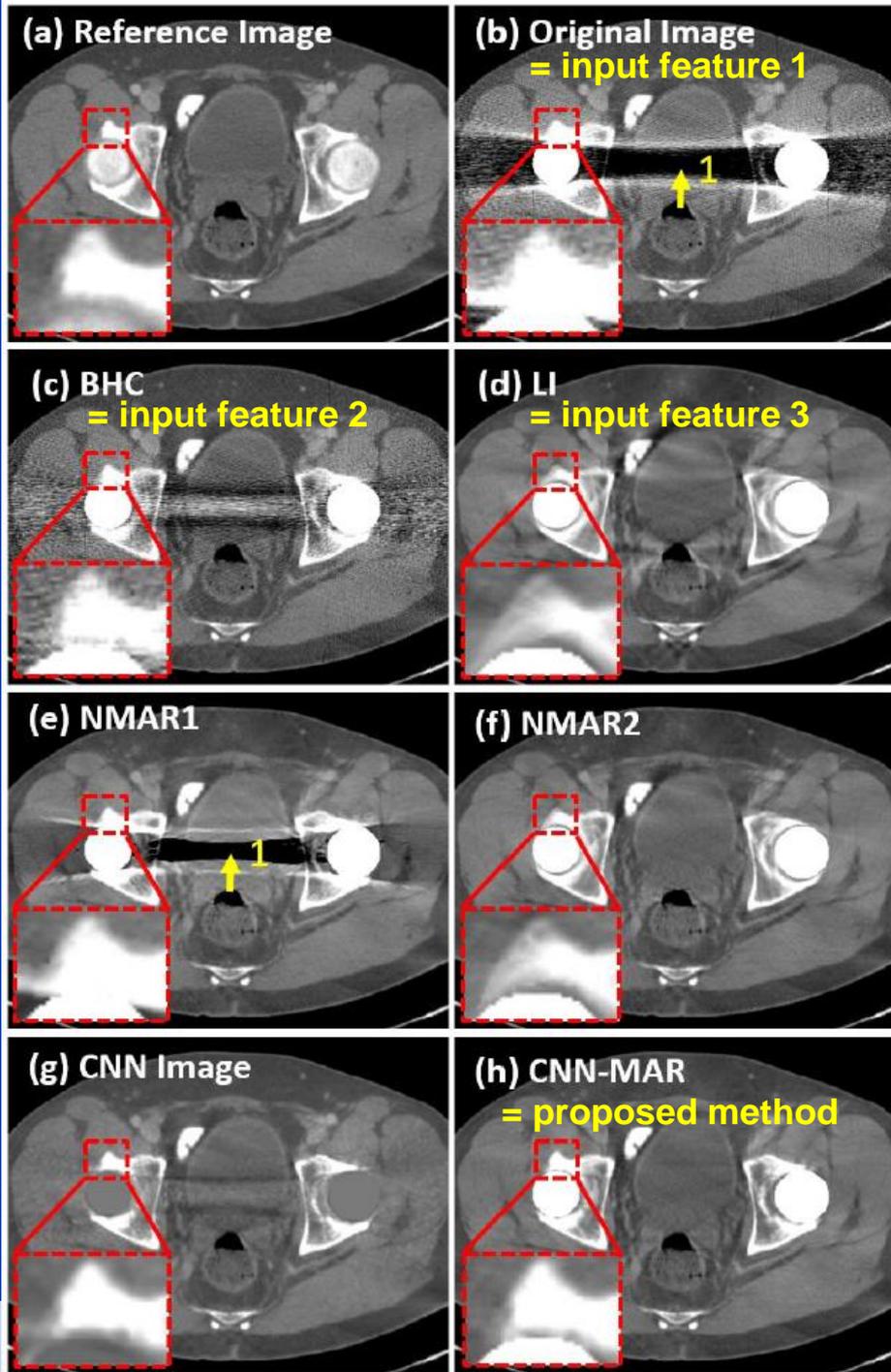
- Input are LI pre-corrected sinograms/images
- First improves the sinograms through a U-Net with mask pyramid (so all parts of the U-Net see the mask)
- Then applies FBP (Radon Inversion Layer) and uses the result as input for a second U-Net, which improves it in image domain
- Unclear how/when the LI and CNN results are combined

MAR Example

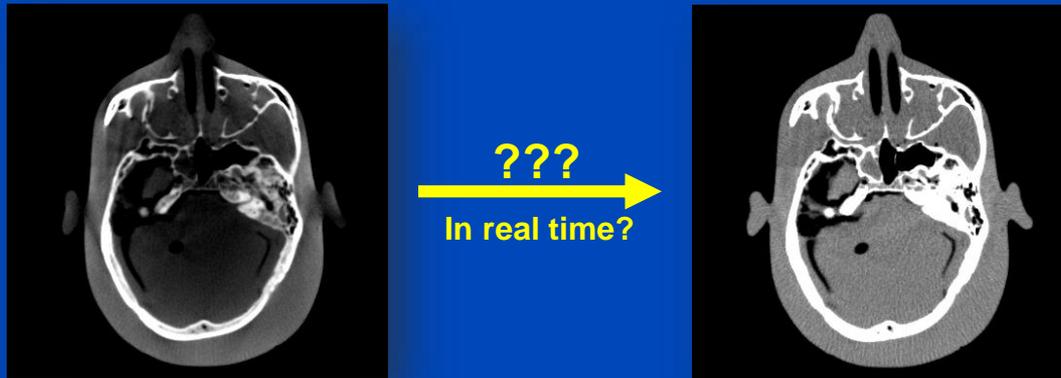
- Deep CNN-driven patch-based combination of the advantages of several MAR methods trained on simulated artifacts



- 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



Deep Scatter Estimation



Monte Carlo Scatter Estimation

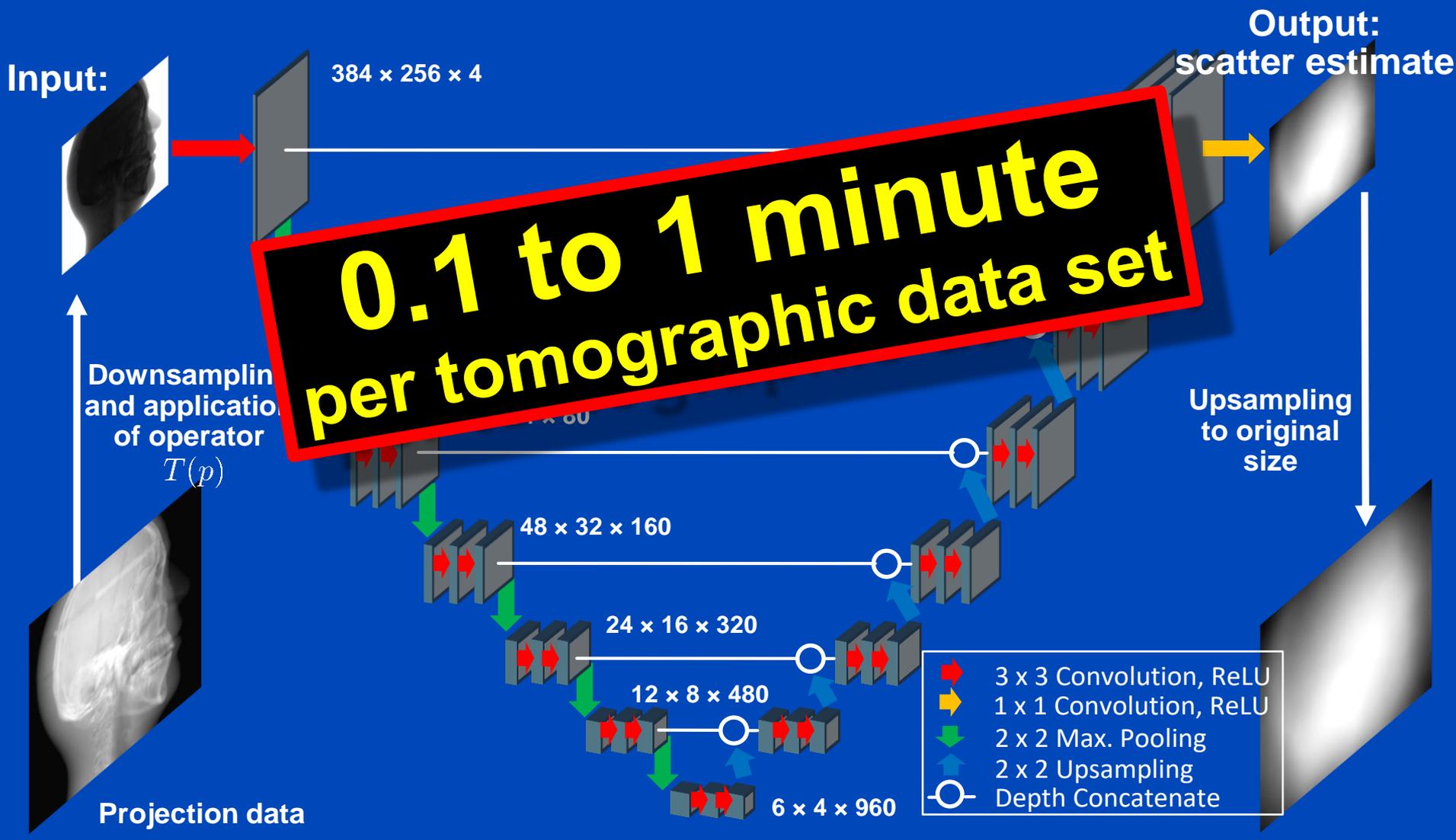
- Simulation of photon trajectories according to physical interaction probabilities.
- Simulating a large number of trajectories well approximates the complete scatter distribution

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

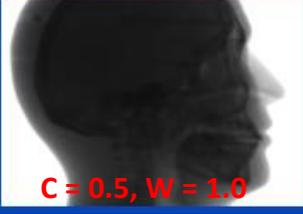
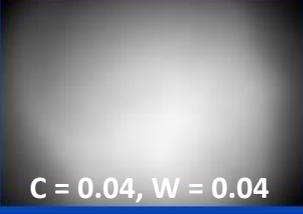


Deep Scatter Estimation

Network architecture & scatter estimation framework



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

Reconstructions of Simulated Data

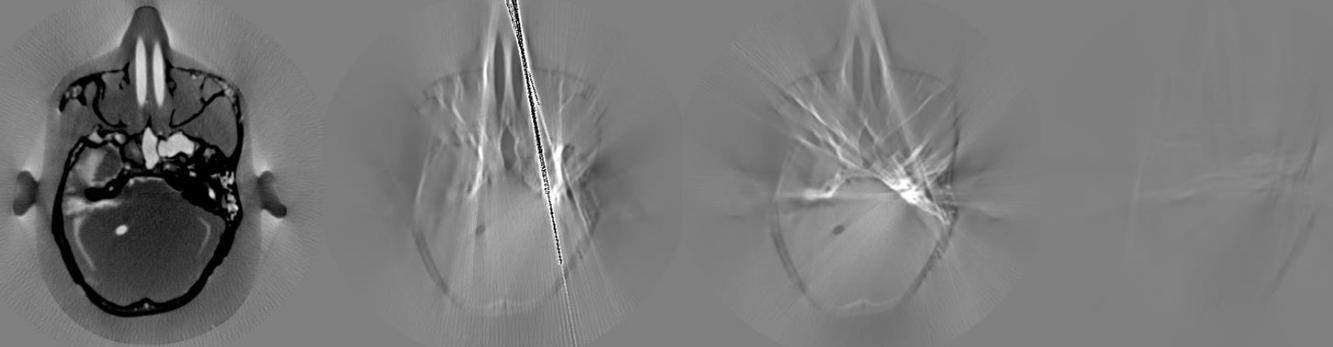
Ground Truth

No Correction

Kernel-Based
Scatter Estimation

Hybrid Scatter
Estimation

Deep Scatter
Estimation



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

CT Reconstruction
Difference to ideal
simulation

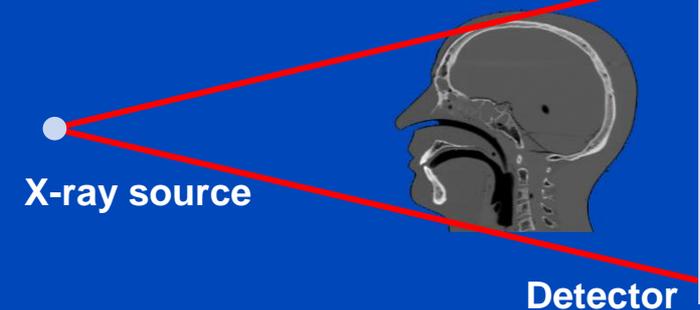
Testing of the DSE Network for Measured Data (120 kV)

DKFZ table-top CT

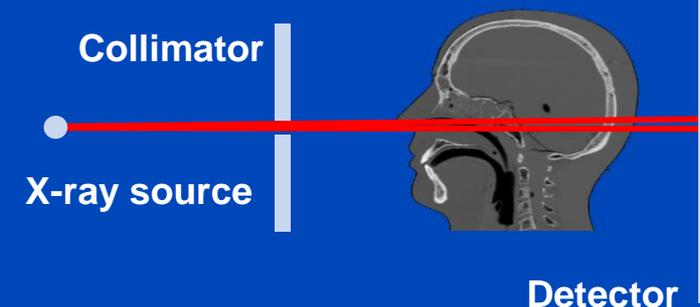


- Measurement of a head phantom at our in-house table-top CT.
- Slit scan measurement serves as ground truth.

Measurement to be corrected



Ground truth: slit scan



Reconstructions of Measured Data

Slit Scan

No Correction

Kernel-Based
Scatter Estimation

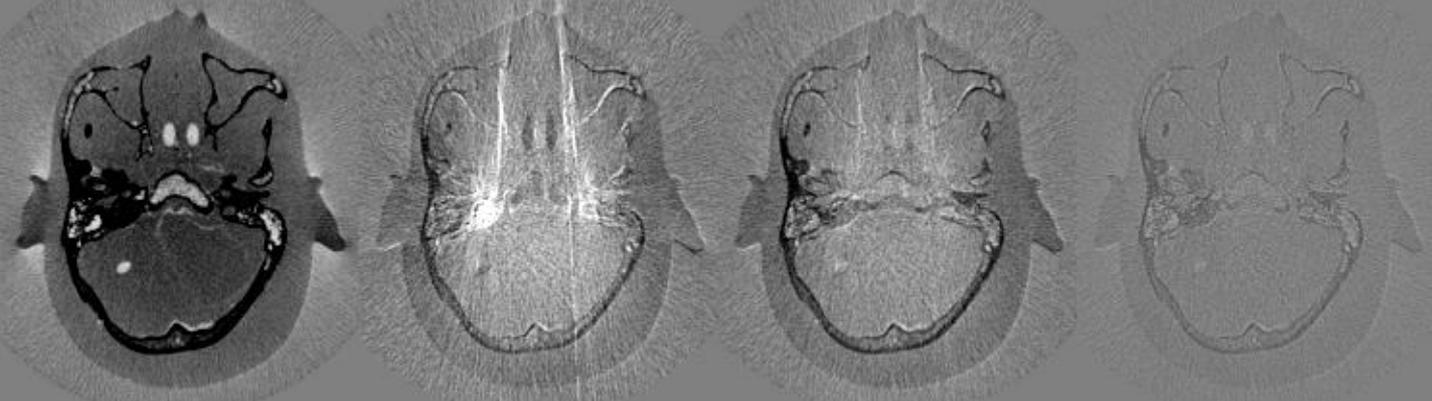
Hybrid Scatter
Estimation

Deep Scatter
Estimation

CT Reconstruction



Difference to slit scan



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

Conclusions on DSE

- DSE needs about 3 ms per CT and 10 ms per CBCT projection (as of 2020).
- DSE is a fast and accurate alternative to MC simulations.
- DSE outperforms kernel-based approaches in terms of accuracy and speed.
- Facts:
 - DSE can estimate scatter from a single (!) x-ray image.
 - DSE can accurately estimate scatter from a primary+scatter image.
 - DSE generalizes to all anatomical regions.
 - DSE works for geometries and beam qualities differing from training.
 - DSE may outperform MC even though DSE is trained with MC.
- DSE is not restricted to reproducing MC scatter estimates.
- DSE can rather be trained with any other scatter estimate, including those based on measurements.

Deep Cardiac Motion Compensation



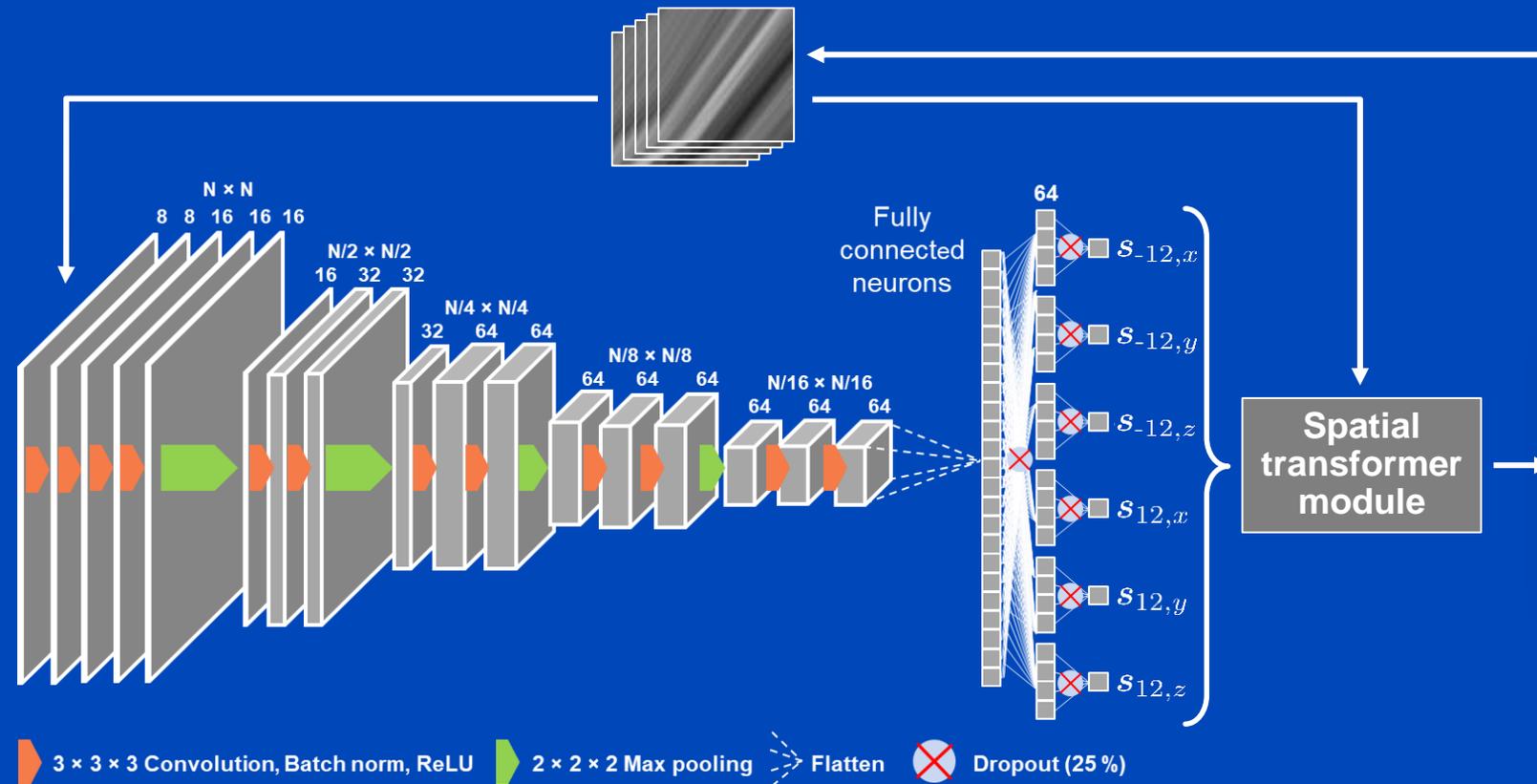
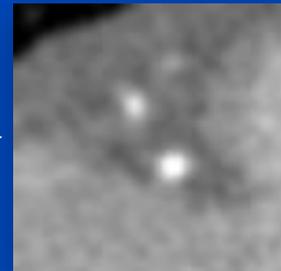
Deep PAMoCo

Network architecture

Initial volume
(with motion artifacts)



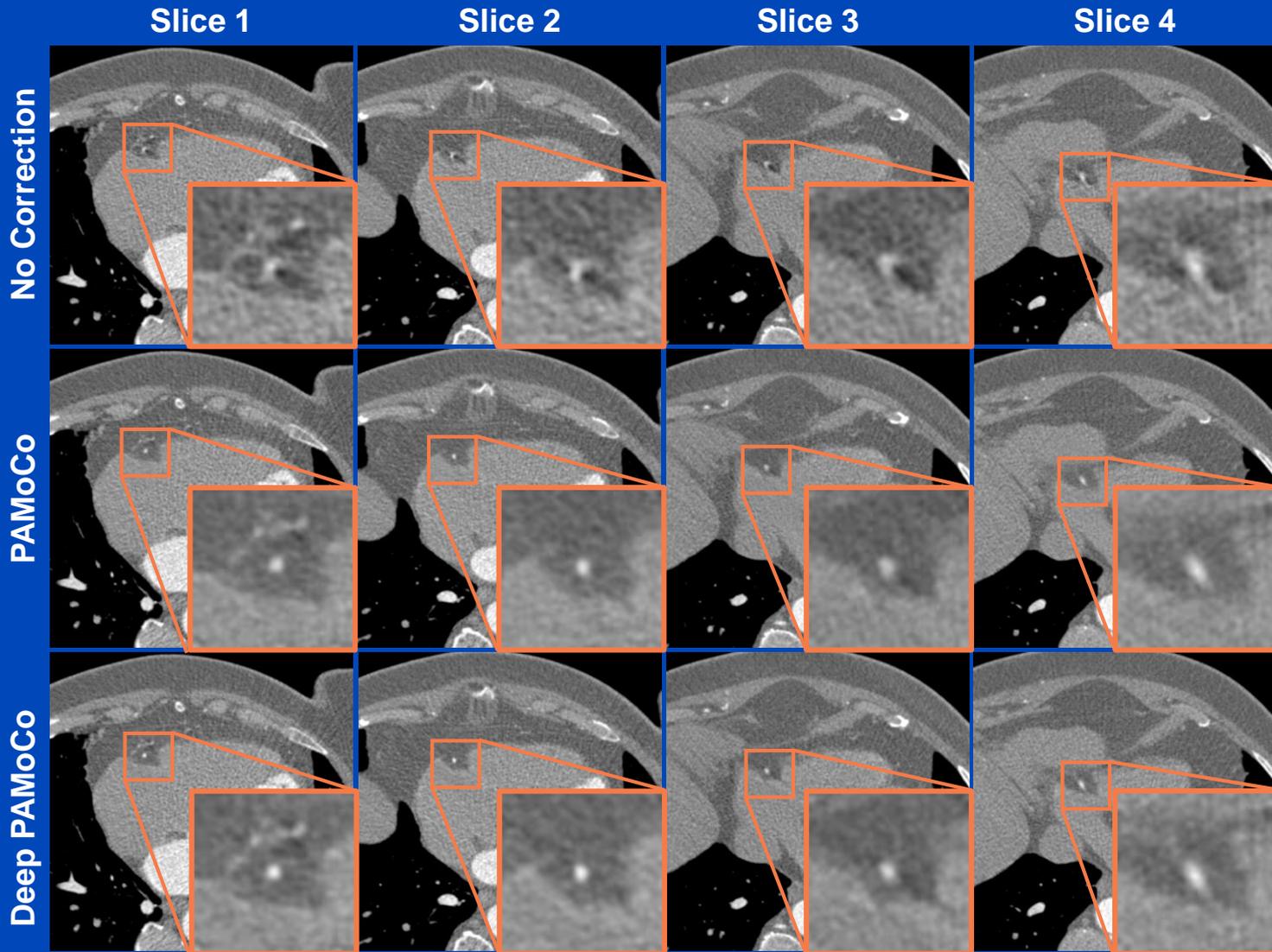
Final volume
(no motion artifacts)



FCN-Layer output: two control points for a cubic spline: for $k = -K$, and for $k = +K$. The third control point at $k = 0$ is $(0, 0, 0)$, i.e. no deformation for the central PAR.

Results

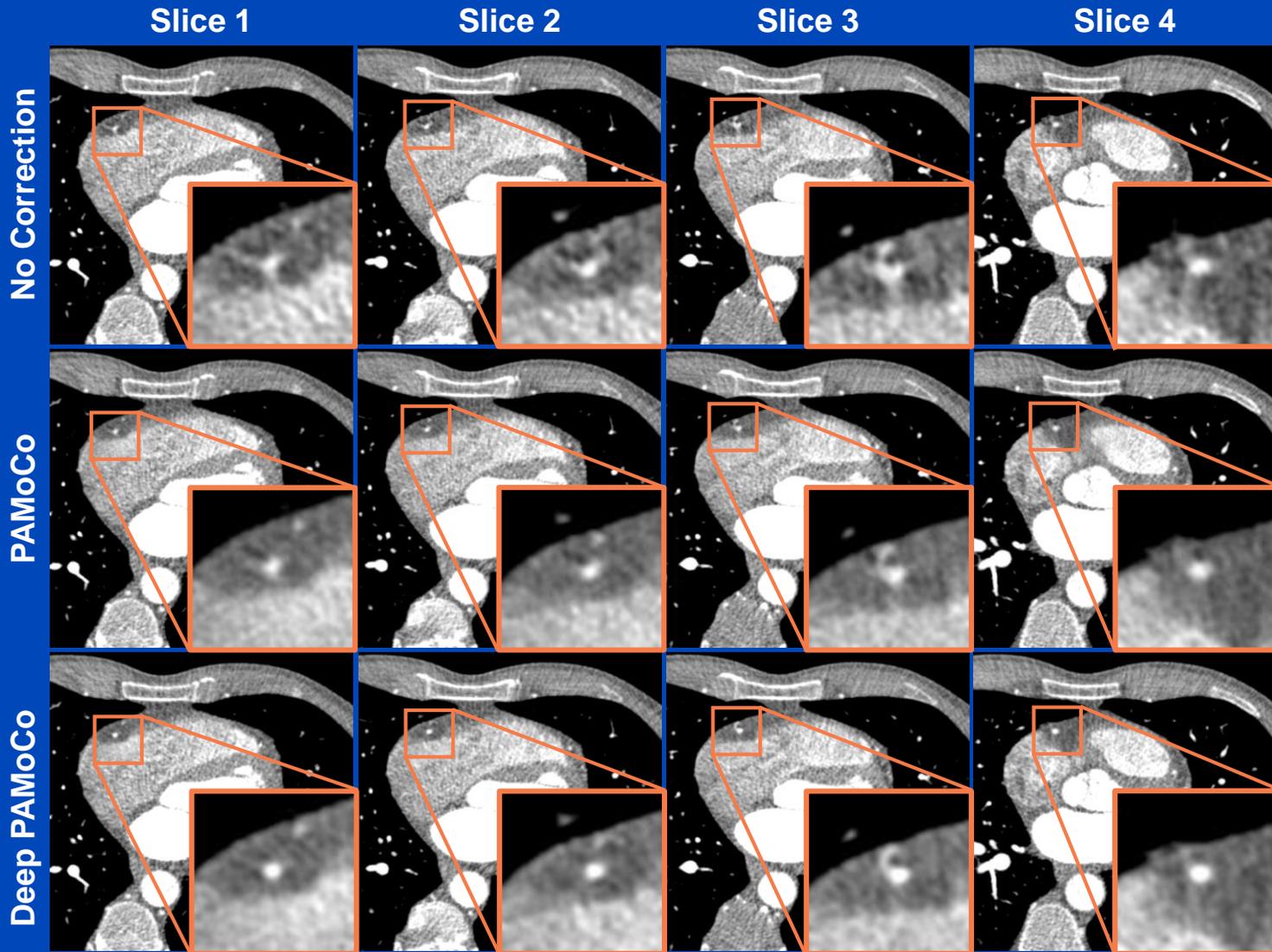
Measurements, patient 1



C = 1000 HU
W = 1000 HU

Results

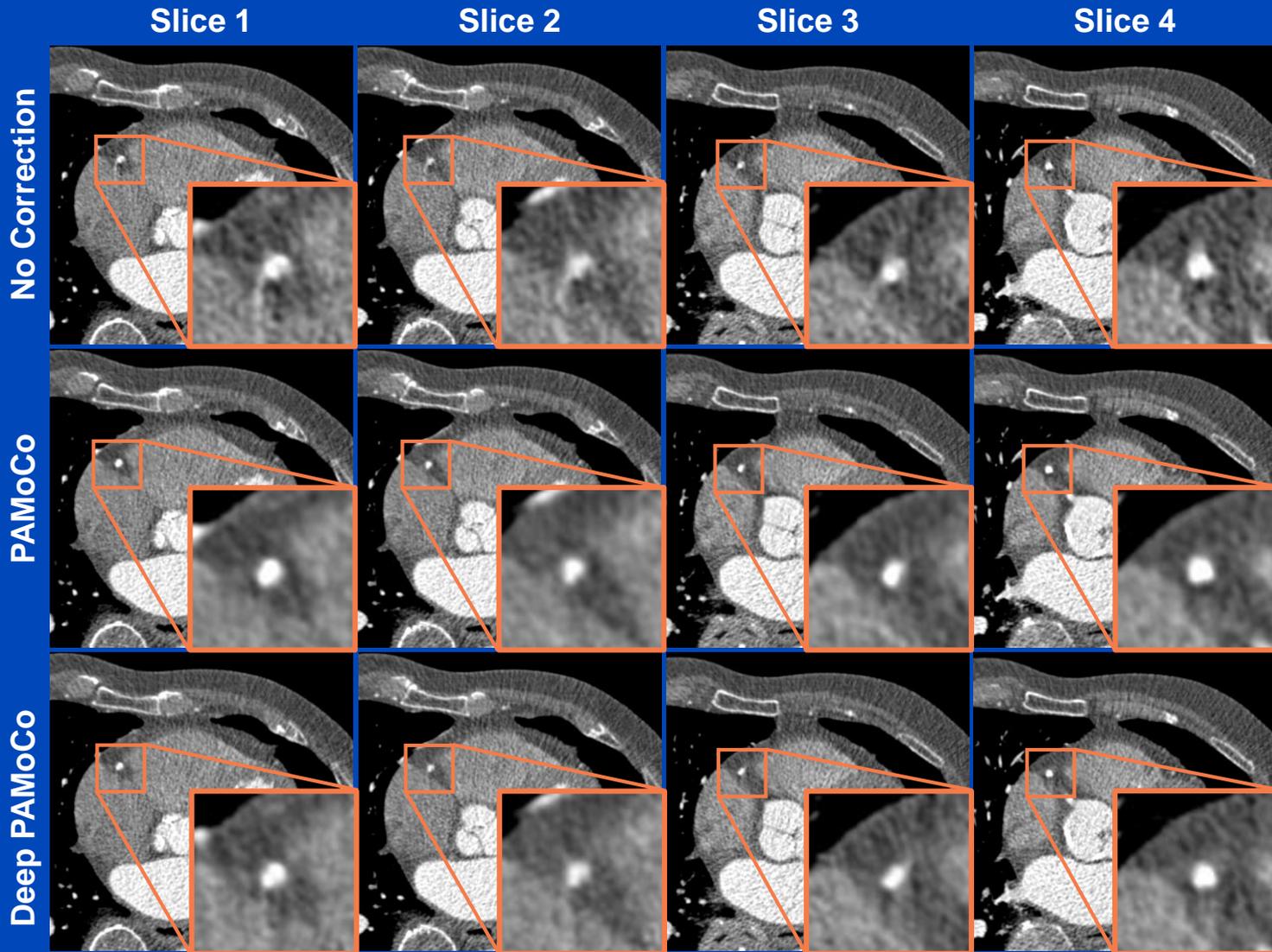
Measurements, patient 2



C = 1000 HU
W = 1000 HU

Results

Measurements, patient 3



C = 1100 HU
W = 1000 HU

4D CBCT MoCo with Deep Image Registration?

- 4D CBCT refers to respiratory-gated CBCT images
- Due to gating, streak artifacts typically occur
- A motion compensation (MoCo) helps to warp the respiratory phases into a target phase. MoCo requires to estimate the motion vector fields (MVFs).
- MVF estimation uses deformable registration.

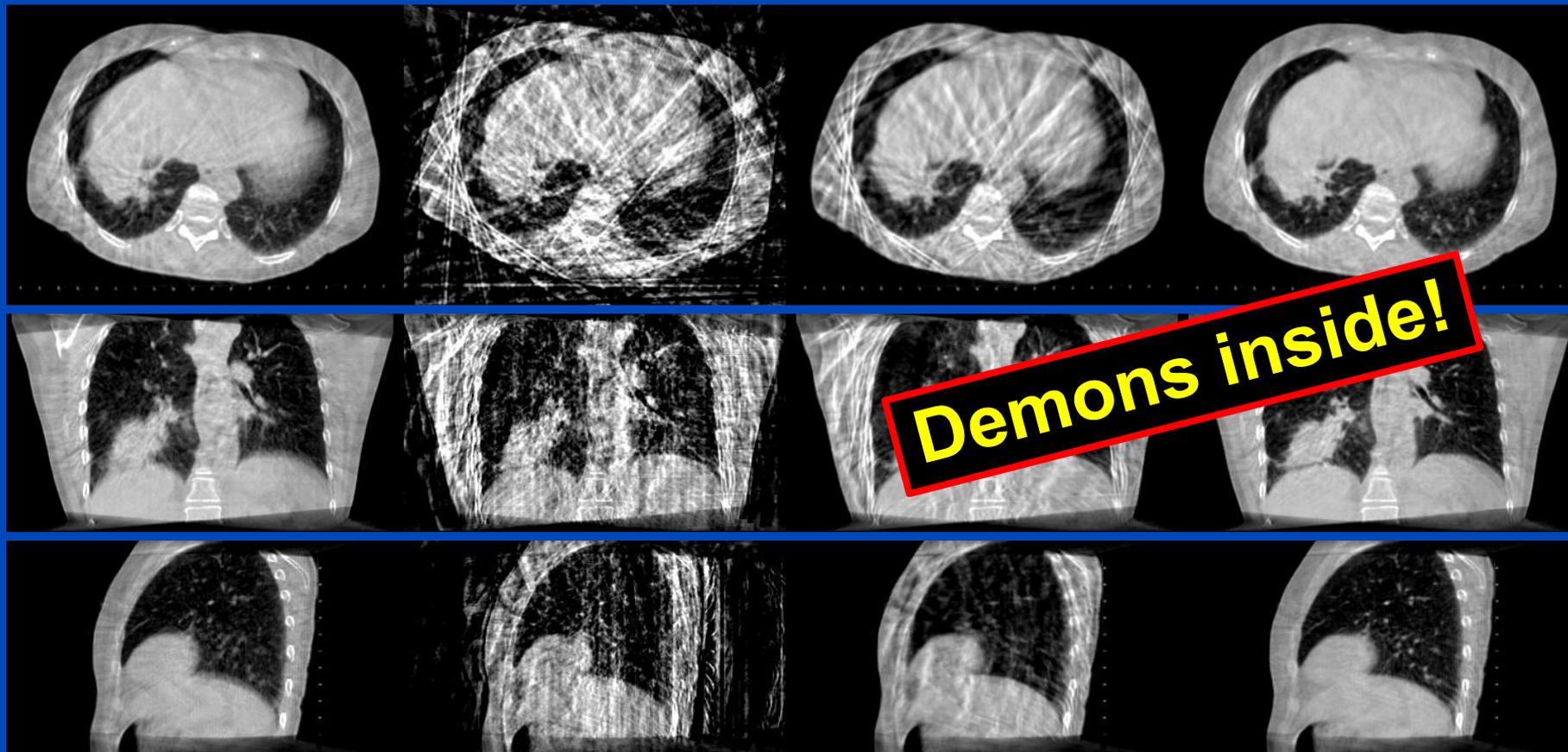
Examples for CBCT MoCo

3D CBCT
Standard

4D gated CBCT
Conventional
Phase-Correlated

sMoCo
Standard Motion
Compensation

acMoCo
Artifact Model-Based
Motion Compensation



sMoCo: Li, Koong, and Xing, "Enhanced 4D cone-beam CT with inter-phase motion model," Med. Phys. 51(9), 3688–3695, 2007.

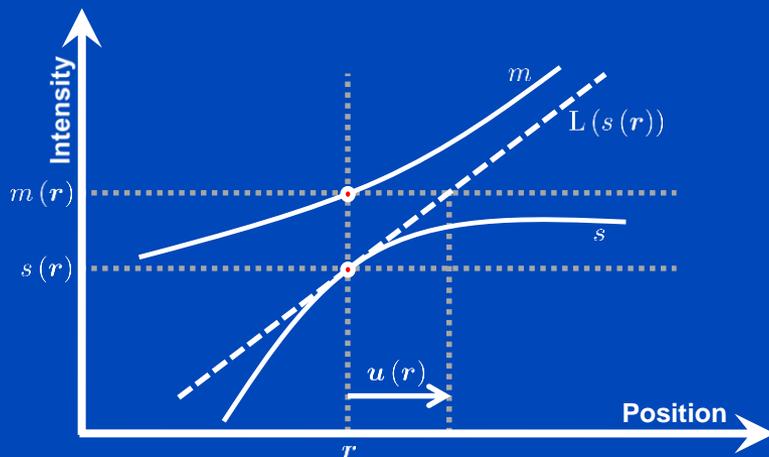
cMoCo: Brehm, Paysan, Oelhafen, Kunz, and Kachelrieß, "Self-adapting cyclic registration for motion-compensated cone-beam CT in image-guided radiation therapy," Med. Phys. 39(12):7603-7618, 2012.

acMoCo: Brehm, Paysan, Oelhafen, and Kachelrieß, "Artifact-resistant motion estimation with a patient-specific artifact model for motion-compensated cone-beam CT" Med. Phys. 40(10):101913, 2013.

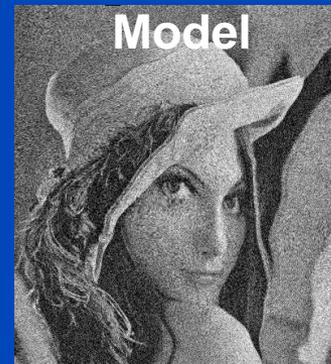
Demons Deformable Registration

- Static target image s
- Model to be deformed m
- Find transformation vector field T , i.e. $s = m \circ T$
- **Demons algorithm**
 - Displacement update u by intensity matching on linear approximation

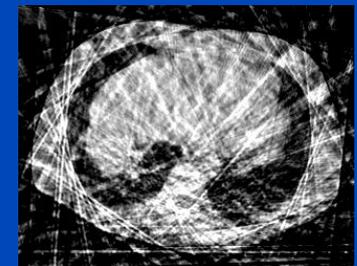
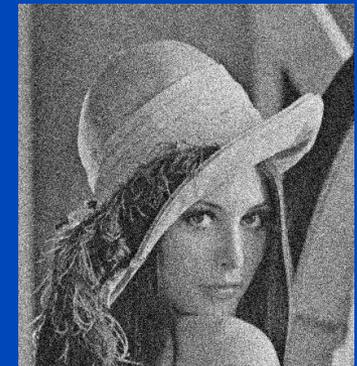
$$u = \frac{m - s}{\|\nabla s\|^2 + (m - s)^2} \nabla s$$



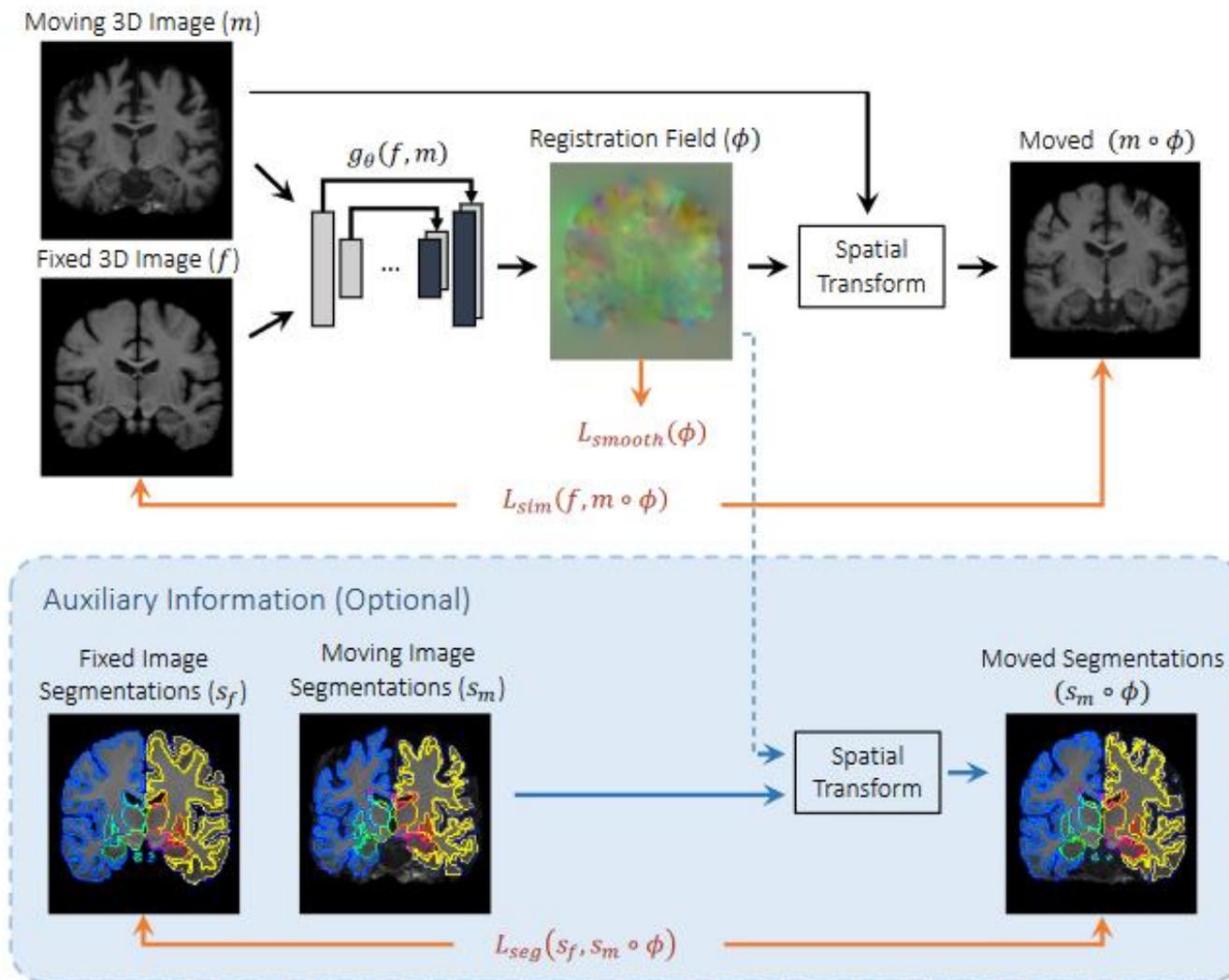
- Regularization
 - Two Gaussian convolution kernels $G_{\text{fluid}}, G_{\text{diffusion}}$
 - $T \leftarrow G_{\text{diffusion}} * (T \circ \exp(G_{\text{fluid}} * u))$



Deformed model matching target



VoxelMorph Deformable Registration



Demons vs. VoxelMorph

- Cost/loss functions of Demons and VoxelMorph are identical if we use the L_2 -norm for the vector field regularization and the MSE for the image similarity

$$C = \arg \min_{\phi} \|m(\phi) - f\|_2^2 + \lambda \|\nabla \phi\|_2^2$$

- Demon's hierarchical registration cascade corresponds to VoxelMorph's hierarchical encoder/decoder stages.
- Both methods can be extended to estimate a diffeomorphic vector field, i.e. a differentiable and invertible vector field.
- Demons minimizes the cost function for every patient, while VoxelMorph learned to minimize it for the training patients and then applies its knowledge to other patients.
- Demons may be slower than VoxelMorph (a thorough comparison is missing), but is certainly more reliable and predictable.

Deep MoCo

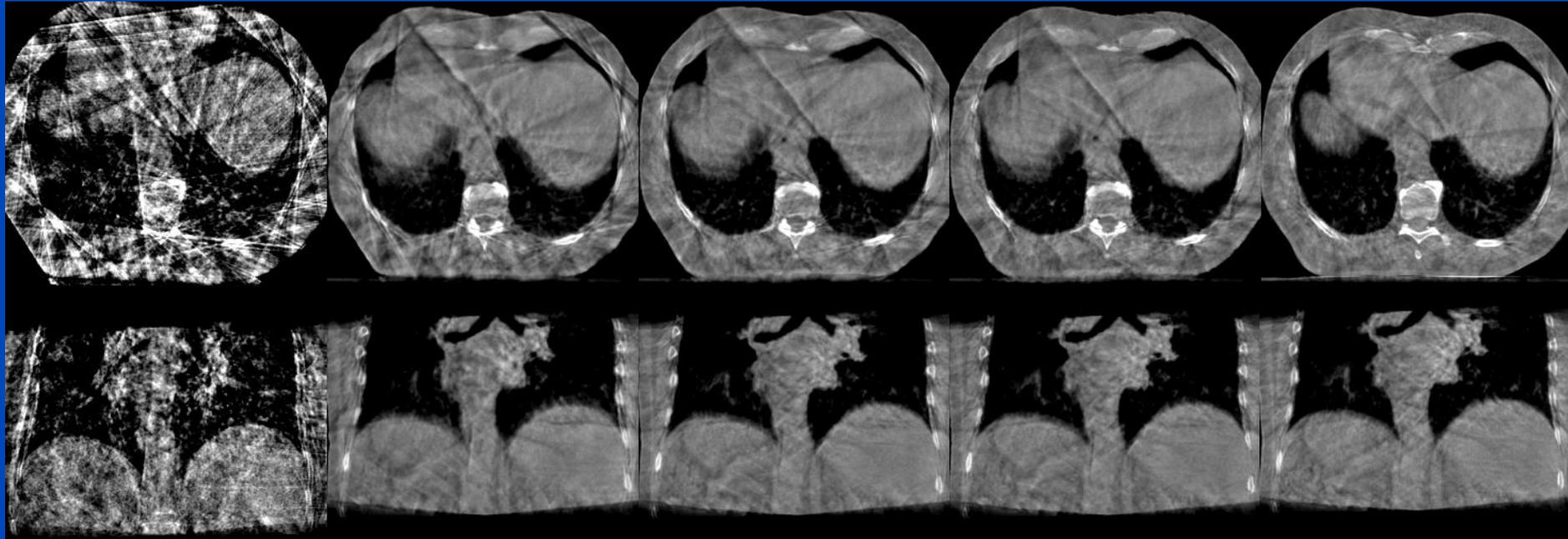
4D FDK

deep sMoCo
(VoxelMorph)

deep cMoCo
(VoxelMorph)

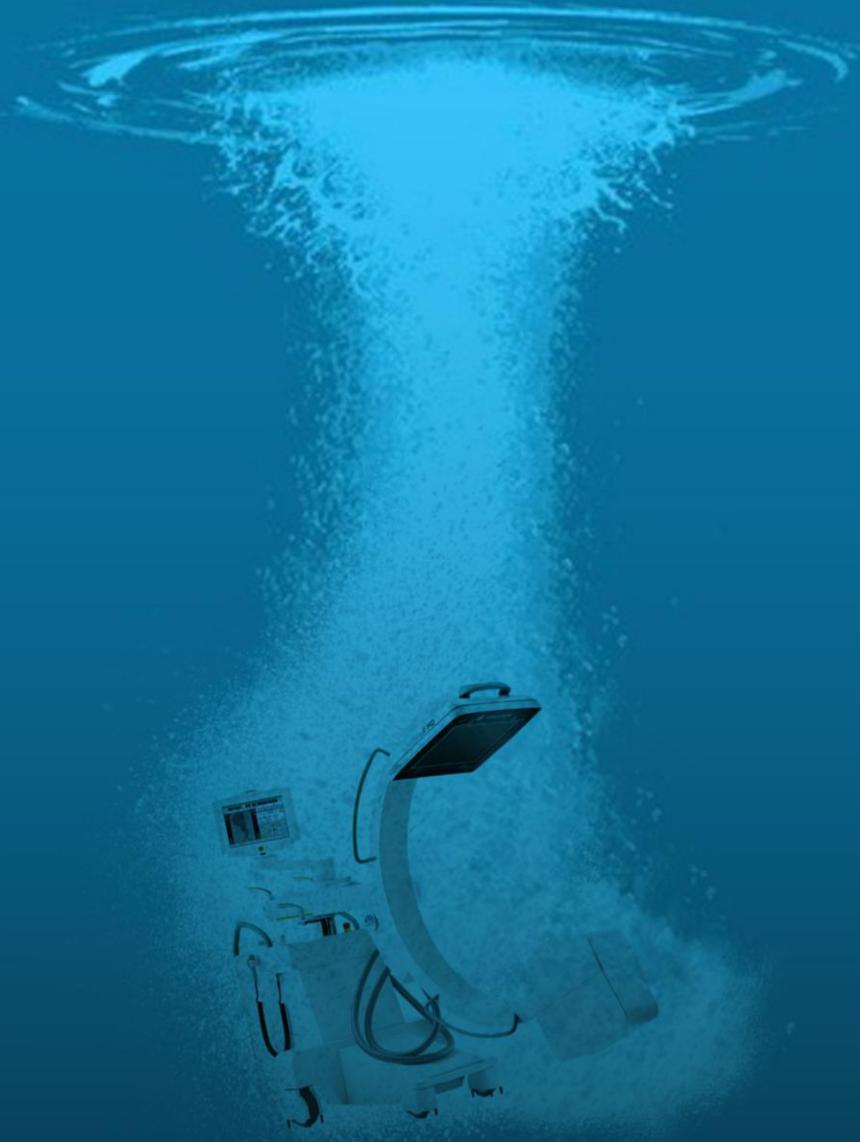
deep acMoCo
(VoxelMorph)

acMoCo
(Demons)



Faster
computation

Less
artifacts



Intervention goes Deep!

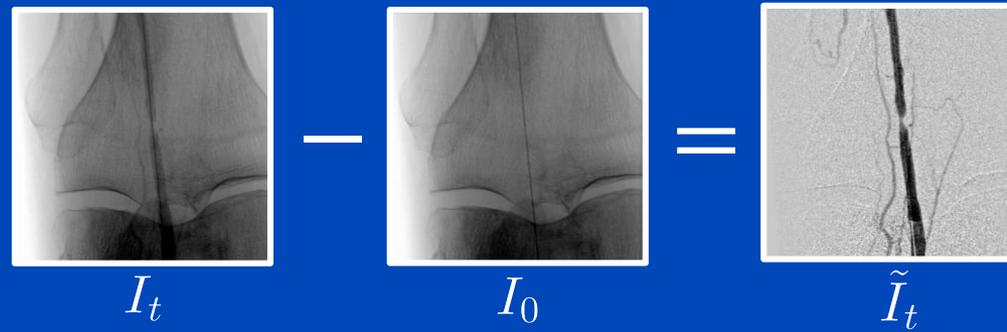
Deep DSA



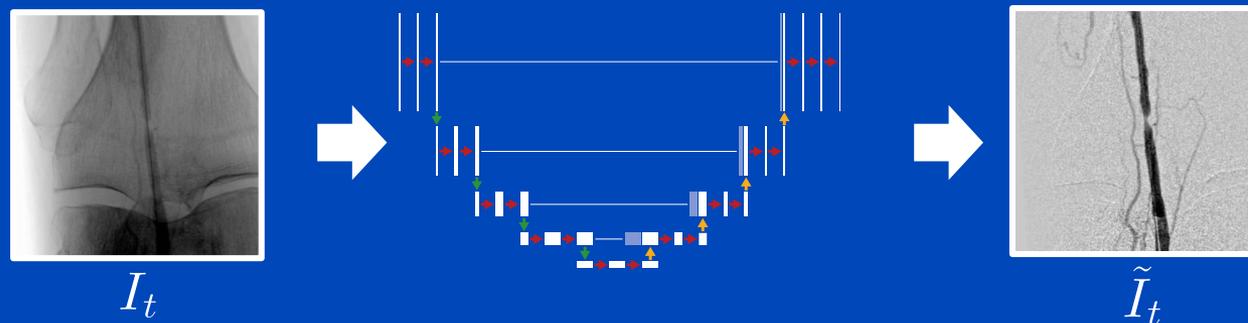
Methods

General principle

Conventional DSA



Deep DSA

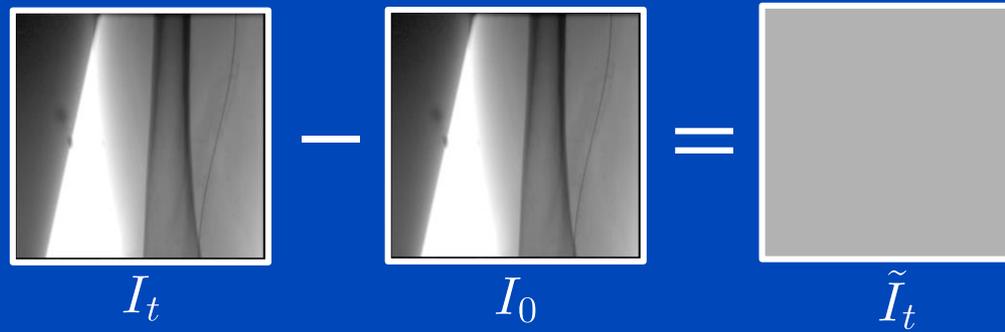


- Train on static cases where ground truth is conventional DSA

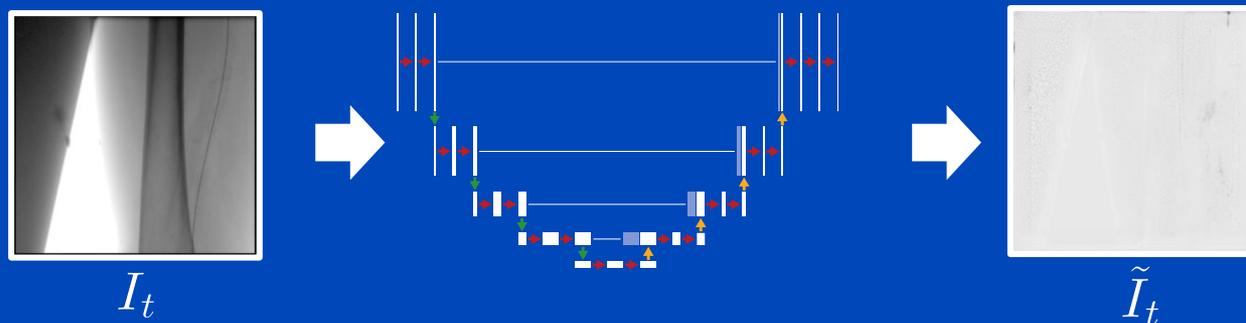
Methods

General principle

Conventional DSA

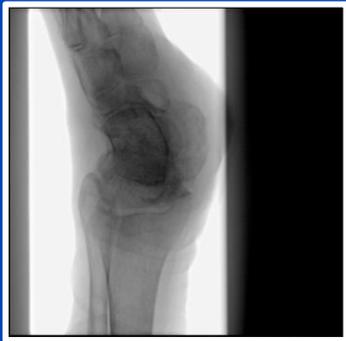


Deep DSA

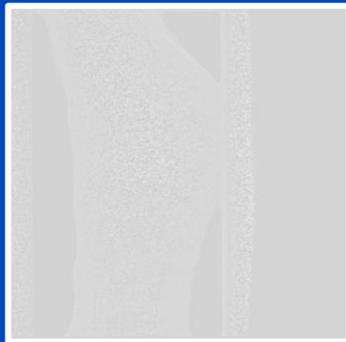


- Train on static cases where ground truth is conventional DSA
- During inference CNN can be applied to both static and dynamic cases

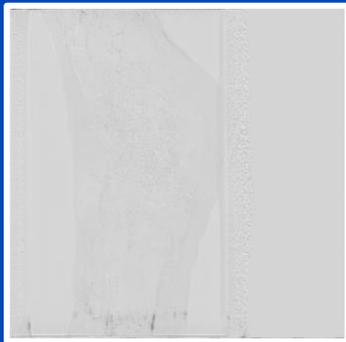
Results



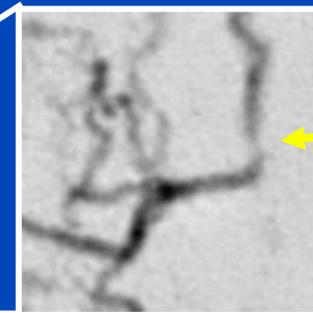
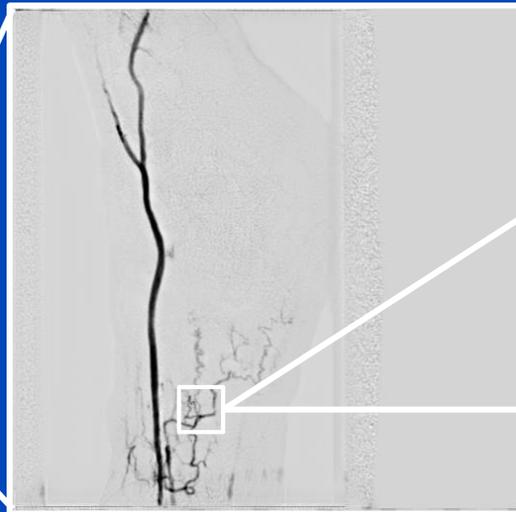
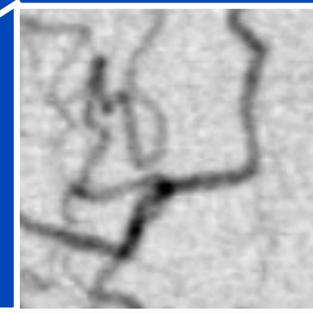
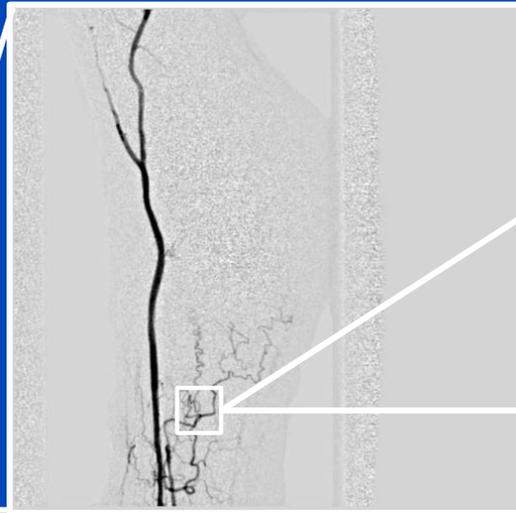
Original x-ray sequence



Ground truth DSA



CNN output

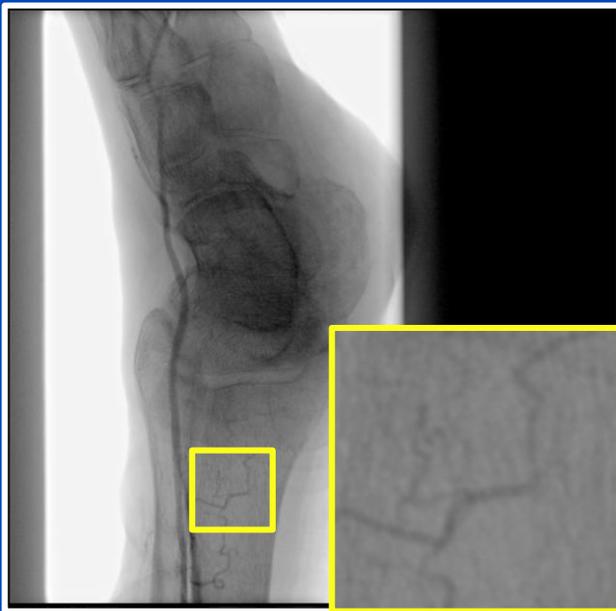


Artificially introduced stenosis?

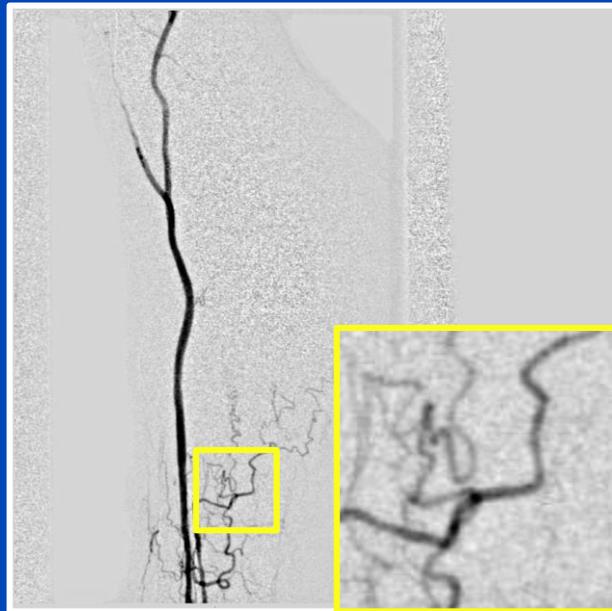
Due to a low amount of training data and a low variability of the training data available to us the results shown on this slide are not optimal, yet.

Deep DSA

Fluoroscopy



DSA (fluoro minus mask)



Deep DSA (from fluoro only)

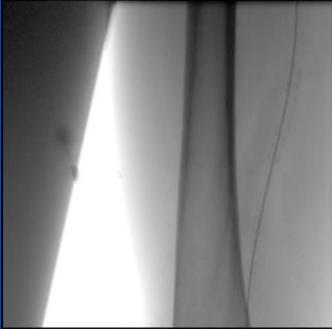


Due to a low amount of training data and a low variability of the training data available to us the results shown on this slide are not optimal, yet.

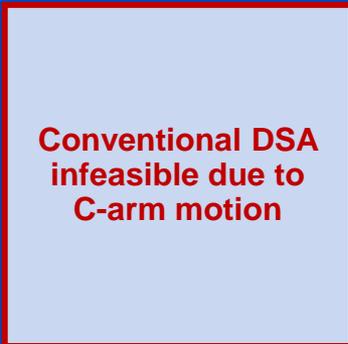
Results

Bolus chase study

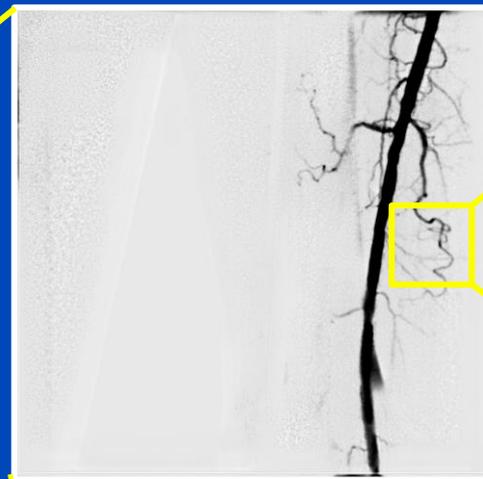
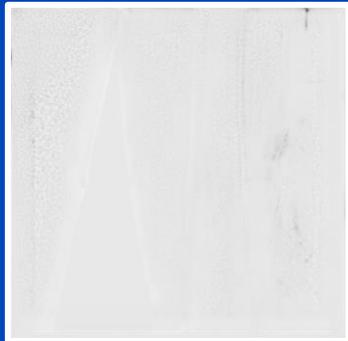
Dynamic fluoroscopy



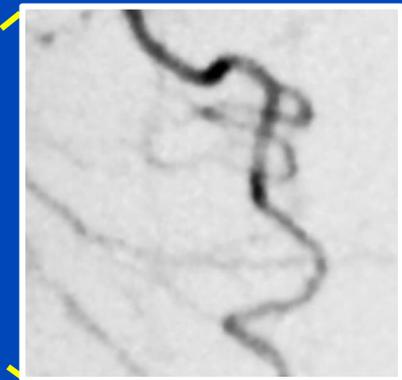
Conventional DSA



Deep DSA

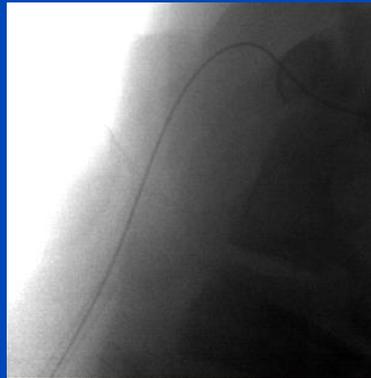


Deep DSA at $t = t_a$



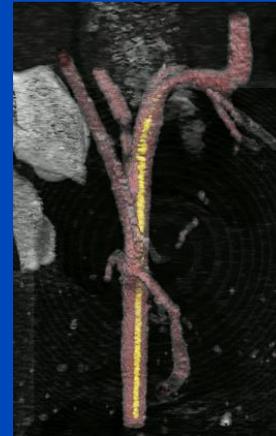
Deep DSA at $t = t_a$

Deep 3D+T Fluoroscopy



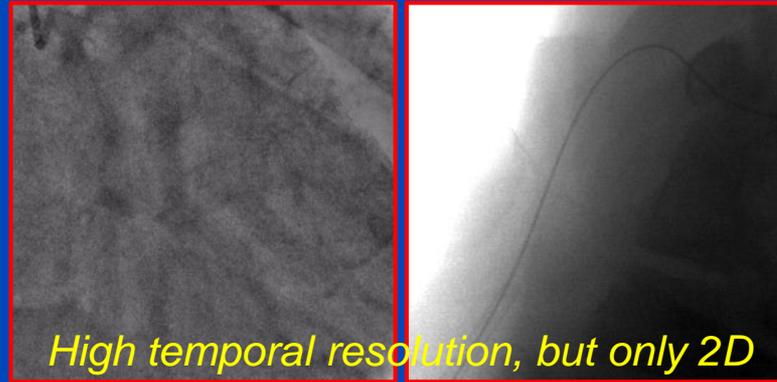
???

At 2D+T dose?

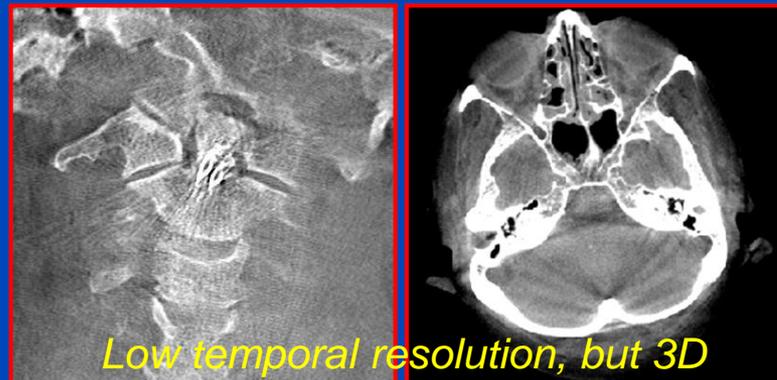


Deep 3D+T Tomographic Fluoroscopy

either 2D+T fluoroscopy



or 3D tomography

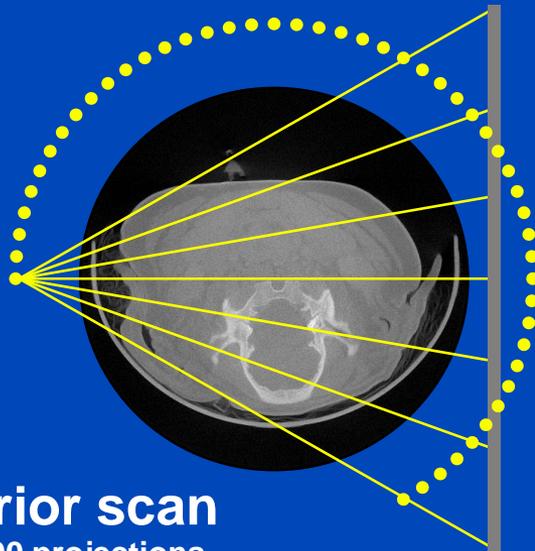


**3D+T
tomographic
fluoroscopy?
At low dose?
How???**

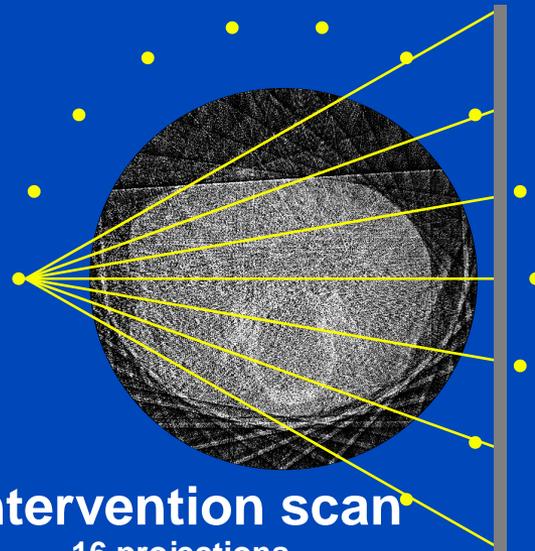


How to Realize 3D+T Fluoroscopy

- 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

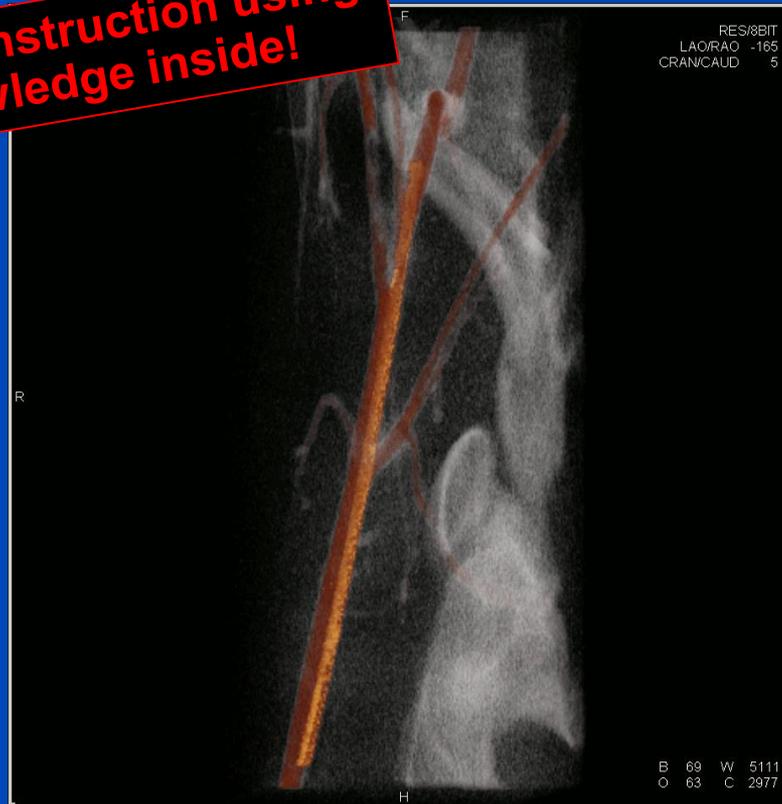


Experimental setup

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!

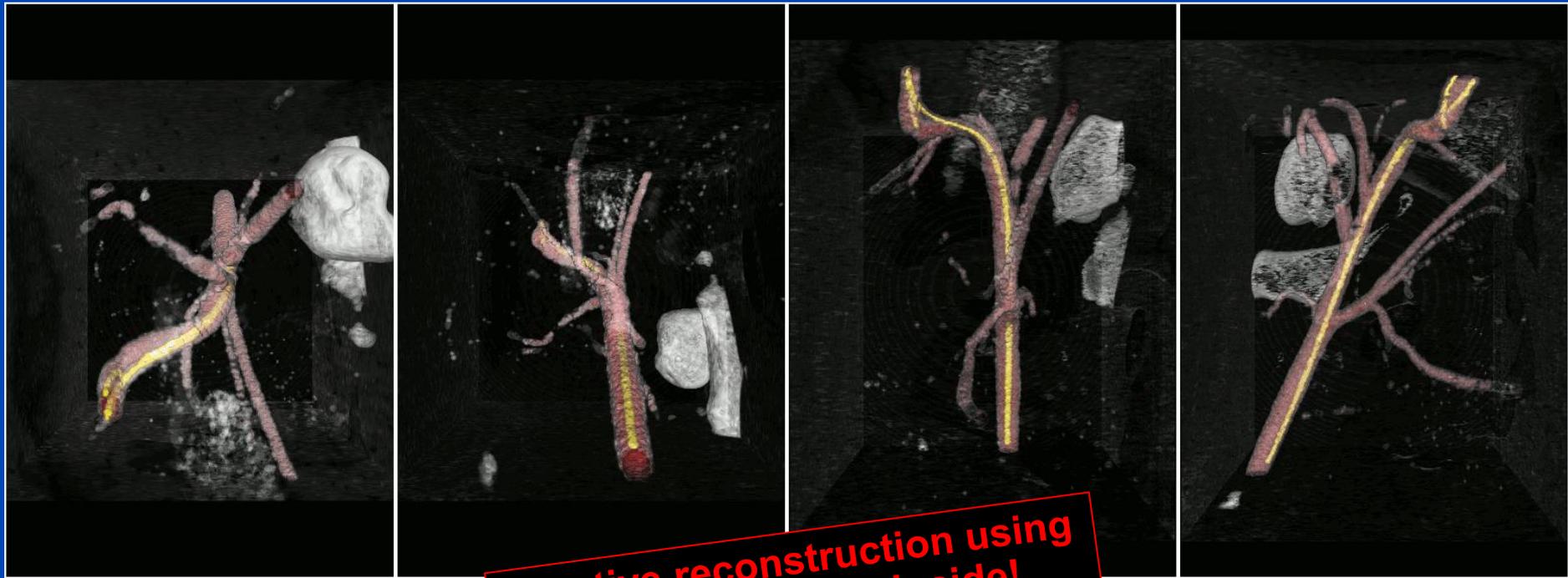


Dose of the yet unoptimized approach: 20 bis 50 $\mu\text{Gy/s}$.

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.

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!**

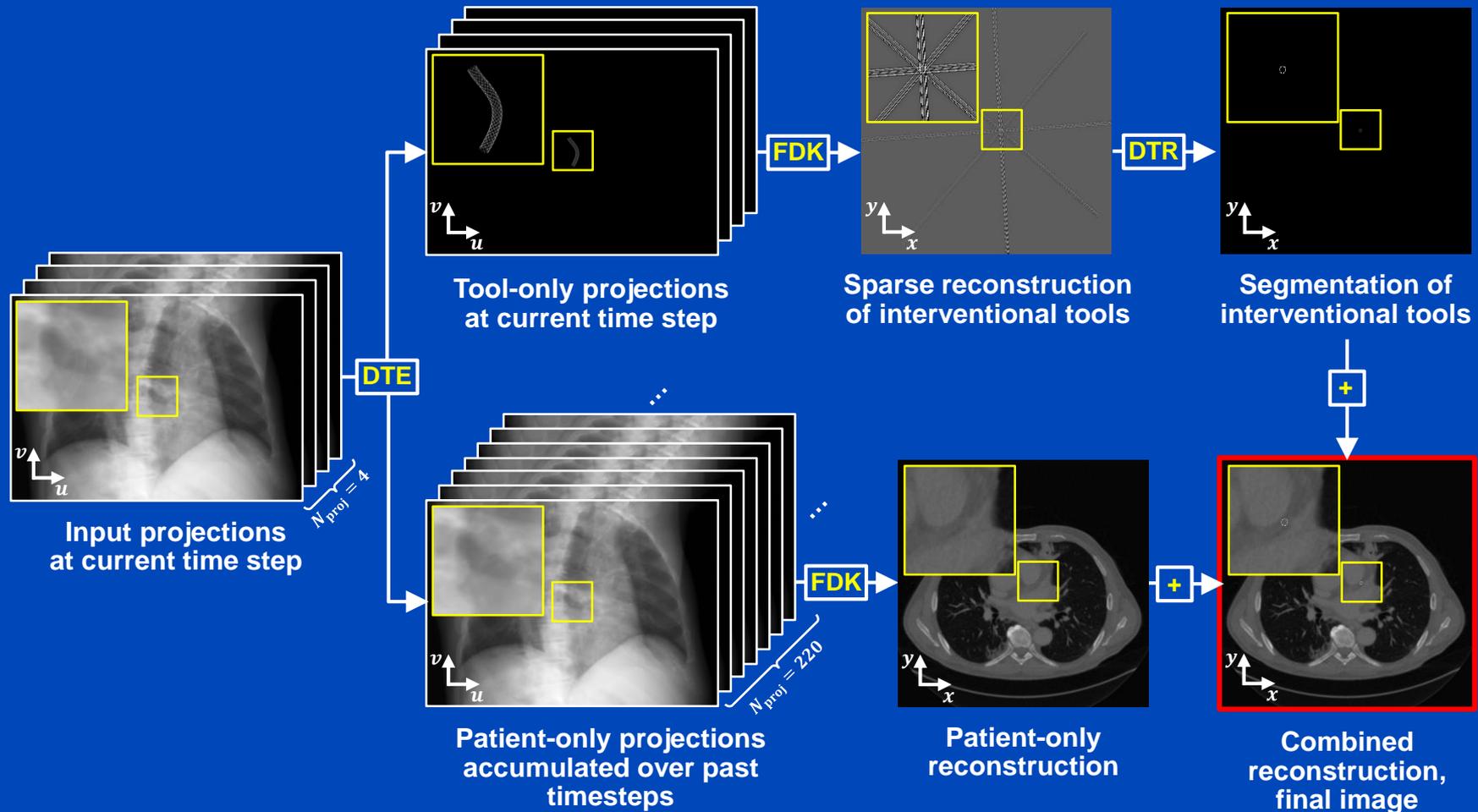
Dose of the yet unoptimized approach: 20 to 50 $\mu\text{Gy/s}$. Obviously, 16 projections are too much.

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.

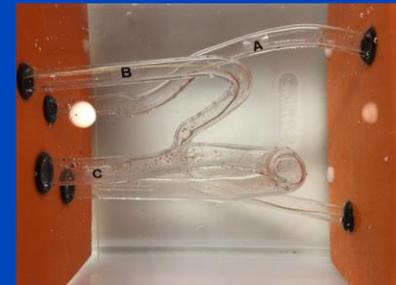


Method

Deep Tool Extraction (DTE), Feldkamp Recon (FDK), Deep Tool Reconstruction (DTR)

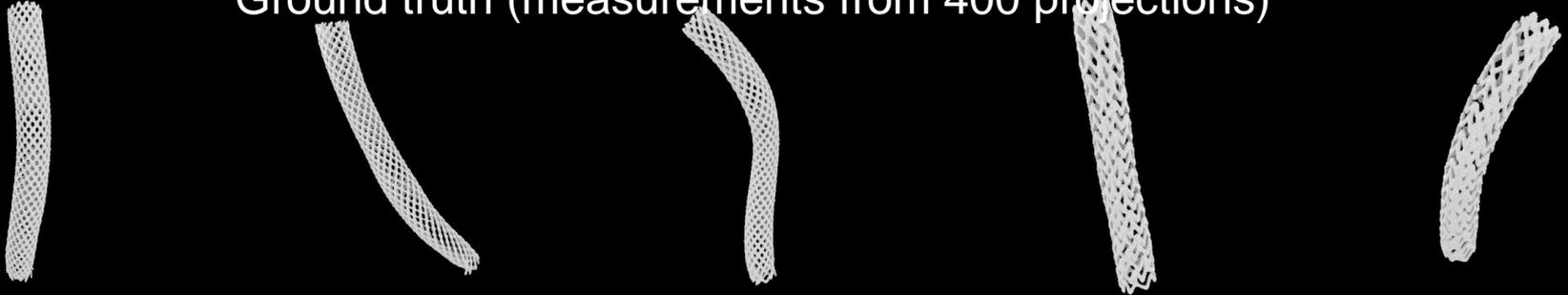


Zeego @ Stanford University

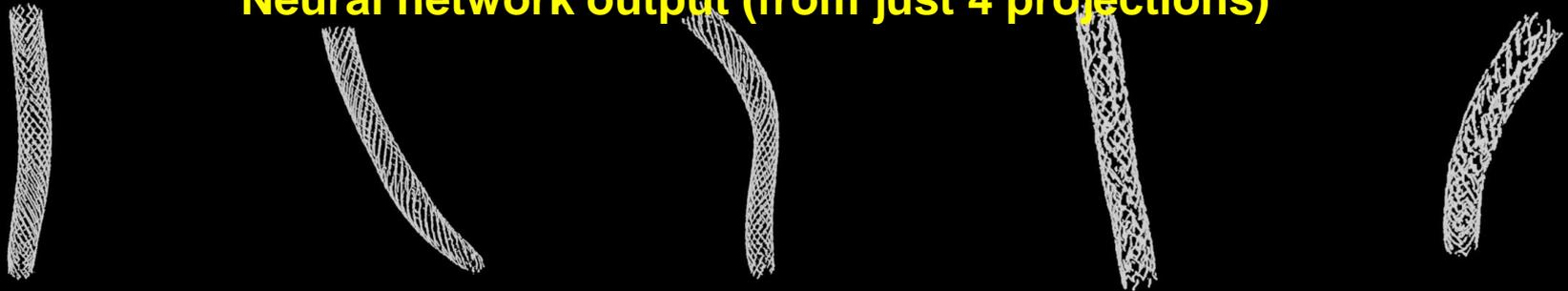


Zeego Measurements with Just 4 Projections

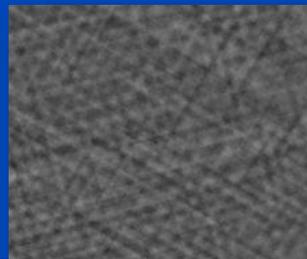
Ground truth (measurements from 400 projections)



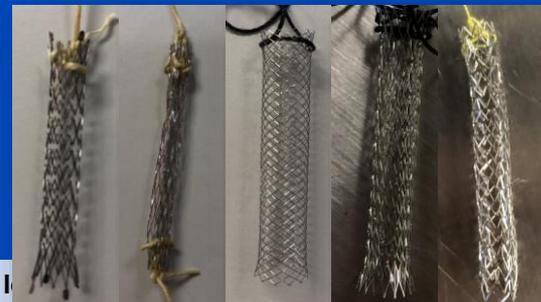
Neural network output (from just 4 projections)



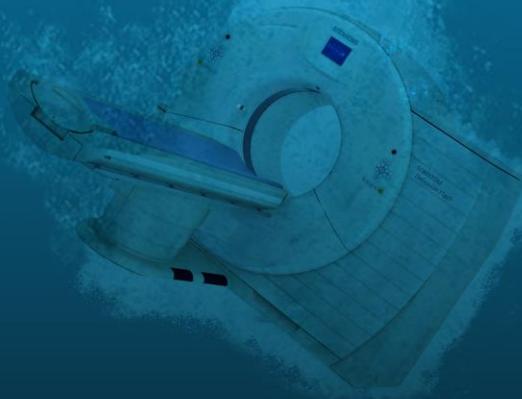
Loop through slices reconstructed
from just 4 projections without AI:



Stent
examples:



Thank You!



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

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

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