



Deep Learning in CT Artifact Correction

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DEUTSCHES
KREBSFORSCHUNGSZENTRUM
IN DER HELMHOLTZ-GEMEINSCHAFT

Content

- **Metal artifact reduction (MAR)**
- **Detruncation**
- **Scatter estimation**
- **Motion compensation**
- **Sparse view artifacts → image reconstruction**
- **Ring artifact reduction**
- **Limited angle artifacts**

Deep MAR Examples

<p>Deep Learning-Based Pre-sliced Residual Metal Artifact Reduction in Computed Tomography</p>	<p>Nan, 2022</p>	<p>Nam, 2022</p>	<p>Compositional Neural Network-based Metal Artifact Reduction</p>	<p>Kim, 2022</p>	<p>Kim, 2022</p>	<p>Deep Transferable Convolutional Dictionary Networks for Metal Artifact Reduction in CT Images</p>	<p>Wang, 2021</p>	<p>Wang, 2021</p>
<p>Unsupervised CT Metal Artifact Learning using Attention-Guided U-Net Architecture</p>	<p>Lee, 2021</p>	<p>Lee, 2021</p>	<p>Deep MAR in Single-Channel with Attention-Guided U-Net Architecture</p>	<p>Kim, 2021</p>	<p>An, 2021</p>	<p>Deep Transferable Convolutional Dictionary Networks for Metal Artifact Reduction in CT Images</p>	<p>Unsupervised domain adaptation for practical metal artifact reduction in X-ray CT</p>	<p>Du, 2020</p>
<p>Refocus CT Encoder-Decoder Network for Metal Artifact Reduction in X-ray CT</p>	<p>Du, 2020</p>	<p>Conditional Neural Network-based Iterative Metal Artifact Reduction</p>	<p>Wetter, 2020</p>	<p>Wetter, 2020</p>	<p>Wetter, 2020</p>	<p>Fast response time unsupervised learning-based metal artifact reduction in CT images</p>	<p>Gjoresby, 2019</p>	<p>Gjoresby, 2019</p>
<p>Deep Neural Network for CT Head Artifact Reduction with a Residual-Like Feature Extraction Module</p>	<p>Gjoresby, 2018</p>	<p>Gjoresby, 2018</p>	<p>Residual Neural Network Architecture for CT Head Artifact Reduction</p>	<p>Gjoresby, 2017</p>	<p>Deep artifact reduction for practical metal artifact reduction in X-ray CT images</p>	<p>Xing, 2019</p>	<p>Xing, 2019</p>	<p>Metal artifact reduction on cervical CT images by deep residual learning</p>
<p>Zhang, 2018</p>	<p>Zhang, 2018</p>	<p>Compositional Neural Network-based Metal Artifact Reduction in X-ray Computed Tomography</p>	<p>Yu, 2018</p>	<p>Yu, 2018</p>	<p>Deep artifact reduction for practical metal artifact reduction in X-ray CT images</p>	<p>Gottschalk, 2022</p>	<p>Gottschalk, 2022</p>	<p>Deep Learning-based Metal Artifact Reduction in the Projection Domain using Attention Guiding in the Projection Domain using Attention Guiding in the Projection Domain</p>
<p>Gottschalk, 2020</p>	<p>Gottschalk, 2020</p>	<p>Deep Learning-based Metal Artifact Reduction in the Projection Domain using Attention Guiding in the Projection Domain</p>	<p>Gottschalk, 2019</p>	<p>Gottschalk, 2019</p>	<p>Visual Non-Metal Network for Metal Artifact Reduction in the Sinogram Domain</p>	<p>Choi, 2022</p>	<p>Choi, 2022</p>	<p>Choi, 2022</p>
<p>Choi, 2022</p>	<p>Choi, 2022</p>	<p>Blum, 2022</p>	<p>Blum, 2022</p>	<p>Yet Enhanced CT Metal Artifact Reduction using Deep Learning</p>	<p>Ghani, 2019</p>	<p>Ghani, 2019</p>	<p>Ghani, 2019</p>	<p>Liao, 2019</p>
<p>Liao, 2019</p>	<p>Liao, 2019</p>	<p>Claus, 2017</p>	<p>Claus, 2017</p>	<p>Zhu, 2023</p>	<p>Zhu, 2023</p>	<p>Zhu, 2023</p>	<p>Wang, 2021</p>	<p>Wang, 2021</p>
<p>Deep artifact reduction in 3D CT images using attention-guided residual learning</p>	<p>Yu, 2021</p>	<p>Yu, 2021</p>	<p>Deep Organism Comparison with Image Prior for Metal Artifact Reduction in CT Images</p>	<p>Yu, 2021</p>	<p>Yu, 2021</p>	<p>A Cross-Domain Metal Trace Restoring Network for Reducing X-Ray CT Metal Artifacts</p>	<p>Peng, 2020</p>	<p>Peng, 2020</p>

DuDoNet: Dual Domain Network for CT Metal Artifact Reduction

Wei-An Lin^{*1} Haofu Liao^{*2} Cheng Peng¹ Xiaohang Sun³ Jingdan Zhang⁴
Jiebo Luo² Rama Chellappa¹ Shaohua Kevin Zhou^{5,6}

¹University of Maryland, College Park ²University of Rochester ³Princeton University
⁴Z2W Corporation ⁵Chinese Academy of Sciences ⁶Peng Cheng Laboratory, Shenzhen

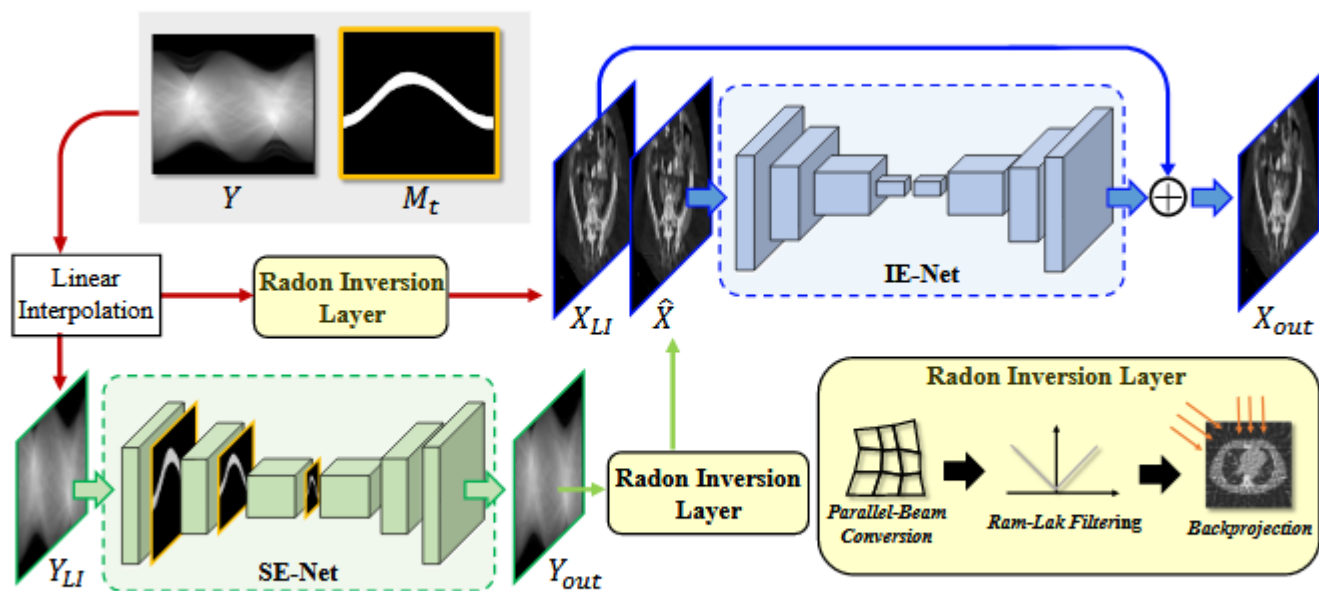


Figure 2: The proposed Dual Domain Network (DuDoNet) for MAR. Given a degraded sinogram Y and a metal trace mask M_t , DuDoNet reduces metal artifacts by simultaneously refining in the sinogram and image domains.

End-to-end. Both nets are U-Nets. SE-Net is trained with an image-based loss.

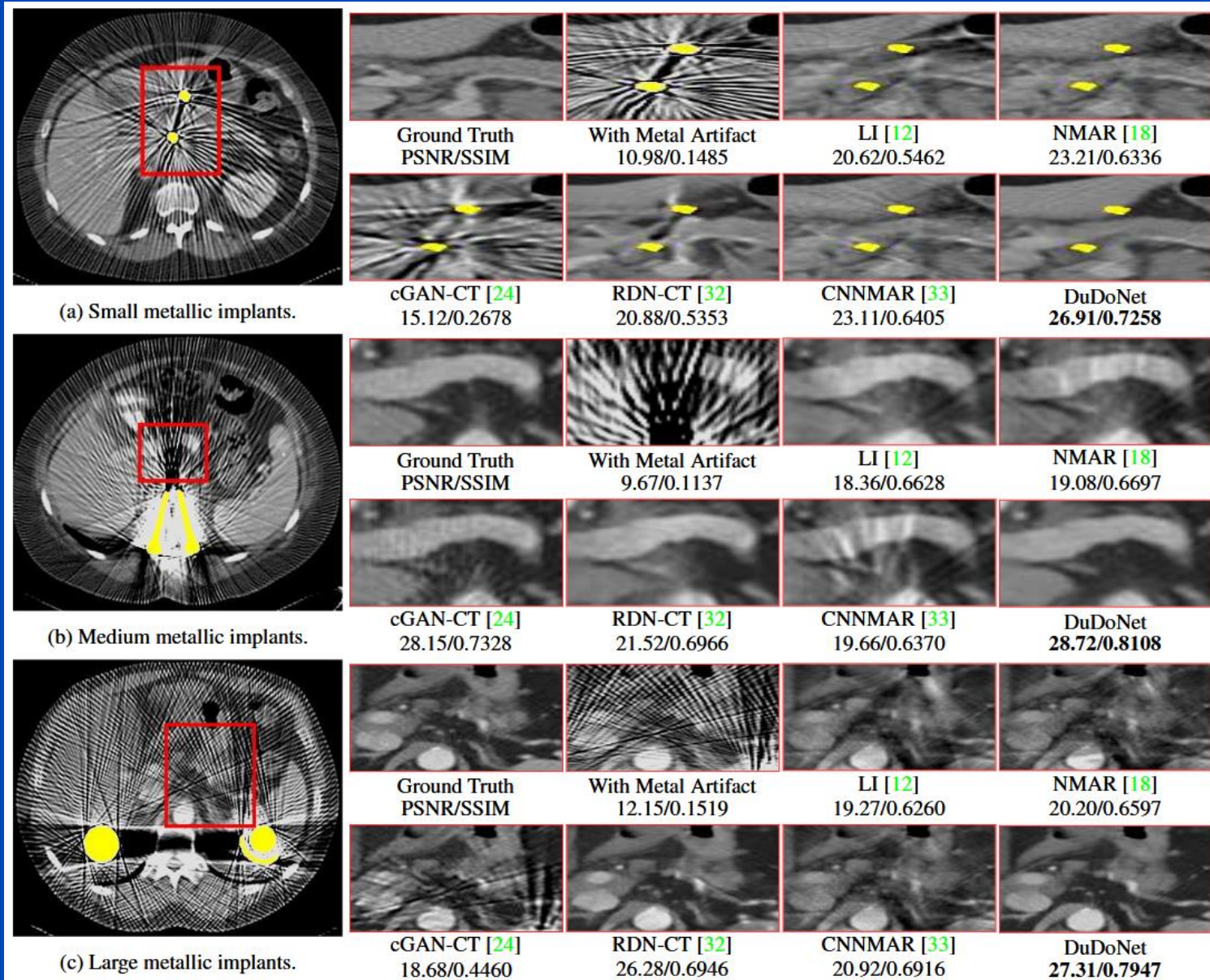
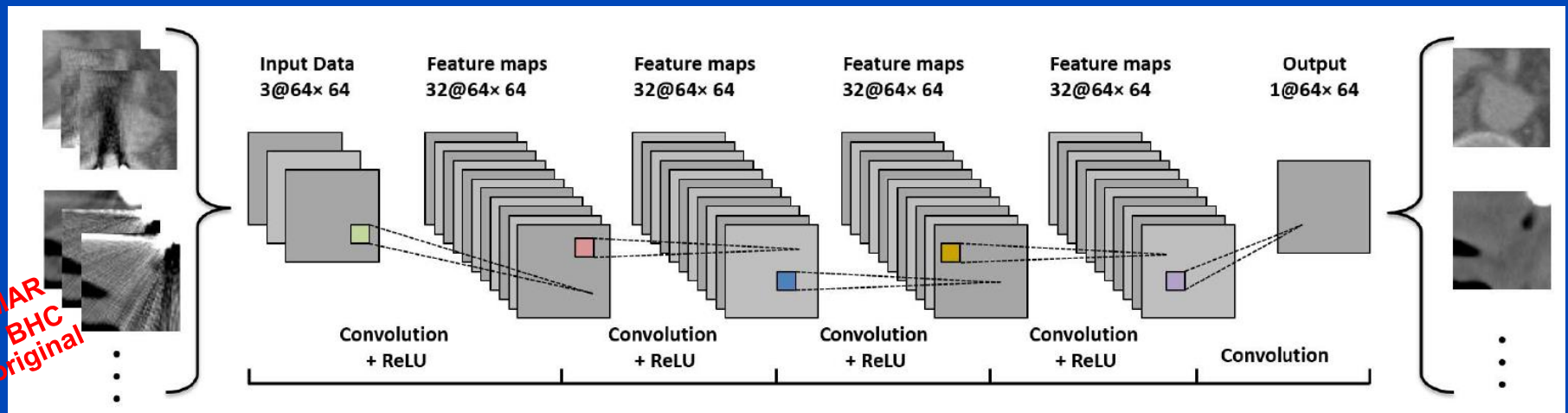


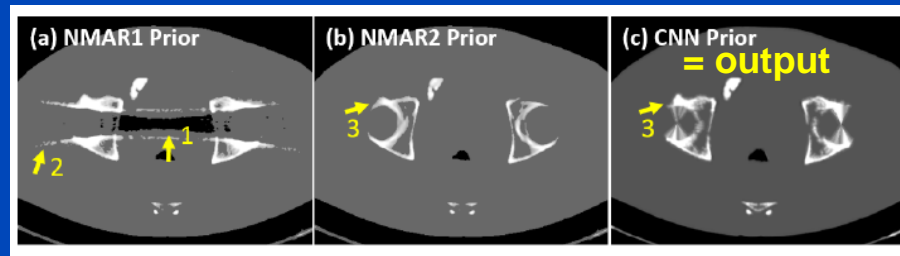
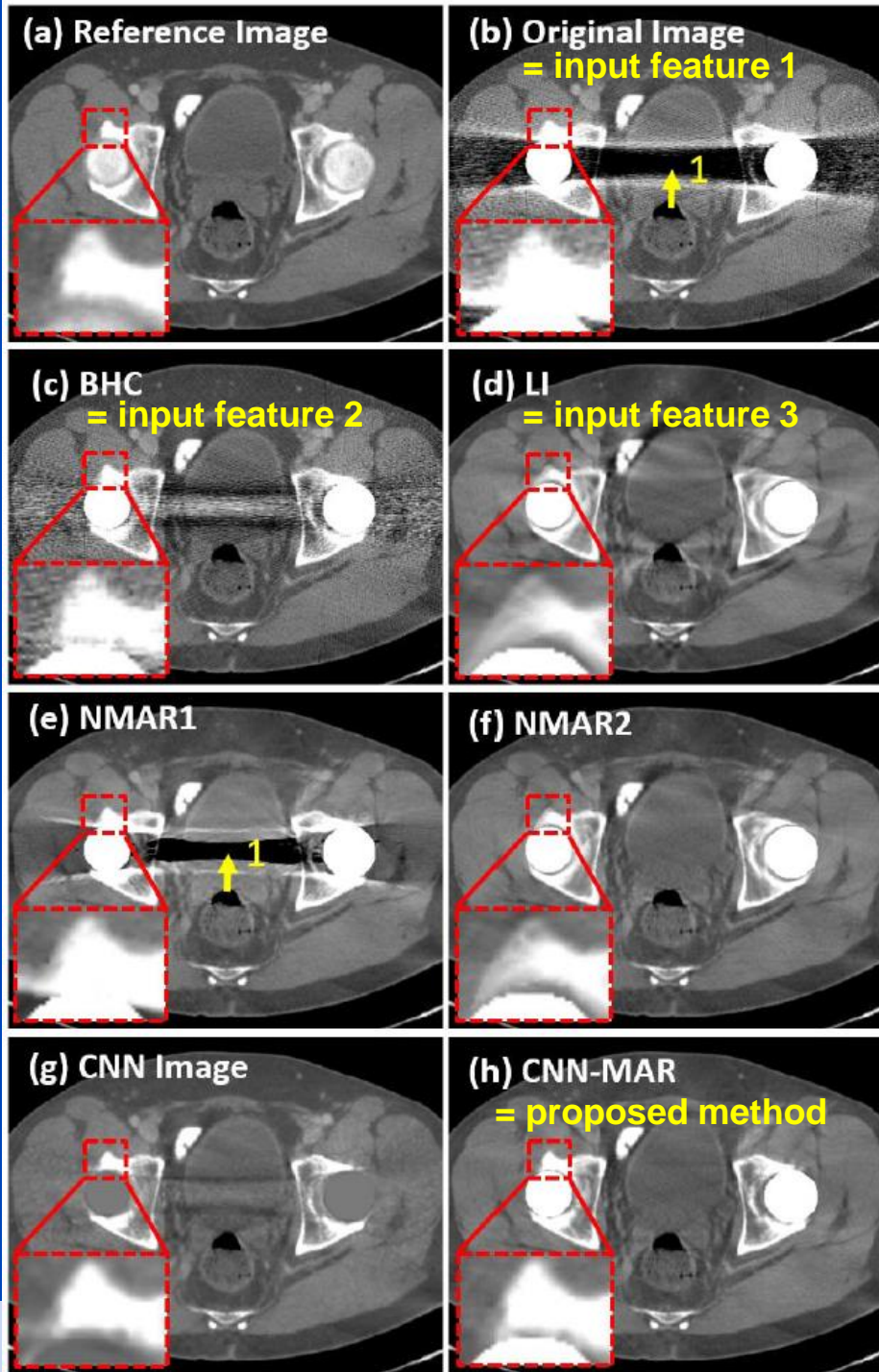
Figure 7: Visual comparisons on MAR for different types of metallic implants.

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



MAR without Machine Learning is a Good Alternative: Frequency Split Normalized MAR^{1,2}

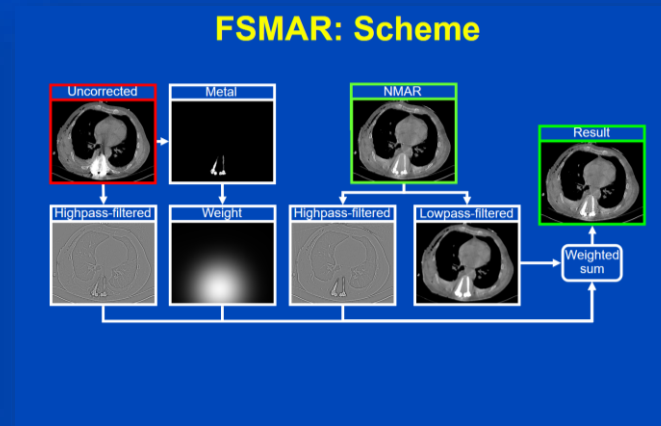
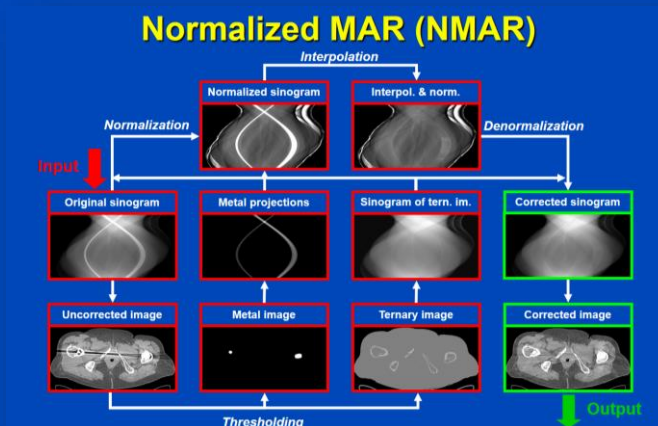
Uncorrected

FSLIMAR

FSNMAR



Patient with bilateral hip prosthesis, Somatom Definition Flash, (C = 40 HU, W = 500 HU).



¹E. Meyer, M. Kachelrieß. Normalized metal artifact reduction (NMAR) in computed tomography. Med. Phys. 37(10):5482-5493, Oct. 2010.

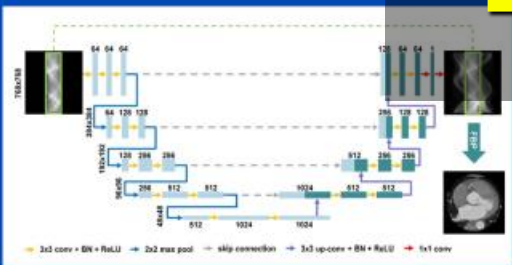
²E. Meyer, M. Kachelrieß. Frequency split metal artifact reduction (FSMAR) in CT. Med. Phys. 39(4):1904-1916, April 2012.

Summary on Deep MAR

- **Most common uses for networks:**
 - Improve image quality in image domain after MAR
 - Use network for the sinogram inpainting
 - Produce a prior image, e.g. for NMAR (currently the best idea)
- **Additional observations:**
 - Training data are often produced by segmenting an artifact-free CT image, adding metal and applying a polychromatic forward projection to different types of tissue separately.
 - As of today, it seems hard to outperform NMAR, or hard to give convincing clinical examples.

Deep learning-based sinogram extension method for interior computed tomography

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²The South Savo Health Care Authority, Mikkelin Central Hospital, Oulu, Finland
³Department of Diagnostic Radiology, Oulu University Hospital, Oulu, Finland
⁴Medical Research Center Oulu, Oulu University Hospital and University of Oulu, Oulu, Finland



Deep Detruncation

Results

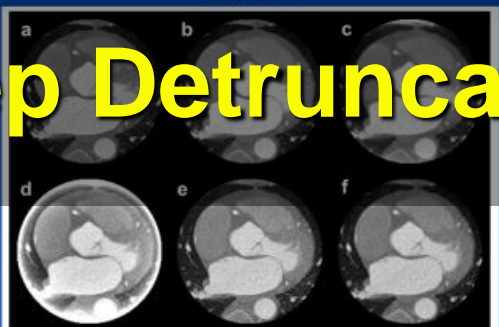
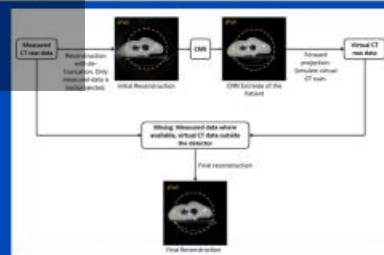


Figure 3. Example reconstructions. a. Original data from sensor. b. Adaptive detraction followed by filtered backprojection. c. Total variation regularization. d. Filtered backprojection. e. FBP-CNN. f. Our Method. Reconstructions have been rescaled to contain the region-of-interest.

Ketola, Jusuo H. J., et al. "Deep learning-based sinogram extension method for interior computed tomography." *Medical Imaging 2021: Physics of Medical Imaging*, Vol. 11985, International Society for Optics and Photonics, 2021. [dkfz.](#)

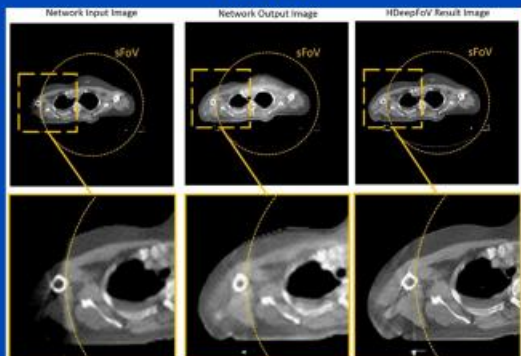
Evaluation of novel AI-based extended field-of-view CT reconstructions

Gabriel Palva Fonseca¹, Alexander Preuhs², Michael Manhart², Guenter Lauritsch², and Andreas Maier²
¹Department of Radiation Oncology (MAASTRO), GROW School for Oncology and Developmental Biology, Maastricht University Medical Center, Maastricht 6229 ET, The Netherlands
²Siemens Healthcare GmbH, Forchheim, Germany
³Baria Rinaldi, Michel C. Orlitz, Wouter J.C. van Elmpt and Frank Verhaeghan
⁴Department of Radiation Oncology (MAASTRO), GROW School for Oncology and Developmental Biology, Maastricht University Medical Center, Maastricht 6229 ET, The Netherlands
 Received 28 February 2021; revised 27 April 2021; accepted for publication 30 April 2021; published 30 May 2021.



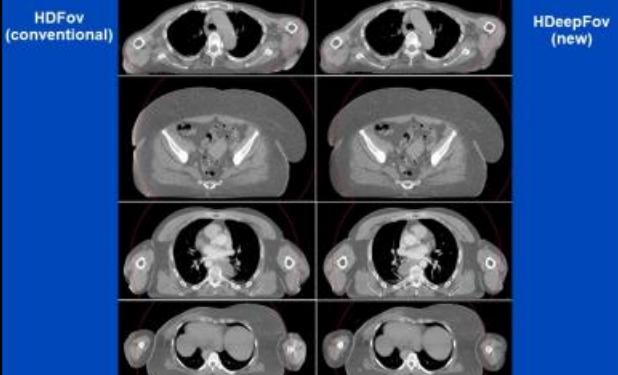
Fonseca, Gabriel Palva, et al. "Evaluation of novel AI-based extended field-of-view CT reconstructions." *Medical Physics* (2021). [dkfz.](#)

Results



Fonseca, Gabriel Palva, et al. "Evaluation of novel AI-based extended field-of-view CT reconstructions." *Medical Physics* (2021). [dkfz.](#)

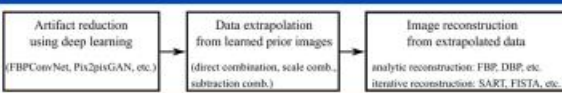
Results



Fonseca, Gabriel Palva, et al. "Evaluation of novel AI-based extended field-of-view CT reconstructions." *Medical Physics* (2021). [dkfz.](#)

Data Extrapolation From Learned Prior Images for Truncation Correction in Computed Tomography

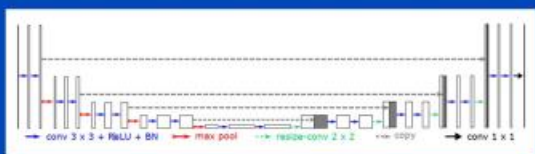
Yixing Huang¹, Alexander Preuhs², Michael Manhart², Guenter Lauritsch², and Andreas Maier², Senior Member, IEEE



Huang, Yixing, et al. "Data Extrapolation from Learned Prior Images for Truncation Correction in Computed Tomography." *IEEE Transactions on Medical Imaging* (2021). [dkfz.](#)

Data Consistent CT Reconstruction from Insufficient Data with Learned Prior Images

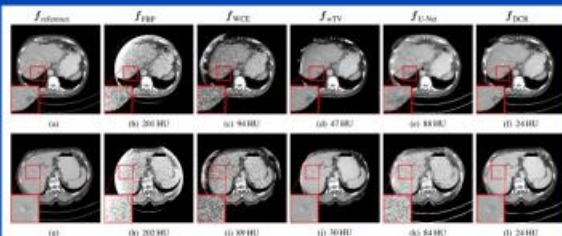
Yixing Huang, Alexander Preuhs, Michael Manhart, Guenter Lauritsch, Andreas Maier



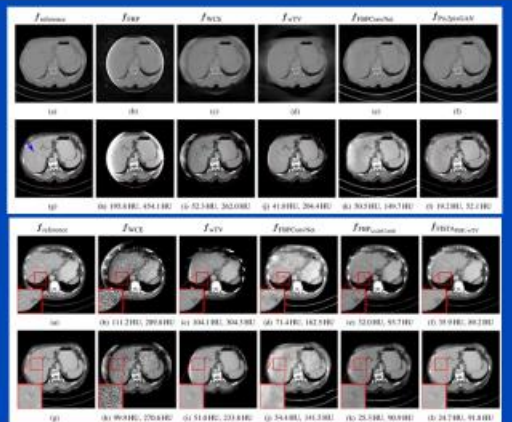
Corrected image is then forward-projected and the projections are combined with the original raw data. Finally, the combined data are reconstructed iteratively.

Huang, Yixing, et al. "Data consistent CT reconstruction from insufficient data with learned prior images." *arXiv preprint arXiv:2005.10034* (2020). [dkfz.](#)

Results



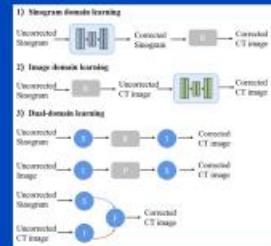
Huang, Yixing, et al. "Data consistent CT reconstruction from insufficient data with learned prior images." *arXiv preprint arXiv:2005.10034* (2020). [dkfz.](#)



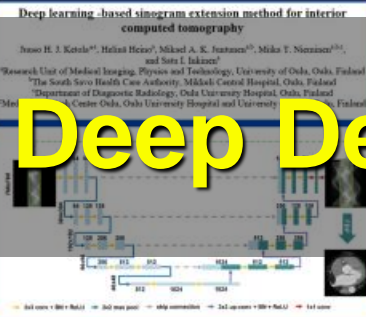
Huang, Yixing, et al. "Data Extrapolation from Learned Prior Images for Truncation Correction in Computed Tomography." *IEEE Transactions on Medical Imaging* (2021). [dkfz.](#)

Deep Detruncation

Classification of DL-based reconstruction methods



- S: Sinogram domain network
- I: Image domain network
- P: Projection operation
- R: Reconstruction operation
- F: Dual-domain information fusion operation



J. H. Kim, et al., Deep learning-based sinogram extension method for interior computed tomography. Medical Imaging: Physics of Medical Imaging, vol. 11959, International Society for Optics and Photonics (2021).

Results

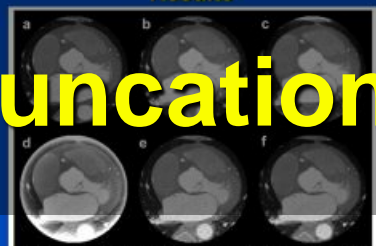
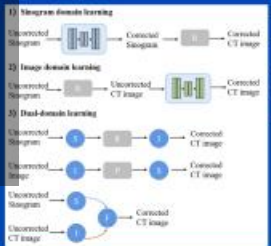


Figure 3. Example reconstructions: a) Original data from sinogram, b) Sinogram extension followed by filtered backprojection, c) Full sinogram reconstruction, d) Filtered backprojection, e) FBP+GAN, f) Our Method. Reconstructions have been windowed to create the visualizations.

J. H. Kim, et al., Deep learning-based sinogram extension method for interior computed tomography. Medical Imaging: Physics of Medical Imaging, vol. 11959, International Society for Optics and Photonics (2021).

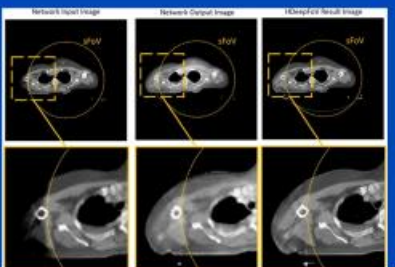
Deep Detruncation

Classification of DL-based reconstruction methods



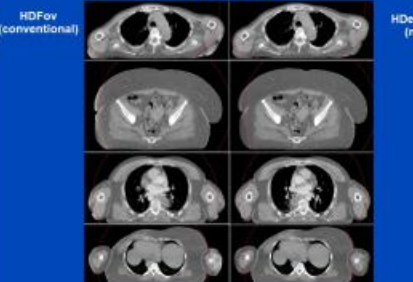
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Results



S. P. Posares, et al., Evaluation of novel AI-based extended field-of-view CT reconstructions. Med Phys, 48(7):2382-2391 (2021).

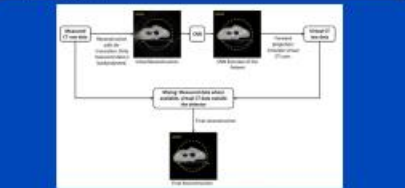
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Evaluation of novel AI-based extended field-of-view CT reconstructions

Gabriel Posares^{1,2}, Alexander Pirsuhn^{1,2}, Michael Mariani^{1,2}, Guenter Lauritsch^{1,2}, and Andreas Maier^{1,2}. ¹Department of Radiation Therapy (MARTINA), GEMF School for Oncology and Developmental Biology, Maastricht University Medical Center, Maastricht 6229 XZ, The Netherlands. ²Steno-Bildgebung, Medizinische Fakultät, Universität zu Köln, Köln 50931, Germany. (Received 29 February 2021; revised 27 April 2021; accepted for publication 30 April 2021; published 11 May 2021)



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Data Extrapolation From Learned Prior Images for Truncation Correction in Computed Tomography

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Data Consistent CT Reconstruction from Insufficient Data with Learned Prior Images

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Generative adversarial networks improve interior computed tomography angiography reconstruction

Juuso H J Kotola^{1,2}, Helena Helio¹, Mikael A K Juntunen^{1,2}, Miika T Nieminen^{1,2,3}, Sattab Sittirak¹, and Sota I. Ishizu¹

- Input: truncated sinogram
- Extended with sinogram extension GAN
- Superimpose original measured data
- reconstruction post-processing GAN is used to yield an improved reconstruction
- original data is superimposed in the sinogram before final filtered backprojection

J. H. Kim, et al., Generative adversarial networks improve interior computed tomography angiography reconstruction. Clinical Phys: Eng Express 7:063001 (2021)

Results

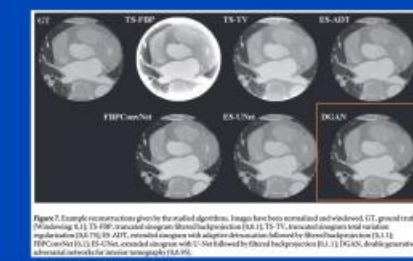


Figure 7. Example reconstructions given by the studied algorithms. Images have been normalized and windowed. CT, ground truth; ES-Net, ES-Net; FBP+GAN, FBP+GAN; GAN, GAN. (a) Original data, (b) ES-Net, (c) FBP+GAN, (d) GAN. (e) Original data, (f) ES-Net, (g) FBP+GAN, (h) GAN. (i) Original data, (j) ES-Net, (k) FBP+GAN, (l) GAN. (m) Original data, (n) ES-Net, (o) FBP+GAN, (p) GAN. (q) Original data, (r) ES-Net, (s) FBP+GAN, (t) GAN. (u) Original data, (v) ES-Net, (w) FBP+GAN, (x) GAN. (y) Original data, (z) ES-Net, (aa) FBP+GAN, (ab) GAN.

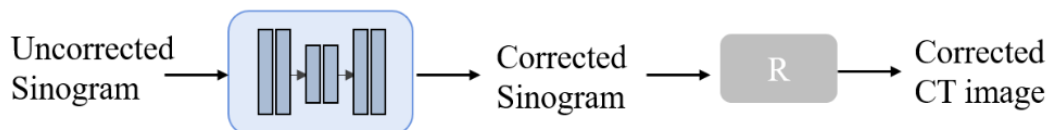
Results

Huang, Yiying, et al., "Data Consistent CT Reconstruction from Insufficient Data with Learned Prior Images." arXiv preprint arXiv:2005.10024 (2020).

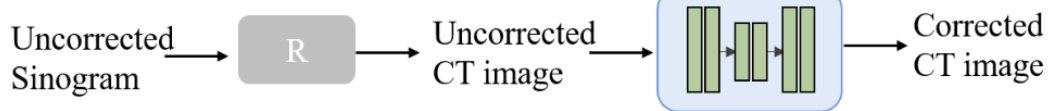
Deep Detruncation

Classification of DL-based reconstruction methods

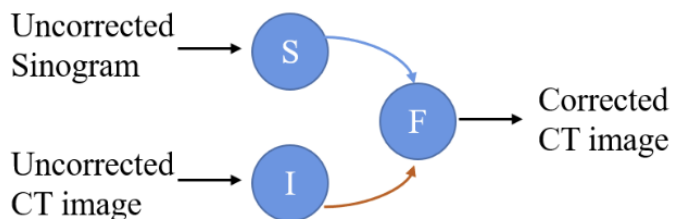
1) Sinogram domain learning



2) Image domain learning



3) Dual-domain learning



- **S**: Sinogram domain network
- **I**: Image domain network
- **P**: Projection operation
- **R**: Reconstruction operation
- **F**: Dual-domain information fusion operation

Deep learning -based sinogram extension method for interior computed tomography

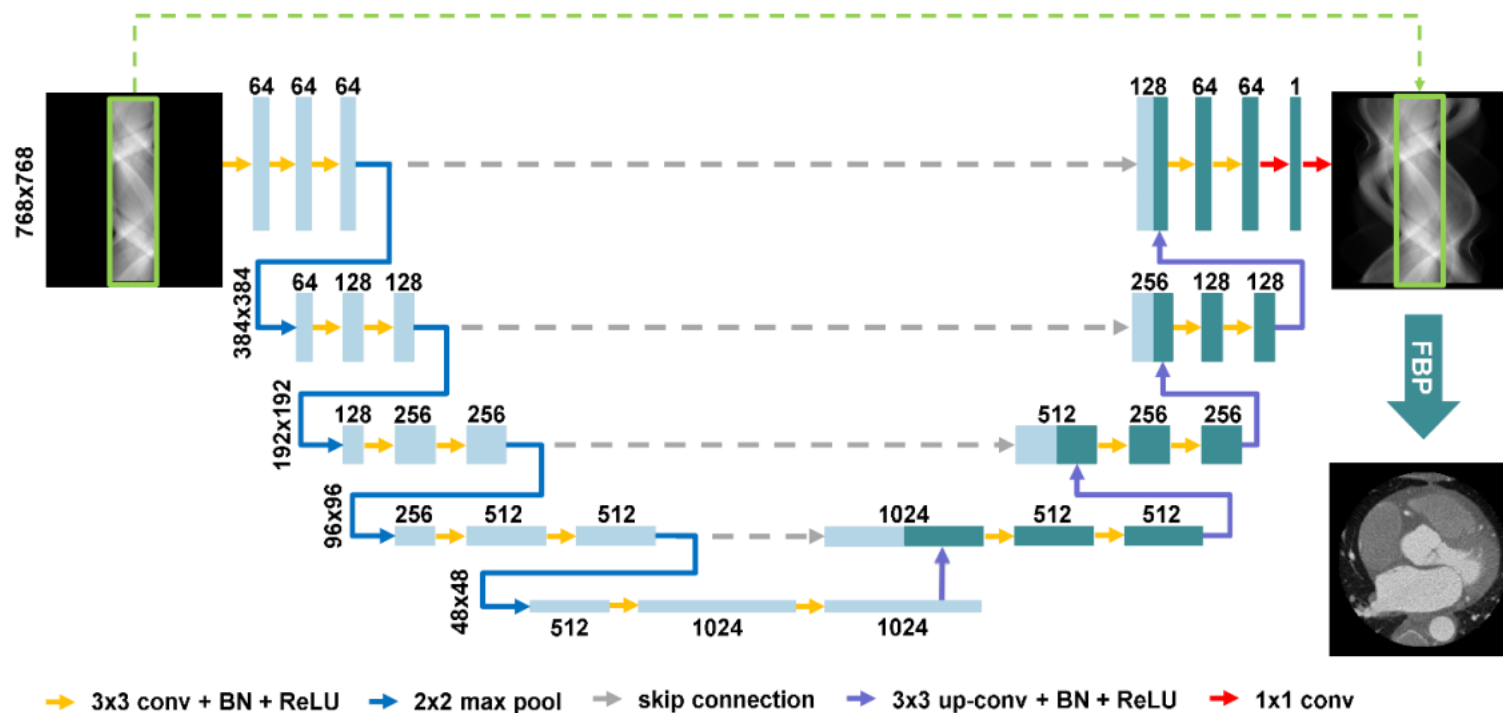
Juuso H. J. Ketola^{*a}, Helinä Heino^a, Mikael A. K. Juntunen^{a,b}, Miika T. Nieminen^{a,b,c},
and Satu I. Inkinen^a

^aResearch Unit of Medical Imaging, Physics and Technology, University of Oulu, Oulu, Finland

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[†]Medical Research Center Oulu, Oulu University Hospital and University of Oulu, Oulu, Finland



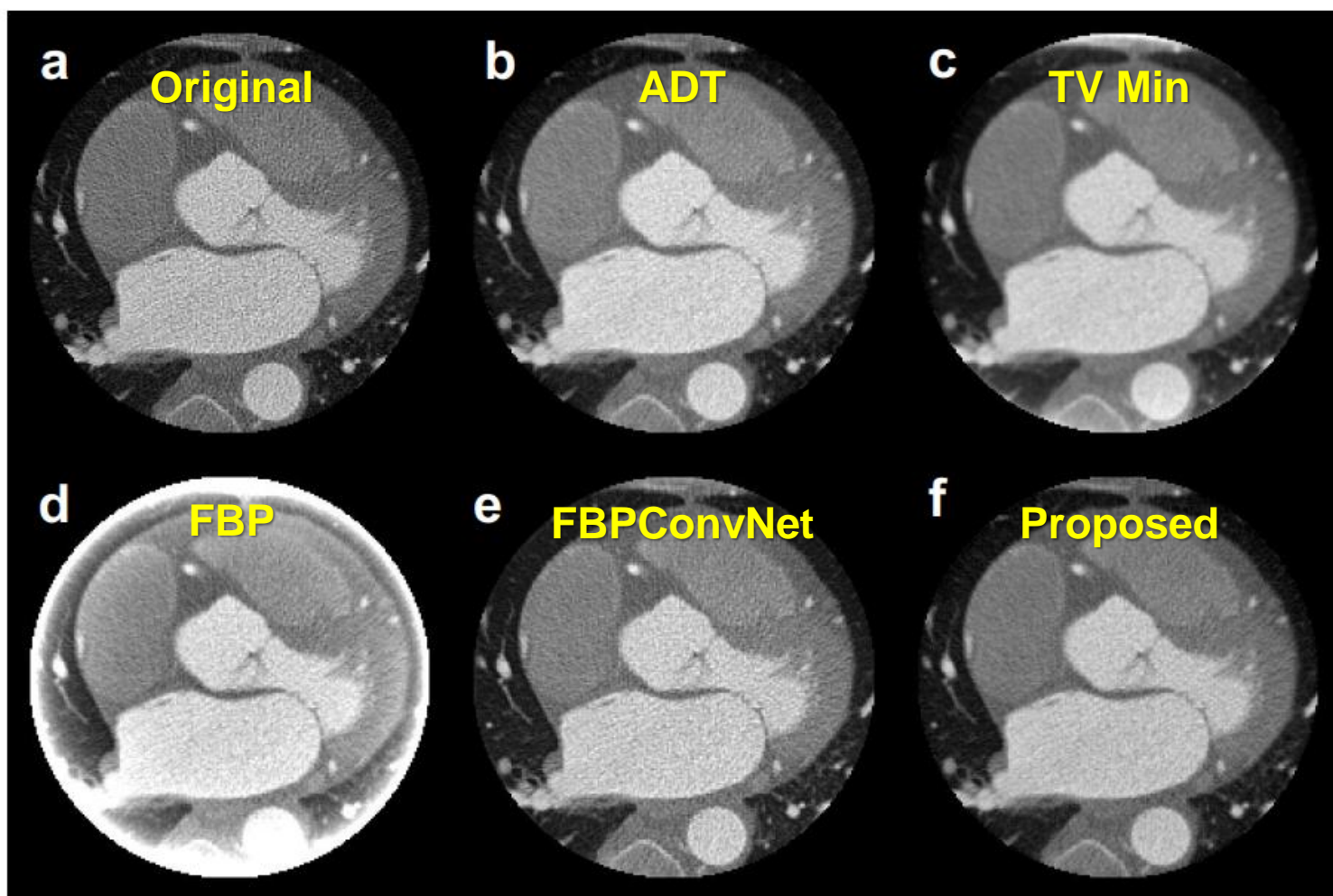


Figure 3. Example reconstructions. a. Original data from scanner. b. Adaptive de-truncation followed by filtered backprojection. c. Total variation regularization. d. Filtered backprojection. e. FBPCConvNet. f. Our Method. Reconstructions have been masked to contain the region-of-interest.

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Department of Radiation Oncology (MAASTRO), GROW School for Oncology and Developmental Biology, Maastricht University Medical Centre+, Maastricht 6229 ET, The Netherlands

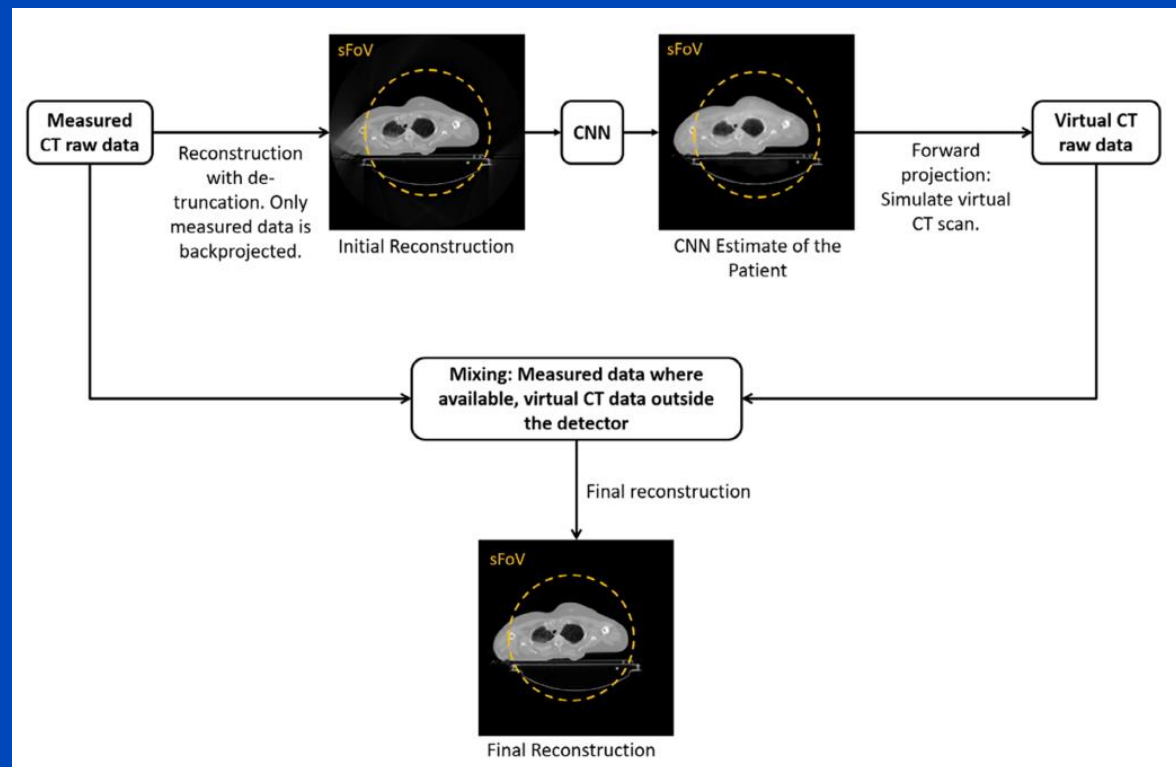
Matthias Baer-Beck* Eric Fournie and Christian Hofmann

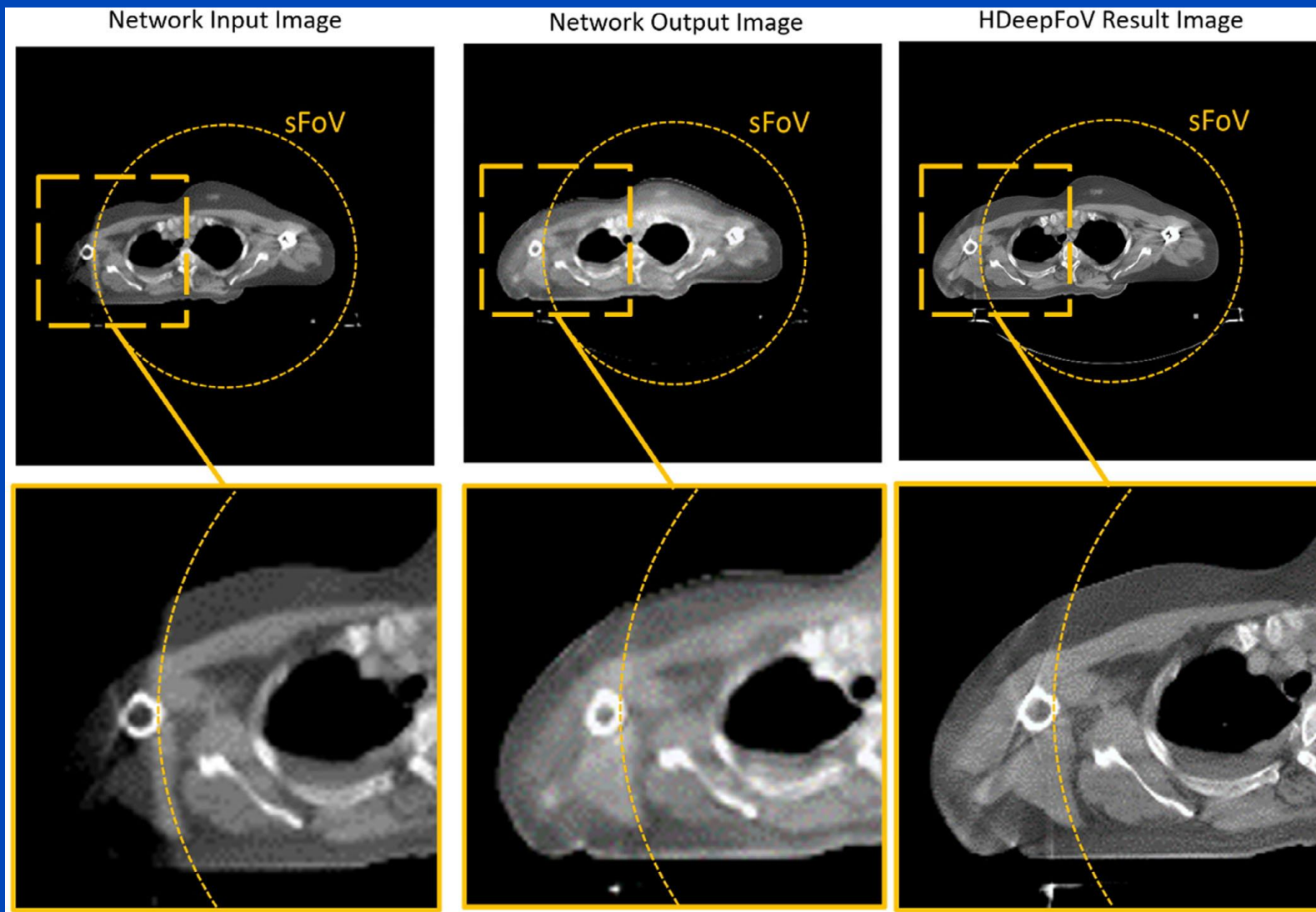
Siemens Healthcare GmbH, Forchheim, Germany

Ilaria Rinaldi, Michel C Ollers, Wouter J.C. van Elmpt and Frank Verhaegen

Department of Radiation Oncology (MAASTRO), GROW School for Oncology and Developmental Biology, Maastricht University Medical Centre+, Maastricht 6229 ET, The Netherlands

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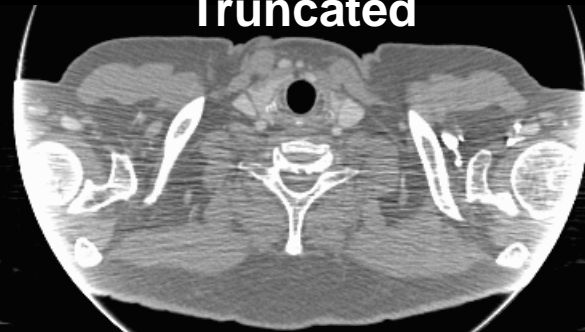




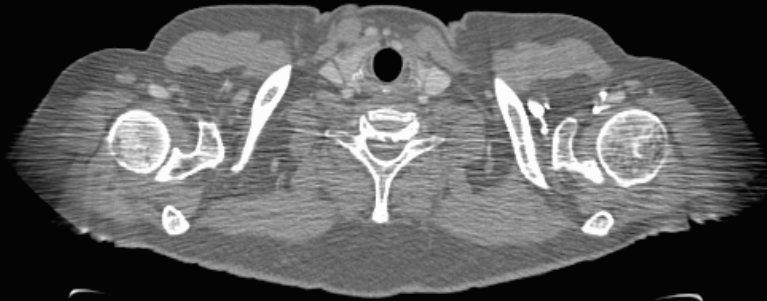
Original



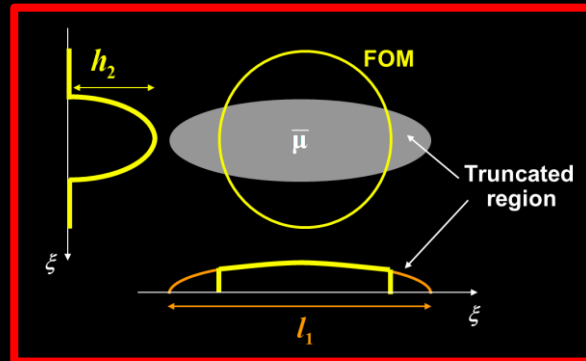
Truncated



ADT corrected



ADT corrected (clipped)

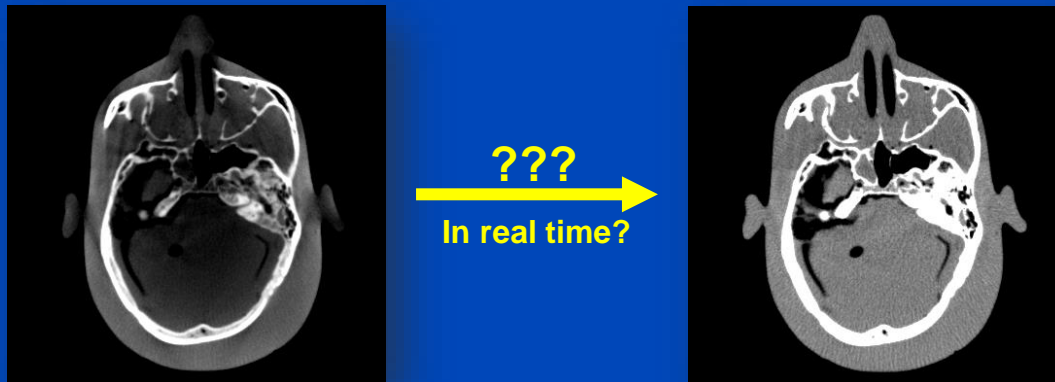


C = 0 HU, W = 1000 HU

Summary on Deep Detruncation

- No need for machine learning to restore the gray values within the FOM.
- Image domain cosmetic detruncation (in particular outside the FOM) can serve as an intermediate step to detruncate CT data.

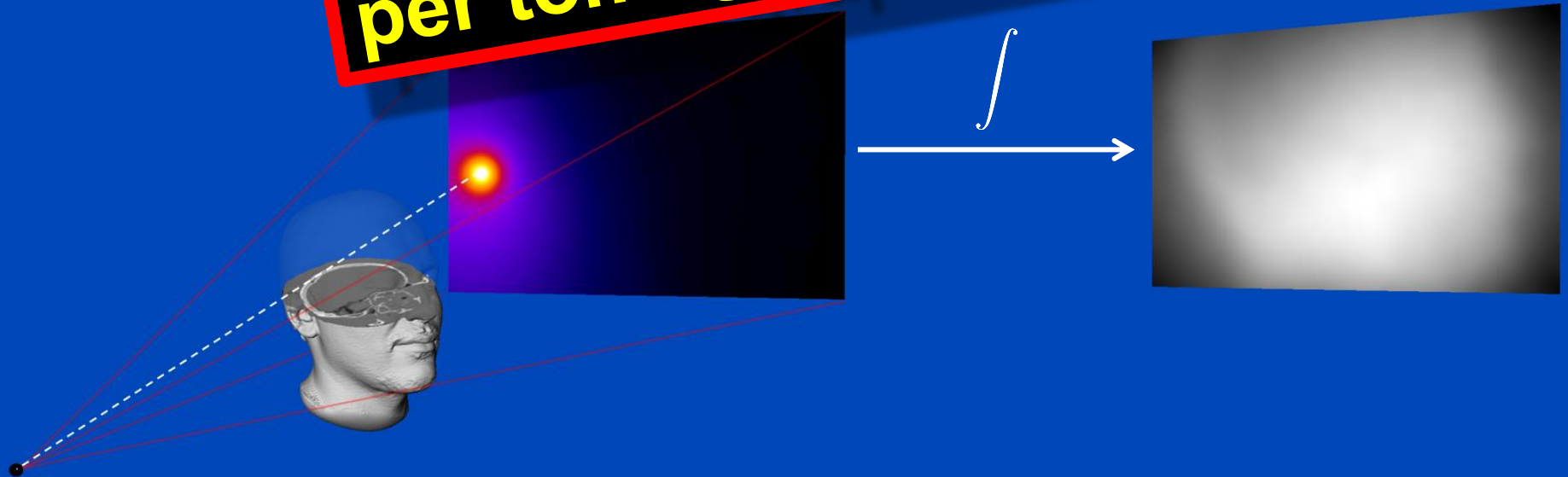
Deep Scatter Estimation



Monte Carlo Scatter Estimation

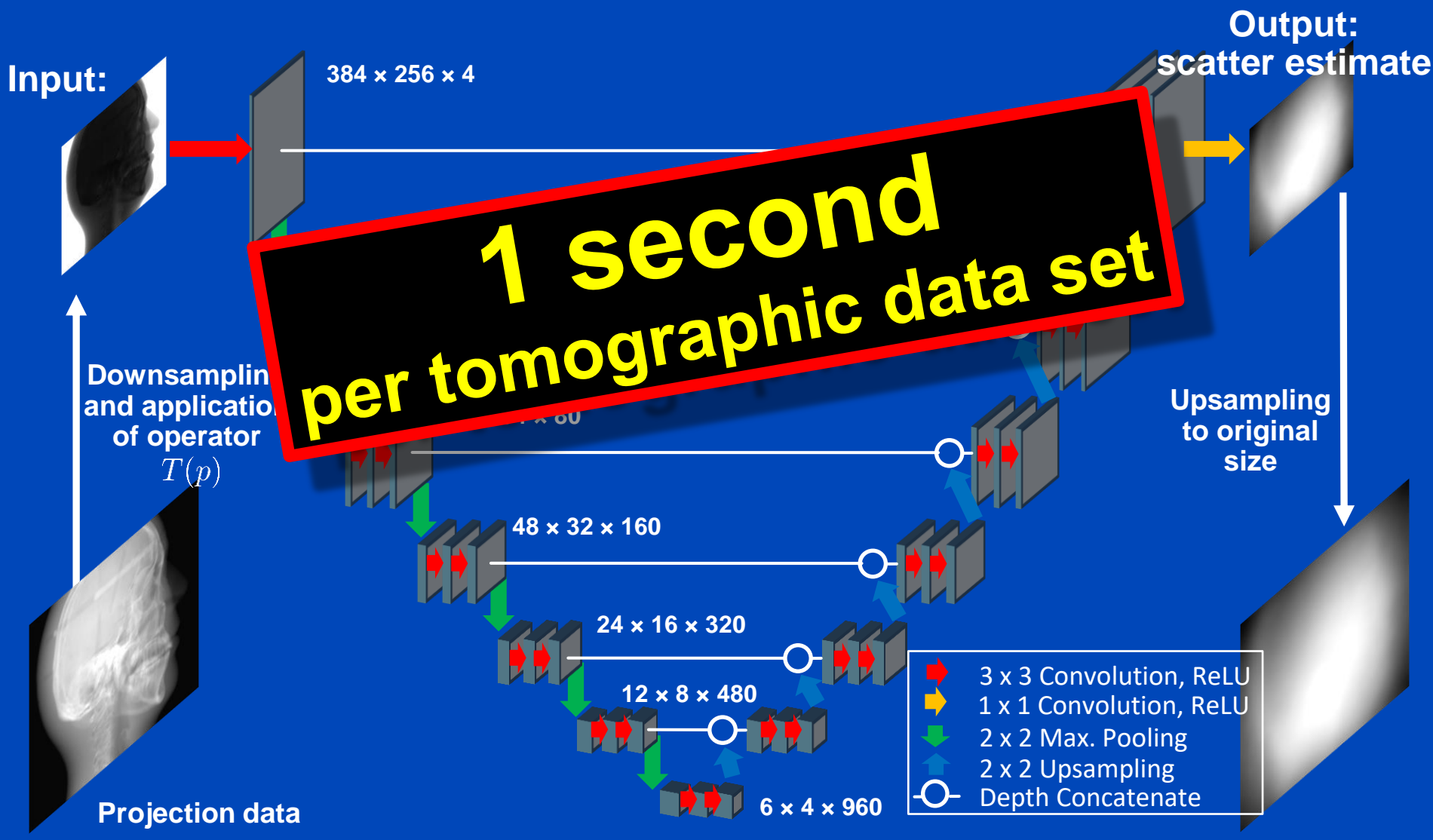
- Simulation of photon trajectories according to physical interaction probabilities.
- Simulating a large number of trajectories well approximates the complete scatter distribution

**1 hour
per tomographic data set**



Deep Scatter Estimation

Network architecture & scatter estimation framework



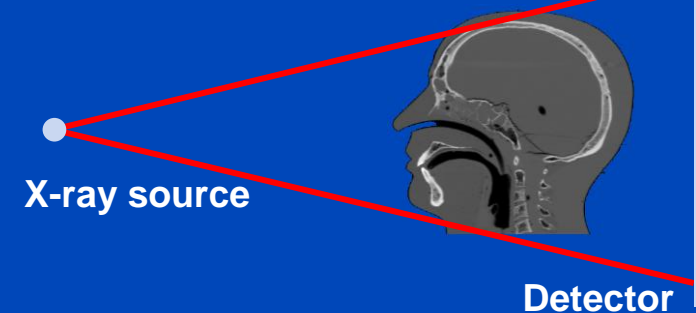
Testing of the DSE Network for Measured Data (120 kV)

DKFZ table-top CT

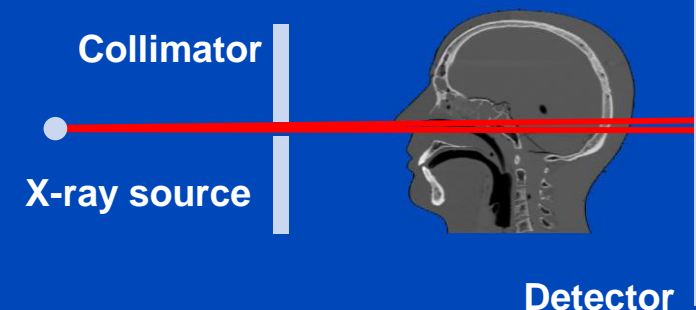


- Measurement of a head phantom at our in-house table-top CT.
- Slit scan measurement serves as ground truth.

Measurement to be corrected



Ground truth: slit scan



Reconstructions of Measured Data

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

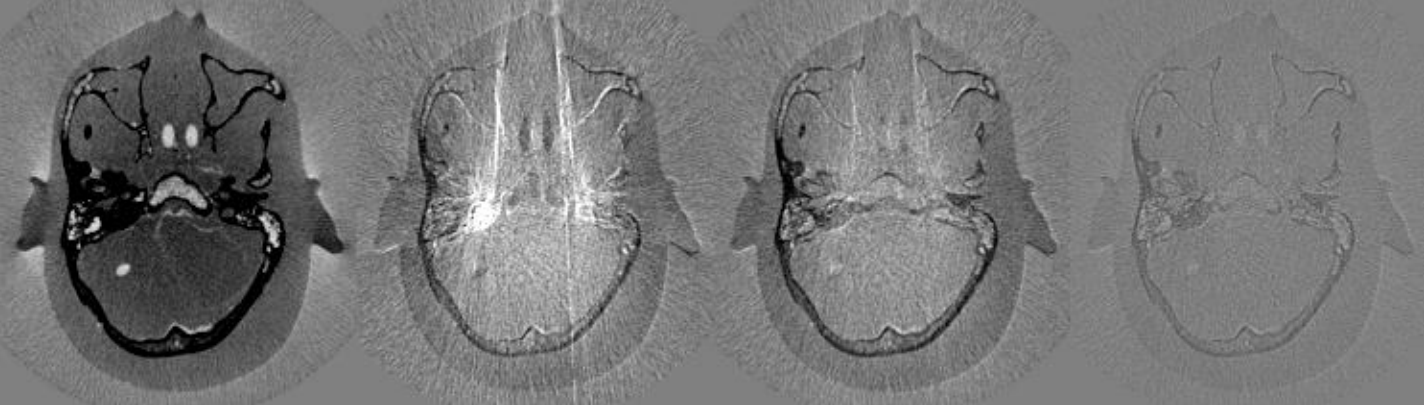
Hybrid Scatter
Estimation

DSE
Deep Scatter
Estimation

CT Reconstruction



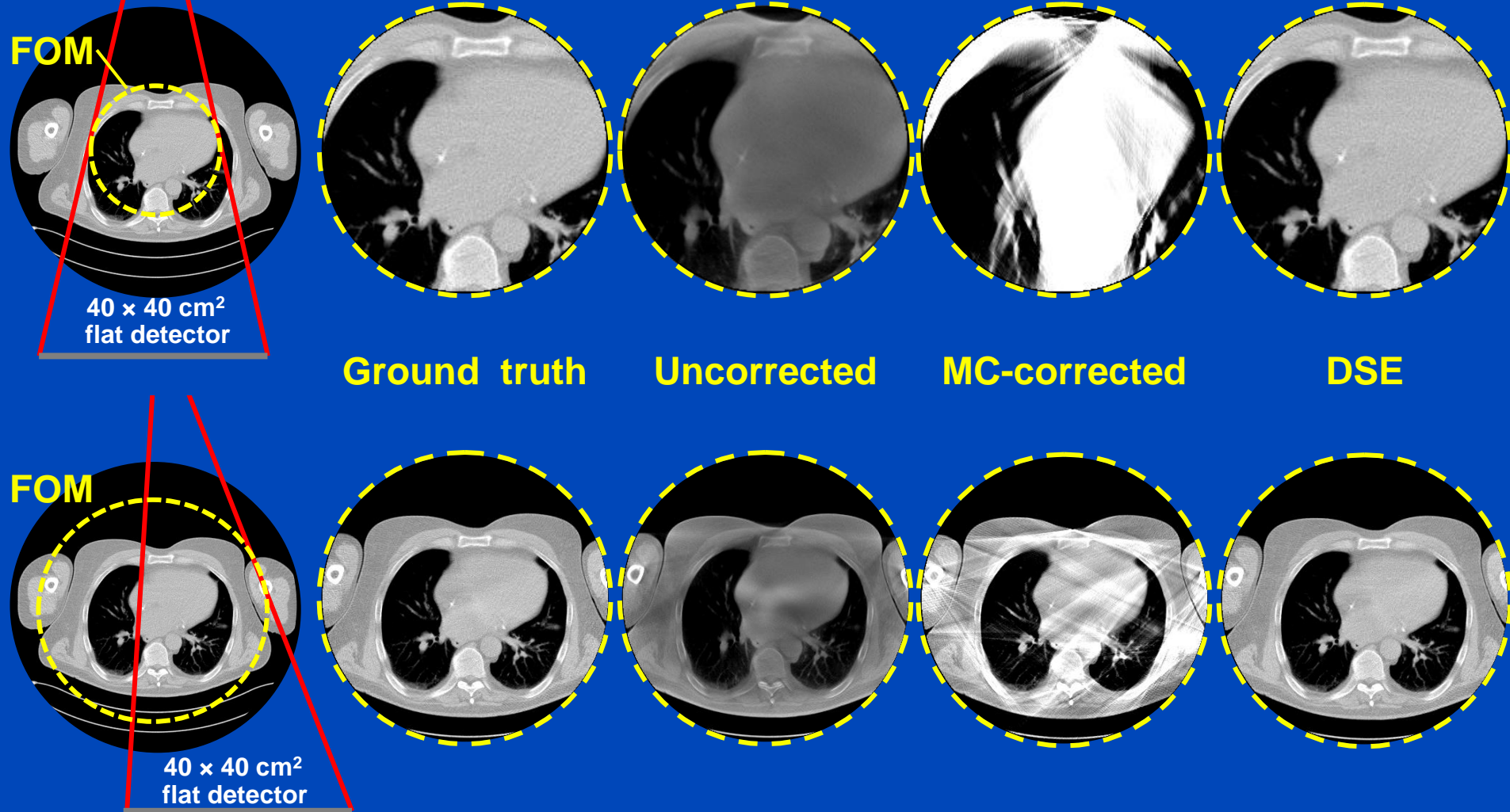
Difference to slit scan



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

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

Truncated DSE



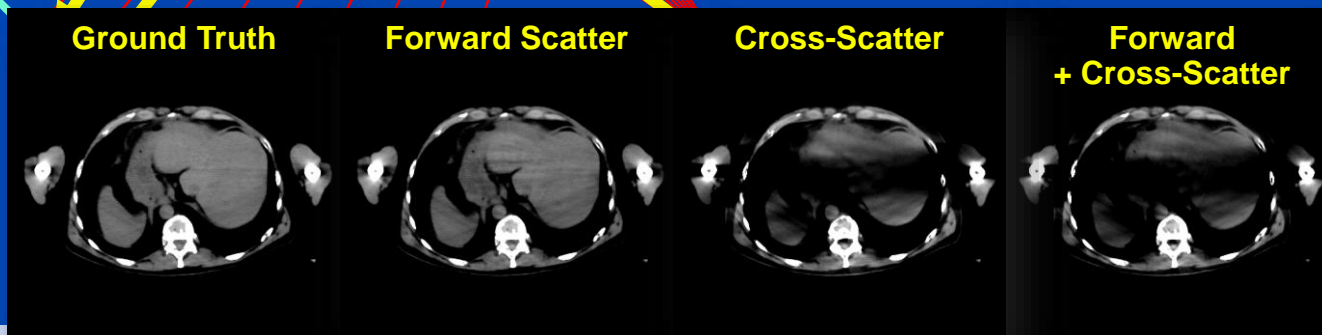
To learn why MC fails at truncated data and what significant efforts are necessary to cope with that situation see [Kachelrieß et al. Effect of detruncation on the accuracy of MC-based scatter estimation in truncated CBCT. Med. Phys. 45(8):3574-3590, August 2018].

Scatter in Dual Source CT (DSCT)



Siemens SOMATOM Force
dual source cone-beam spiral CT

$$q = -\ln \frac{I_{\text{primary}} + S_{\text{forward}} + \rho S_{\text{cross}}}{I_0}$$



C = 40 HU, W = 300 HU, with 2D anti-scatter grid

Scatter in Dual Source CT: xDSE

Ground Truth

Uncorrected

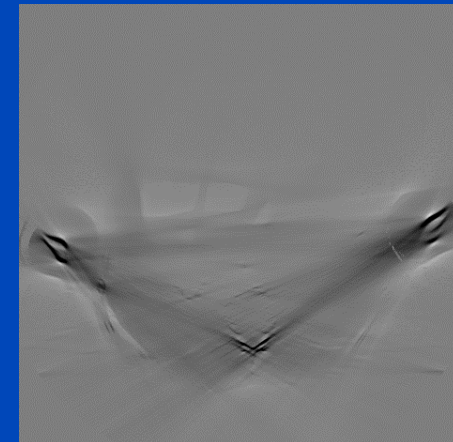
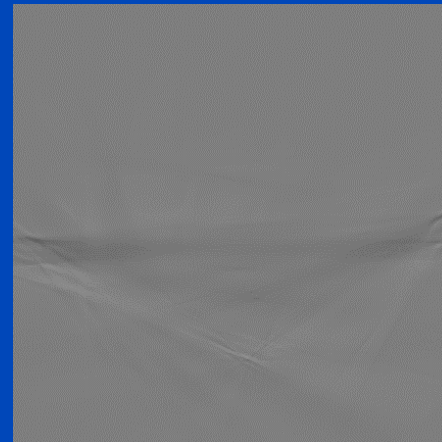
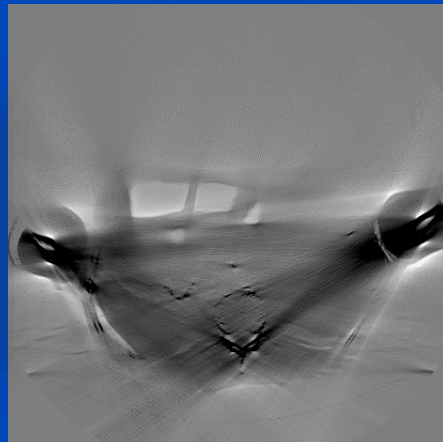
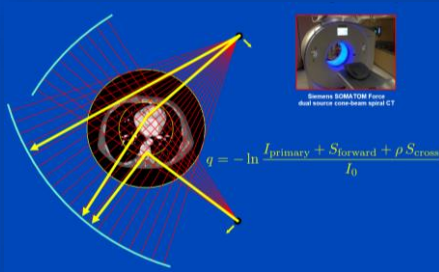
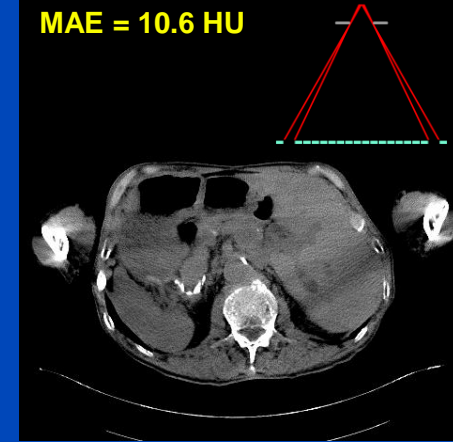
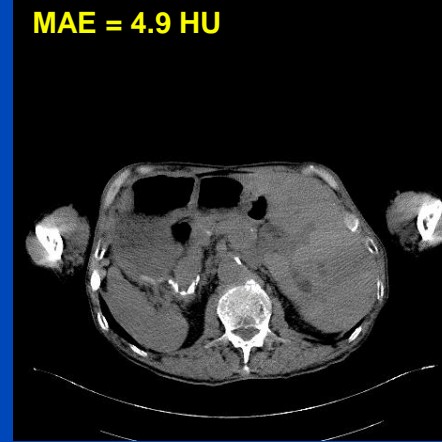
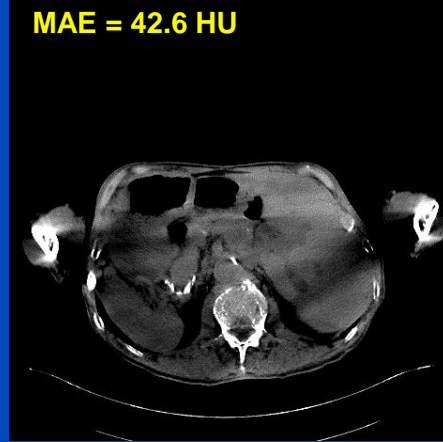
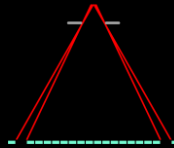
xDSE (2D, xSSE)

Measurement-based

MAE = 42.6 HU

MAE = 4.9 HU

MAE = 10.6 HU



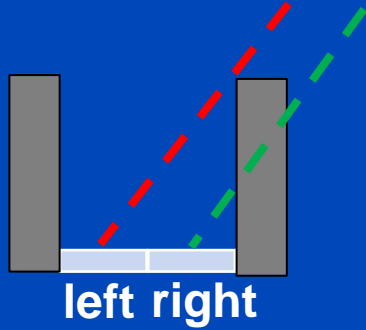
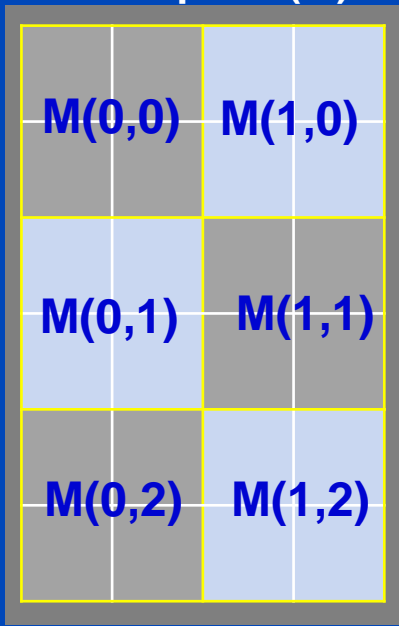
xDSE (2D, xSSE) maps

primary + forward scatter + cross-scatter + cross-scatter approximation → cross-scatter

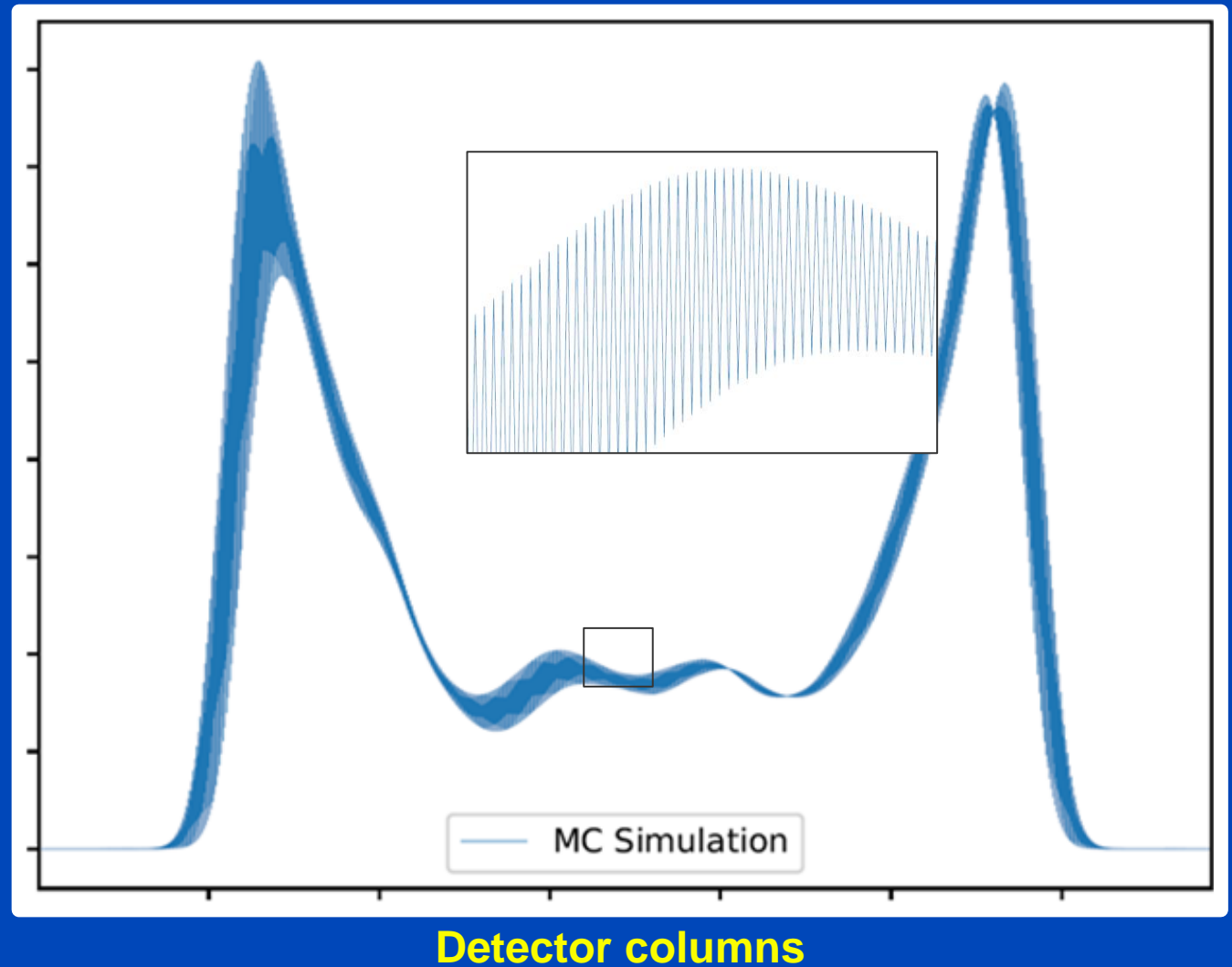
Images $C = 40$ HU, $W = 300$ HU, difference images $C = 0$ HU, $W = 300$ HU

Scatter for Coarse ASG

Four subpixels (S)
merged to one
macropixel (M)

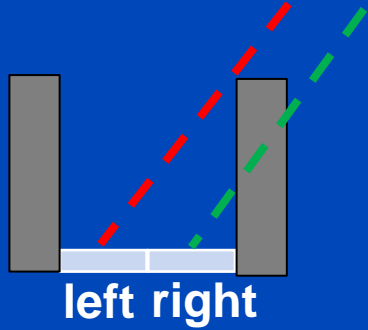
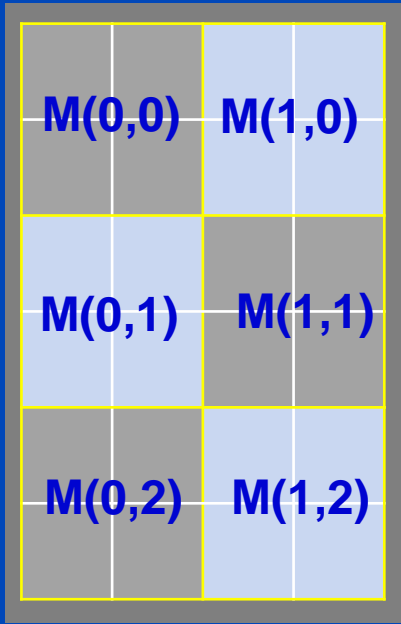


Scatter distribution averaged over all detector rows



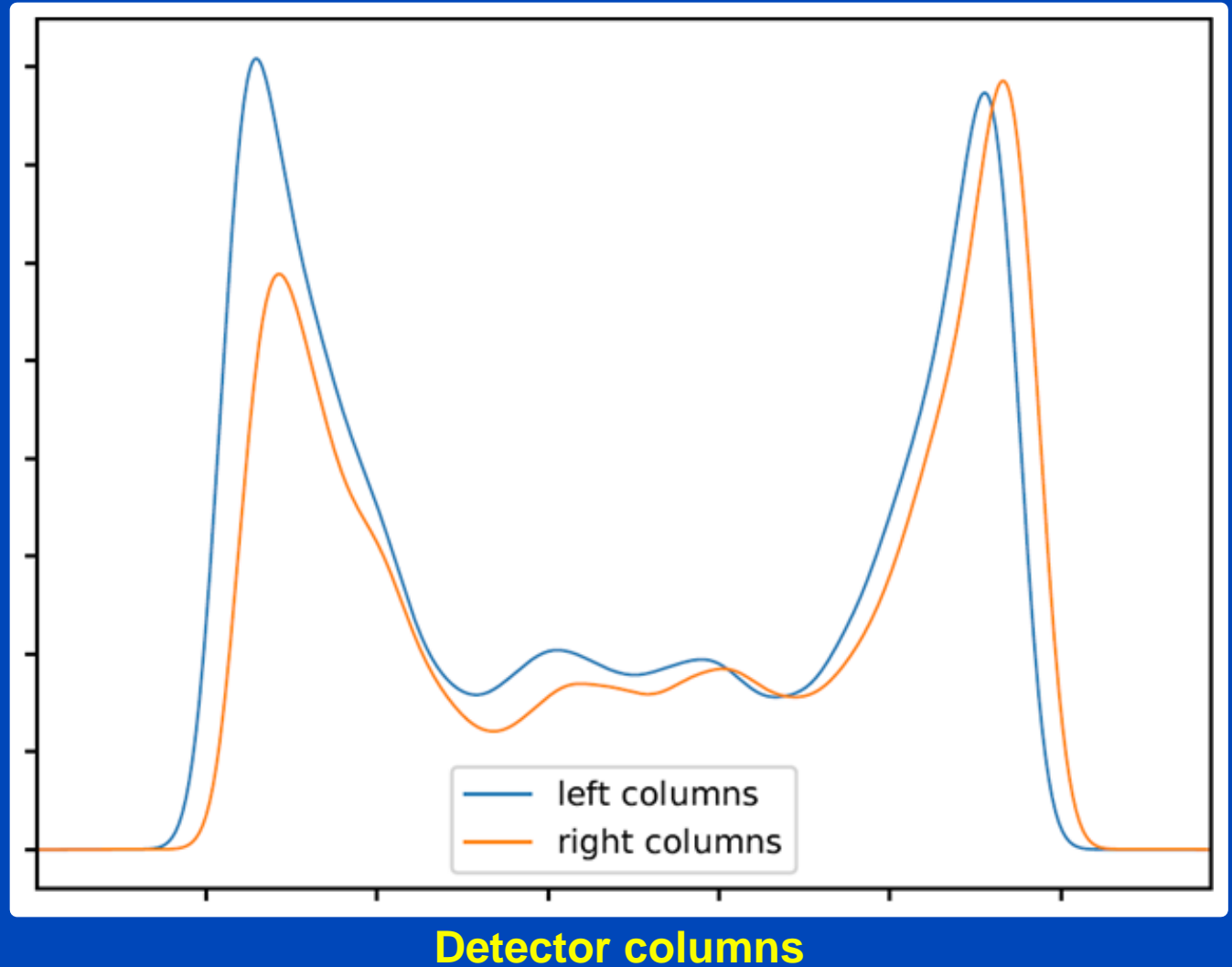
Scatter for Coarse ASG

left right

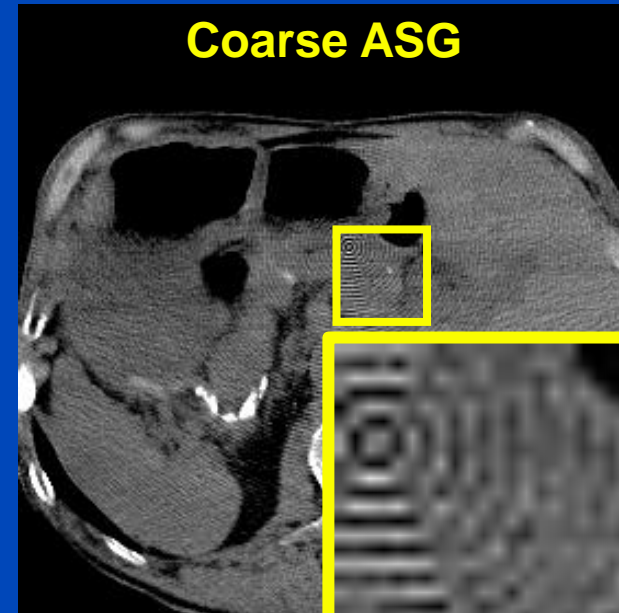
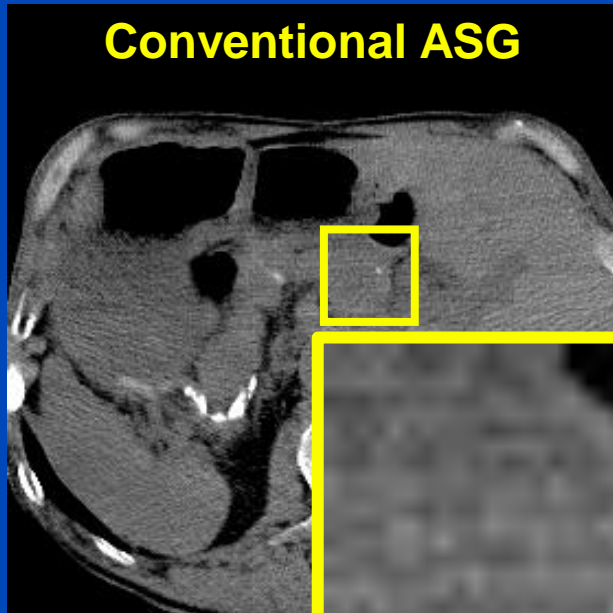


β →

Scatter distribution averaged over all detector rows



Scatter Artifacts of Coarse ASG



Coarse ASGs can lead to scatter-induced moiré artifacts.

Reconstruction: $C = 40$ HU, $W = 300$ HU

Network Architecture

Detector dimension

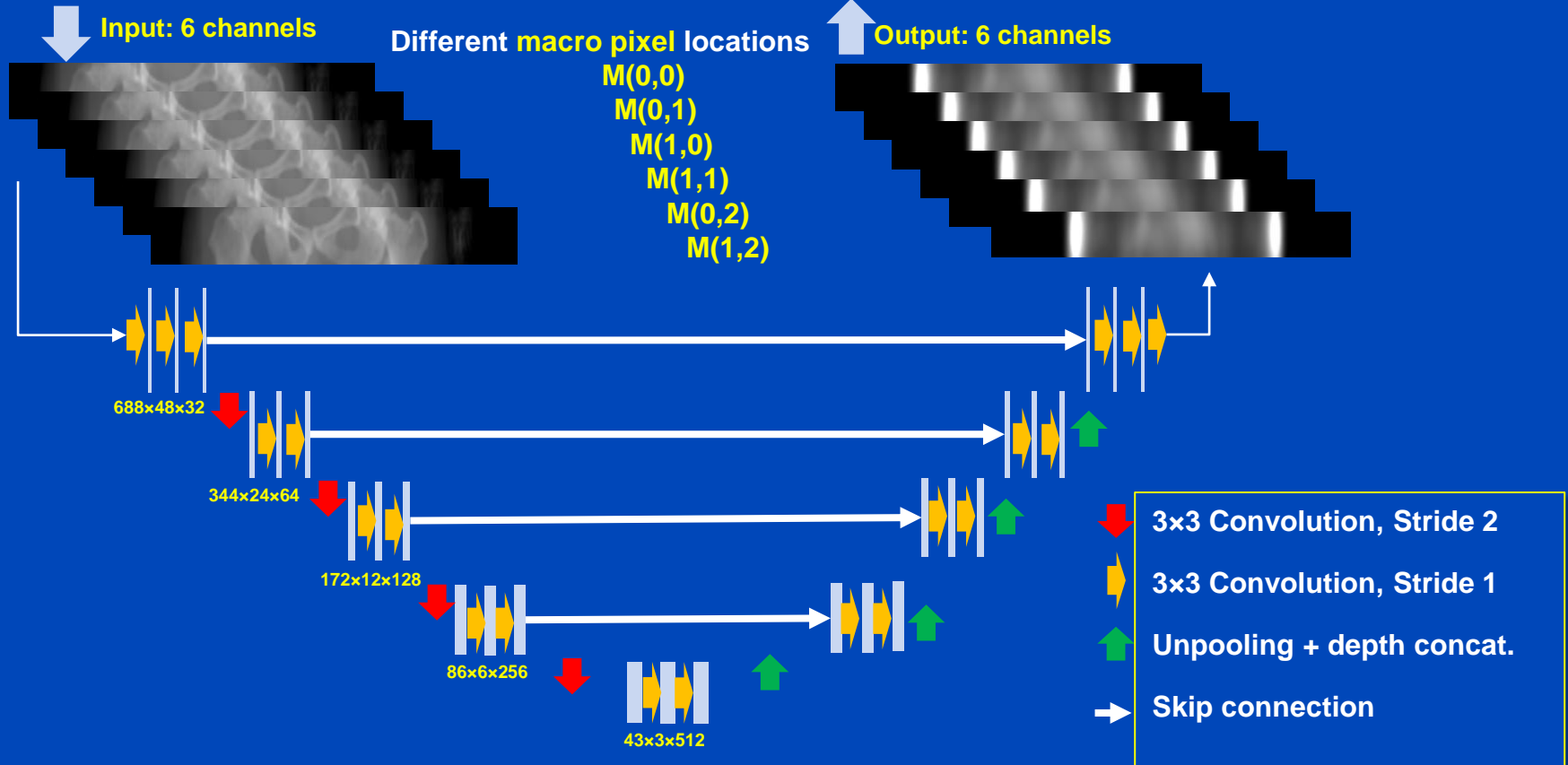
1376x144

Input mapping

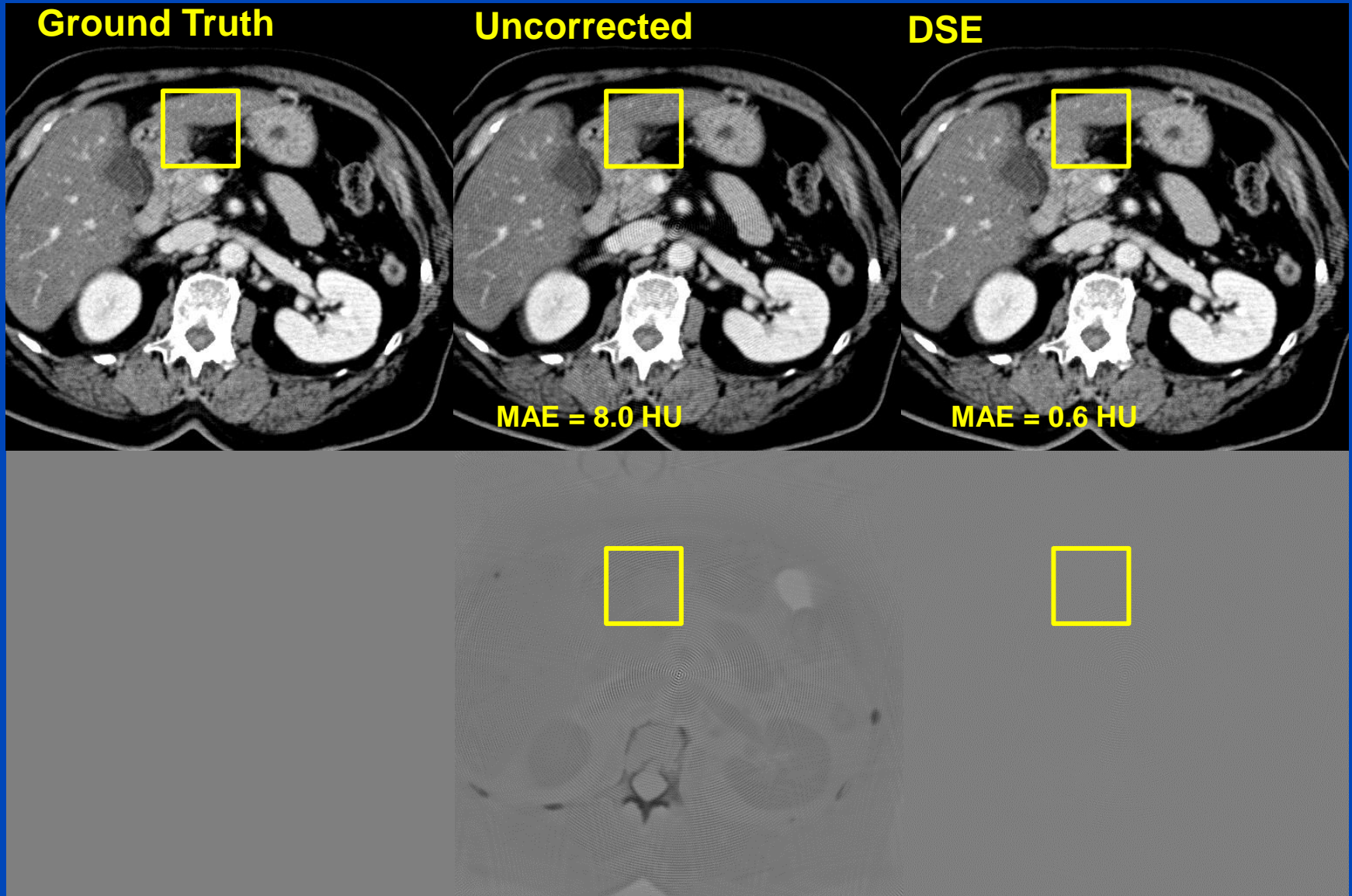
$$p = -\ln\left(\frac{I_{\text{primary}}}{I_0} + \frac{I_{\text{scatter}}}{I_0}\right)$$

Each channel corresponds to a different pixel position between the lamellae of the ASG

Merging 6 different channels to obtain total scatter correction term

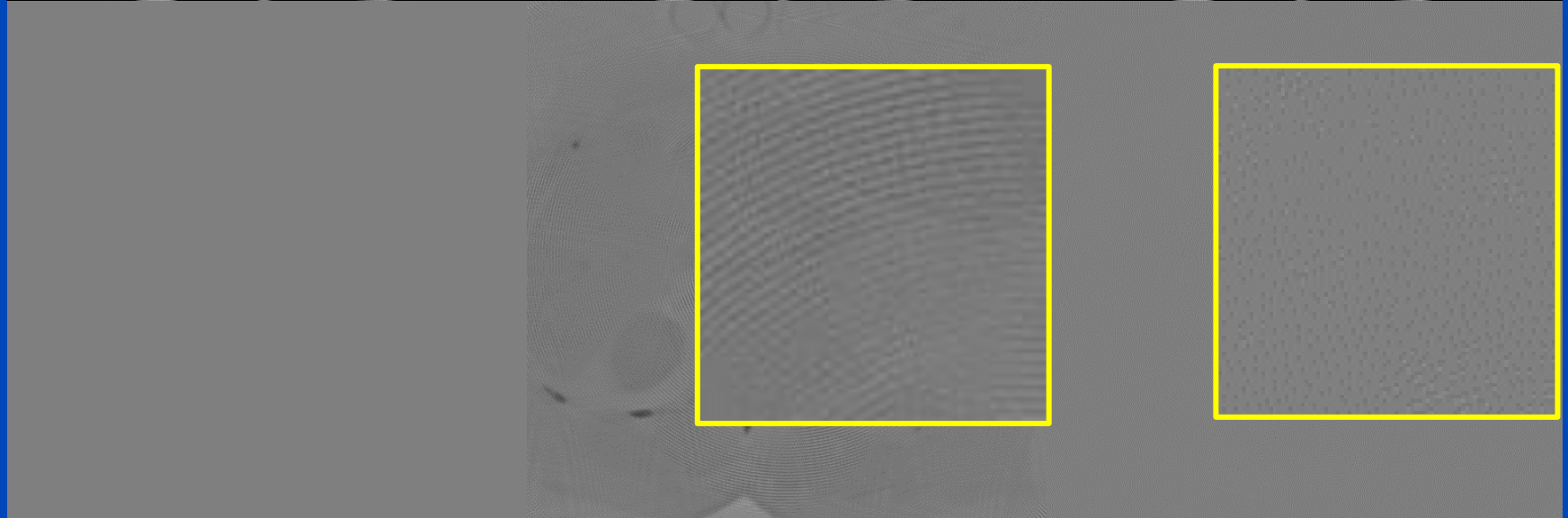
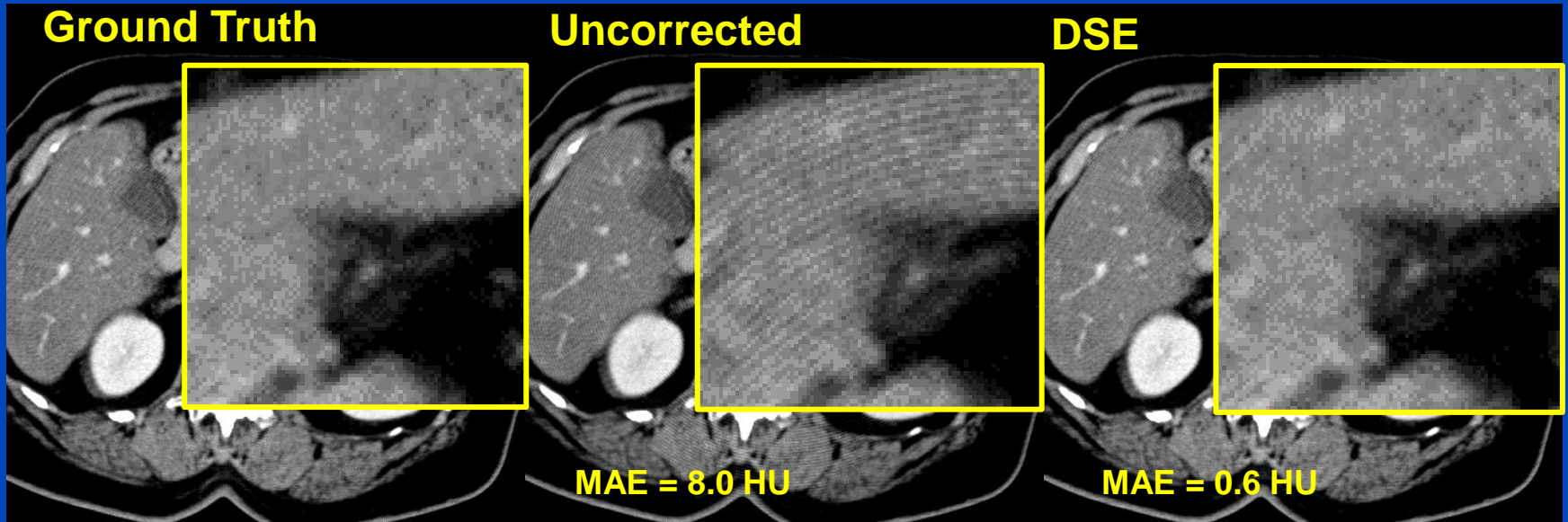


Results in Reconstructed Images



Simulated Reconstruction $C = 0$ HU, $W = 400$ HU,
Difference to GT $C = 0$ HU, $W = 50$ HU

Results in Reconstructed Images

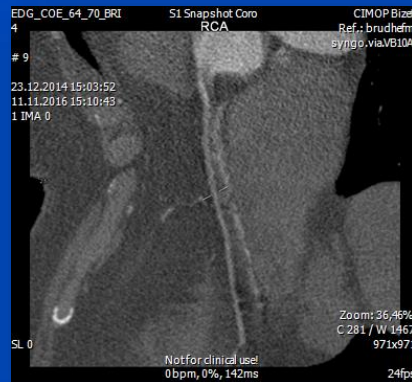


Simulated Reconstruction $C = 0$ HU, $W = 400$ HU,
Difference to GT $C = 0$ HU, $W = 50$ HU

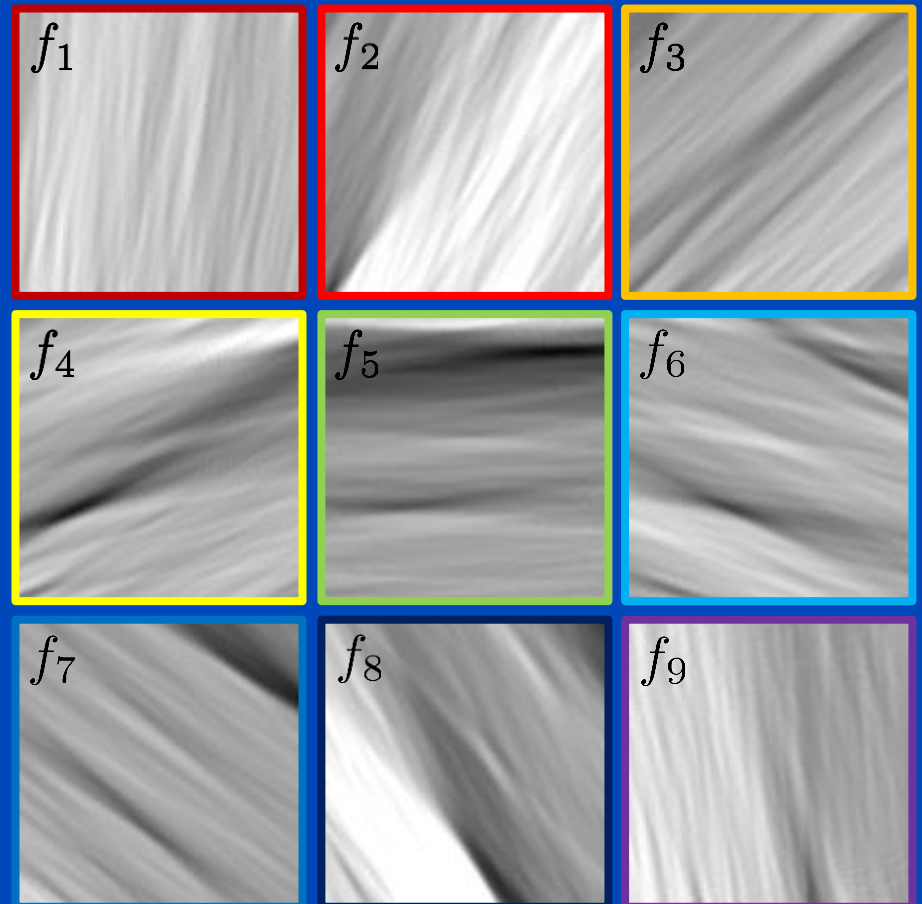
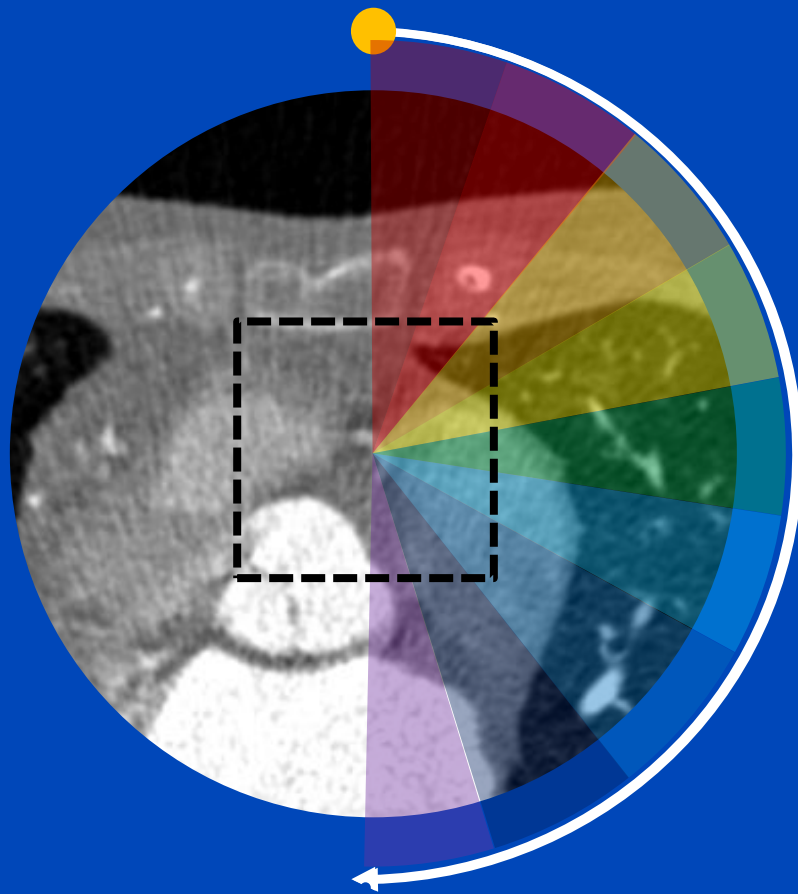
Conclusions on DSE

- DSE needs about 3 ms per CT projection (as of 2020).
- DSE is a fast and accurate alternative to MC simulations.
- DSE outperforms other approaches.
- 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. It can be trained with any other scatter estimate, including those based on measurements.

Deep Cardiac Motion Compensation

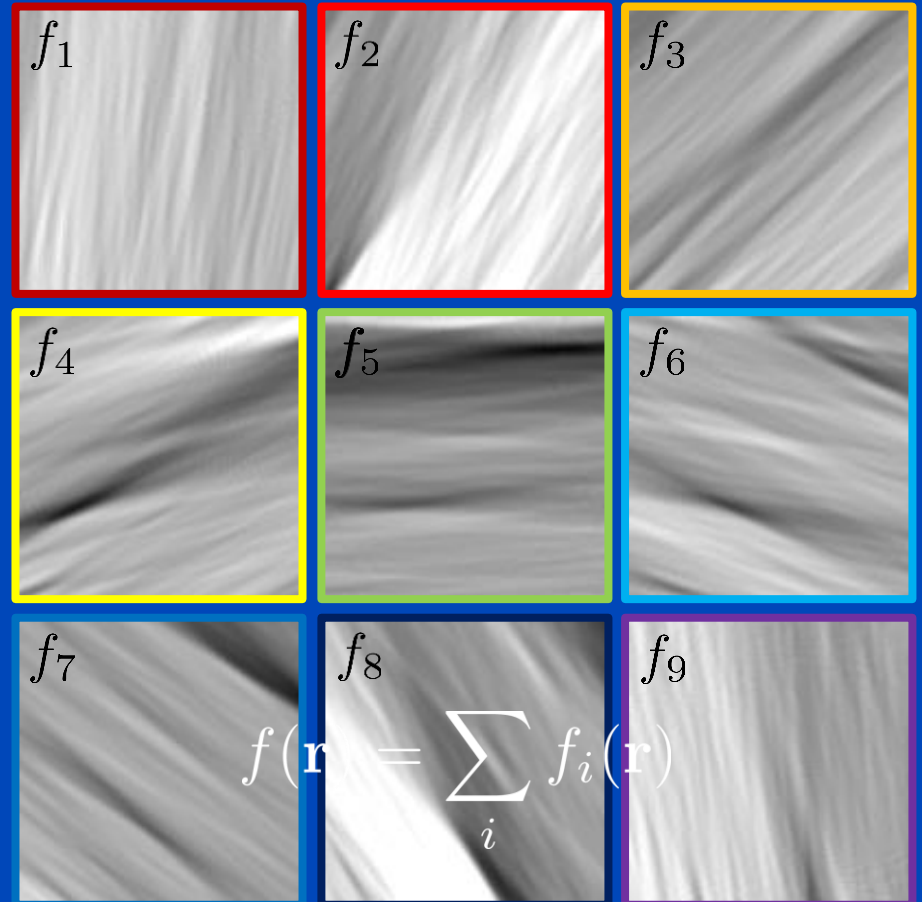
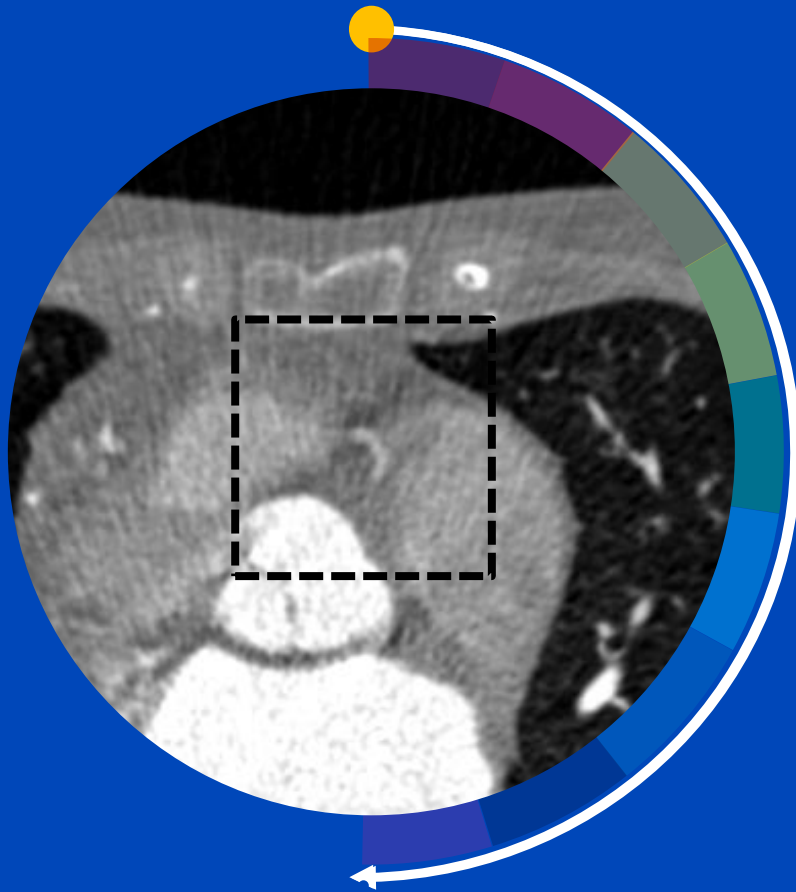


Partial Angle-Based Motion Compensation (PAMoCo)

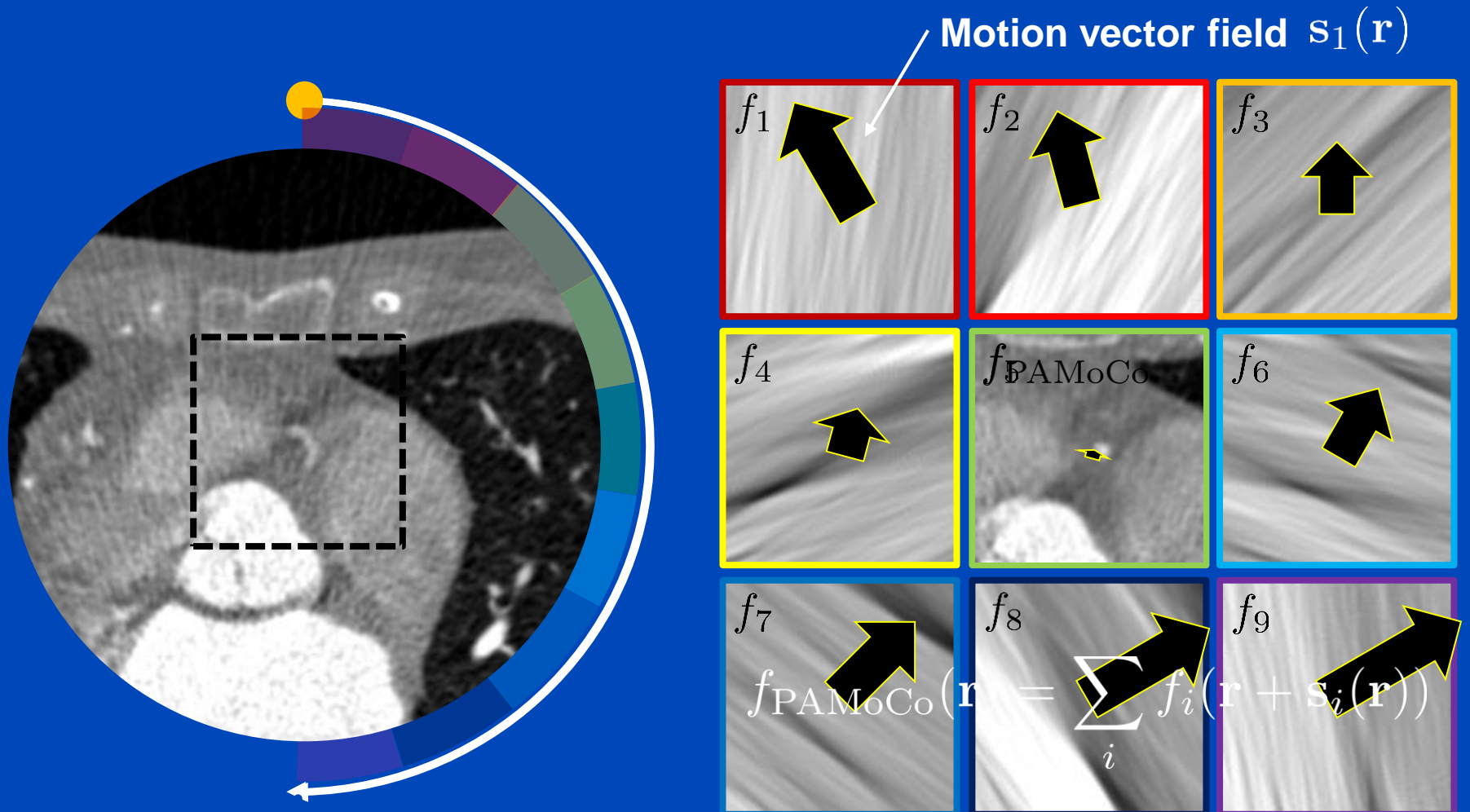


Animated rotation time = 100 × real rotation time

Partial Angle-Based Motion Compensation (PAMoCo)



Partial Angle-Based Motion Compensation (PAMoCo)

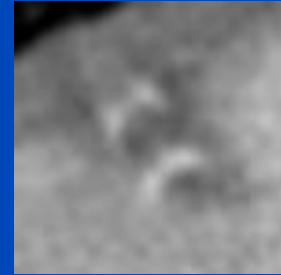


Apply motion vector fields (MVFs) to partial angle reconstructions

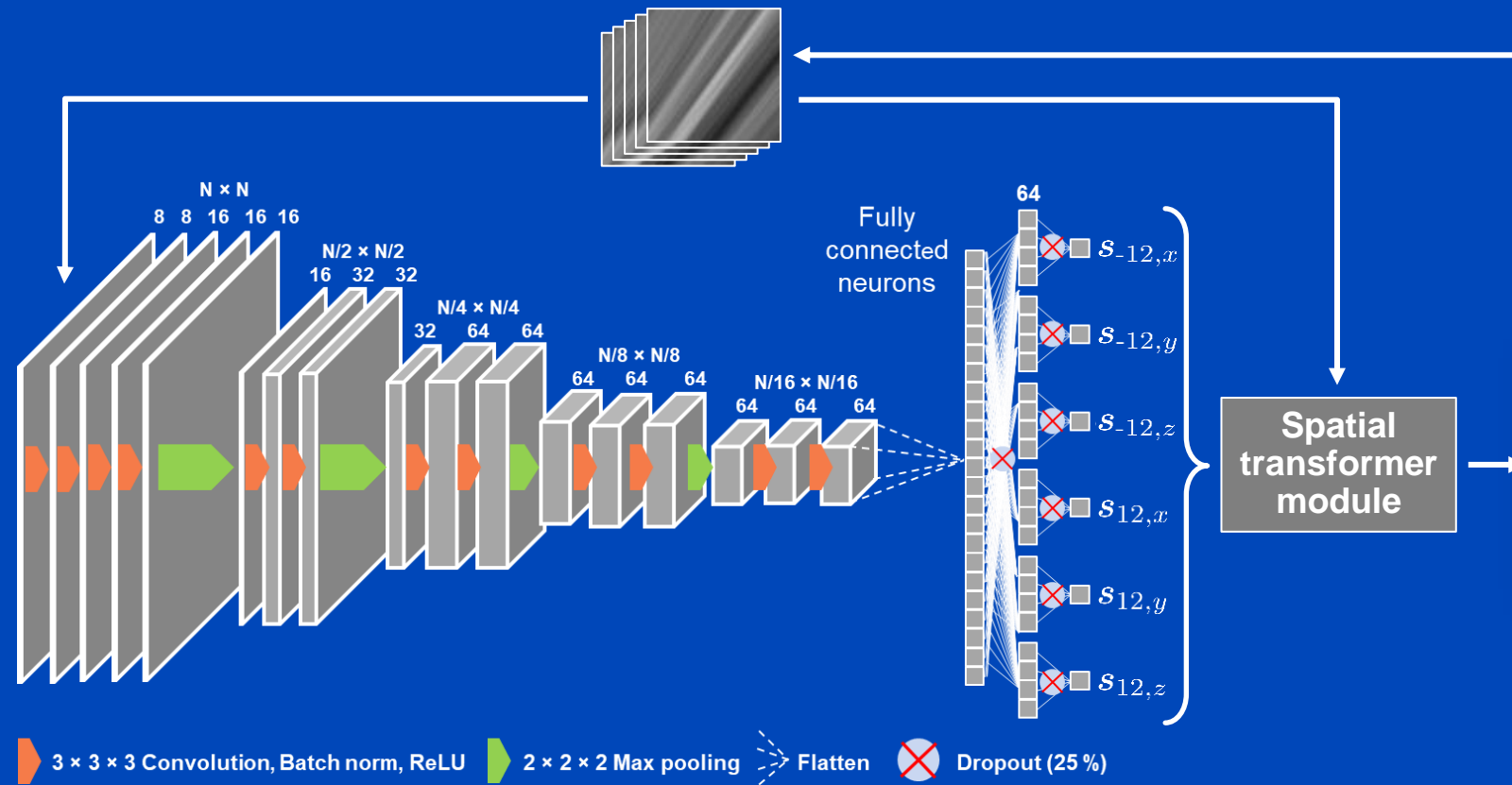
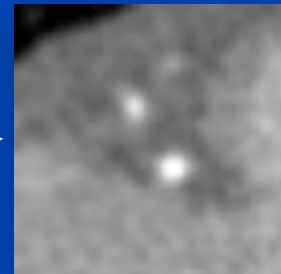
Deep PAMoCo

Network architecture

Initial volume
(with motion artifacts)

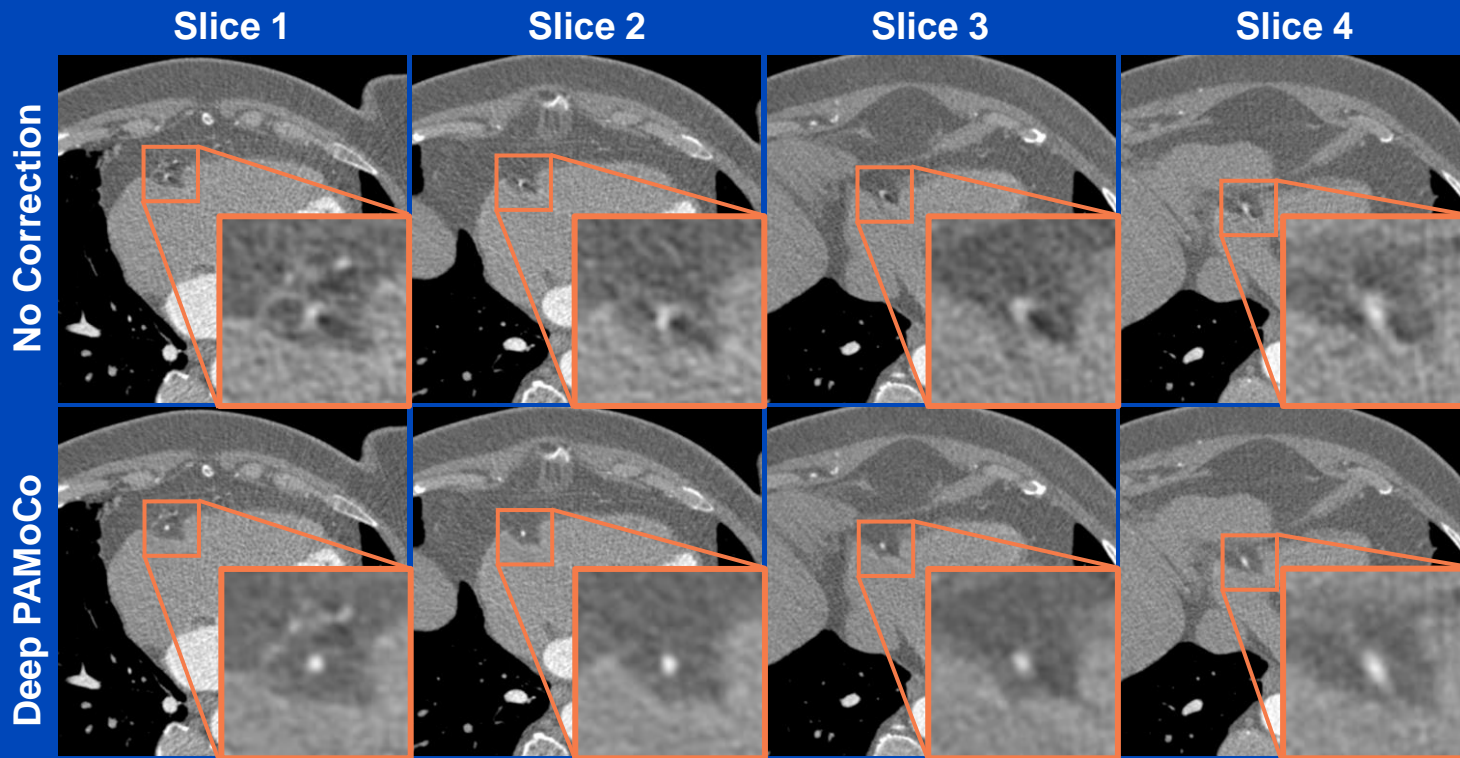


Final volume
(no motion artifacts)



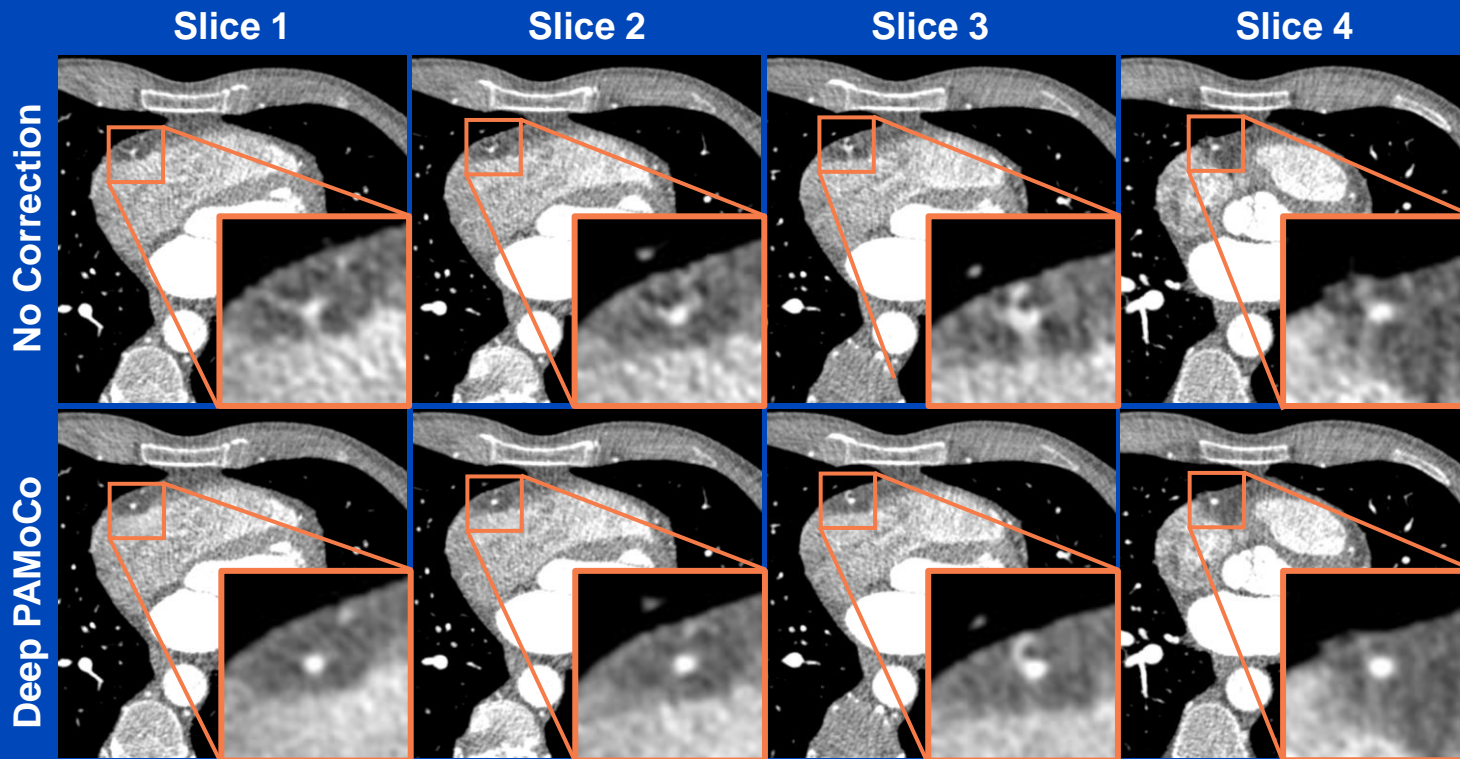
FCN-Layer output: two control points for a cubic spline: for $k = -K$, and for $k = +K$. The third control point at $k = 0$ is $(0, 0, 0)$, i.e. no deformation for the central PAR.

Results



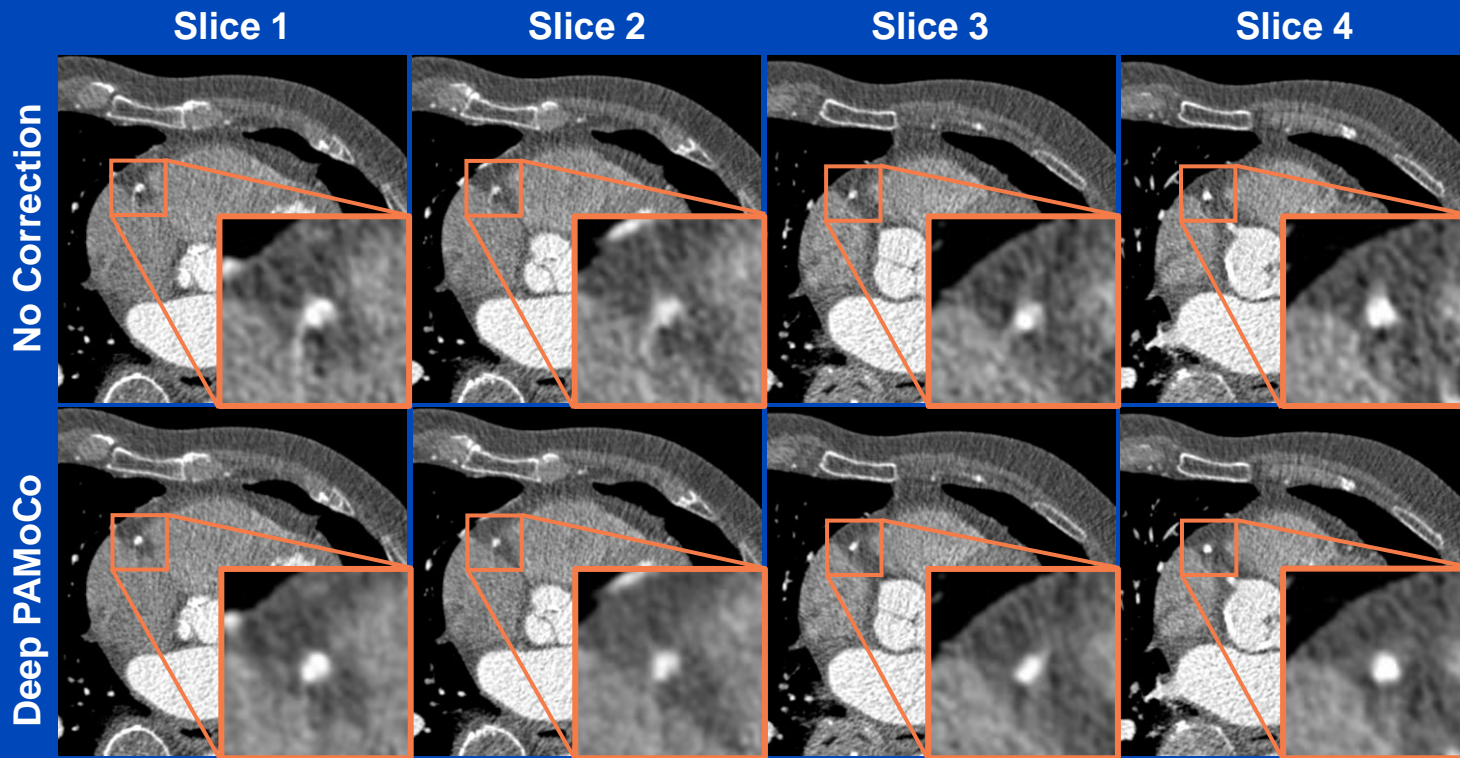
C = 1000 HU
W = 1000 HU

Results



C = 1000 HU
W = 1000 HU

Results



C = 1100 HU
W = 1000 HU

Handle Irregular Motion?

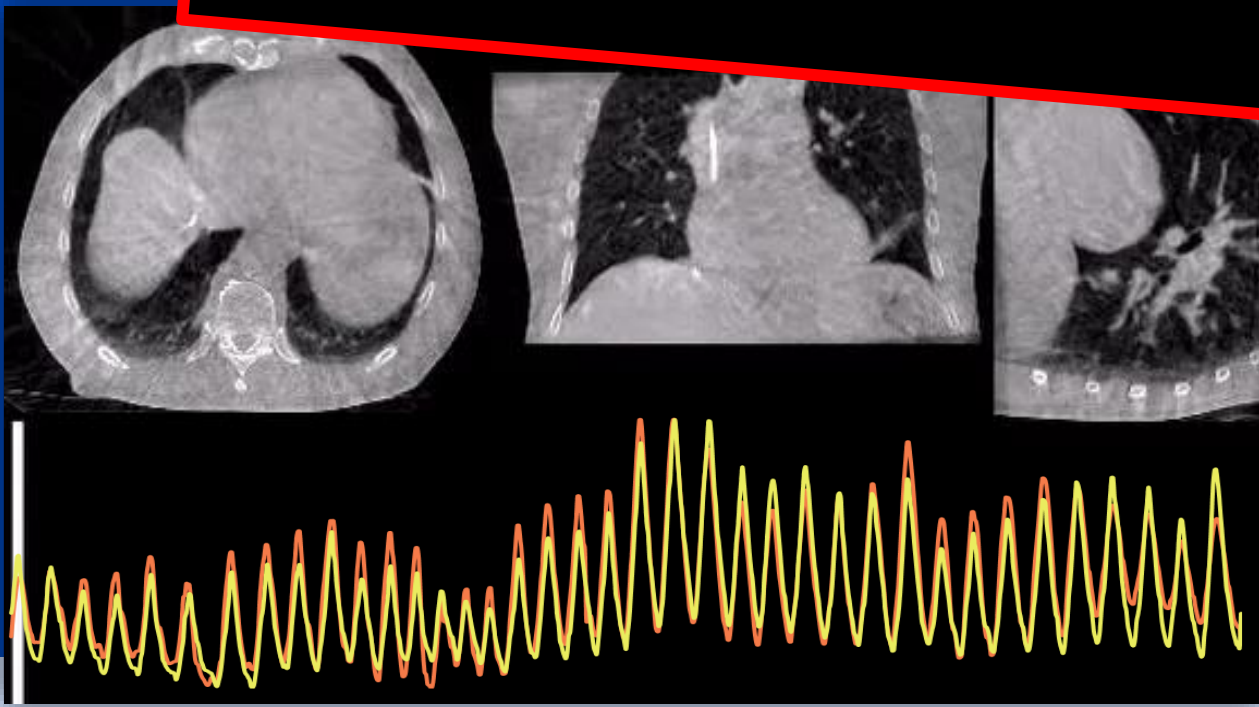
See our talk tomorrow

Deep 4D CT and 4D CBCT MoCo of Periodic and Non-Periodic Patient Motion with Single-View Temporal Resolution

Session: AI applications in CT

Time: Wednesday, 3:00 PM (3rd talk)

Room: N227B



- Varian TrueBeam system
- 60 s CBCT acquisition
- 10 fps detector frame rate
- irregular breathing
- aperiodic motion
- no gating signal
- reconstruction of every time point (600 volumes)
- 100 ms temporal resolution

Are the Methods Reliable?

- **Studies about explainability of AI in CT image formation are more than sparse.**
- **My thoughts:**
 - **Cosmetic corrections: Unclear if noise reduction, metal artifact reduction etc. is removing/adding lesions. The whole process is a black box.**
 - **Physical corrections: A clear physical meaning and rawdata fidelity appear more reliable. Examples:**
 - » **MAR or detruncation networks where the NN output is used only to forward project and inpaint/extrapolate the rawdata**
 - » **Scatter correction that estimates a smooth physically realistic (trained with MC) scatter signal in intensity domain**
 - » **Use motion compensation networks that estimate motion vectors rather than motion correction networks that manipulate voxel values**

Thank You!



The 8th International Conference on Image Formation in X-Ray Computed Tomography

August 5 – August 9, 2024, Bamberg, Germany
www.ct-meeting.org



Conference Chair

Marc Kachelrieß, German Cancer Research Center (DKFZ), Heidelberg, Germany

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

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

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