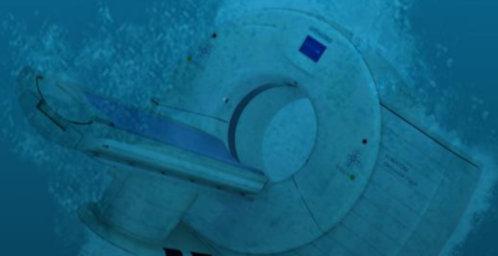
Deep Learning in CT Artifact Correction



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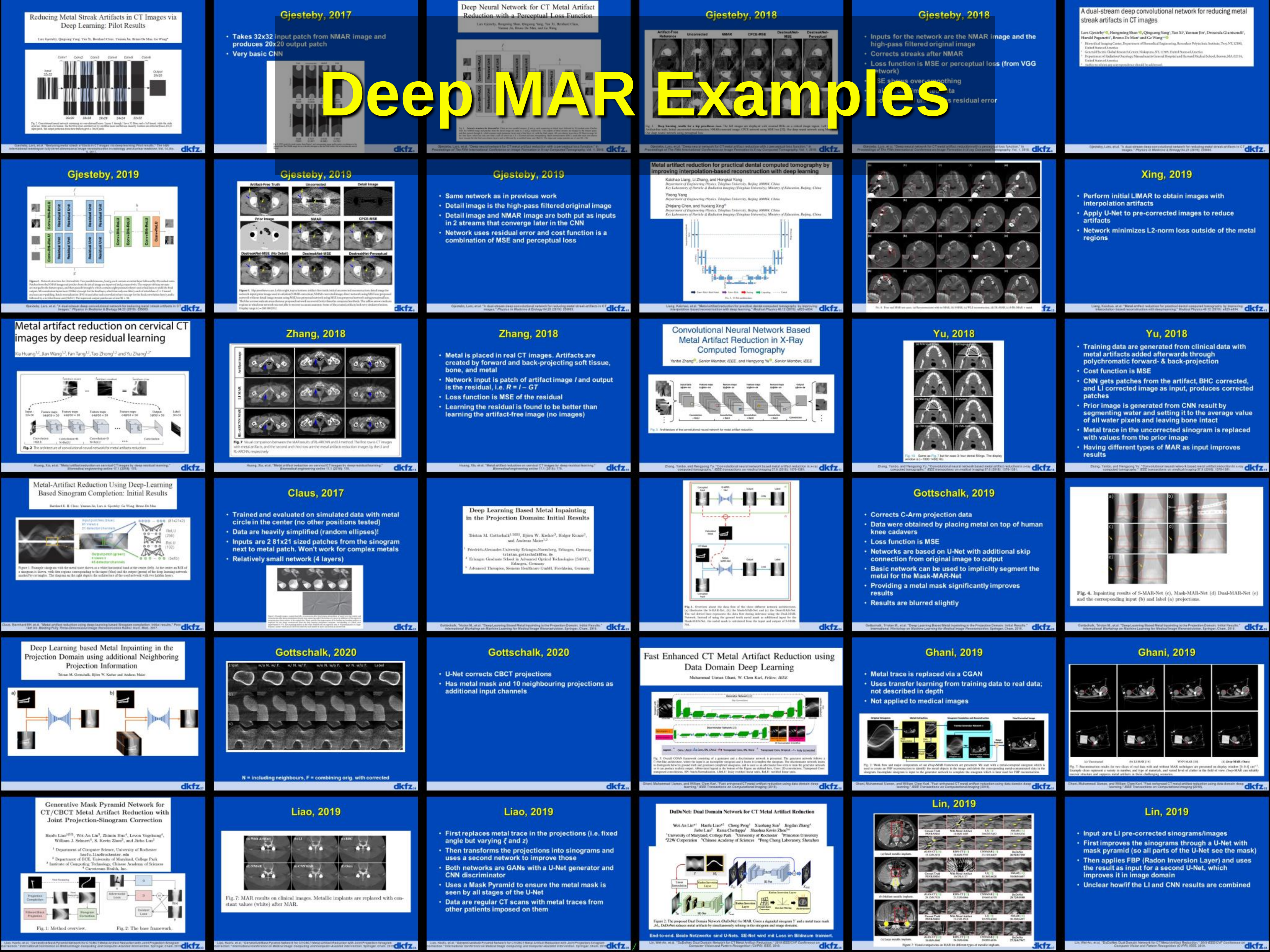
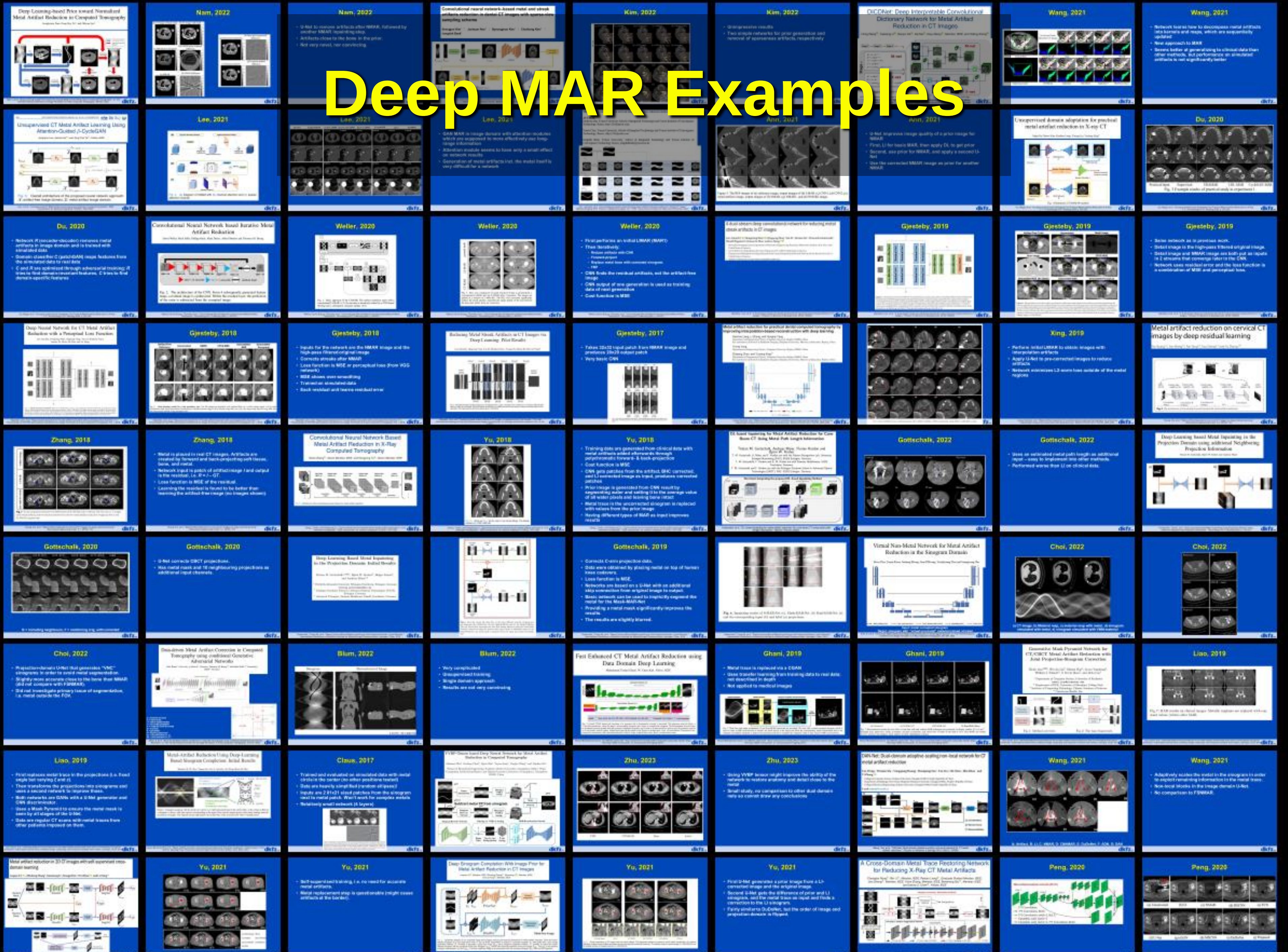
Content

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

Deep MAR Examples



Deep MAR Examples



DuDoNet: Dual Domain Network for CT Metal Artifact Reduction

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Jiebo Luo[2] Rama Chellappa[1] Shaohua Kevin Zhou[5,6]
[1]University of Maryland, College Park [2]University of Rochester [3]Princeton University
[4]Z2W Corporation [5]Chinese Academy of Sciences [6]Peng Cheng Laboratory, Shenzhen

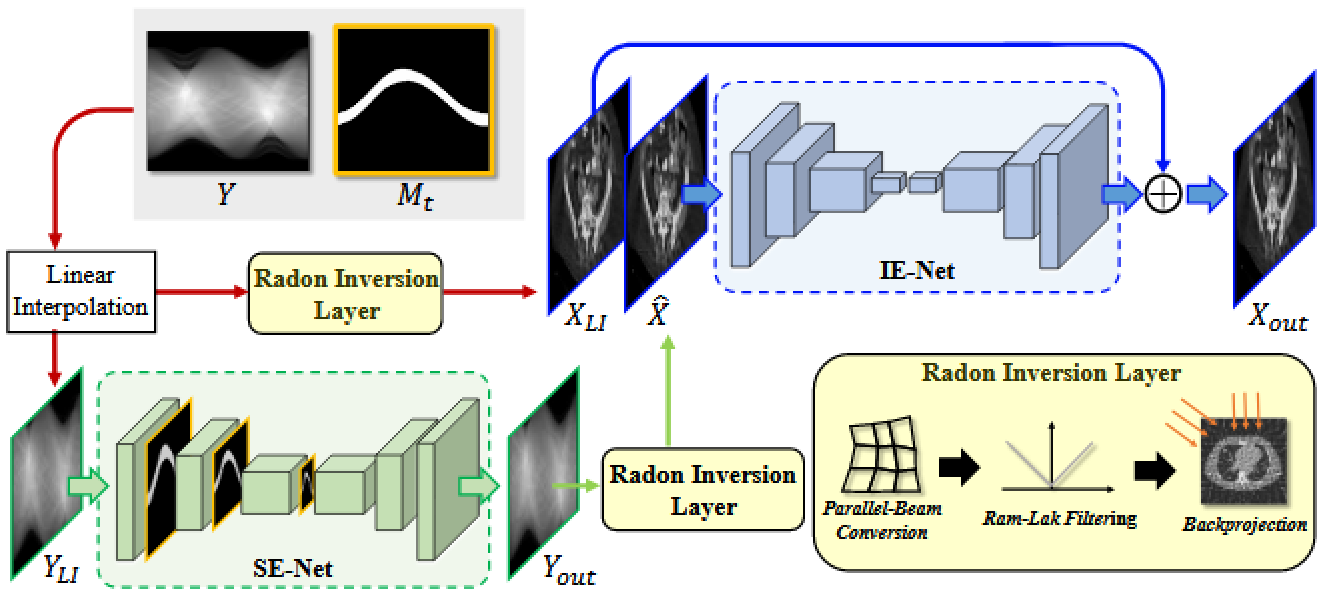


Figure 2: The proposed Dual Domain Network (DuDoNet) for MAR. Given a degraded sinogram Y and a metal trace mask $\mathcal{M}_t$, DuDoNet reduces metal artifacts by simultaneously refining in the sinogram and image domains.

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

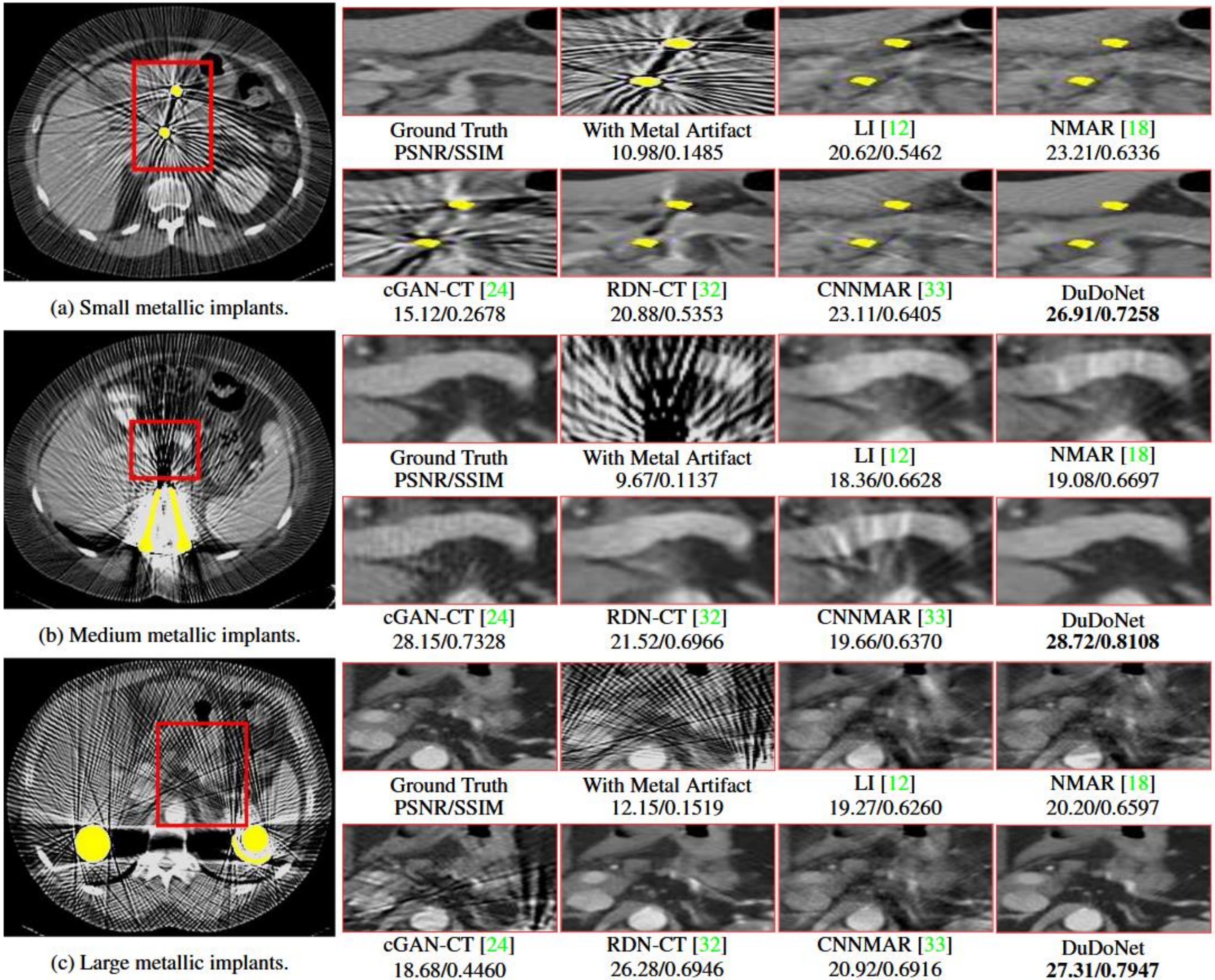
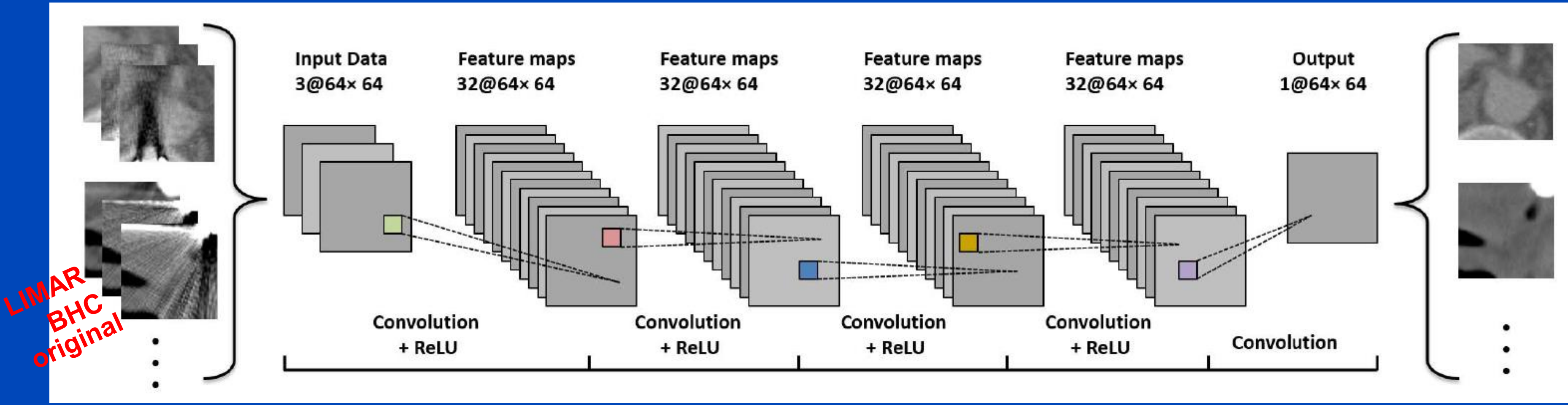


Figure 7: Visual comparisons on MAR for different types of metallic implants.

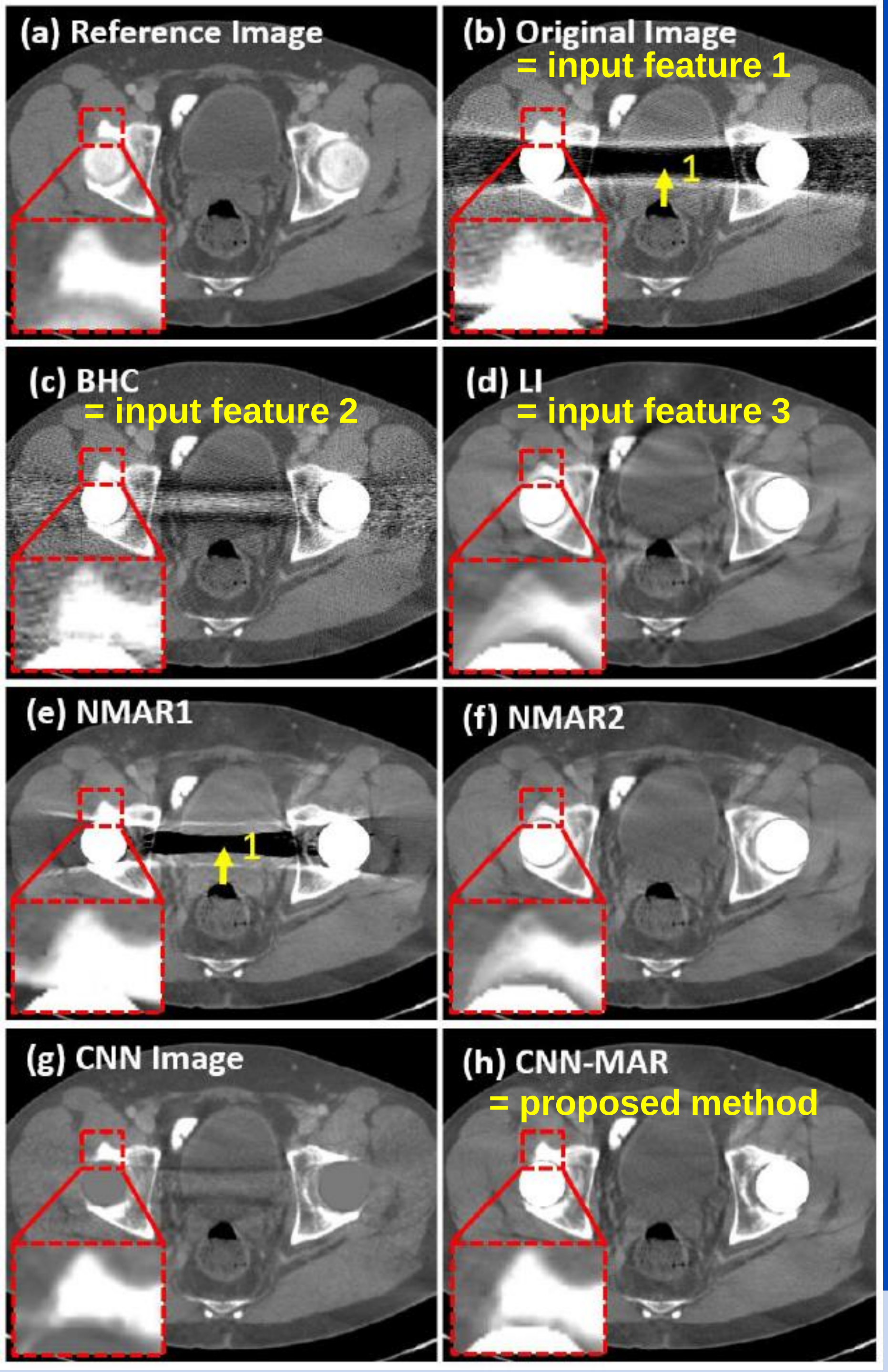
MAR Example

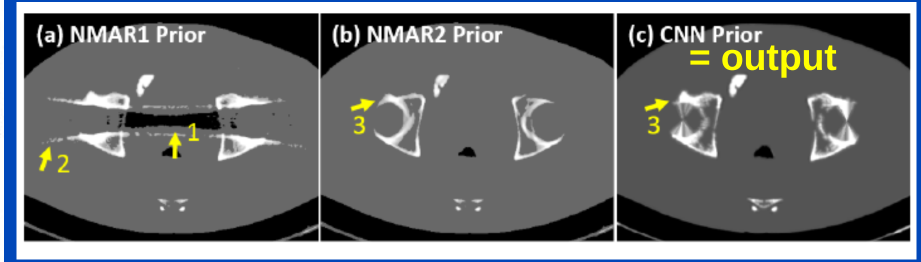
- Deep CNN-driven patch-based combination of the advantages of several MAR methods trained on simulated artifacts



- 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

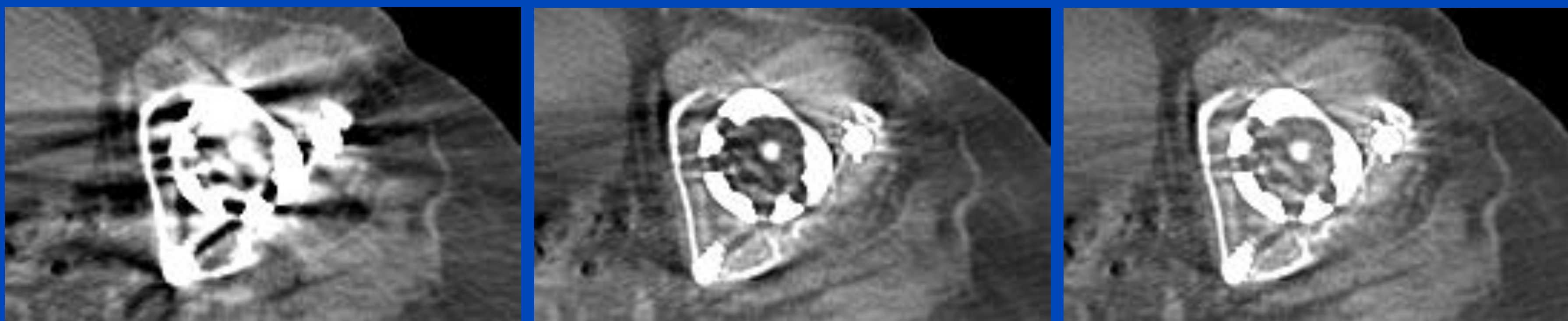
Yanbo Zhang and Hengyong Yu. Convolutional Neural Network Based Metal Artifact Reduction in X-Ray Computed Tomography. TMI 37(6):1370-1381, June 2018.


(a) Reference Image
(b) Original Image
= input feature 1
1
(c) BHC
= input feature 2
(d) LI
= input feature 3
(e) NMAR1
1
(f) NMAR2
(g) CNN Image
(h) CNN-MAR
= proposed method

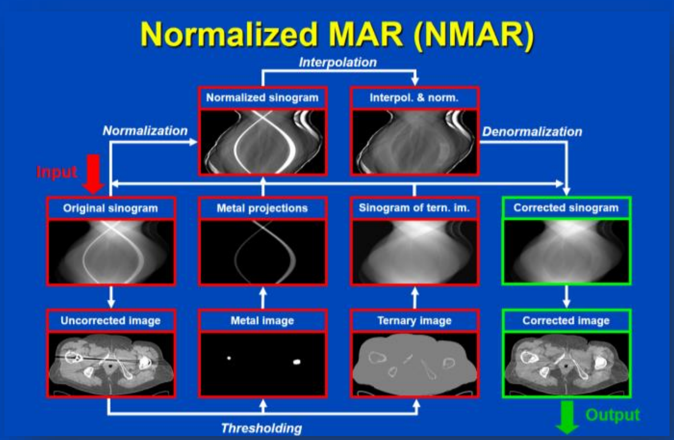

(a) NMAR1 Prior
1
2
(b) NMAR2 Prior
3
(c) CNN Prior
= output
3

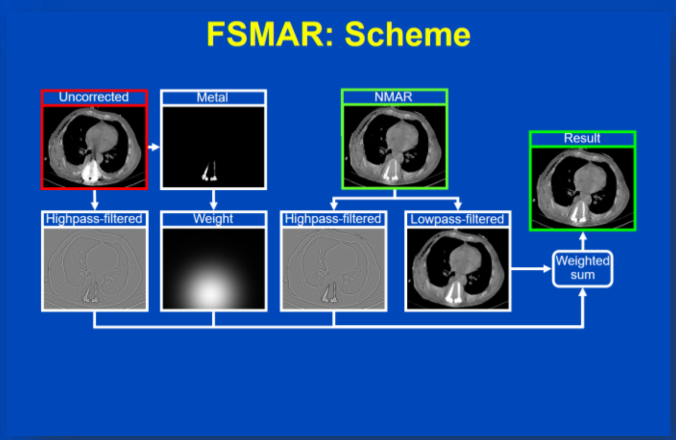
MAR without Machine Learning is a Good Alternative: Frequency Split Normalized MAR[1,2]

Uncorrected FSLIMAR FSNMAR



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



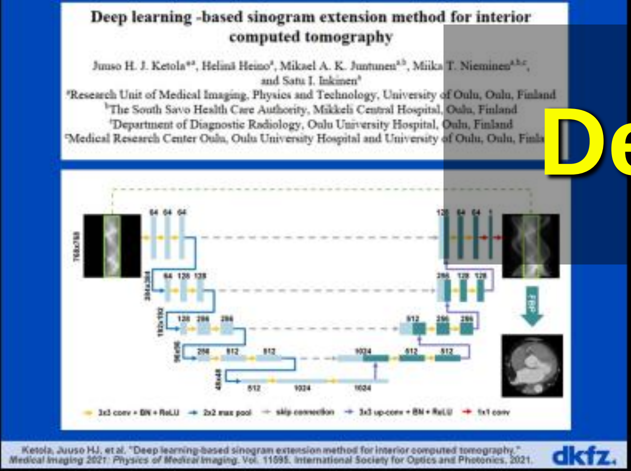


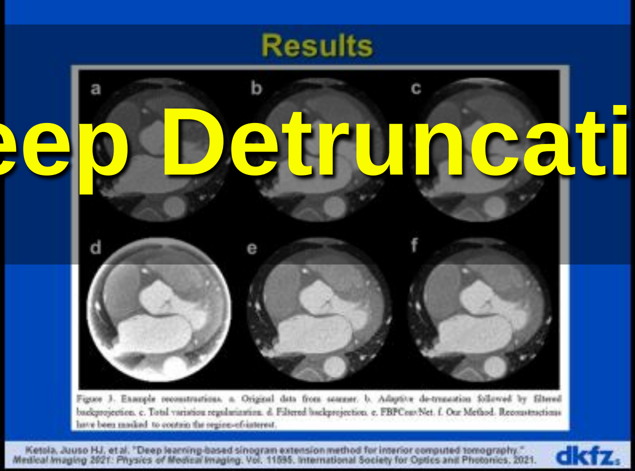
[1]E. Meyer, M. Kachelrieß. Normalized metal artifact reduction (NMAR) in computed tomography. Med. Phys. 37(10):5482-5493, Oct. 2010.
[2]E. Meyer, M. Kachelrieß. Frequency split metal artifact reduction (FSMAR) in CT. Med. Phys. 39(4):1904-1916, April 2012.

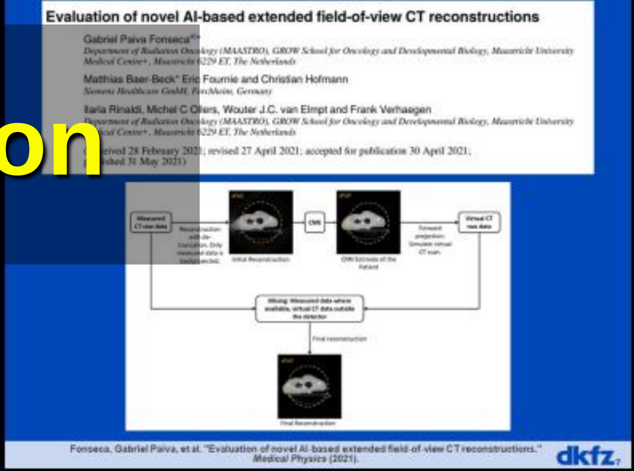
Summary on Deep MAR

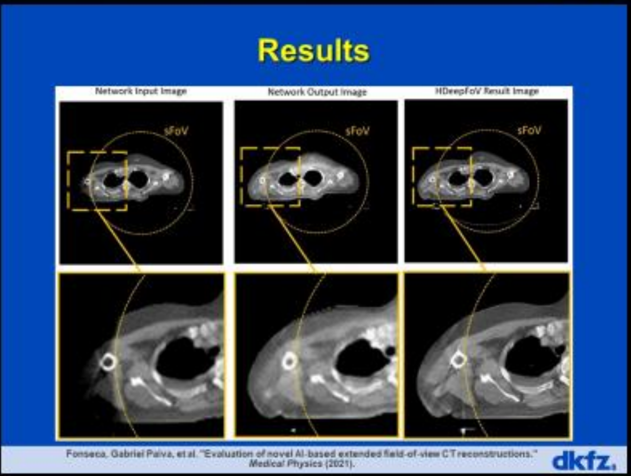
- **Most common uses for networks:**
  - Improve image quality in image domain after MAR
  - Use network for the sinogram inpainting
  - Produce a prior image, e.g. for NMAR (currently the best idea)
- **Additional observations:**
  - Training data are often produced by segmenting an artifact-free CT 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.

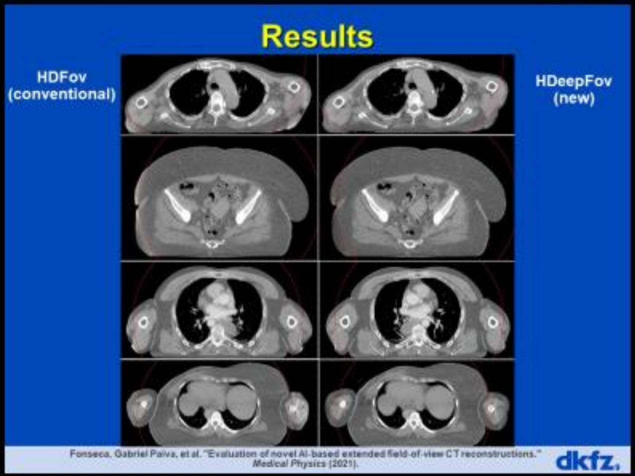
Deep Detruncation

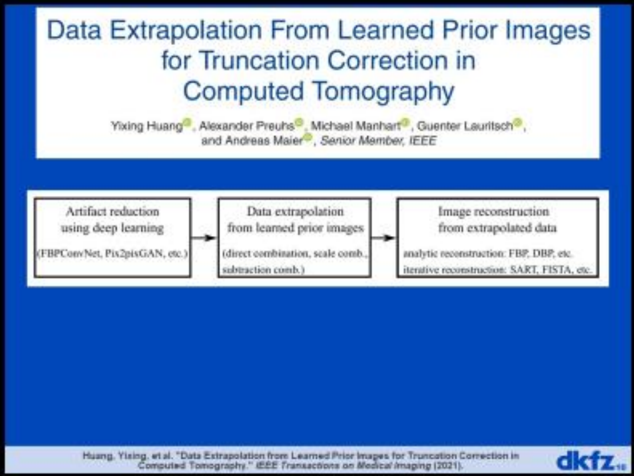


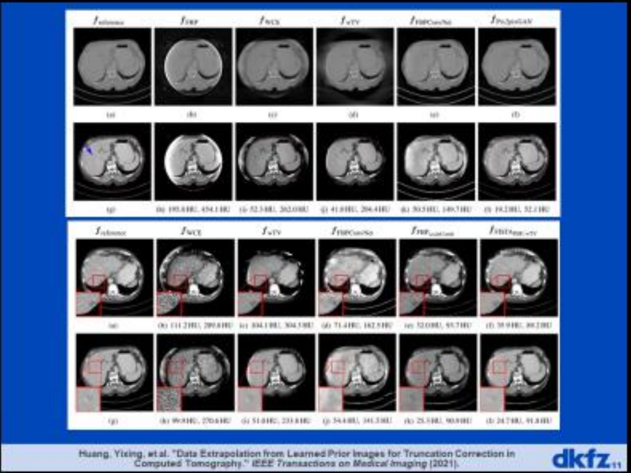


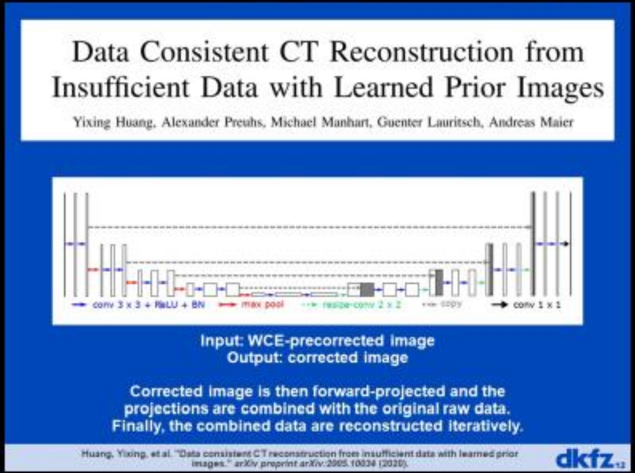


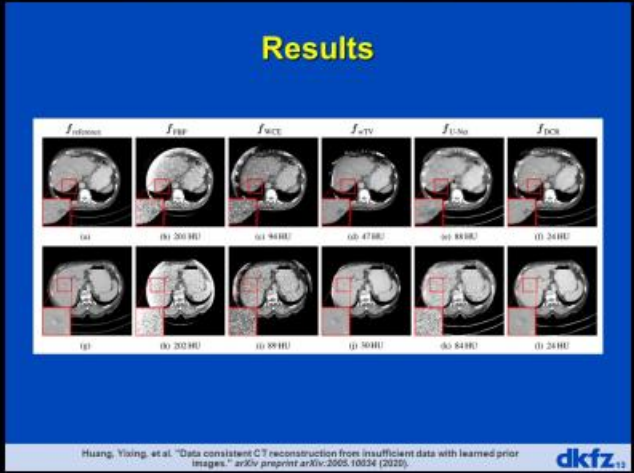


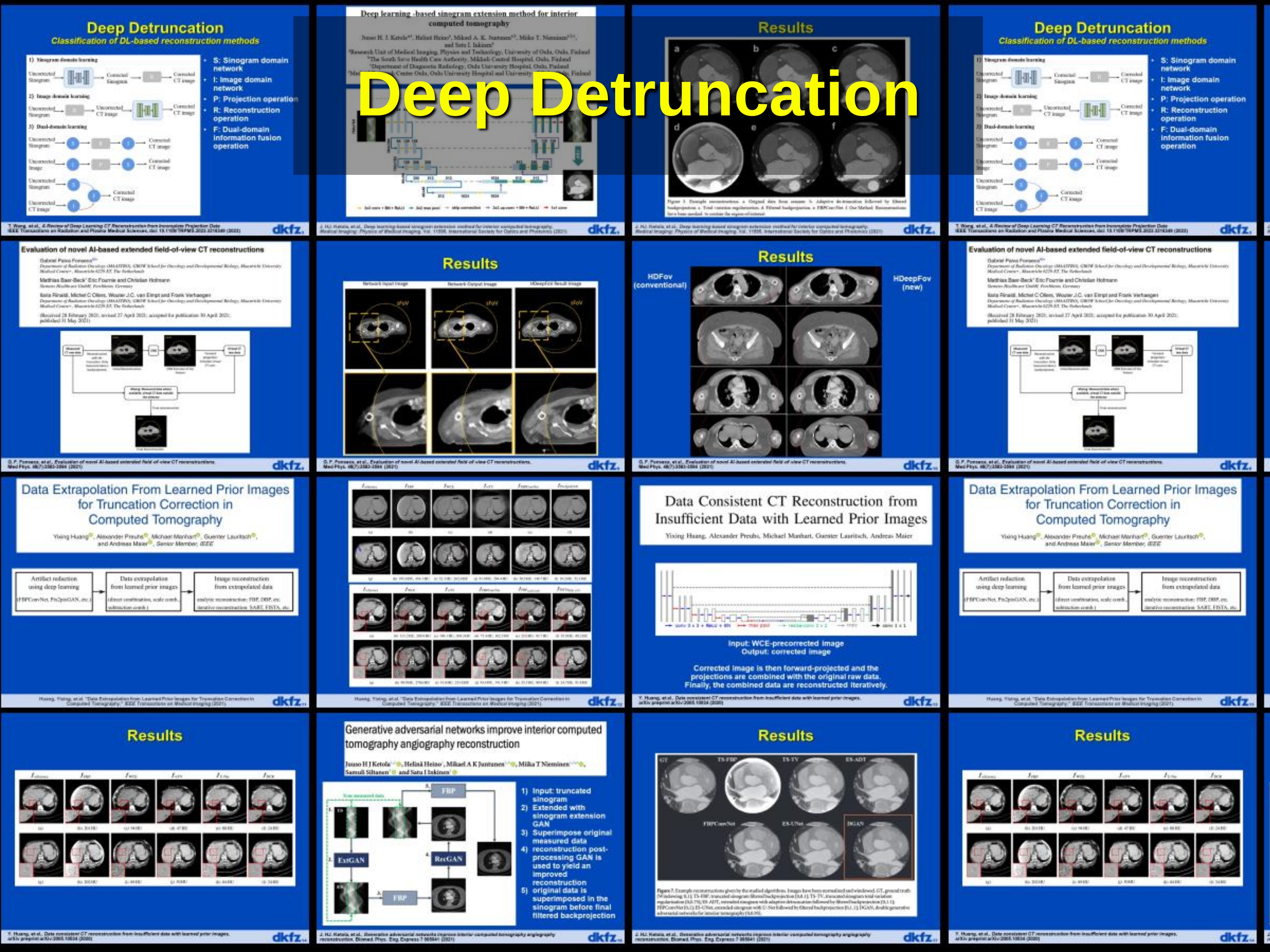






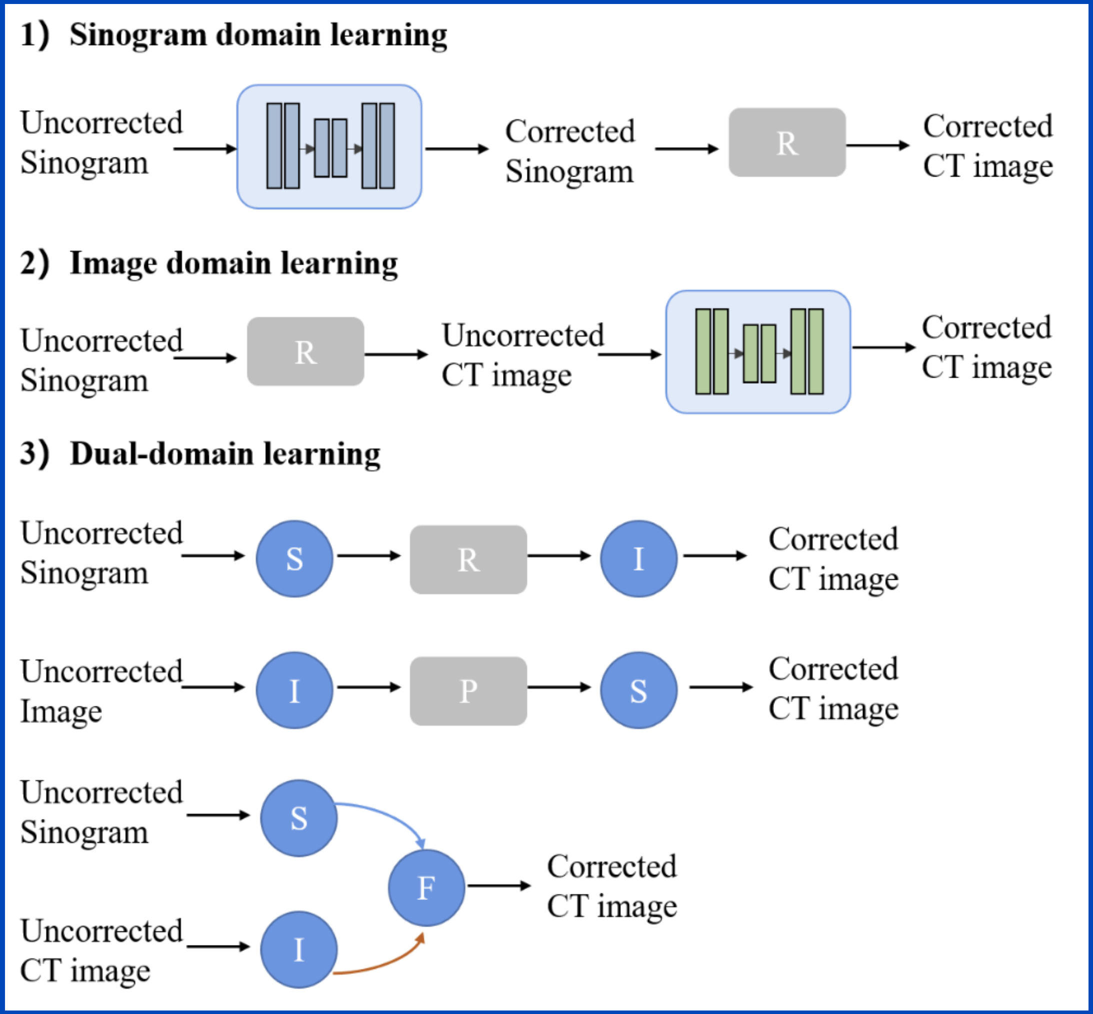





Deep Detruncation
Deep Detruncation
Classification of DL-based reconstruction methods
S: Sinogram domain network
I: Image domain network
P: Projection operation
R: Reconstruction operation
F: Dual-domain information fusion operation
Deep learning -based sinogram extension method for interior computed tomography
Results
Evaluation of novel AI-based extended field-of-view CT reconstructions
HDFov (conventional)
HDeepFov (new)
Data Extrapolation From Learned Prior Images for Truncation Correction in Computed Tomography
Artifact reduction using deep learning
Data extrapolation from learned prior images
Image reconstruction from extrapolated data
Data Consistent CT Reconstruction from Insufficient Data with Learned Prior Images
Input: WCE-precorrected image
Output: corrected image
Corrected image is then forward-projected and the projections are combined with the original raw data. Finally, the combined data are reconstructed iteratively.
Generative adversarial networks improve interior computed tomography angiography reconstruction
1) Input: truncated sinogram
2) Extended with sinogram extension GAN
3) Superimpose original measured data
4) reconstruction post-processing GAN is used to yield an improved reconstruction
5) original data is superimposed in the sinogram before final filtered backprojection
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**

T. Wang, et al., *A Review of Deep Learning CT Reconstruction from Incomplete Projection Data*
IEEE Transactions on Radiation and Plasma Medical Sciences, doi: 10.1109/TRPMS.2023.3316349 (2023)

Deep learning -based sinogram extension method for interior computed tomography

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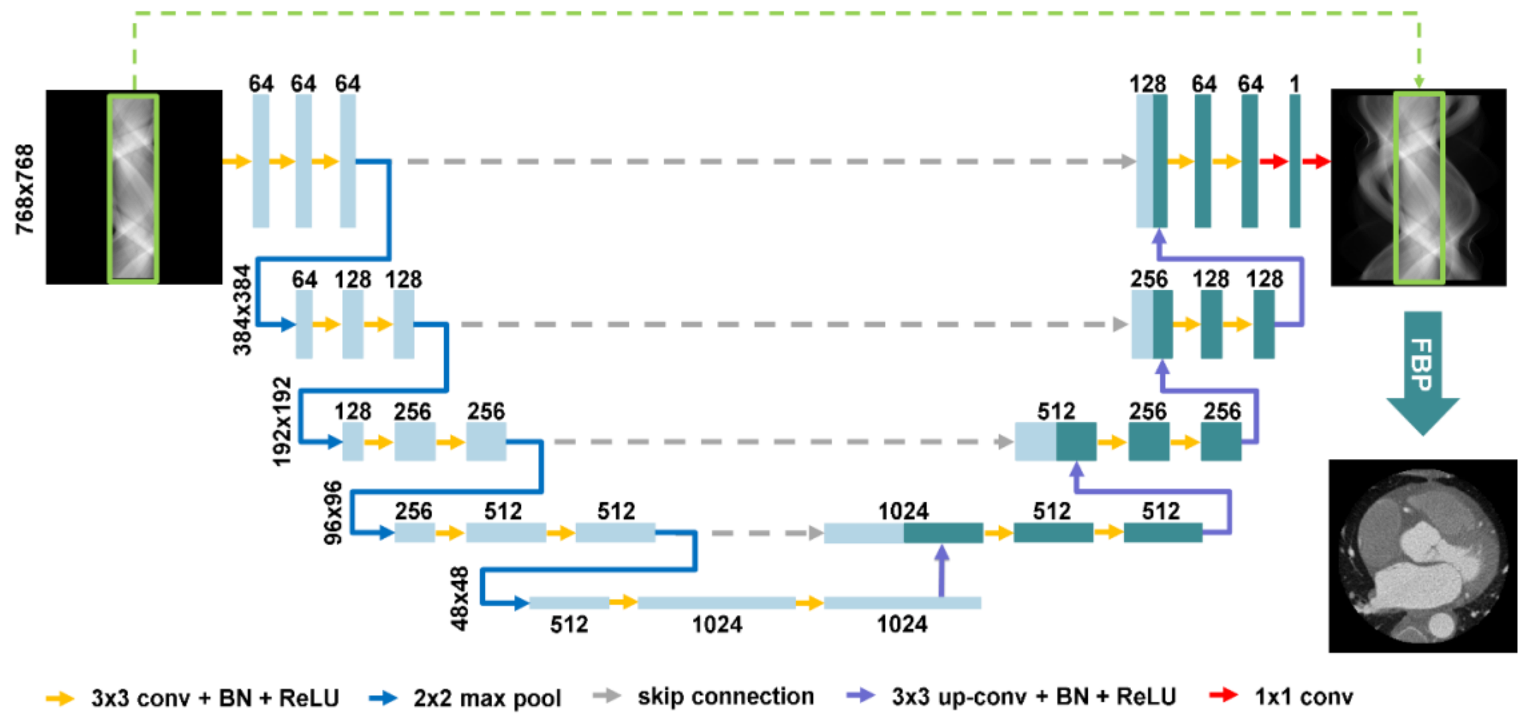
[c]Department of Diagnostic Radiology, Oulu University Hospital, Oulu, Finland
[c]Medical Research Center Oulu, Oulu University Hospital and University of Oulu, Oulu, Finland



Ketola, Juuso HJ, et al. "Deep learning-based sinogram extension method for interior computed tomography." *Medical Imaging 2021: Physics of Medical Imaging*. Vol. 11595. International Society for Optics and Photonics, 2021.

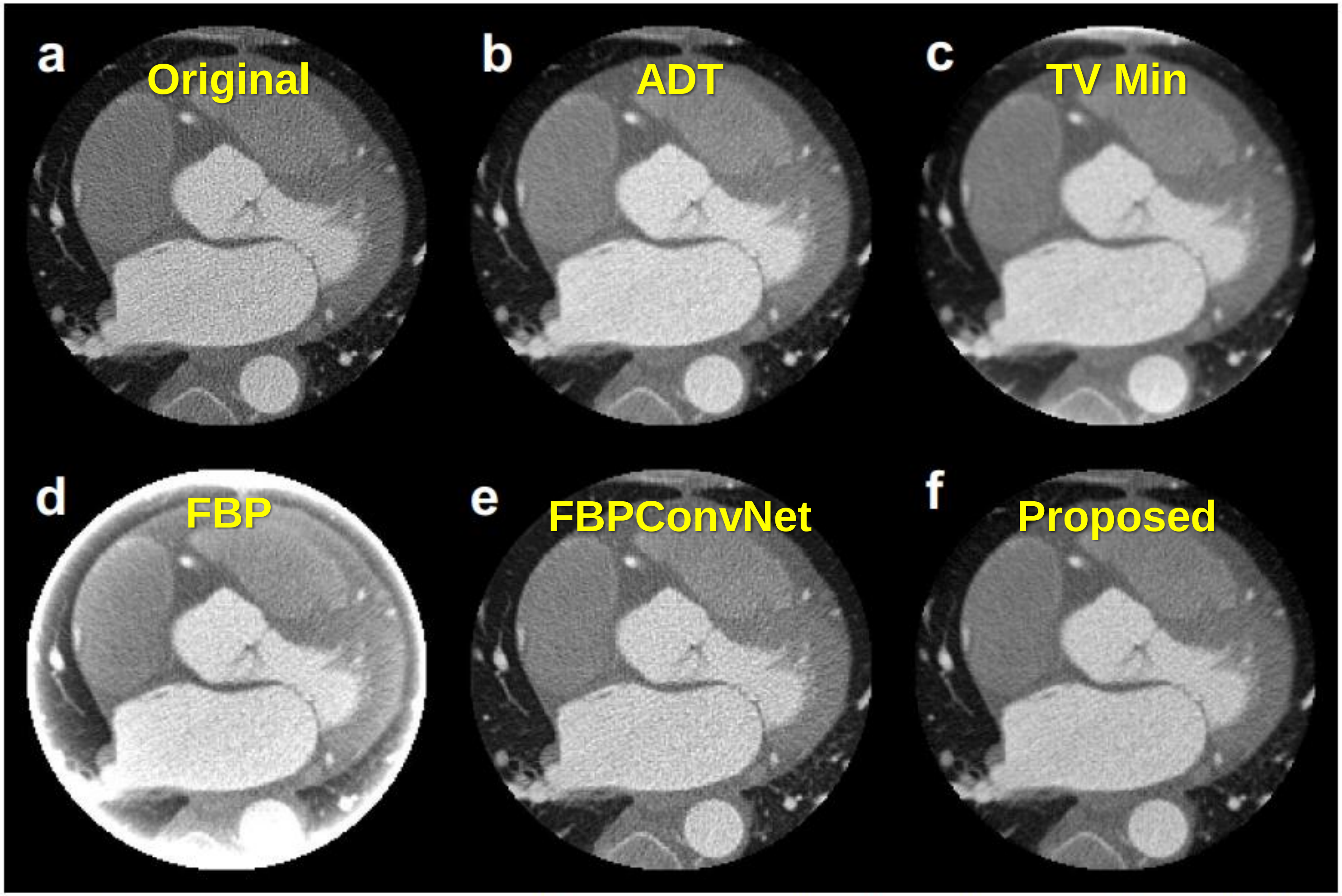


Figure 3. Example reconstructions. a. Original data from scanner. b. Adaptive de-truncation followed by filtered backprojection. c. Total variation regularization. d. Filtered backprojection. e. FBPConvNet. f. Our Method. Reconstructions have been masked to contain the region-of-interest.

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

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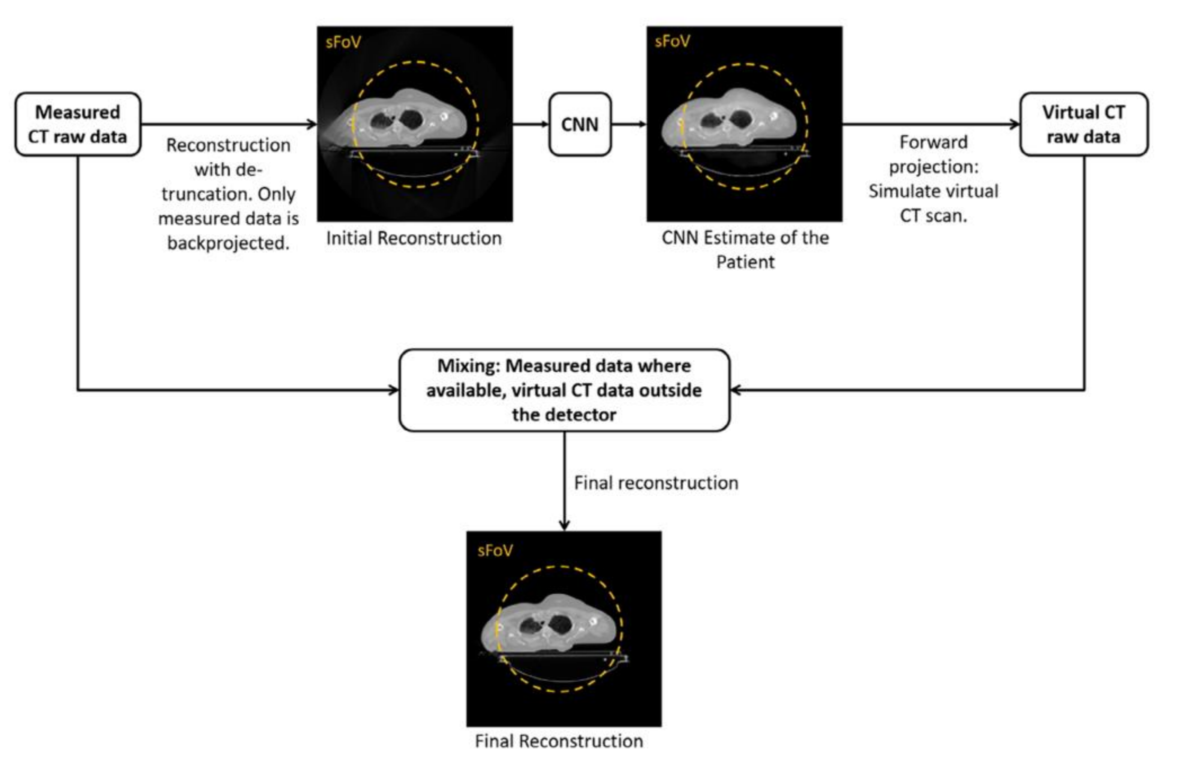
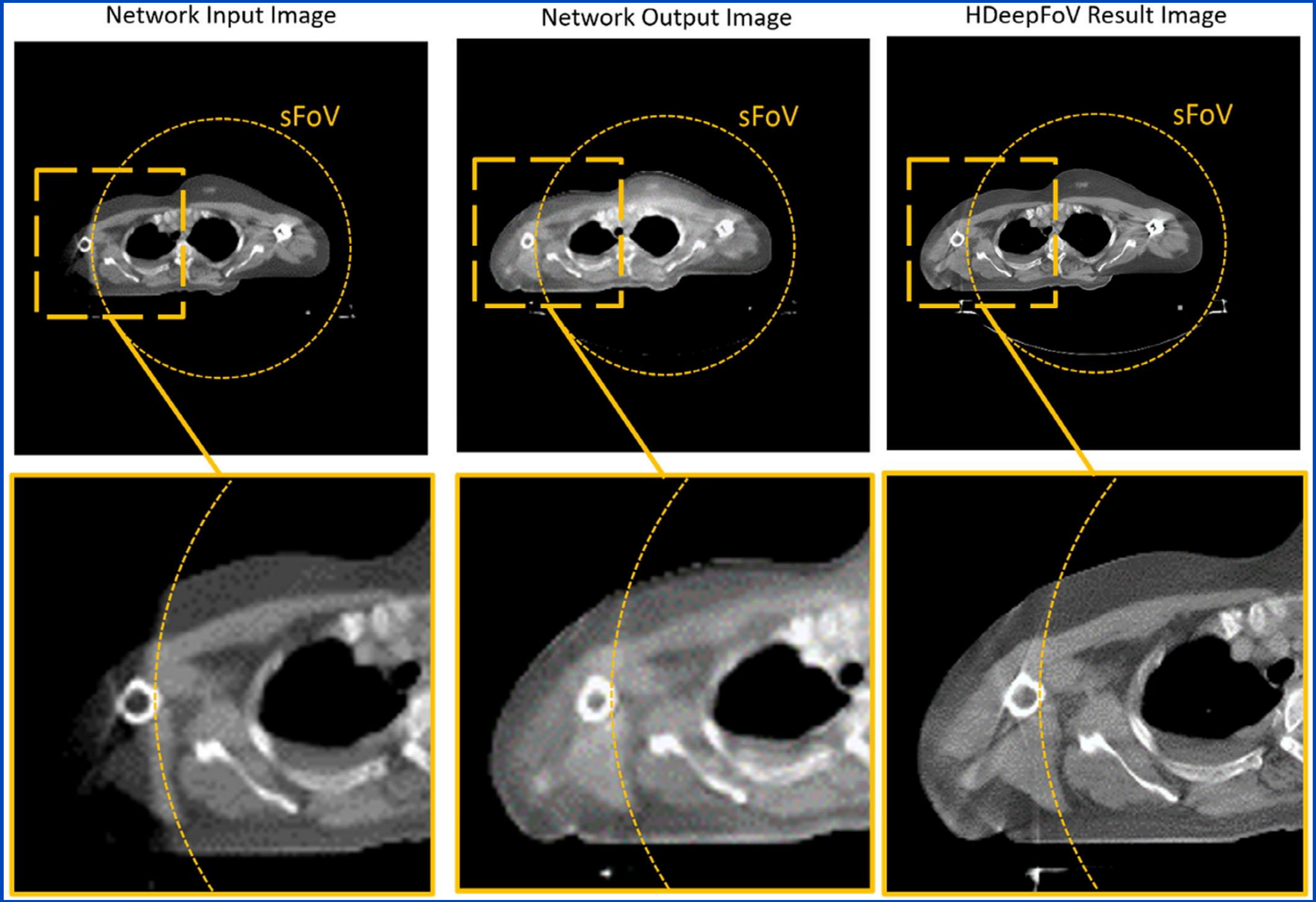




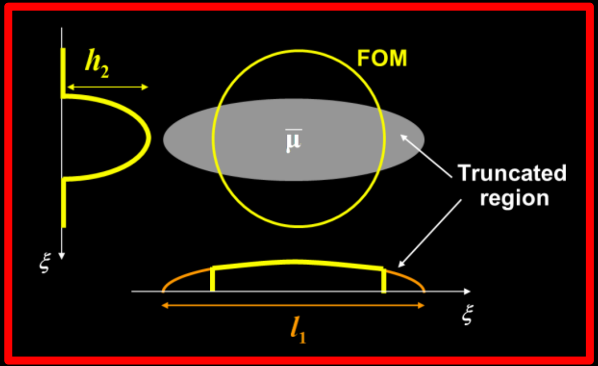
Fonseca, Gabriel Paiva, et al. "Evaluation of novel AI-based extended field-of-view CT reconstructions." *Medical Physics* (2021).

Original

Truncated

ADT corrected

ADT corrected (clipped)



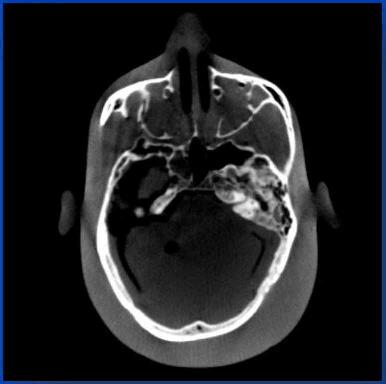
C = 0 HU, W = 1000 HU

K. Sourbelle, M. Kachelrieß, and W.A. Kalender, “Reconstruction from truncated projections in CT using adaptive detruncation,” Eur Radiol 15:1008–1014, 2005.

Summary on Deep Detruncation

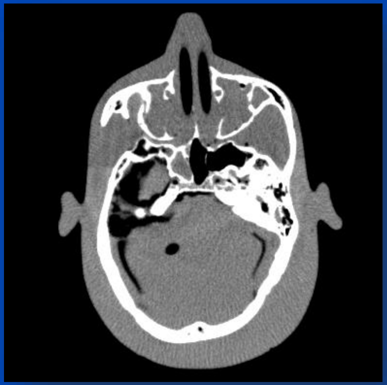
- No need for machine learning to restore the gray values within the FOM.
- Image domain cosmetic detruncation (in particular outside the FOM) can serve as an intermediate step to detruncate CT data.

Deep Scatter Estimation



???

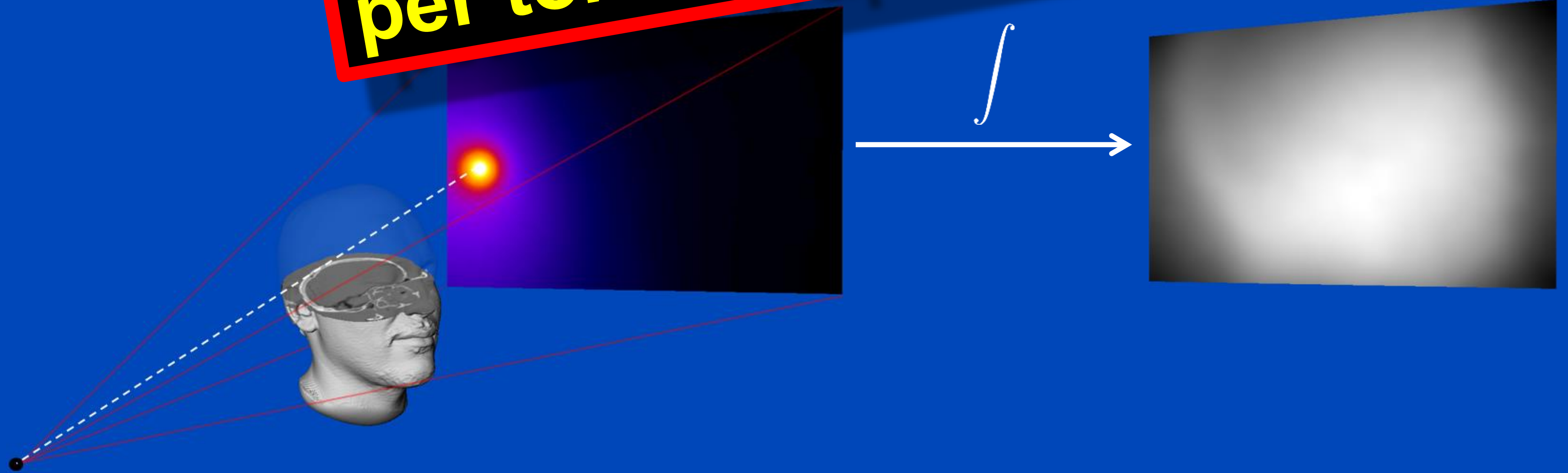
In real time?



Monte Carlo Scatter Estimation

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

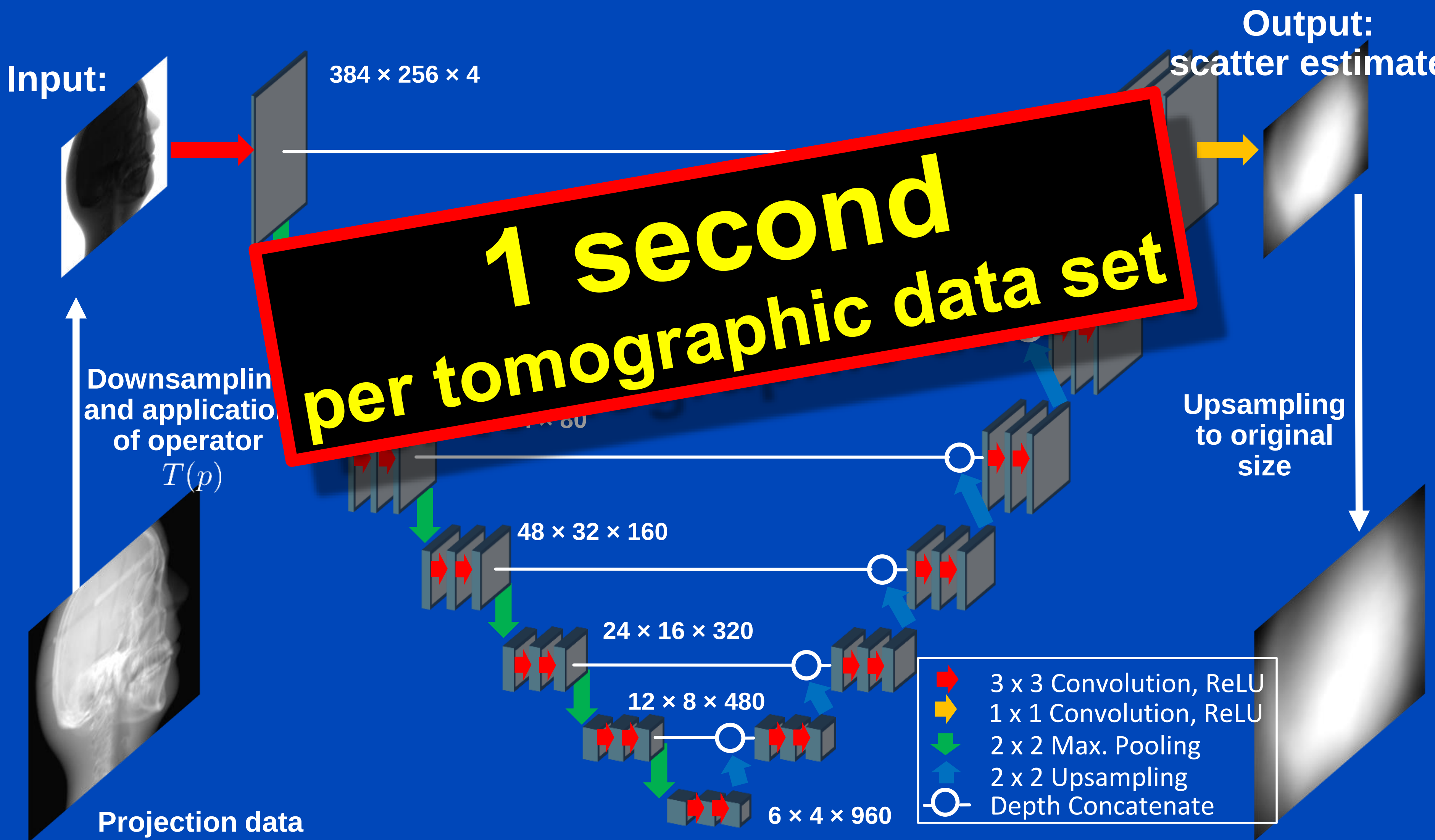
1 hour per tomographic data set



dkfz.

Deep Scatter Estimation

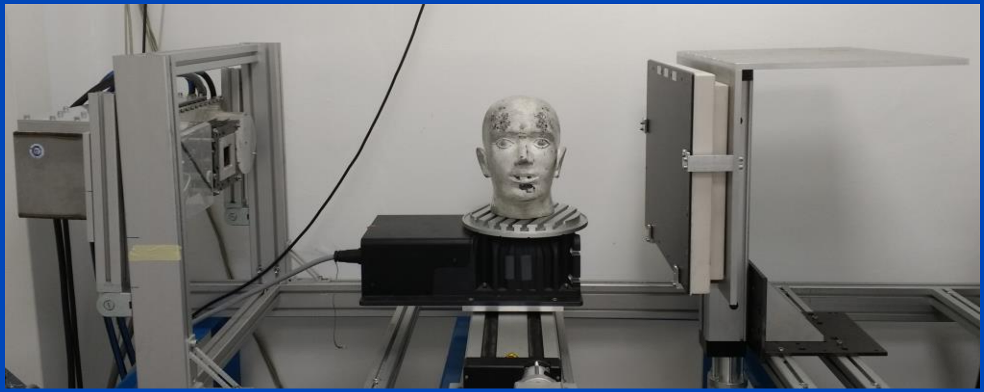
Network architecture & scatter estimation framework



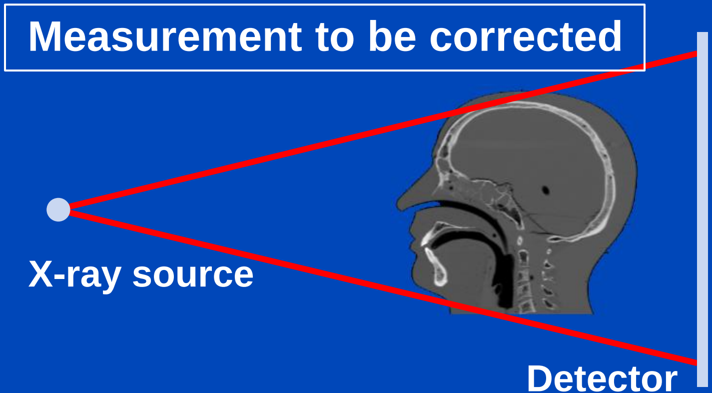
J. Maier, M. Kachelrieß et al. Deep scatter estimation (DSE). SPIE 2017 and Journal of Nondestructive Evaluation 37:57, July 2018.
J. Maier, M. Kachelrieß et al. Robustness of DSE. Med. Phys. 46(1):238-249, January 2019.

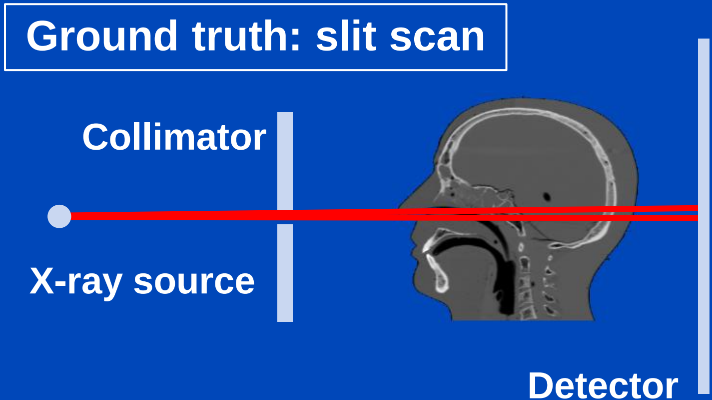
Testing of the DSE Network for Measured Data (120 kV)

DKFZ table-top CT



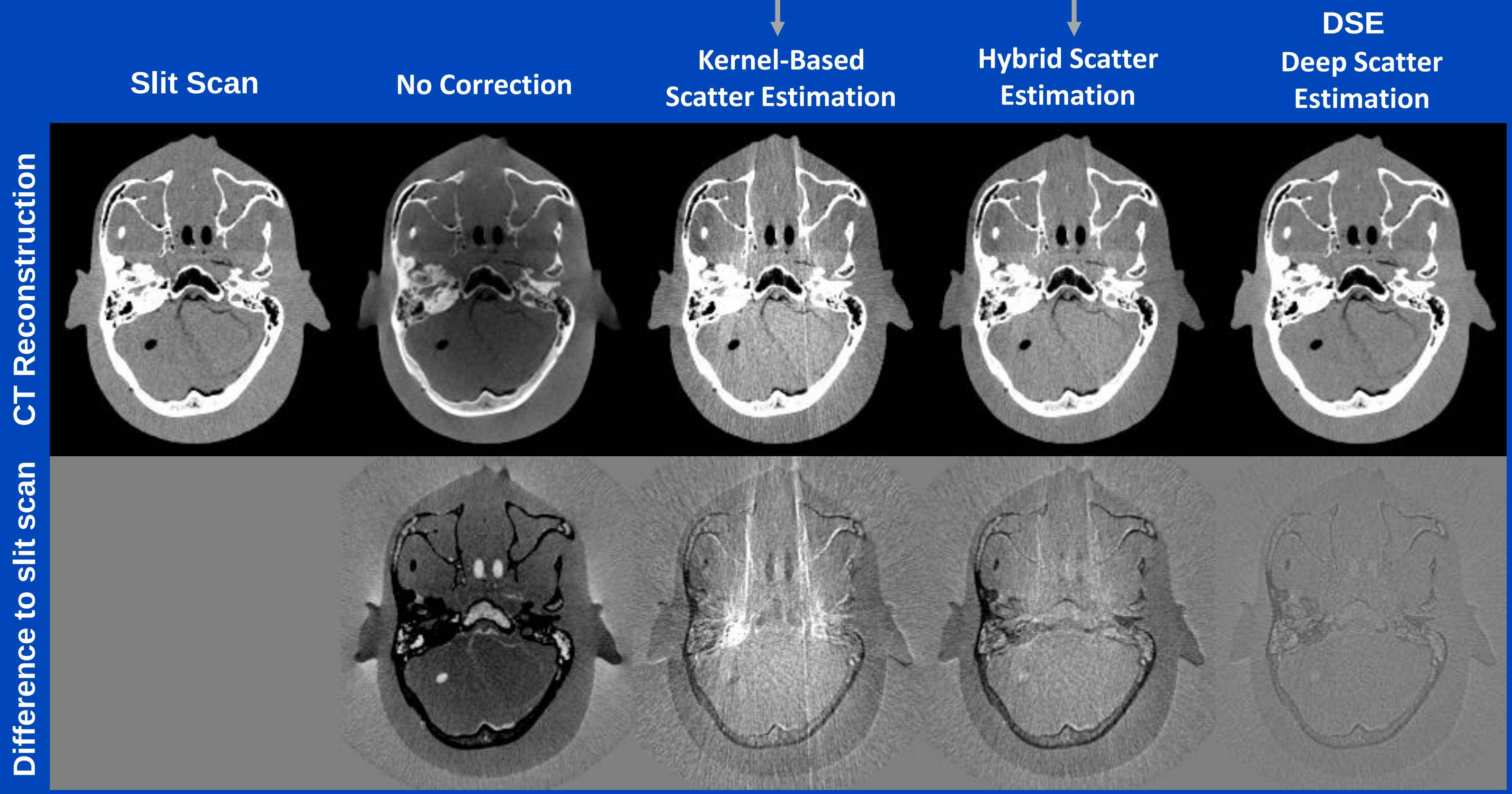
- Measurement of a head phantom at our in-house table-top CT.
- Slit scan measurement serves as ground truth.





Reconstructions of Measured Data

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

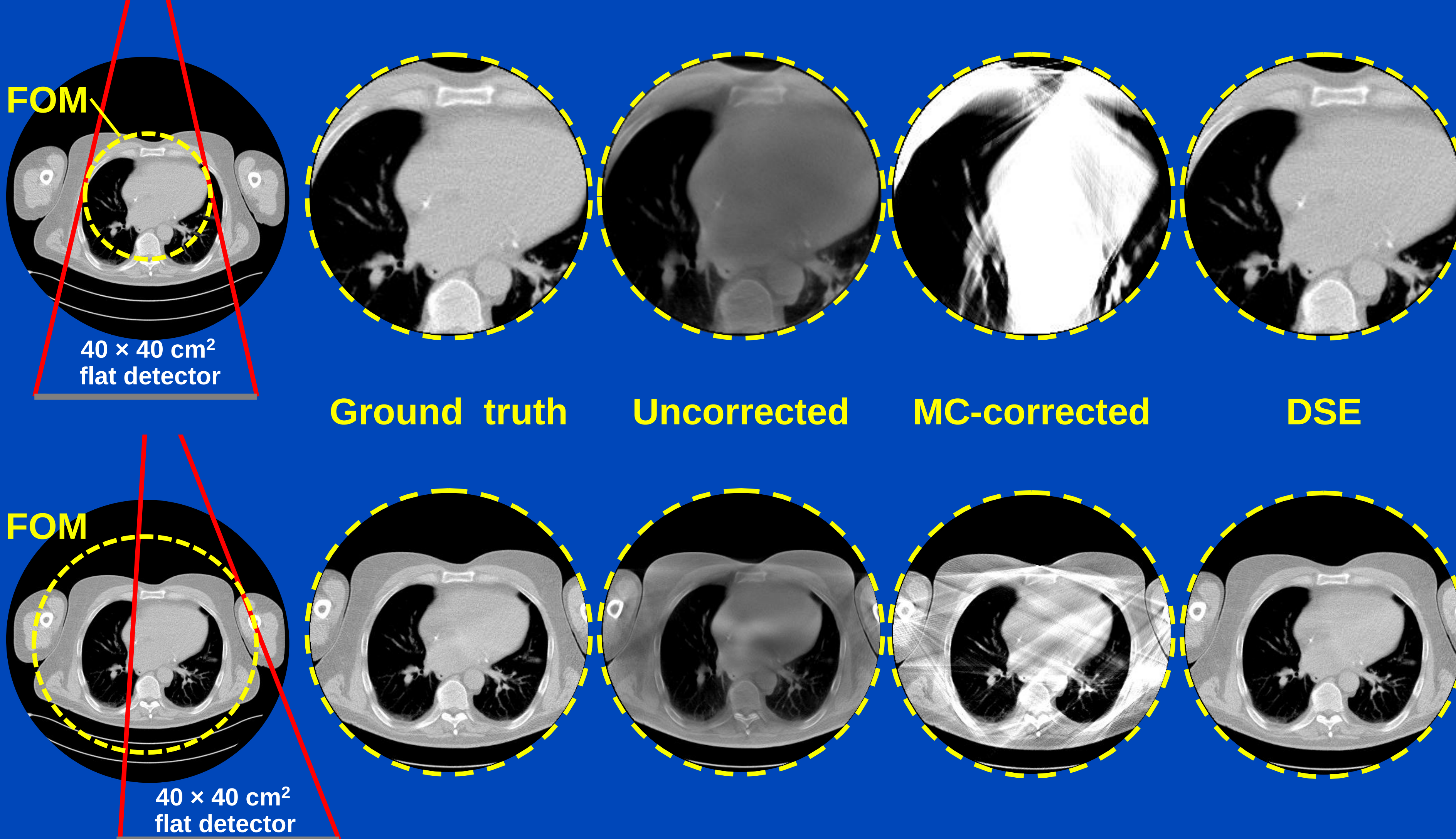


C = 0 HU, W = 1000 HU

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.

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

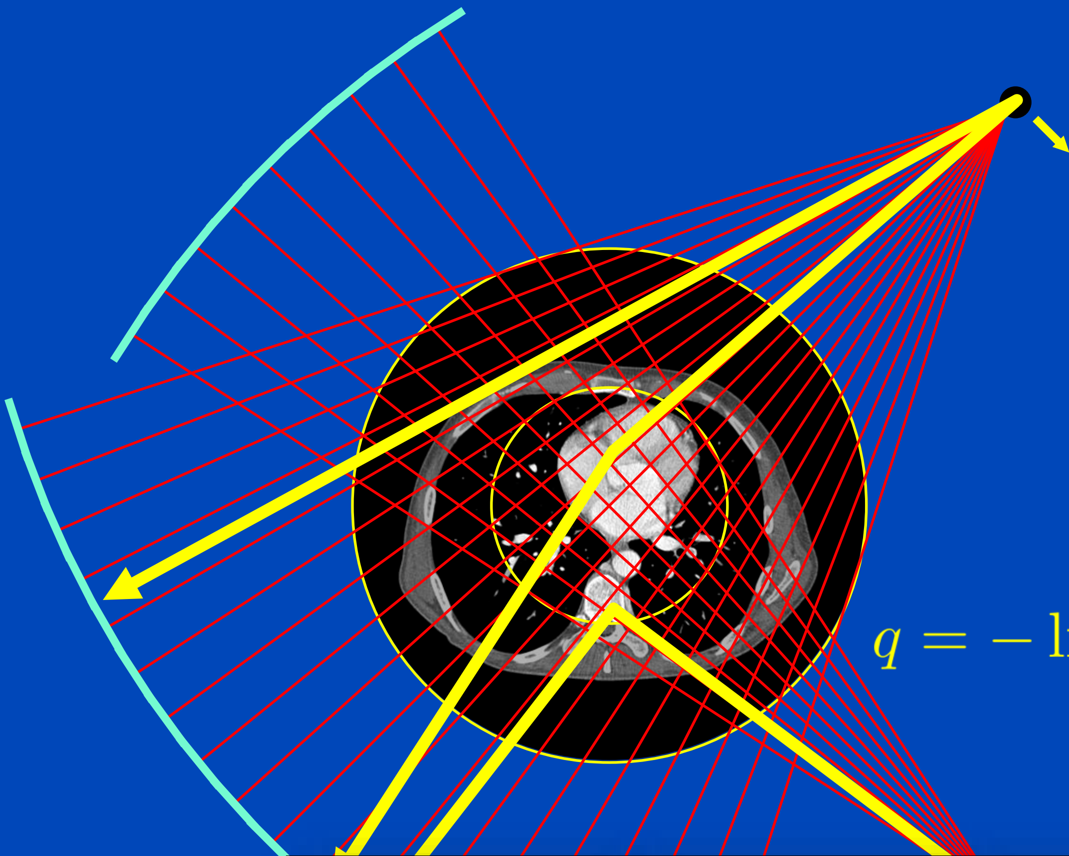
Truncated DSE



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].

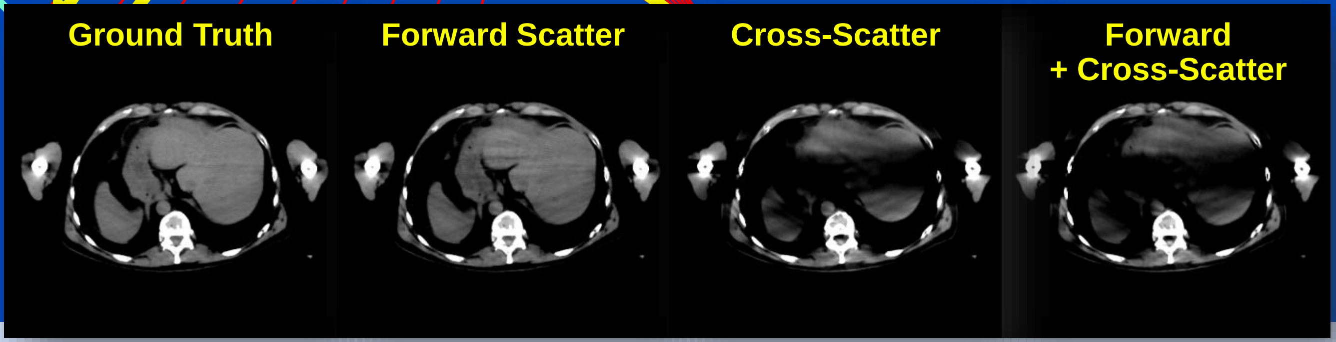
J. Maier, M. Kachelrieß et al. Deep scatter estimation (DSE). SPIE 2017 and Journal of Nondestructive Evaluation 37:57, July 2018.
J. Maier, M. Kachelrieß et al. Robustness of DSE. Med. Phys. 46(1):238-249, January 2019.

Scatter in Dual Source CT (DSCT)



Siemens SOMATOM Force
dual source cone-beam spiral CT

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



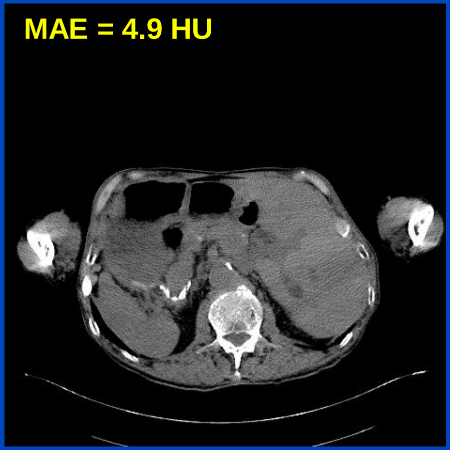
C = 40 HU, *W* = 300 HU, with 2D anti-scatter grid

Scatter in Dual Source CT: xDSE

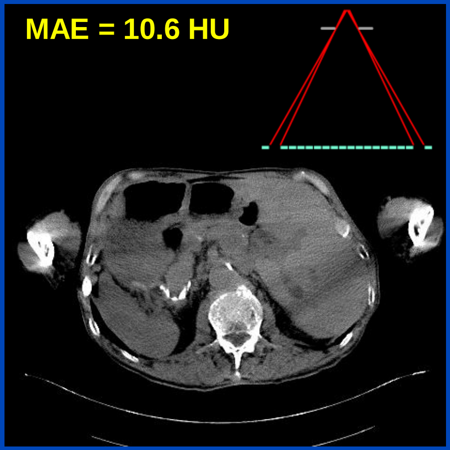
Ground Truth

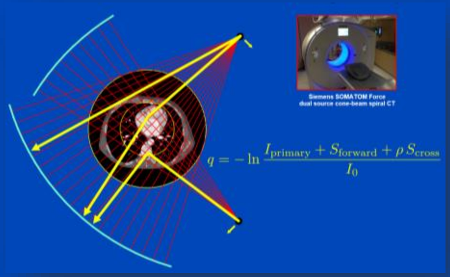
Uncorrected

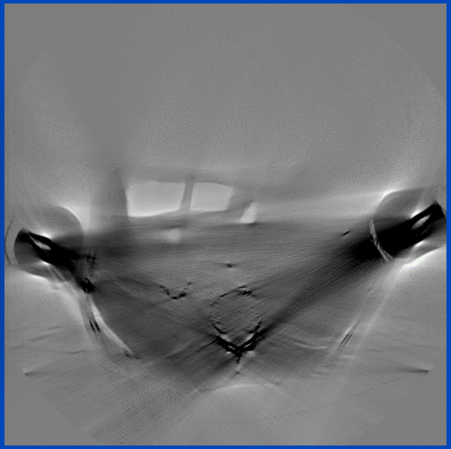
xDSE (2D, xSSE)

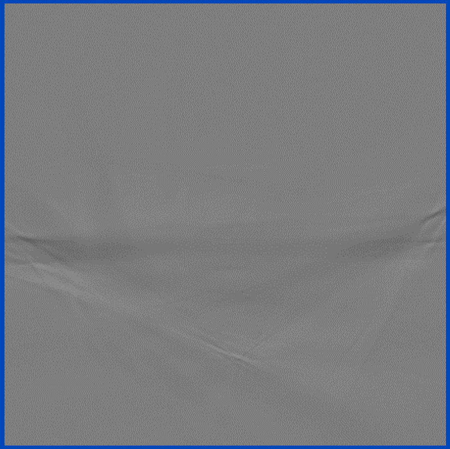


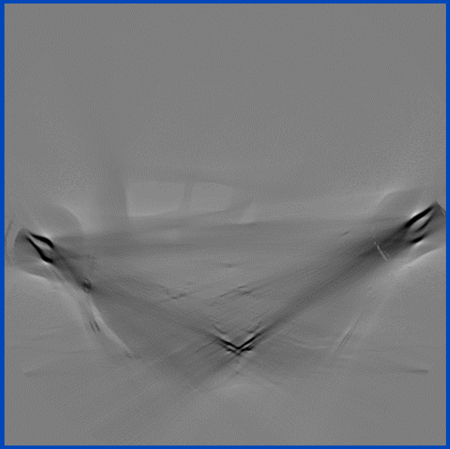
Measurement-based









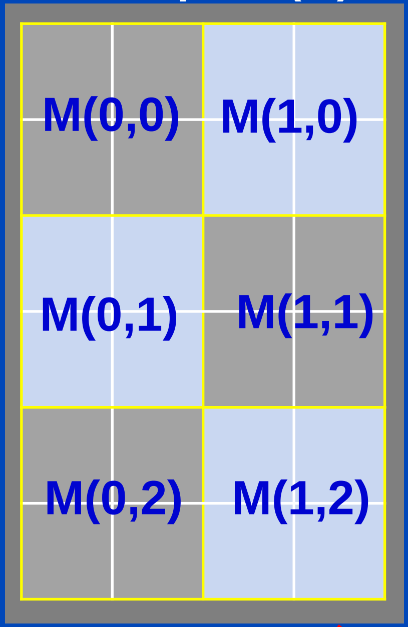


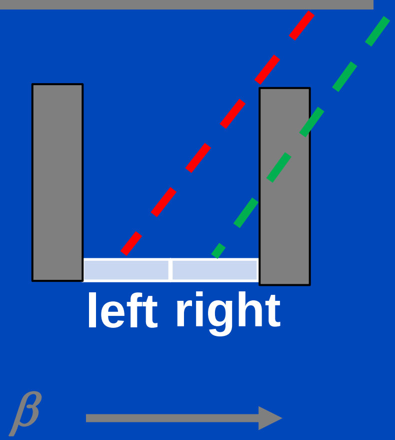
xDSE (2D, xSSE) maps
primary + forward scatter + cross-scatter + cross-scatter approximation → cross-scatter

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

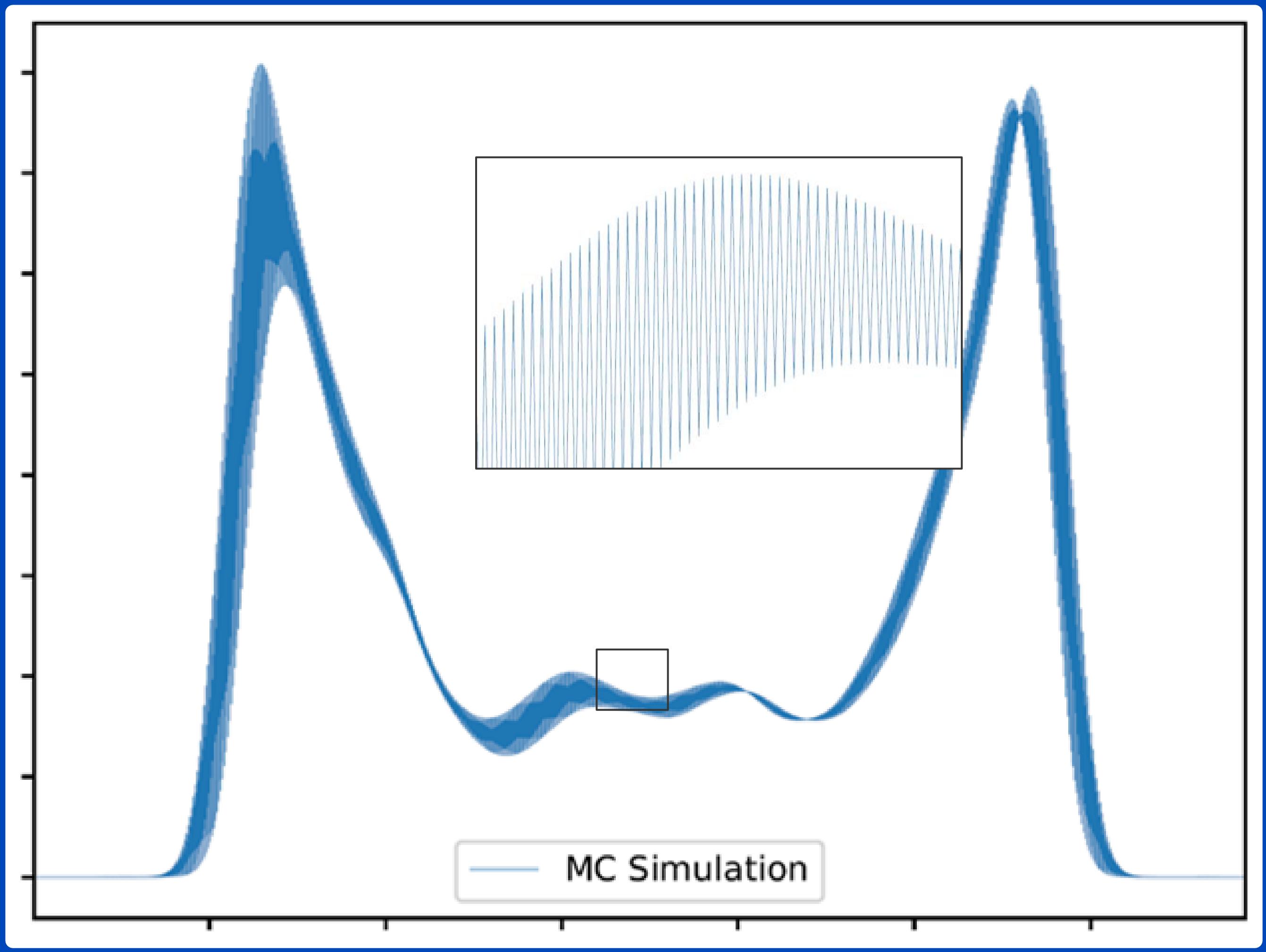
Scatter for Coarse ASG

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





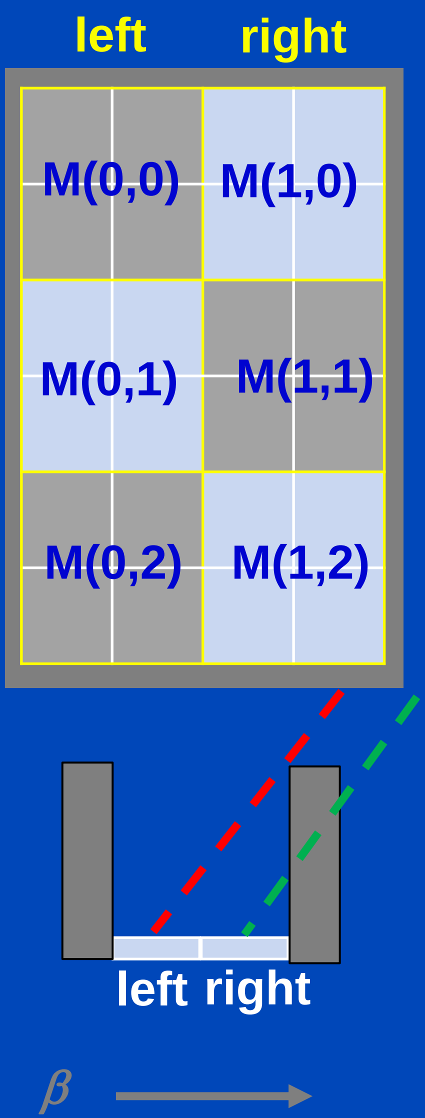
Scatter distribution averaged over all detector rows



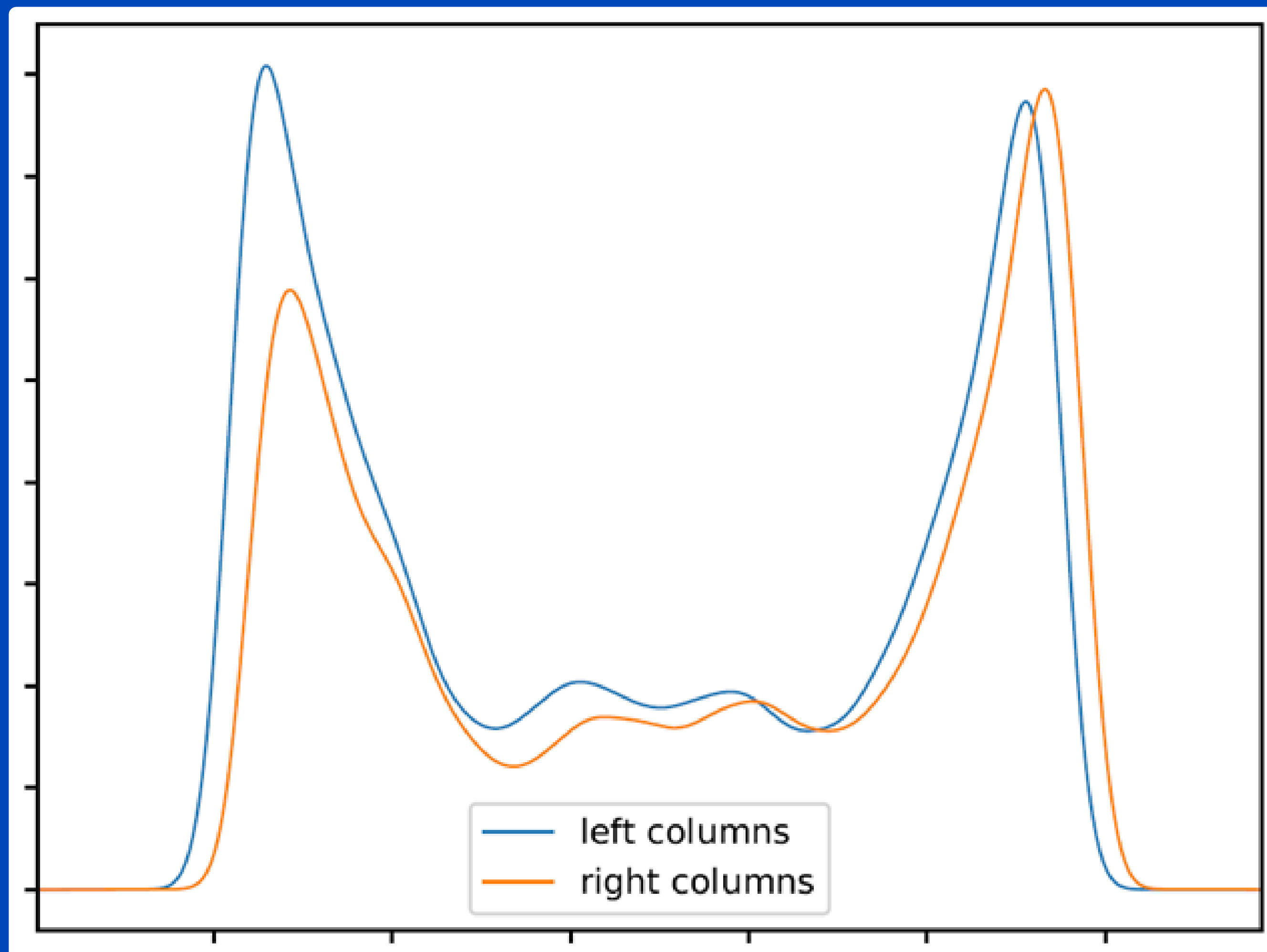
Detector columns

J. Erath, M. Kachelrieß et al. Deep scatter estimation for coarse anti-scatter grids as used in photon-counting CT. Proceedings of the 7th International Conference on Image Formation in X-Ray Computed Tomography:190-193, June 2022.

Scatter for Coarse ASG



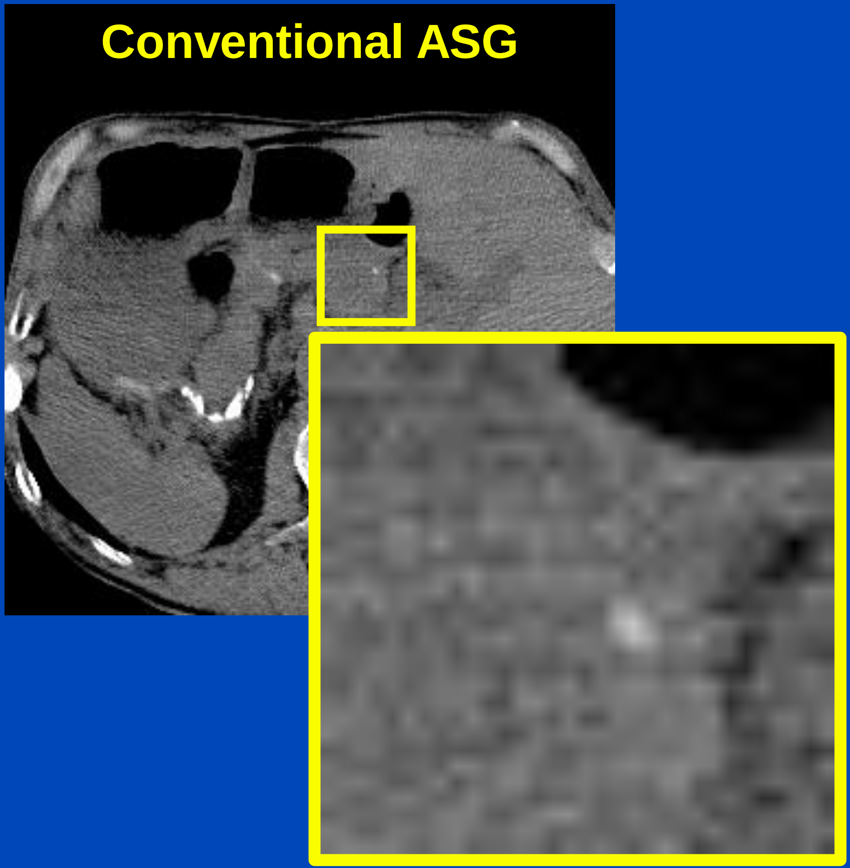
Scatter distribution averaged over all detector rows

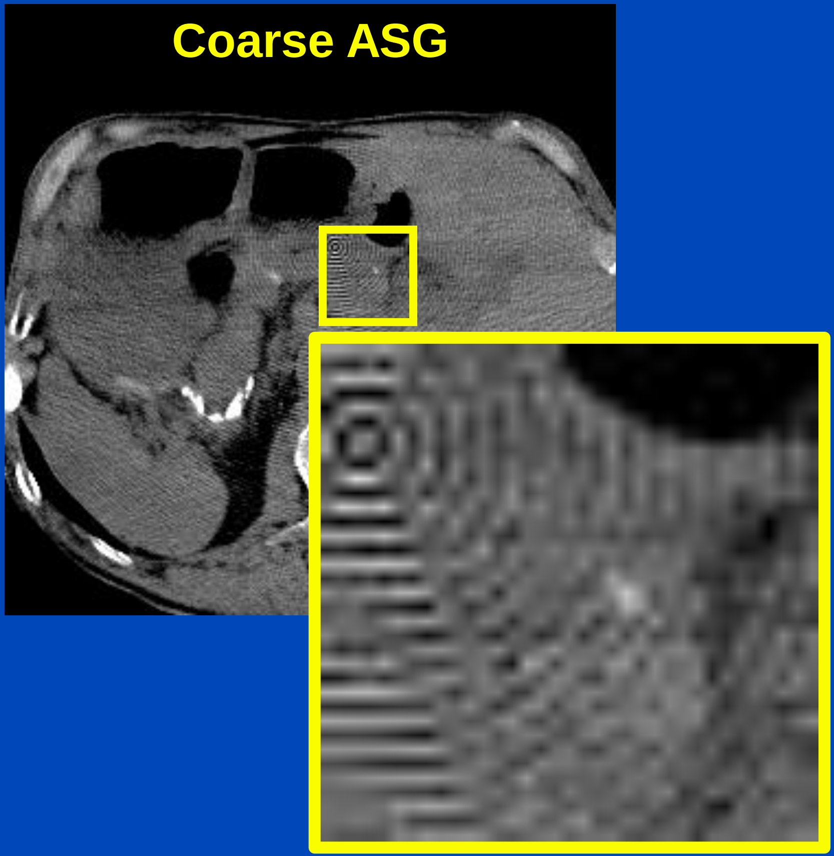


Detector columns

J. Erath, M. Kachelrieß et al. Deep scatter estimation for coarse anti-scatter grids as used in photon-counting CT. Proceedings of the 7th International Conference on Image Formation in X-Ray Computed Tomography:190-193, June 2022.

Scatter Artifacts of Coarse ASG





Coarse ASGs can lead to scatter-induced moiré artifacts.

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

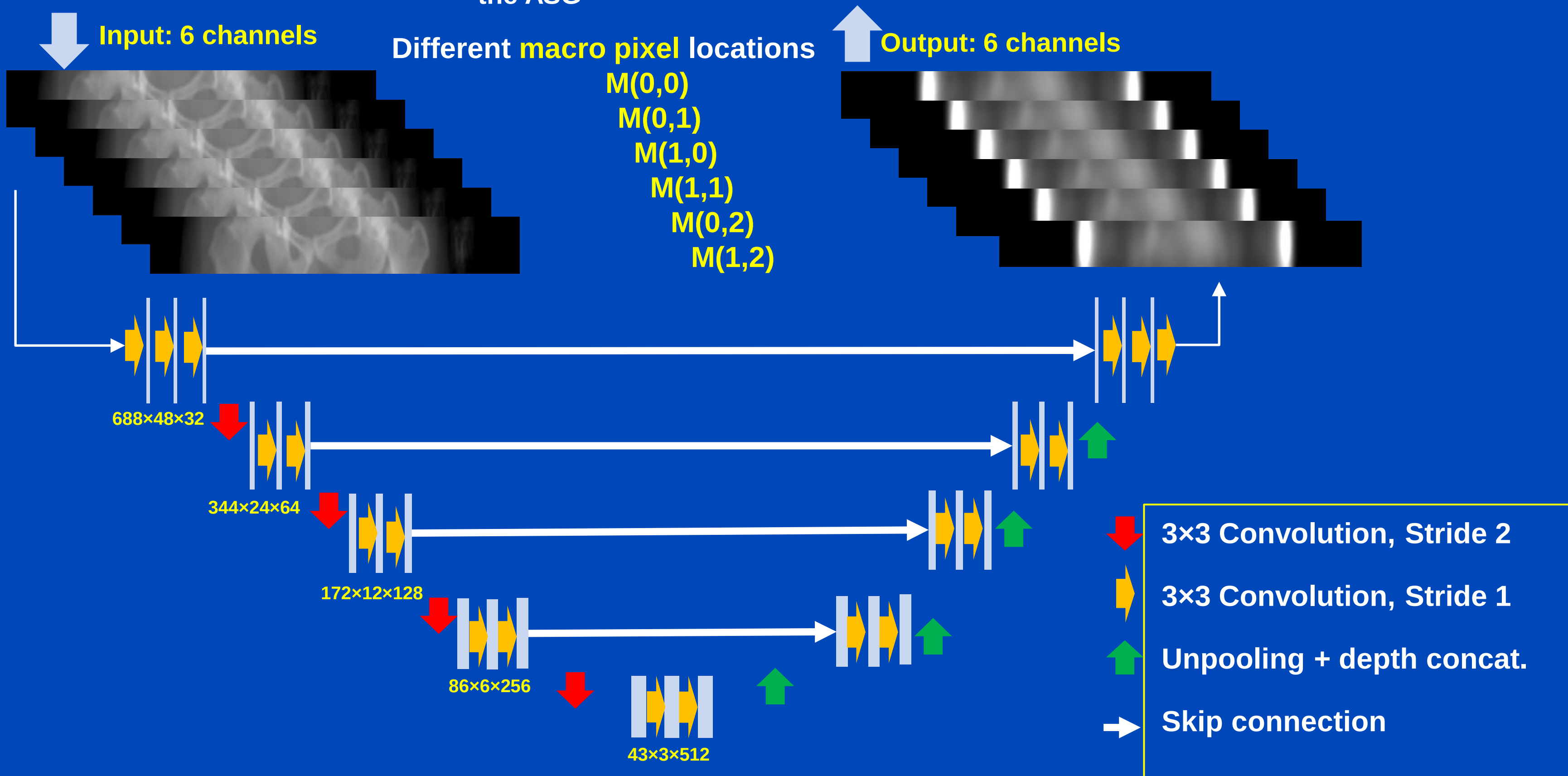
Network Architecture

Detector dimension
1376×144
Input mapping

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

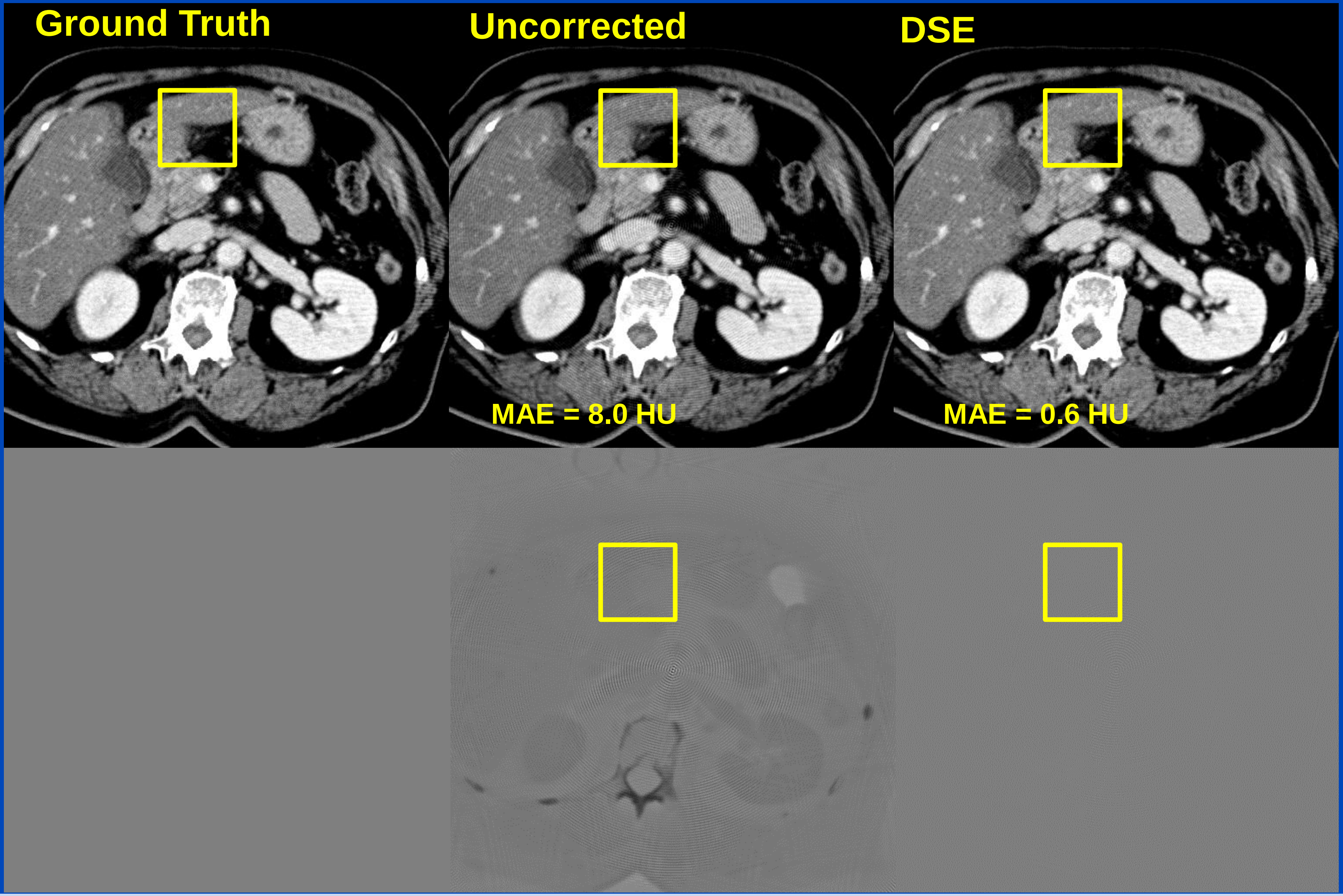
Each channel corresponds to a different pixel position between the lamellae of the ASG

Merging 6 different channels to obtain total scatter correction term



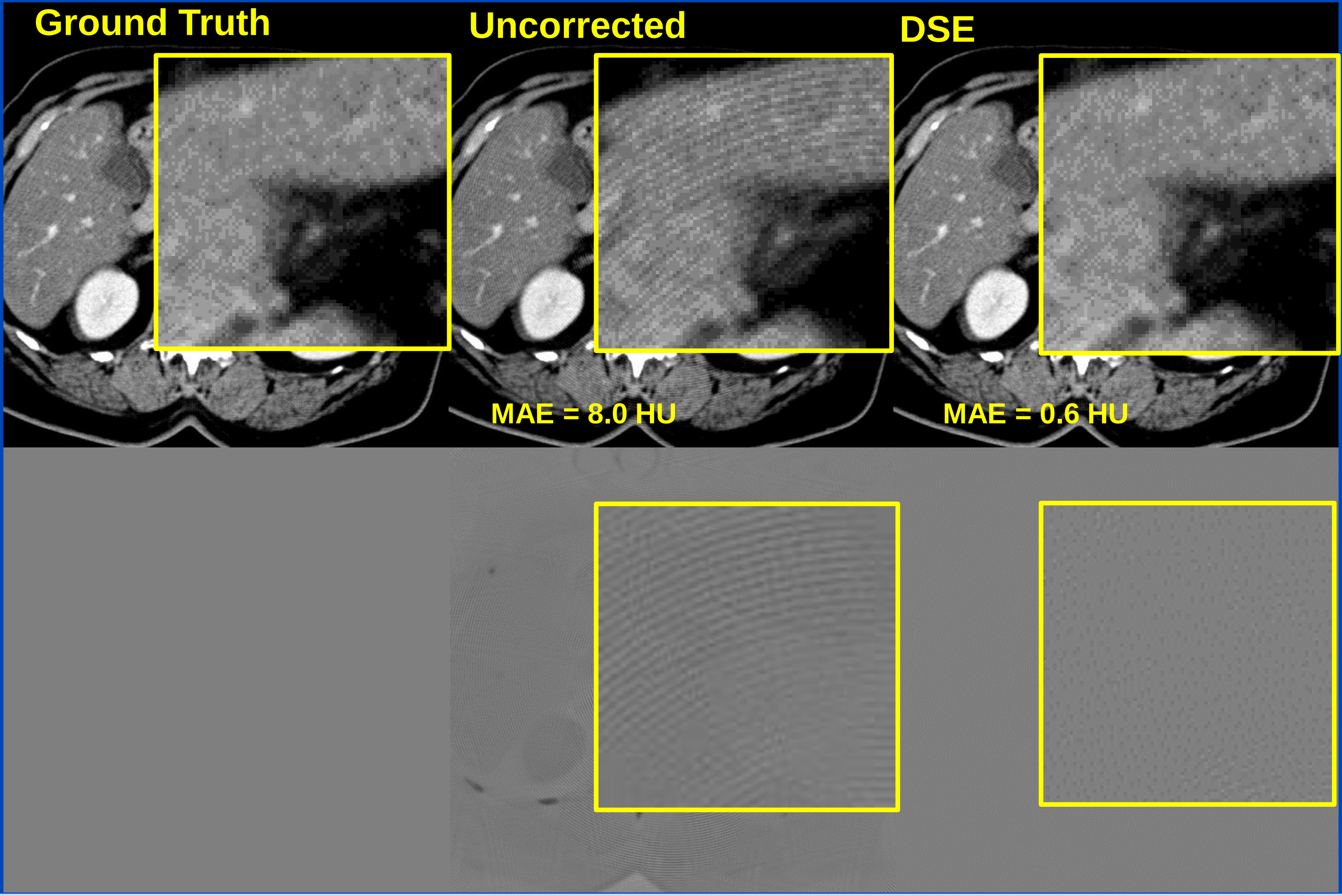
J. Erath, M. Kachelrieß et al. Deep scatter estimation for coarse anti-scatter grids as used in photon-counting CT. Proceedings of the 7th International Conference on Image Formation in X-Ray Computed Tomography:190-193, June 2022.

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

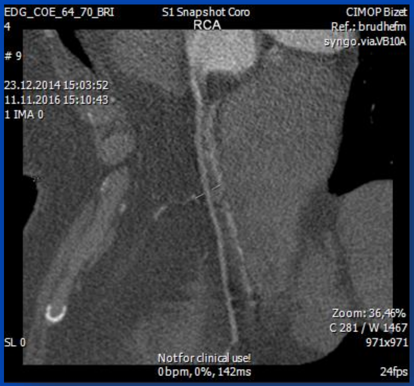


Simulated Reconstruction *C* = 0 HU, *W* = 400 HU,
Difference to GT *C* = 0 HU, *W* = 50 HU

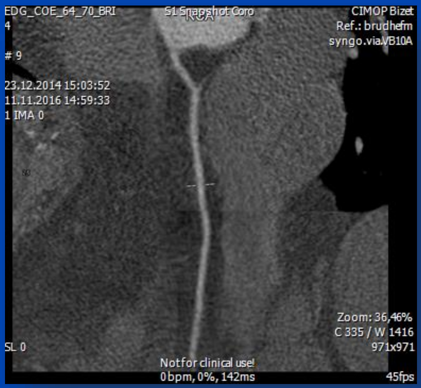
Conclusions on DSE

- 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.

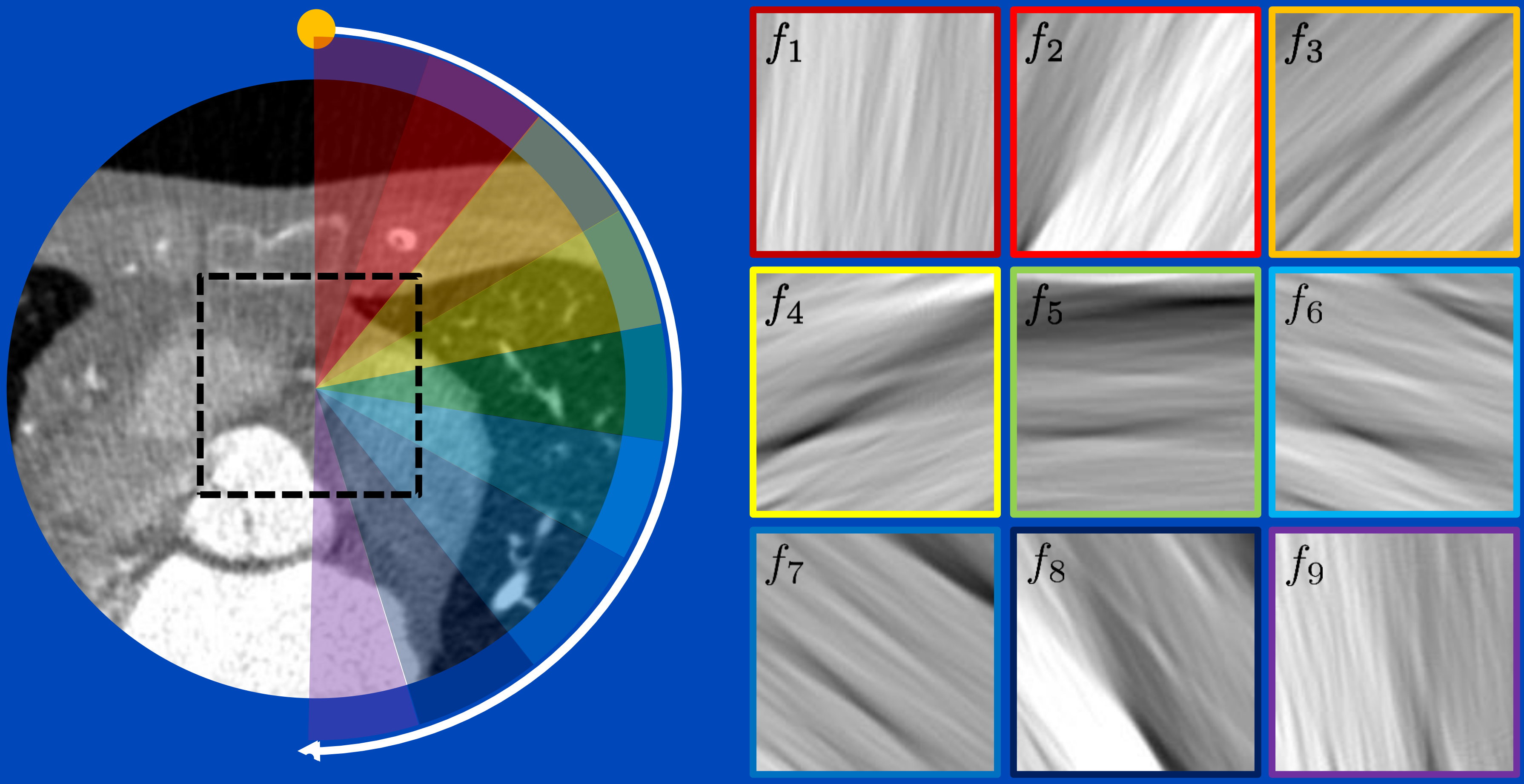
Deep Cardiac Motion Compensation



???

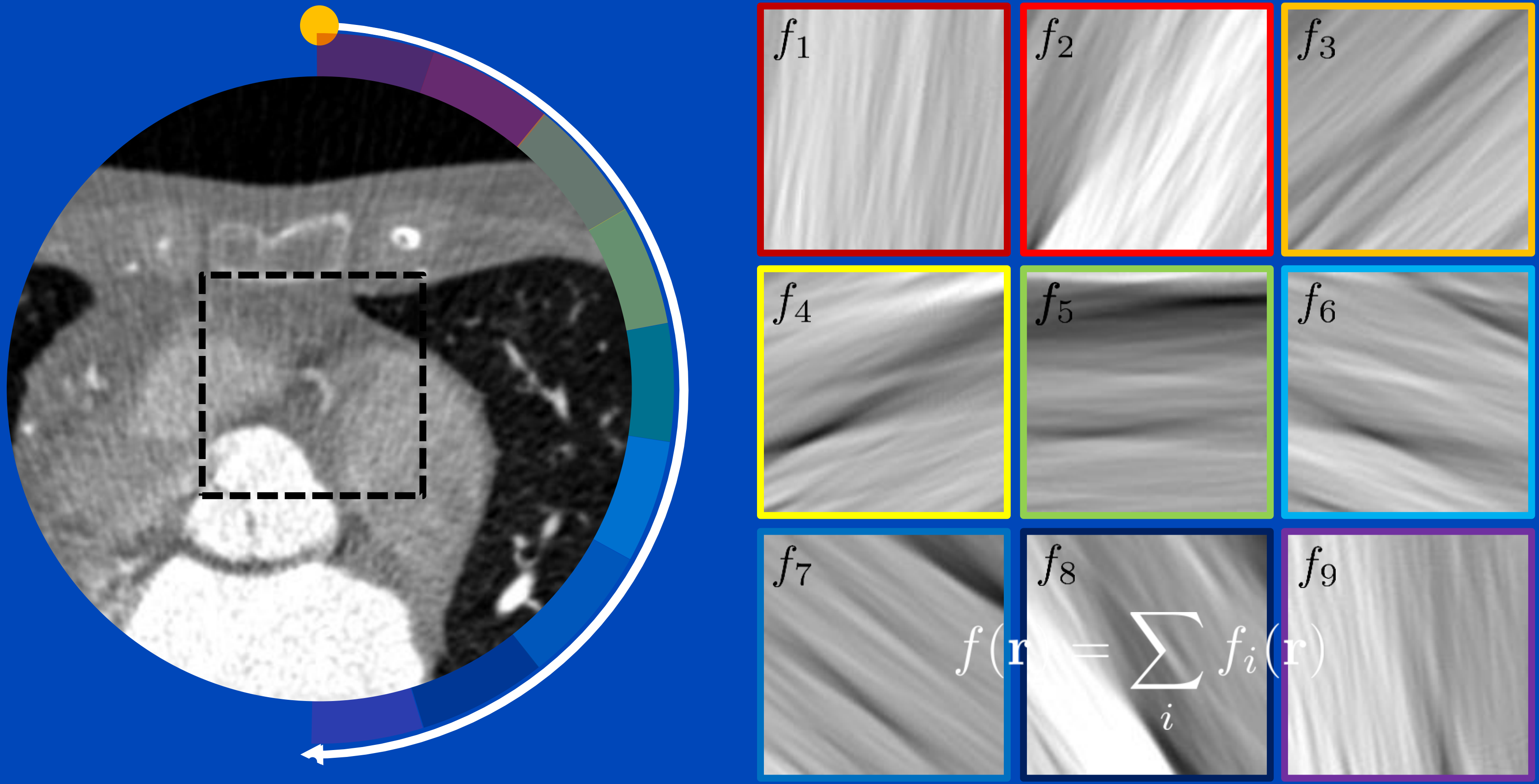


Partial Angle-Based Motion Compensation (PAMoCo)

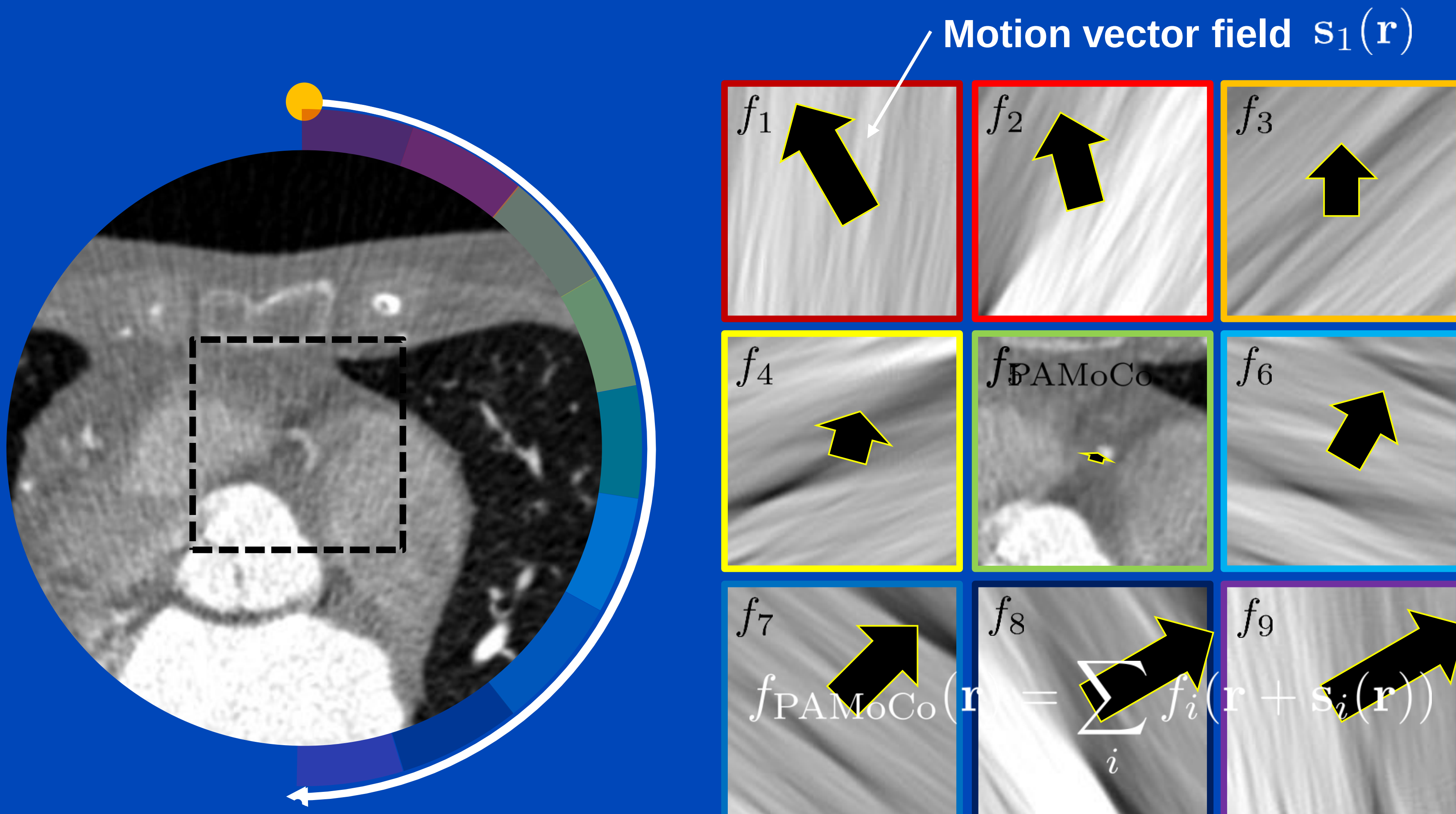


Animated rotation time = 100 × real rotation time

Partial Angle-Based Motion Compensation (PAMoCo)



Partial Angle-Based Motion Compensation (PAMoCo)

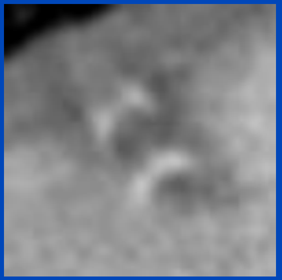


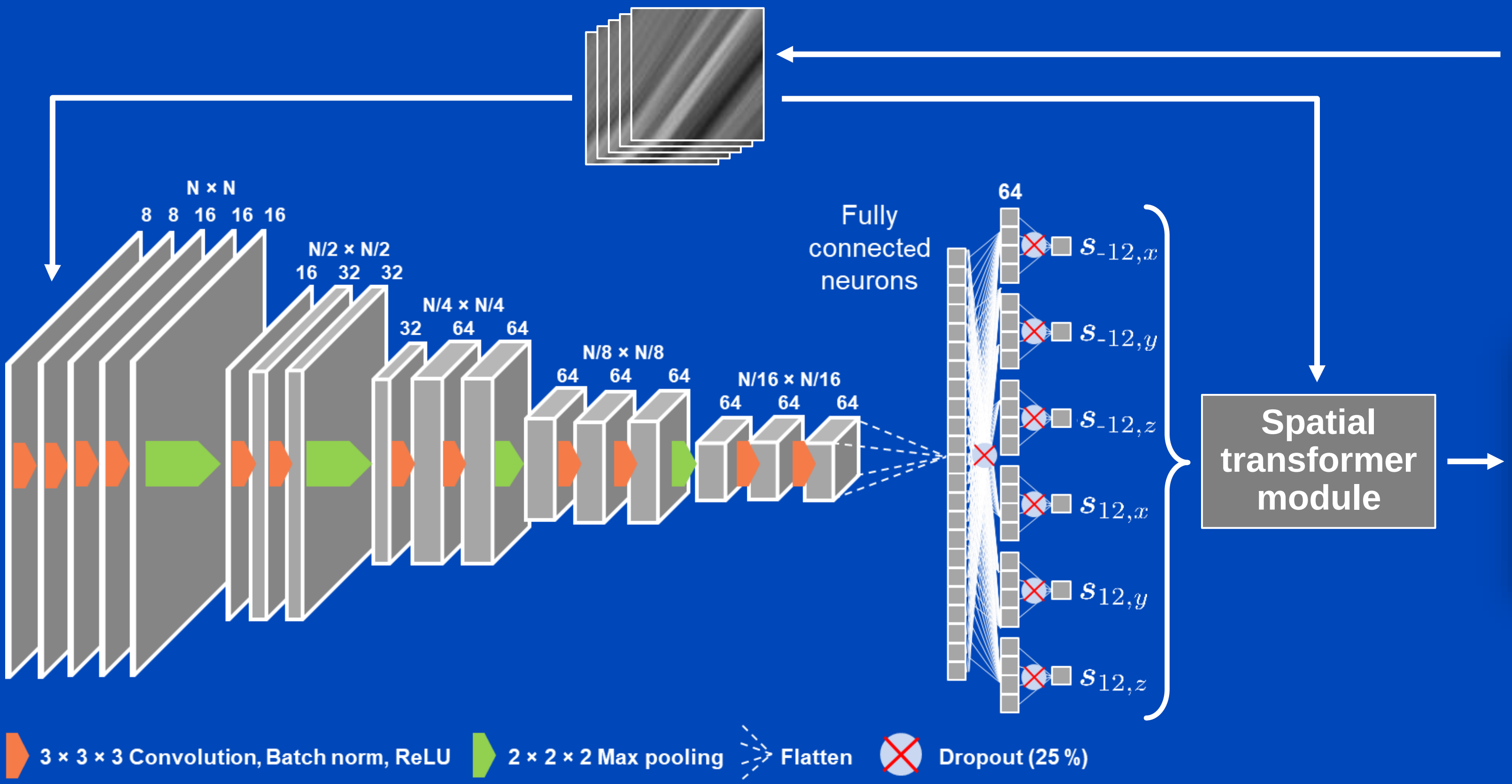
Apply motion vector fields (MVFs) to partial angle reconstructions

Deep PAMoCo

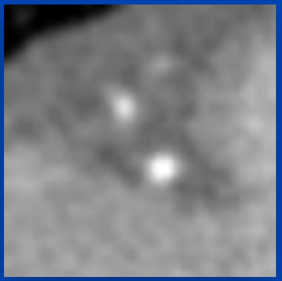
Network architecture

Initial volume
(with motion artifacts)





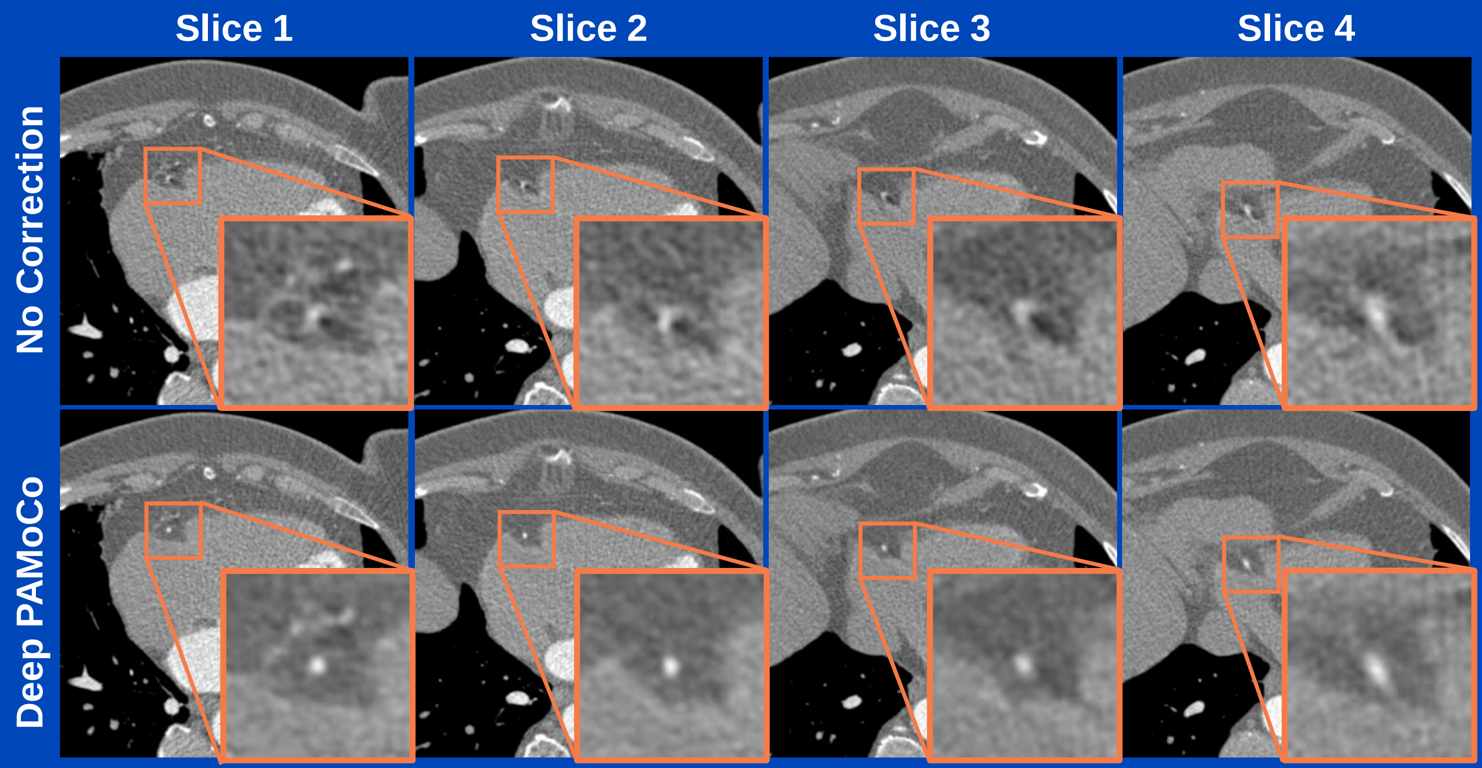
Final volume
(no motion artifacts)



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.

J. Maier, S. Lebedev, J. Erath, E. Eulig, S. Sawall, E. Fournié, K. Stierstorfer, M. Lell, and M. Kachelrieß. Deep learning-based coronary artery motion estimation and compensation for short-scan cardiac CT. Med. Phys. 48(7):3559-3571, July 2021.

Results



C = 1000 HU
W = 1000 HU

J. Maier, S. Lebedev, J. Erath, E. Eulig, S. Sawall, E. Fournié, K. Stierstorfer, M. Lell, and M. Kachelrieß. Deep learning-based coronary artery motion estimation and compensation for short-scan cardiac CT. Med. Phys. 48(7):3559-3571, July 2021.

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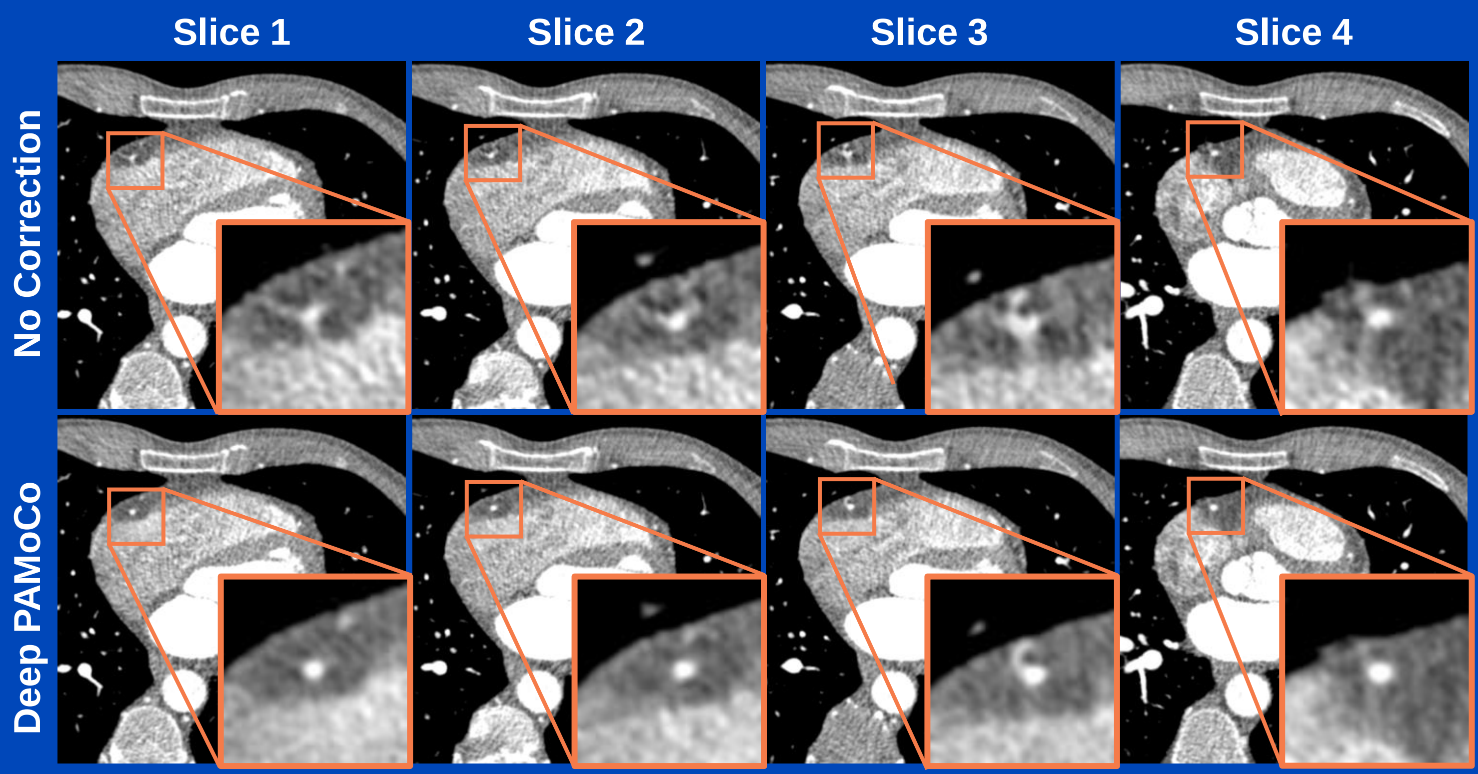
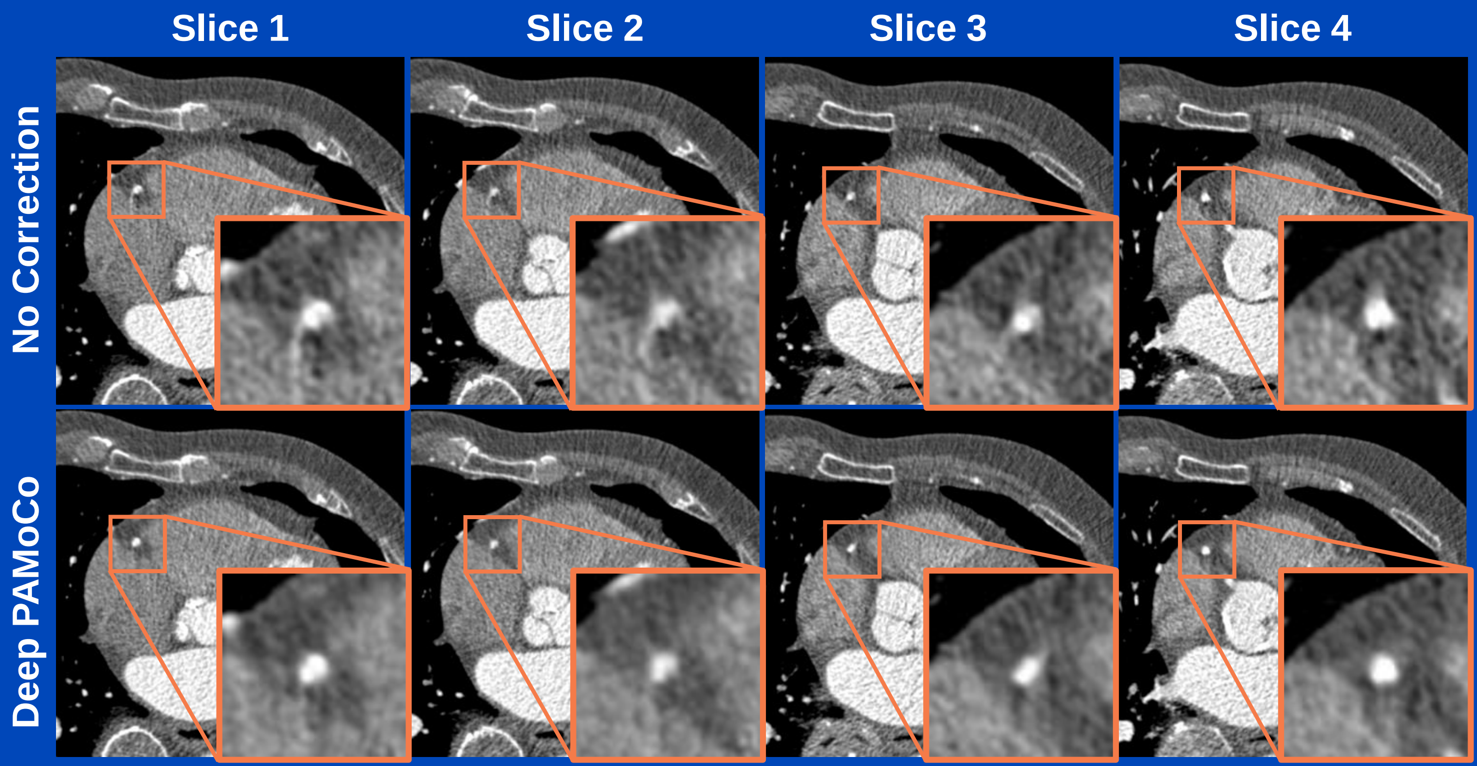


C = 1000 HU
W = 1000 HU

J. Maier, S. Lebedev, J. Erath, E. Eulig, S. Sawall, E. Fournié, K. Stierstorfer, M. Lell, and M. Kachelrieß. Deep learning-based coronary artery motion estimation and compensation for short-scan cardiac CT. Med. Phys. 48(7):3559-3571, July 2021.

Results



C = 1100 HU
W = 1000 HU

J. Maier, S. Lebedev, J. Erath, E. Eulig, S. Sawall, E. Fournié, K. Stierstorfer, M. Lell, and M. Kachelrieß. Deep learning-based coronary artery motion estimation and compensation for short-scan cardiac CT. Med. Phys. 48(7):3559-3571, July 2021.

H Handle Irregular Motion?

S ?

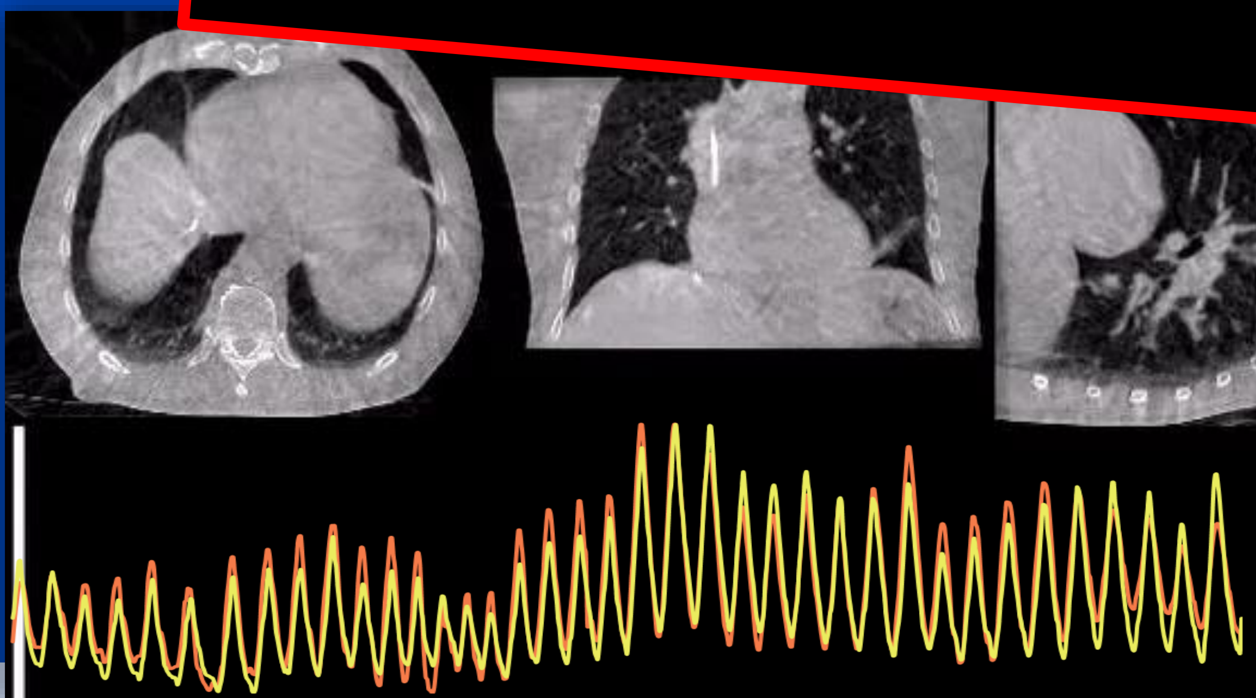
See our talk tomorrow

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 acquisiton
- 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 than manipulate voxel values

Thank You!

The 8th International Conference on

Image Formation in X-Ray Computed Tomography

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.