AI-Based Image Formation

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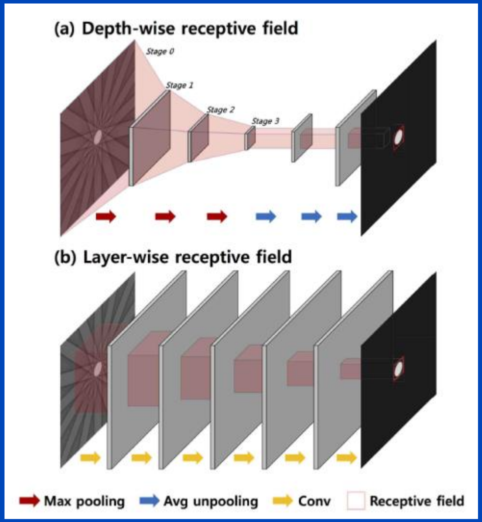
DEUTSCHES
KREBSFORSCHUNGSZENTRUM
IN DER HELMHOLTZ-GEMEINSCHAFT

Dose Reduction

Sparse View Restoration Example



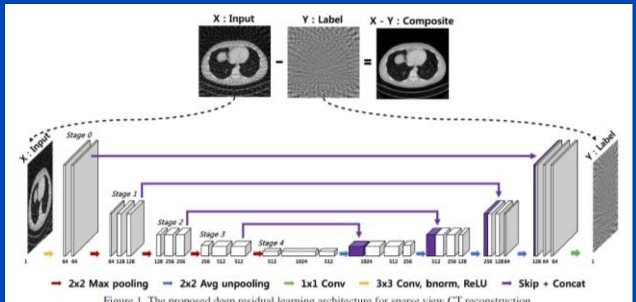
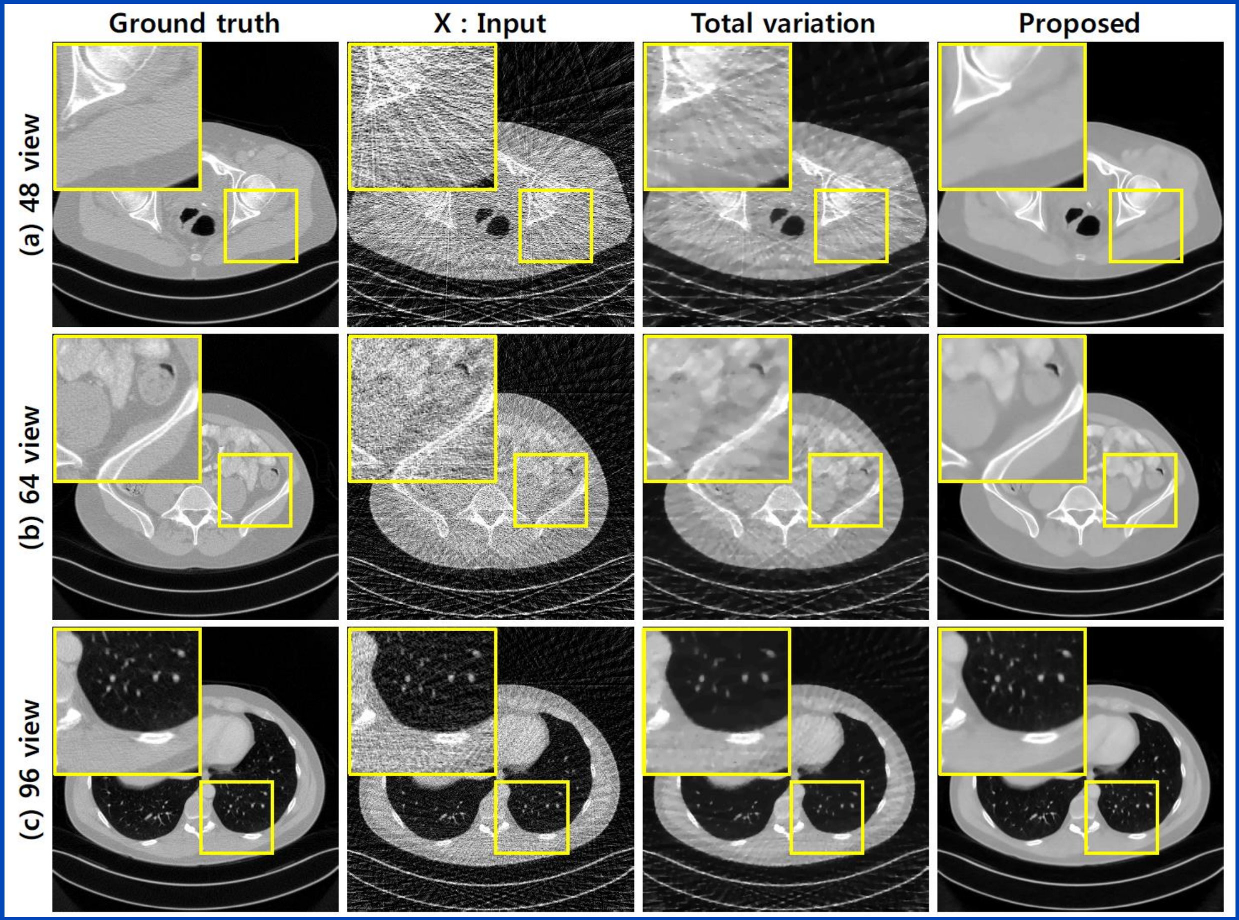
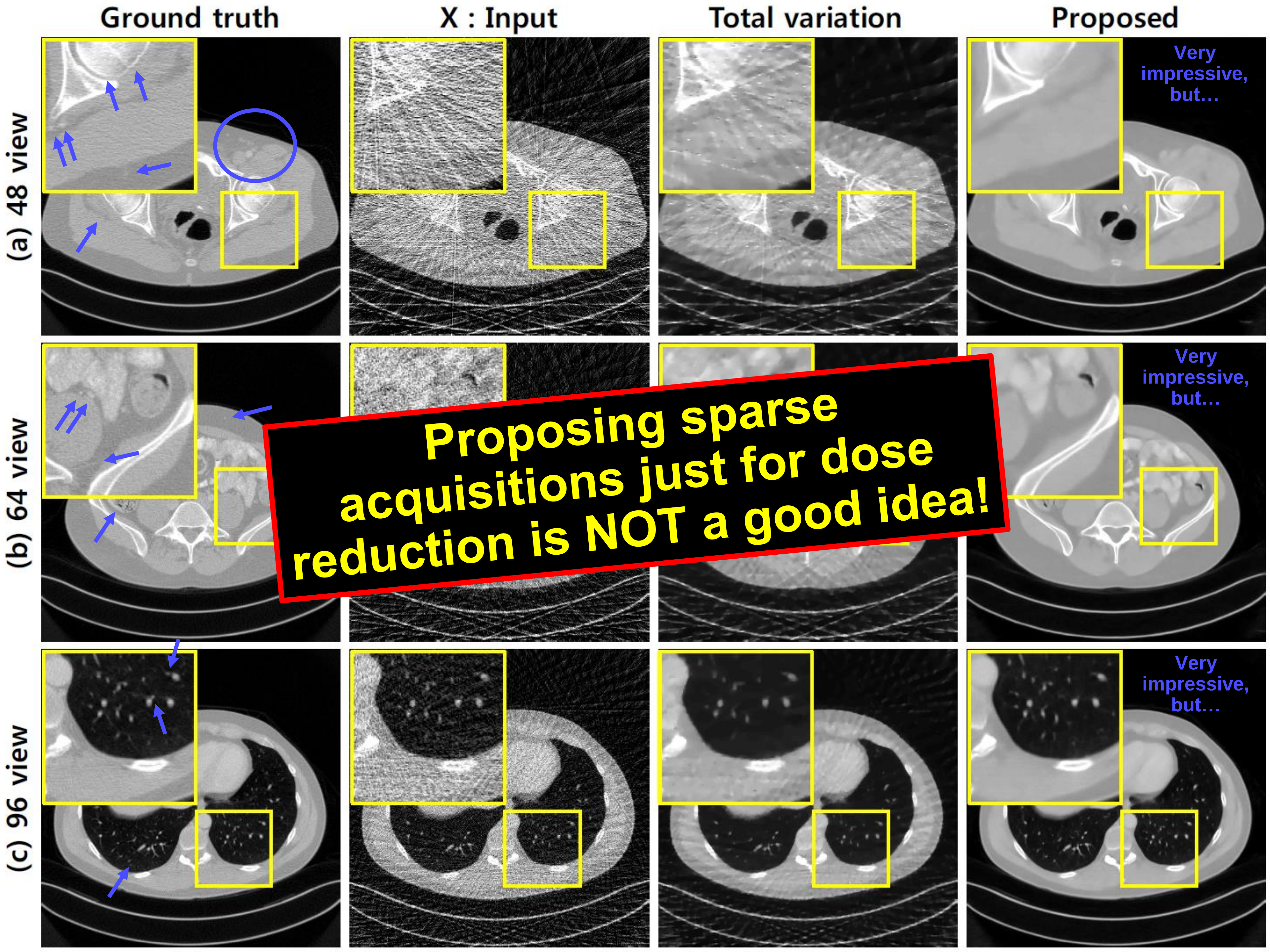


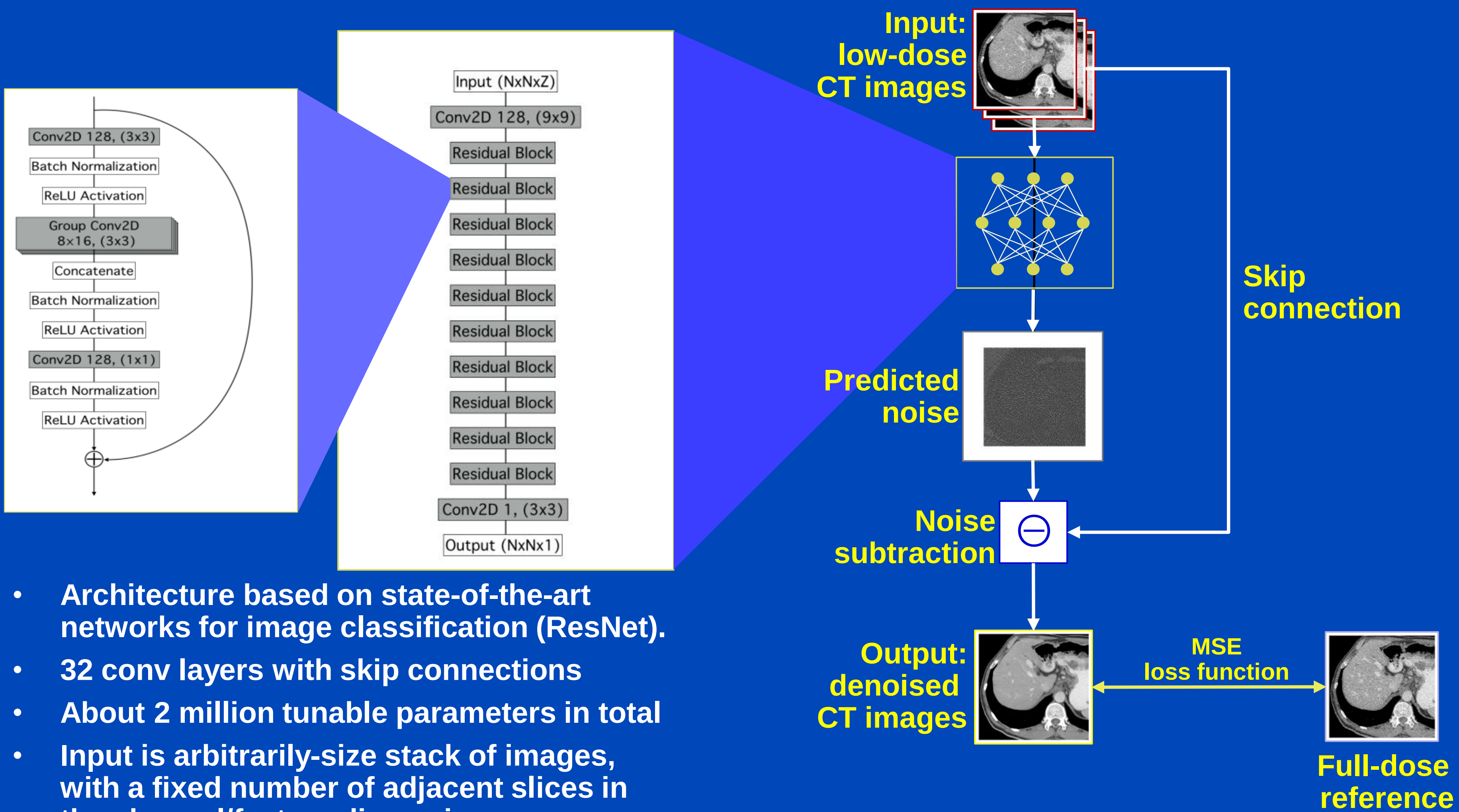
Figure 1. The proposed deep residual learning architecture for sparse view CT reconstruction.



Yo Seob Han, Jaejun Yoo and Jong Chul Ye. Deep Residual Learning for Compressed Sensing CT Reconstruction via Persistent Homology Analysis. ArXiv 2016.


Ground truth
X : Input
Total variation
Proposed
(a) 48 view
(b) 64 view
(c) 96 view
Very impressive, but…
Very impressive, but…
Very impressive, but…
Proposing sparse acquisitions just for dose reduction is NOT a good idea!

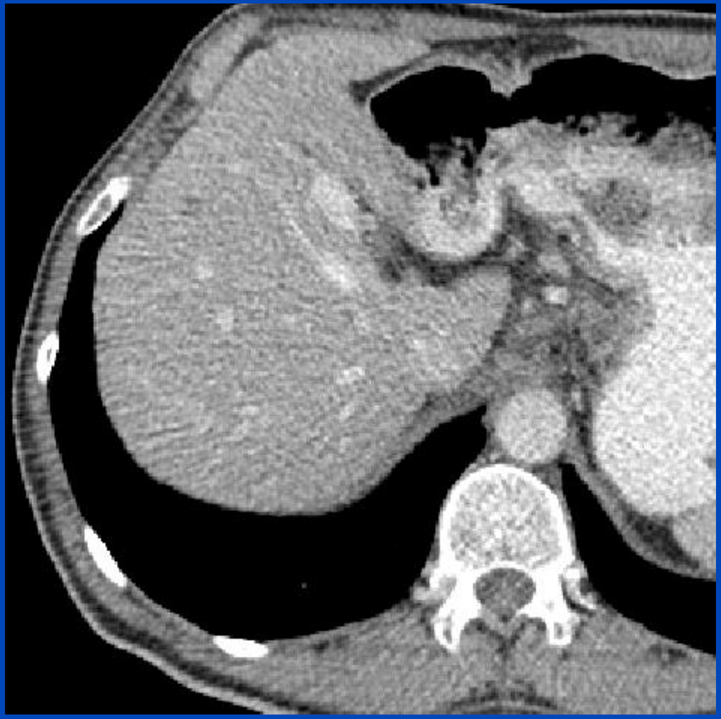
Noise Removal

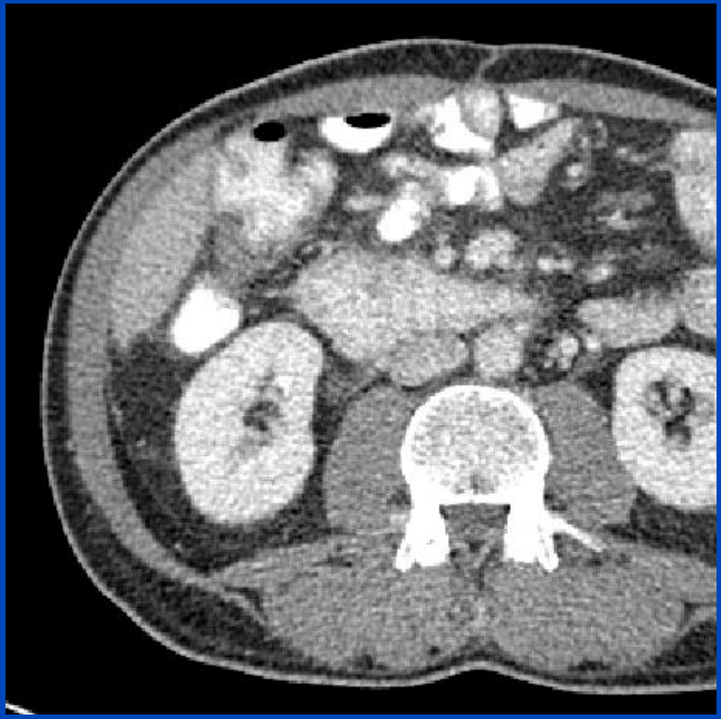


- Architecture based on state-of-the-art networks for image classification (ResNet).
- 32 conv layers with skip connections
- About 2 million tunable parameters in total
- Input is arbitrarily-size stack of images, with a fixed number of adjacent slices in the channel/feature dimension.

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

Noise Removal





Low dose images (1/4 of full dose)

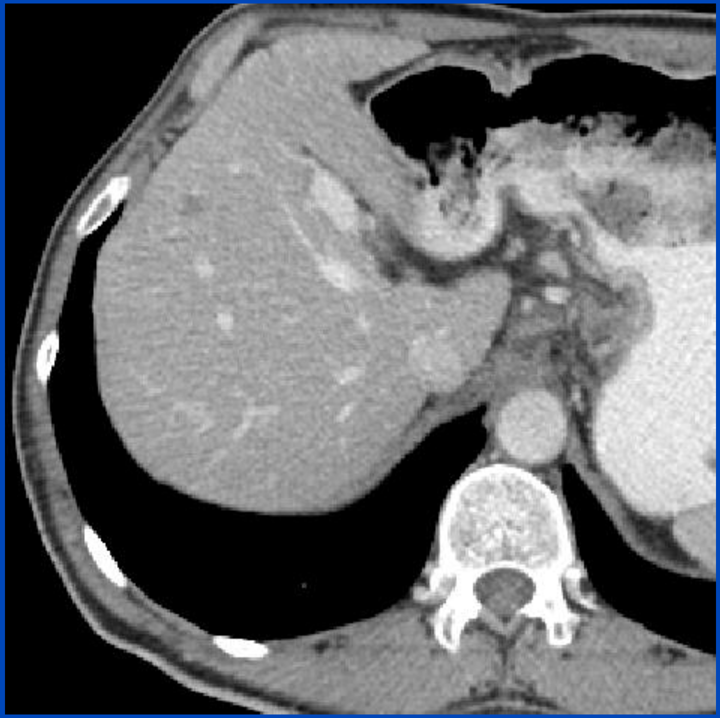
Andrew D. Missert, Shuai Leng, Lifeng Yu, and Cynthia H. McCollough. Noise Subtraction for Low-Dose CT Images Using a Deep Convolutional Neural Network. Proceedings of the 5th CT-Meeting: 399-402, 2018.

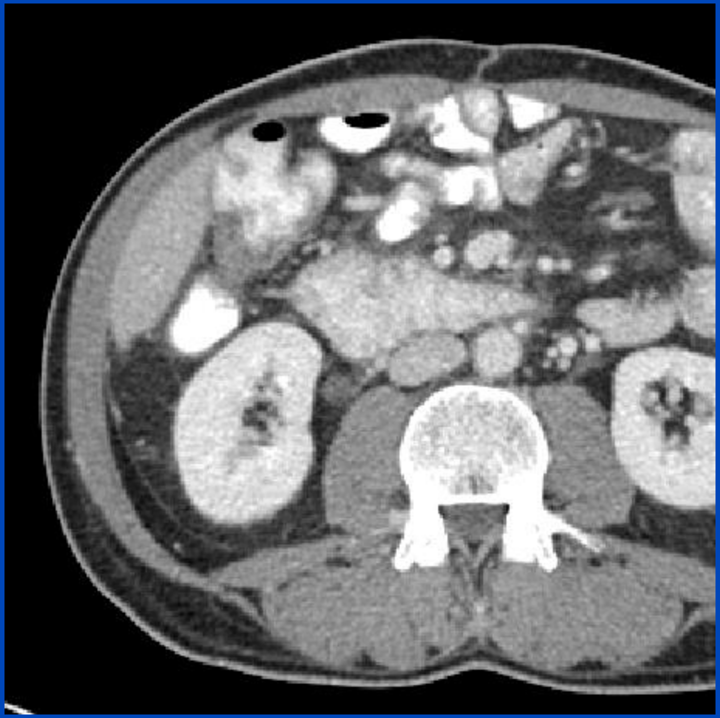
Noise Removal

Denoised low dose

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

Noise Removal





Full dose

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

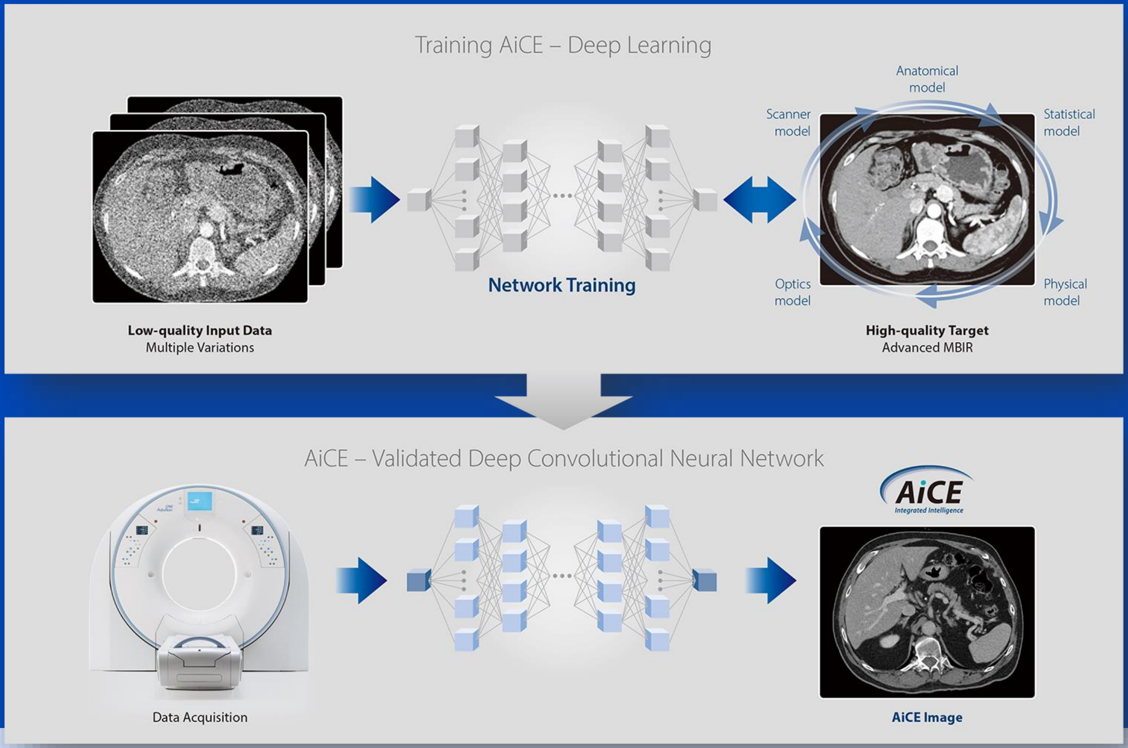
Noise Removal

Denoised full dose

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

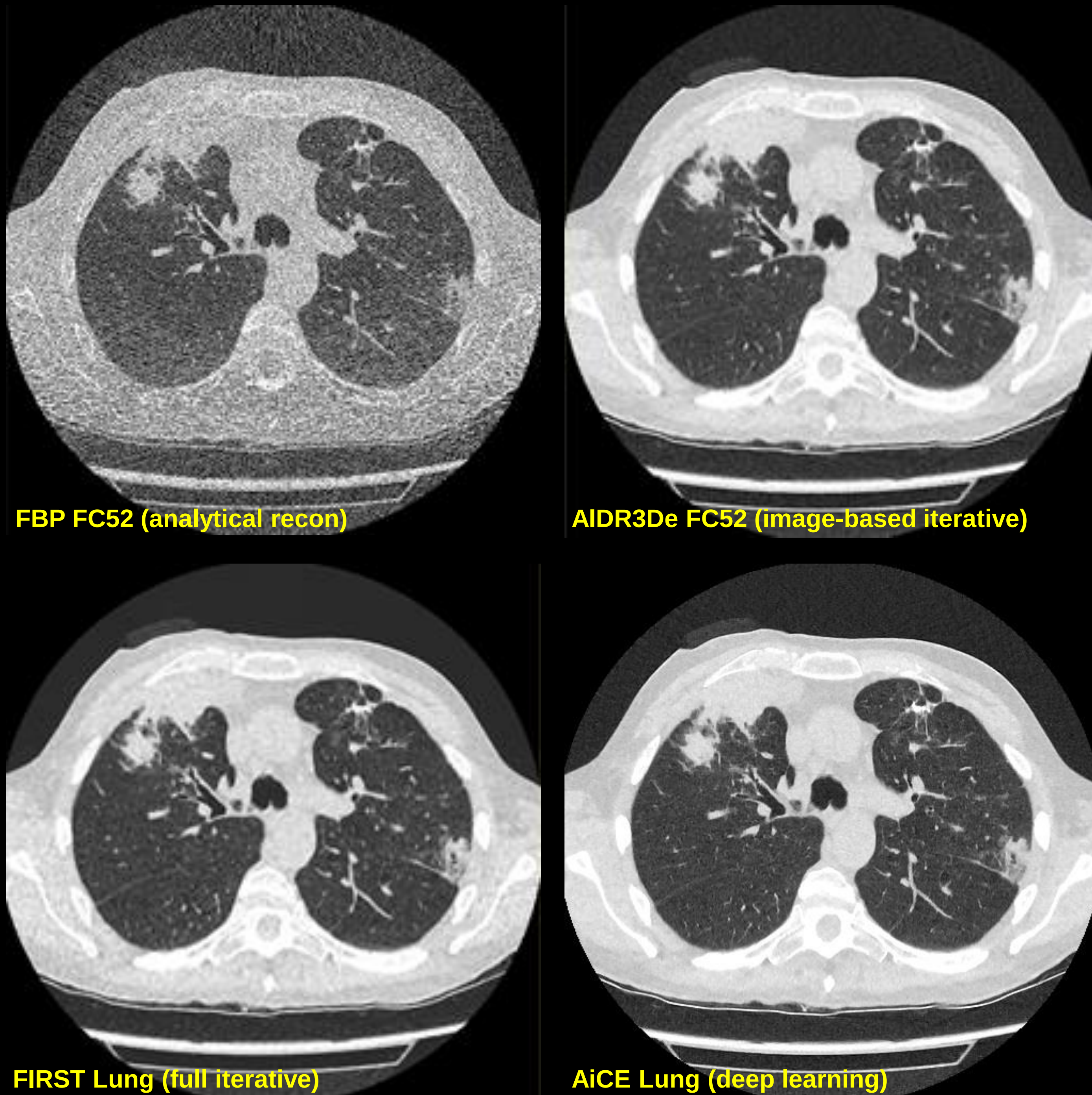
Canon's AiCE

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



Information taken from https://global.medical.canon/products/computed-tomography/aice_dlr

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

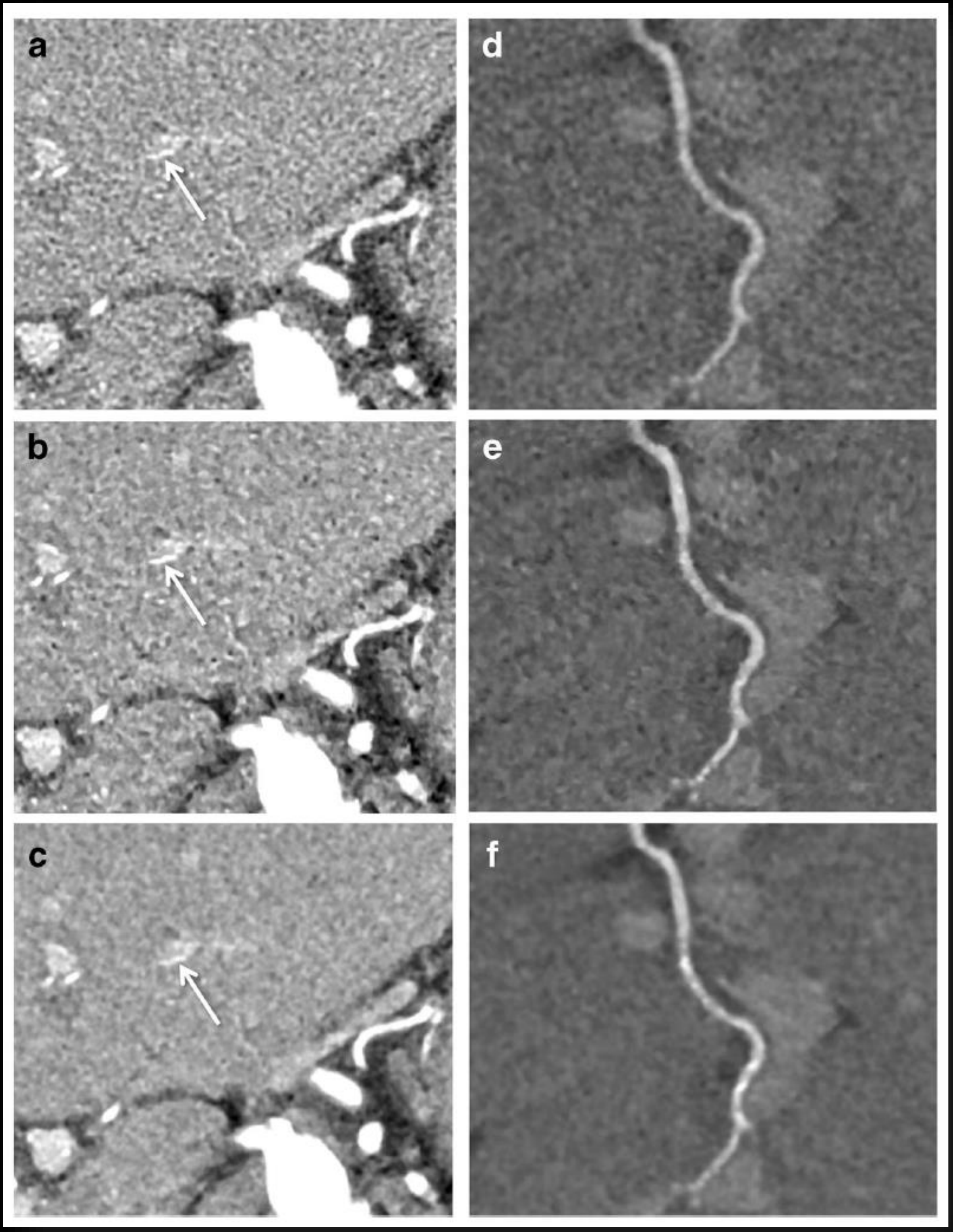


Courtesy of
Radboudumc,
the Netherlands

AIDR 3D

First

AiCE



GE's True Fidelity

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

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

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Jean-Baptiste Thibault[‡], *Charles A. Bouman*[⋆]

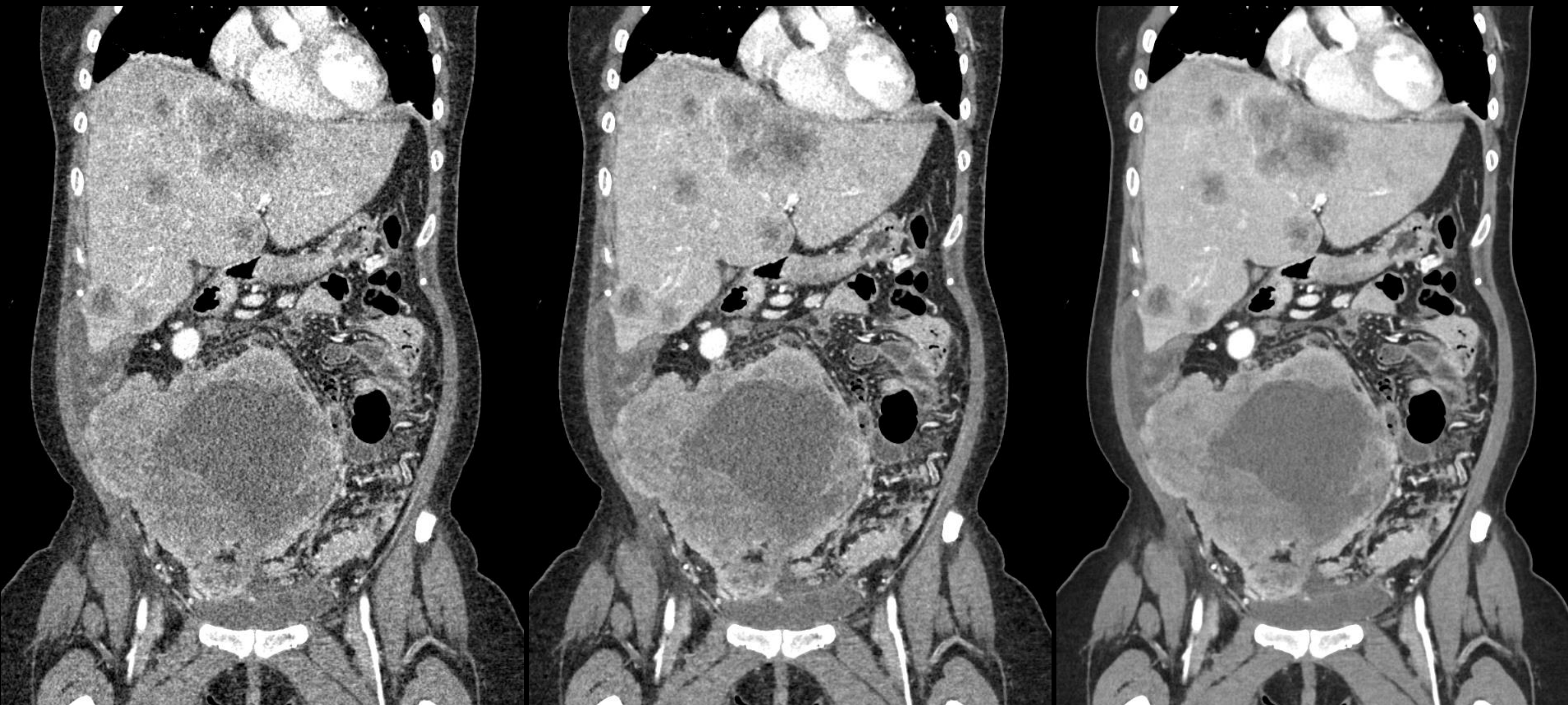
[⋆] Electrical and Computer Engineering at Purdue University
[†] Electrical and Computer Engineering at Marquett University
[‡] GE Healthcare
[⊕] Electrical Engineering at University of Notre Dame

ABSTRACT

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

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

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

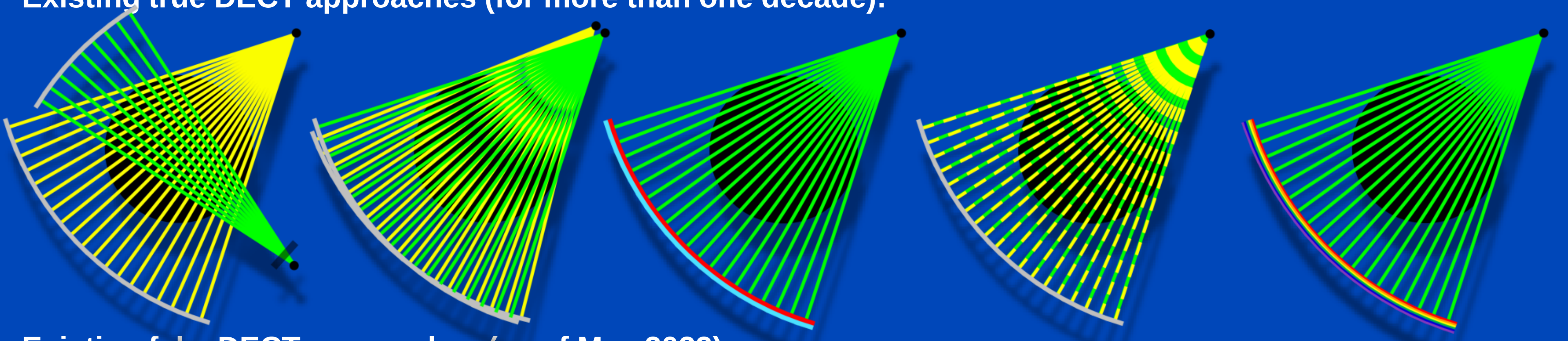


FBP ASIR V 50% True Fidelity

Courtesy of GE Healthcare

True and Fake DECT

Existing true DECT approaches (for more than one decade):



Existing fake DECT approaches (as of May 2022):

[1] J. Ma, Y. Liao, Y. Wang, S. Li, J. He, D. Zeng, Z. Bian, "Pseudo dual energy CT imaging using deep learning-based framework: basic material estimation", *SPIE Medical Imaging 2018*.

[2] W. Zhao, T. Lv, P. Gao, L. Shen, X. Dai, K. Cheng, M. Jia, Y. Chen, L. Xing, "A deep learning approach for dual-energy CT imaging using a single-energy CT data", *Fully3D 2019.*

[3] D. Lee, H. Kim, B. Choi, H. J. Kim, "Development of a deep neural network for generating synthetic dual-energy chest x-ray images with single x-ray exposure", PMB 64(11), 2019.

[4] L. Yao, S. Li, D. Li, M. Zhu, Q. Gao, S. Zhang, Z. Bian, J. Huang, D. Zeng, J. Ma, "Leveraging deep generative model for direct energy-resolving CT imaging via existing energy-integrating CT images", *SPIE Medical Imaging 2020*.

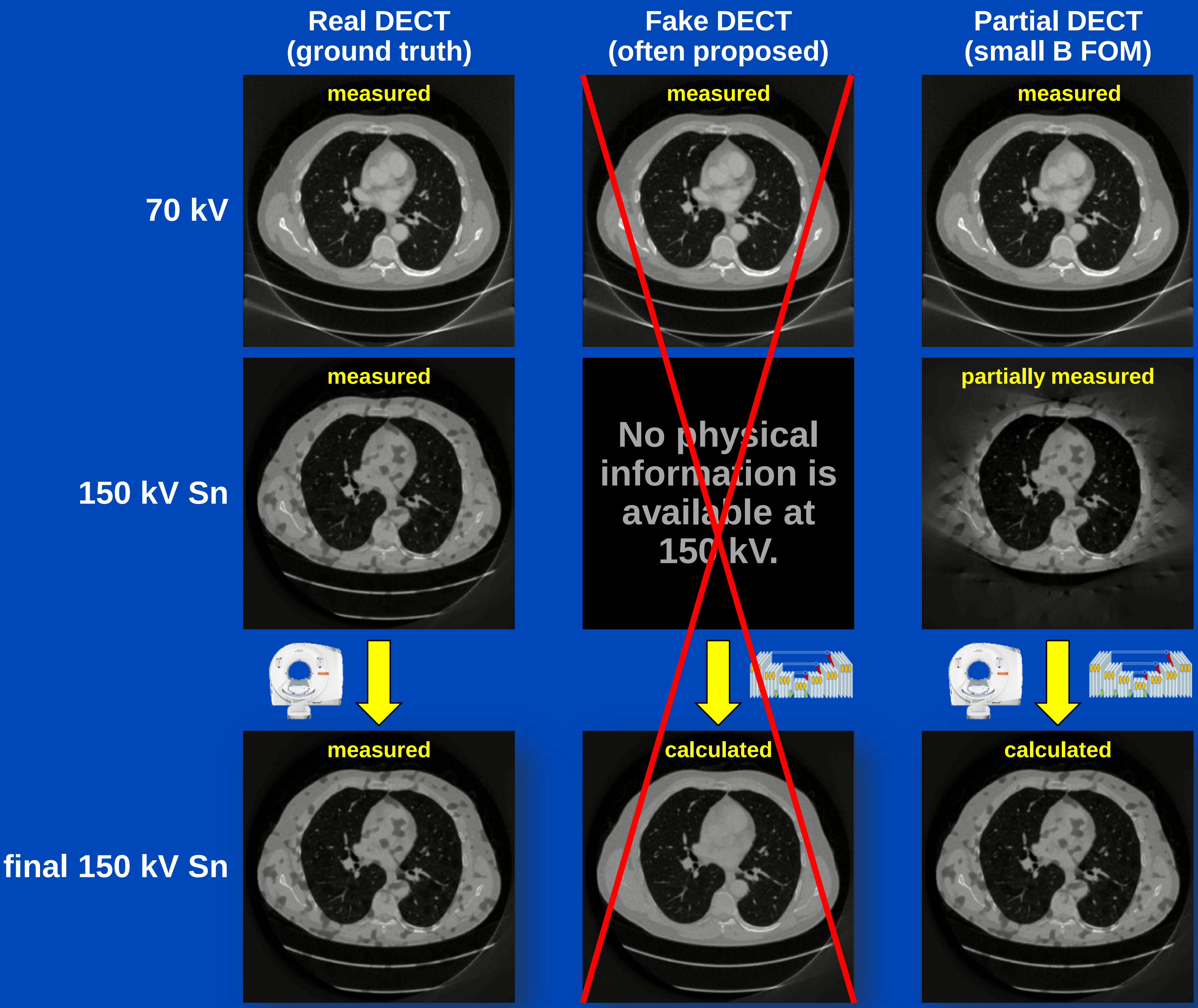
[5] D. P. Clark, F. R. Schwartz, D. Marin, J. C. Ramirez-Giraldo, C. T. Badea, "Deep learning based spectral extrapolation for dual-source, dual-energy x-ray CT", Med. Phys. 47 (9): 4150–4163, 2020.

[6] C. K. Liu, C. C. Liu, C. H. Yang, H. M. Huang, "Generation of brain dual-energy CT from single-energy CT using deep learning", Journal of Digital Imaging 34(1):149–161, 2021.

[7] T. Lyu, W. Zhao, Y. Zhu, Z. Wu, Y. Zhang, Y. Chen, L. Luo, S. Li, L. Xing, "Estimating dual-energy CT imaging from single-energy CT data with material decomposition convolutional neural network", Medical Image Analysis 70:1–10, 2021.

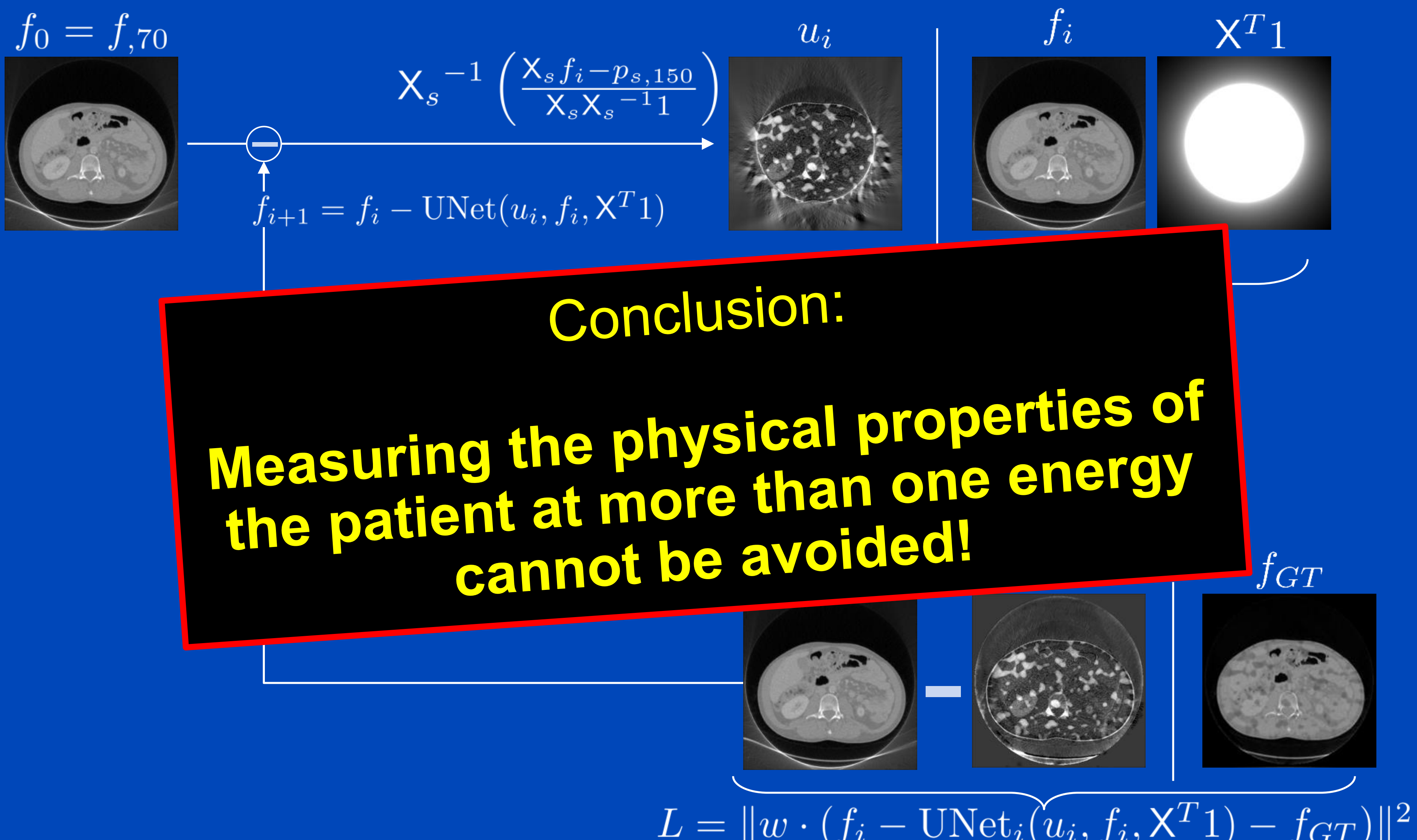
[8] F. R. Schwartz, D. P. Clark, Y. Ding, J. C. Ramirez-Giraldo, C. T. Badea, D. Marin, "Evaluating renal lesions using deep-learning based extension of dual-energy FoV in dual-source CT—A retrospective pilot study", European Journal of Radiology 139:109734, 2021.

[9] Y. Li, X. Tie, K. Li, J. W. Garrett, G.-H. Chen, "Deep-En-Chroma: mining the spectral fingerprints in single-kV CT acquisitions using energy integration detectors", *SPIE Medical Imaging 2022*.



Real DECT
(ground truth)
Fake DECT
(often proposed)
Partial DECT
(small B FOM)
70 kV
150 kV Sn
final 150 kV Sn
measured
measured
measured
measured
partially measured
No physical information is available at 150 kV.
measured
calculated
calculated

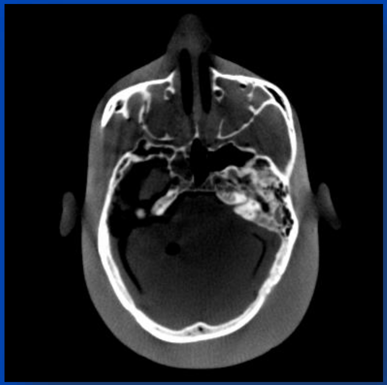
Algorithm for Partial DECT



Conclusion:

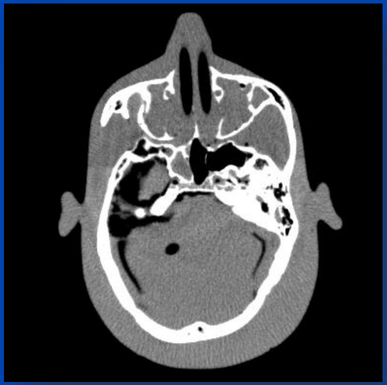
Measuring the physical properties of the patient at more than one energy cannot be avoided!

Deep Scatter Estimation



???

In real time?

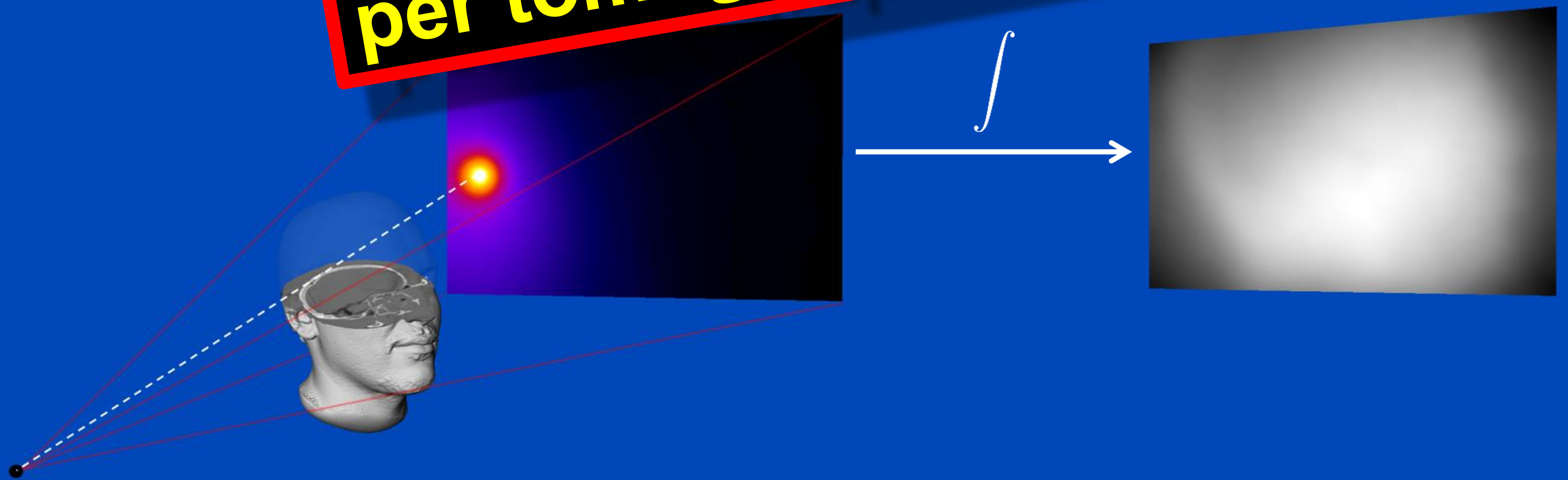


Monte Carlo Scatter Estimation

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

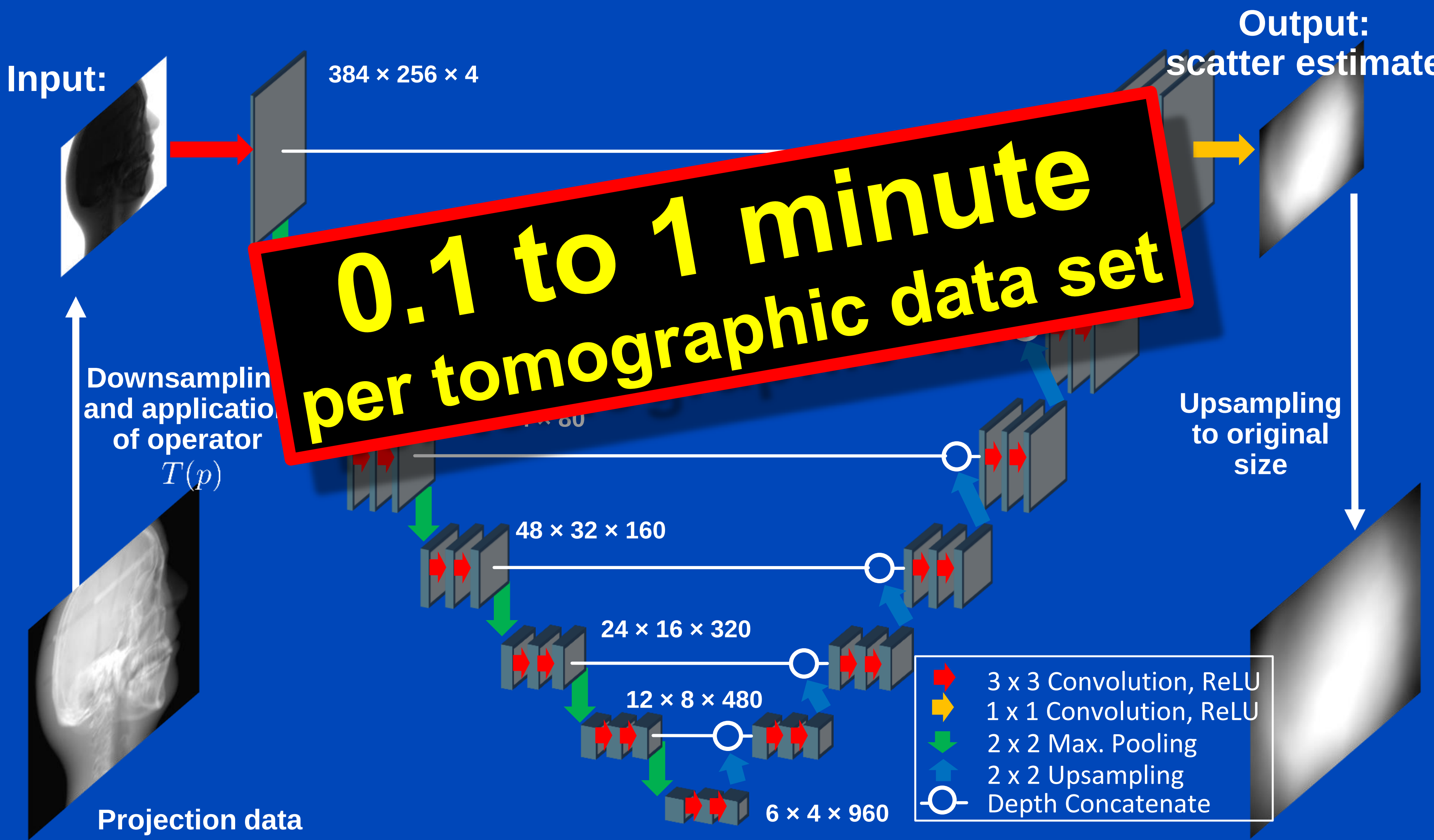
1 to 10 hours per tomographic data set

…mplete scatter distribution



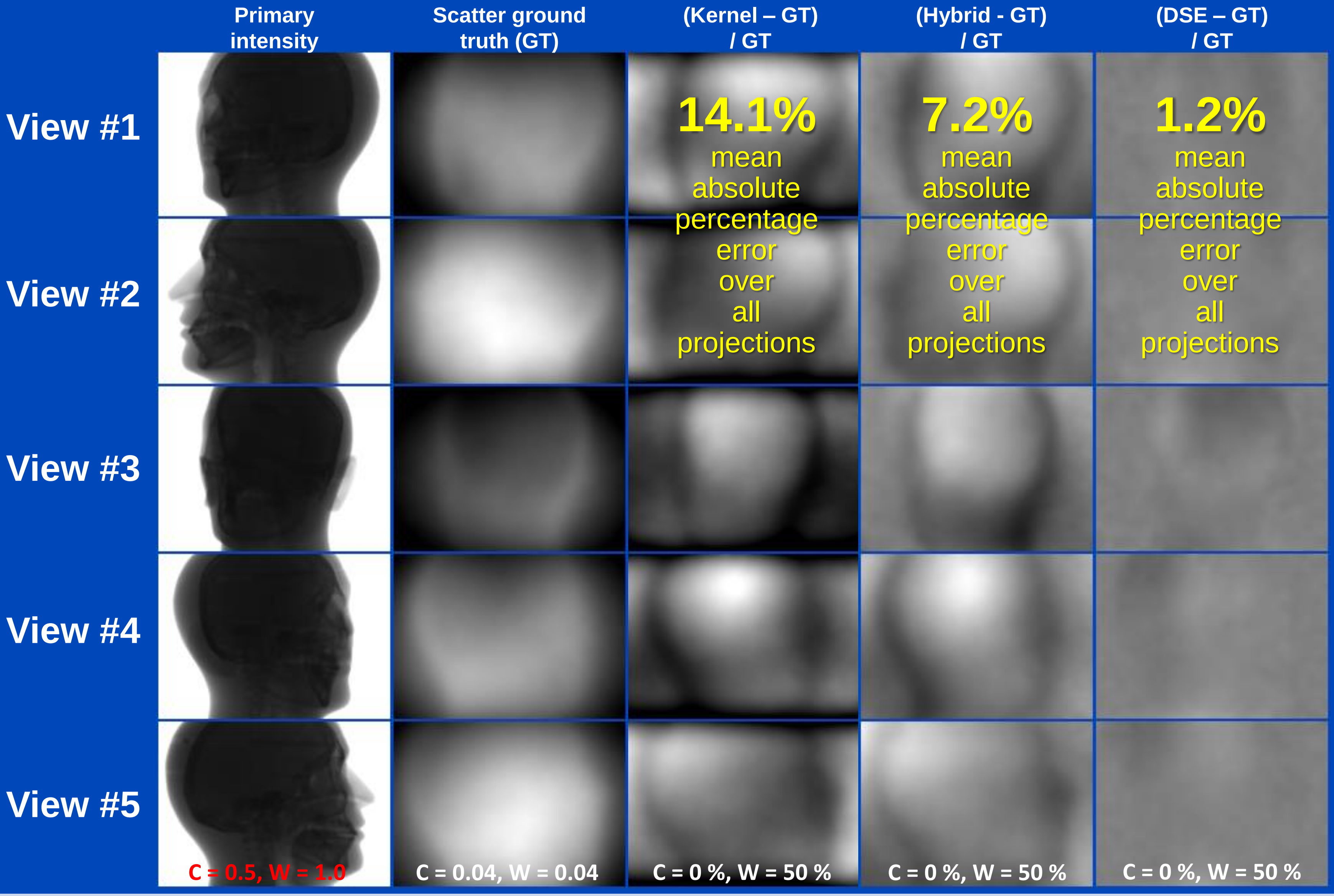
Deep Scatter Estimation

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.

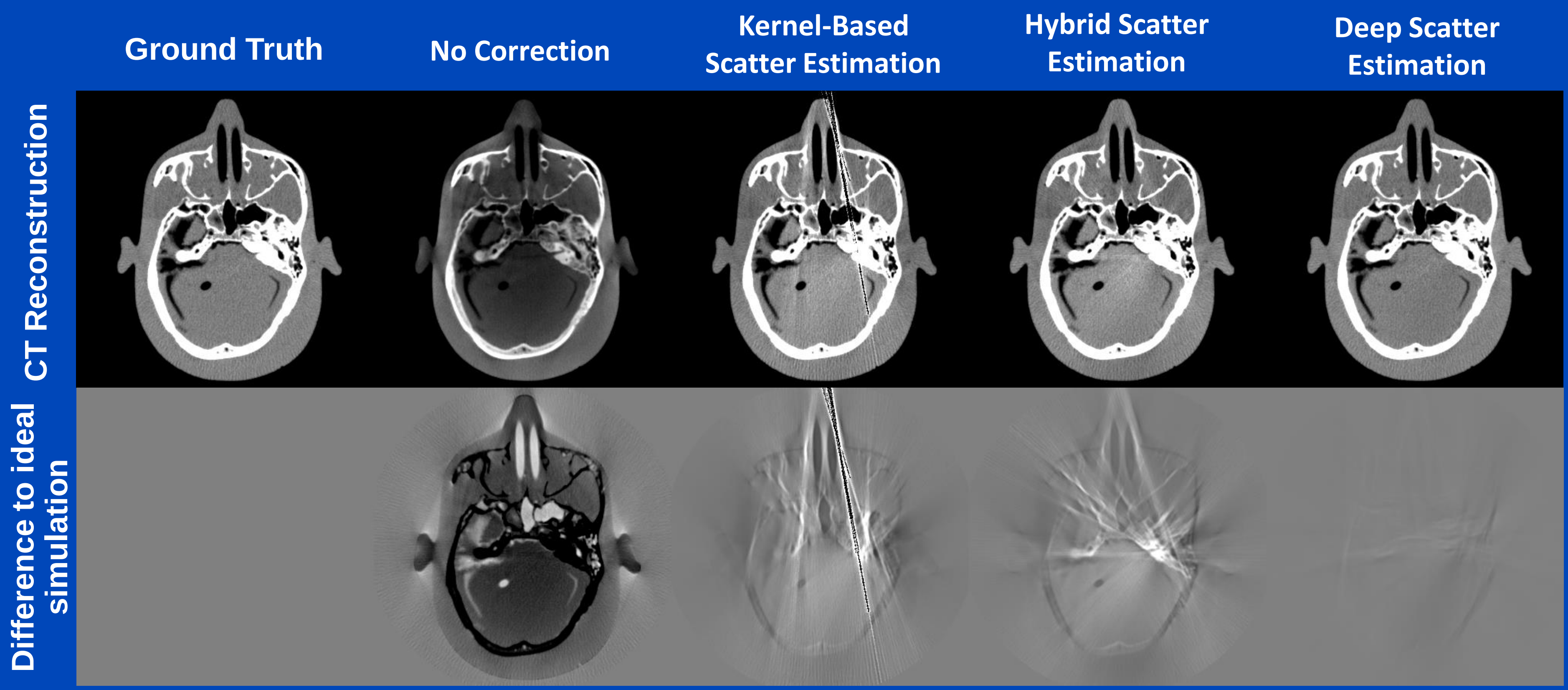
Results on Simulated Projection Data



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

dkfz.

Reconstructions of Simulated Data

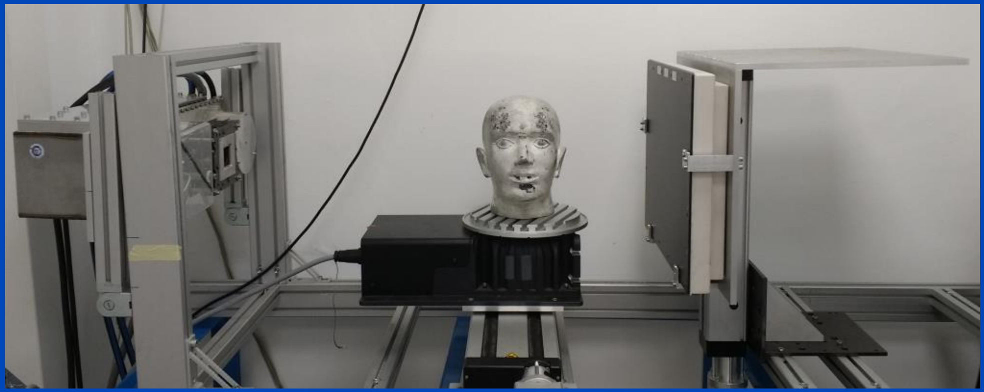


C = 0 HU, W = 1000 HU

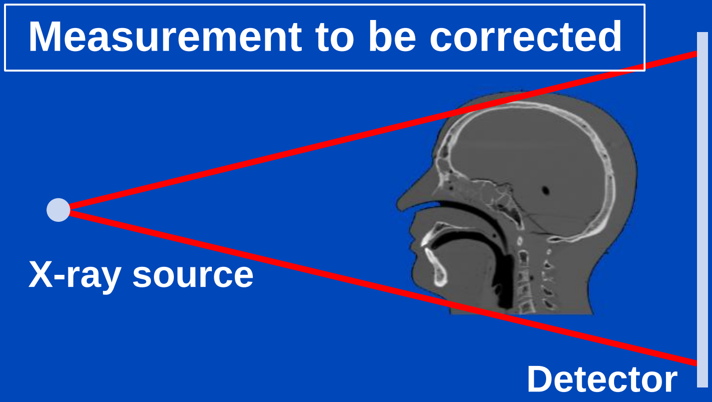
J. Maier, M. Kachelrieß et al. Deep scatter estimation (DSE). SPIE 2017 and Journal of Nondestructive Evaluation 37:57, July 2018.
J. Maier, M. Kachelrieß et al. Robustness of DSE. Med. Phys. 46(1):238-249, January 2019.

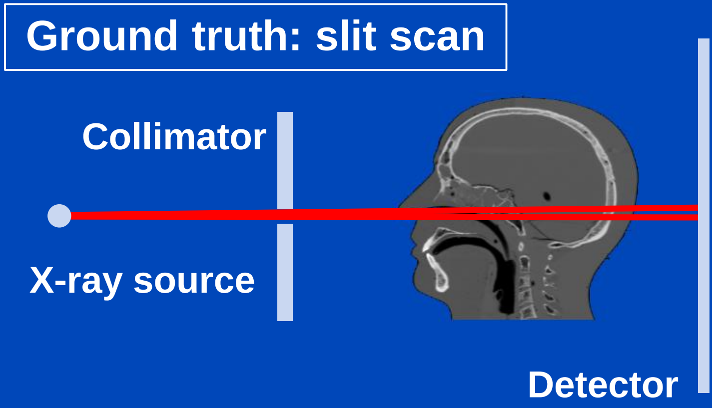
Testing of the DSE Network for Measured Data (120 kV)

DKFZ table-top CT



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





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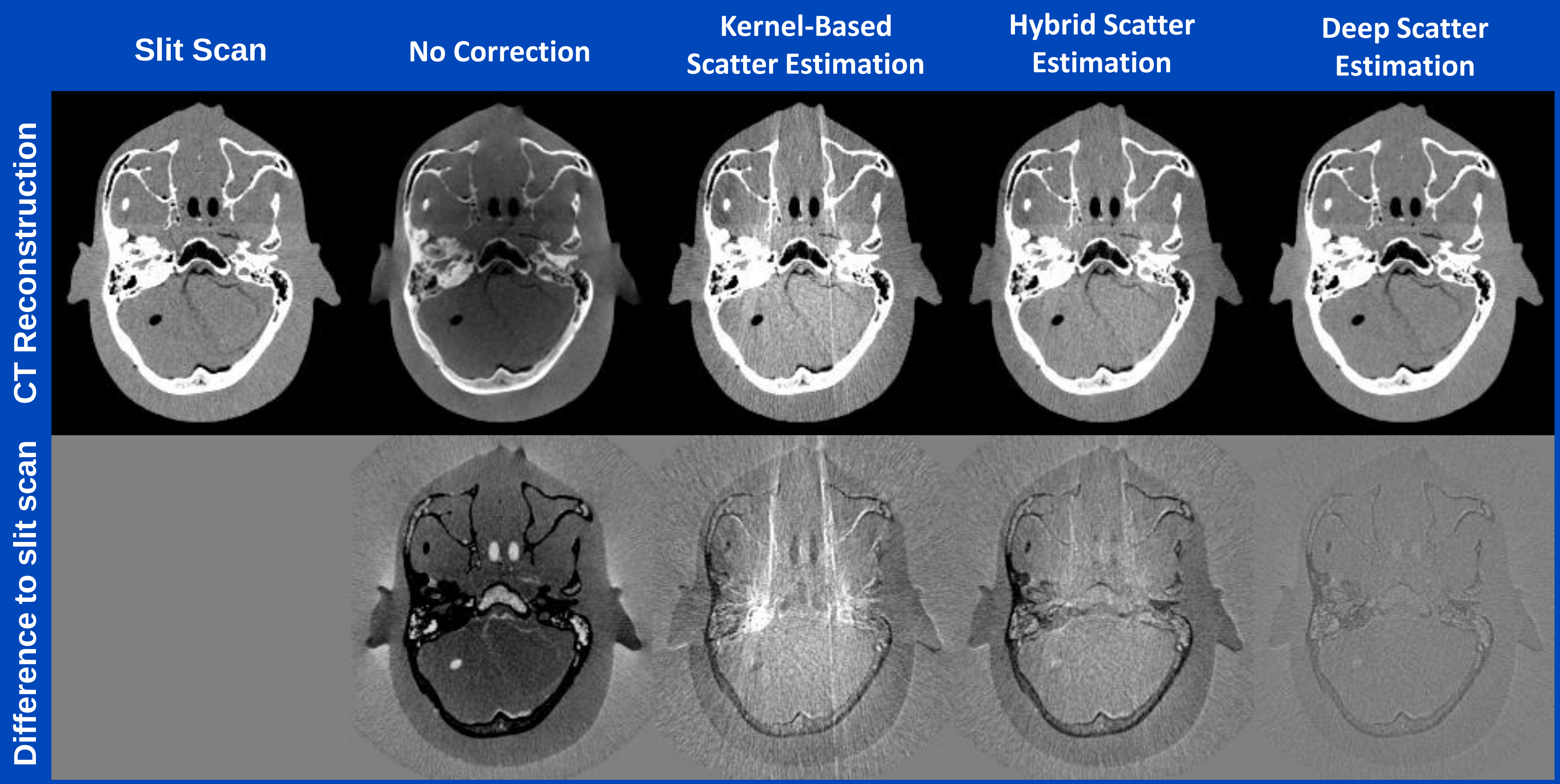
J. Maier, M. Kachelrieß et al. Robustness of DSE. Med. Phys. 46(1):238-249, January 2019.

dkfz.

Reconstructions of Measured Data

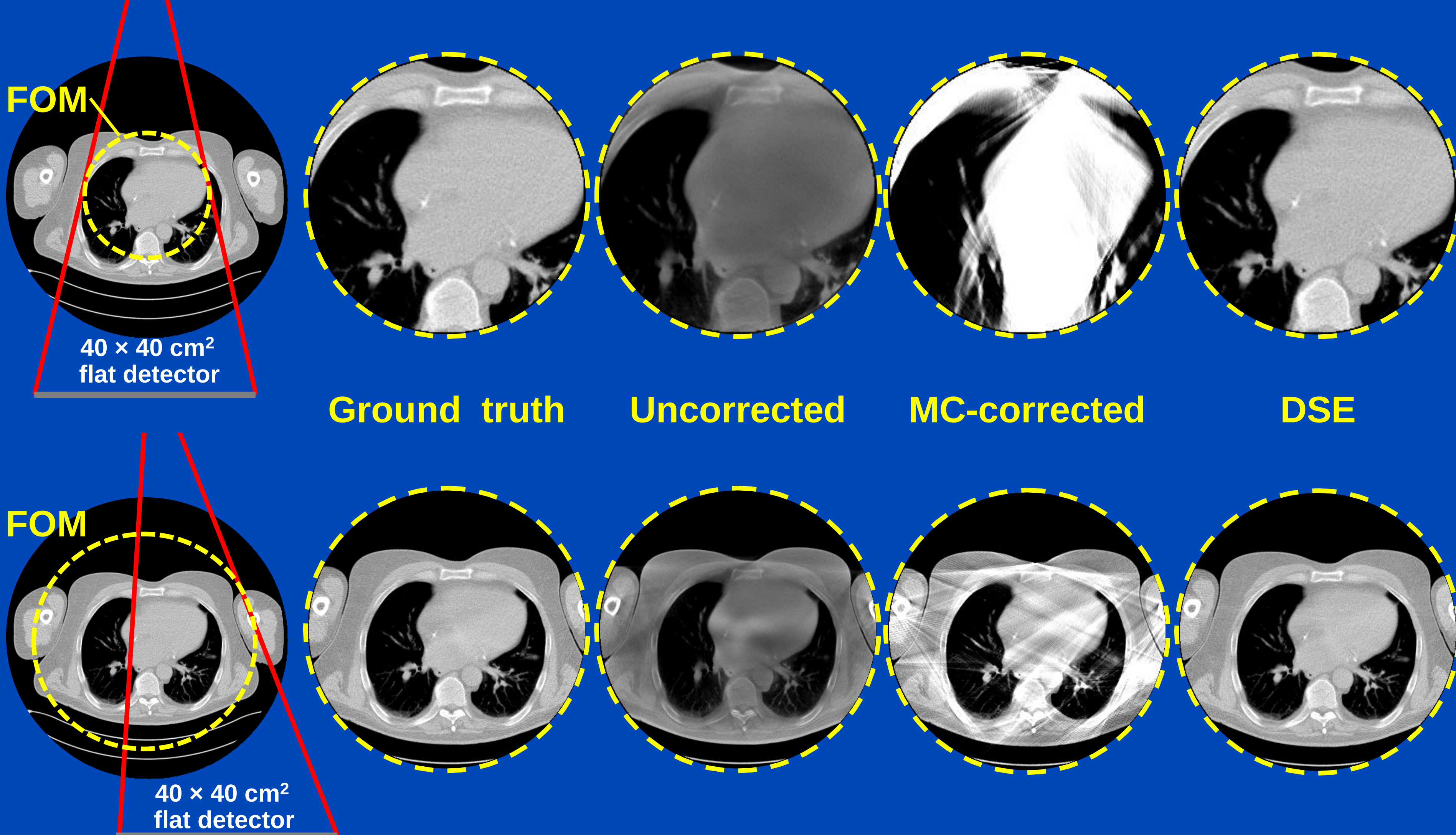


C = 0 HU, *W* = 1000 HU

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

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

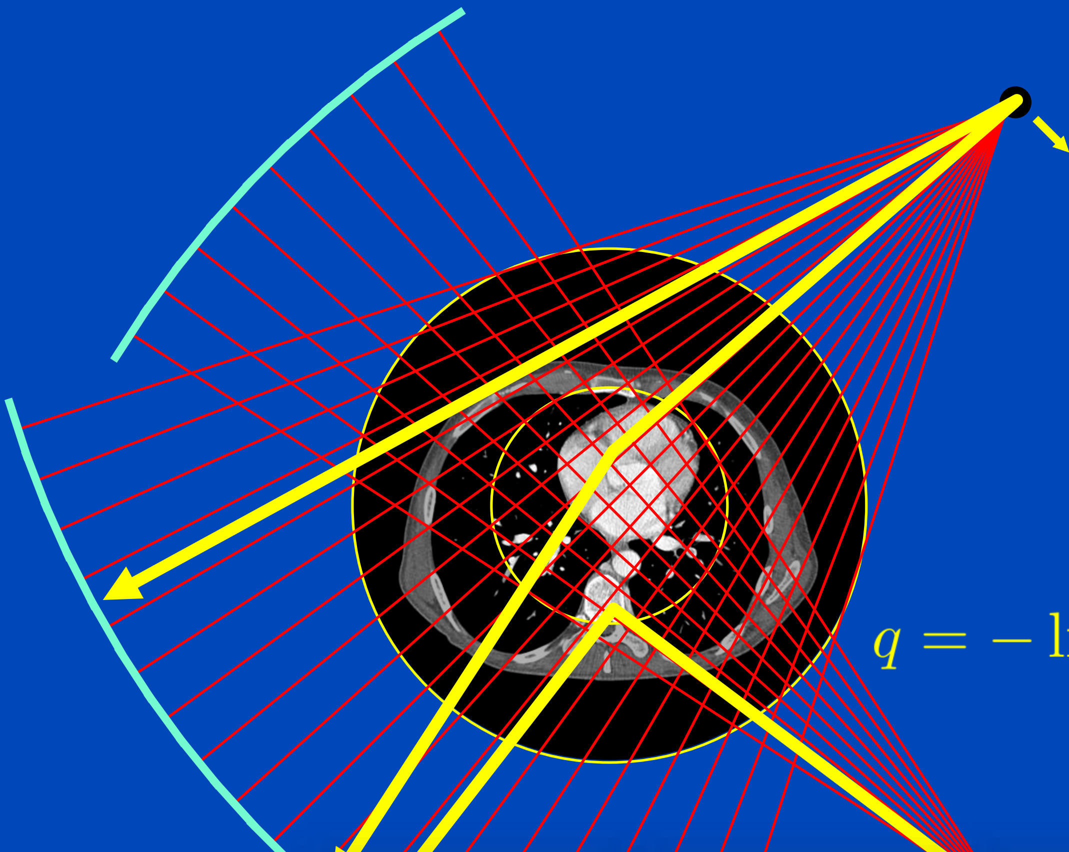
Truncated DSE[1,2]



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

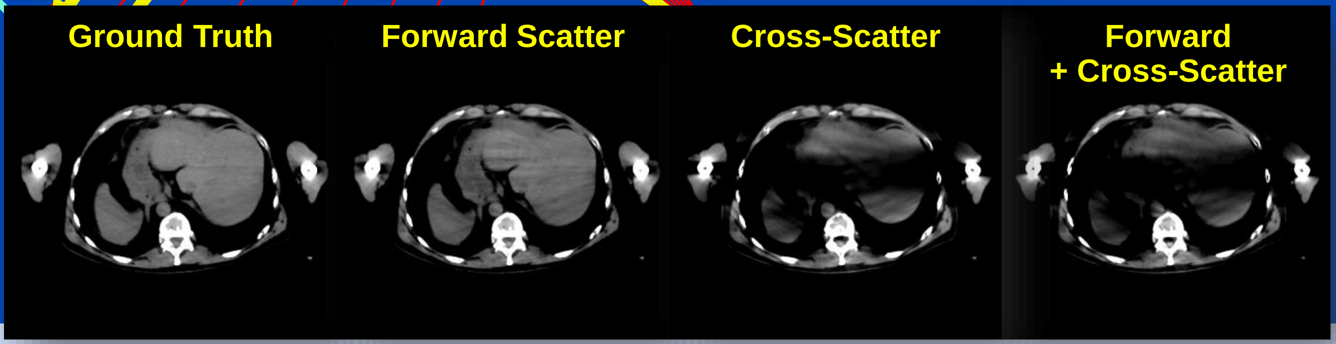
[1] J. Maier, M. Kachelrieß et al. Deep scatter estimation (DSE) for truncated cone-beam CT (CBCT). RSNA 2018.
[2] J. Maier, M. Kachelrieß et al. Robustness of DSE. Med. Phys. 46(1):238-249, January 2019.

Scatter in Dual Source CT (DSCT)



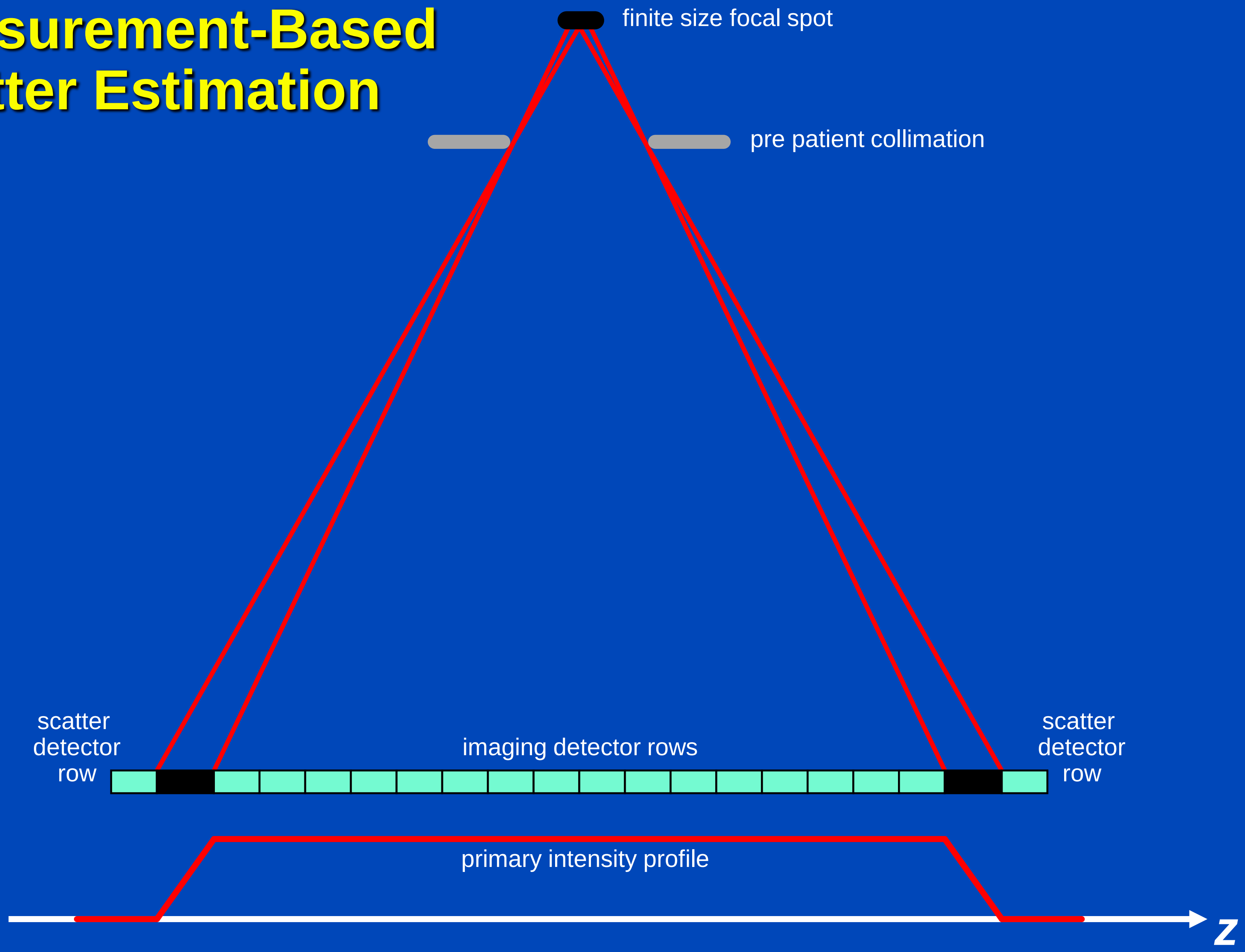
Siemens SOMATOM Force
dual source cone-beam spiral CT

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



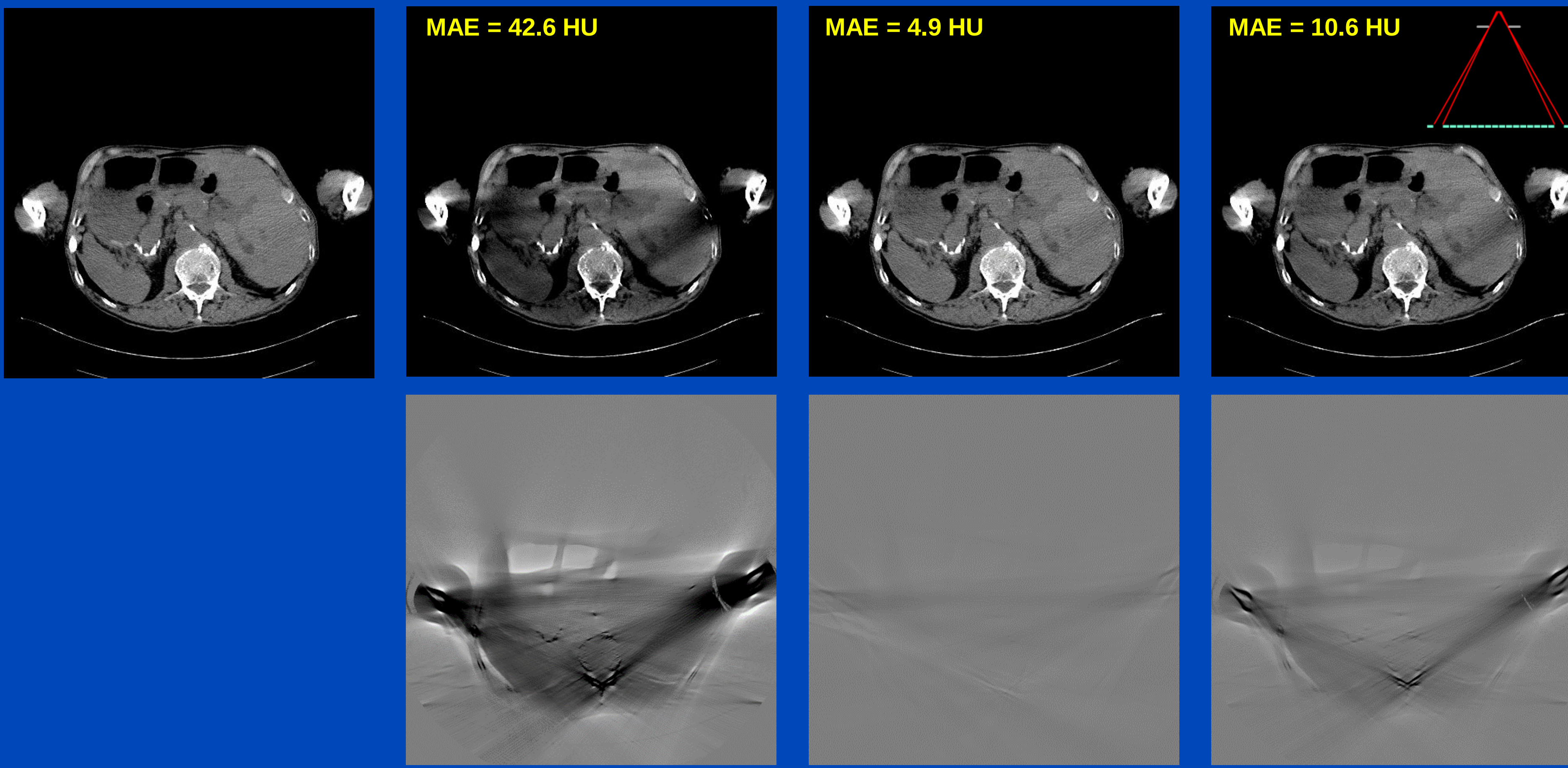
C = 40 HU, W = 300 HU, with 2D anti-scatter grid

Measurement-Based Scatter Estimation



Cross-DSE

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

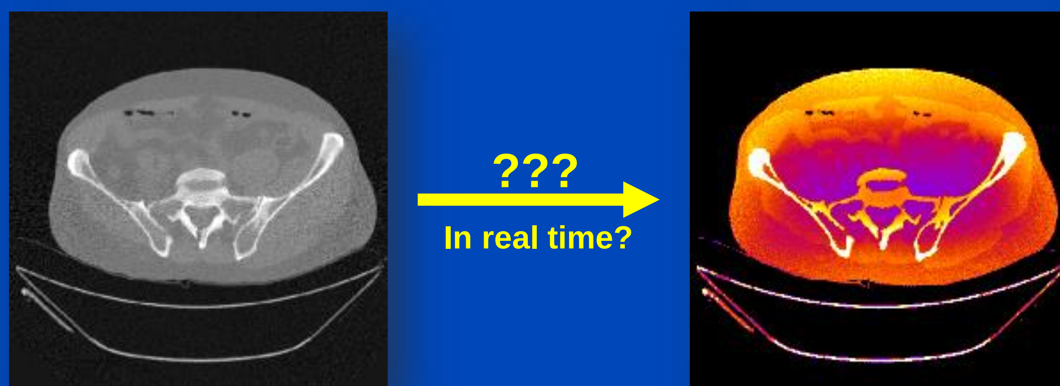
J. Erath, T. Vöth, J. Maier, E. Fournié, M. Petersilka, K. Stierstorfer, and M. Kachelrieß. Deep learning-based forward and cross-scatter correction in dual source CT. Med. Phys. 48:4824–4842, July 2021.

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.
- Facts:
  - DSE can estimate scatter from a single (!) x-ray 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.

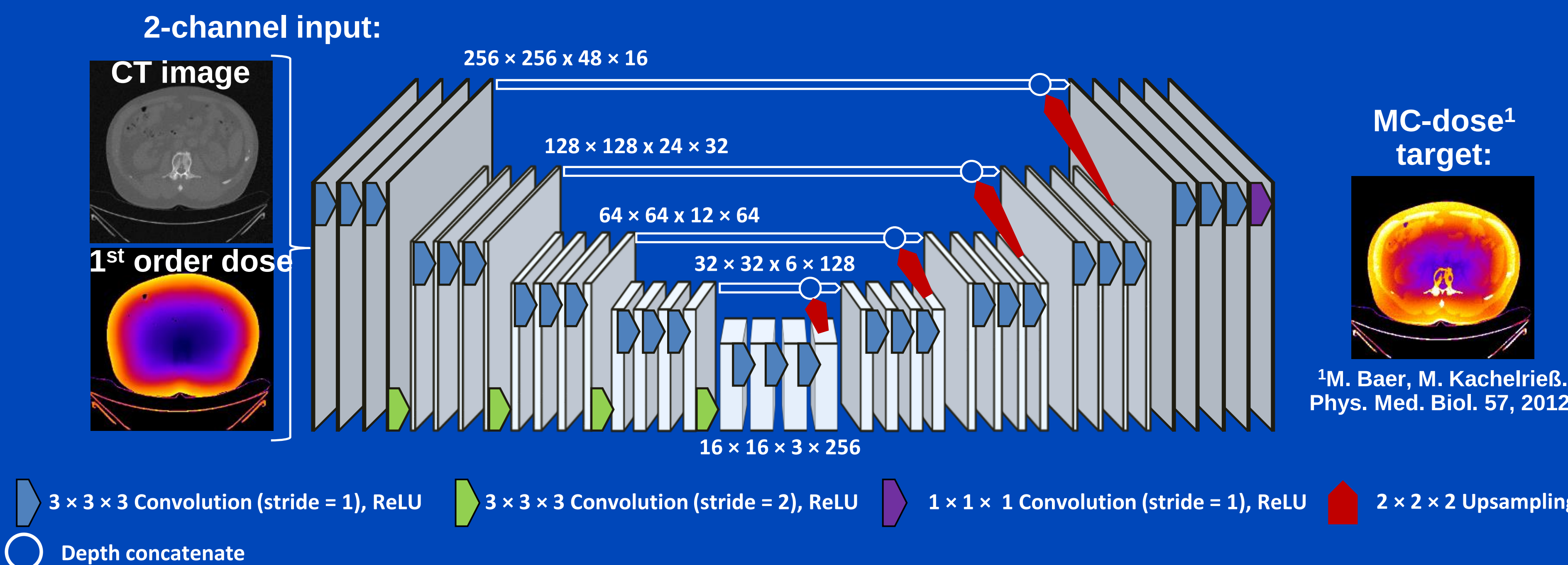
Interested in DSE for photon counting CT?
See first talk in session
RPS 2313, Sunday 9:30, Room Z.

Deep Dose Estimation



Deep Dose Estimation (DDE)

- Combine fast and accurate CT dose estimation using a deep convolutional neural network.
- Train the network to reproduce MC dose estimates given the CT image and a first-order dose estimate.



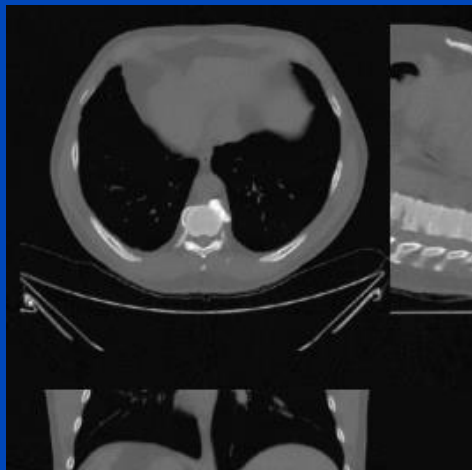
[1]M. Baer, M. Kachelrieß. Phys. Med. Biol. 57, 2012.

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

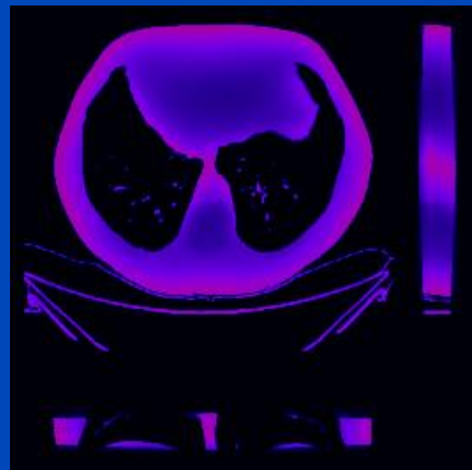
Results

Thorax, tube A, 120 kV, with bowtie

CT image



First order dose

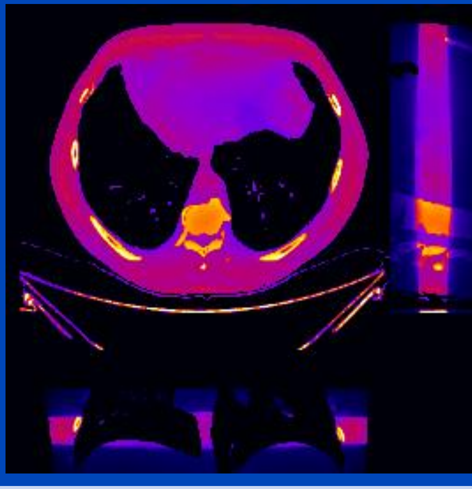


	MC	DDE
48 slices	1 h	0.25 s
whole body	20 h	5 s

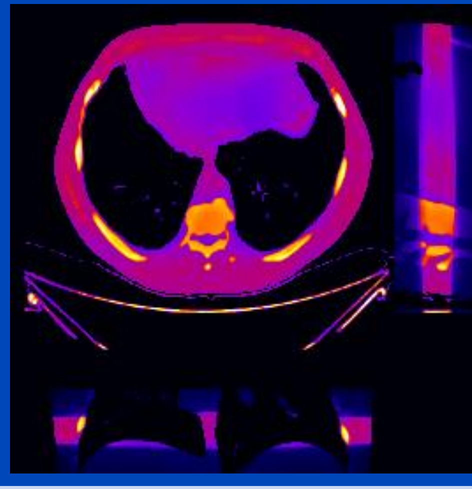
MC uses 16 CPU kernels
DDE uses one Nvidia Quadro P600 GPU

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

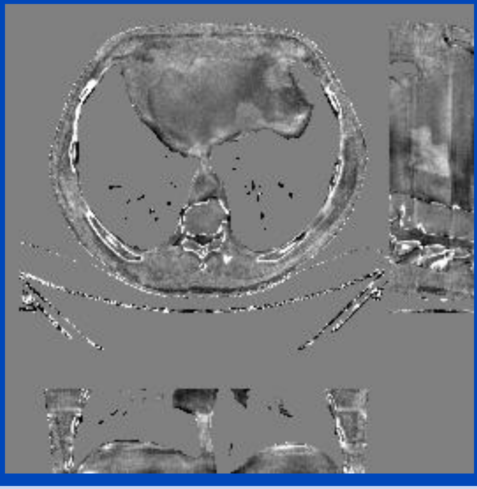
MC ground truth



DDE



Relative error



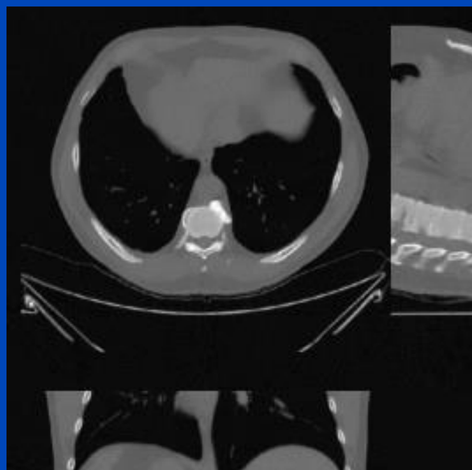
C = 0%
W = 40%

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

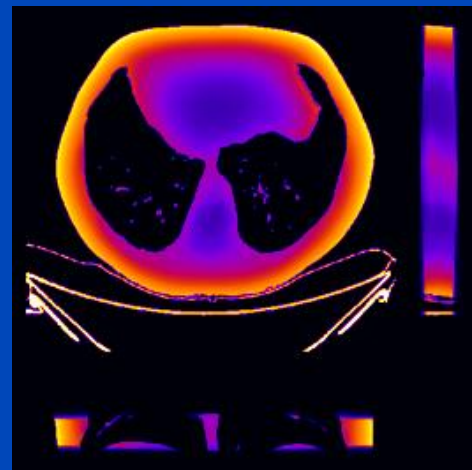
Results

Thorax, tube A, 120 kV, no bowtie

CT image



First order dose



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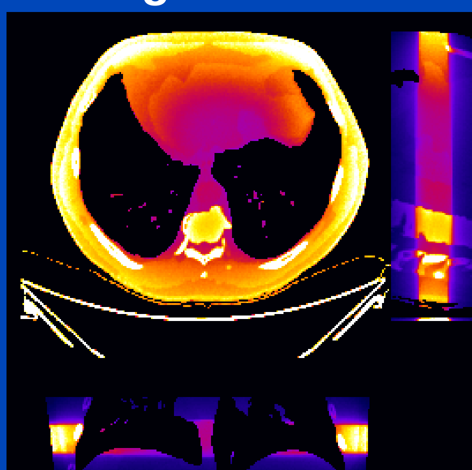
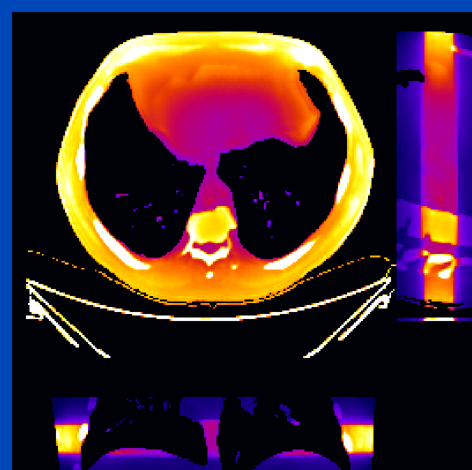
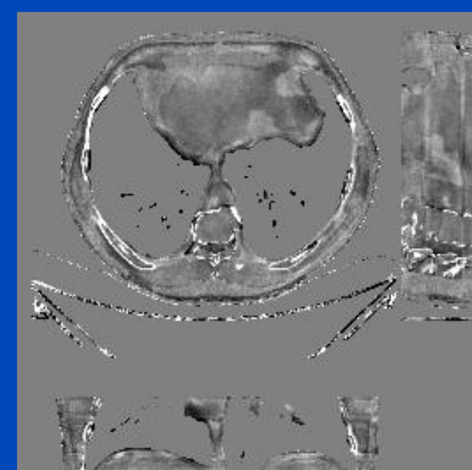
MC ground truth



DDE



Relative error



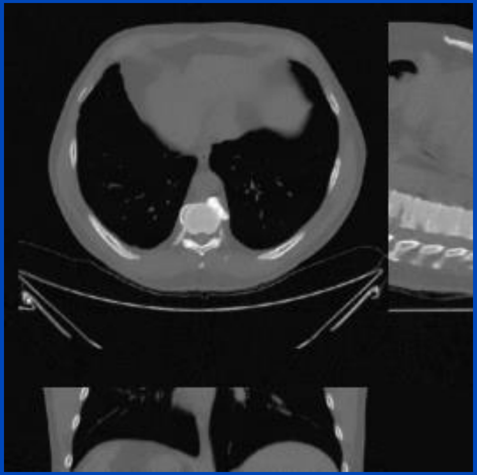
C = 0%
W = 40%

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

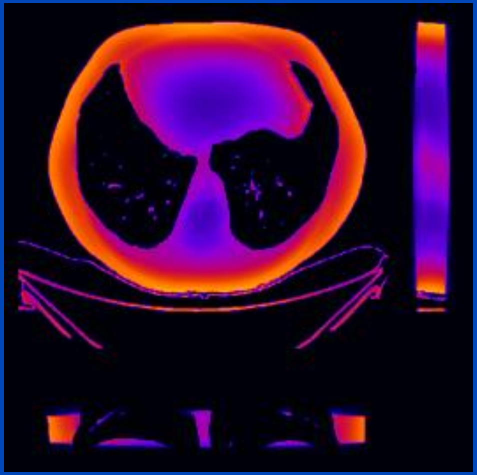
Results

Thorax, tube B, 120 kV, no bowtie

CT image



First order dose

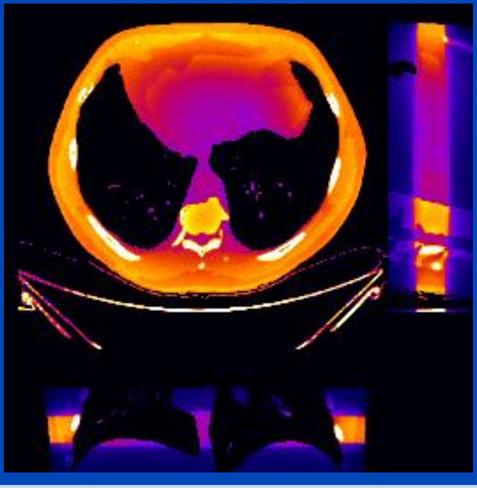


	MC	DDE
48 slices	1 h	0.25 s
whole body	20 h	5 s

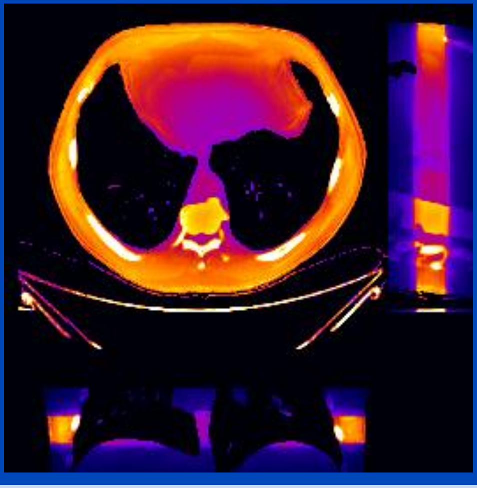
MC uses 16 CPU kernels
DDE uses one Nvidia Quadro P600 GPU

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

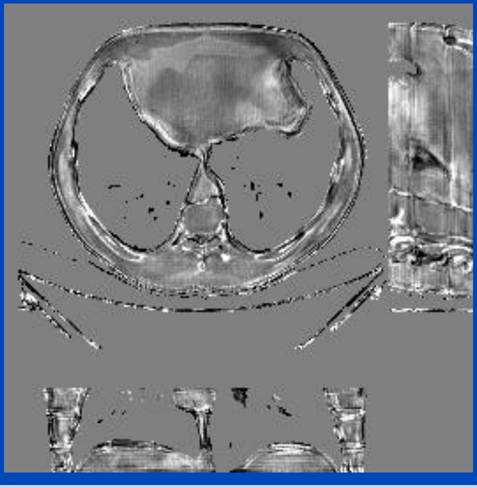
MC ground truth



DDE



Relative error



C = 0%
W = 40%

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

dkfz.

Conclusions on DDE

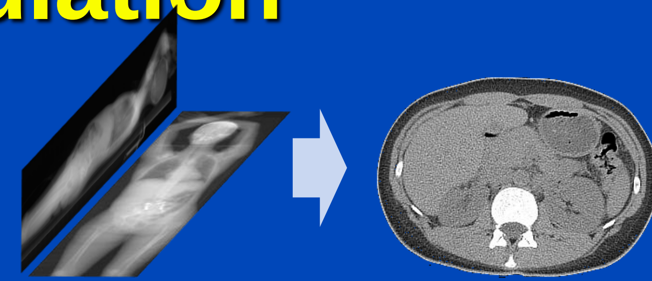
- DDE provides accurate dose predictions
  - for circle scans
  - for sequence scans
  - for partial scans (less than 360°)
  - for limited angle scans (less than 180°)
  - for spiral scans
  - for different tube voltages
  - for scans with and without bowtie filtration
  - for scans with tube current modulation
- In practice it may therefore be not necessary to perform separate training runs for these cases.
- Thus, accurate real-time patient dose estimation may become feasible with DDE.

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

Patient Risk-Minimizing Tube Current Modulation

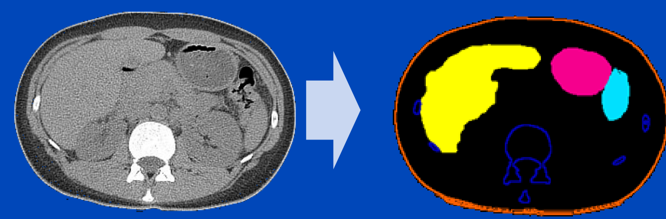
1. Coarse reconstruction from two scout views

– E.g. X. Ying, et al. X2CT-GAN: Reconstructing CT from biplanar x-rays with generative adversarial networks. CVPR 2019.



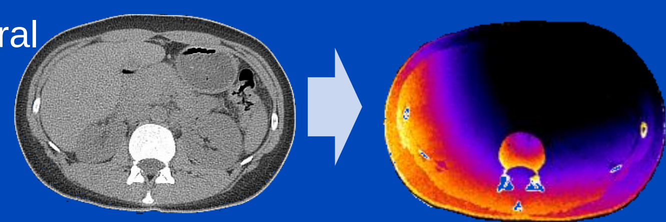
2. Segmentation of radiation-sensitive organs

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



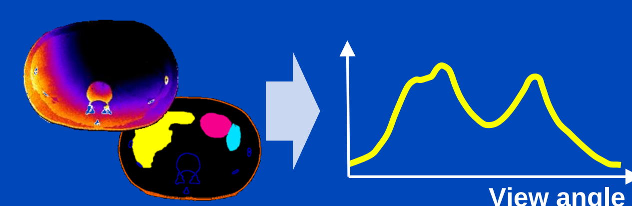
3. Calculation of the effective dose per view using the deep dose estimation (DDE)

– J. Maier, E. Eulig, S. Dorn, S. Sawall and M. Kachelrieß. Real-time patient-specific CT dose estimation using a deep convolutional neural network. IEEE Medical Imaging Conference Record, M-03-178: 3 pages, Nov. 2018.

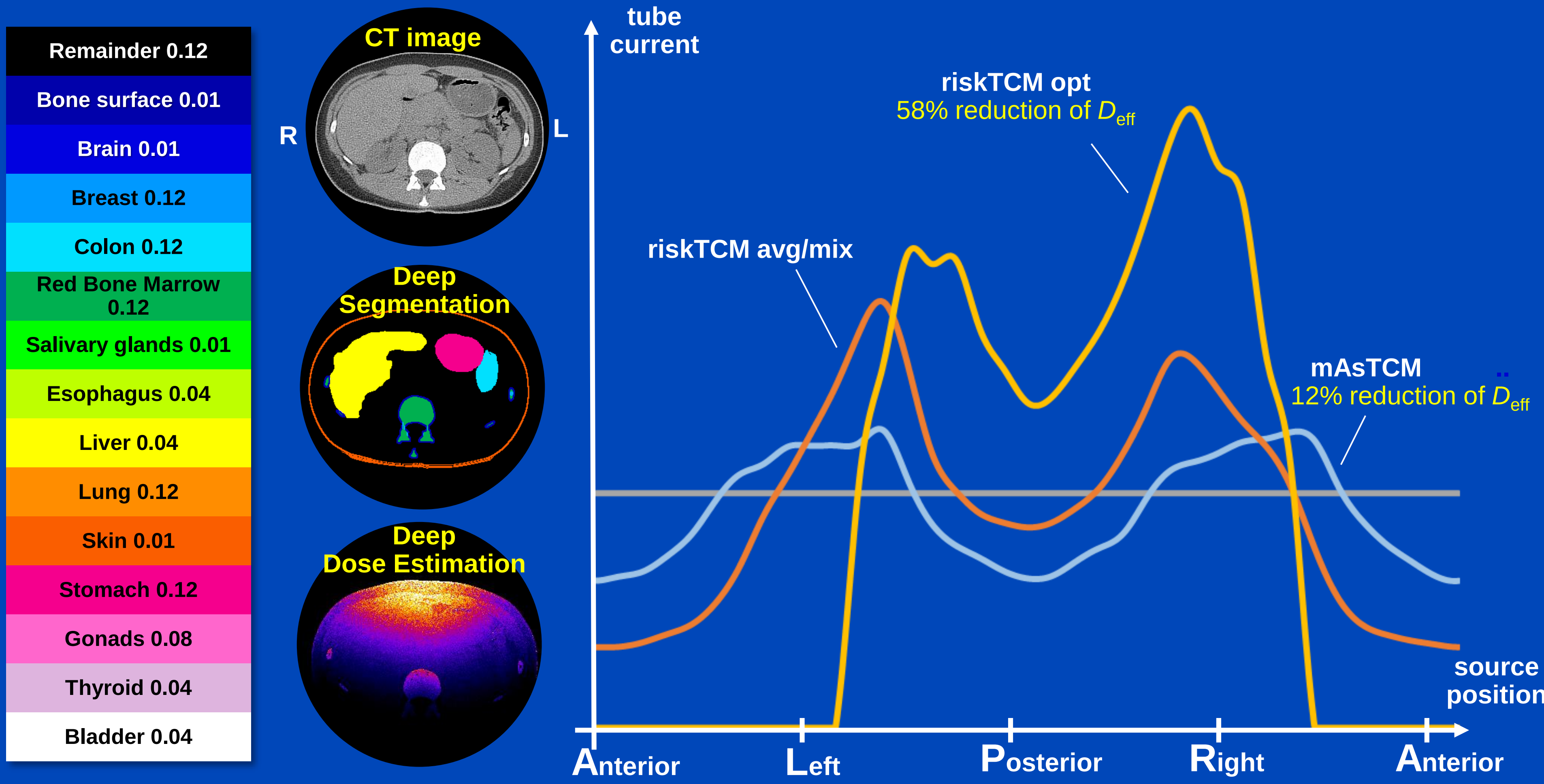


4. Determination of the tube current modulation curve that minimizes the radiation risk

– L. Klein, C. Liu, J. Steidel, L. Enzmann, M. Knaup, S. Sawall, A. Maier, M. Lell, J. Maier, and M. Kachelrieß. Patient-specific radiation risk-based tube current modulation for diagnostic CT. Med. Phys. 49: in press, 2022.

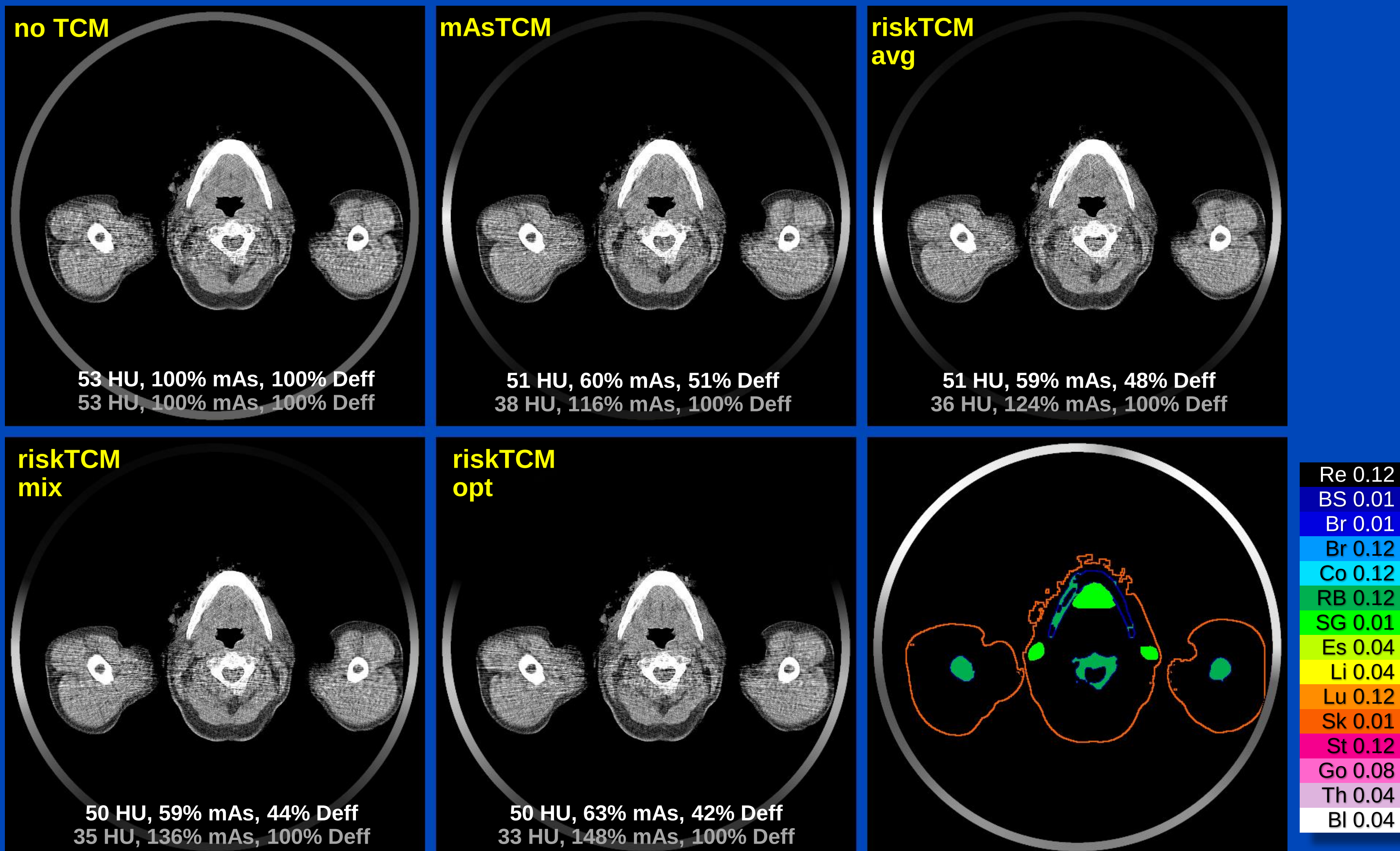


More details see first talk in RPS 1213 Friday 8:00 in Room Z.



L. Klein, C. Liu, J. Steidel, L. Enzmann, M. Knaup, S. Sawall, A. Maier, M. Lell, J. Maier, and M. Kachelrieß.
Patient-specific radiation risk-based tube current modulation for diagnostic CT. Med. Phys. 49: in press, 2022.

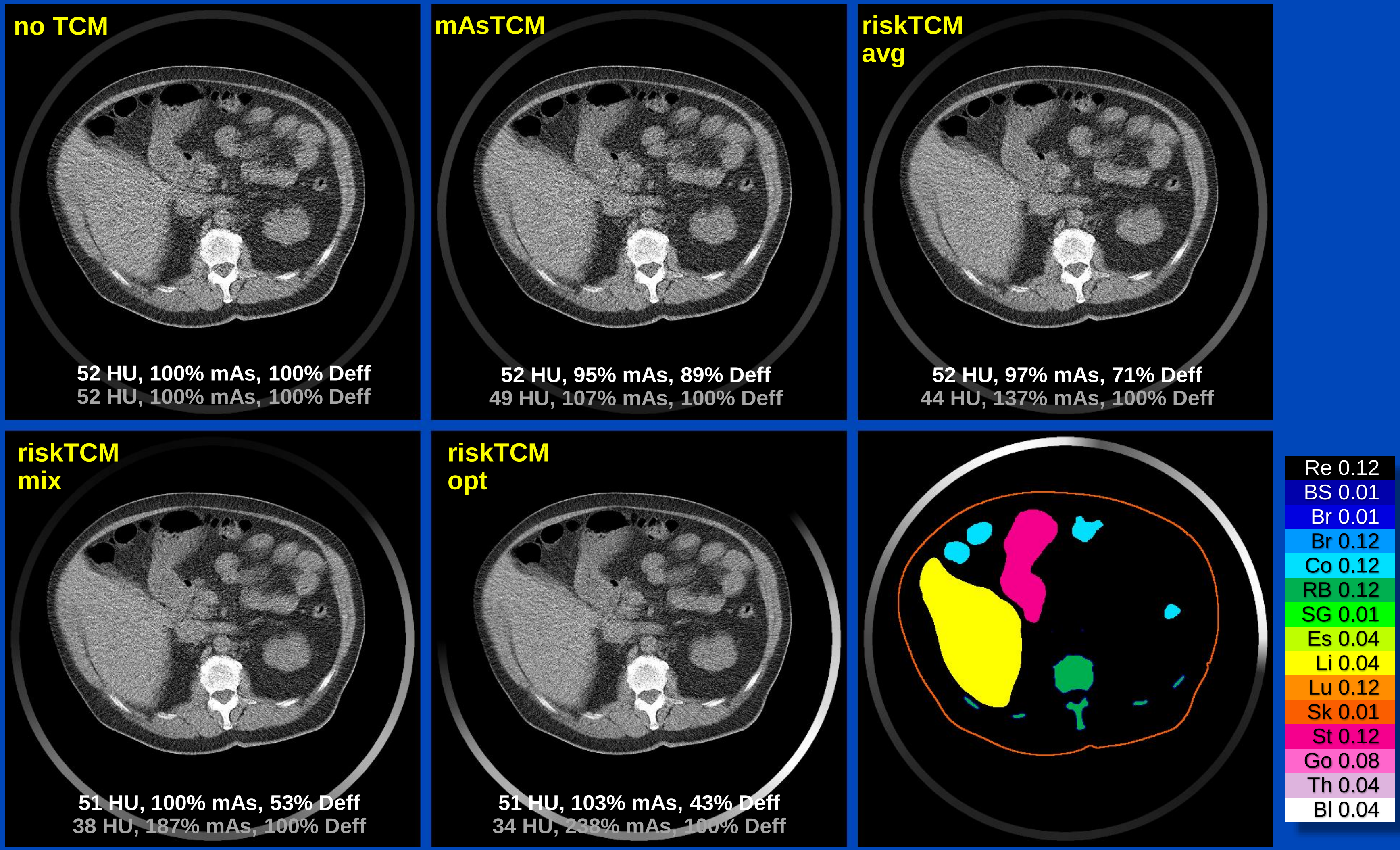
Patient 03 - Neck



C = 25 HU, *W* = 400 HU

L. Klein, C. Liu, J. Steidel, L. Enzmann, M. Knaup, S. Sawall, A. Maier, M. Lell, J. Maier, and M. Kachelrieß.
Patient-specific radiation risk-based tube current modulation for diagnostic CT. Med. Phys. 49: in press, 2022.

Patient 04 - Abdomen

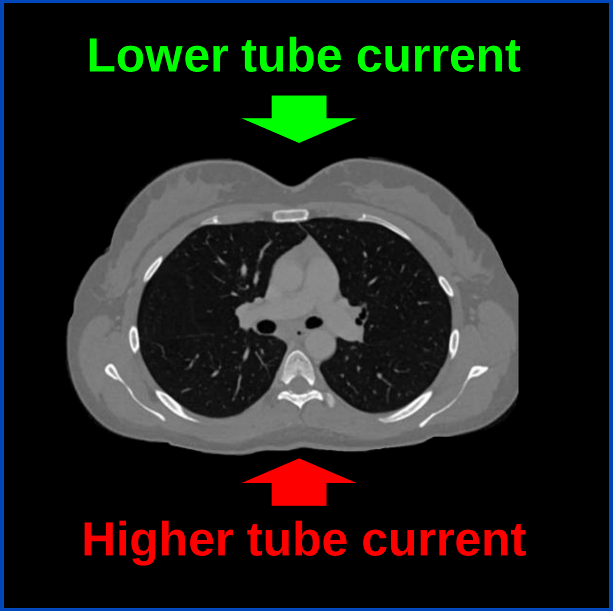


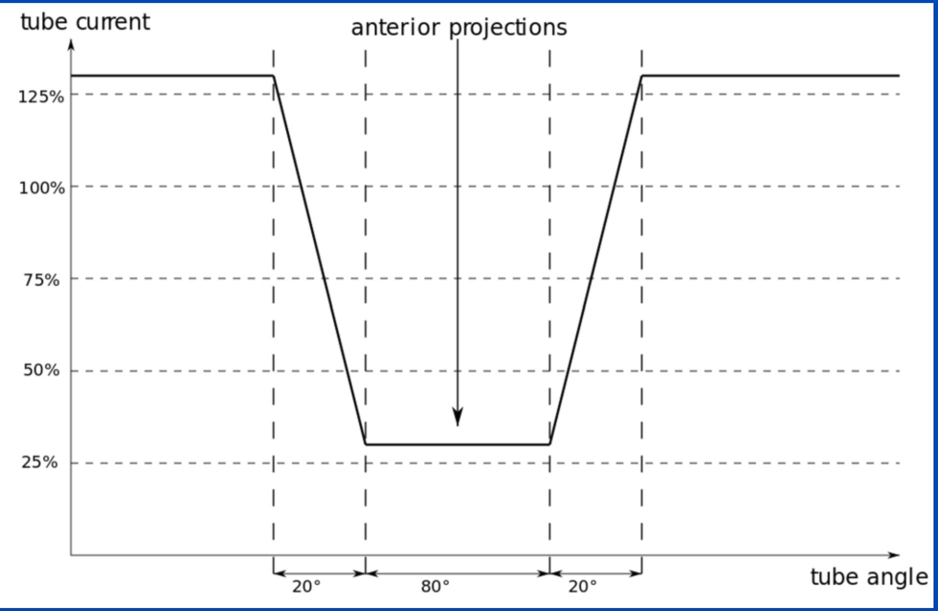
C = 25 HU, *W* = 400 HU

L. Klein, C. Liu, J. Steidel, L. Enzmann, M. Knaup, S. Sawall, A. Maier, M. Lell, J. Maier, and M. Kachelrieß.
Patient-specific radiation risk-based tube current modulation for diagnostic CT. Med. Phys. 49: in press, 2022.

riskTCM vs. Breast-Specific TCM

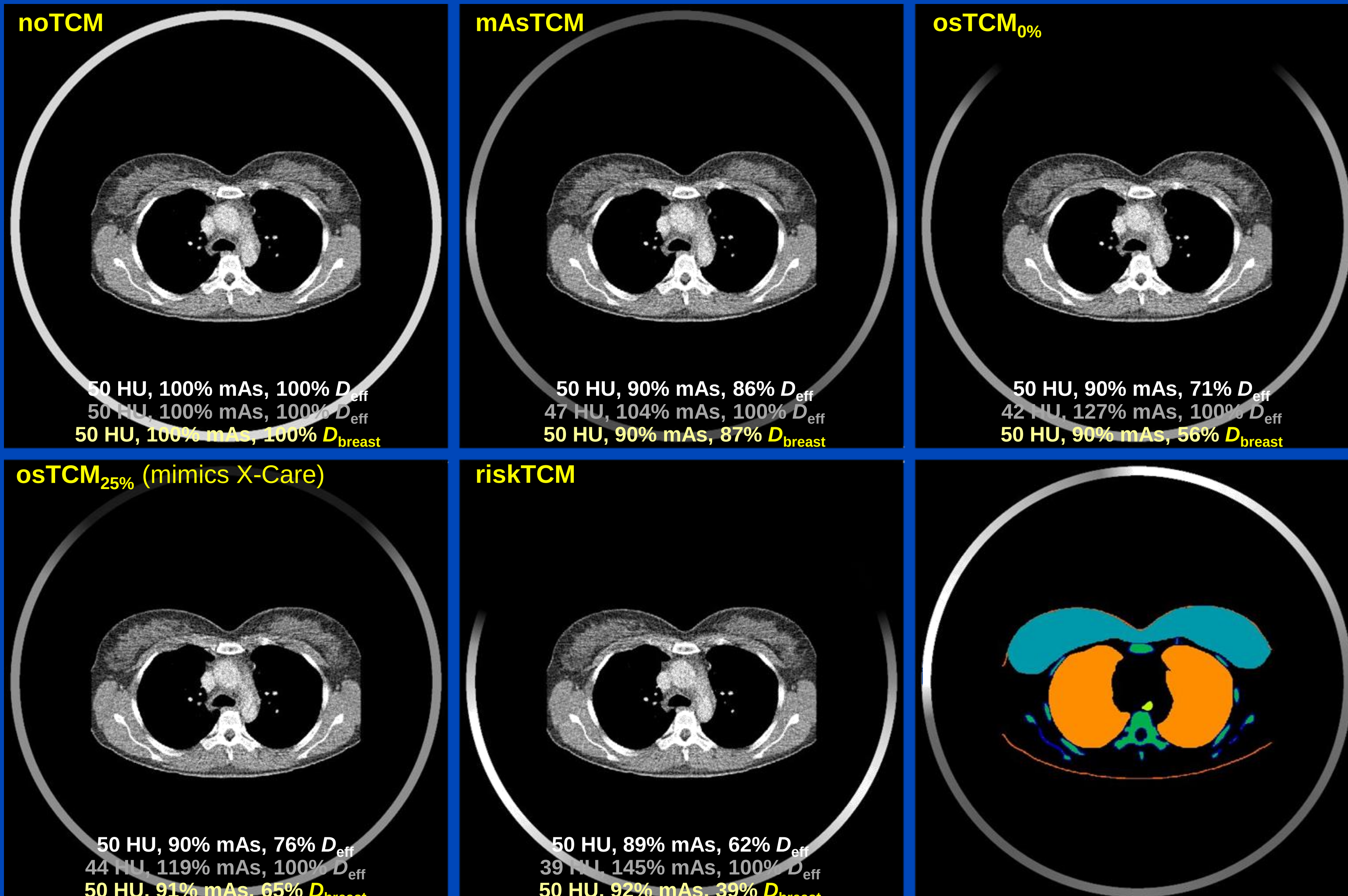
- osTCM mimics X-Care (Siemens Healthineers)
- Reduces the tube current to 25% for the anterior 120°
- Higher tube current for the remaining 240°





D. Ketelsen et al. Automated computed tomography dosesaving algorithm to protect radiosensitive tissues: estimation of radiation exposure and image quality considerations. Invest Radiol, 47(2):148–52, 2012

Results

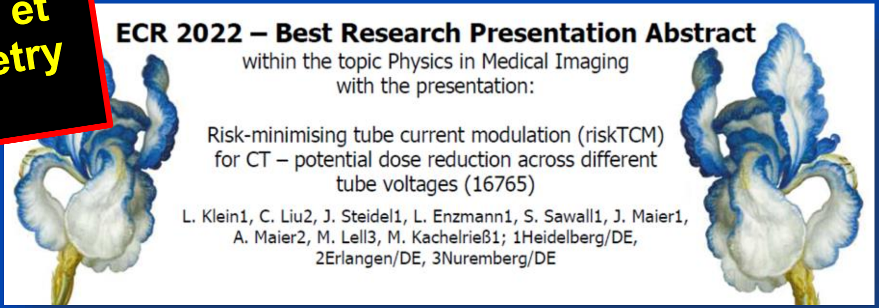


Data courtesy of Prof. Lell, Nürnberg. C = 25 HU, W = 400 HU

Conclusions on RiskTCM

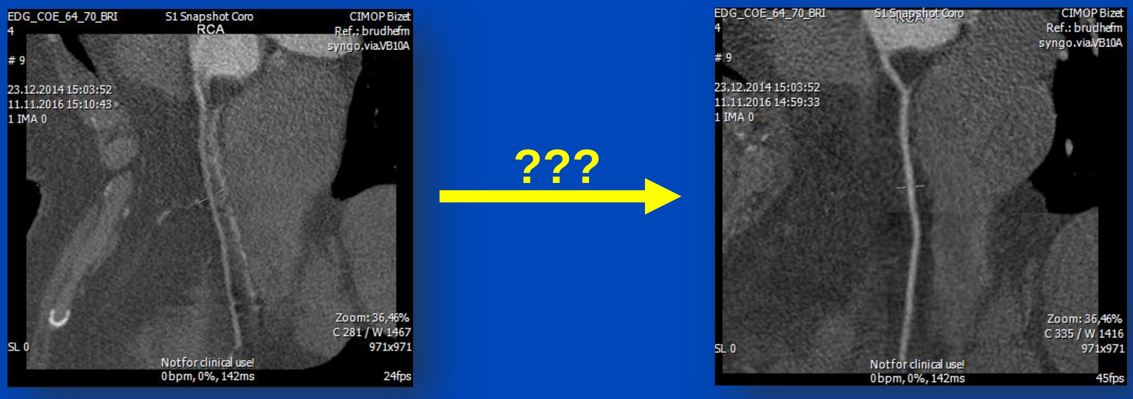
- Risk-specific TCM minimizes the patient risk.
- With D_{eff} as a risk model riskTCM can reduce risk by up to 50% and more, compared with the gold standard mAsTCM.
- Other risk models, in particular age-, weight- and sex-specific models, can be used with riskTCM as well.
- Note:
  - mAsTCM = good for the x-ray tube
  - riskTCM = good for the patient
  - detector flux equalizing TCM = good for the detector

More details see scientific presentation by Klein et al. in session RPS 1213 “Advances in CT dosimetry and radiobiology” Friday 8:00 in Room Z.

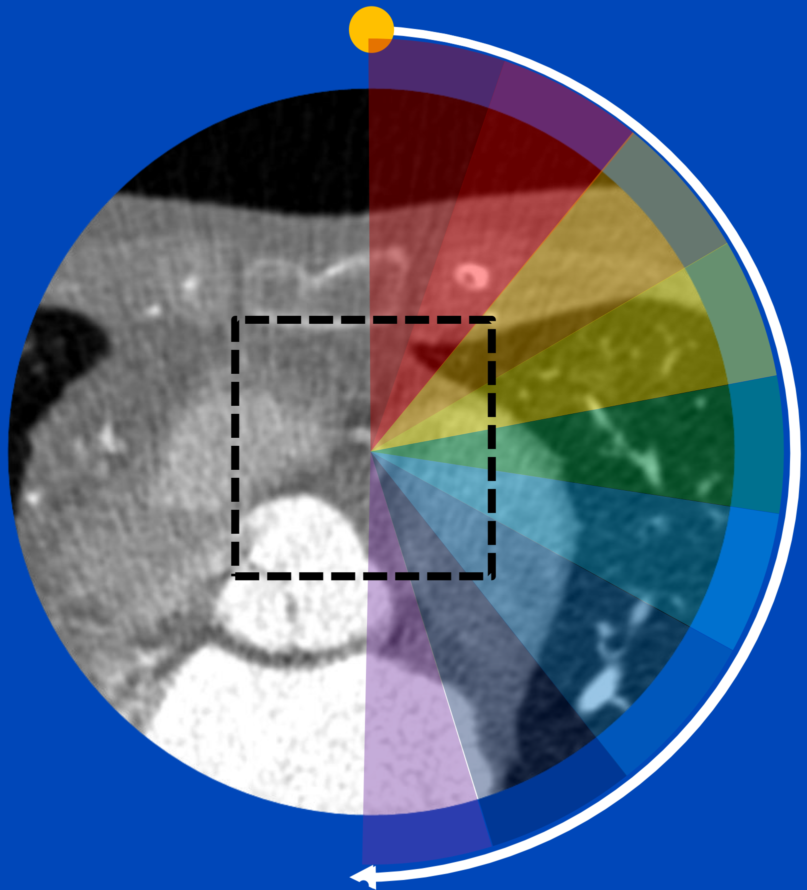


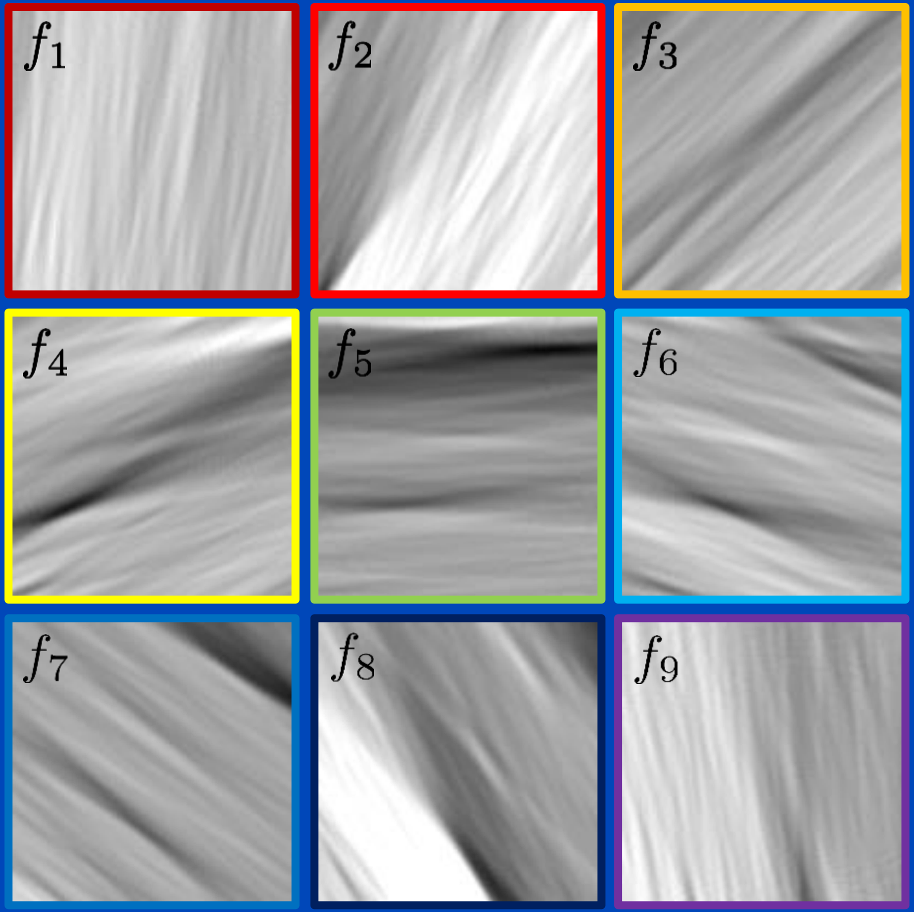
L. Klein, C. Liu, J. Steidel, L. Enzmann, M. Knaup, S. Sawall, A. Maier, M. Lell, J. Maier, and M. Kachelrieß.
Patient-specific radiation risk-based tube current modulation for diagnostic CT. Med. Phys. 49: in press, 2022.

Deep Cardiac Motion Compensation



Partial Angle-Based Motion Compensation (PAMoCo)





Animated rotation time = 100 × real rotation time

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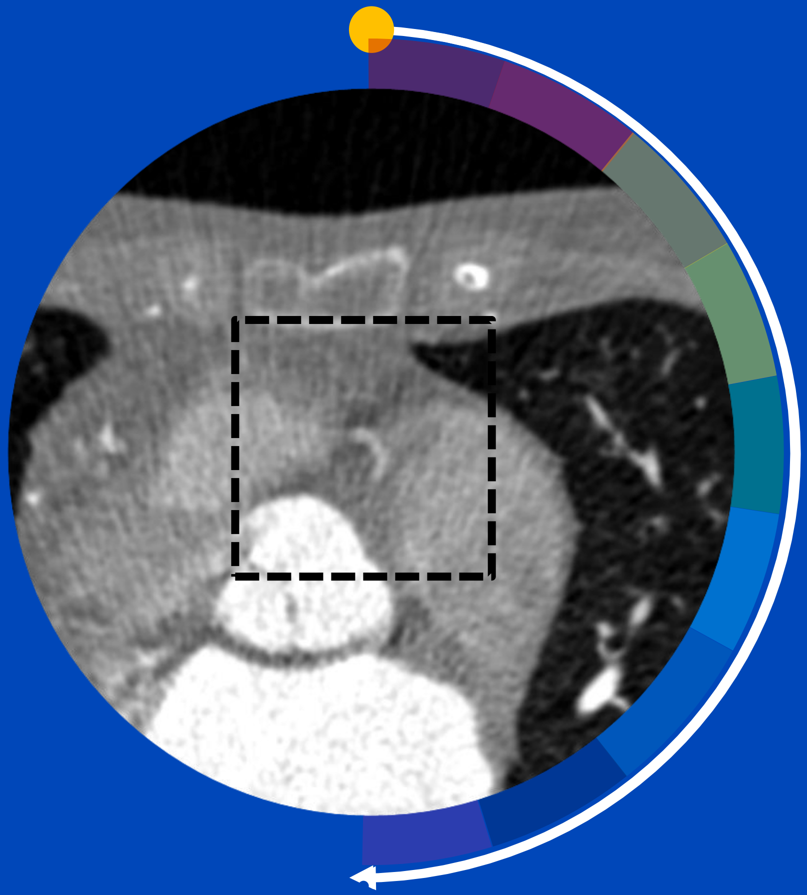
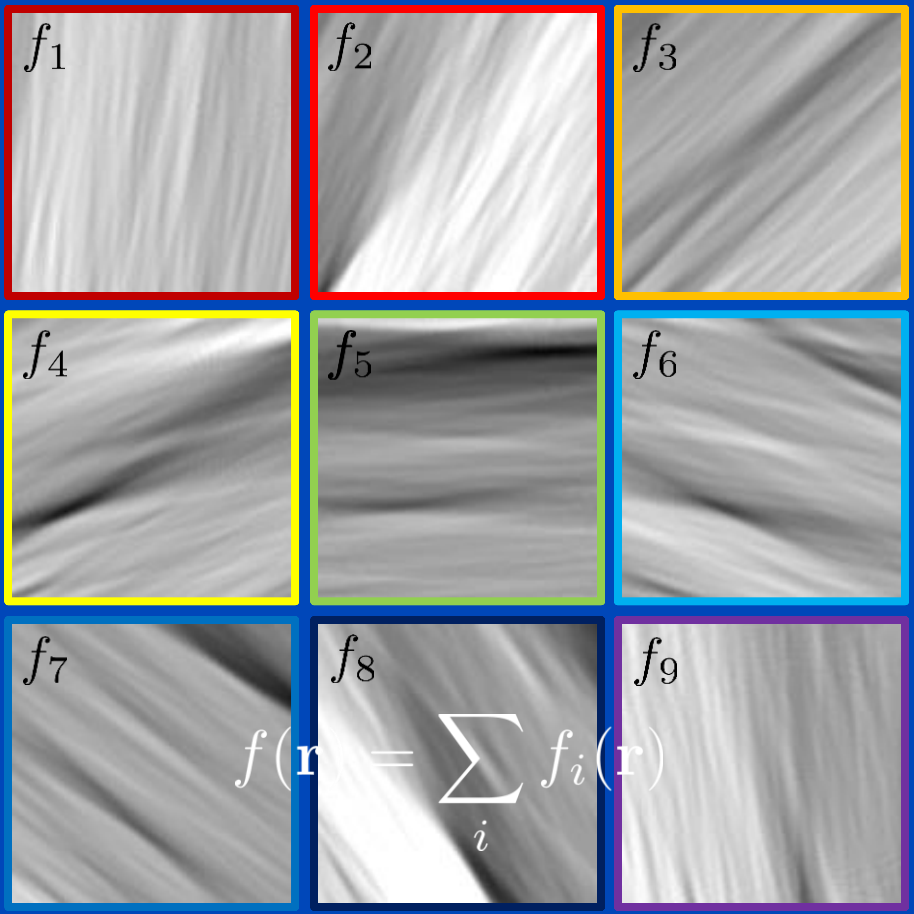
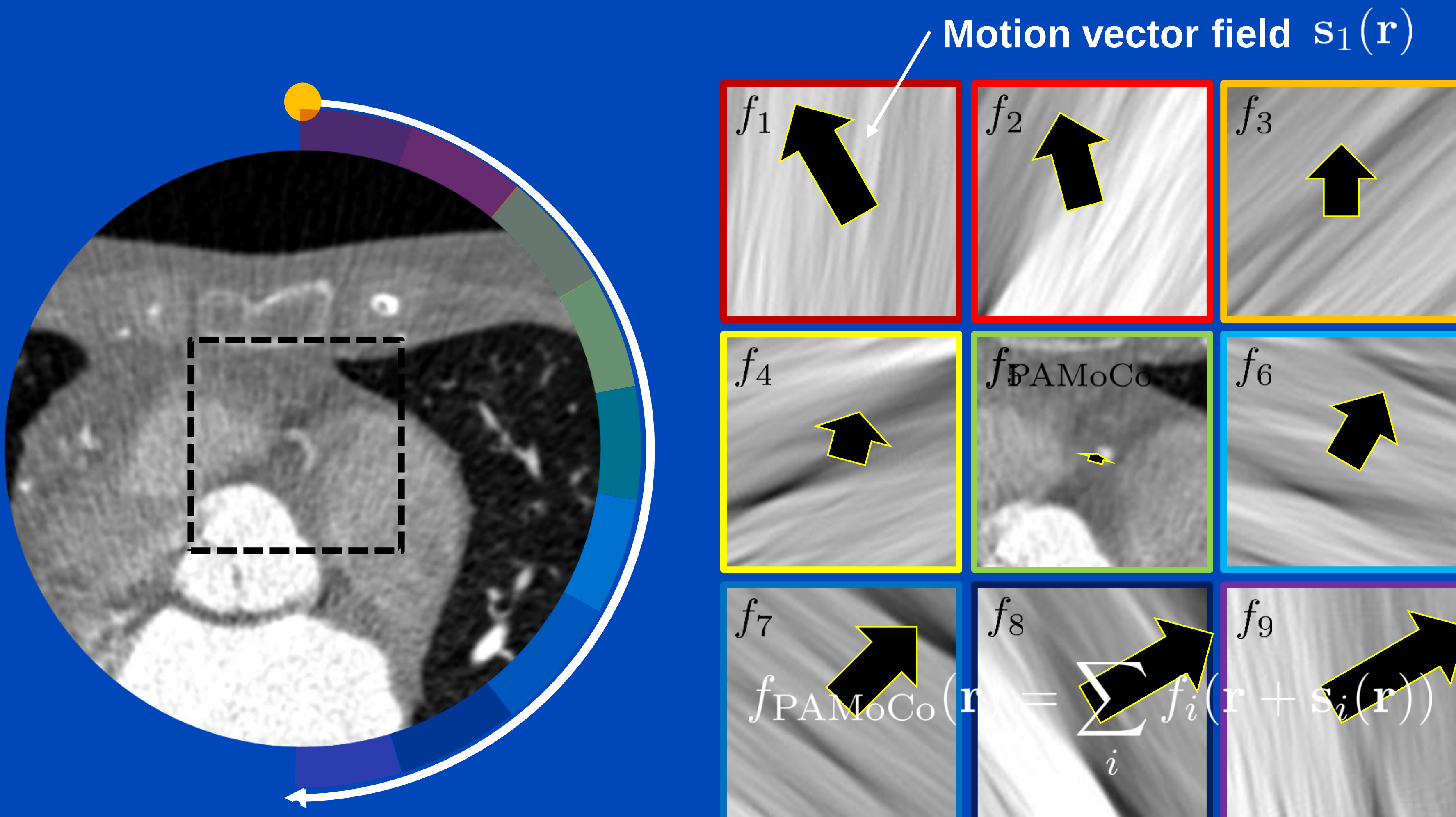
Partial Angle-Based Motion Compensation (PAMoCo)





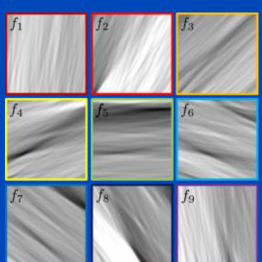
Partial Angle-Based Motion Compensation (PAMoCo)



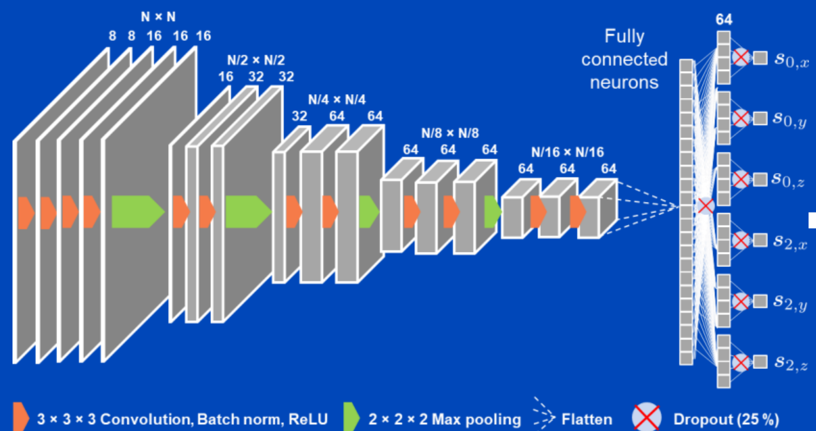
Apply motion vector fields (MVFs) to partial angle reconstructions

Deep Partial Angle-Based Motion Compensation (Deep PAMoCo)

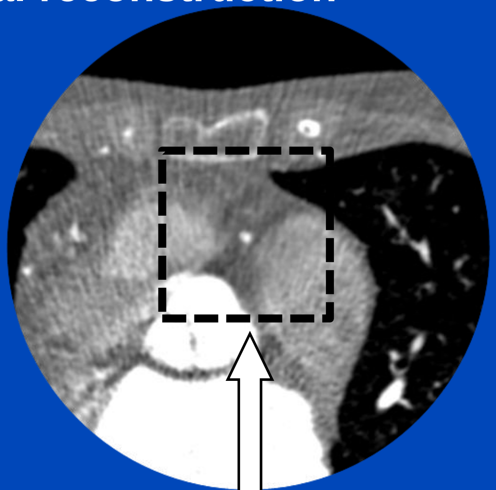
PARs centered around coronary artery



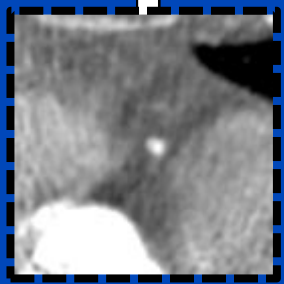
Neural network to predict parameters of a motion model



Reinsertion of patch into initial reconstruction



Spatial transformer

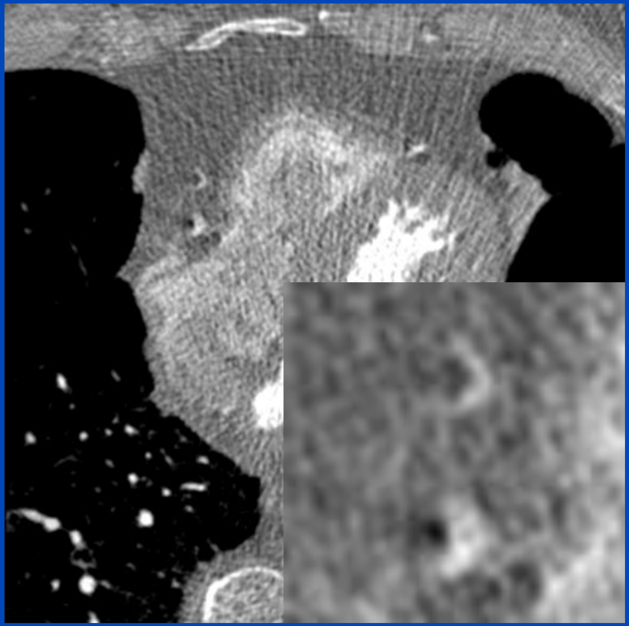


Application of the motion model to the PARs via a spatial transformer[1]

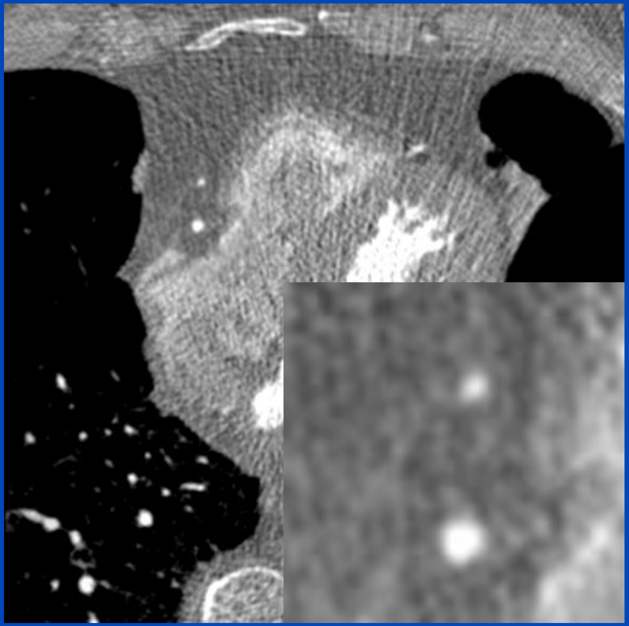
[1] M. Jaderberg et al., "Spatial transformer networks", NIPS 2015: 2017–2025 (2015).

Patient 1

Original



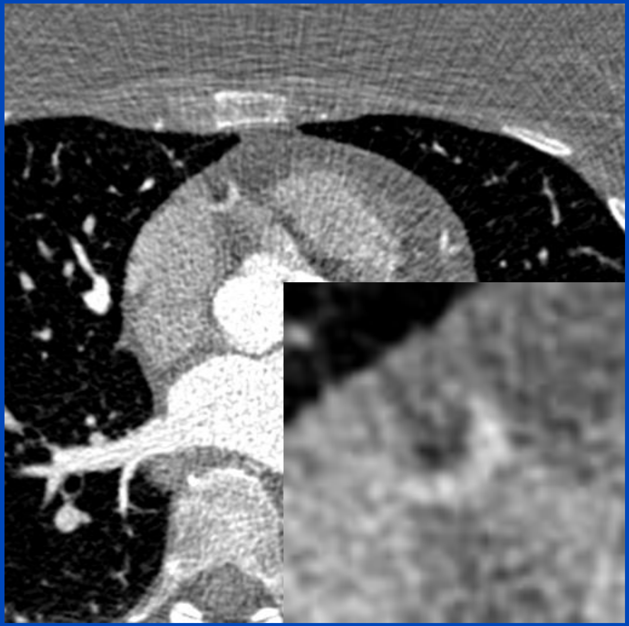
Deep PAMoCo



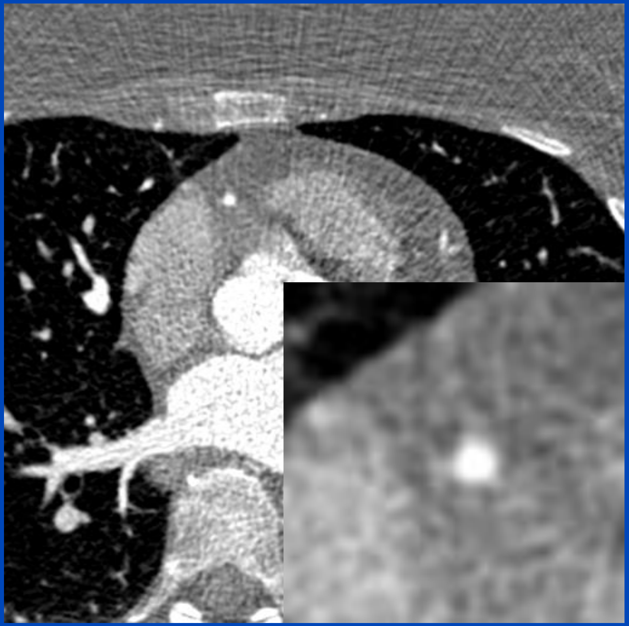
C = 0 HU, *W* = 1400 HU

Patient 2

Original



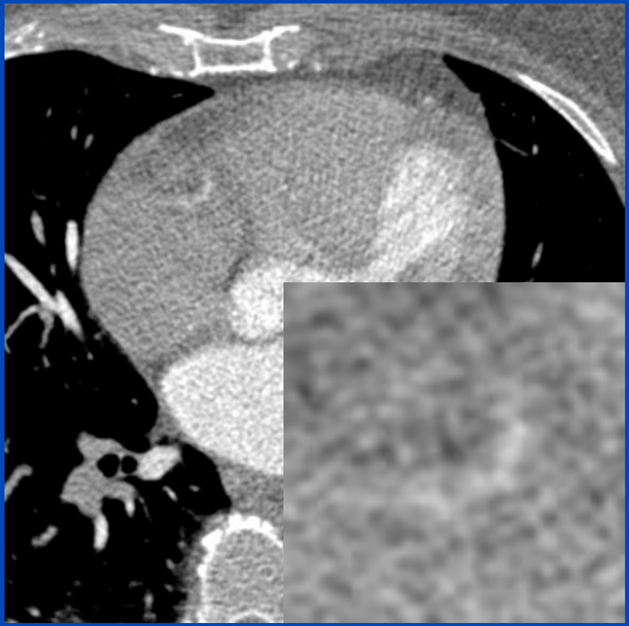
Deep PAMoCo



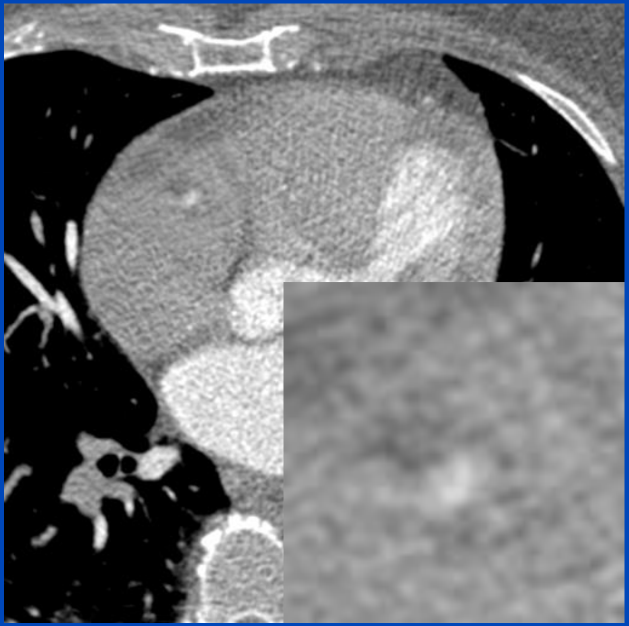
C = 0 HU, *W* = 1600 HU

Patient 3

Original



Deep PAMoCo

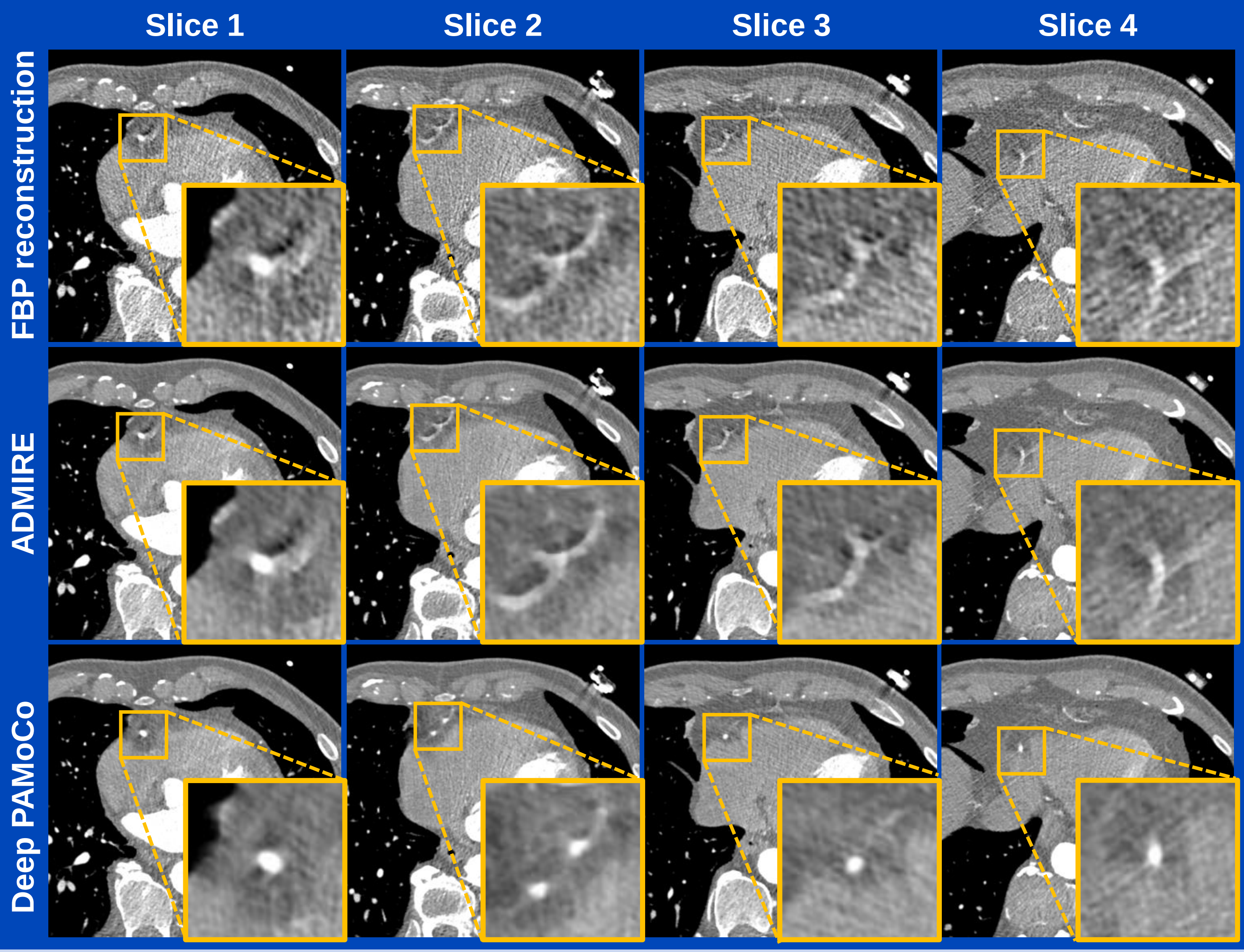


C = 0 HU, *W* = 1000 HU

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.

Patient 4

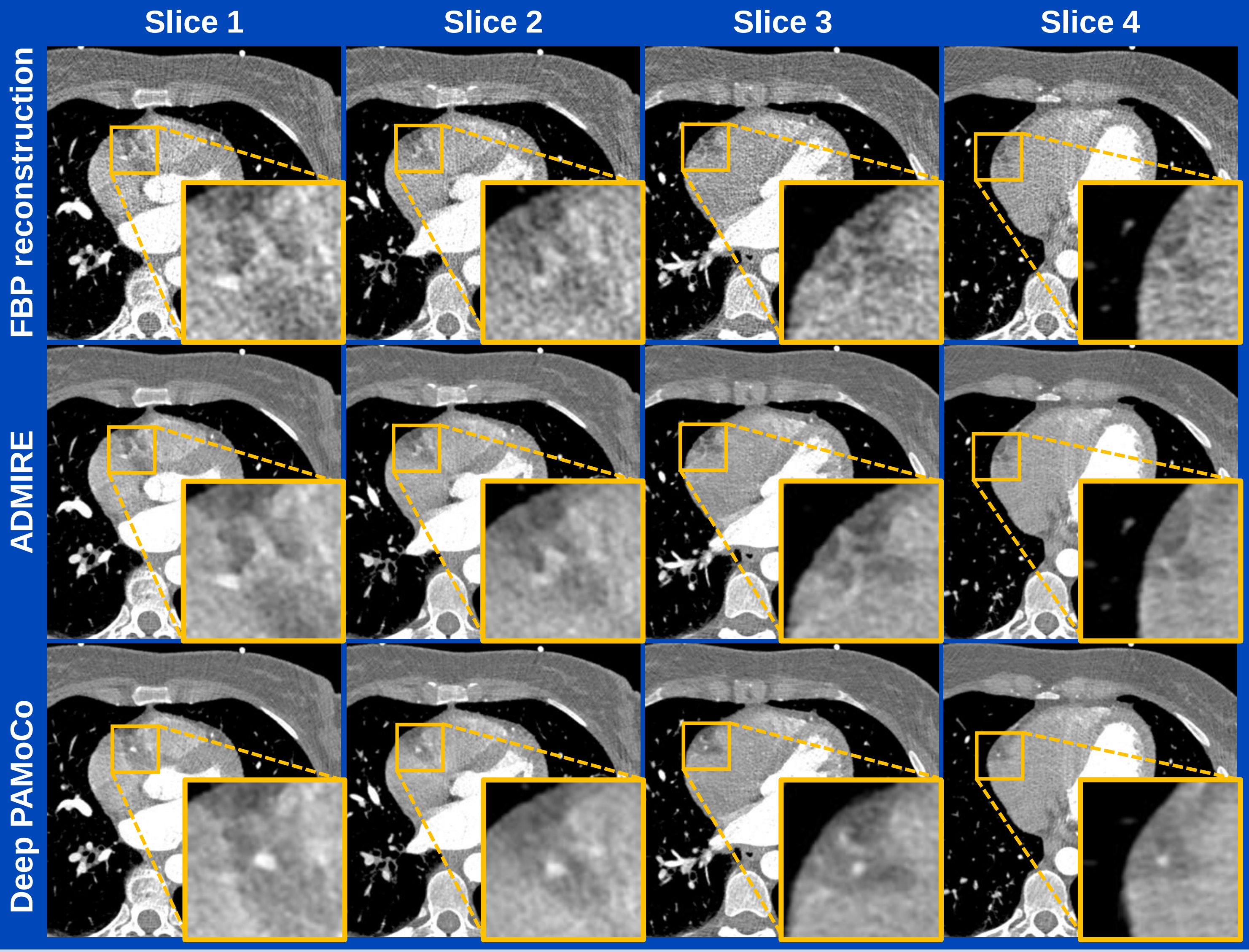
Measurements at a Siemens Somatom AS



C = 0 HU, W = 1200 HU

Patient 5

Measurements at a Siemens Somatom AS

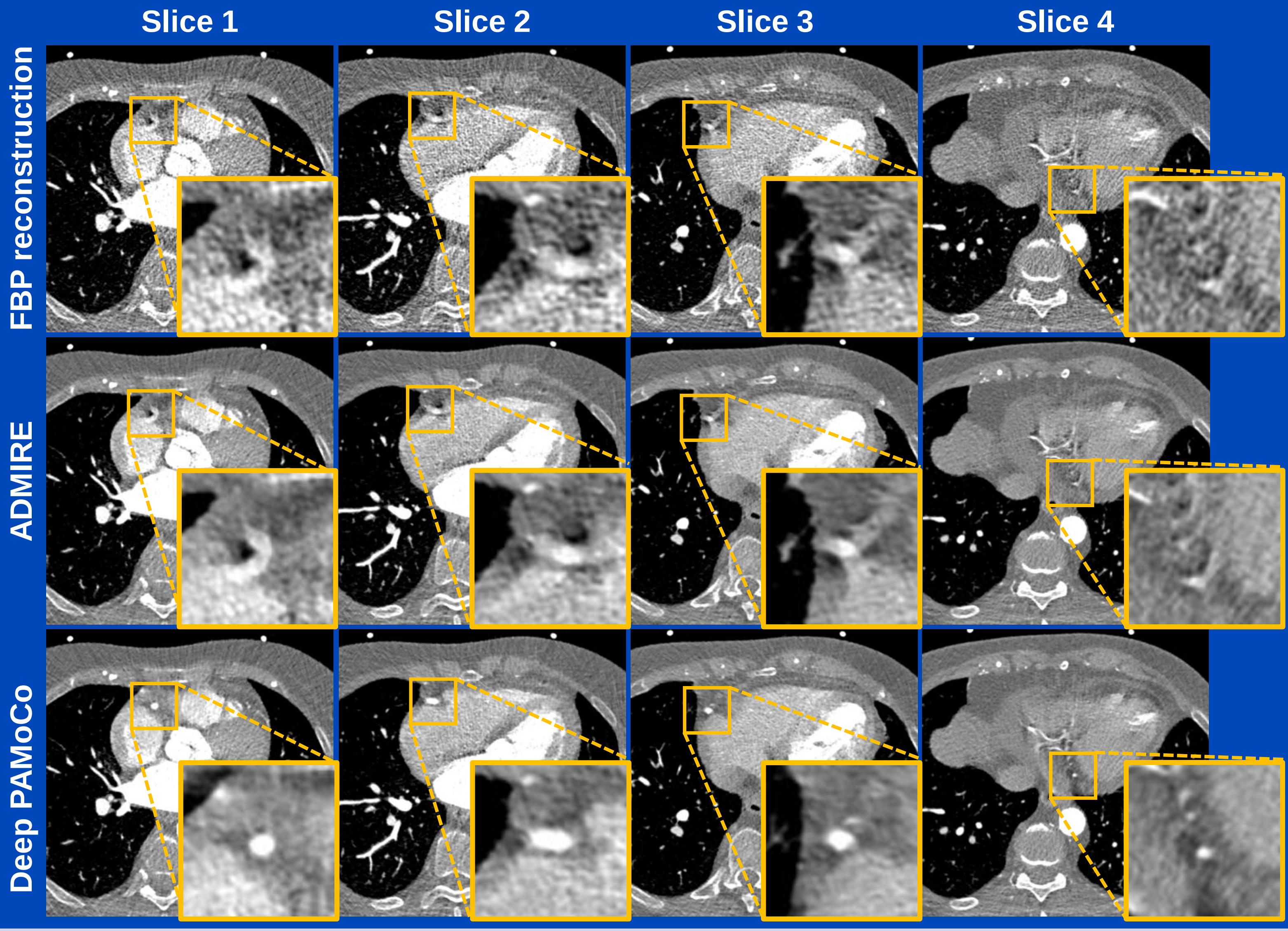


C = 0 HU, W = 1200 HU

dkfz.

Patient 6

Measurements at a Siemens Somatom AS



C = 0 HU, W = 1400 HU

Thank You!

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

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

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