



Deep Learning in CT Artifact Correction

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DEUTSCHES
KREBSFORSCHUNGSZENTRUM
IN DER HELMHOLTZ-GEMEINSCHAFT

Content

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

Deep MAR Examples

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

Lei Gengyi, Qingyao Yang, Tao Xu, Baohua Chen, Xiaohu Fu, Binbin Shi, Guo Gang

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

Gjesteby, 2017

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

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

Lei Gengyi, Qingyao Yang, Tao Xu, Baohua Chen, Xiaohu Fu, Binbin Shi, Guo Gang

Gjesteby, 2018

- Inputs for the network are the NMAR image and the high-pass filtered original image
- Corrects streaks after NMAR
- Loss function is MSE or perceptual loss (from VGG network)
- SE blocks over something like a residual error

Gjesteby, 2018

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

Lei Gengyi, Qingyao Yang, Tao Xu, Baohua Chen, Xiaohu Fu, Binbin Shi, Guo Gang

Gjesteby, 2019

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- Network uses residual error and cost function is a combination of MSE and perceptual loss

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

Xiaohu Fu, Li Zhang, and Yongqiang Yang

Xing, 2019

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

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Metal artifact reduction on cervical CT images by deep residual learning

Qi Huang¹, Jian Wang¹, Fan Tang¹, Tao Zhang² and Yu Zhang¹

Zhang, 2018

Zhang, 2018

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

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

Nanli Zhang¹, Senan Member, IEEE, and Hongyong Yu¹, Senior Member, IEEE

Yu, 2018

Yu, 2018

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

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

Richard E. Cole, Yuesu Lu, A. Gensley, Gu Yang, Shuang Shi

Claus, 2017

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

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

Shihua M. Gattabadi¹, Rishu W. Kruger¹, Balraj Kumar¹, and Andrew Mauer¹

Gottschalk, 2019

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

Gottschalk, 2019

Gottschalk, 2019

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

Shihua M. Gattabadi, Rishu W. Kruger, and Andrew Mauer

Gottschalk, 2020

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

Gottschalk, 2020

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

Fast Enhanced CT Metal Artifact Reduction using Data Domain Deep Learning

Muhammad Usman Ghani, W. Chen Kurt, Fellow, IEEE

Ghani, 2019

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

Ghani, 2019

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

Huili Liao¹, Wei An Liu¹, Zhiliang Han¹, Lixun Yin¹, William J. Sekerac², S. Kevin Zhou¹, and Jiebo Luo¹

Liao, 2019

Liao, 2019

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

DuoNet: Dual Domain Network for CT Metal Artifact Reduction

Wei An Liu¹, Huili Liao¹, Cheng Peng¹, Xiaohua Guo¹, Jiebo Luo¹, Jiebo Luo¹, Rana Chellappa², Shaohua Kevin Zhou¹

Lin, 2019

Lin, 2019

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

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

Kaichao Liang, Li Zhang, and Hongkai Yang

Department of Engineering Physics, Tsinghua University, Beijing 100084, China

Key Laboratory of Particle & Radiation Imaging (Tsinghua University), Ministry of Education, Beijing, China

Yirong Yang

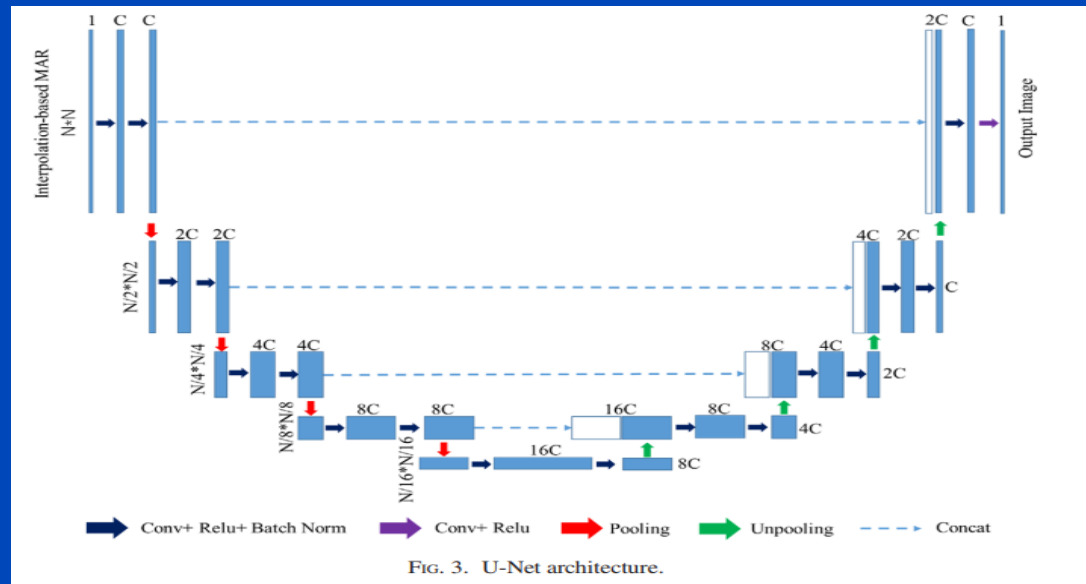
Department of Engineering Physics, Tsinghua University, Beijing 100084, China

Zhiqiang Chen, and Yuxiang Xing^{a)}

Department of Engineering Physics, Tsinghua University, Beijing 100084, China

Key Laboratory of Particle & Radiation Imaging (Tsinghua University), Ministry of Education, Beijing, China

LI-MAR
image in



nicer image
out

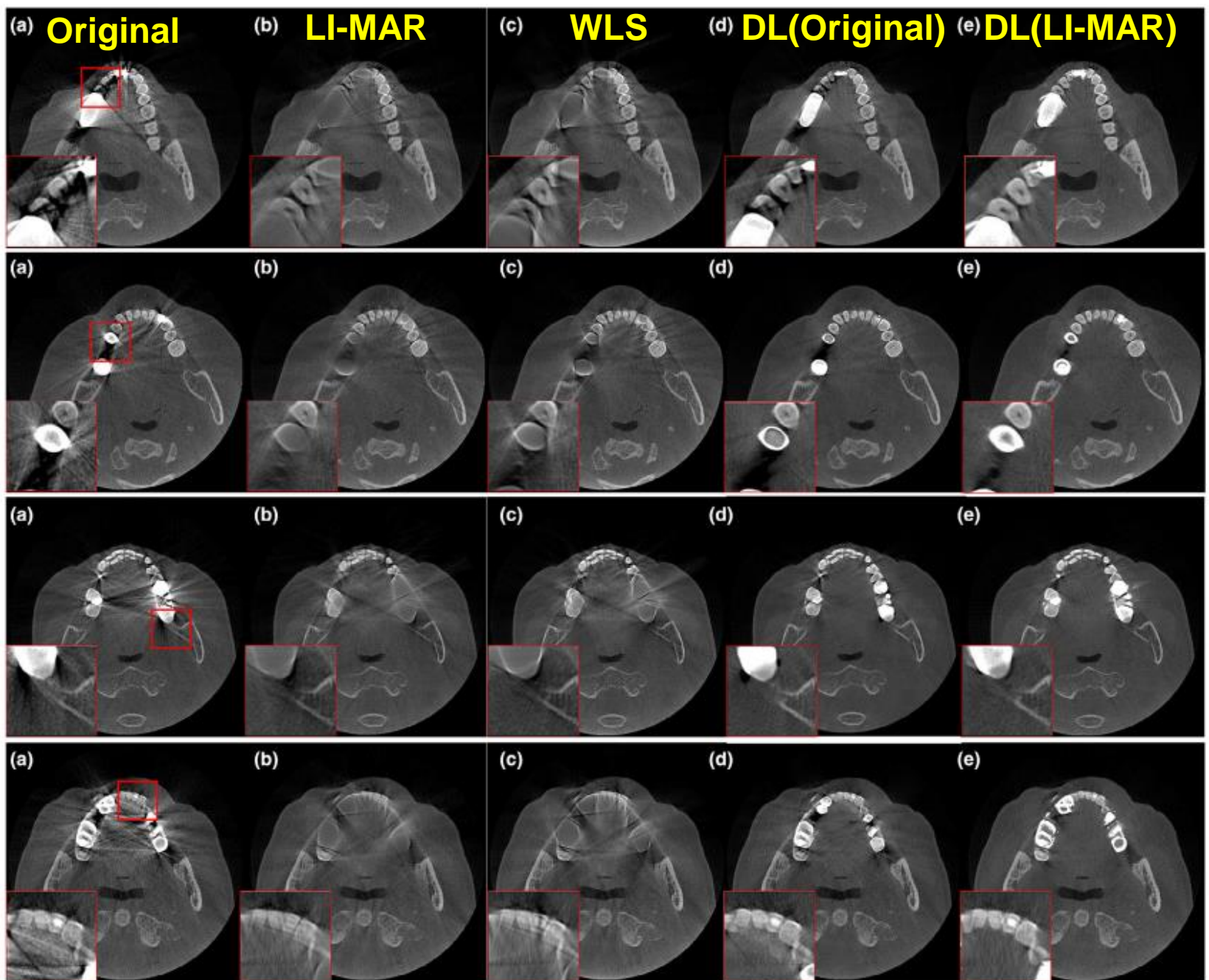
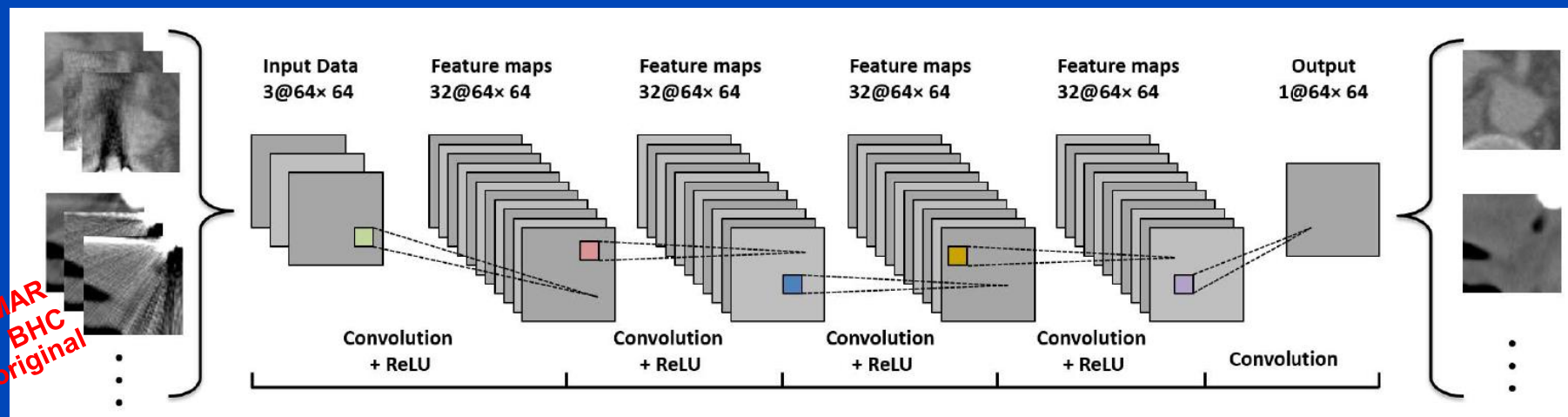


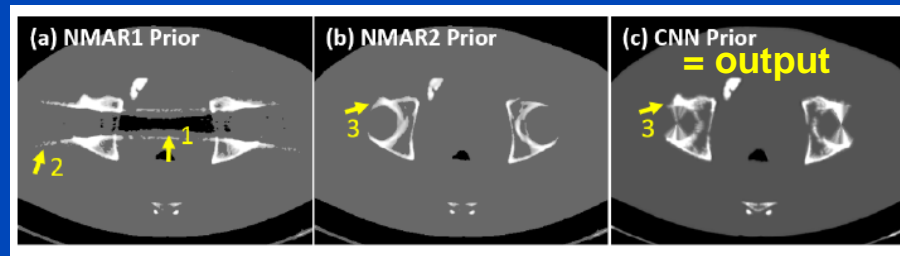
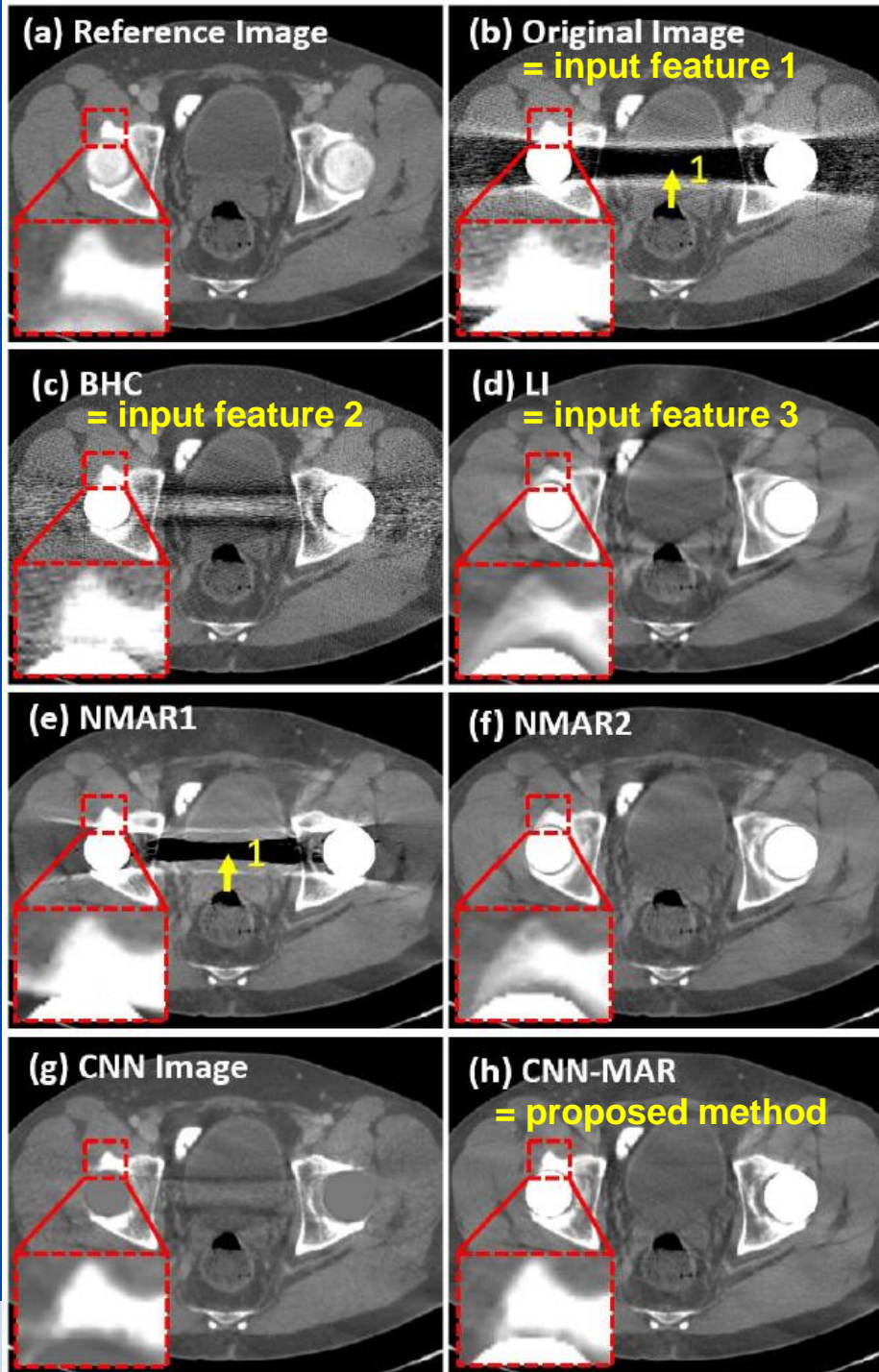
FIG. 8. Four real MAR test cases. (a) Reconstructions with no MAR, (b) I-MAR, (c) WLS reconstruction, (d) DL-MAR, (e) I-DL-MAR + metal.

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

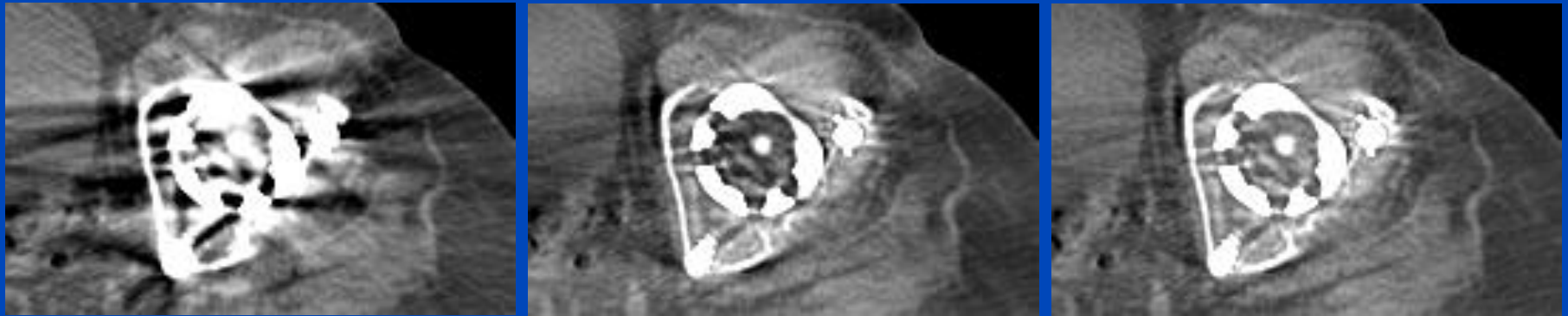


MAR without Machine Learning is a Good Alternative: Frequency Split Normalized MAR^{1,2}

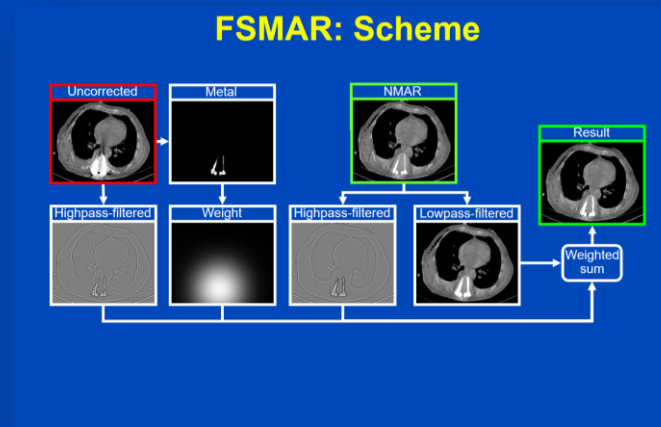
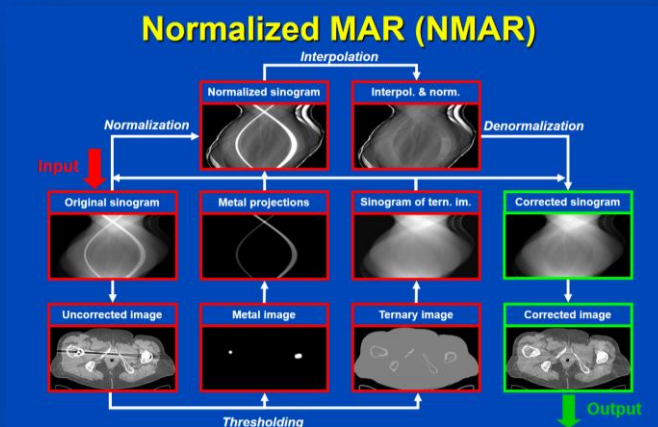
Uncorrected

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.

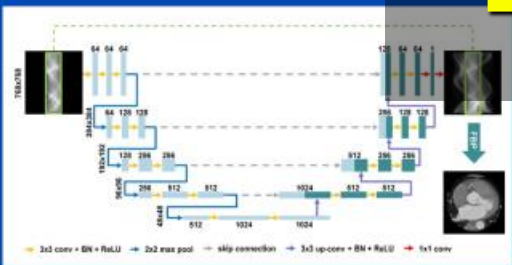
²E. Meyer, M. Kachelrieß. Frequency split metal artifact reduction (FSMAR) in CT. Med. Phys. 39(4):1904-1916, April 2012.

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
- **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

Jusuo H. J. Ketola^{1*}, Helmi Heino¹, Mikael A. K. Junninen^{2,3}, Mikko T. Nieminen^{3,4,5}, and Sami I. Jakinen¹
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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

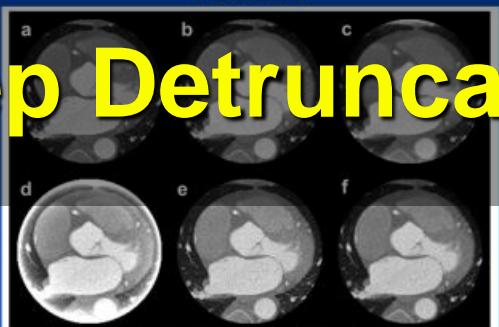


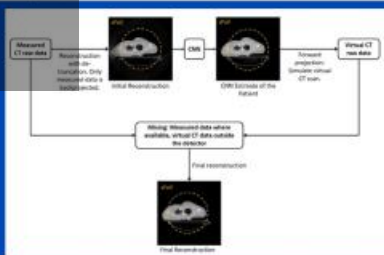
Figure 3. Example reconstructions. a. Original data from sensor. b. Adaptive detraction followed by filtered backprojection. c. Total variation regularization. d. Filtered backprojection. e. FBP-CNN. f. Our Method. Reconstructions have been rescaled to contain the region-of-interest.

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.

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

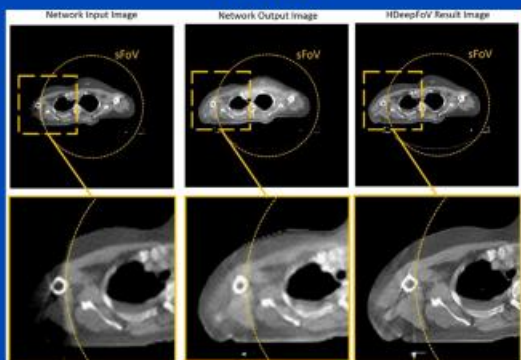
Gabriel Palva Fonseca¹, Alexander Preuhs², Michael Manhart², Guenter Lauritsch², and Andreas Maier²
¹Department of Radiation Oncology (MAASTRO), GROW School for Oncology and Developmental Biology, Maastricht University Medical Center, Maastricht 6229 ET, The Netherlands
²Siemens Healthcare GmbH, Forchheim, Germany
³Baria Rinaldi, Michel C. Orlitz, Wouter J.C. van Elmpt and Frank Verhaeghan
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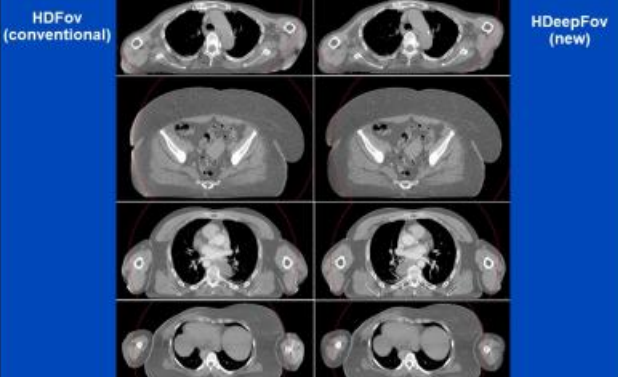
Fonseca, Gabriel Palva, et al. "Evaluation of novel AI-based extended field-of-view CT reconstructions." *Medical Physics* (2021).

Results



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

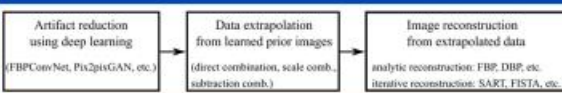
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Data Extrapolation From Learned Prior Images for Truncation Correction in Computed Tomography

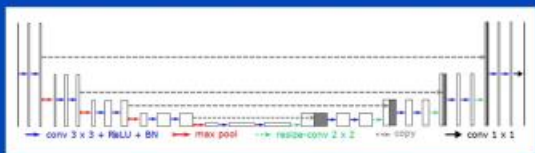
Yixing Huang¹, Alexander Preuhs², Michael Manhart², Guenter Lauritsch², and Andreas Maier², Senior Member, IEEE



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

Data Consistent CT Reconstruction from Insufficient Data with Learned Prior Images

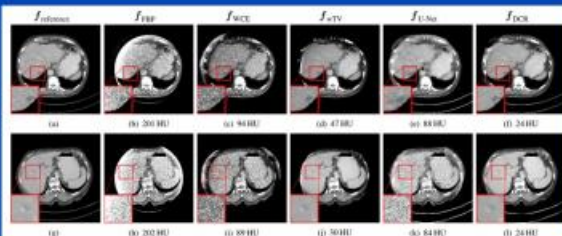
Yixing Huang, Alexander Preuhs, Michael Manhart, Guenter Lauritsch, Andreas Maier



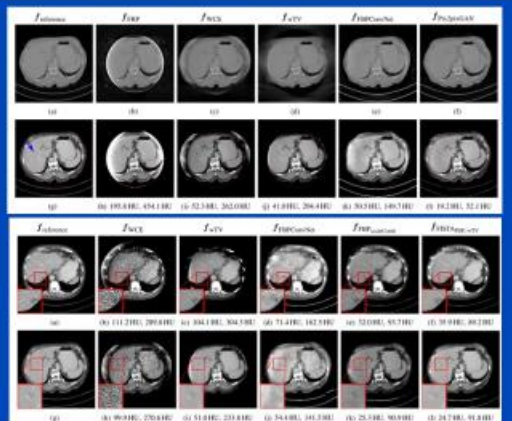
Corrected image is then forward-projected and the projections are combined with the original raw data. Finally, the combined data are reconstructed iteratively.

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

Results



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Deep learning -based sinogram extension method for interior computed tomography

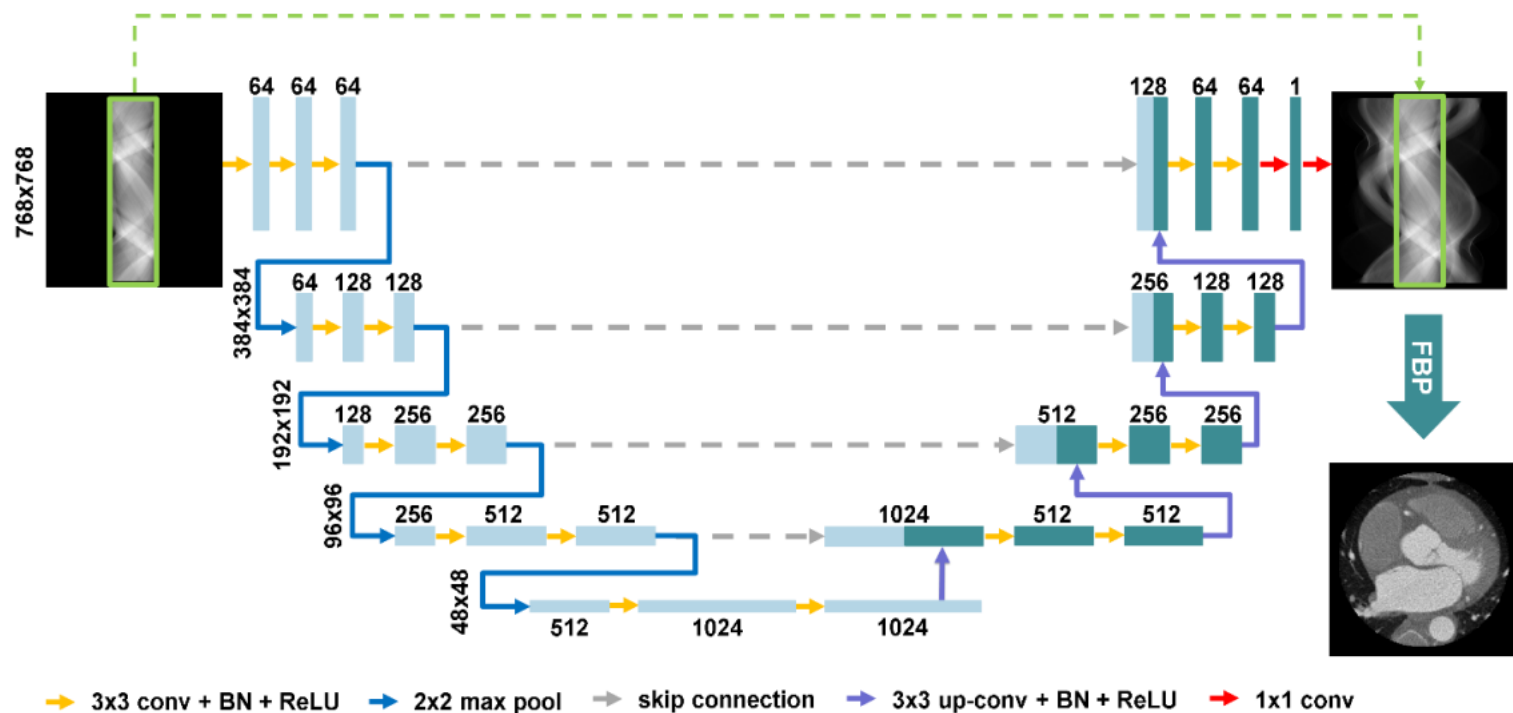
Juuso H. J. Ketola^{*a}, Helinä Heino^a, Mikael A. K. Juntunen^{a,b}, Miika T. Nieminen^{a,b,c},
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^cDepartment of Diagnostic Radiology, Oulu University Hospital, Oulu, Finland

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



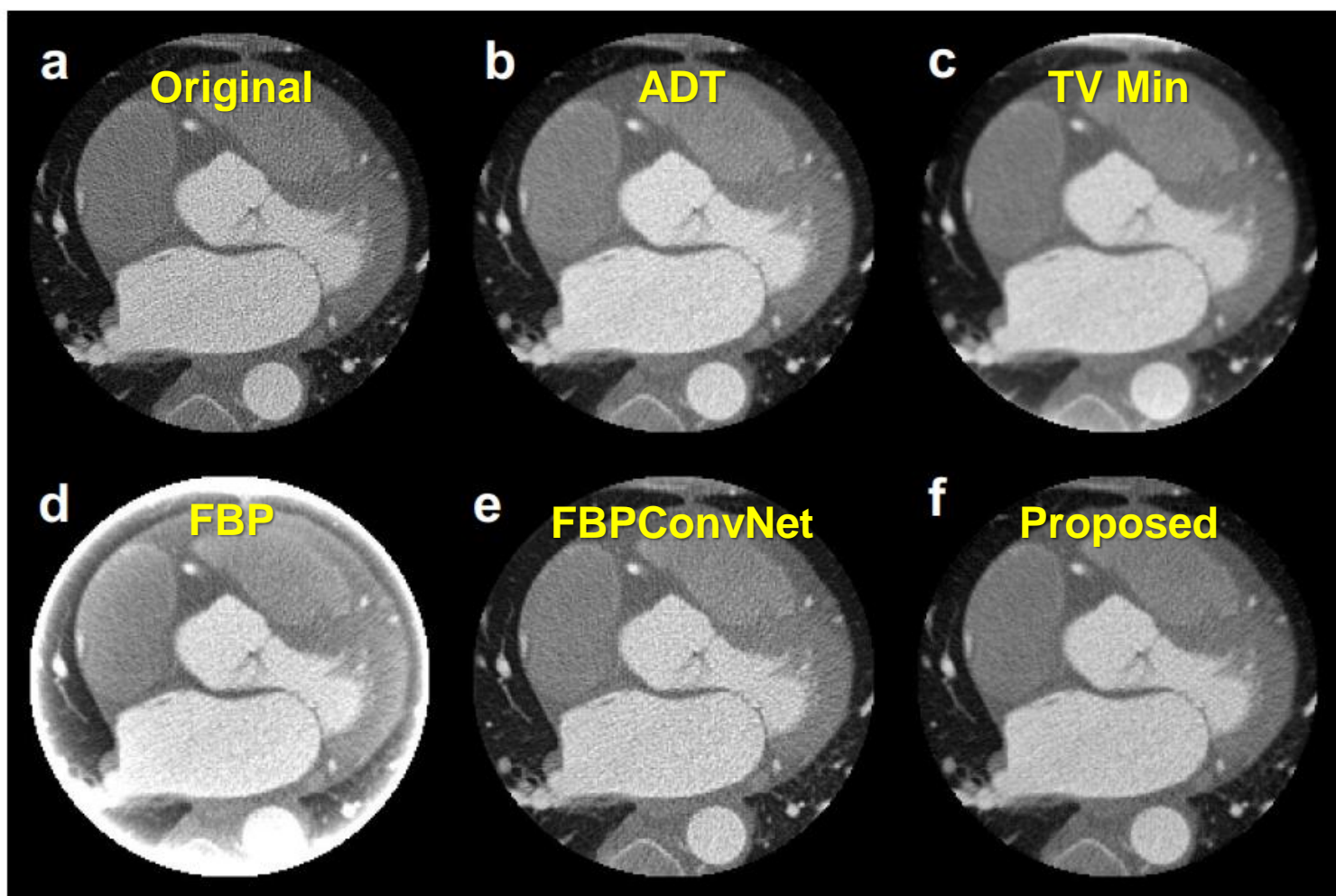


Figure 3. Example reconstructions. a. Original data from scanner. b. Adaptive de-truncation followed by filtered backprojection. c. Total variation regularization. d. Filtered backprojection. e. FBPCConvNet. f. Our Method. Reconstructions have been masked to contain the region-of-interest.

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

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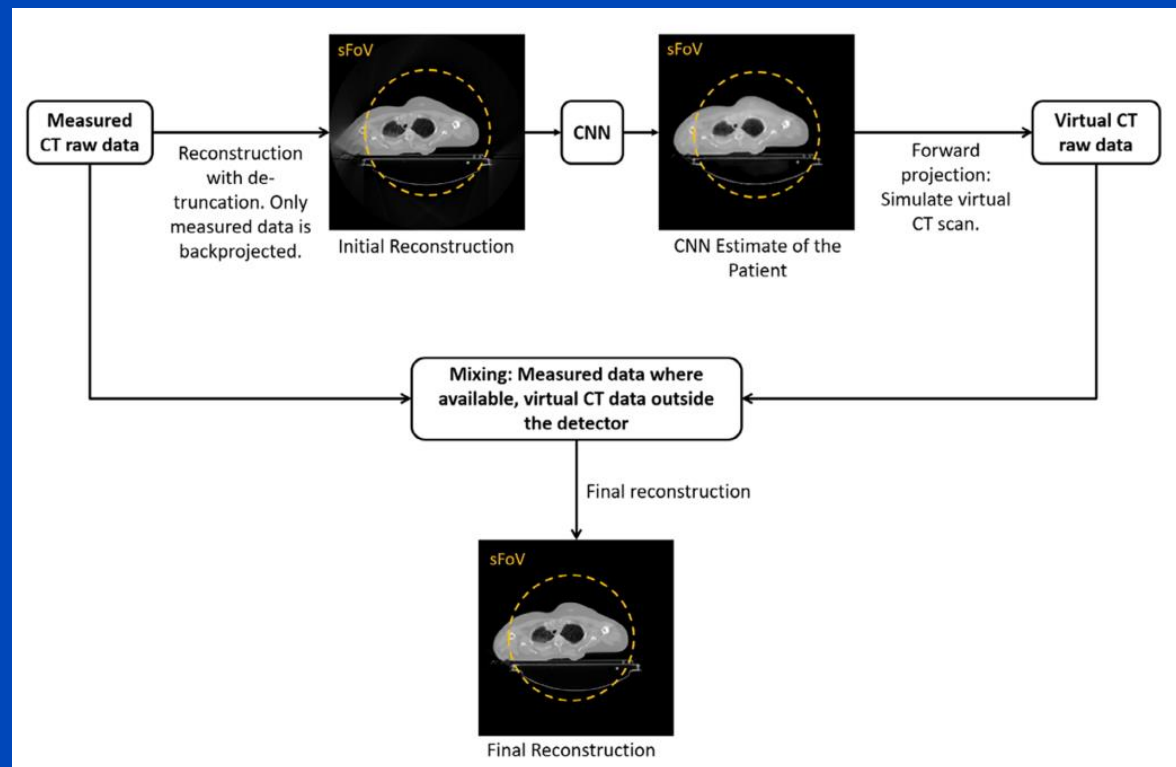
Matthias Baer-Beck* Eric Fournie and Christian Hofmann

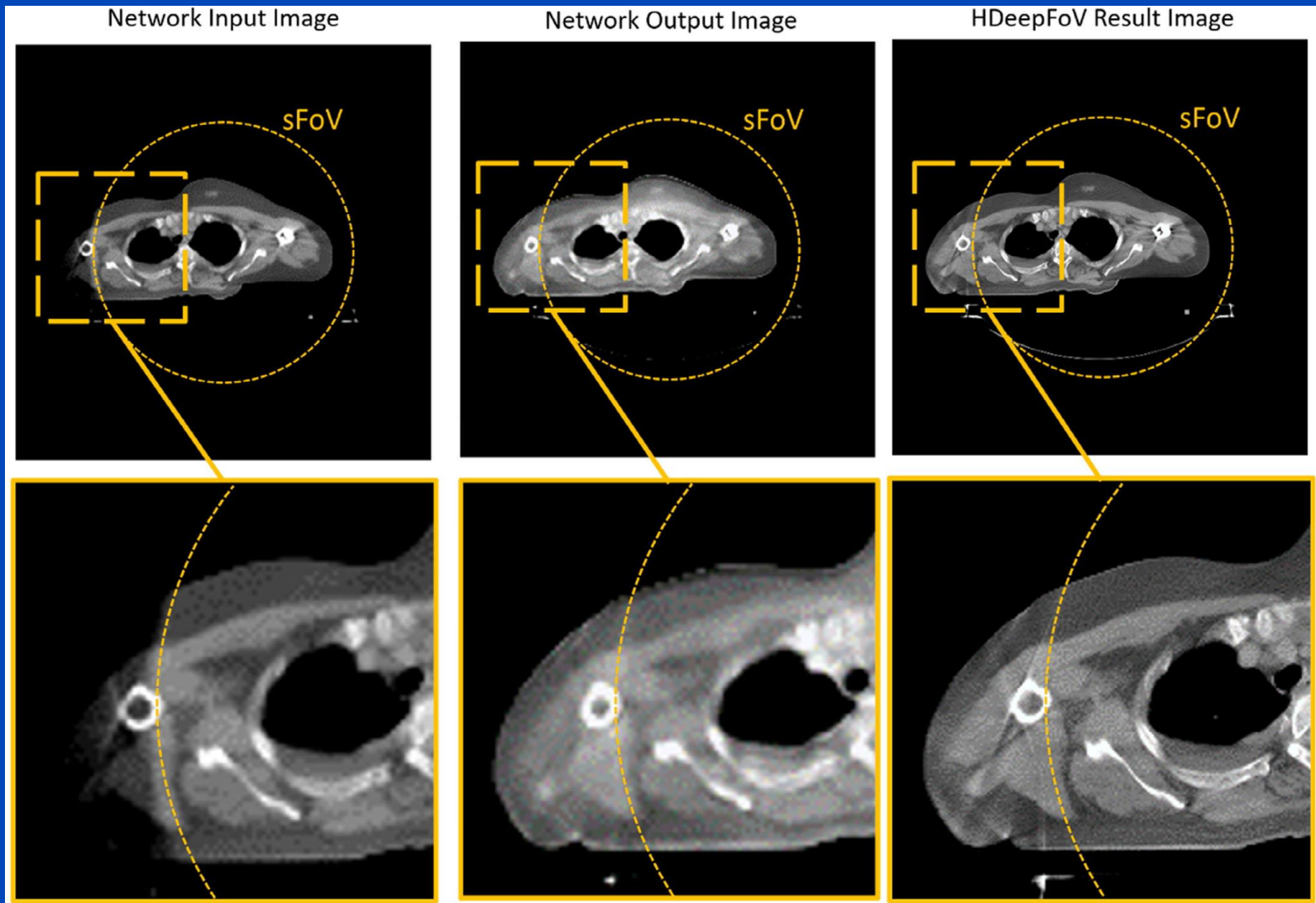
Siemens Healthcare GmbH, Forchheim, Germany

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

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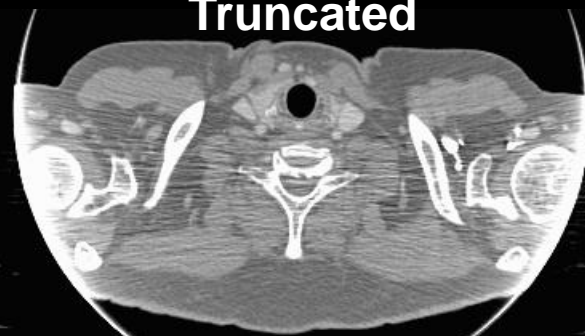




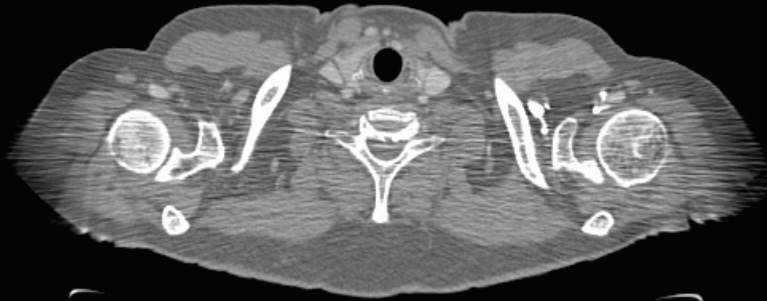
Original



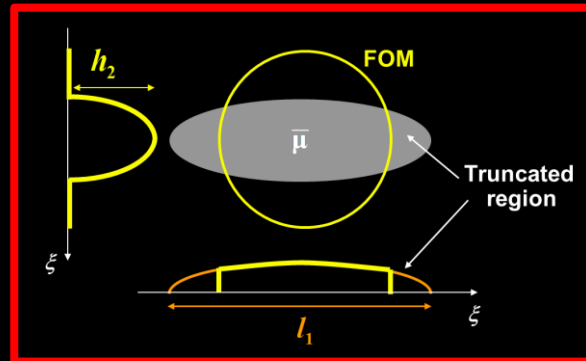
Truncated



ADT corrected



ADT corrected (clipped)

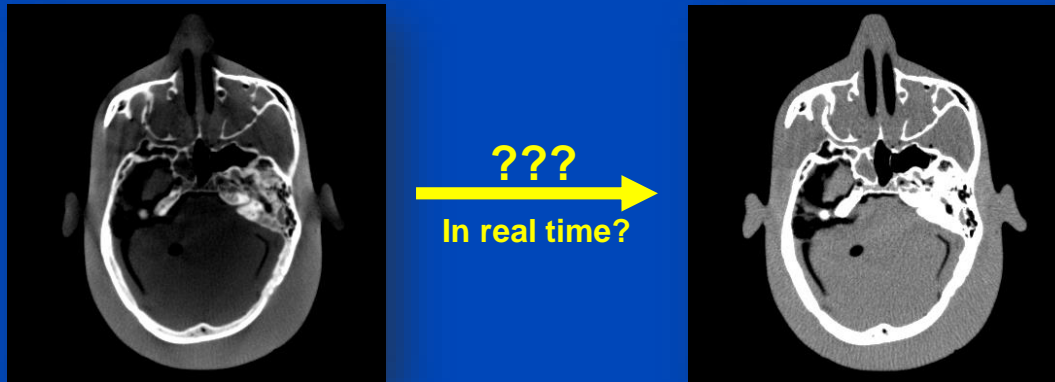


$C = 0 \text{ HU}$, $W = 1000 \text{ HU}$

Summary on Deep Detruncation

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

Deep Scatter Estimation



Monte Carlo Scatter Estimation

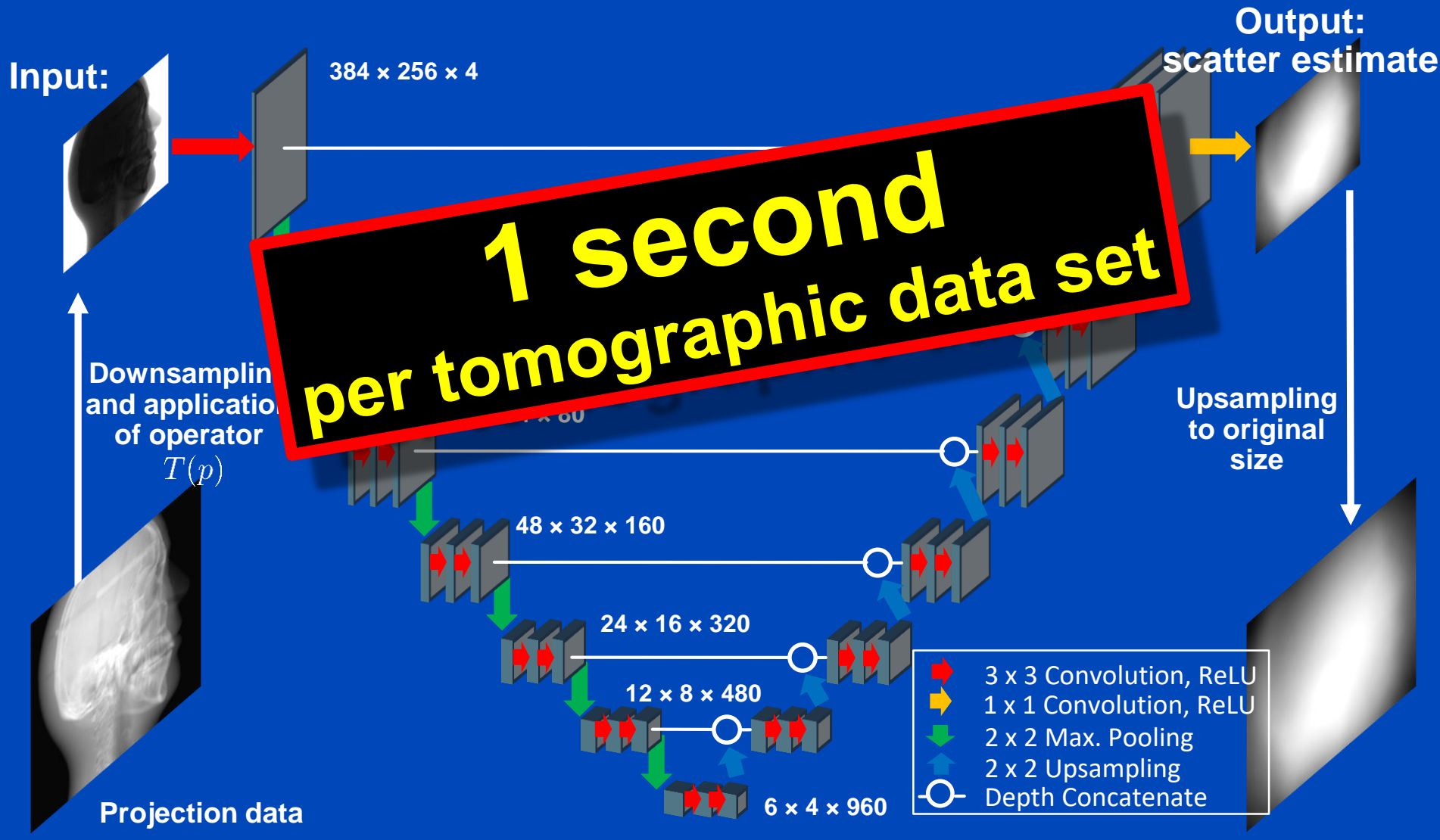
- Simulation of photon trajectories according to physical interaction probabilities.
- Simulating a large number of trajectories well approximates the complete scatter distribution

**1 hour
per tomographic data set**



Deep Scatter Estimation

Network architecture & scatter estimation framework



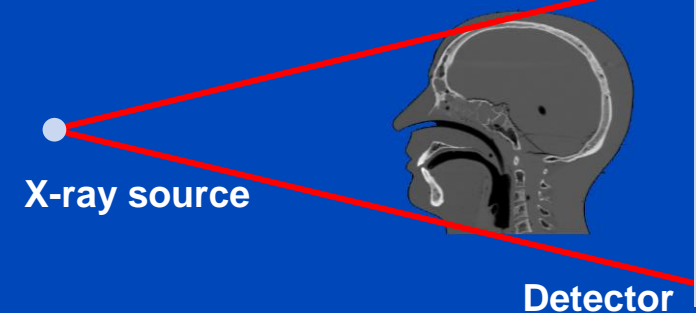
Testing of the DSE Network for Measured Data (120 kV)

DKFZ table-top CT

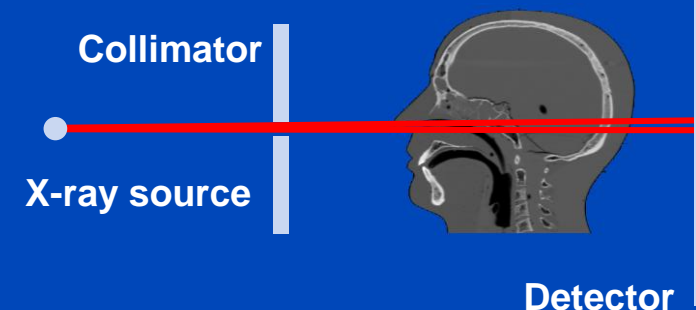


- Measurement of a head phantom at our in-house table-top CT.
- Slit scan measurement serves as ground truth.

Measurement to be corrected



Ground truth: slit scan



Reconstructions of Measured Data

Slit Scan

No Correction

Kernel-Based
Scatter Estimation

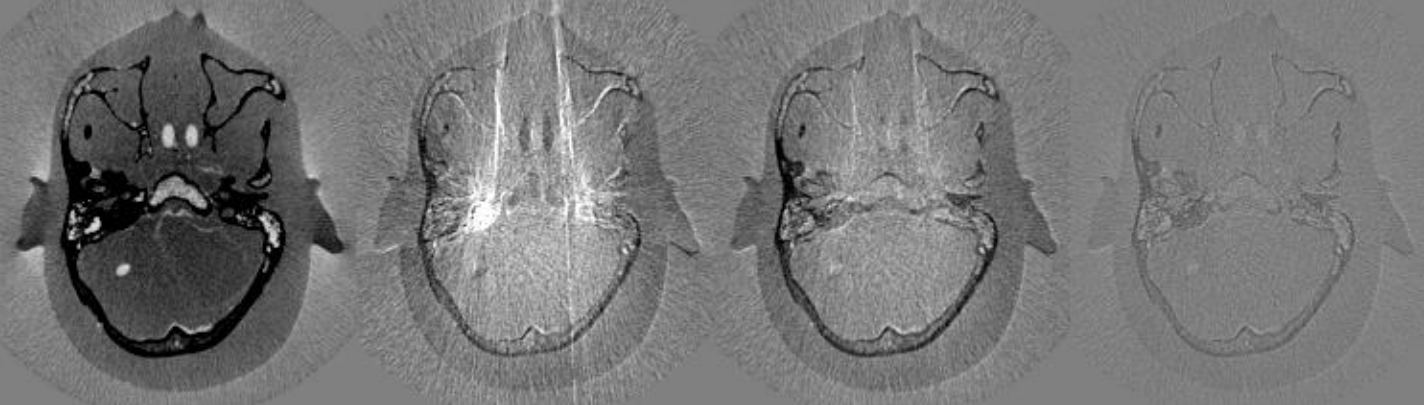
Hybrid Scatter
Estimation

Deep Scatter
Estimation

CT Reconstruction



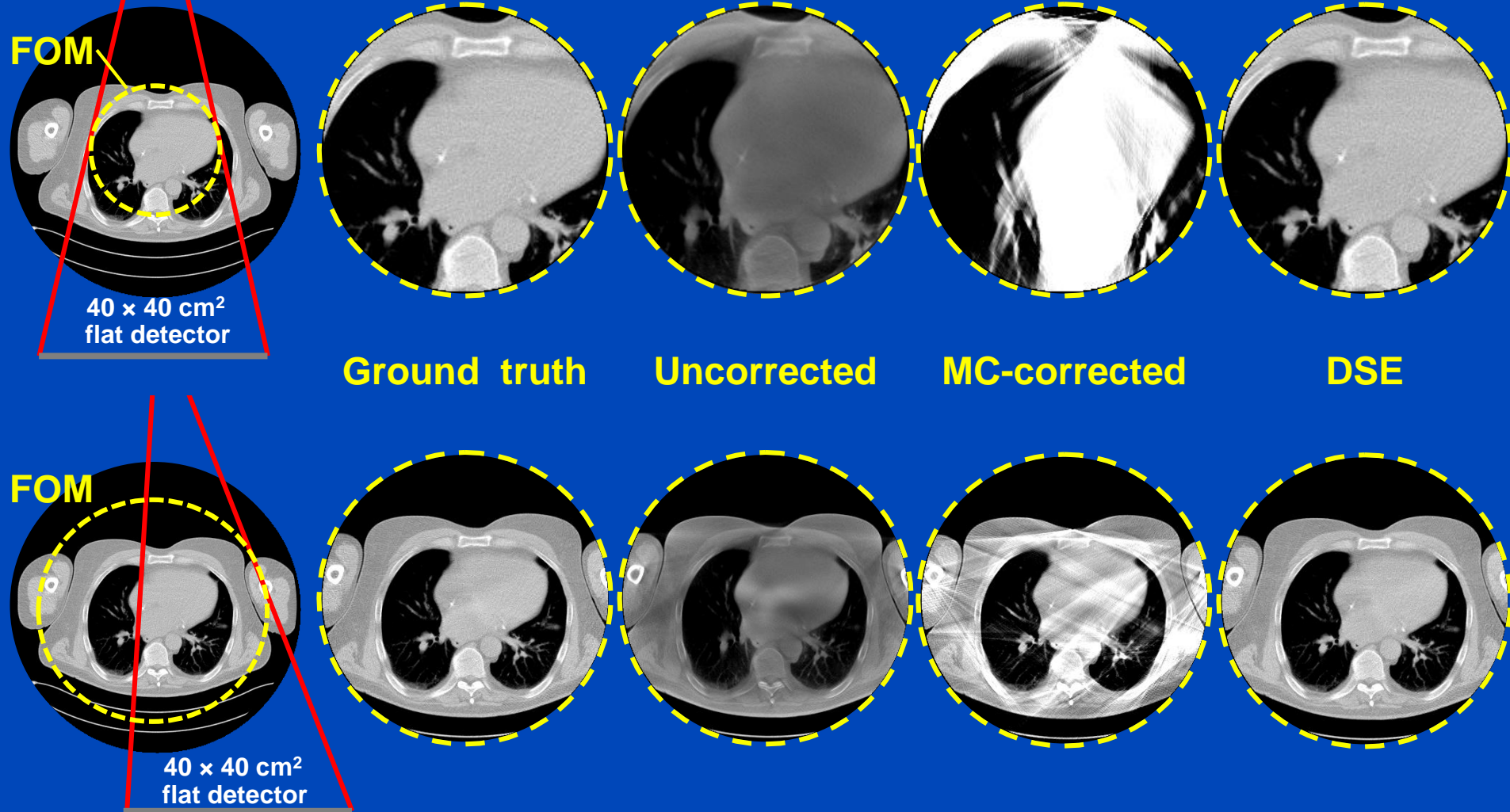
Difference to slit scan



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

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



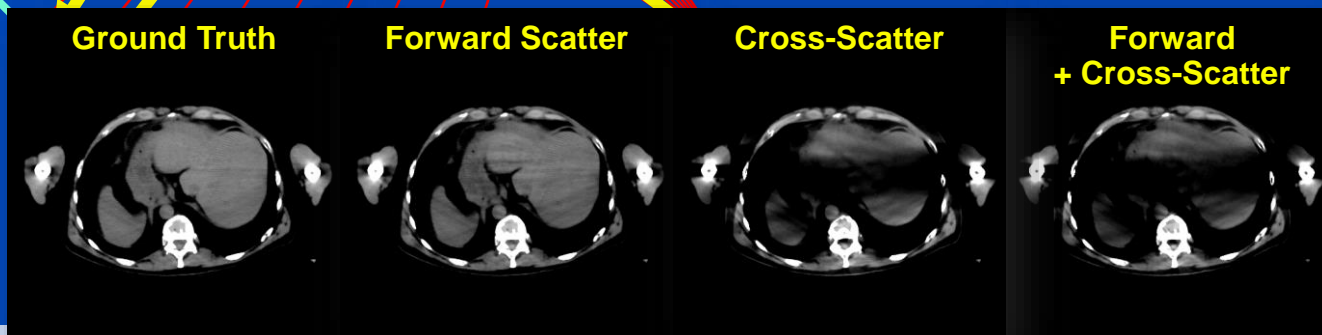
To learn why MC fails at truncated data and what significant efforts are necessary to cope with that situation see [Kachelrieß et al. Effect of detruncation on the accuracy of MC-based scatter estimation in truncated CBCT. Med. Phys. 45(8):3574-3590, August 2018].

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

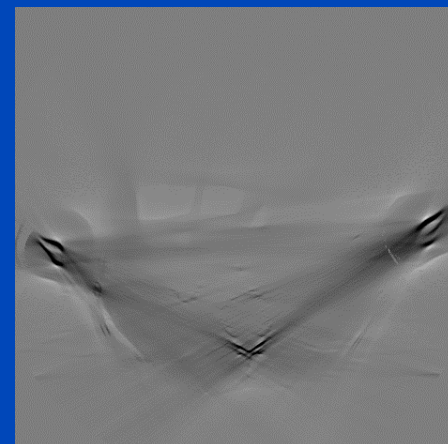
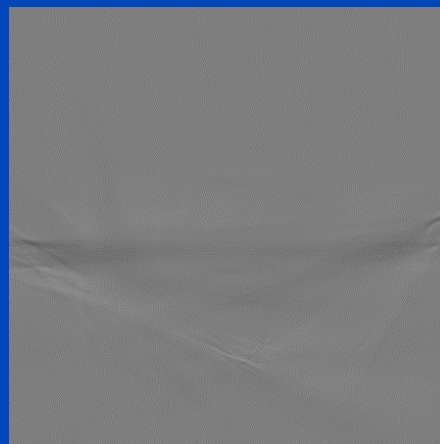
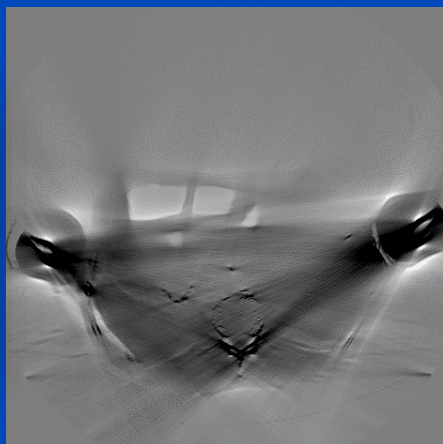
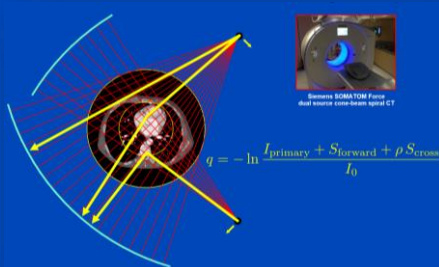
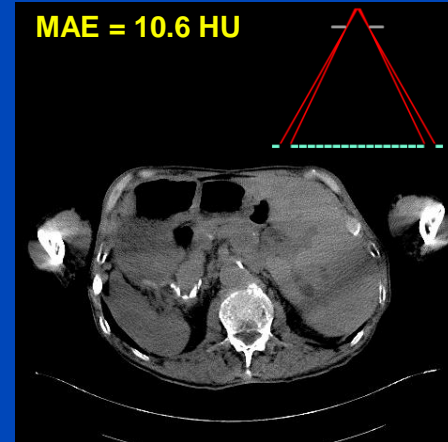
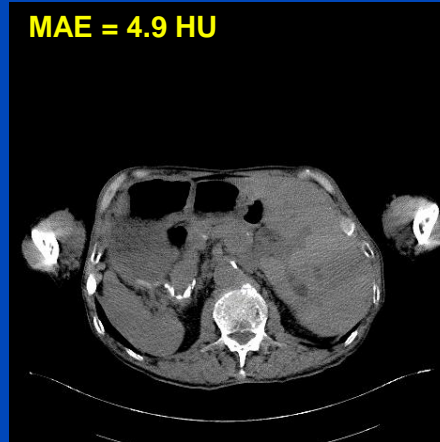
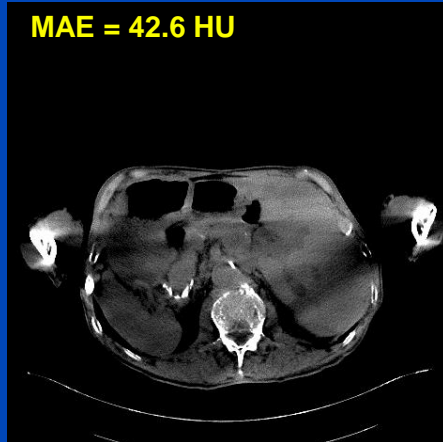
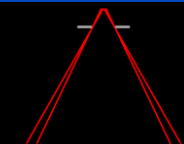
xDSE (2D, xSSE)

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

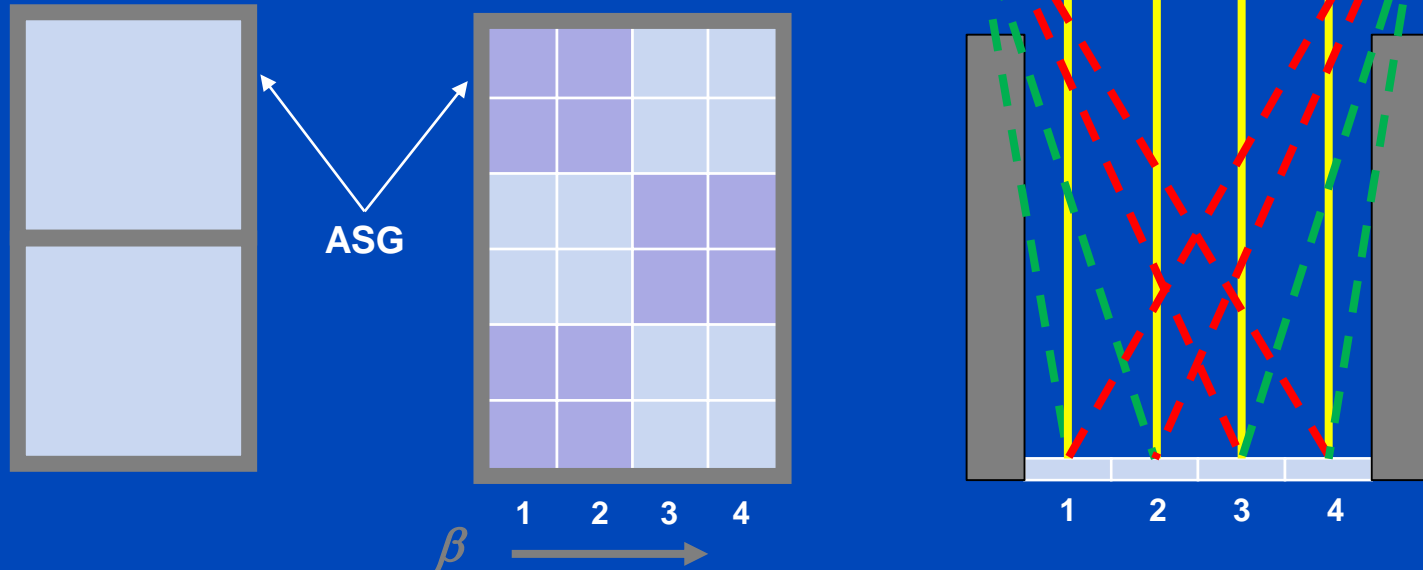
Energy-integrating
detector

Photon-counting
detector

- Primary radiation
- Scatter measured by the detector
- Scatter attenuated by the ASG

Conventional ASG
Each pixel
surrounded
by ASG

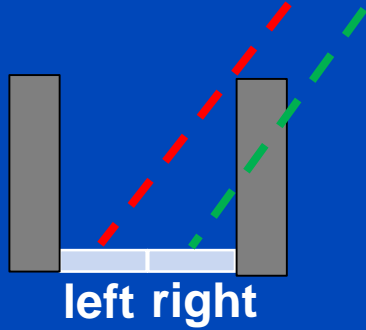
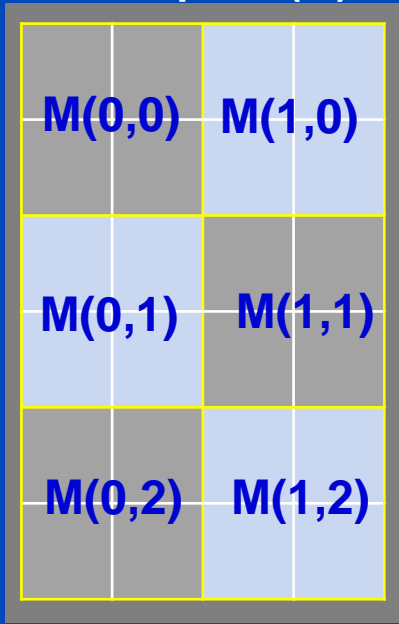
Coarse ASG
Several pixels
surrounded
by ASG



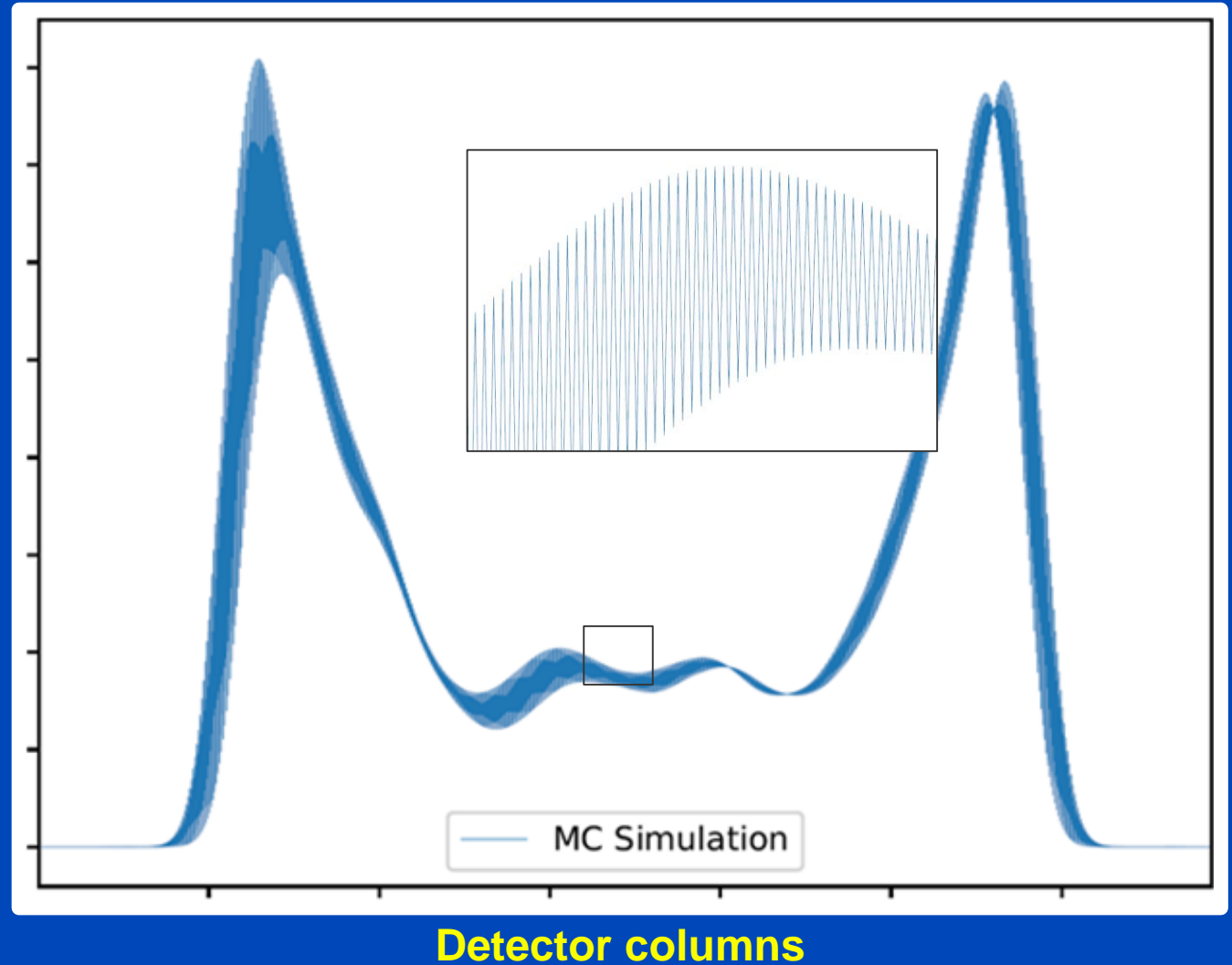
The coarse ASG leads to changes in scatter intensity between neighboring pixels, depending on the incident angle of the photon.

Scatter for Coarse ASG

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

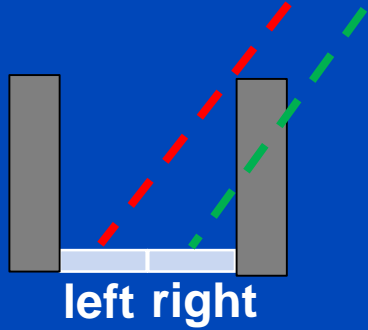
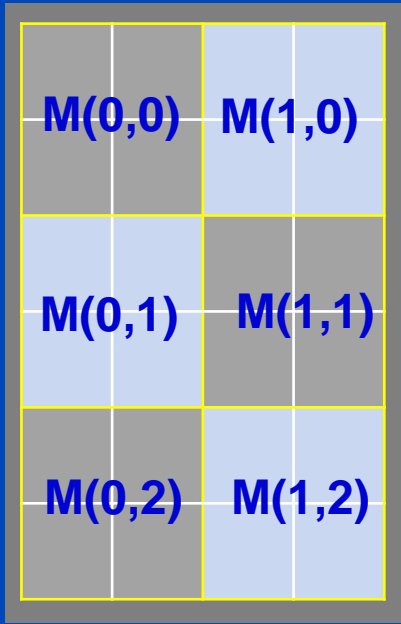


Scatter distribution averaged over all detector rows

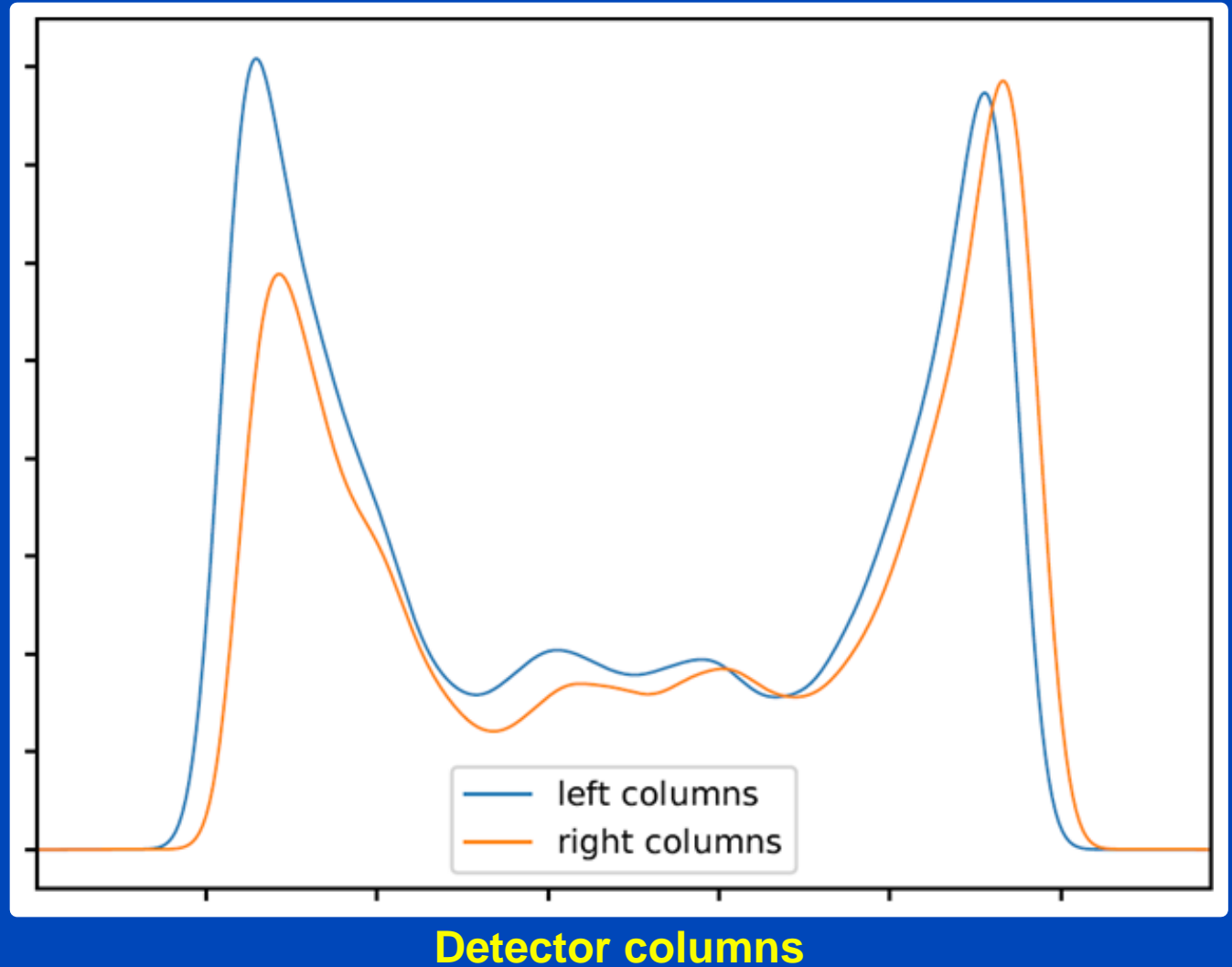


Scatter for Coarse ASG

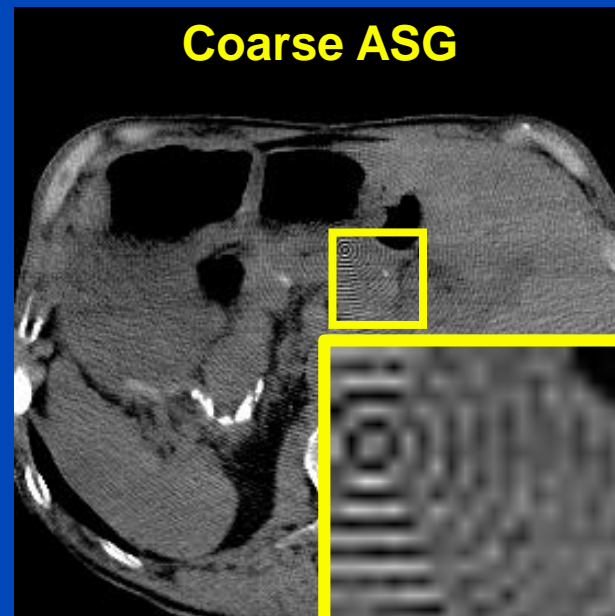
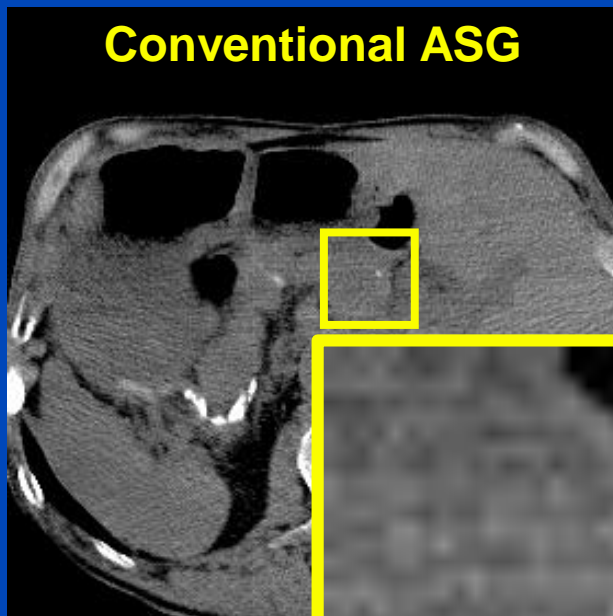
left right



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

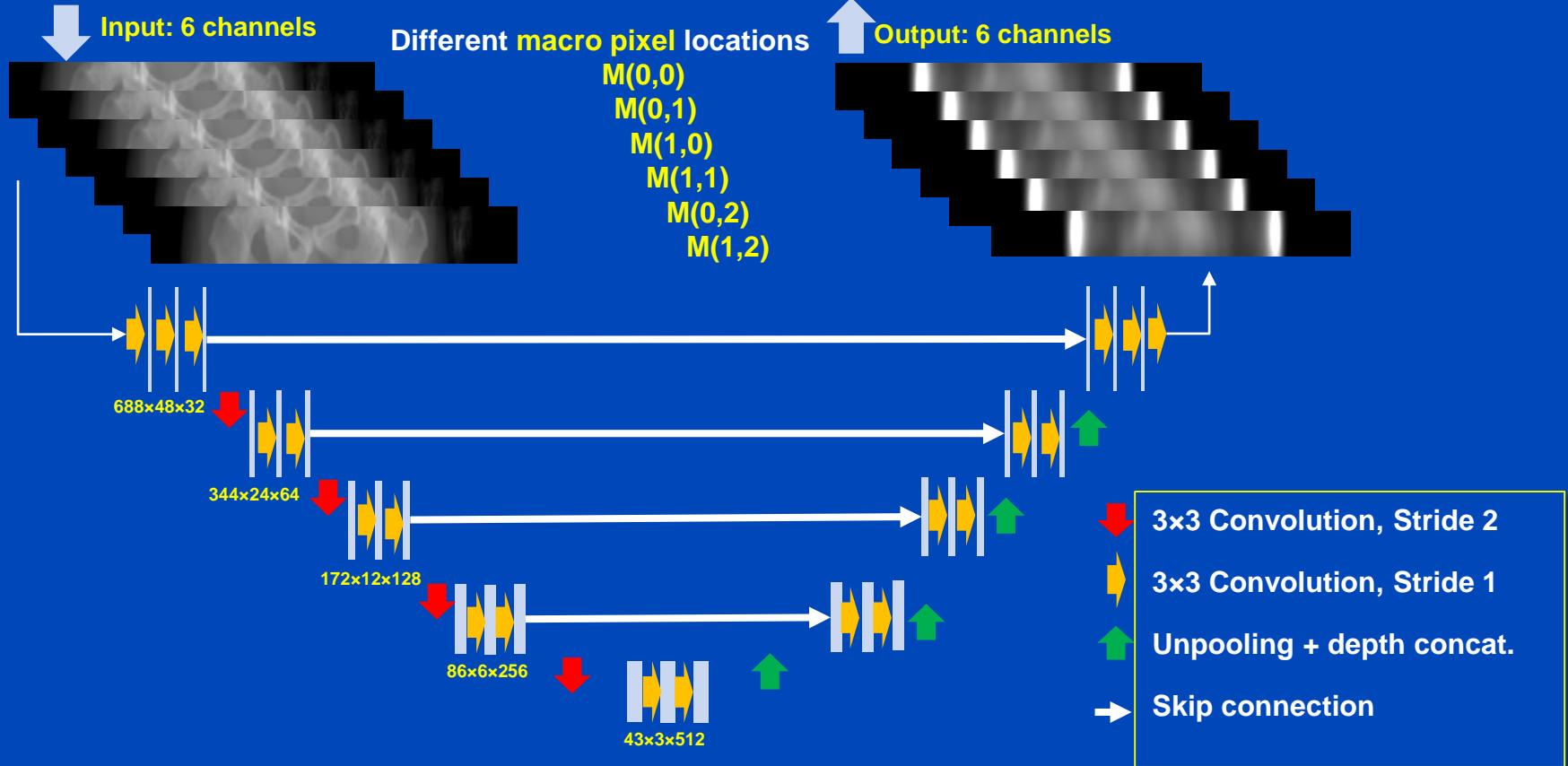
1376x144

Input mapping

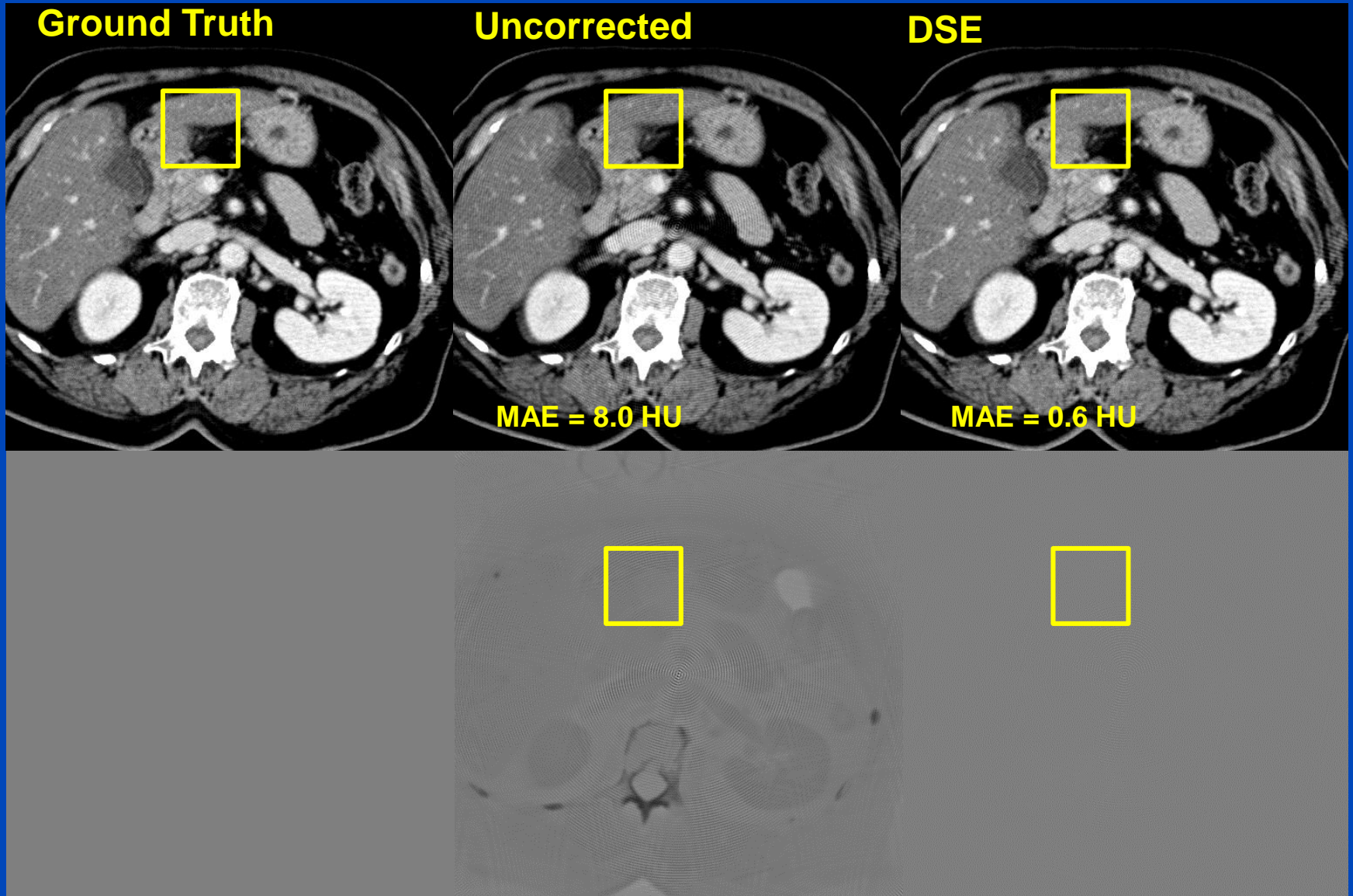
$$p = -\ln\left(\frac{I_{\text{primary}}}{I_0} + \frac{I_{\text{scatter}}}{I_0}\right)$$

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

Merging 6 different channels to obtain total scatter correction term

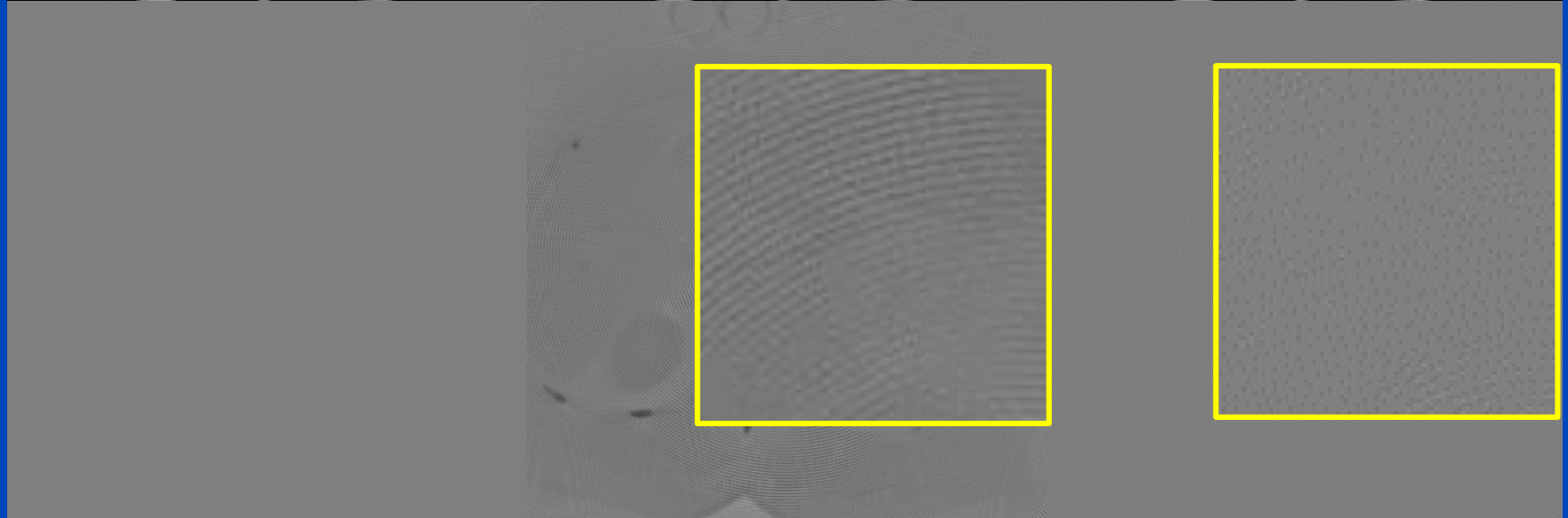
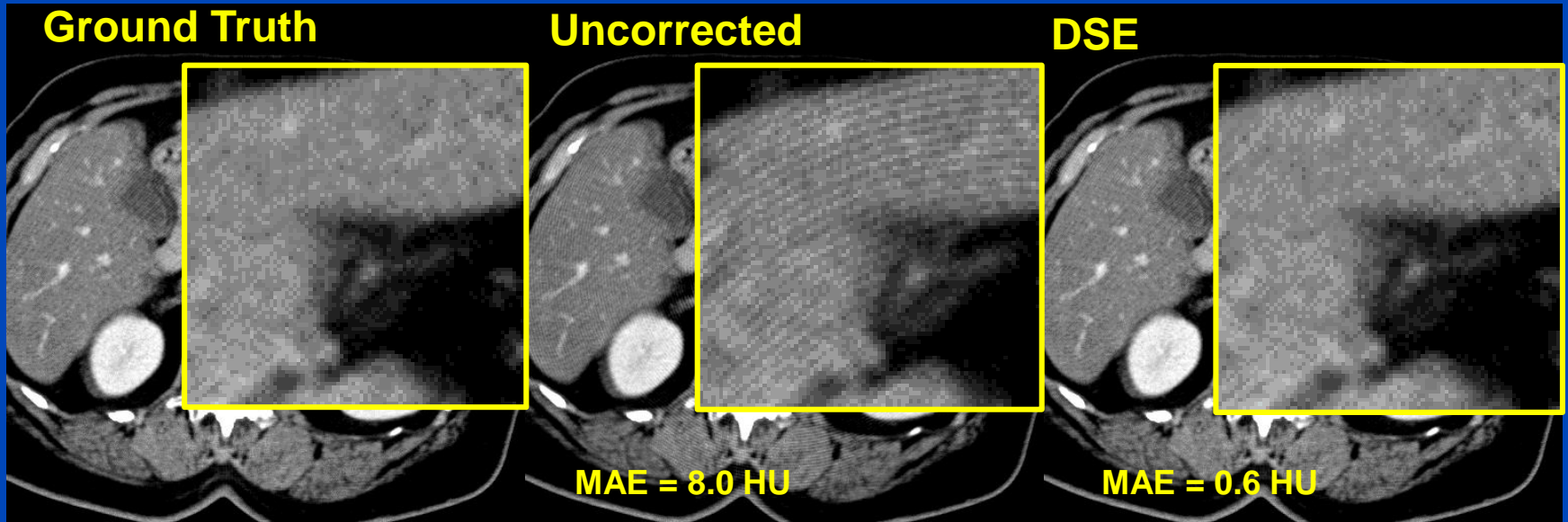


Results in Reconstructed Images



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

Results in Reconstructed Images

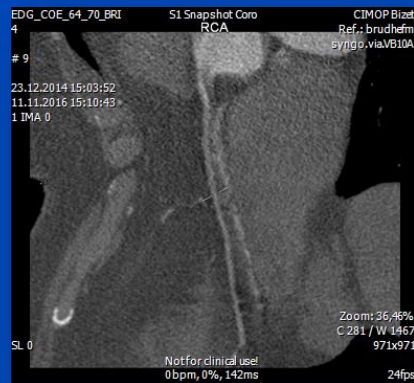


Simulated Reconstruction $C = 0$ HU, $W = 400$ HU,
Difference to GT $C = 0$ HU, $W = 50$ HU

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.

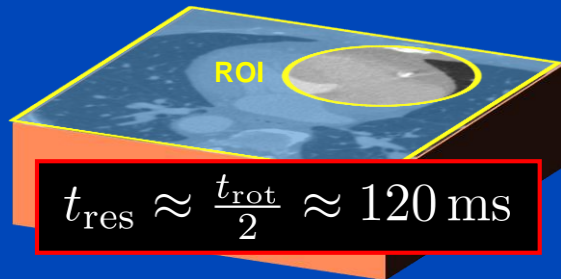
Deep Cardiac Motion Compensation



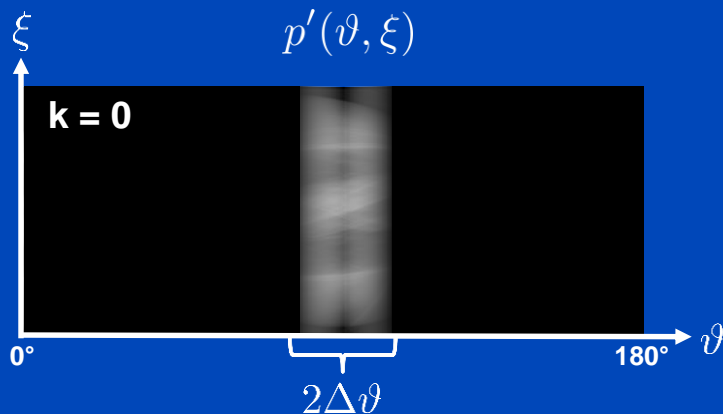
PAMoCo

Generate $2K+1$ Partial Angle Reconstructions

Initial segmented stack volume



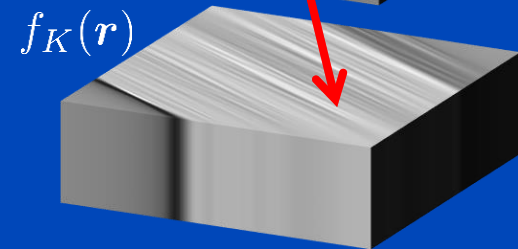
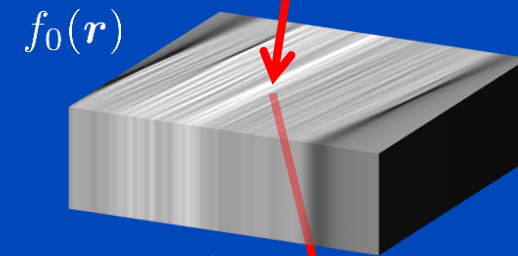
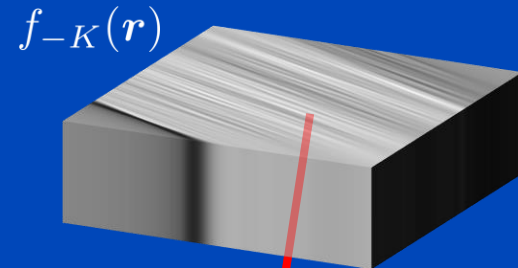
Subdivide the projection data $p'(\vartheta, \xi)$ into $2K + 1$ overlapping sectors



$$p_k(\vartheta, \xi) = w_k(\vartheta)p'(\vartheta, \xi)$$

$$w_k(\vartheta) = \Lambda((\vartheta - \vartheta_k)/2\Delta\vartheta)$$

Partial angle reconstructions $f_k(\mathbf{r})$



$$t_{\text{res}} \approx \frac{t_{\text{rot}}/2}{(2K+1)/2} \approx 10 \text{ ms}$$

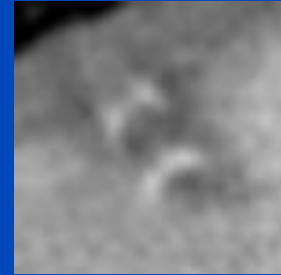
$$\text{FWHM} = \Delta\vartheta$$

$$K = 12$$

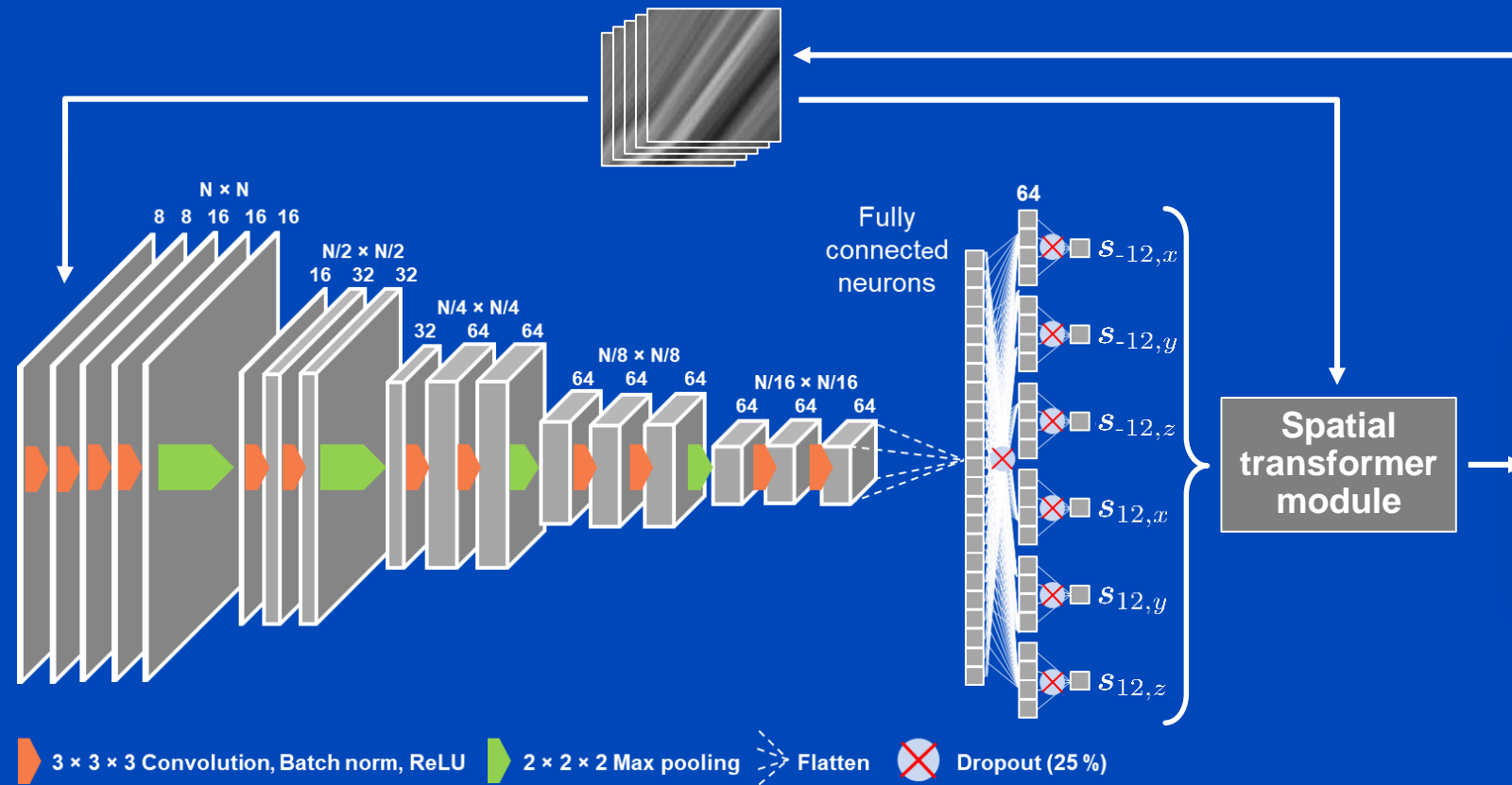
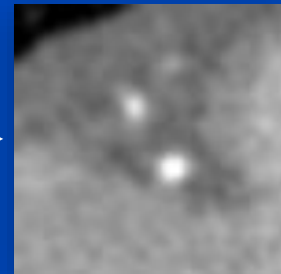
Deep PAMoCo

Network architecture

Initial volume
(with motion artifacts)

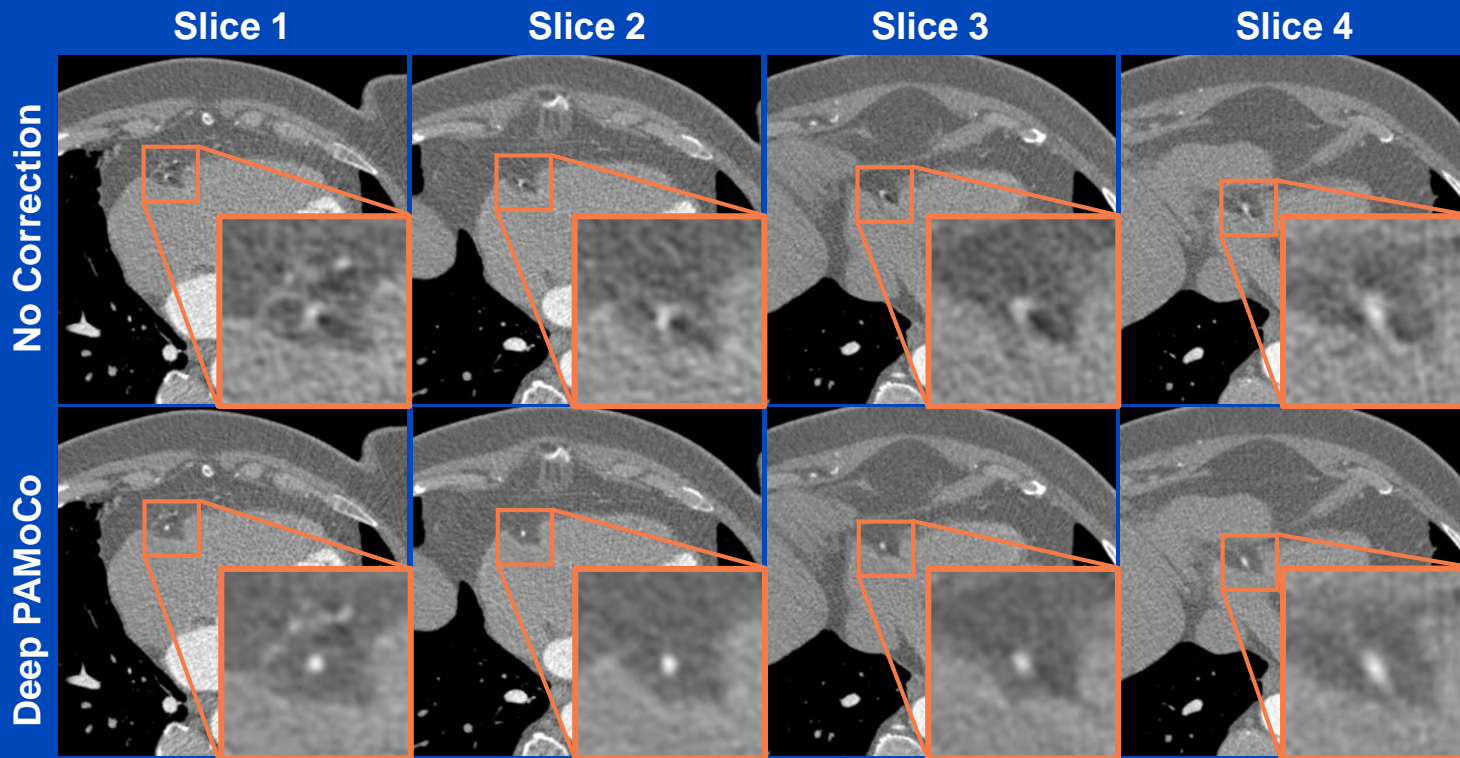


Final volume
(no motion artifacts)



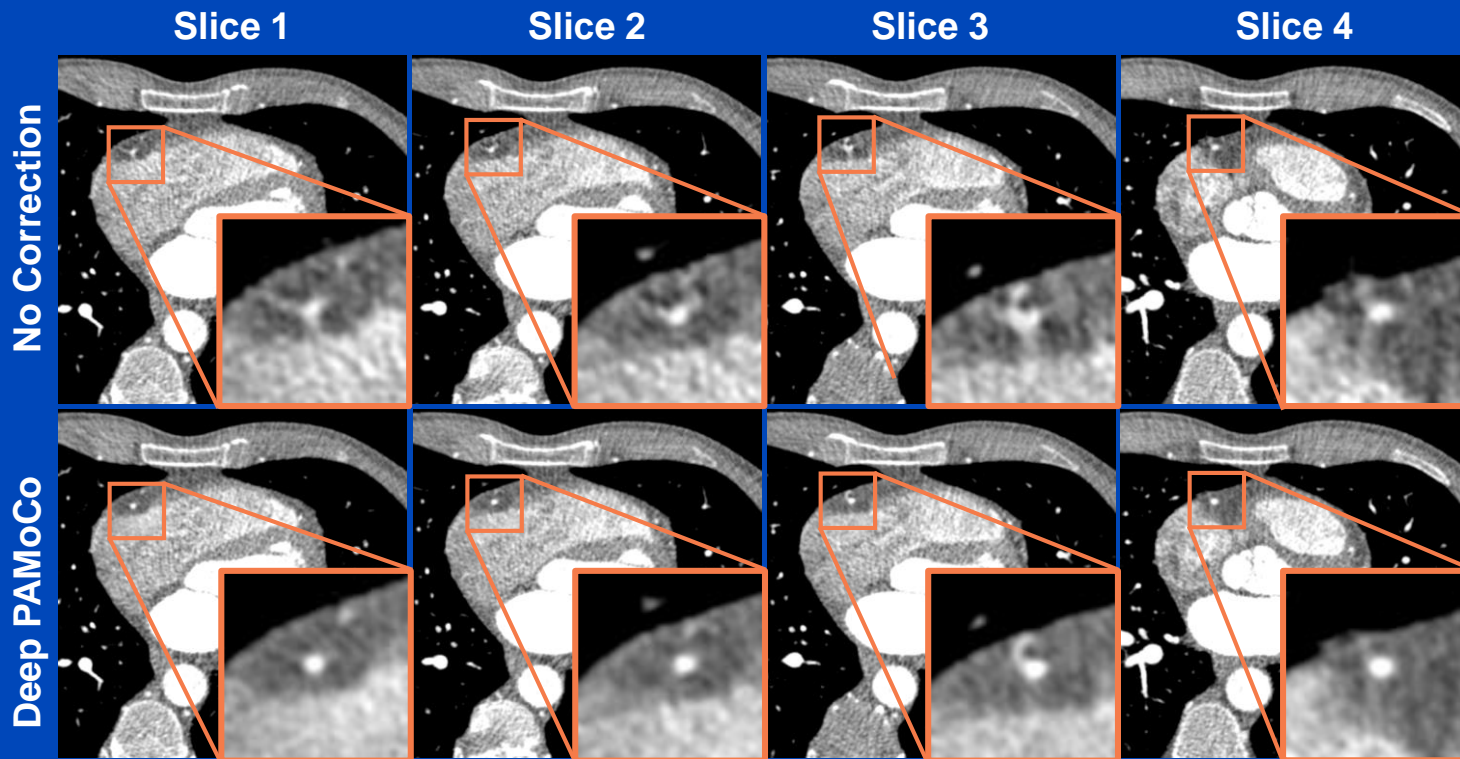
FCN-Layer output: two control points for a cubic spline:
for $k = -K$, and for $k = +K$. The third control point at $k = 0$ is $(0, 0, 0)$, i.e. no deformation for the central PAR.

Results



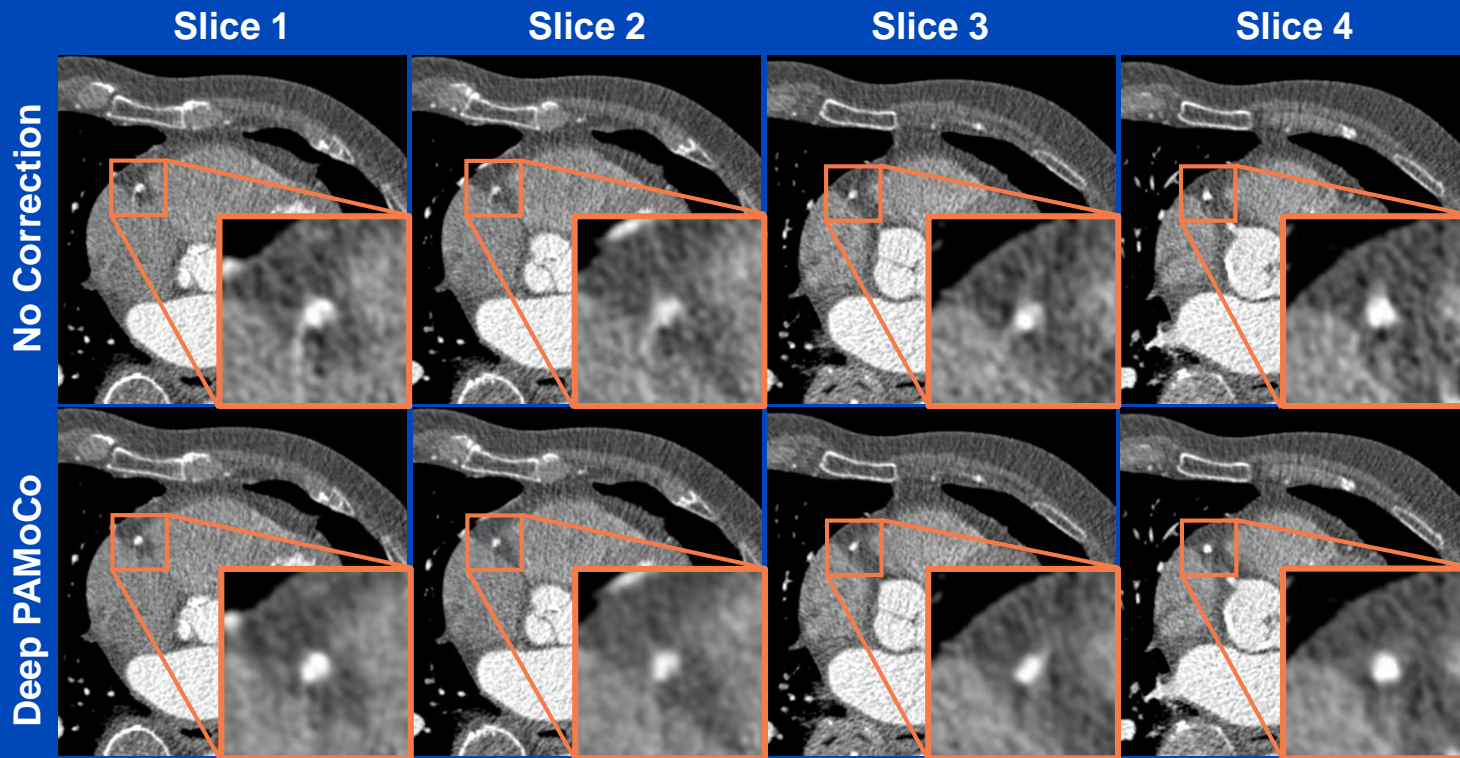
C = 1000 HU
W = 1000 HU

Results



C = 1000 HU
W = 1000 HU

Results



C = 1100 HU
W = 1000 HU

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**
 - » **Motion correction networks that estimate motion vectors rather than manipulating the voxel values**

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.