



Deep Learning in CT Artifact Correction

Marc Kachelrieß

German Cancer Research Center (DKFZ)

Heidelberg, Germany

www.dkfz.de/ct

dkfz.

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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

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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

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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. $R = I - G_I$
- 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

Nanhe Zhang¹, Senan Memric¹, and Hongyong Yu¹, Senan Memric, 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, Yuesha Li, A. Gengyi, Guo Gang, Binbin 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

Binbin Shi, Gengyi Geng¹, Binbin Shi, Yuesha Li¹, and Senan Memric¹

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

Binbin Shi, Gengyi Geng, Binbin Shi, and Senan Memric

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, Karl, Felton, 2022

Ghani, 2019

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

Ghani, 2019

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

Huili Liao¹, Wei An Liu¹, Zhiliang Han¹, Leona Yipghorn¹, 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 ξ 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

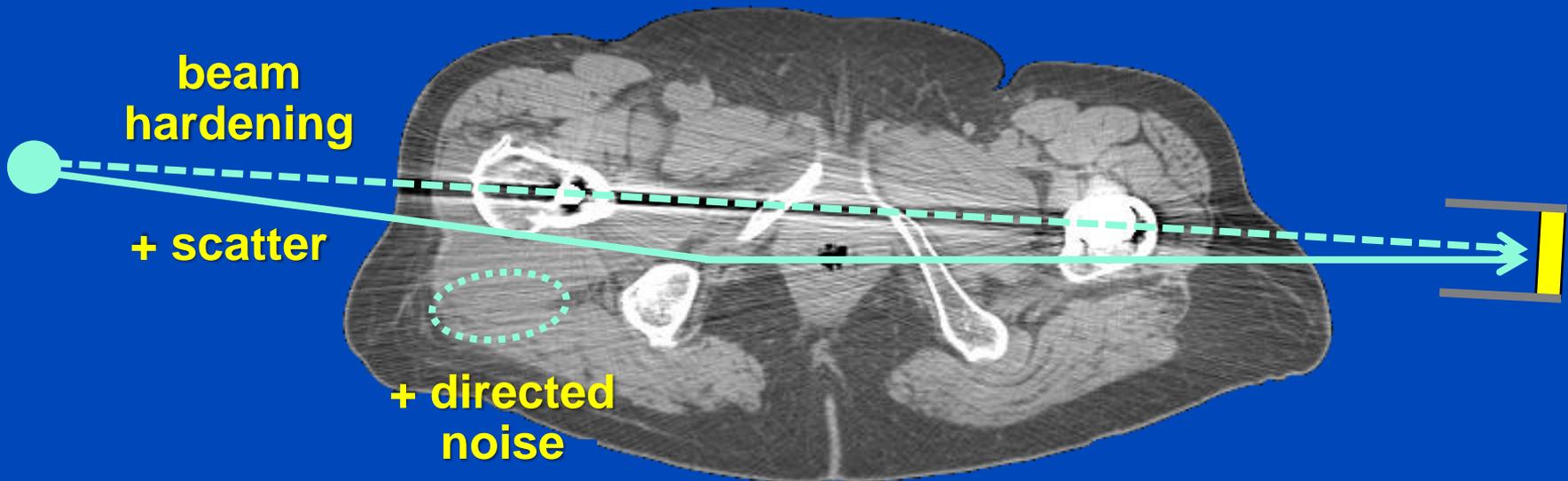
Wei An Liu¹, Huili Liao¹, Cheng Peng¹, Xiaohua Guo¹, Jiebo Luo¹, Jiebo Luo¹, Rama Chellappa², Shaohua Kevin Zhou¹

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

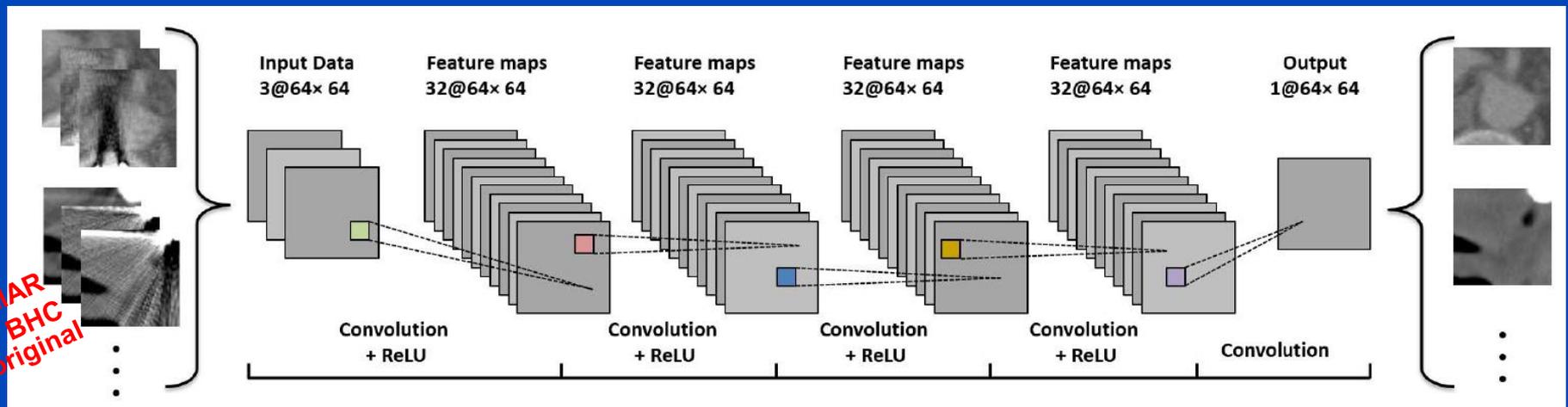
Metal artifacts are



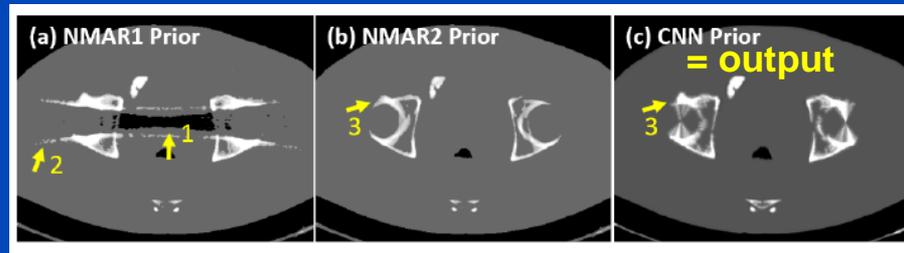
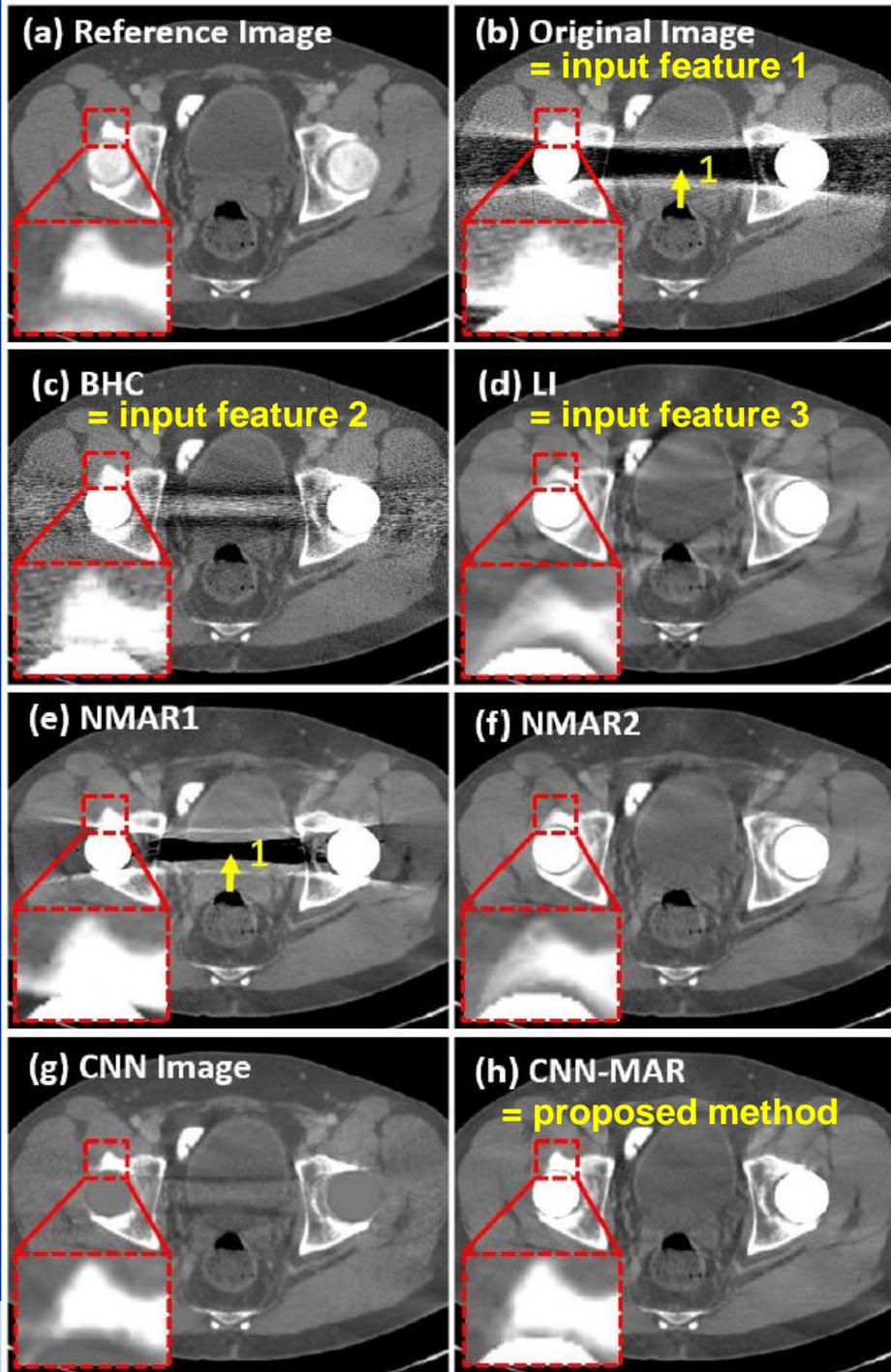
+ increased susceptibility to sampling artifacts and motion.

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



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

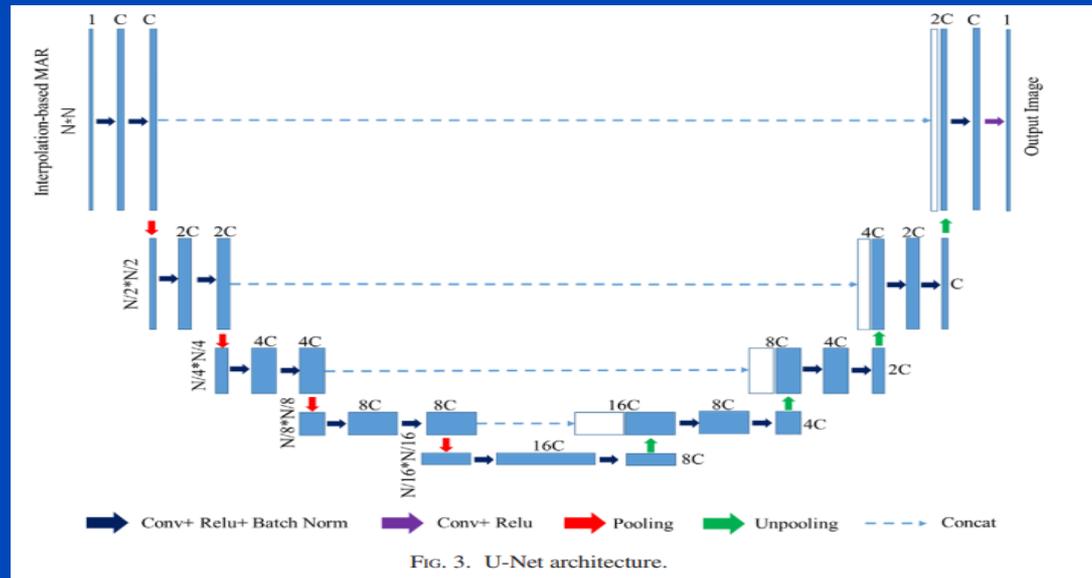
Department of Engineering Physics, Tsinghua University, Beijing 100084, China

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

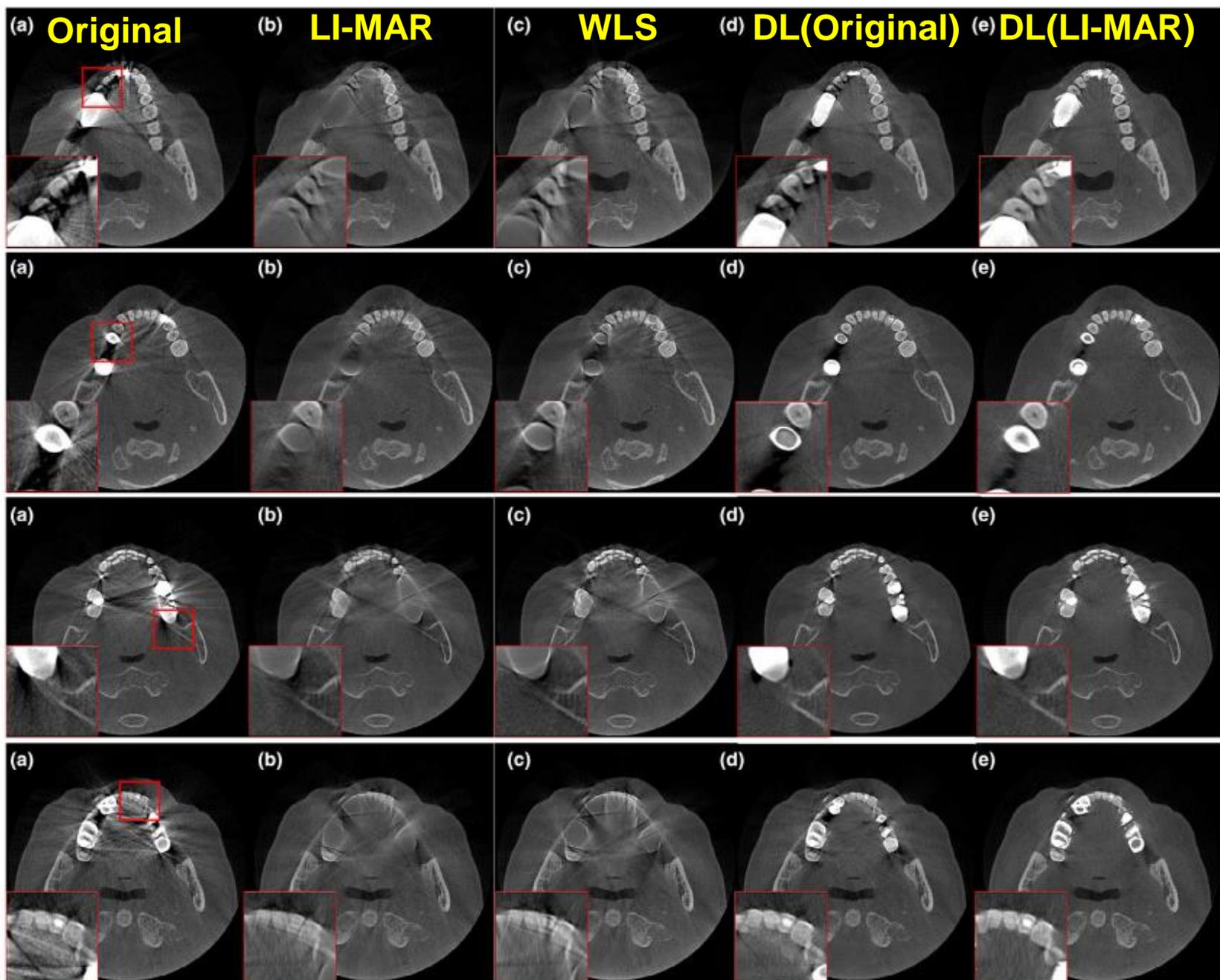


FIG. 8. Four real MAR test cases. (a) Reconstructions with no MAR, (b) I-MAR, (c) WLS reconstruction, (d) DL-MAR, (e) I-DL-MAR + metal.

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

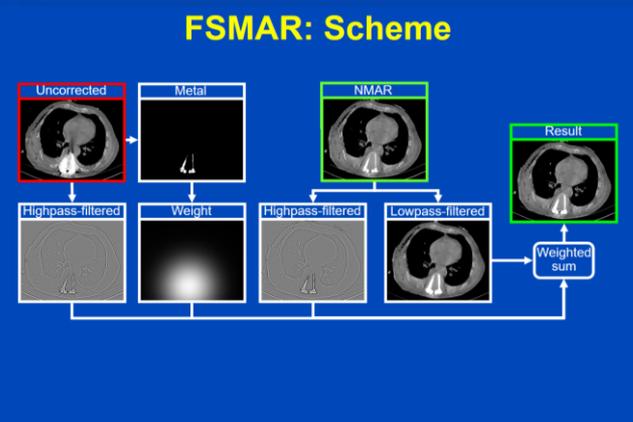
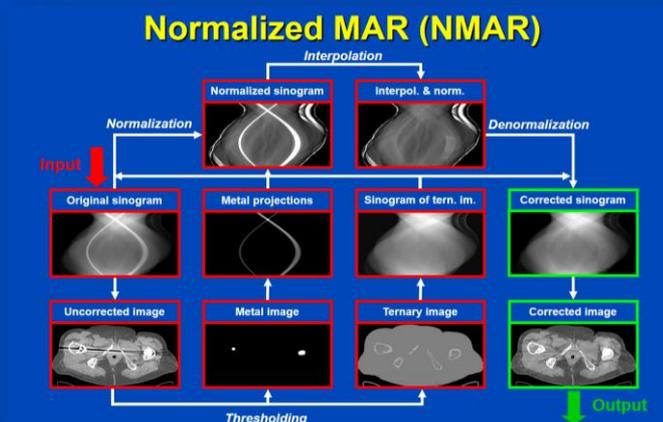
Uncorrected

FSLIMAR

FSNMAR



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



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.

Overview

- Correction in sinogram raw-data domain:
 - Nauwynck et al., Ring Artifact Reduction in Sinogram Space Using Deep Learning, Proc. CT Meeting 2020:486-489, 2020
- Correction in image domain:
 - Chang et al., A Hybrid Ring Artifact Reduction Algorithm Based on CNN in CT Images, July 30 1107.21107v26, 2019
 - Chao et al., Removal of Computed Tomography Ring Artifacts via Radial Basis Function Artificial Neural Networks, Phys. Med. Biol. 64(23):235015, 2019
 - Kornilov et al., Deep Neural Networks for Ring Artifacts Segmentation and Correction in Fragments of CT Images, 20th FRUCT conference:181-193, 2021
 - Wang et al., Removing Ring Artifacts in CBCT Images via Generative Adversarial Networks with Unidirectional Relative Total Variation Loss, Neural Computing and Applications 31(9):5475-5485, 2019
 - Ly et al., Image Denoising and Ring Artifacts Removal for Spectral CT via Deep Neural Networks, IEEE Access 8:14877-14887, 2020
- Correction in both, sinogram raw-data and image domain:
 - Fang et al., Comparison of Ring Artifacts Removal by Using Neural Network in Different Domains, MIC, 2019
 - Fang et al., Removing Ring Artifacts for Photon-Counting Detectors Using Neural Networks in Different Domains, IEEE Access 8:42447-42457, 2020

A hybrid ring artifact reduction algorithm based on CNN in CT images

Chang, Shaohui, Chen, Xi, Duan, Jiyuan, Mou, Xuanqin

Deep RAR Examples

Chang et al. (2019)

- The reference data for this image-based correction are taken from 10 full dose clinical CT images.
- Ring artifacts are simulated on these data to generate a data base of 777 paired images for supervised training of a CNN.
- Two channel input: 64x64 image patches of uncorrected and W (Wavelet-Poisson) corrected images are used as inputs.

The output of the network is directly the difference images of the original and the W (reduction data compared to the original) images. The W reduction data compared to the original images is the difference between the original image and the W reduction data.

Architecture of the used CNN. Mutual correlation and decision criterion.

Chang et al. (2019)- Results and My Conclusion

The network works very simple and contains only a few convolutional layers. Maybe this is the reason why the performance of the network is good. It is as if the remaining artifacts tend to have a low frequency larger respective field might be better.

The results of their hybrid method do not look convincing at all. Even though there are some artifacts that are removed, the way correcting are introduced (e.g. for instance the lung and air region in the 40-20 range).

Deep Neural Networks for Ring Artifacts Segmentation and Corrections in Fragments of CT Images

Antti Korhonen¹, Esa Salonen², Iina Rantanen³, Sami Takkinen⁴,
¹Department of Applied Physics, Tampere University, Tampere, Finland
²Department of Applied Physics, Tampere University, Tampere, Finland
³National Research Nuclear University MEPhI Moscow, Russia
⁴National Institute of Advanced Industrial Science and Technology, Tsukuba, Japan

FRUCT = Finnish-Russian University Cooperation in Telecommunications

Kornilov et al. (2021)

- This work addresses corrections of remaining ring artifacts after vendor corrections (hard- and/or software-based) in micro CT. Actually these artifacts are typically arcs, not full rings.
- Their dataset consists of 8 reconstructions (6 for training, 1 for validation and 1 for testing) of sand and sandstone samples (from a Bruker SkyScan 1172 micro CT). They applied automated and manual segmentations to the ring artifact areas (in total ~2000 segmented artifacts). These artifacts are then transferred to "clean" regions in order to generate training and validation data pairs.
- A two stage correction is implemented: first a U-Net is used to find and segment the artifact, and then a second CNN with some convolutional layers is used to perform an inpainting. The training of each stage is performed successively. A 2D U-Net and 3D U-Net are compared.

Kornilov et al. (2021)- Results and My Conclusion

Results for the segmentation part (left) and final image (right).

- My conclusion:**
 - Well written paper (or abstract) which addresses the problems of partial ring artifacts.
 - Unfortunately, they only show the result images above their different windows which do not really make the point that the 3D CNN is the best algorithm, which is what the labels show.

Chang et al. (2019)

Removal of computed tomography ring artifacts via radial basis function artificial neural networks

Yuhe Shi, Shih-Wei Chen, Shi-Hong Tang, Hsin-Jung Peng, Hsin-Wei Chen, 2019

Chao et al. (2019)

- An image-based correction is proposed which removes stripes in polar coordinates. The point of this paper is that the network architecture is very simple.
- The data consist of 140 clean brain images and 300 abdomen images, where the authors added 16, respectively 30 different simulated ring artifacts. For testing data a set of 40 brain images is simulated and the algorithm is tested on measured abdomen data.

Procedure:

- Transformation of volume slice in polar coordinates and perform high-pass filtering.
- Low-pass along horizontal direction (after this step there needs to be a classification of artifacts first).
- Application of 3-layer neural network with 1 input nodes (trained on simulated artifacts). I guess the output is here an offset with respect to the original image (not mentioned).

Chao et al. (2019)- Results and My Conclusion

Results for the simulated validation data (left) and measured data (right).

- My conclusion:**
 - The results look good and also corrections of measured data are shown.
 - The network is extremely simple, but so is the problem: Selected lines are inpainted by this network. It is not clear to me whether the performance is good for post restoration of each artifact? It really applied only in the artifact area. As the main problem and method was applied to the entire volume of the artifact piece. If the authors did this by hand, the method shown here is useless. In this case another net in the fashion of Kornilov et al. (2021) should be used to segment the artifact in-slices.

Ring Artifact Reduction in Sinogram Space Using Deep Learning

M. Nauwynck¹, S. Richter², A. H. van Rossum¹, J. De Boerwaerd¹, J. Sijber¹

Nauwynck et al. (2020)

- Here a ring artifact correction in sinogram space is proposed.
- Clean data from the Cancer Imaging Archive (45640 images) are forward projected. Ring artifacts are extracted from measured data with ring artifacts (from Tomobank) and randomly sampled on the clean data to get training pairs. The dataset was divided into training (42240 samples), validation (1000 samples) and test set (2400 samples).
- A 2D U-Net is used with a custom loss function that consists of a L1-loss and a Sobel-loss.

Architecture of the used U-Net.

Used loss function, $\alpha = 0.8$, $\beta = 0.2$.

Nauwynck et al. (2020) - Results and My Conclusion

Comparison of performance of the proposed method (RMSE) before corrections on the simulated dataset regarding P380 and P385. Resulting CT reconstructions of the proposed method (RMSE) for measured data.

- My conclusion:**
 - Their approach is the most intuitive to handle this issue in raw-data domain, simulate training pairs (by using measured reference ring artifacts) and use a 2D U-Net to train on the labeled data and finally perform the correction.
 - The results on measured data look good but they are not better than the comparison results. Low-frequency artifacts still remain. Maybe they were under-represented in their training data.

Removing ring artifacts in CBCT images via generative adversarial networks with unidirectional relative total variation loss

Zheng Wang¹, Jianyu Li², Qi Menghui³

Wang et al. (2019)

- Here a GAN is used to remove ring artifacts from CT volumes. The image is first transferred to polar coordinates, where ring artifacts appear as lines.
- 10 different ring artifacts are simulated on each of the 10000 brain CT images in the training dataset. The testing dataset contained 1000 simulated images and additionally 20 CBCT images with real ring artifacts.

Understandable relative variation loss (LRTV):

$$L_{LRTV} = \sum_{i=1}^N \sum_{j=1}^N |I_{ij} - I_{ji}|$$

Perceptual loss:

$$L_{perceptual} = \sum_{l=1}^L \sum_{c=1}^C |f_l(I_{img}) - f_l(I_{gt})|$$

Total loss:

$$L_{total} = L_{LRTV} + \lambda L_{perceptual}$$

Wang et al. (2019) - Results and My Conclusion

Corrected volume slices shown in sagittal, coronal and axial views. The software says it is from the training data. The images are not really clear.

- My conclusion:**
 - The paper is as presented written. It is shown that the transition to polar coordinates, as well as the use of TV loss are beneficial for the correction.
 - The design of the results is very loud. Actually only is only able to see differences in the corrections in the last image row, where no 3D is used.

Comparison of Ring Artifacts Removal by Using Neural Network in Different Domains

Wai Fang, Liang Li, Senior Member, IEEE

Method	RMSE	Results	RMSE (100)	RMSE (100)	RMSE (100)
Proposed	0.0012	0.0012	0.0012	0.0012	0.0012
U-Net	0.0015	0.0015	0.0015	0.0015	0.0015
GAN	0.0018	0.0018	0.0018	0.0018	0.0018

Fang et al. (2019)

- This paper provides a comparison of different deep ring artifact correction methods: in projection domain, in image domain (cartesian), in image domain (polar) and a combined "comprehensive" model. All use a 5-stage U-Net and the latter on both, raw-data and volume data simultaneously (backprojection layer implemented).
- Clean data is acquired from the AAPM Low Dose CT Grand Challenge. Ring artifacts are simulated by adding stripes in the sinogram data. The data was split into training (4800 images), validation (600 images) and testing datasets (526 images) and an MSE loss function is used.

Left: Three different types of algorithms tested in this work. Top: The proposed comprehensive model that uses information from image and projection domain.

Fang et al. (2019) - Results and My Conclusion

Results for the different networks compared to a conventional Wavelet Fourier WFT correction on simulated data (left), volume data (right).

- My conclusion:**
 - The interesting point in this abstract is the comparison of different deep learning methods in different domains.
 - On simulated data the results look good but this study lacks a real experiment.
 - The paper of this work follows on the next slides.

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

WEI FANG¹, LIANG LI¹ (Senior Member, IEEE), and ZHIQING CHEN²

Results for different energy bins. Close-ups of the results.

- My conclusion:**
 - A good thing about this paper is that they use measured data for training.
 - The results have some inconsistencies, e.g. where does the dark streak come from. High frequency in the yellow arrow? Furthermore, the remaining volume loss is very high. The result is a visual effect due to the noise suppression, however the authors show no MTFs.
 - A more severe problem of this paper is that I don't know why this method is needed at all. They used some conventional methods to test their data. Are these methods computationally too expensive to be used routinely? No answer is given.

Fang et al. (2020)

- This publication is the reviewed paper of the work shown on the previous slides. The same idea and similar experiments are shown. Here the authors additionally show results for measured noise data on a PCD (A/D500-eV FRUCTS, Sandusky, PA) which has 256 pixels with pixel size 0.5 mm x 2 mm.
- As in Fang et al. (2019) the authors compare the ring artifact correction results of a deep learning correction in projection domain, in image domain (cartesian), in image domain (polar), and a comprehensive model. The network architecture is that of a U-Net.
- The training, validation and test data are the same as on slide 19. Their model to simulate ring artifacts on projection data consists of a constant factor and an offset.

Fang et al. (2020) - Results and My Conclusion

Architecture of the used U-Net.

- My conclusion:**
 - This paper is very helpful, especially because it compares different domains for deep learning correction.
 - Their method combining projection and image domain, shows the best results.
 - It seems that a correction in projection domain outperforms image domain corrections. Maybe the performance of an image-based correction could be improved by using a U-Net.
 - The correction in image domain works better on cartesian coordinates than on polar coordinates. This is consistent with Wang et al. (2019) too. Wang et al. first performs a correction to polar coordinates in order to get better results. As this paper is better overall, I would not try their option.

Image Denoising and Ring Artifacts Removal for Spectral CT via Deep Neural Network

YANG YU¹, YUEYU ZHANG¹, FENG HE^{1,2}, AN HUI¹, ZHONGJIAN LI¹, SHANGYUAN GUO¹, CHENYUAN FAN¹, BANG WU^{1,2}, AND YING FENG^{1,2}

Architecture of the network. They use Fully Connected, Convolutional, and Pooling layers.

- My conclusion:**
 - Well written paper with a good idea.
 - The network architecture is very simple.
 - The results on measured data look good but they are not better than the comparison results. Low-frequency artifacts still remain. Maybe they were under-represented in their training data.

Lv et al. (2020)

- This work focusses on denoising and ring artifact reduction of PCDT data in image domain via a CNN.
- They solely process measured data. To have ground truth data available they perform a noise suppression via a Split-Bregman algorithm and an iterative image-based ring artifact correction.
- The total number of CT images used for training, validation and testing was 2240, in the ratio 1:1.5. An MSE-like cost function is used.
- The PCD they are using is not specified, experiments were performed with 8 energy bins with thresholds ranging from 25 keV to 50 keV.

Architecture of the network. They use Fully Connected, Convolutional, and Pooling layers.

- My conclusion:**
 - The network architecture is very simple.
 - The results on measured data look good but they are not better than the comparison results. Low-frequency artifacts still remain. Maybe they were under-represented in their training data.

Lv et al. (2020) - Results and My Conclusion

Results for different energy bins. Close-ups of the results.

- My conclusion:**
 - A good thing about this paper is that they use measured data for training.
 - The results have some inconsistencies, e.g. where does the dark streak come from. High frequency in the yellow arrow? Furthermore, the remaining volume loss is very high. The result is a visual effect due to the noise suppression, however the authors show no MTFs.
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Ring Artifact Reduction: Literature

- Correction in sinogram/rawdata domain:
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- Correction in image domain:
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 - Chao et al., *Removal of Computed Tomography Ring Artifacts via Radial Basis Function Artificial Neural Networks*, Phys. Med. Biol. 64(23):235015, 2019
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 - Wang et al., *Removing Ring Artifacts in CBCT via GAN with Unidirectional Relative Total Variation Loss*, Neural Computing and Applications 31(9):5147-5158, 2019
 - Lv et al., *Image Denoising and Ring Artifacts Removal for Spectral CT via Deep Neural Network*, IEEE Access 8:225594-225601, 2020
- Correction in both, sinogram/raw-data and image domain:
 - Fang et al., *Comparison of Ring Artifacts Removal by Using Neural Network in Different Domains*, MIC, 2019
 - Fang et al., *Removing Ring Artefacts for Photon-Counting Detectors Using Neural Networks in Different Domains*, IEEE Access 8:42447-42457, 2020

Ring Artifact Reduction: Comments

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

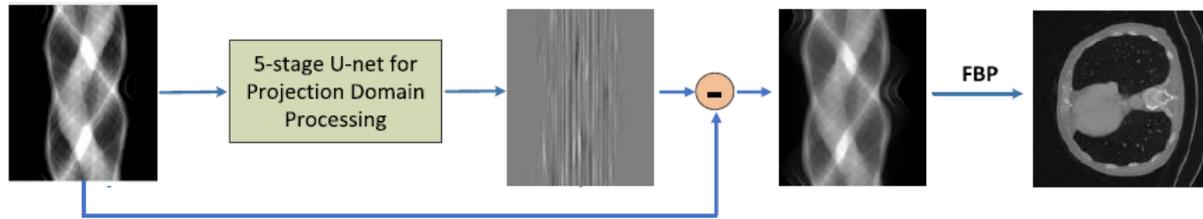


FIGURE 3. The diagram of ring artefacts removal in projection domain.

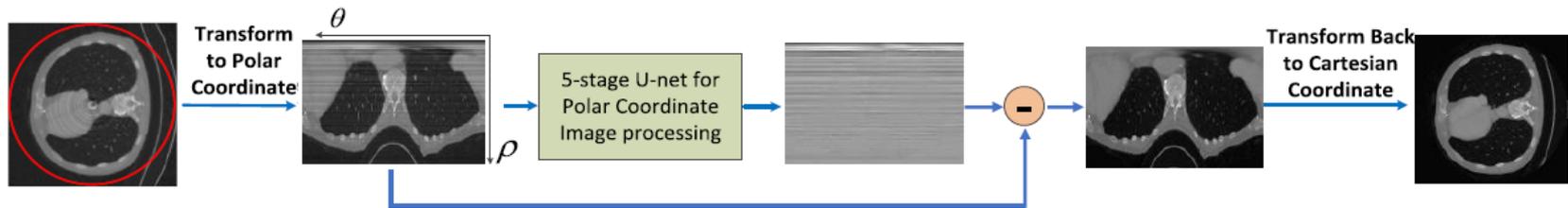


FIGURE 4. The diagram of ring artefacts removal in polar coordinate system.

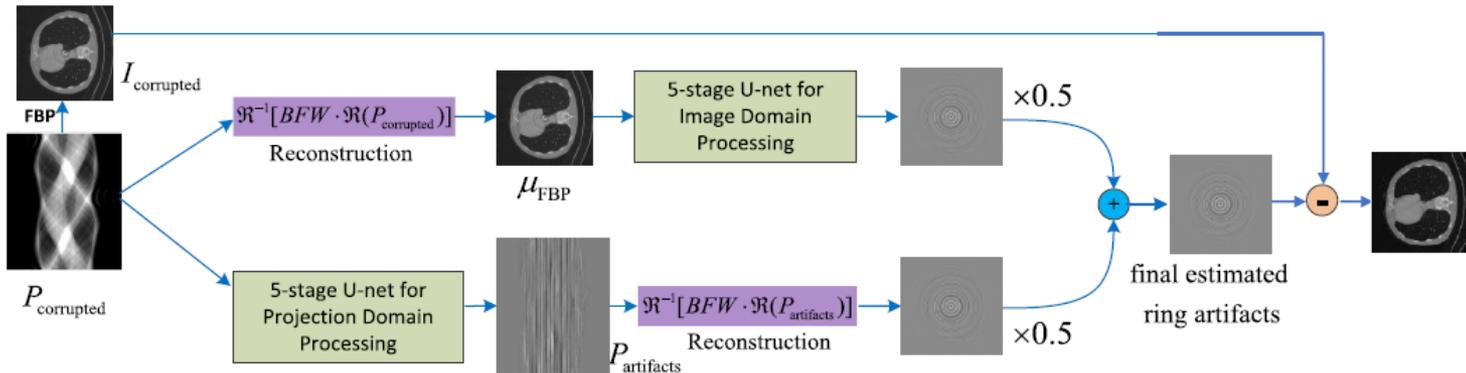
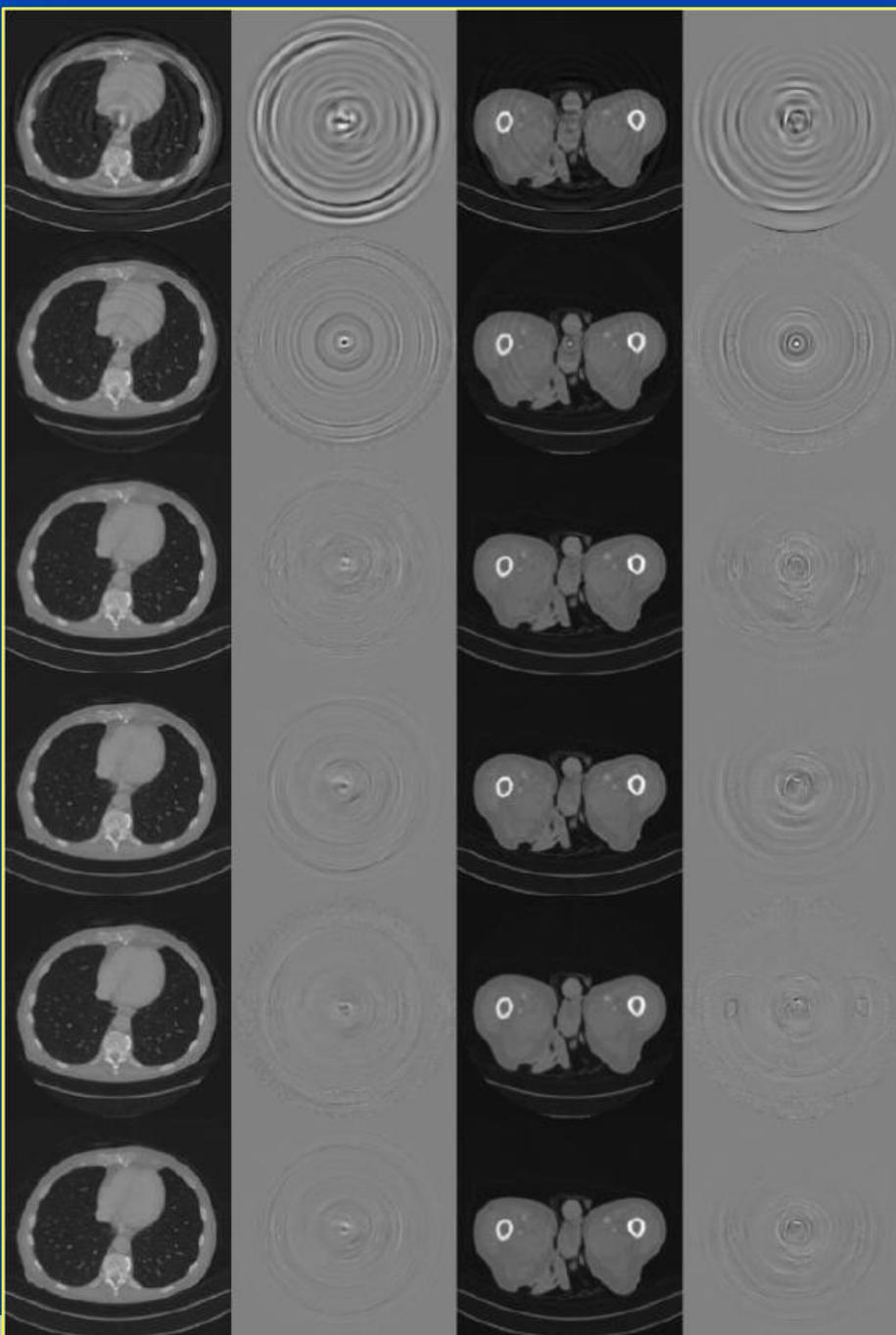


FIGURE 5. The diagram of ring artefacts removal using a comprehensive model.

Wavelet projection domain



Wavelet polar image domain

U-net image domain

U-net projection domain

U-net polar image domain

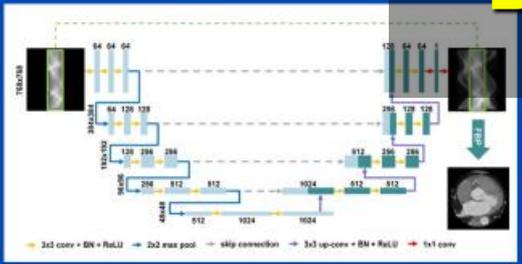
U-net in both domains

Summary on Deep RAR

- Similar comments as for deep MAR apply here.
- Often, the images are resampled to polar coordinates before being manipulated by the network.
- Deep learning, as of today, provides incremental improvements compared to conventional RAR methods.

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. Jakulin¹
¹Research Unit of Medical Imaging, Physics and Technology, University of Oulu, Oulu, Finland
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



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

Results

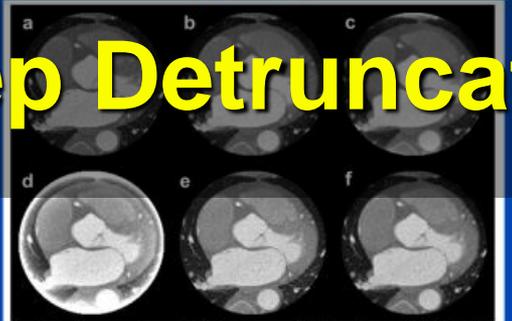


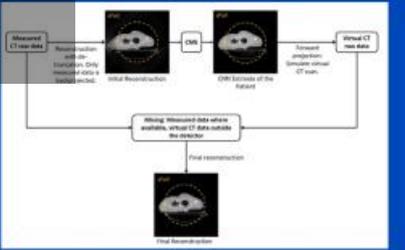
Figure 3. Example reconstructions. a. Original data from scanner. b. Adaptive truncation followed by filtered backprojection. c. Total variation regularization. d. Filtered backprojection. e. FBPCNet. f. Our Method. Reconstructions have been rescaled to contain the region-of-interest.

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

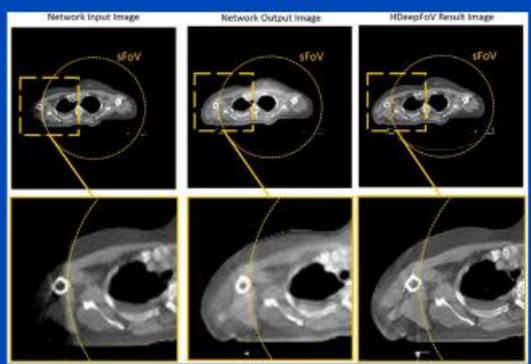
Gabriel Palva Fonseca¹, Alexander Preuhs², Michael Manhart², Guenter Lauritsch², and Andreas Maier²
¹Department of Radiation Oncology (MAASTRO), GROW School for Oncology and Developmental Biology, Maastricht University Medical Center, Maastricht 6229 XZ, The Netherlands
²Siemens Healthcare GmbH, Forchheim, Germany
³Baria Rinaldi, Michel C. Orlas, Wouter J.C. van Elmpt and Frank Verhaeghan
⁴Department of Radiation Oncology (MAASTRO), GROW School for Oncology and Developmental Biology, Maastricht University Medical Center, Maastricht 6229 XZ, The Netherlands

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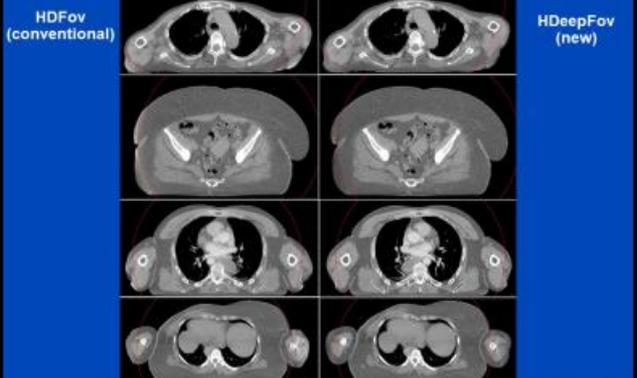
Fonseca, Gabriel Palva, et al. "Evaluation of novel AI-based extended field-of-view CT reconstructions." *Medical Physics* (2021). **dkfz.**

Results



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

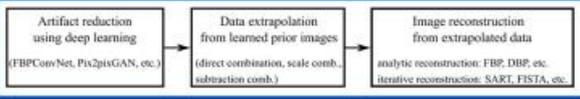
Results



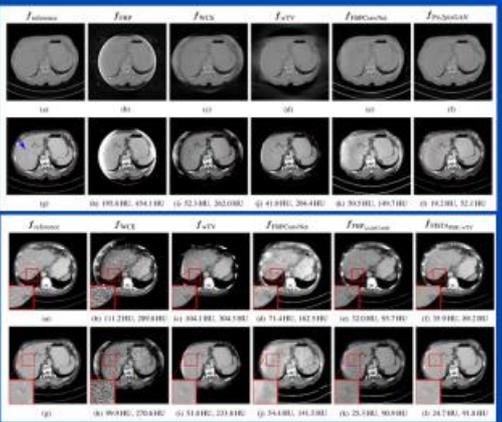
Fonseca, Gabriel Palva, et al. "Evaluation of novel AI-based extended field-of-view CT reconstructions." *Medical Physics* (2021). **dkfz.**

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

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



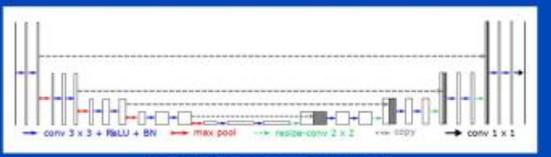
Huang, Yixing, et al. "Data Extrapolation from Learned Prior Images for Truncation Correction in Computed Tomography." *IEEE Transactions on Medical Imaging* (2021). **dkfz.**



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

Data Consistent CT Reconstruction from Insufficient Data with Learned Prior Images

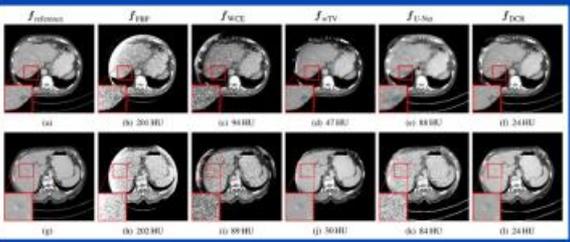
Yixing Huang, Alexander Preuhs, Michael Manhart, Guenter Lauritsch, Andreas Maier



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

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

Results



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

Deep learning -based sinogram extension method for interior computed tomography

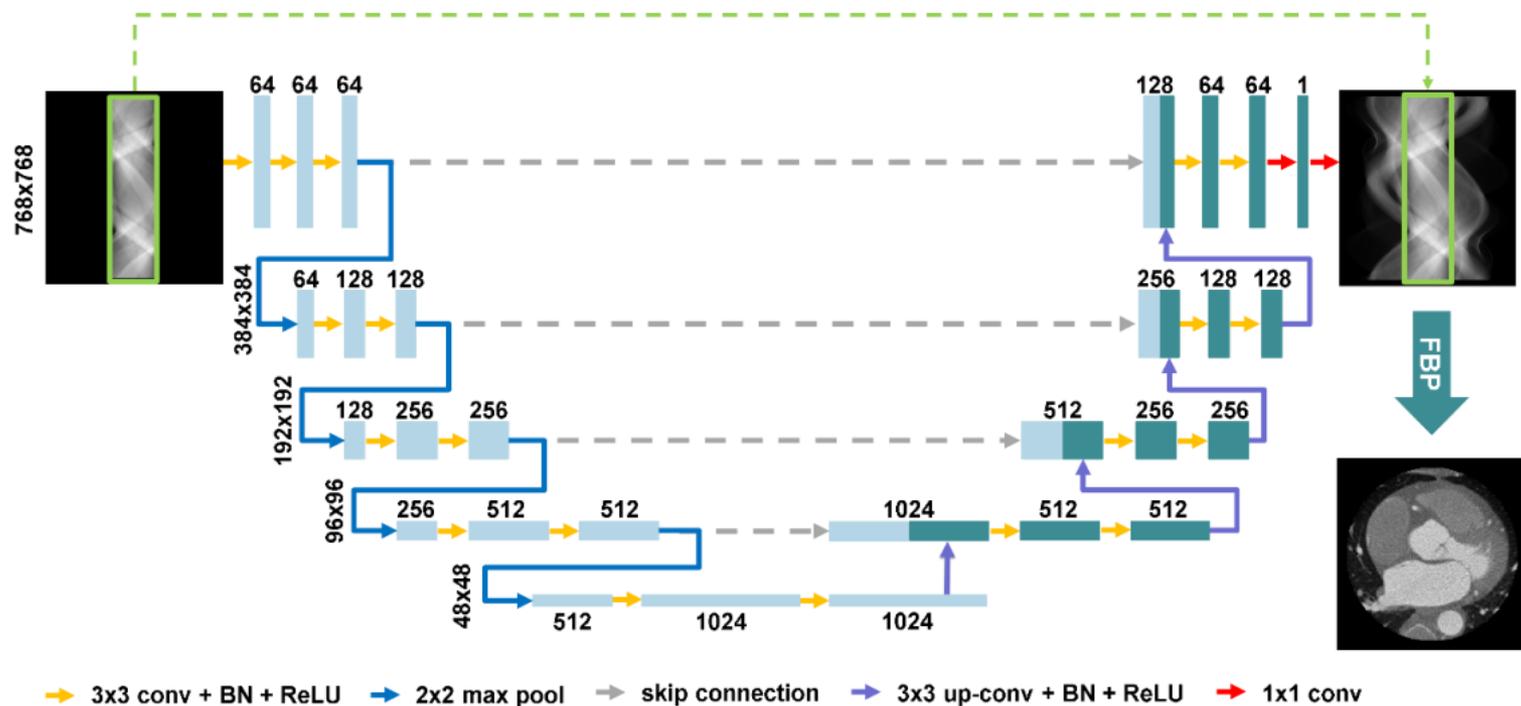
Juuso H. J. Ketola^{*a}, Helinä Heino^a, Mikael A. K. Juntunen^{a,b}, Miika T. Nieminen^{a,b,c},
and Satu I. Inkinen^a

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

^bThe South Savo Health Care Authority, Mikkeli Central Hospital, Oulu, Finland

^cDepartment of Diagnostic Radiology, Oulu University Hospital, Oulu, Finland

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



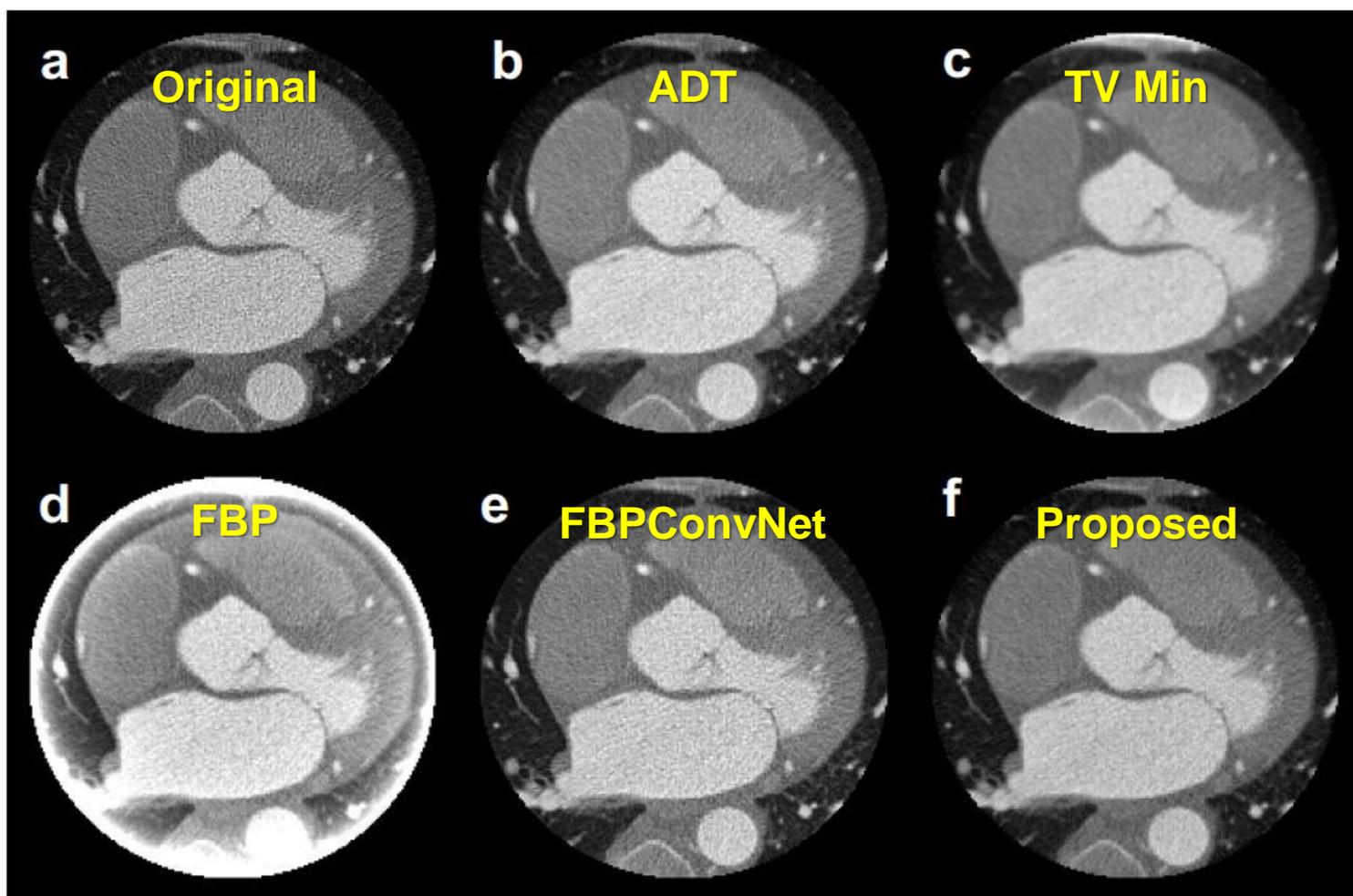


Figure 3. Example reconstructions. a. Original data from scanner. b. Adaptive de-truncation followed by filtered backprojection. c. Total variation regularization. d. Filtered backprojection. e. FBPCConvNet. f. Our Method. Reconstructions have been masked to contain the region-of-interest.

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

Gabriel Paiva Fonseca^{a)*}

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

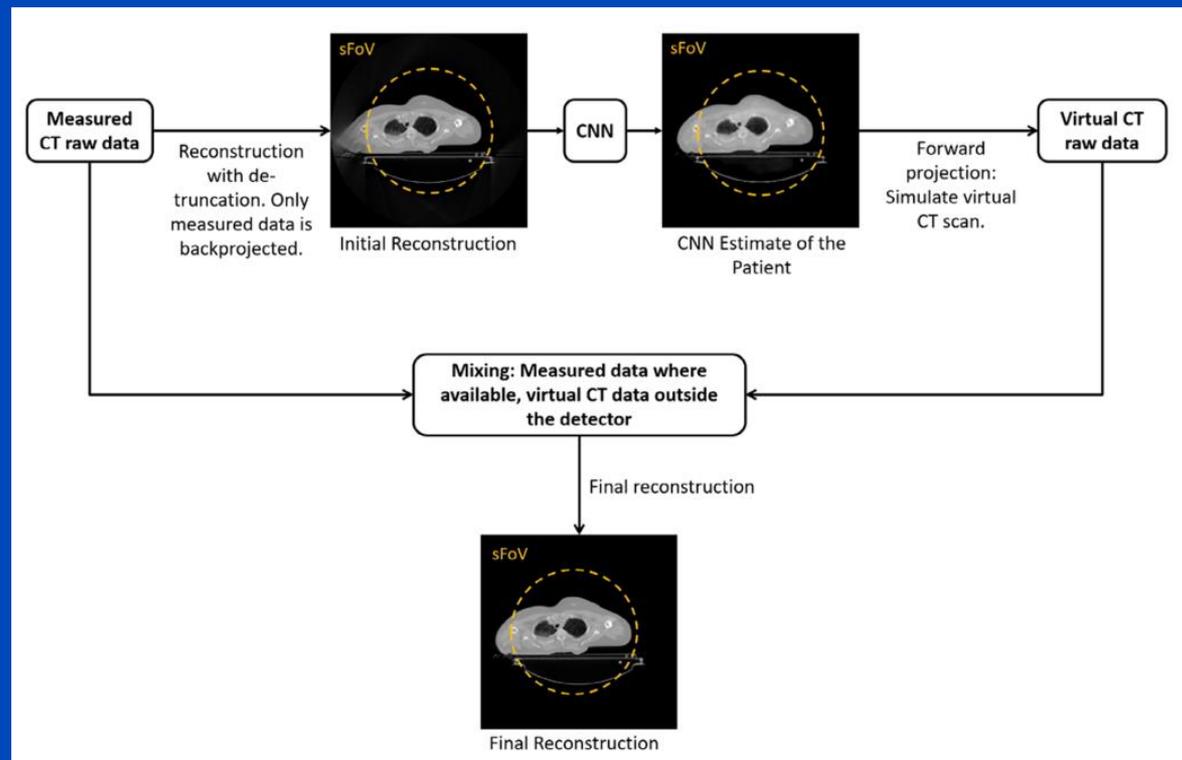
Matthias Baer-Beck* Eric Fournie and Christian Hofmann

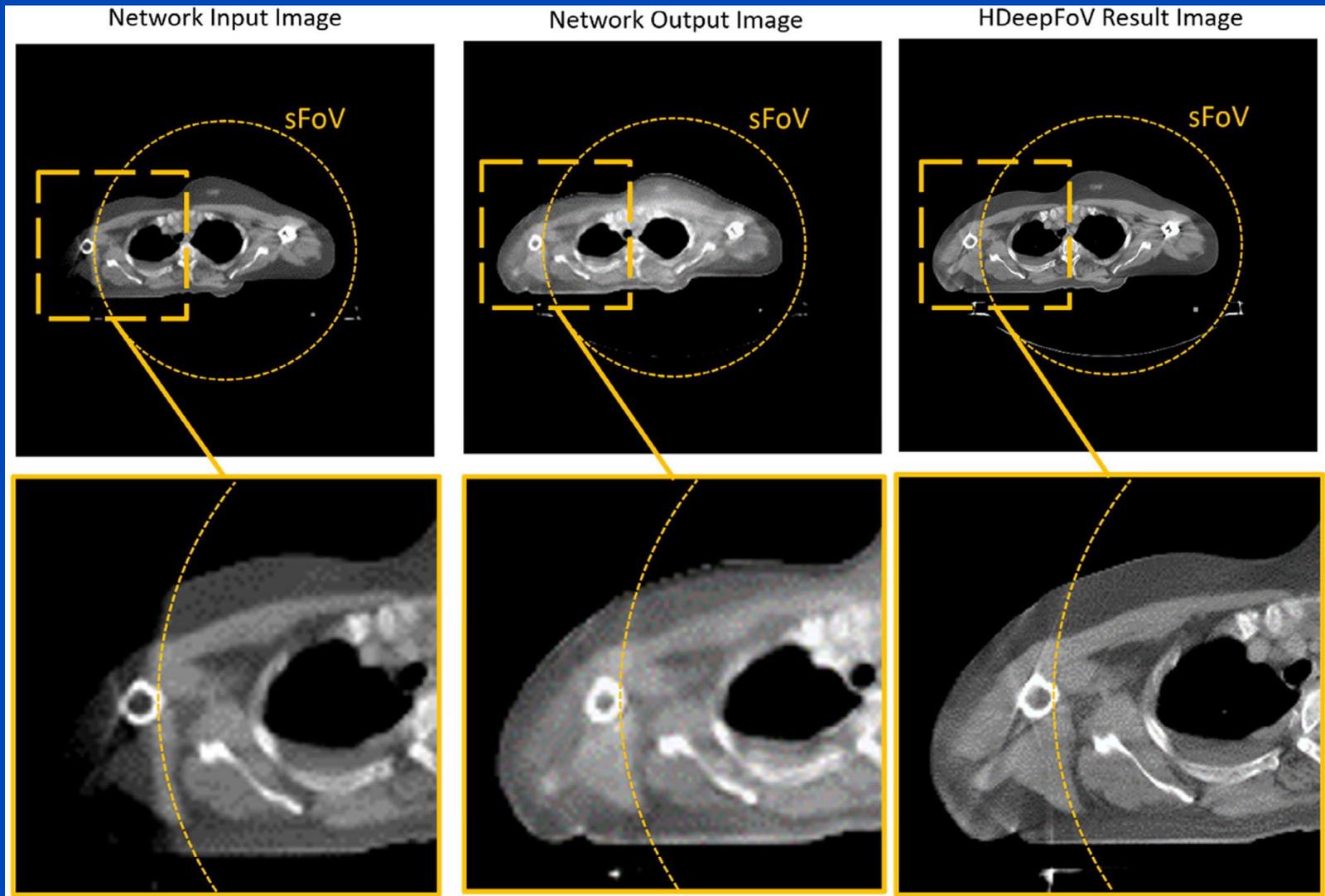
Siemens Healthcare GmbH, Forchheim, Germany

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

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

(Received 28 February 2021; revised 27 April 2021; accepted for publication 30 April 2021; published 31 May 2021)

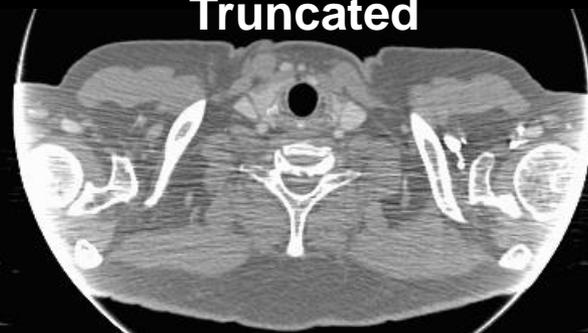




Original



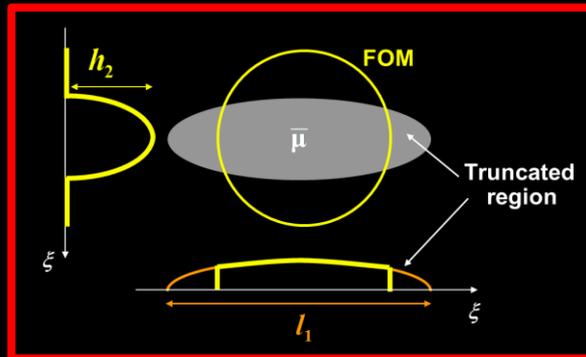
Truncated



ADT corrected



ADT corrected (clipped)



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

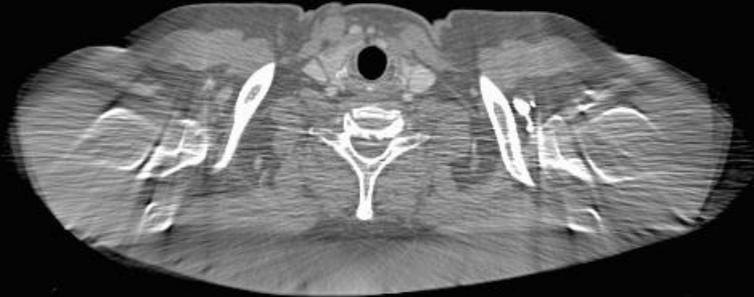
Original



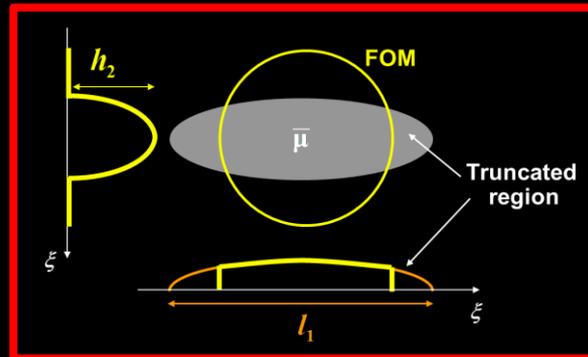
Truncated



ADT corrected



ADT corrected (clipped)

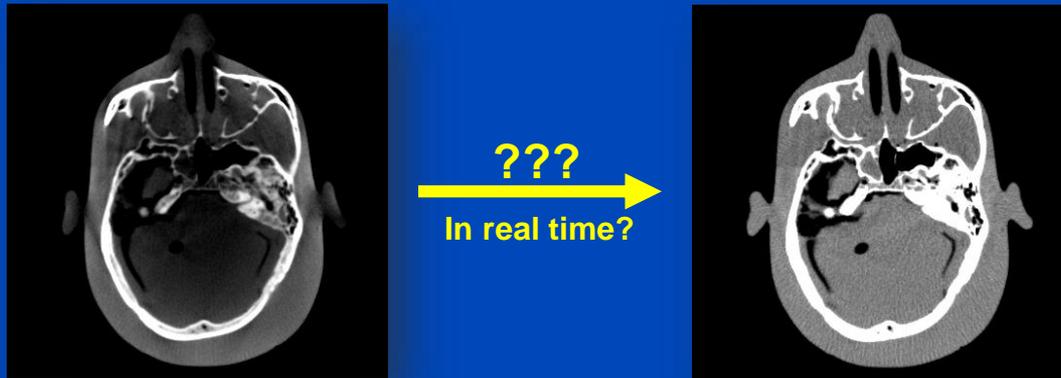


C = 0 HU, W = 1000 HU

Summary on Deep Detruncation

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

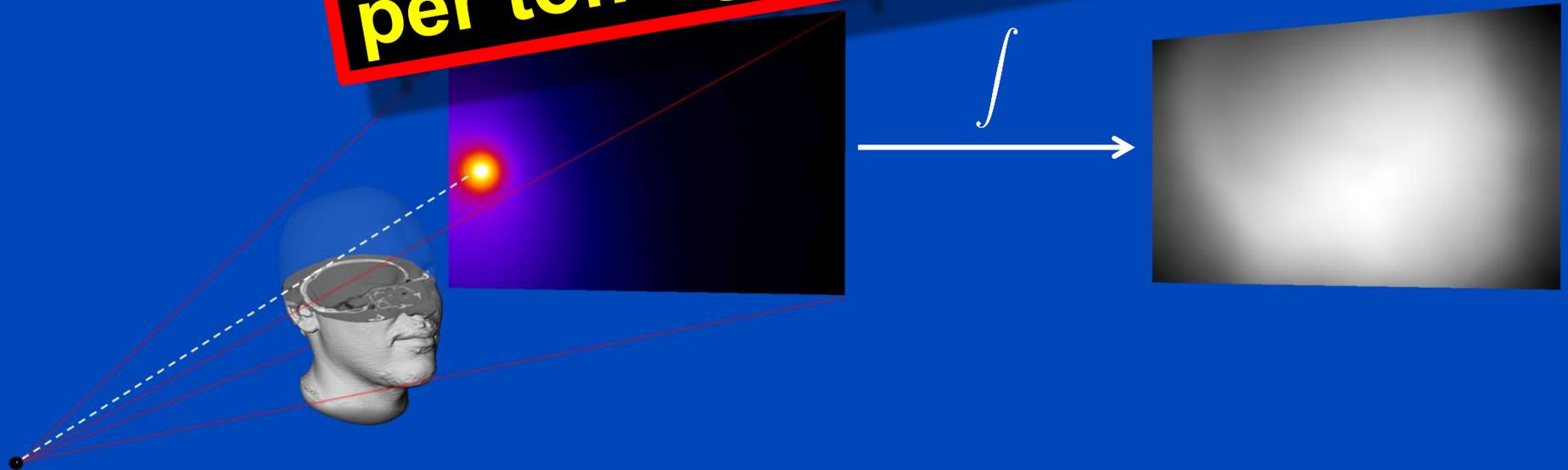
Deep Scatter Estimation



Monte Carlo Scatter Estimation

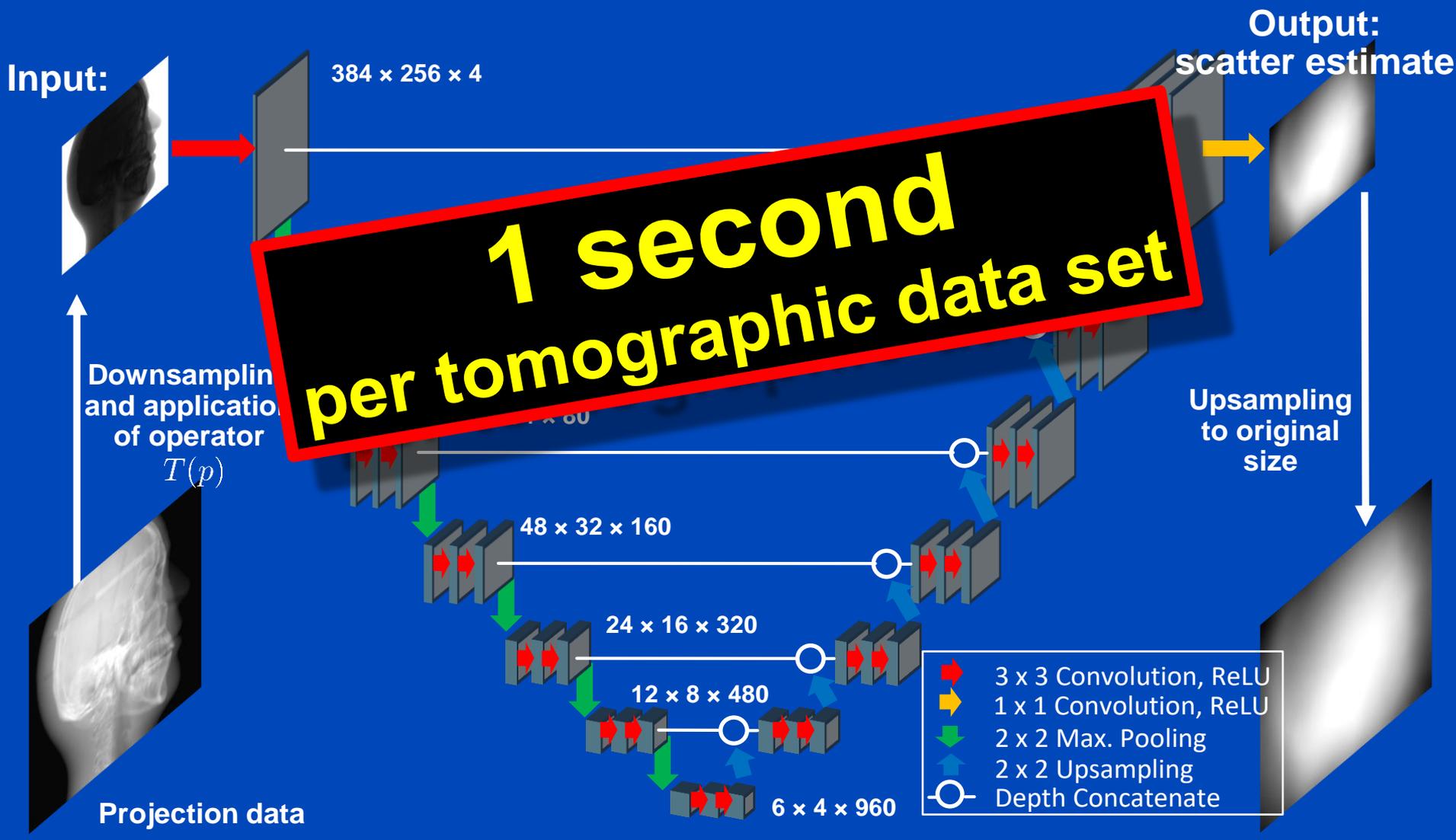
- Simulation of photon trajectories according to physical interaction probabilities.
- Simulating a large number of trajectories well approximates the complete scatter distribution

**1 hour
per tomographic data set**



Deep Scatter Estimation

Network architecture & scatter estimation framework



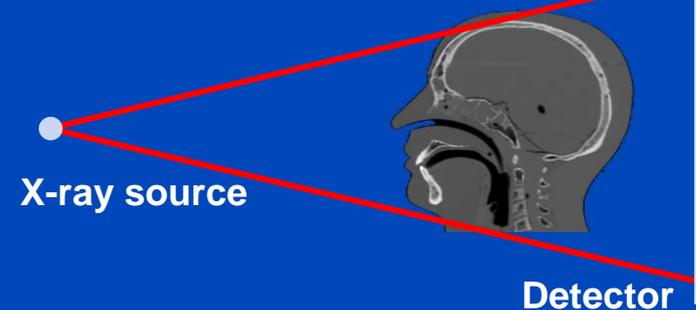
Testing of the DSE Network for Measured Data (120 kV)

DKFZ table-top CT

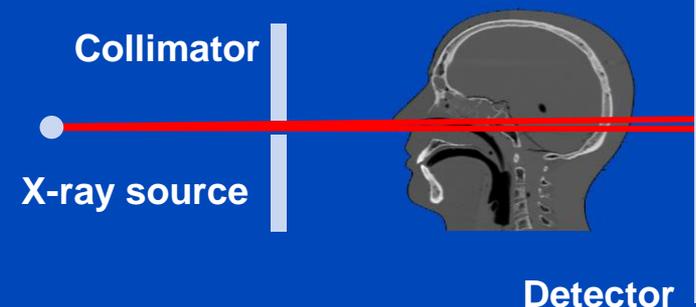


- Measurement of a head phantom at our in-house table-top CT.
- Slit scan measurement serves as ground truth.

Measurement to be corrected



Ground truth: slit scan



Reconstructions of Measured Data

Slit Scan

No Correction

Kernel-Based
Scatter Estimation

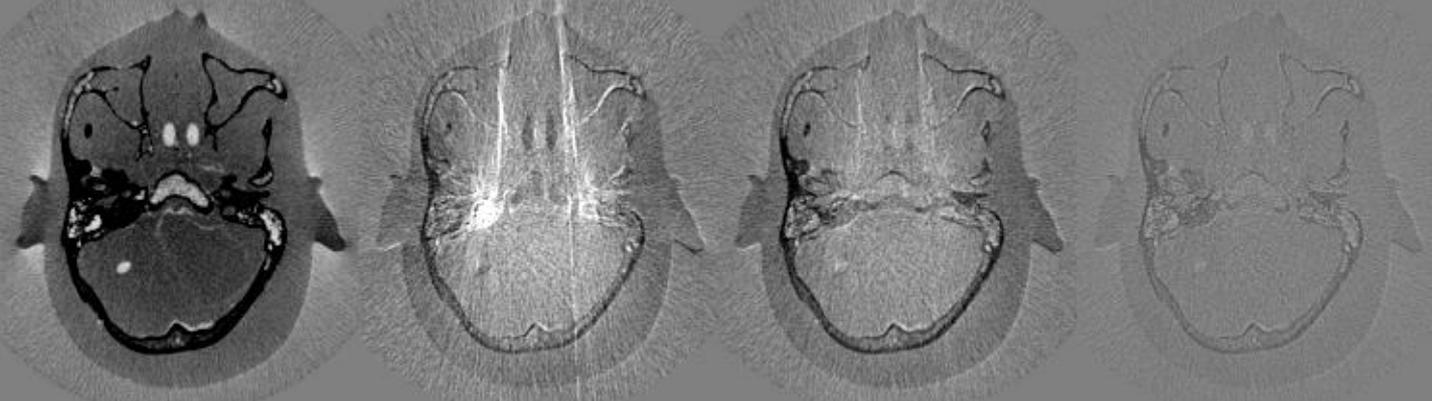
Hybrid Scatter
Estimation

Deep Scatter
Estimation

CT Reconstruction



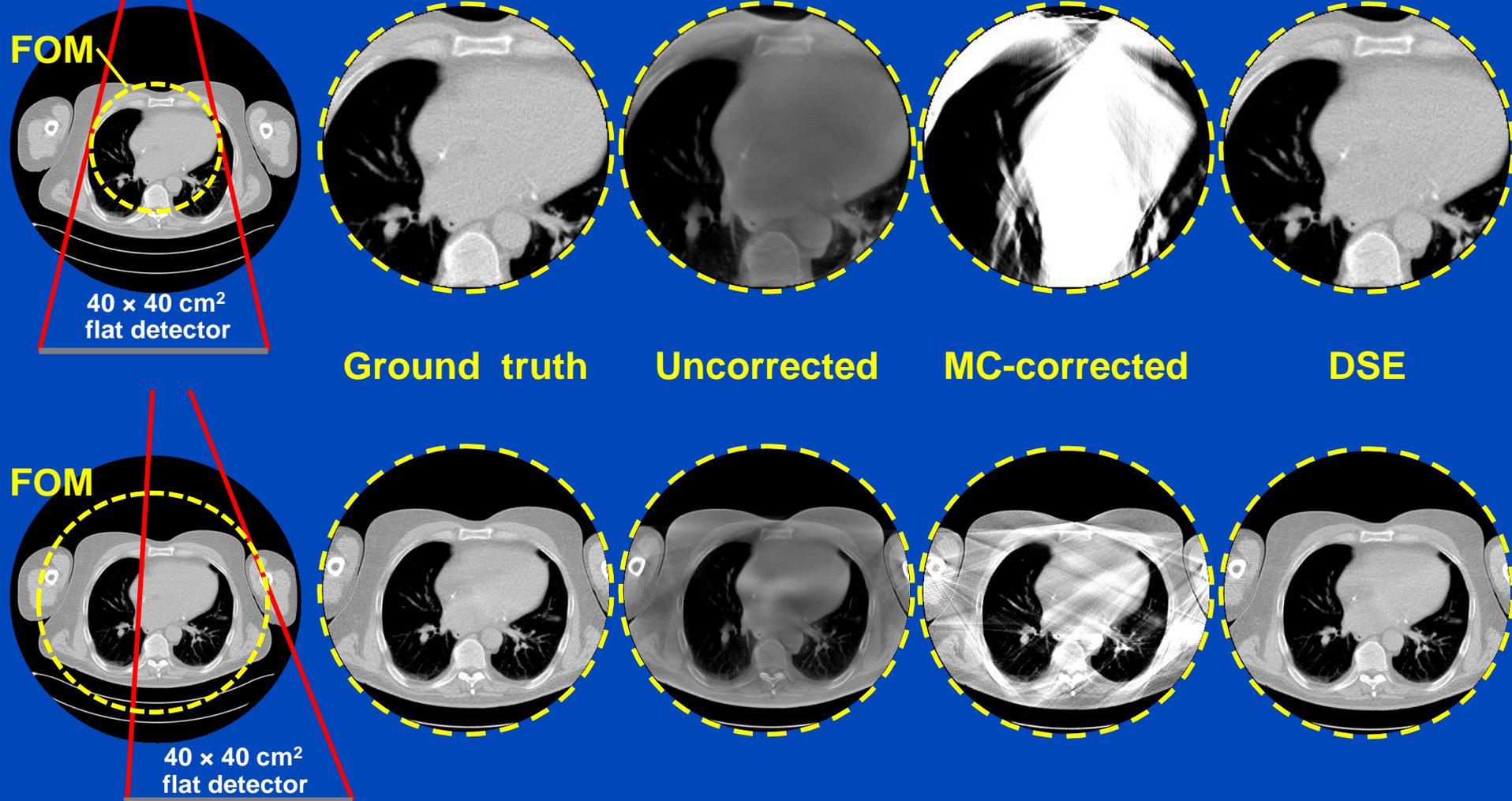
Difference to slit scan



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

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].

Results

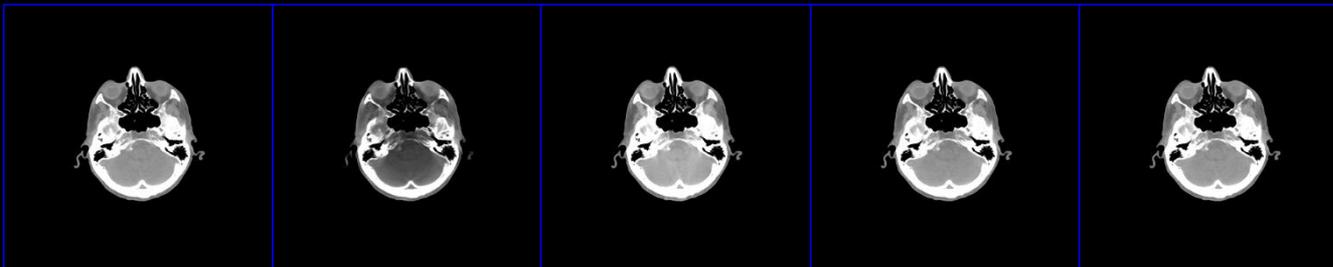
	Testing Head	Thorax	Abdomen
Training			
KSE			
Head	14.5	26.8	32.5
Thorax	16.2	18.5	19.4
Abdomen	16.8	22.1	17.8
All data	14.9	20.5	19.3
HSE (Truncated prior, 22 cm FOM)			
-	6.2	293.2	237.6
HSE (Truncated prior, shifted detector, 40 cm FOM)			
-	-	22.9	26.5
DSE, $M_{ep} : e^{-p_{sim}} \rightarrow S_{MC}$			
Head	3.9	17.6	23.5
Thorax	12.2	2.5	11.6
Abdomen	27.1	13.2	2.3
All data	4.7	2.5	2.4
DSE, $M_p : p_{sim} \rightarrow S_{MC}$			
Head	1.3	14.9	15.2
Thorax	6.7	1.6	7.7
Abdomen	15.7	12.1	1.5
All data	1.7	1.6	1.6
DSE, $M_{pep} : p_{sim} \cdot e^{-p_{sim}} \rightarrow S_{MC}$			
Head	1.2	21.1	32.7
Thorax	8.8	1.5	9.1
Abdomen	11.9	10.9	1.3
All data	1.8	1.4	1.4

Mean absolute percentage error of the kernel-based scatter estimation (KSE), the hybrid scatter estimation (HSE) and the deep scatter estimation (DSE) with respect to the ground truth scatter distribution (MC simulation). Training data were generated simulating head, thorax and abdomen data at 120 kV, 140 kV. The training was performed for head, thorax and abdomen data separately as well as using all data together (left column). DSE was trained for three different mappings ($M_{ep} : e^{-p_{sim}} \rightarrow S_{MC}$, $M_p : p_{sim} \rightarrow S_{MC}$, $M_{pep} : p \cdot e^{-p_{sim}} \rightarrow S_{MC}$). Note that there are no training data for the HSE as it is optimized on a coarse MC simulation of the testing data.

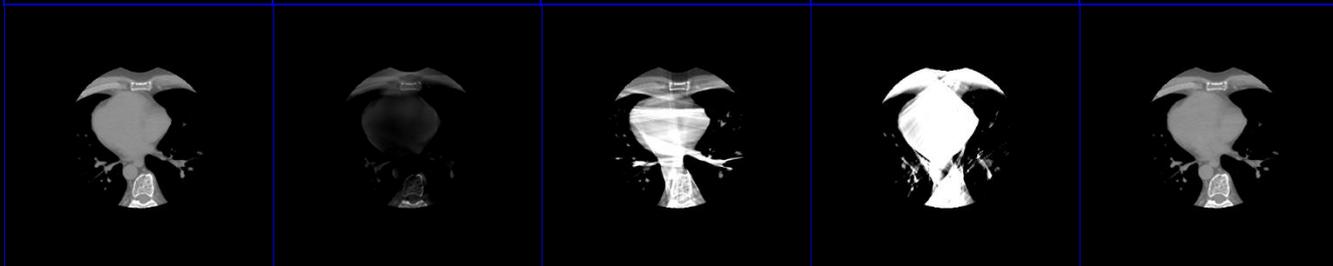
Values shown are the mean absolute percentage errors (MAPEs) of the testing data. Note that thorax and head suffer from truncation due to the small size of the 40x30 cm flat detector.

Ground truth No correction KSE HSE DSE

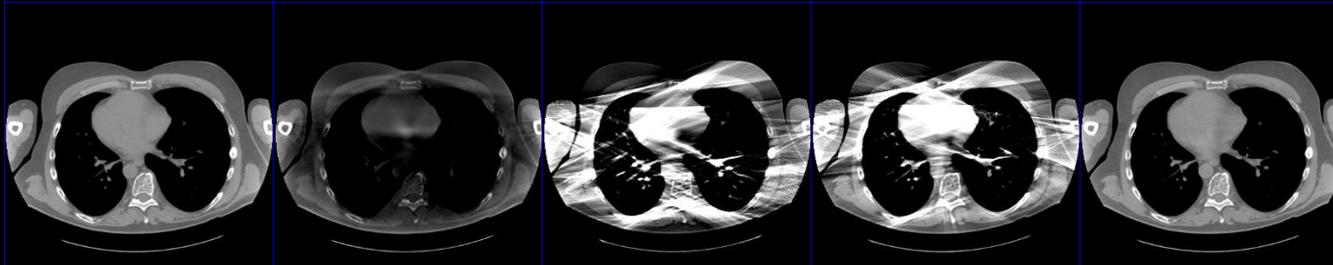
**Head, 140 kV,
22 cm FOM**



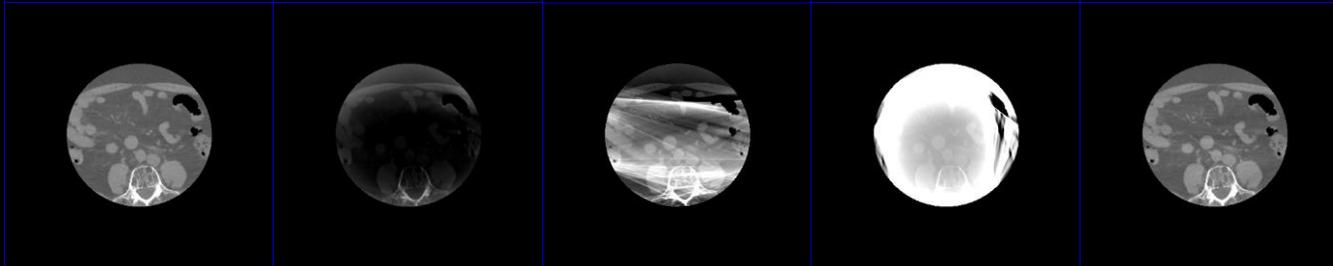
**Thorax, 140 kV,
22 cm FOM**



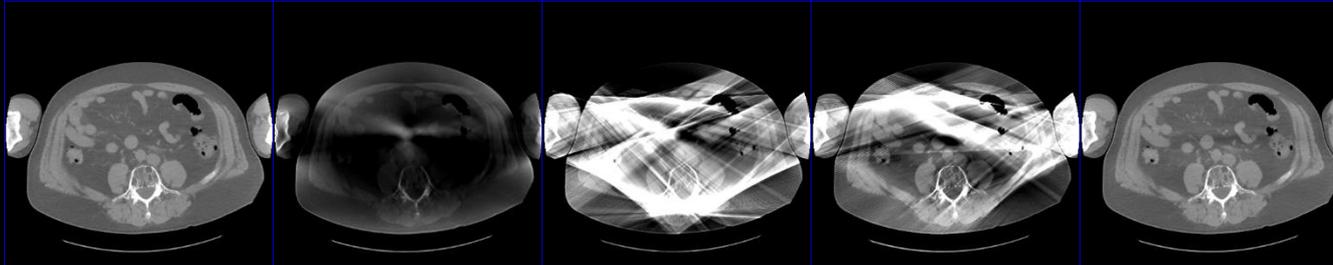
**Thorax, 140 kV,
40 cm FOM
(shifted detector)**



**Abdomen, 140 kV,
22 cm FOM**



**Abdomen, 140 kV,
40 cm FOM
(shifted detector)**



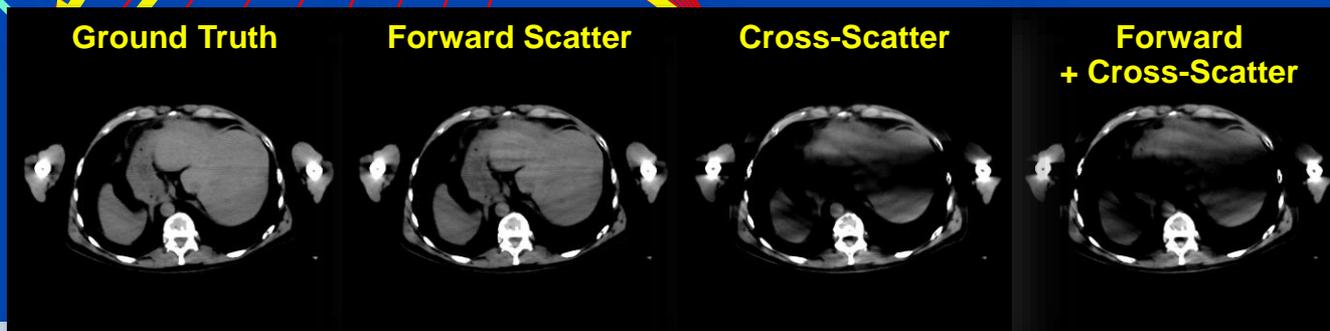
**C = 0 HU
W = 700 HU**

Scatter in Dual Source CT (DSCT)



Siemens SOMATOM Force
dual source cone-beam spiral CT

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



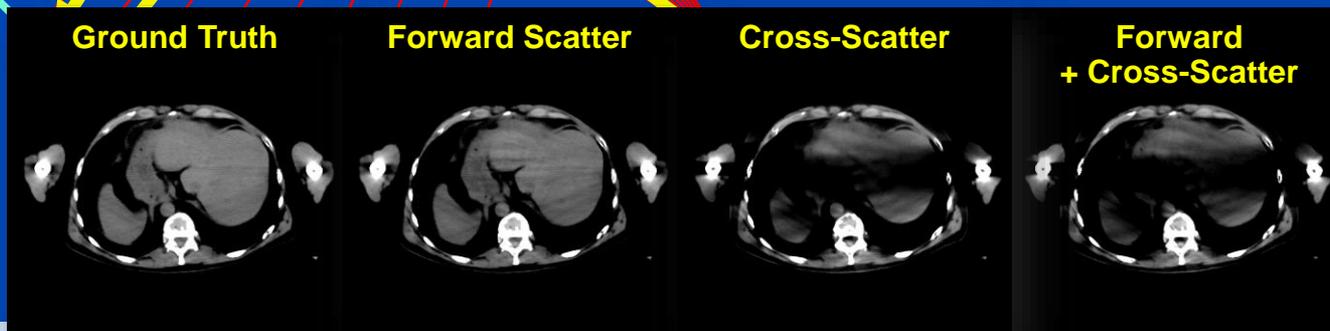
C = 40 HU, W = 300 HU, with 2D anti-scatter grid

Scatter in Dual Source CT (DSCT)



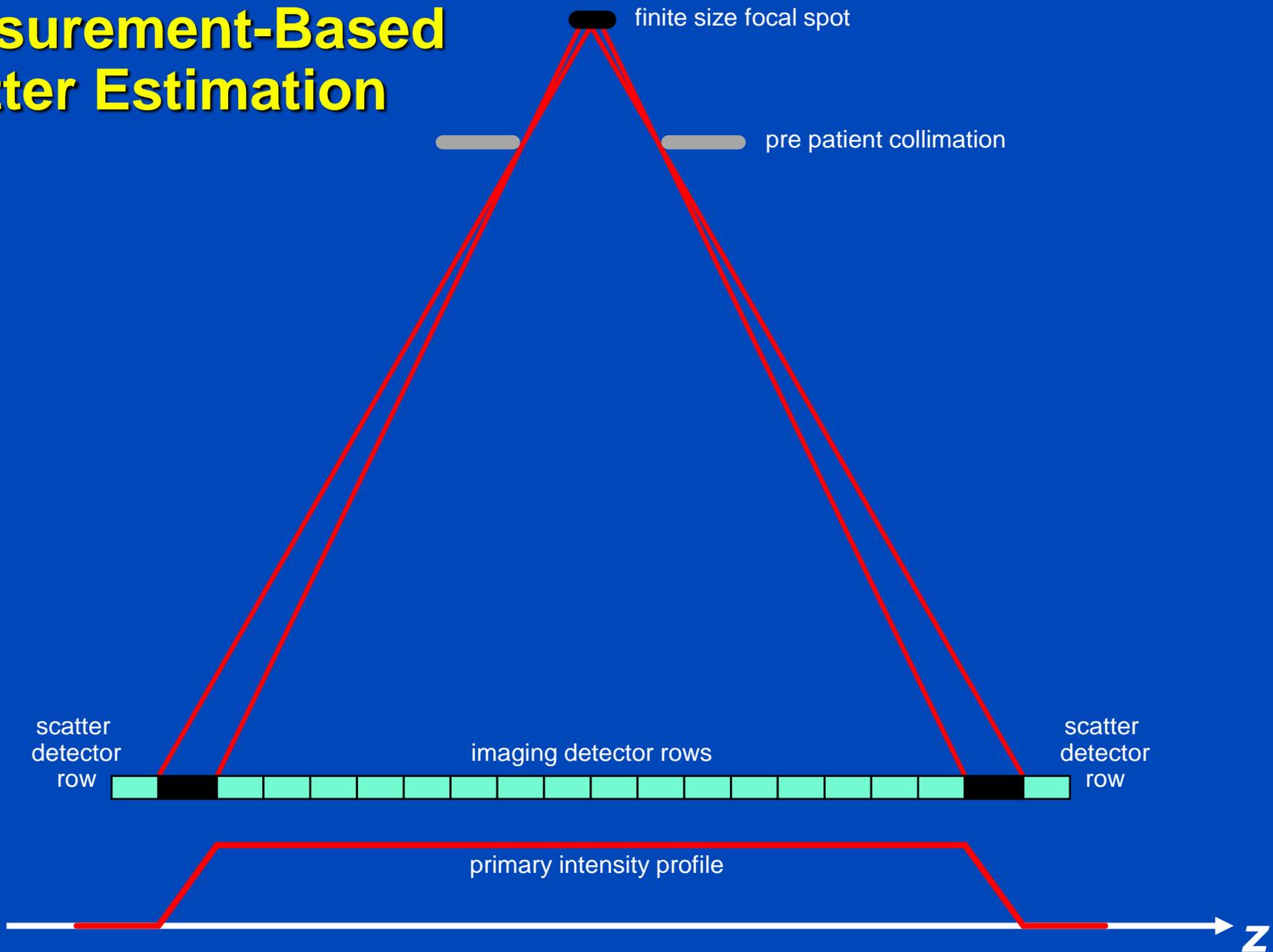
Siemens SOMATOM Force
dual source cone-beam spiral CT

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



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

Measurement-Based Scatter Estimation



Scatter in Dual Source CT: xDSE

Ground Truth

Uncorrected

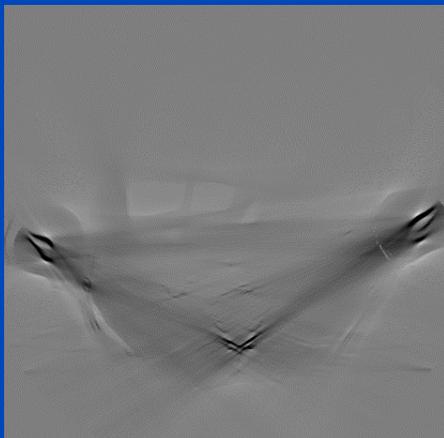
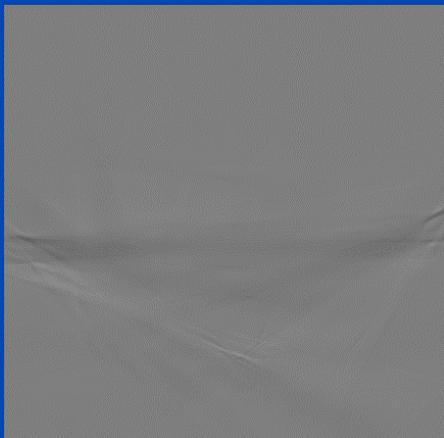
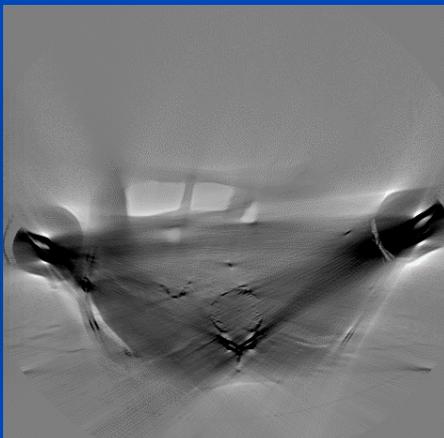
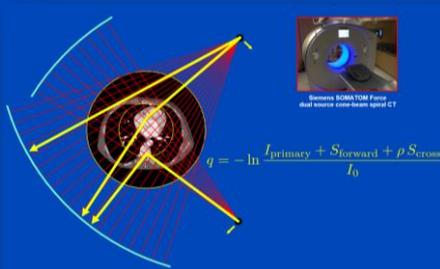
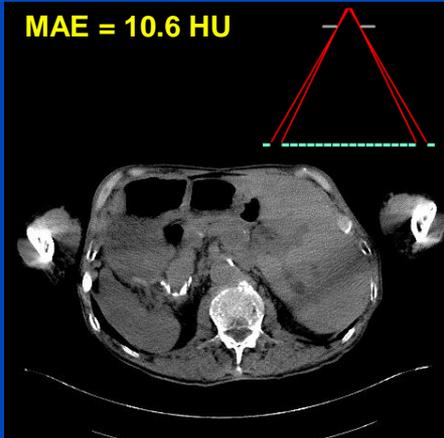
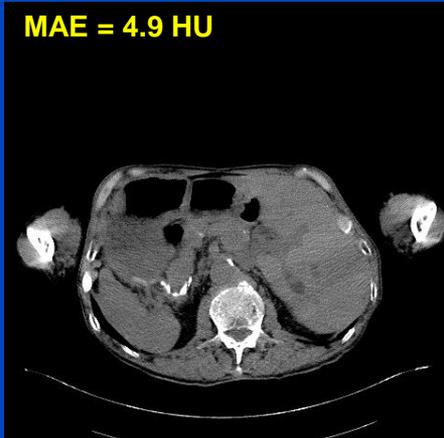
xDSE (2D, xSSE)

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

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.

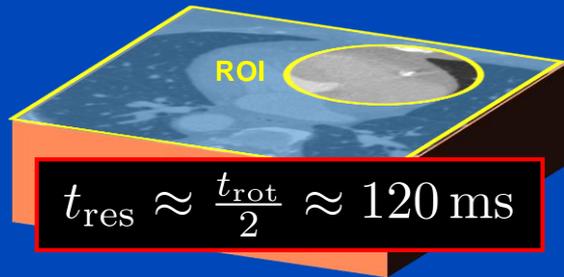
Deep Cardiac Motion Compensation



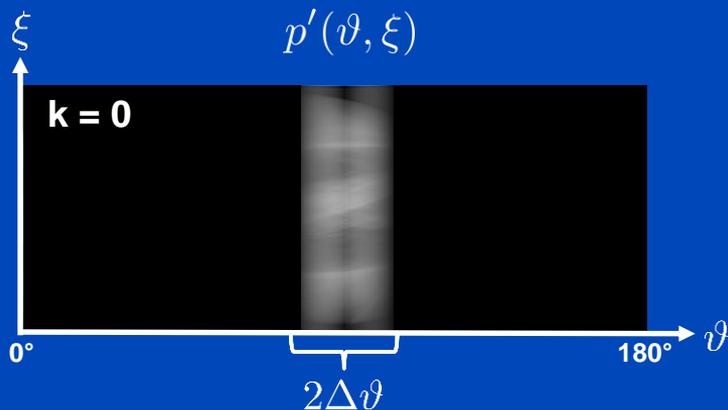
PAMoCo

Generate 2K+1 Partial Angle Reconstructions

Initial segmented stack volume

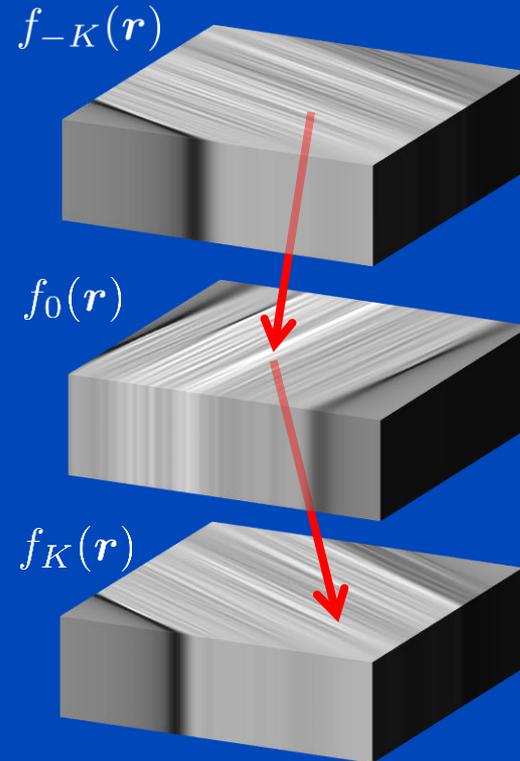


Subdivide the projection data $p'(\vartheta, \xi)$ into $2K + 1$ overlapping sectors



$$p_k(\vartheta, \xi) = w_k(\vartheta)p'(\vartheta, \xi)$$
$$w_k(\vartheta) = \Lambda((\vartheta - \vartheta_k)/2\Delta\vartheta)$$

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



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

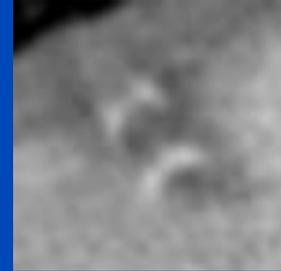
$$\text{FWHM} = \Delta\vartheta$$

$$K = 12$$

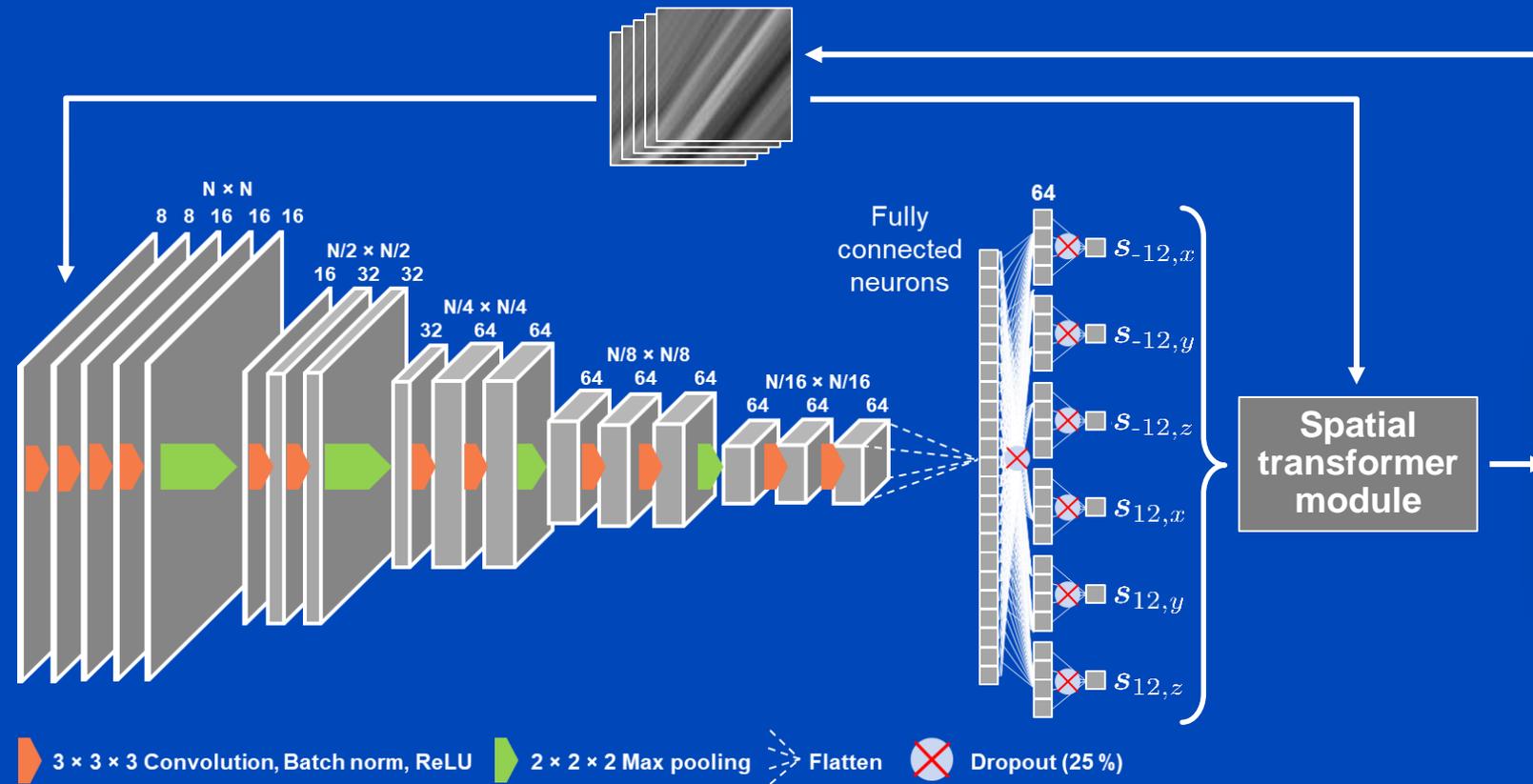
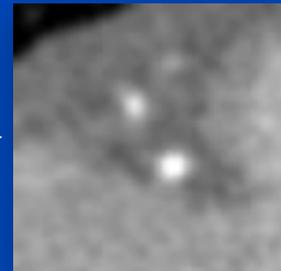
Deep PAMoCo

Network architecture

Initial volume
(with motion artifacts)

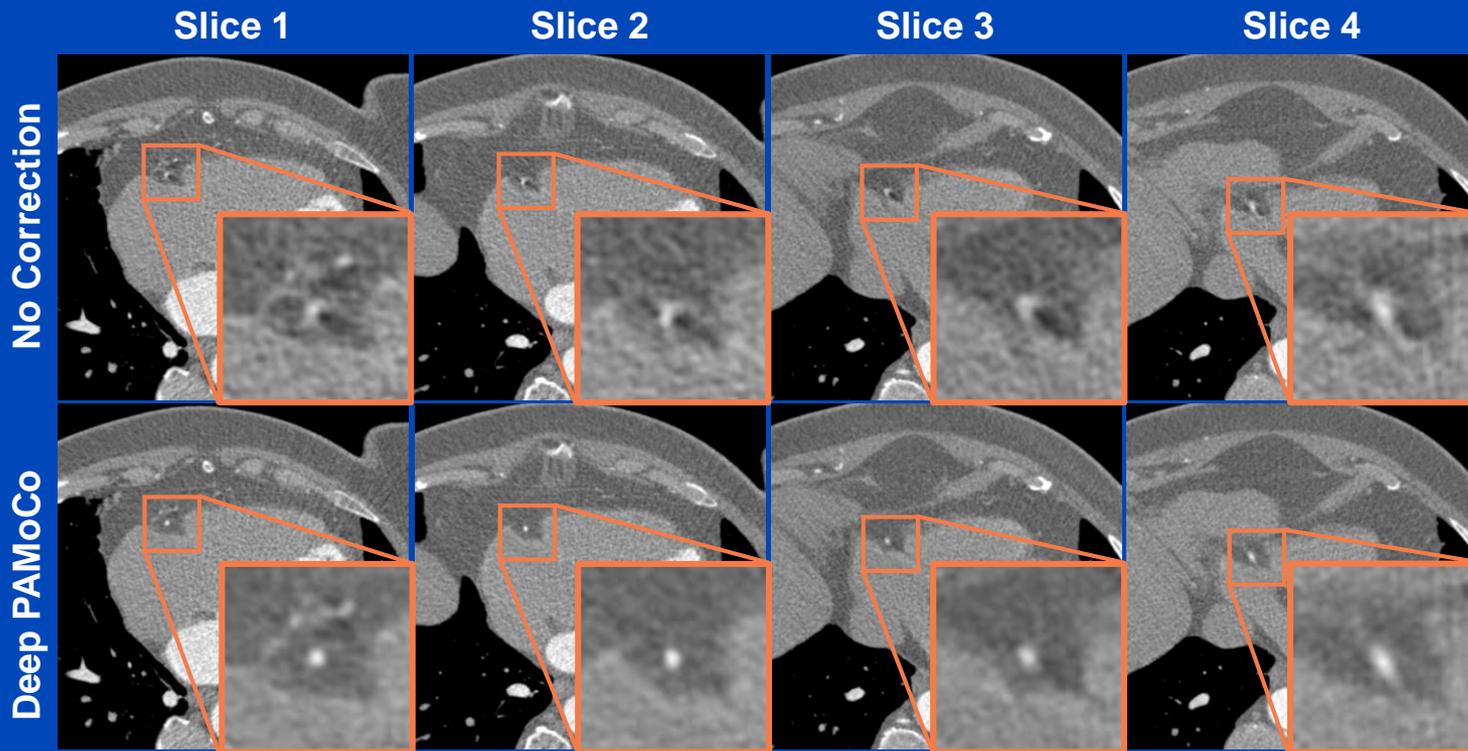


Final volume
(no motion artifacts)



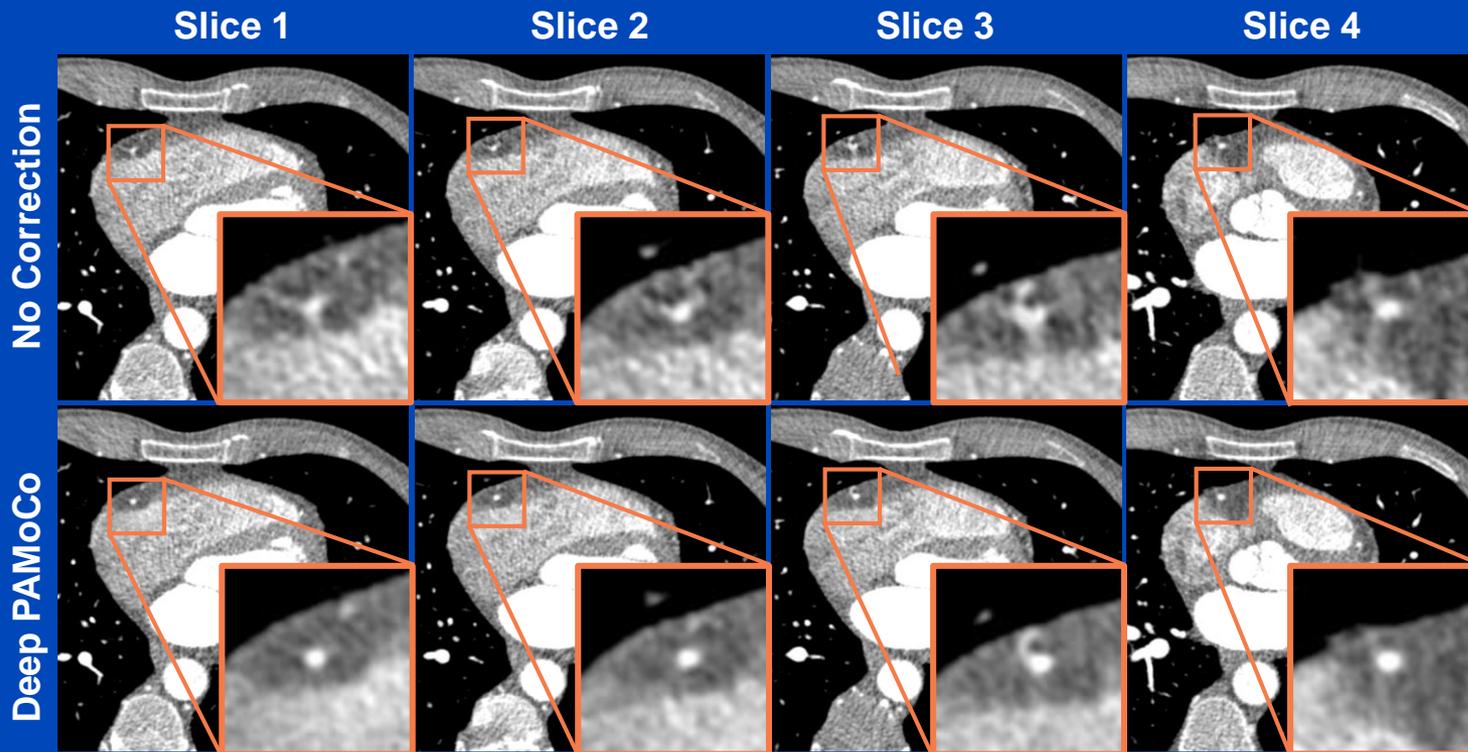
FCN-Layer output: two control points for a cubic spline:
for $k = -K$, and for $k = +K$. The third control point at $k = 0$ is $(0, 0, 0)$, i.e. no deformation for the central PAR.

Results



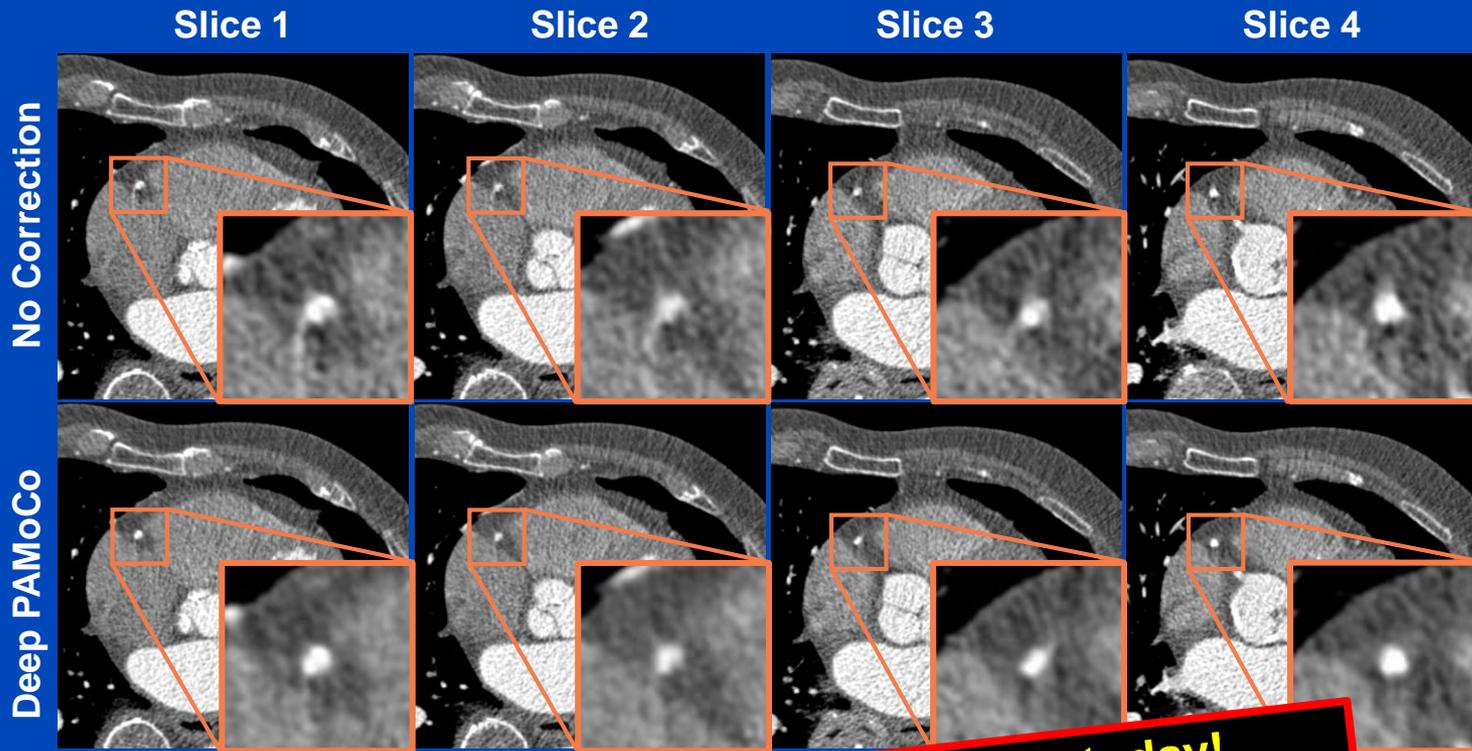
C = 1000 HU
W = 1000 HU

Results



C = 1000 HU
W = 1000 HU

Results



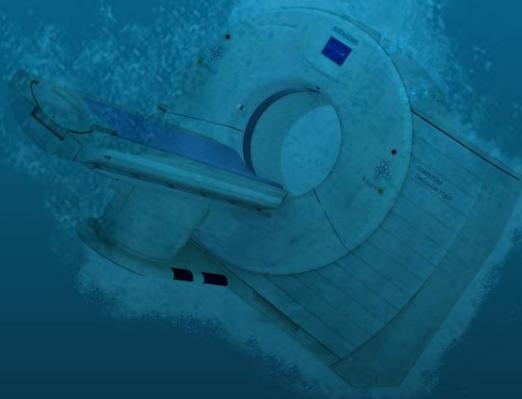
More on Deep PAMoCo upcoming today!
Joscha Maier et al.
Room E351, Session SSPH05, starting 1:30 PM

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.