Deep Learning in CT

Marc Kachelrieß

German Cancer Research Center (DKFZ)

Heidelberg, Germany

www.dkfz.de/ct

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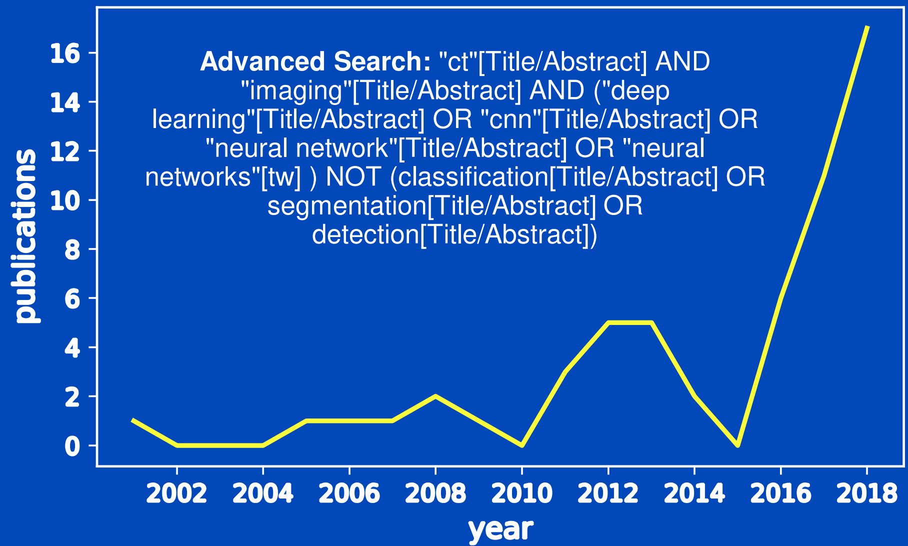
Aim

To give a coarse and critical overview of deep learning applications in CT image formation.



Source: pubmed.gov

There is a nice special issue on machine learning for image reconstruction: IEEE TMI 37(6), 2018

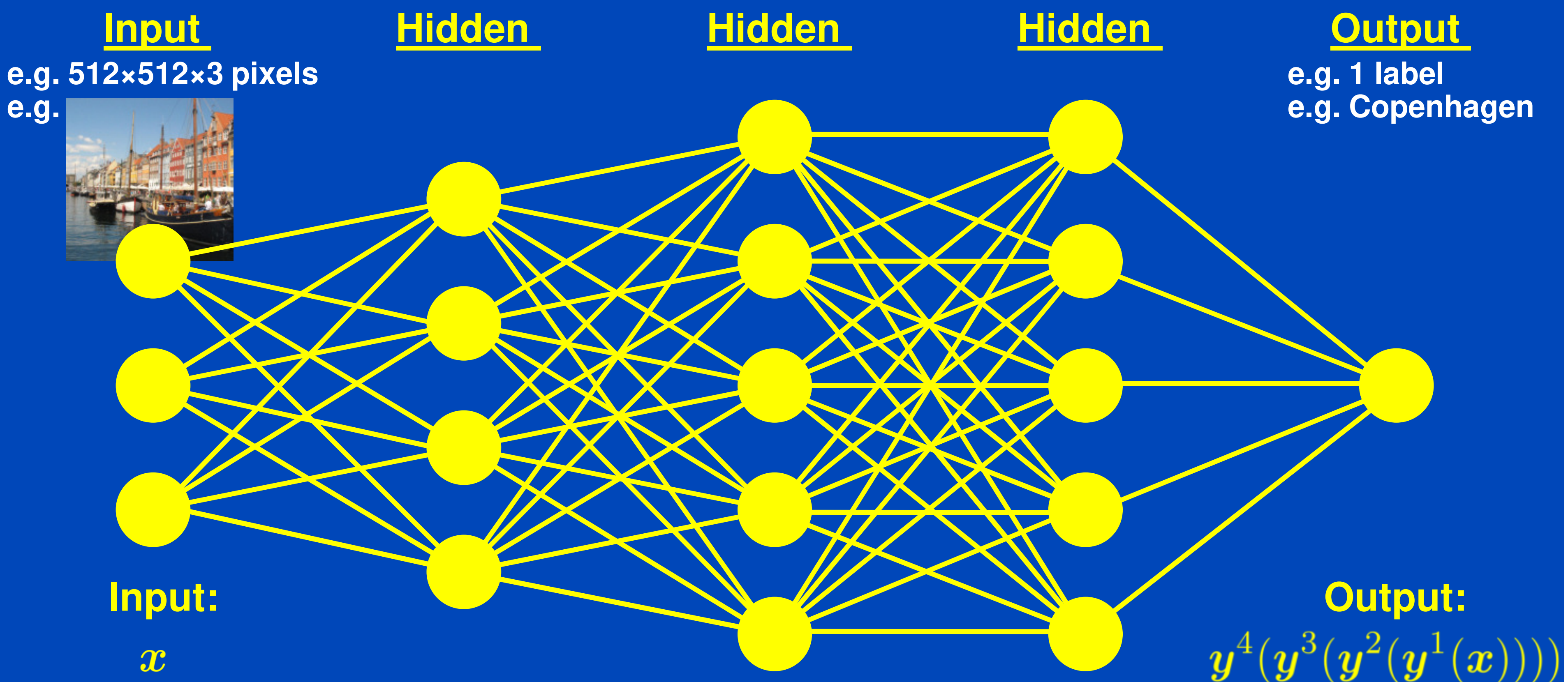
Conventional image post processing applications, such as image segmentation, image registration, image classification etc. as well as CAD applications are not part of this lecture.

Categories of Deep Learning Used in CT Image Formation so Far

- Replacement of missing data
  - LowRes → HighRes nice images
  - SparseView → FullView nice images
  - LowDose → HighDose nice images
  - LimitedAngle → FullAngle nice images
  - ...
- Replacement of lengthy computations
  - Reconstruction (learn denoisers, learn regularizers, learn iterations, ...)
  - Scatter estimation
  - Dose estimation
  - ...
- Other
  - Material decomposition
  - Pseudo CT from MR
  - Motion artifact recognition
  - 3D DSA from a contrast scan
  - Tomosynthesis
  - ...

Fully Connected Neural Network

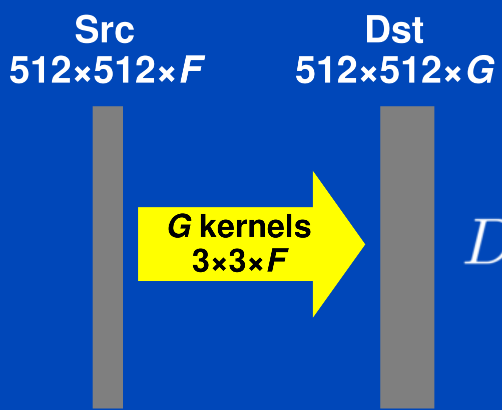
- **Each layer fully connects to previous layer**
- **Difficult to train (many parameters in *W* and *b*)**
- **Spatial relations not necessarily preserved**



$$\boldsymbol{y}(\boldsymbol{x}) = \boldsymbol{f}(\boldsymbol{W}\cdot\boldsymbol{x}+\boldsymbol{b}) \quad \text{with} \quad \boldsymbol{f}(\boldsymbol{x}) = \big(f(x_1), f(x_2), \ldots\big) \quad \text{with} \quad f(x) = x \vee 0 = \text{ReLU}$$

Convolutional Neural Network (CNN)

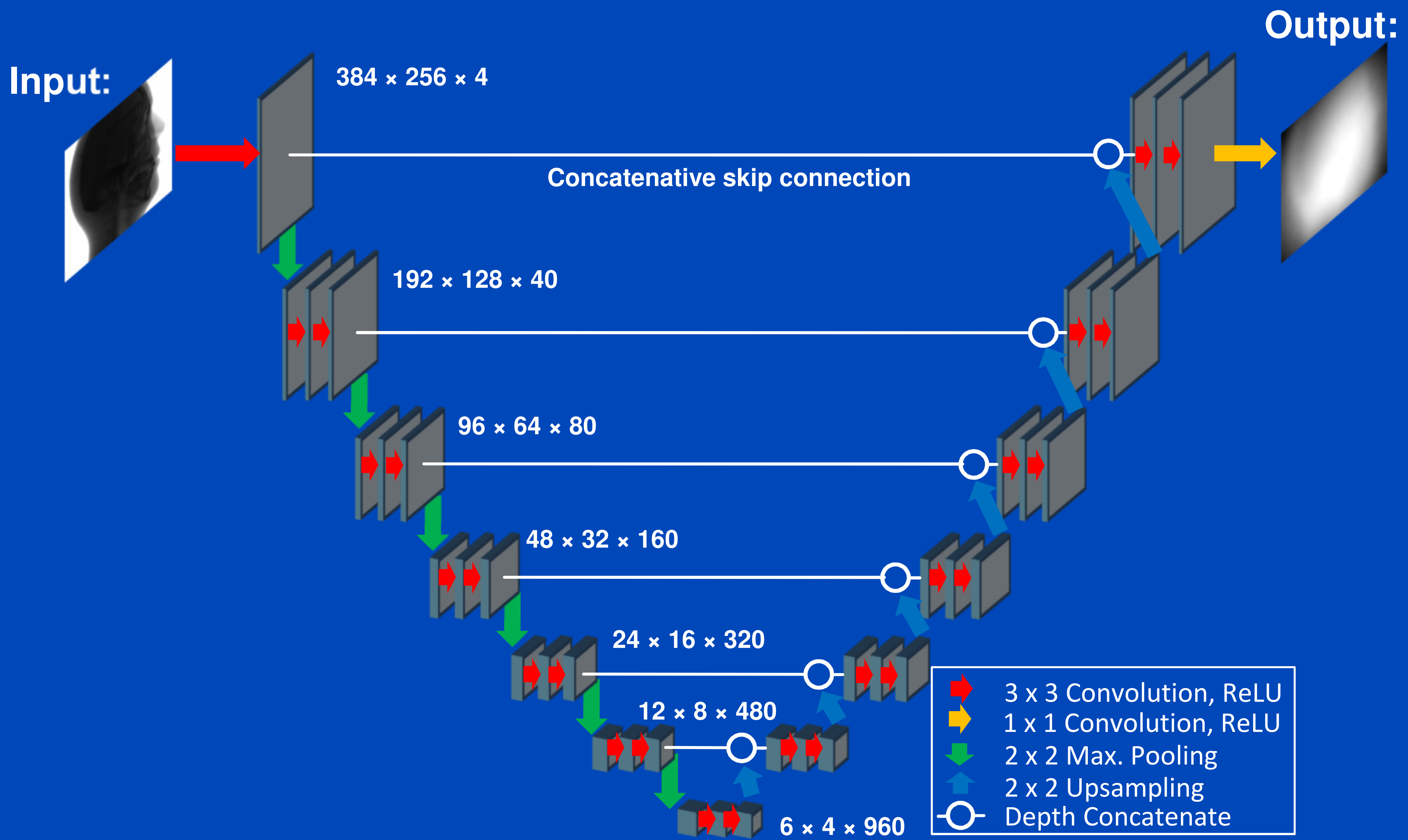
- Replace dense *W* in $y(x) = f(W \cdot x + b)$ by a sparse matrix *W* with sparsity being of convolutional type.
- CNNs consist (mainly) of convolutional layers.
- Convolutional layers are not fully connected.
- Convolutional layers are connected by small, say 3×3, convolution kernels whose entries need to be found by training.
- CNNs preserve spatial relations to some extent.



$$D_{i,j,g} = \sum_f S_{i,j,f} * K^g_{i,j,f} = \sum_{a,b,f} S_{i-a,j-b,f} K^g_{a,b,f}$$

Attention: No convolution in depth direction!

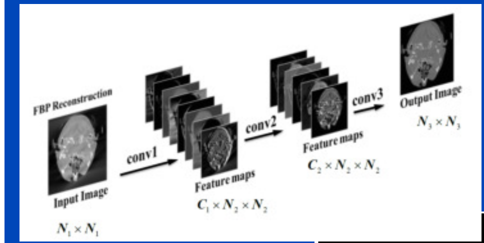
U-Net


Output:
Input:
384 × 256 × 4
Concatenative skip connection
192 × 128 × 40
96 × 64 × 80
48 × 32 × 160
24 × 16 × 320
12 × 8 × 480
6 × 4 × 960
3 x 3 Convolution, ReLU
1 x 1 Convolution, ReLU
2 x 2 Max. Pooling
2 x 2 Upsampling
Depth Concatenate

Part 1:

Replacement of Missing Data

Limited Angle Example



GT | FBP (150°) | CNN

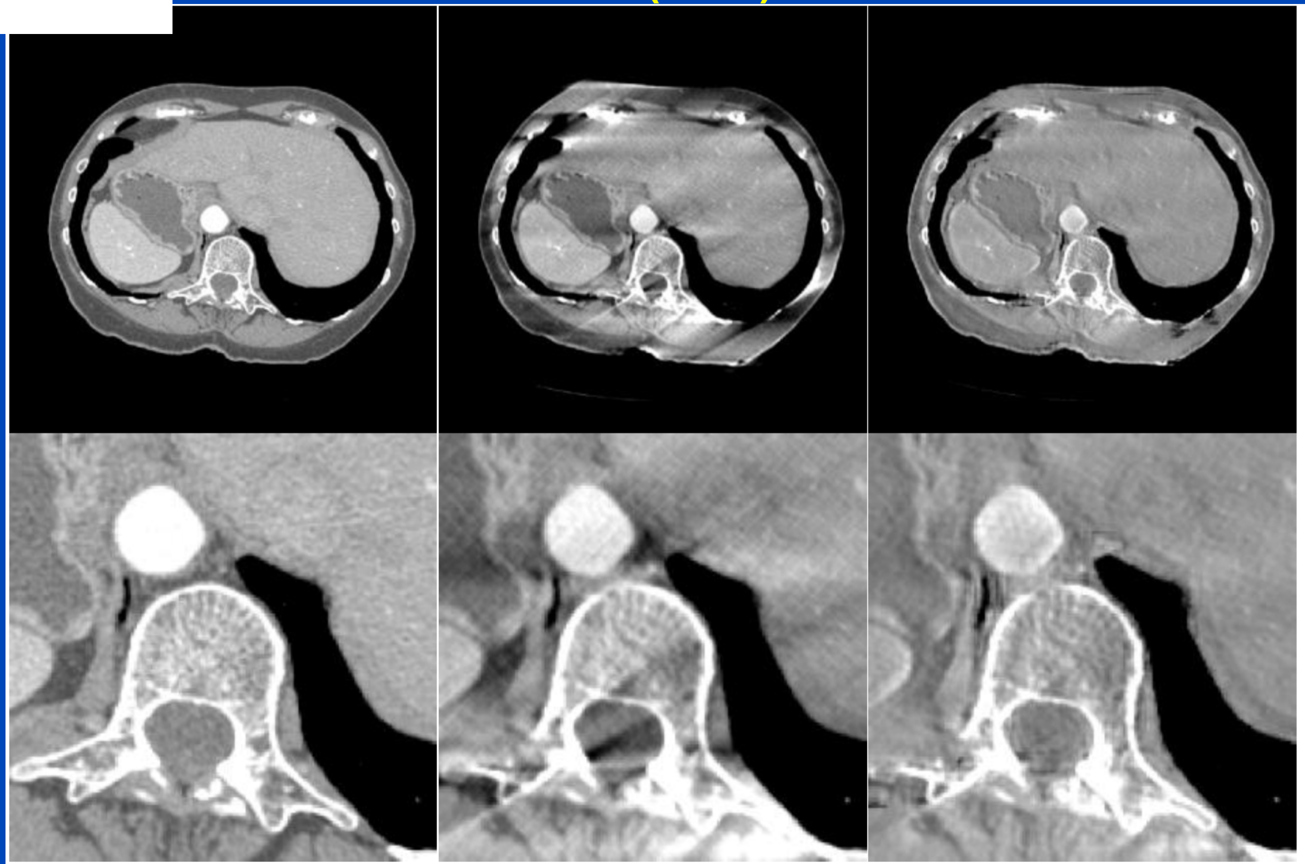
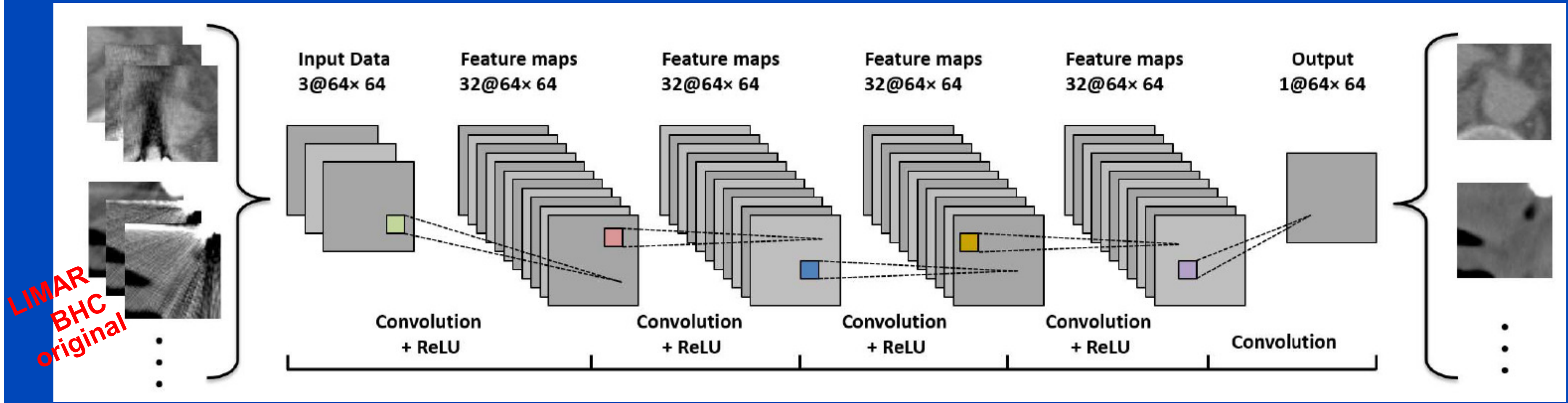


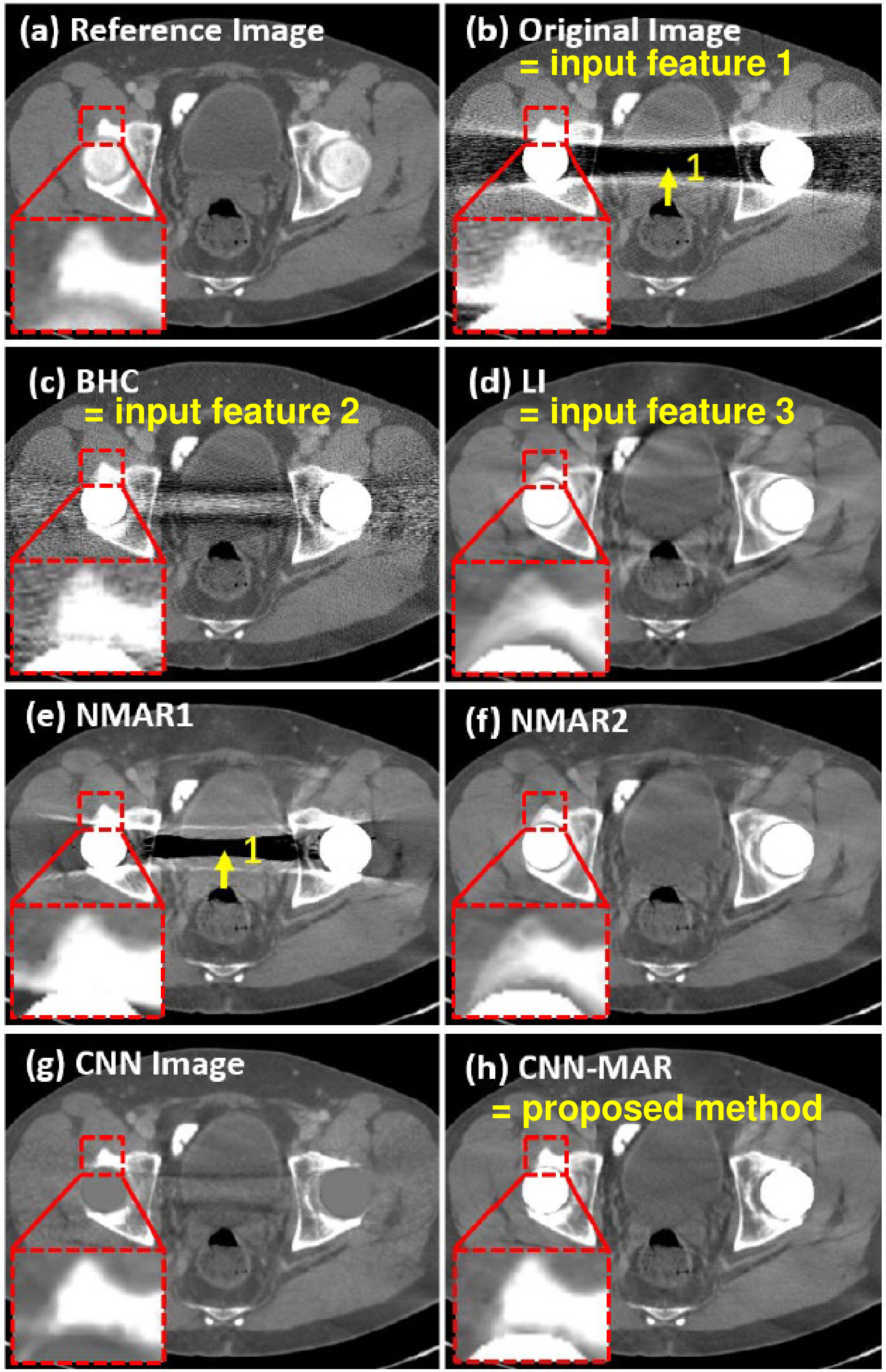
Image Prediction for Limited-Angle Tomography via Deep Learning with Convolutional Neural Network.
Hanming Zhang, Liang Li, Kai Qiao, Linyuan Wang, Bin Yan, Lei Li, Guoen Hu. arXiv 2016.

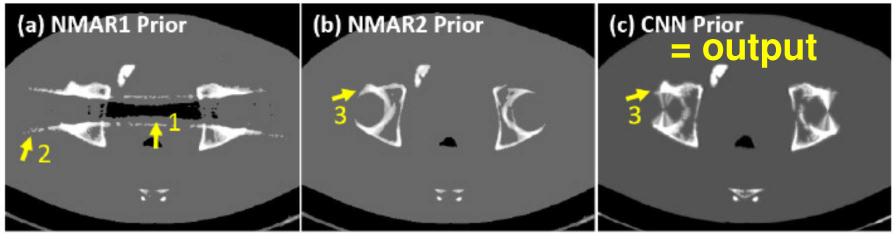
MAR Example

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



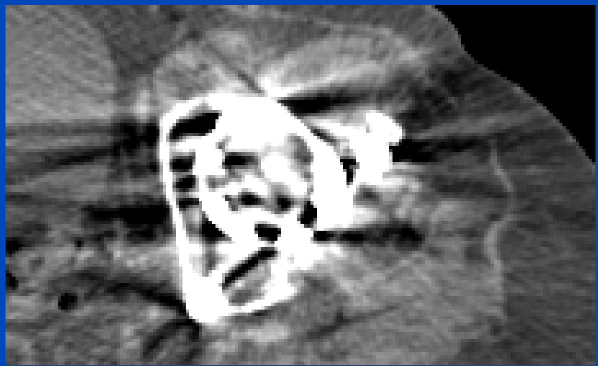
- followed by segmentation into tissue classes
- followed by forward projection of the CNN prior and replacement of metal areas of the original sinogram
- followed by reconstruction


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

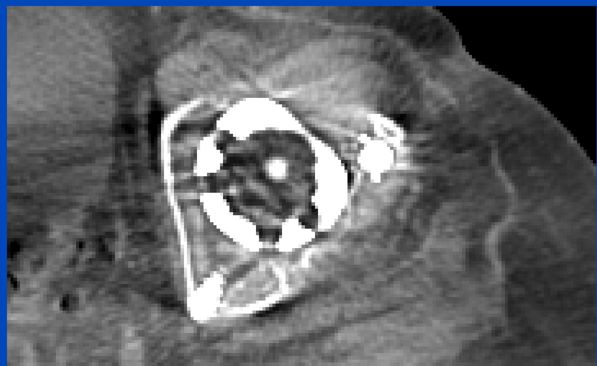

(a) NMAR1 Prior
1
2
(b) NMAR2 Prior
3
(c) CNN Prior
= output
3

MAR without Machine Learning: Frequency Split Normalized MAR[1,2]

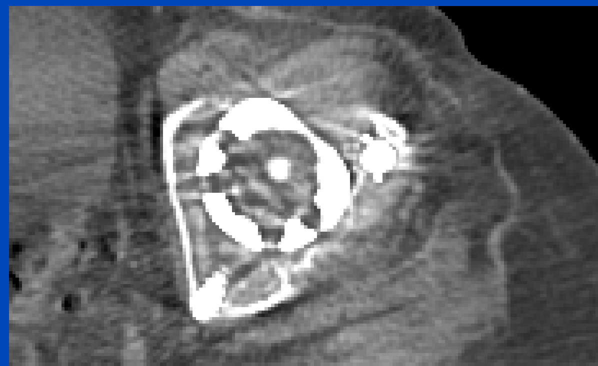
Uncorrected



LIMAR



FSNMAR



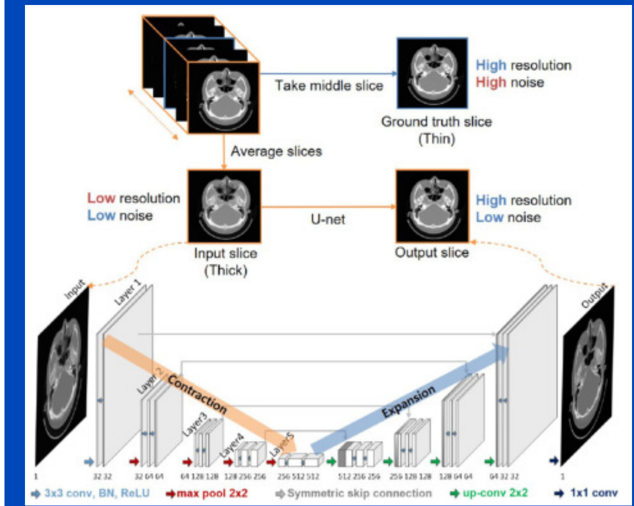
Patient with bilateral hip prosthesis, Somatom Definition Flash, (C=40/W=500).

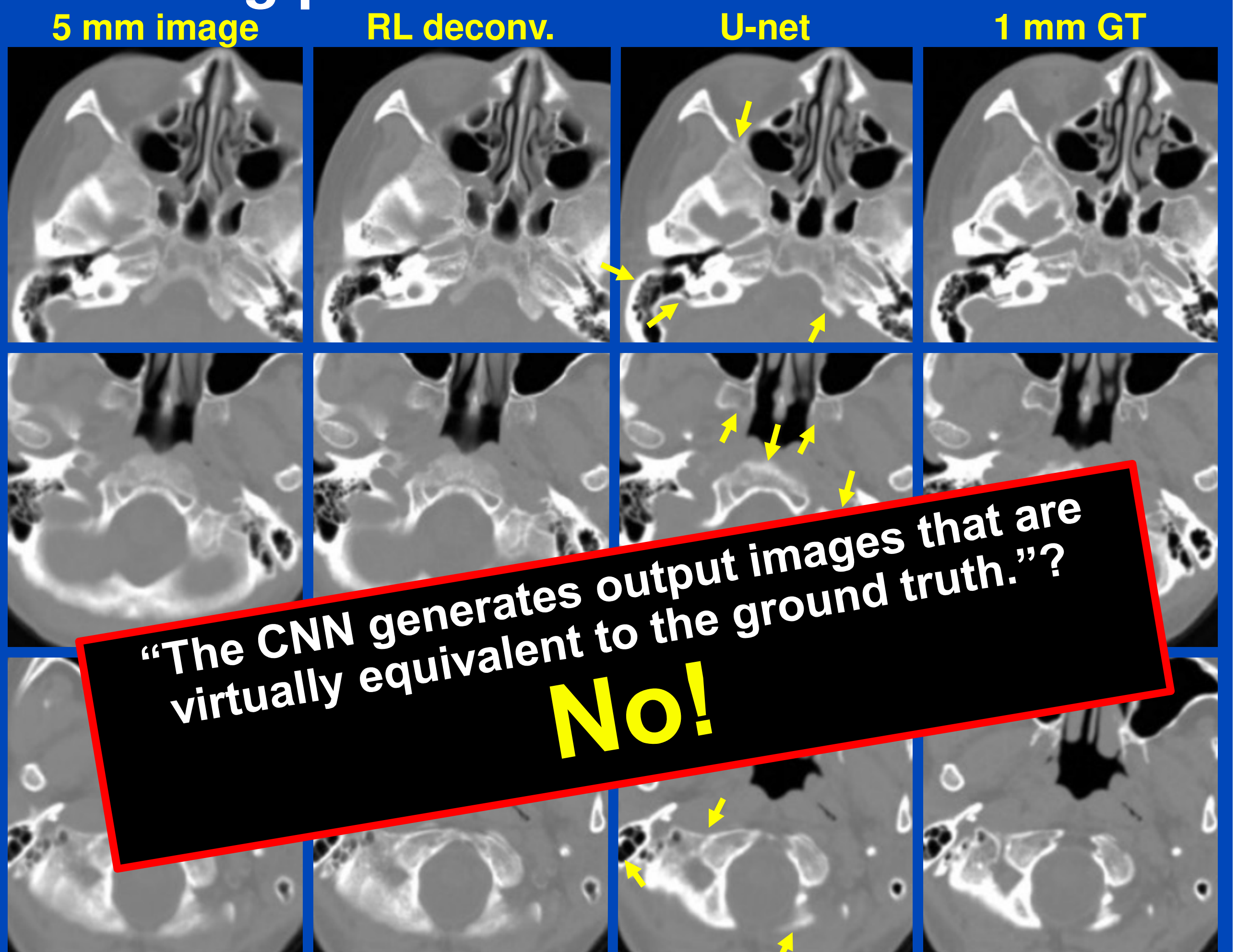
[1]E. Meyer, M. Kachelrieß. Normalized metal artifact reduction (NMAR) in computed tomography. Med. Phys. 37(10):5482-5493, Oct. 2010.

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

Resolution Improvement Example

- 2D U-net to converts 5 mm thick images into 1 mm ones.
- E.g. to "replace a scanning protocol for a 1 mm slice with a 5 mm protocol"



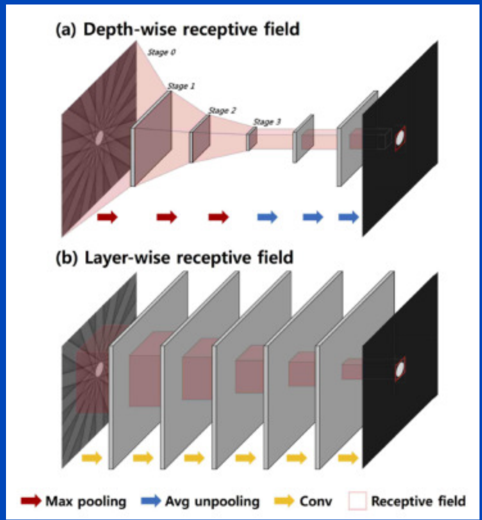


"The CNN generates output images that are virtually equivalent to the ground truth."?

No!

Junyoung Park, Donghwi Hwang, Kyeong Yun Kim, Seung Kwan Kang, Yu Kyeong Kim and Jae Sung Lee. Computed tomography super-resolution using deep convolutional neural network. Phys. Med. Biol. 63: 145011, 2018

Sparse View Reconstruction Example



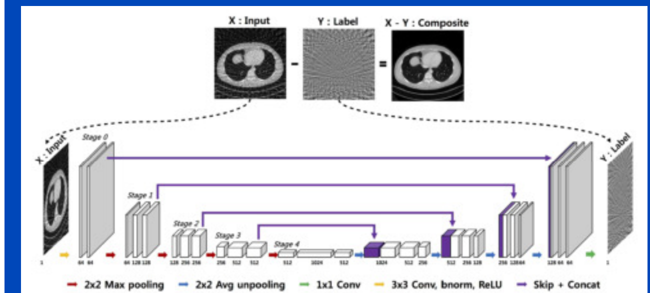
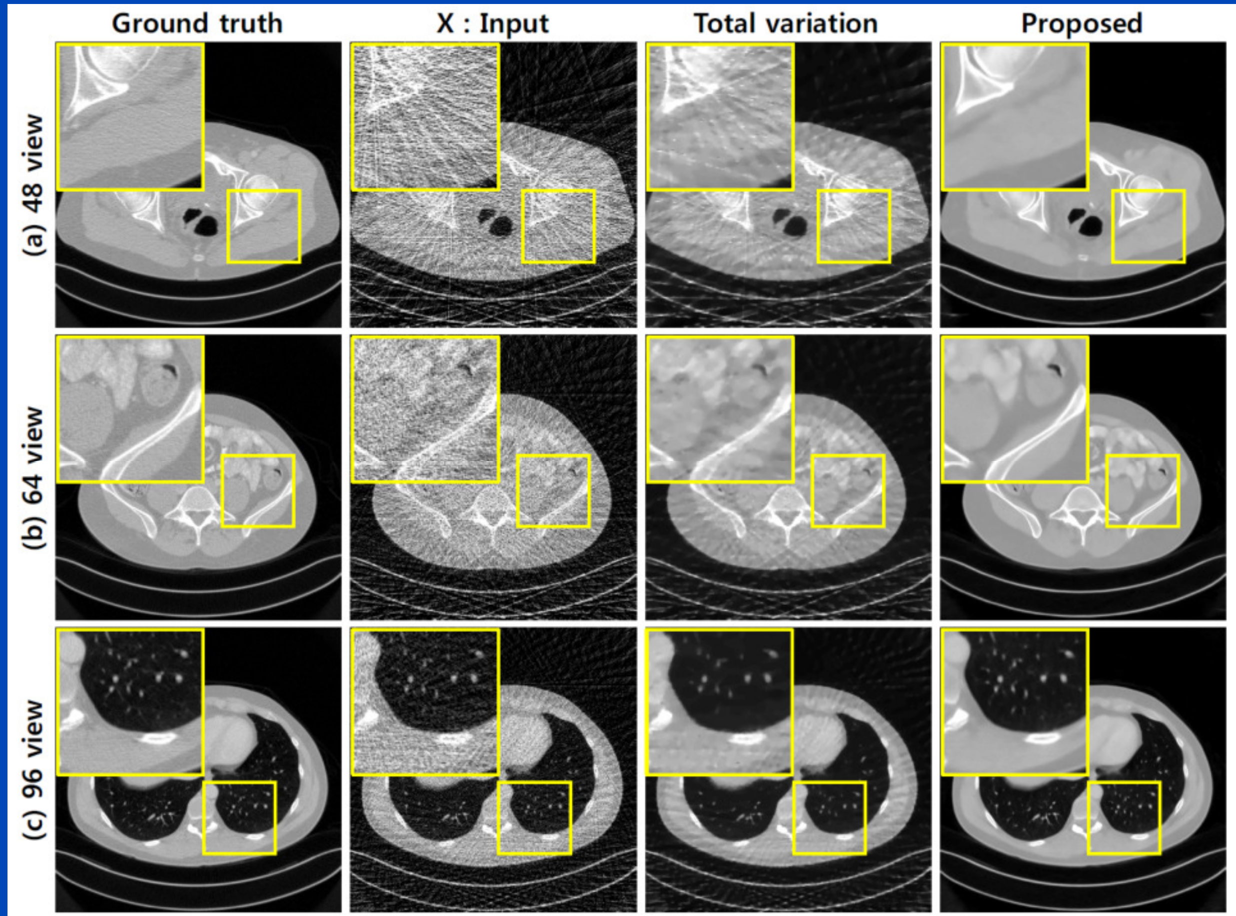
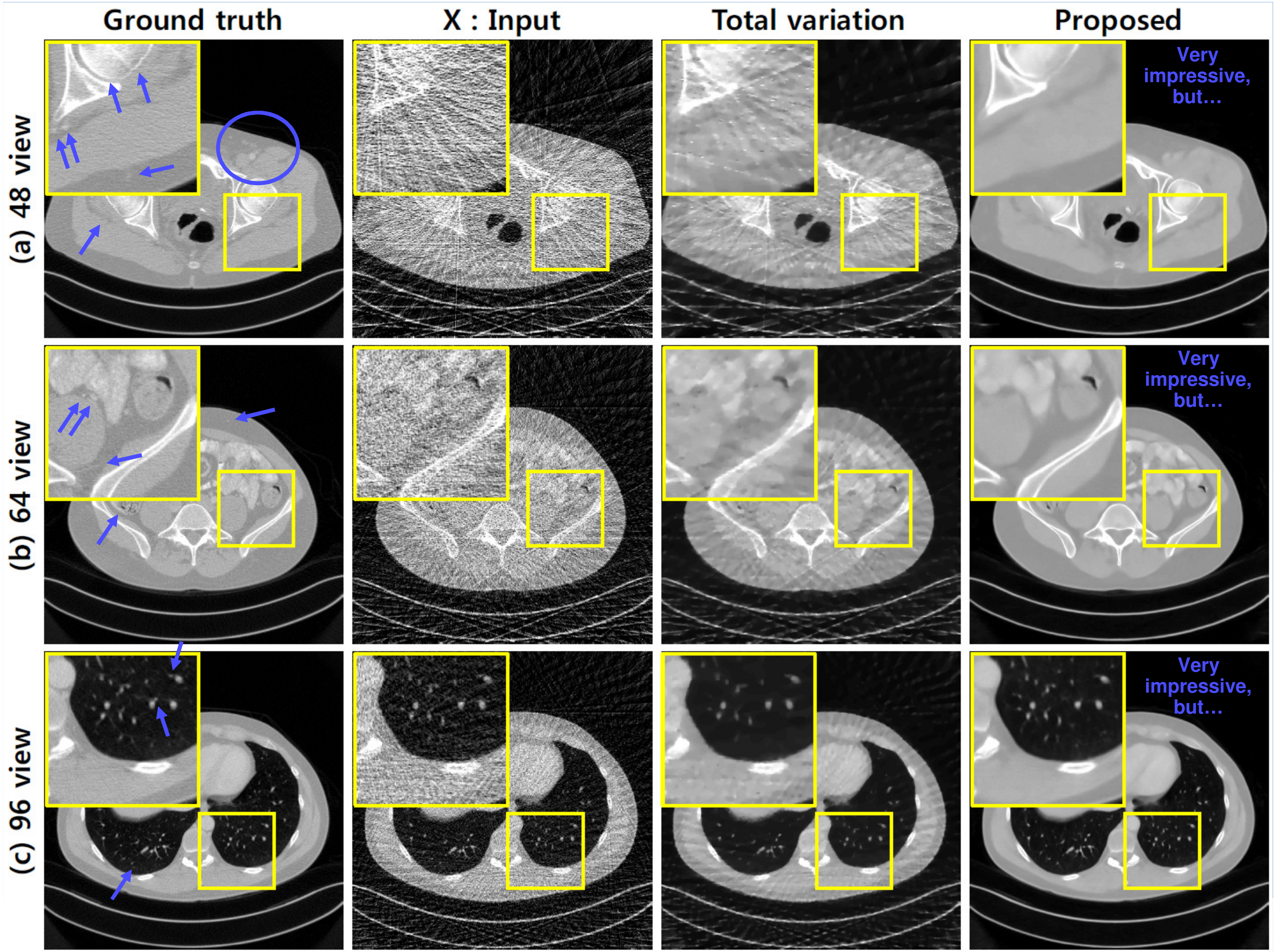


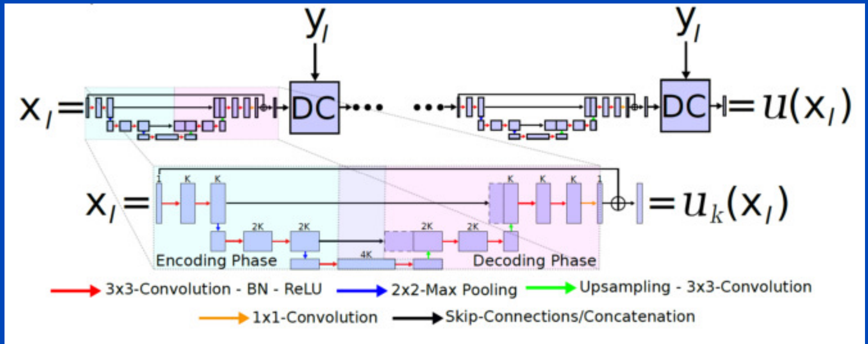
Figure 1. The proposed deep residual learning architecture for sparse view CT reconstruction.

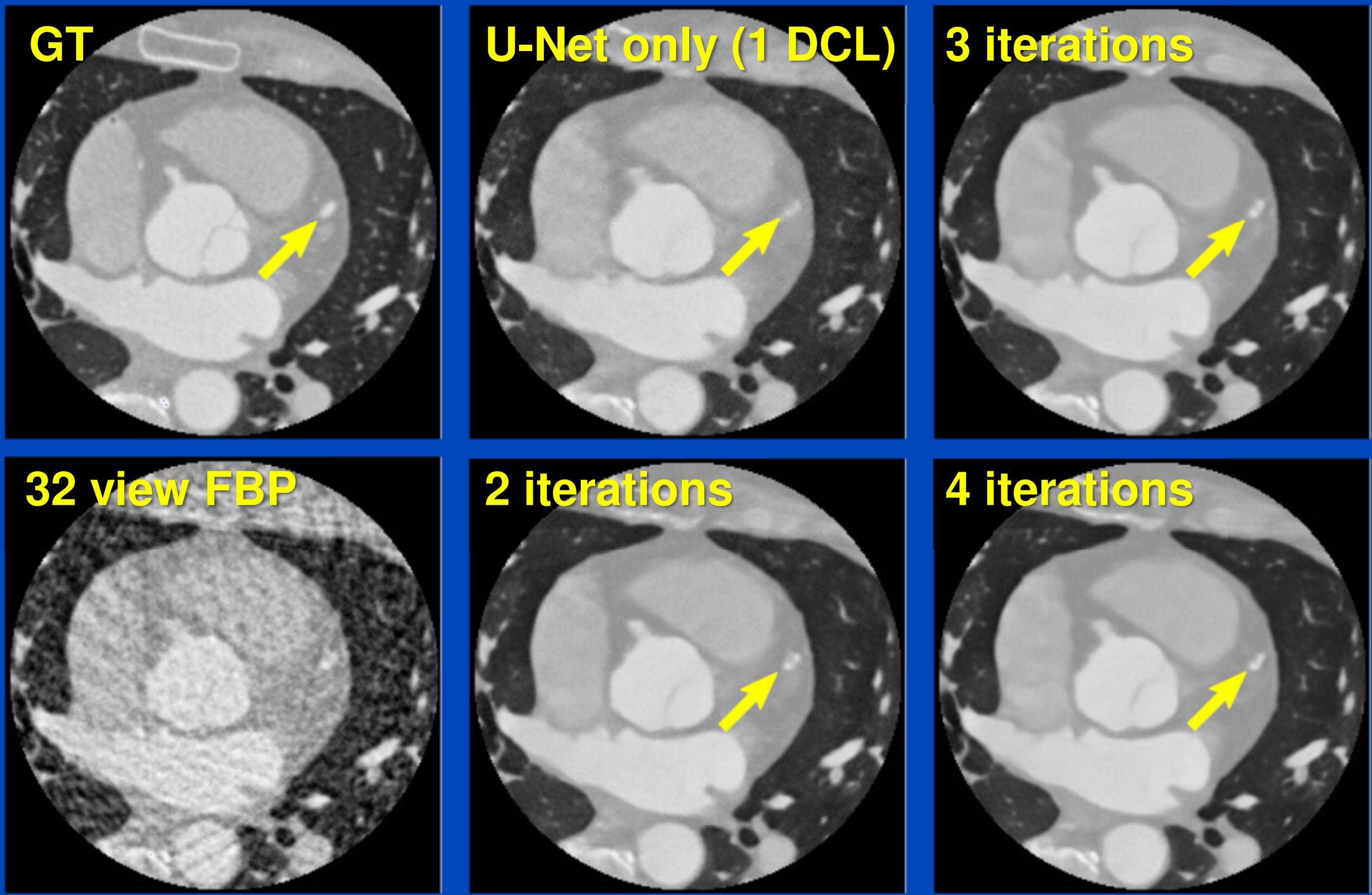


Yo Seob Han, Jaejun Yoo and Jong Chul Ye. Deep Residual Learning for Compressed Sensing CT Reconstruction via Persistent Homology Analysis. ArXiv 2016.


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…

Sparse CT Recon with Data Consistency Layers (DCLs)

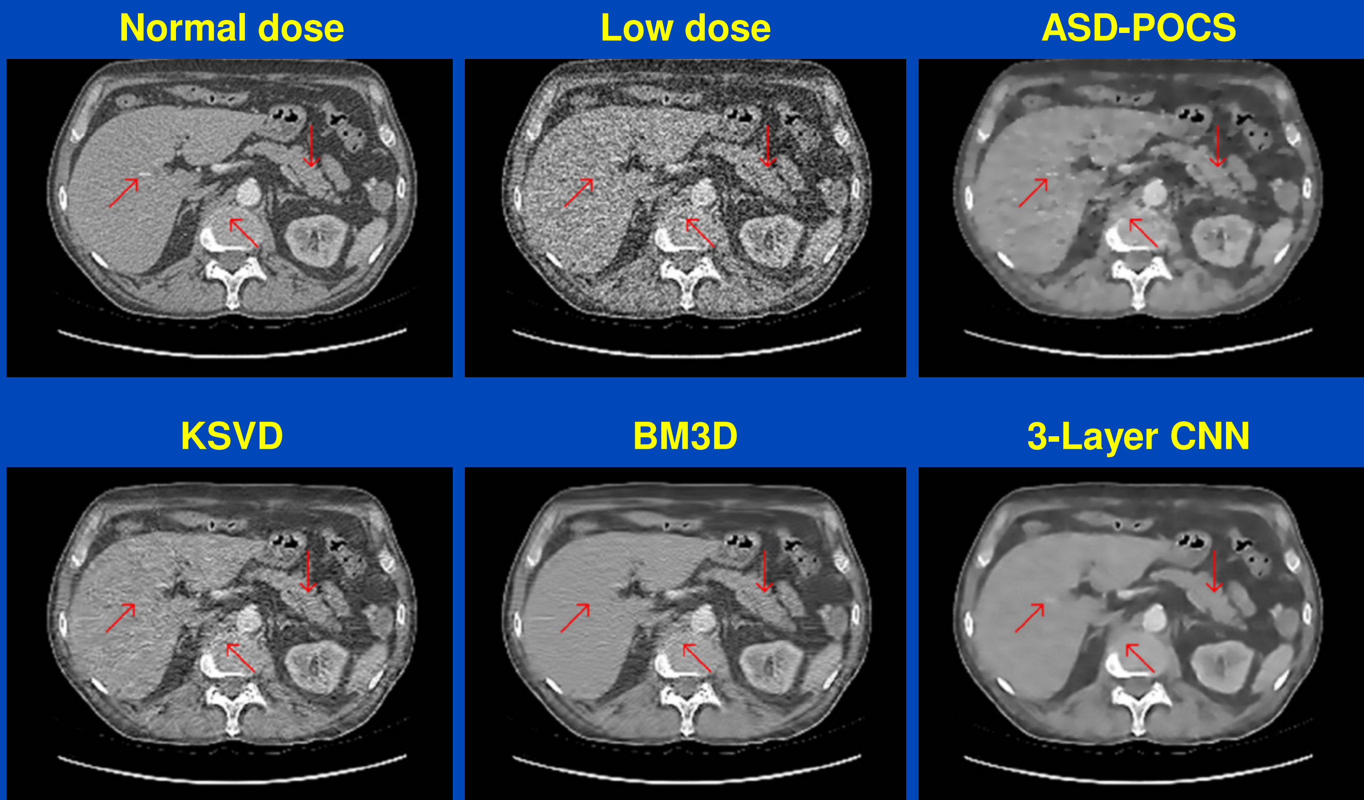




A. Kofler, M. Kachelrieß, et al. A U-Nets Cascade for Sparse View Computed Tomography, MICCAI 2018

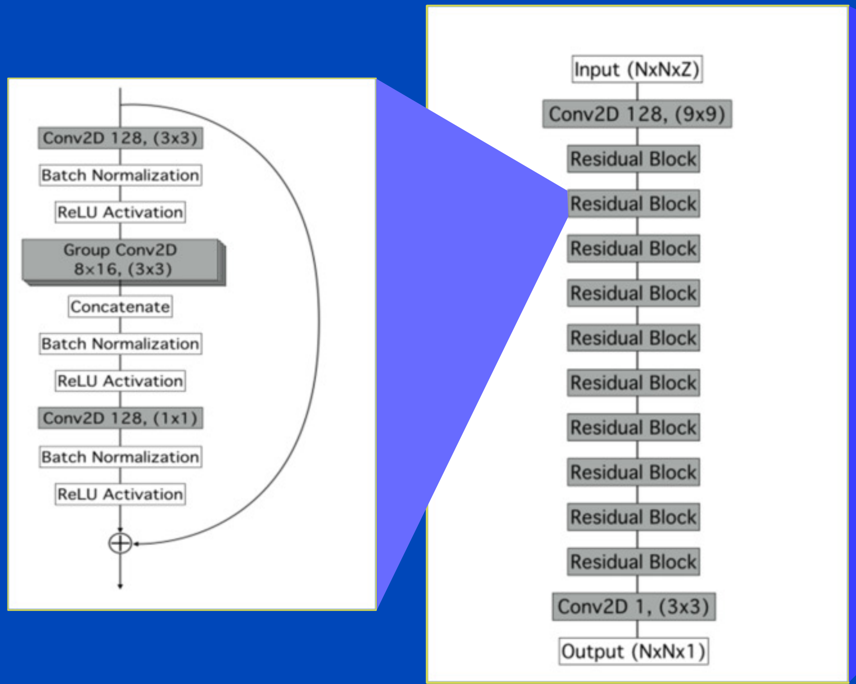
Noise Removal Example 1

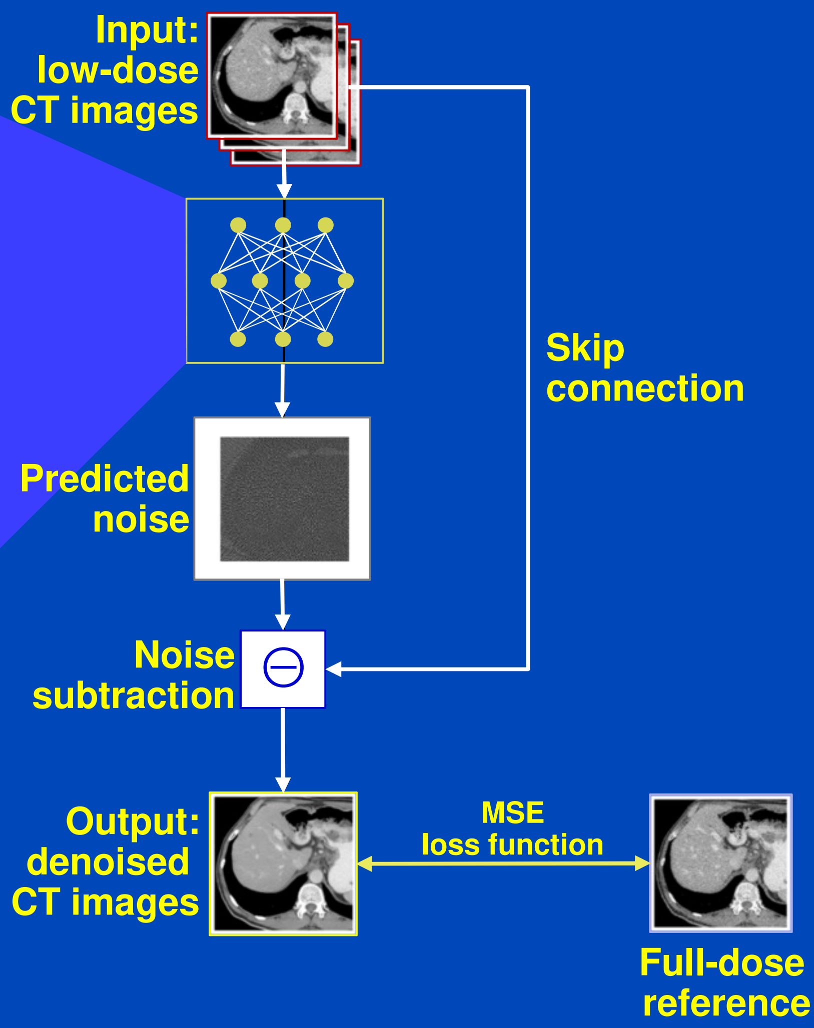
- 3-Layer CNN uses low dose and corresponding normal dose image patches for training



Hu Chen, Yi Zhan, Weihua Zhang, Peixi Liao, Ke Li, Jiliu Zhou, and Ge Wang. Low-dose CT via convolutional neural network. Biomedical Optics Express 8(2):278381, February 2017.

Noise Removal Example 2

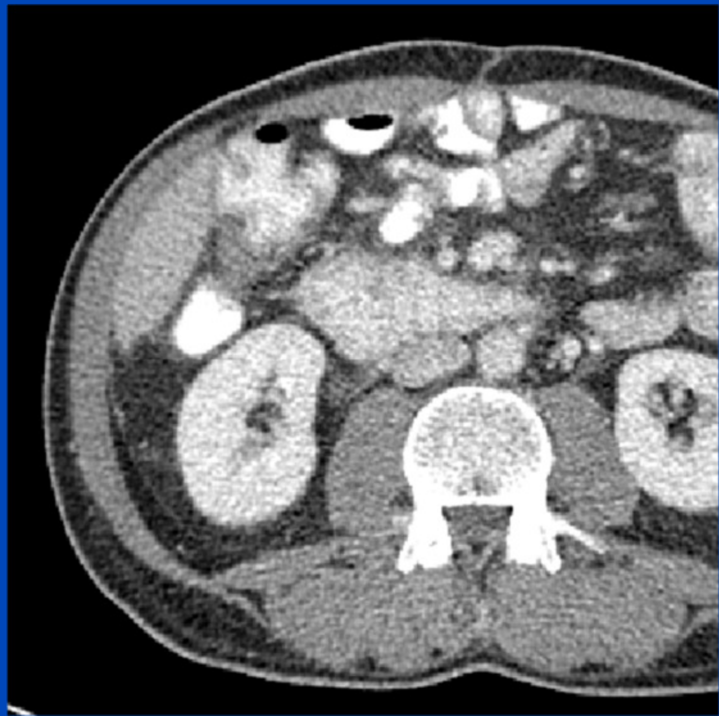




- Architecture based on state-of-the art networks for image classification (ResNet).
- 32 conv layers with skip connections
- About 2 million tunable parameters in total
- Input is arbitrarily-size stack of images, with a fixed number of adjacent slices in the channel/feature dimension.

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 CT-Meeting 2018.

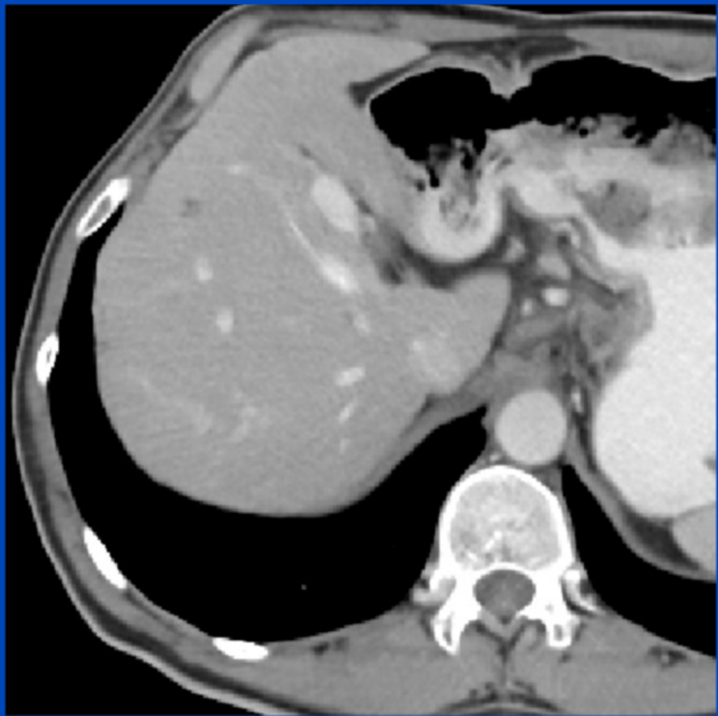
Noise Removal Example 2



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 CT-Meeting 2018.

Noise Removal Example 2



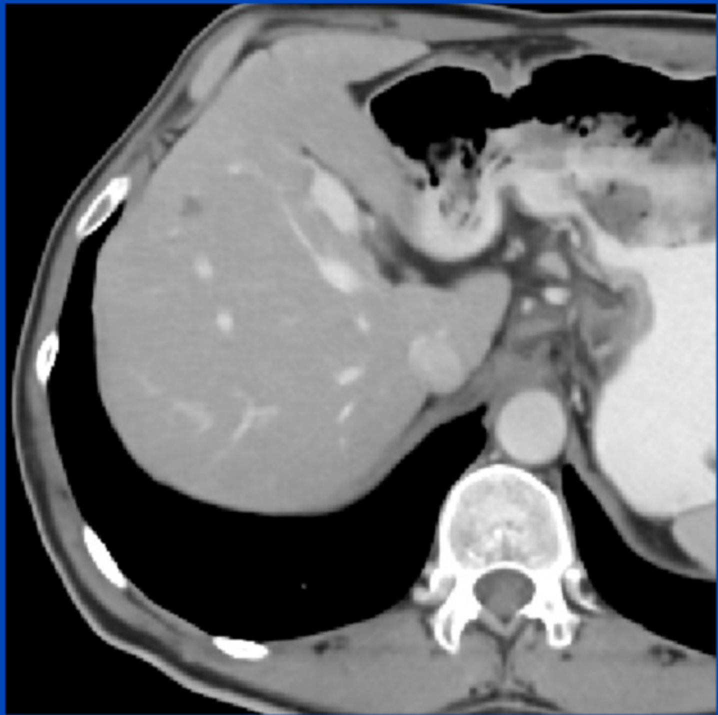
Denoised low dose

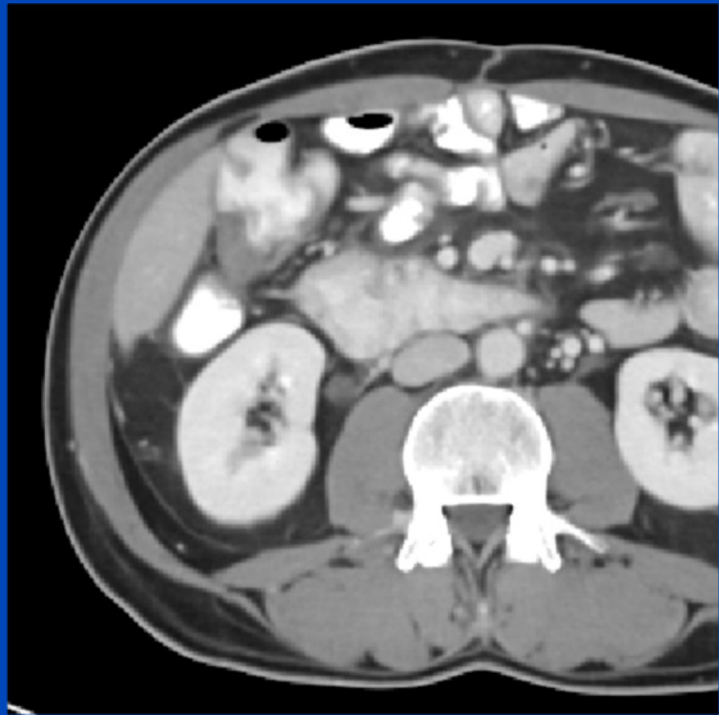
Noise Removal Example 2

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 CT-Meeting 2018.

Noise Removal Example 2





Denoised full dose

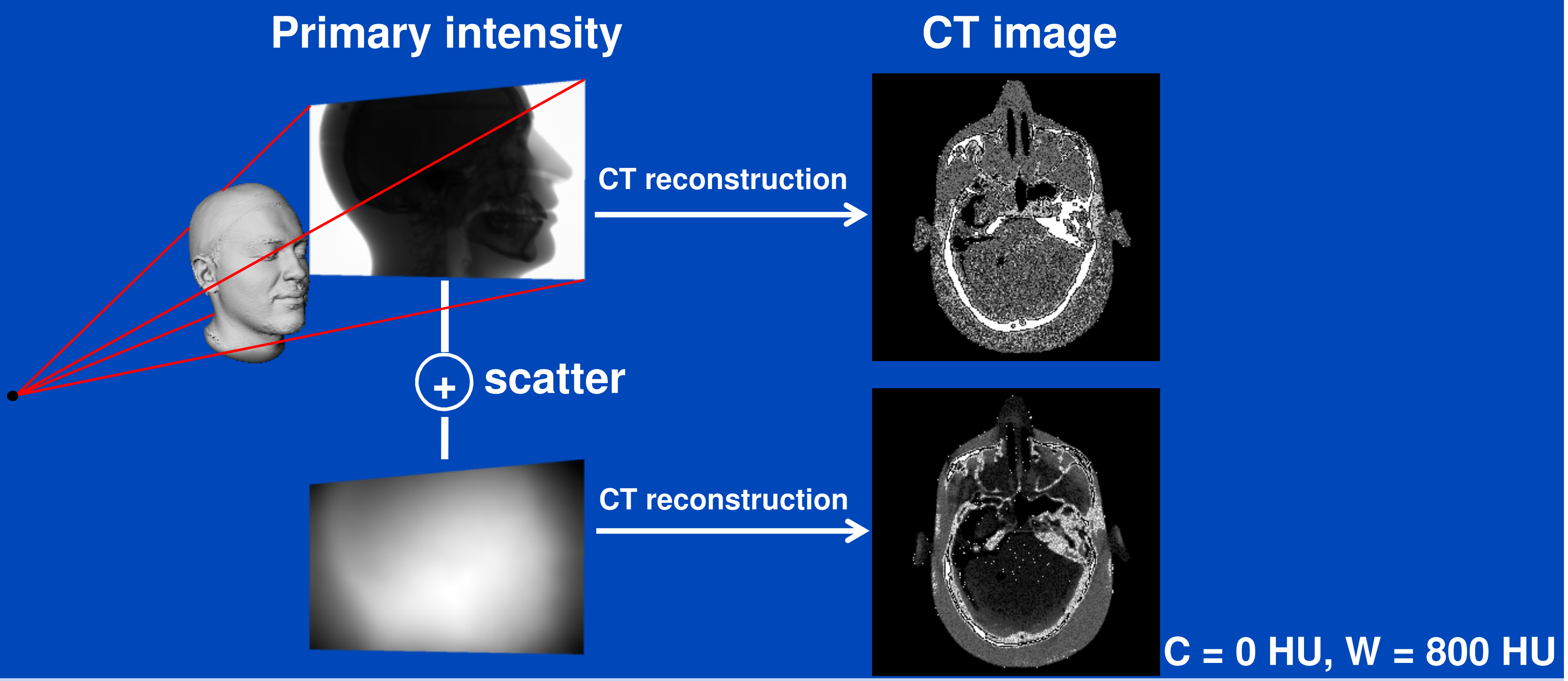
Andrew D. Missert, Shuai Leng, Lifeng Yu, and Cynthia H. McCollough. Noise Subtraction for Low-Dose CT Images Using a Deep Convolutional Neural Network. Proceedings of the CT-Meeting 2018.

Part 2:

Replacement of Lengthy Computations

Scatter

- X-ray scatter is a major cause of image quality degradation in CT and CBCT.
- Appropriate scatter correction is crucial to maintain the diagnostic value of the CT examination.



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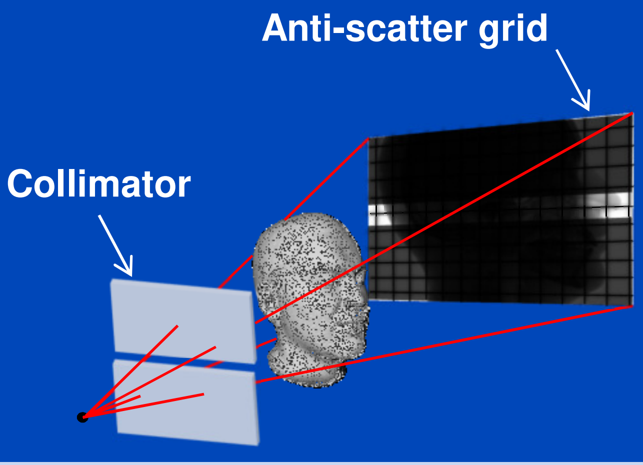
Scatter Correction

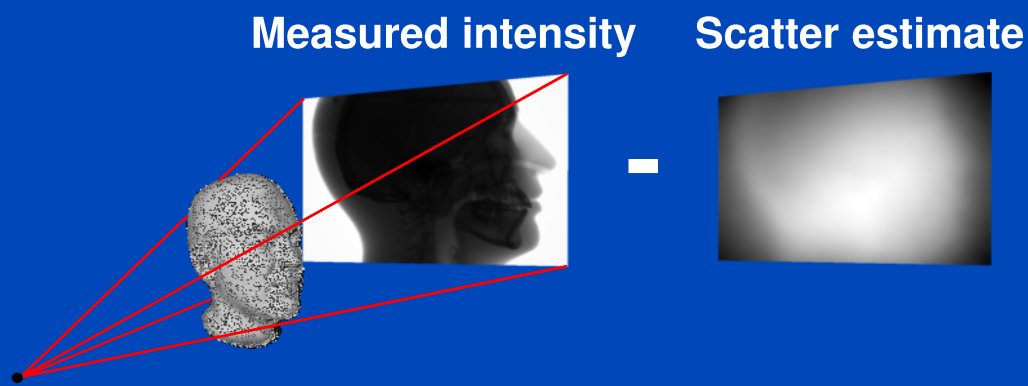
Scatter suppression

- Anti-scatter grids
- Collimators
- …

Scatter estimation

- Monte Carlo simulation
- Kernel-based approaches
- Boltzmann transport
- Primary modulation
- Beam blockers
- …



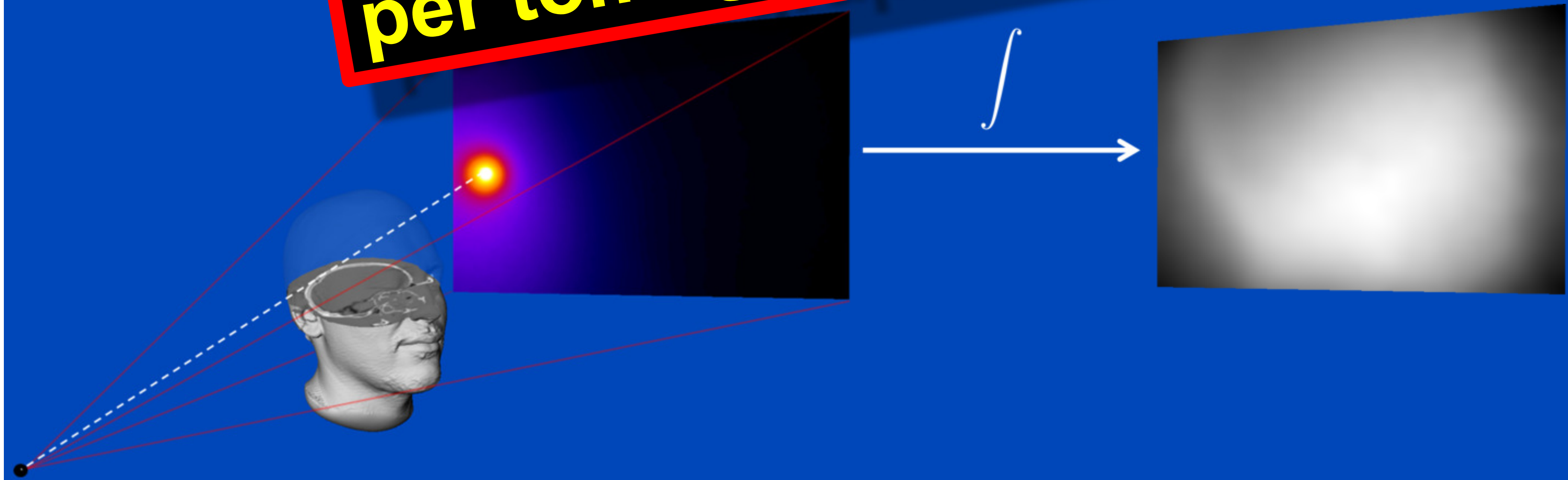


Monte Carlo Scatter Estimation

- Simulation of photon trajectories according to physical interaction probabilities.
- Simulating a large numb ries well approxima

1 to 10 hours
per tomographic data set

mplete scatter distribution

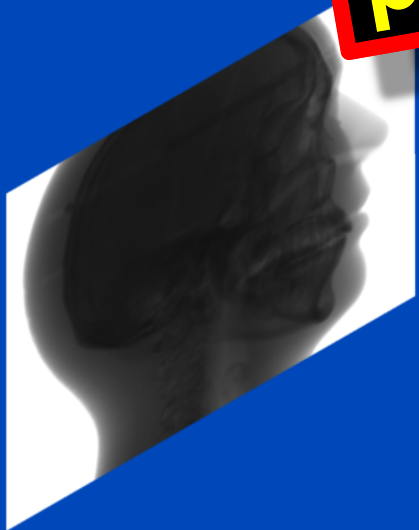


Deep Scatter Estimation (DSE)

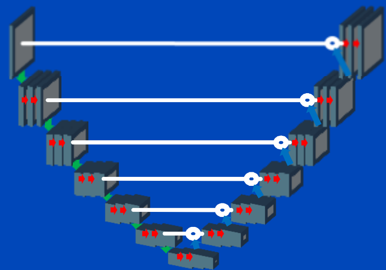
Train a deep convolutional neural network (CNN) to
estimate scatter using a functio... d
projection data as in...

0.1 to 1 minute
per tomographic data set

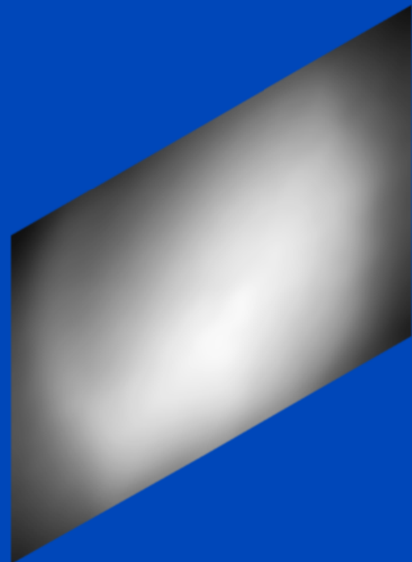
Input: $T(p)$



Convolutional neural network



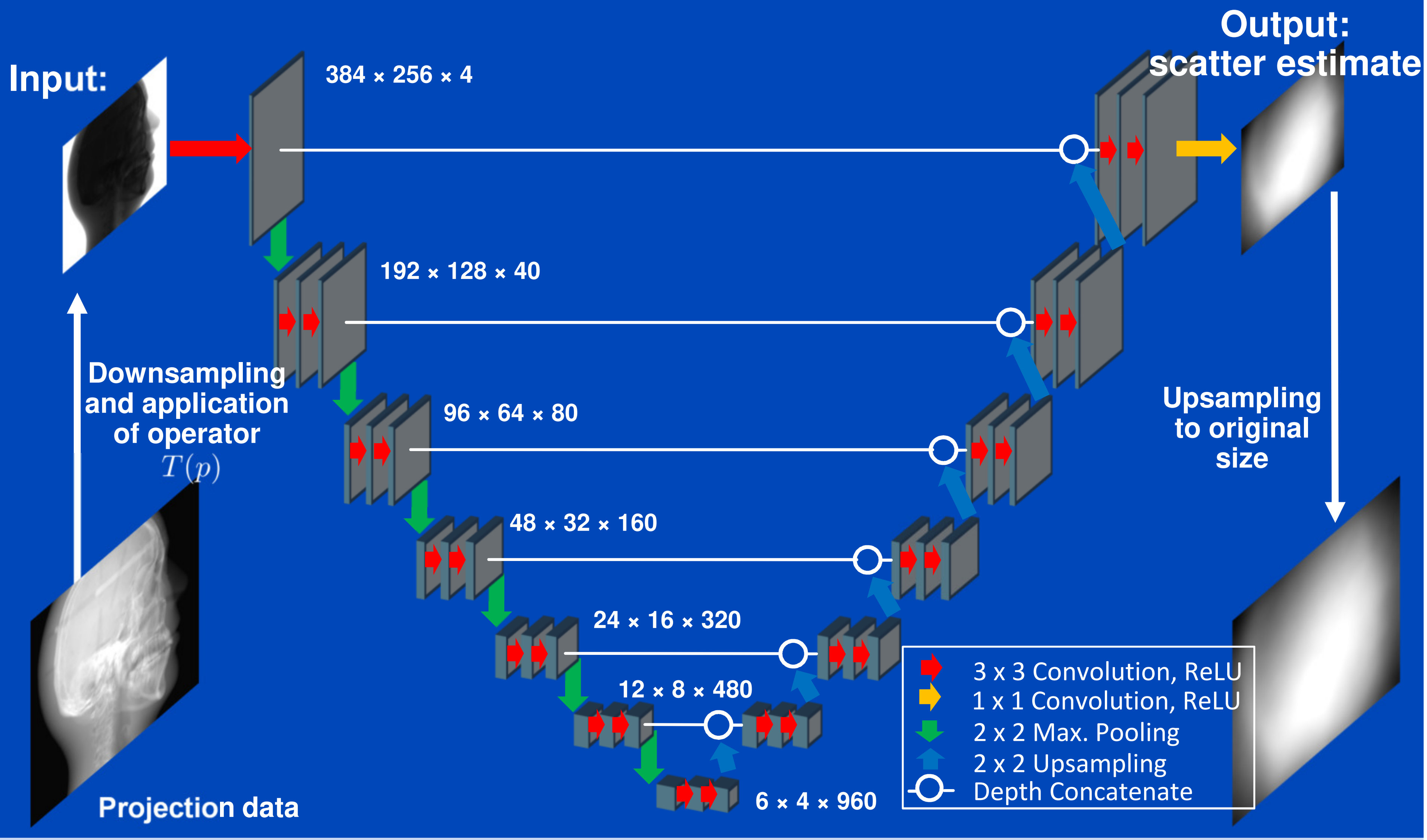
Scatter estimate



J. Maier, M. Kachelrieß et al. Deep scatter estimation (DSE): Accurate real-time scatter estimation for X-ray CT using a deep convolutional neural network. Journal of Nondestructive Evaluation 37:57, July 2018.

Deep Scatter Estimation

Network architecture & scatter estimation framework



J. Maier, M. Kachelrieß et al. Deep scatter estimation (DSE): Accurate real-time scatter estimation for X-ray CT using a deep convolutional neural network. Journal of Nondestructive Evaluation 37:57, July 2018.

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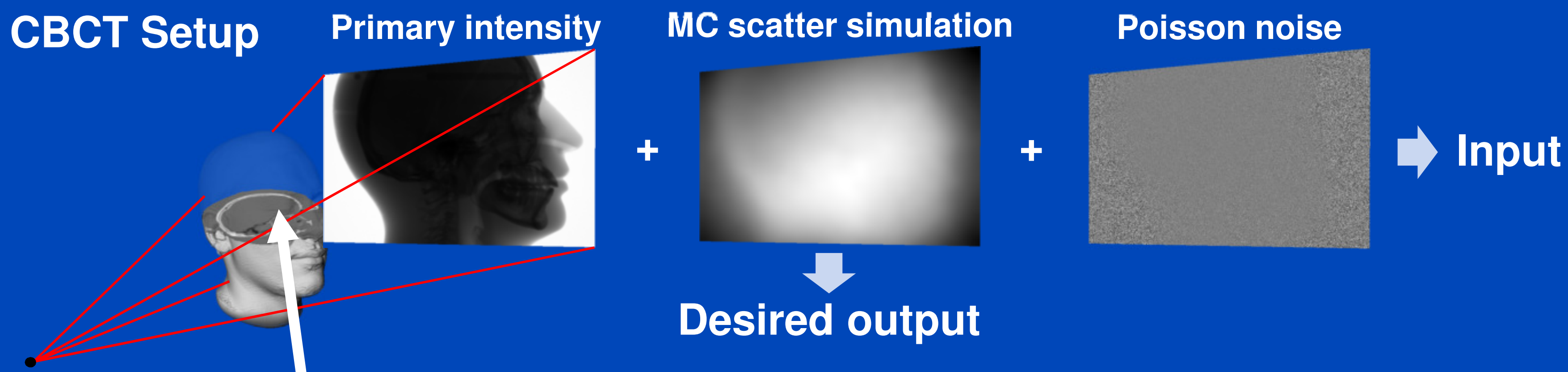
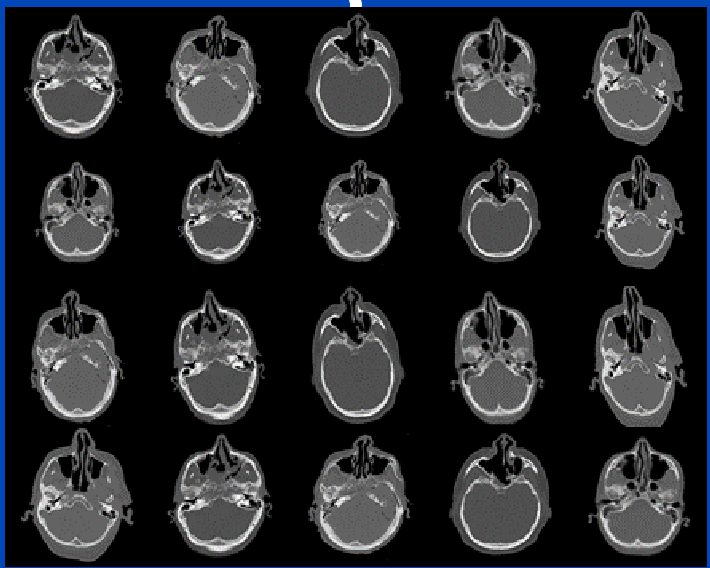
Training the DSE Network





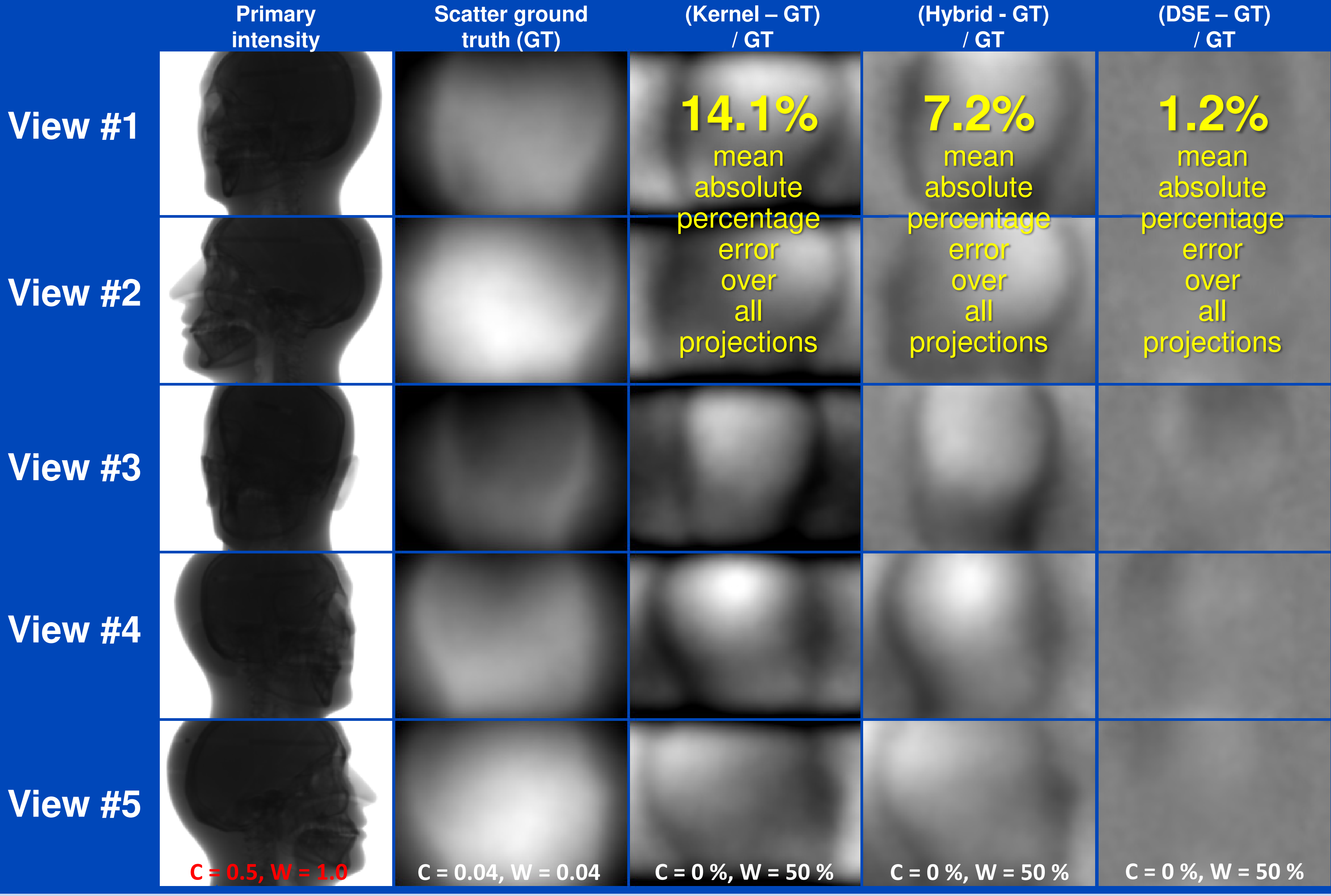
- Simulation of 12000 flat detector projection using data of different heads.
- Simulate different tube voltages.
- Splitting into 80% training and 20% validation data.
- Optimize weights of the CNN to reproduce the Monte Carlo scatter estimates:

$$(\boldsymbol{w}, \boldsymbol{b}) = \arg\min_{\boldsymbol{w},\boldsymbol{b}} \|\mathrm{DSE}_{\boldsymbol{w},\boldsymbol{b}}(T(p)) - I_{\mathrm{MC}}\|_2^2$$

- Training on a GeForce GTX 1080 for 80 epochs.

J. Maier, M. Kachelrieß et al. Deep scatter estimation (DSE): Accurate real-time scatter estimation for X-ray CT using a deep convolutional neural network. Journal of Nondestructive Evaluation 37:57, July 2018.

Results on Simulated Projection Data



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

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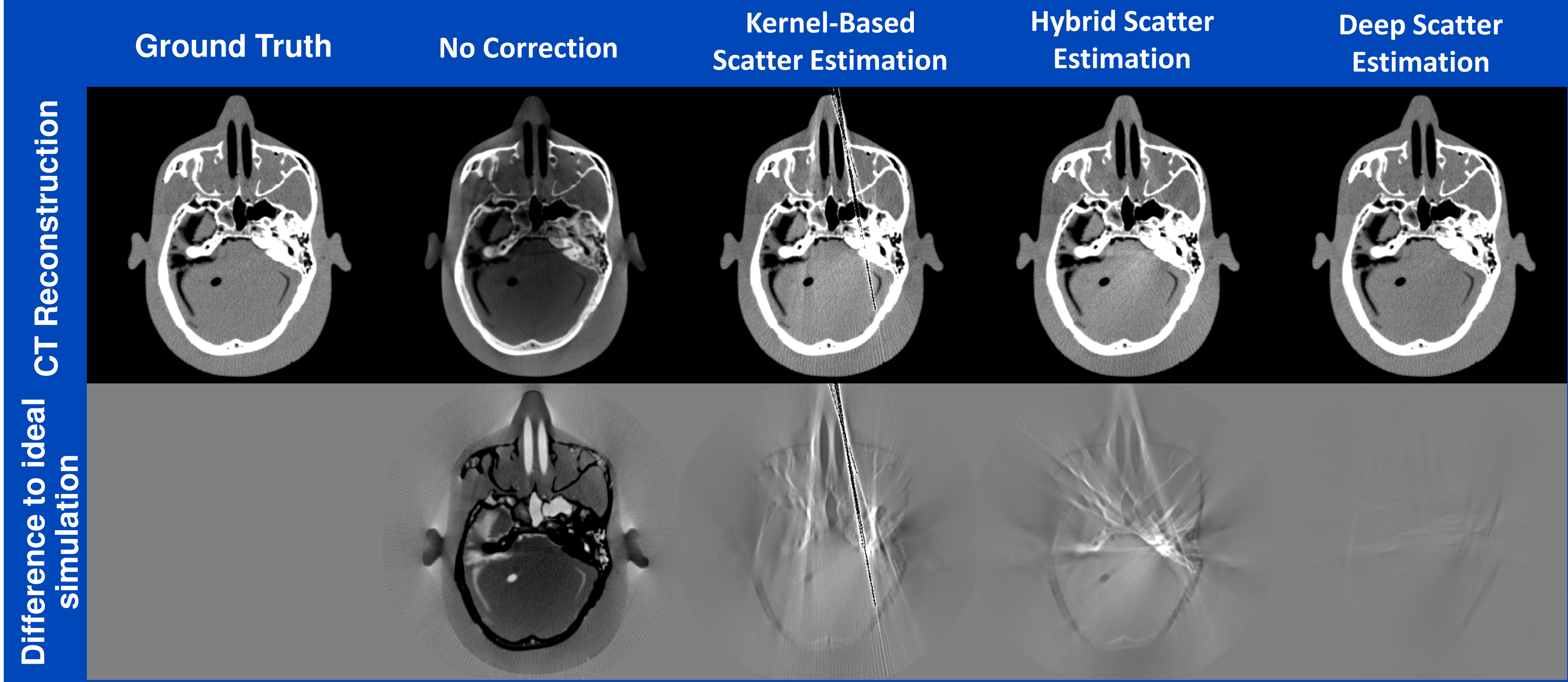
Reconstructions of Simulated Data

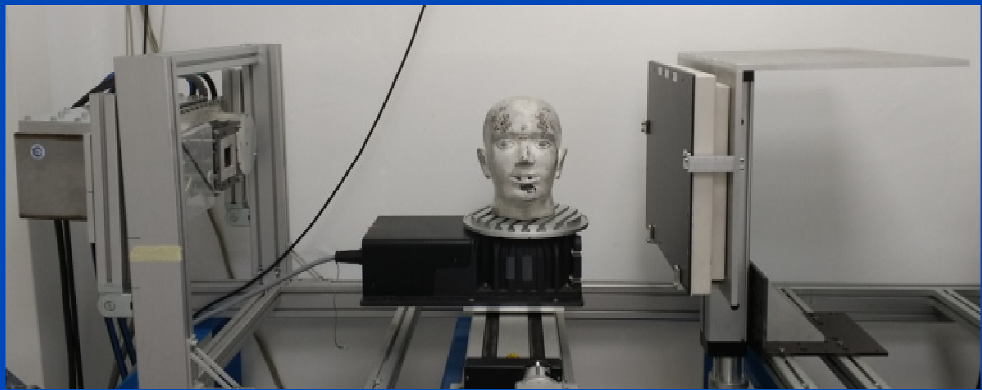


C = 0 HU, W = 1000 HU

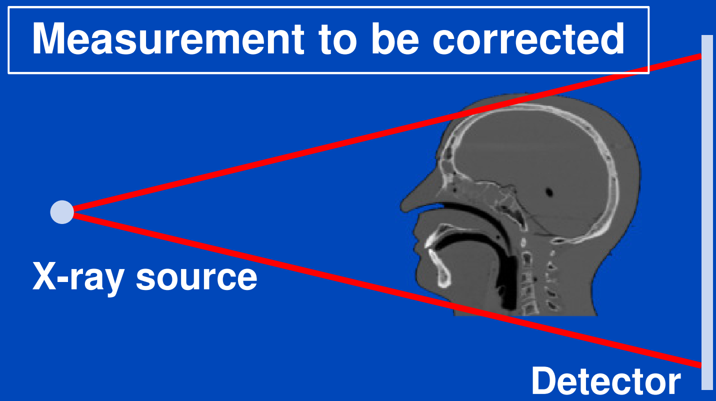
J. Maier, M. Kachelrieß et al. Deep scatter estimation (DSE): Accurate real-time scatter estimation for X-ray CT using a deep convolutional neural network. Journal of Nondestructive Evaluation 37:57, July 2018.

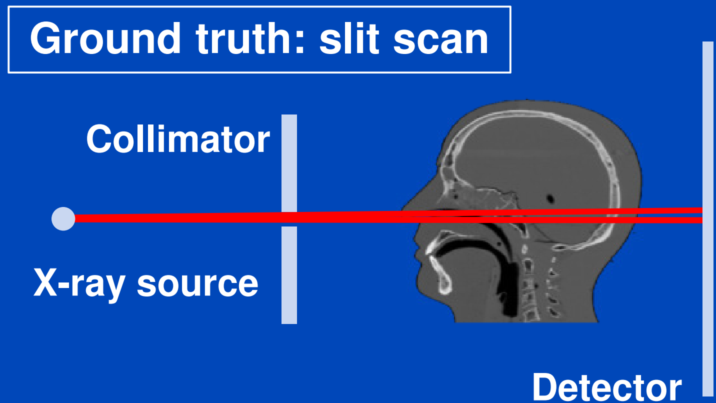
Testing of the DSE Network for Measured Data (120 kV)

DKFZ table-top CT



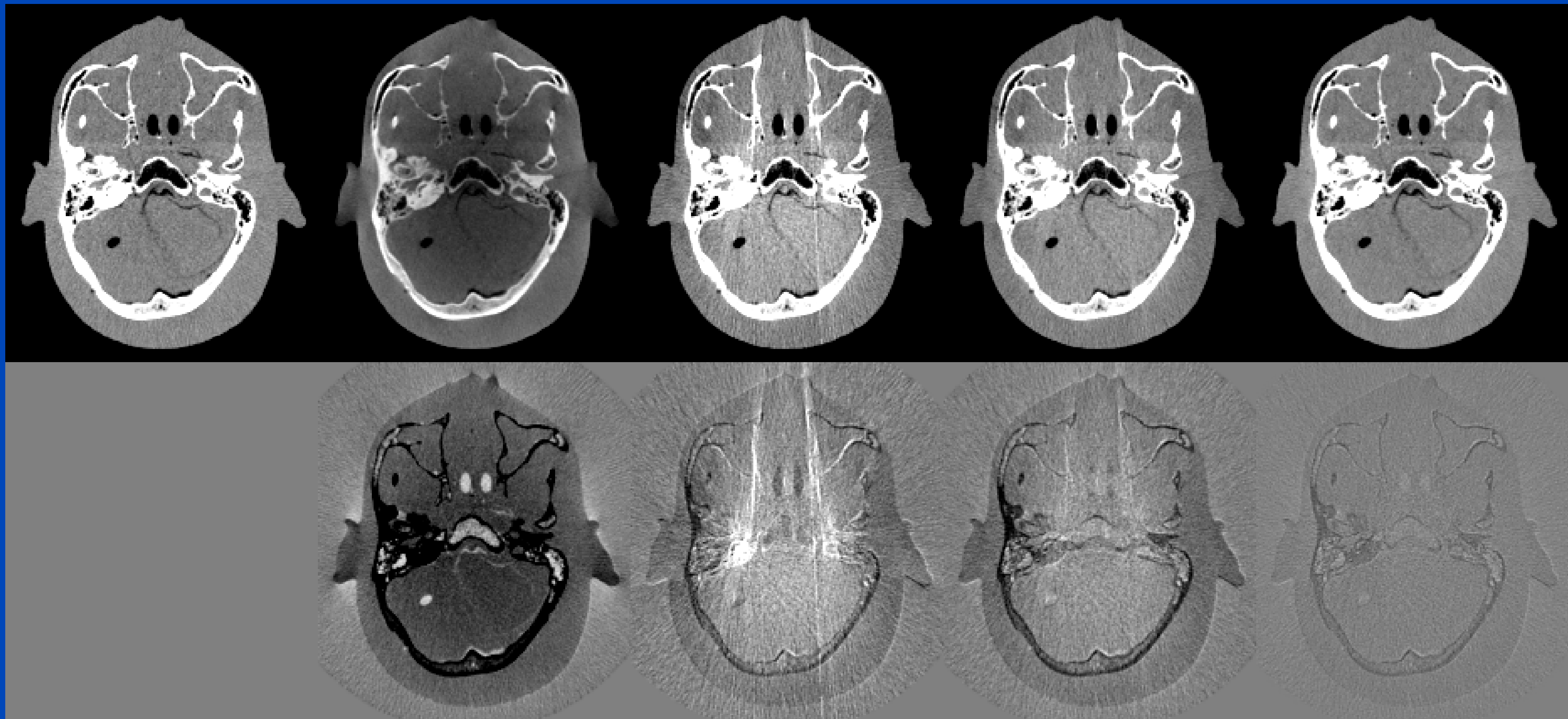
- Measurement of a head phantom at our in-house table-top CT.
- Slit scan measurement serves as ground truth.





J. Maier, M. Kachelrieß et al. Deep scatter estimation (DSE): Accurate real-time scatter estimation for X-ray CT using a deep convolutional neural network. Journal of Nondestructive Evaluation 37:57, July 2018.

Reconstructions of Measured Data

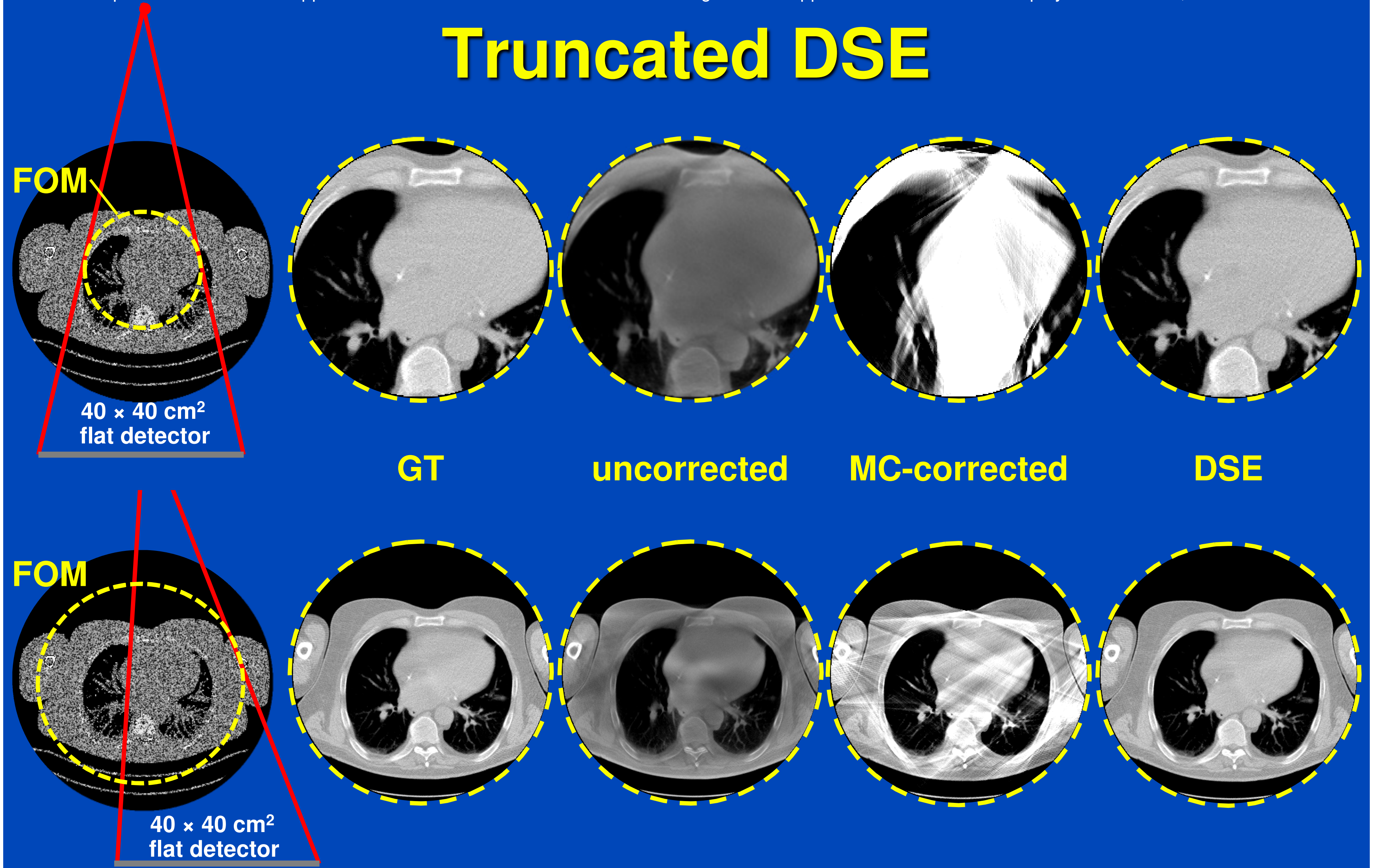


C = 0 HU, W = 1000 HU

J. Maier, M. Kachelrieß et al. Deep scatter estimation (DSE): Accurate real-time scatter estimation for X-ray CT using a deep convolutional neural network. Journal of Nondestructive Evaluation 37:57, July 2018.

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

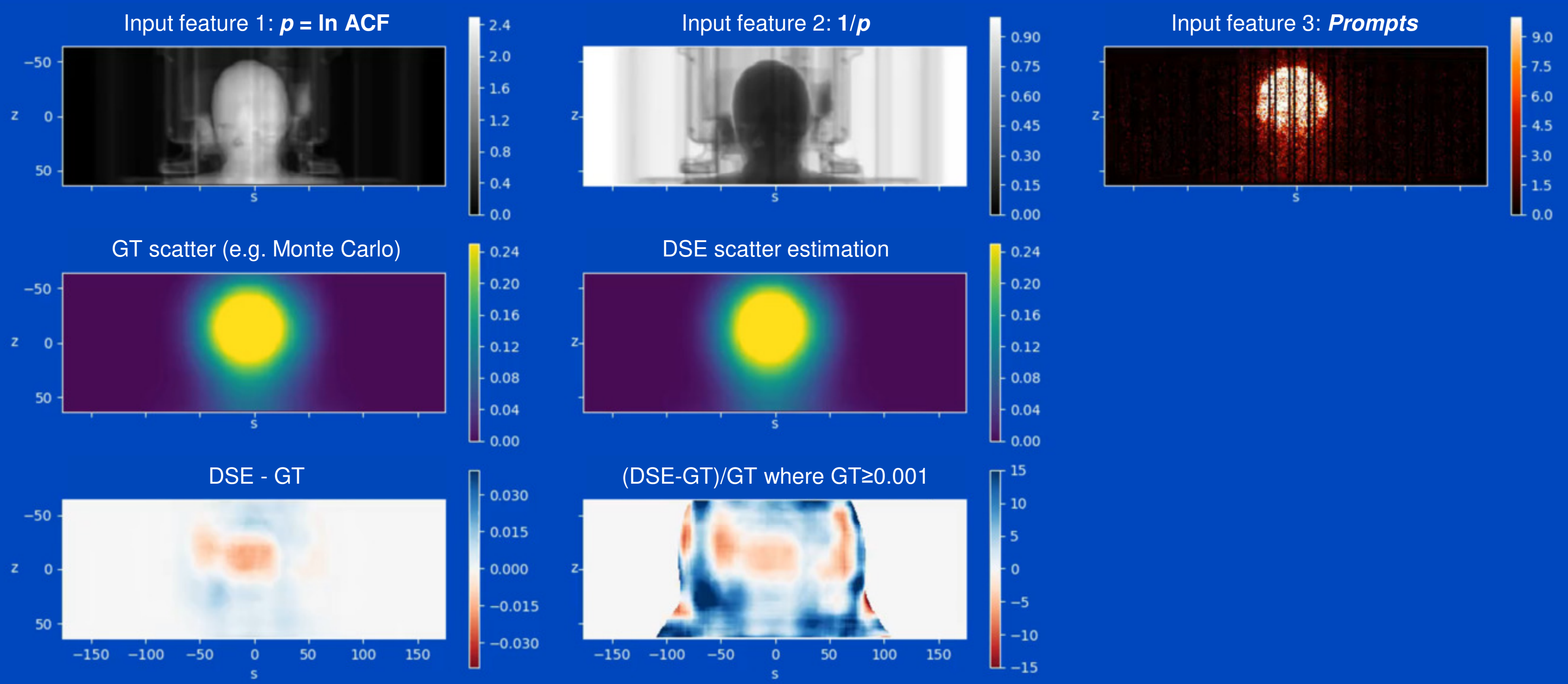


To learn why MC fails at truncated data and what significant efforts are necessary to cope with that situation see [Kachelrieß et al. Effect of detruncation on the accuracy of MC-based scatter estimation in truncated CBCT. Med. Phys. 45(8):3574-3590, August 2018].

Conclusions on DSE

- DSE needs about 20 ms per projection. It is a fast and accurate alternative to Monte Carlo (MC) simulations.
- DSE outperforms kernel-based approaches in terms of accuracy and speed.
- Interesting observations
  – DSE can estimate scatter from a single (!) x-ray image.
  – DSE can accurately estimate scatter from a primary+scatter image.
  – DSE cannot accurately estimate scatter from a primary only image.
  – DSE may thus outperform MC even though DSE is trained with MC.
- DSE is not restricted to reproducing MC scatter estimates.
- DSE can rather be trained with any other scatter estimate, including those based on measurements.

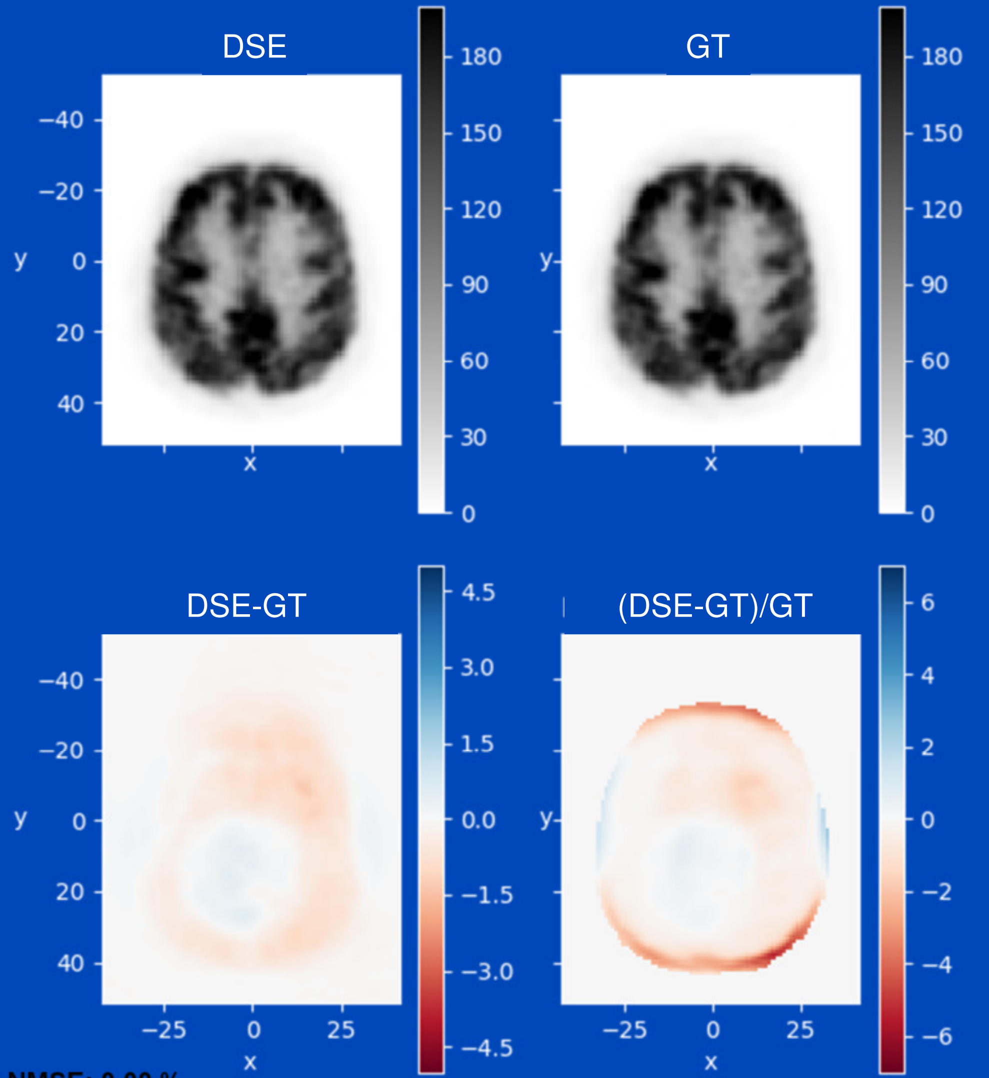
DSE for PET



Bed position f55d49, NMAE: 1.09 %, NMSE: 0.00 %
252 projection angles, 25 fps. DSE filtered in angular direction (Gaussian, FWHM 3.5 projections) for display

Y. Berker, J. Maier, and M. Kachelrieß. Deep scatter estimation in PET: Fast scatter correction using a convolutional neural network. Proc. IEEE MIC 2018.

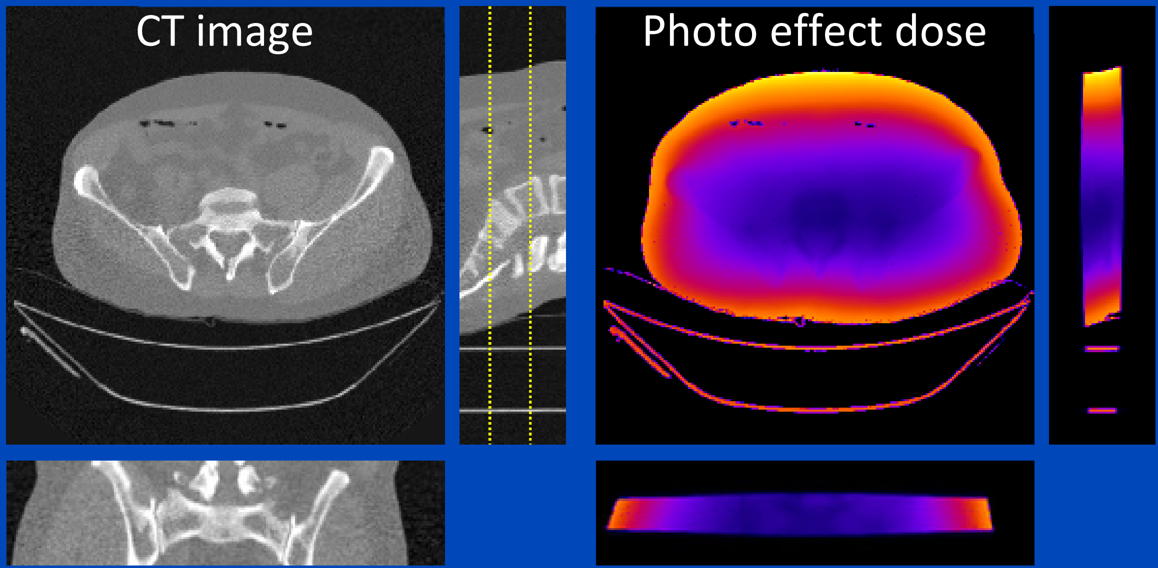
DSE for PET



Bed position f55d49, NMAE: 1.09 %, NMSE: 0.00 %
Reconstruction, transaxial (a.u.)

Y. Berker, J. Maier, and M. Kachelrieß. Deep scatter estimation in PET:
Fast scatter correction using a convolutional neural network. Proc. IEEE MIC 2018.

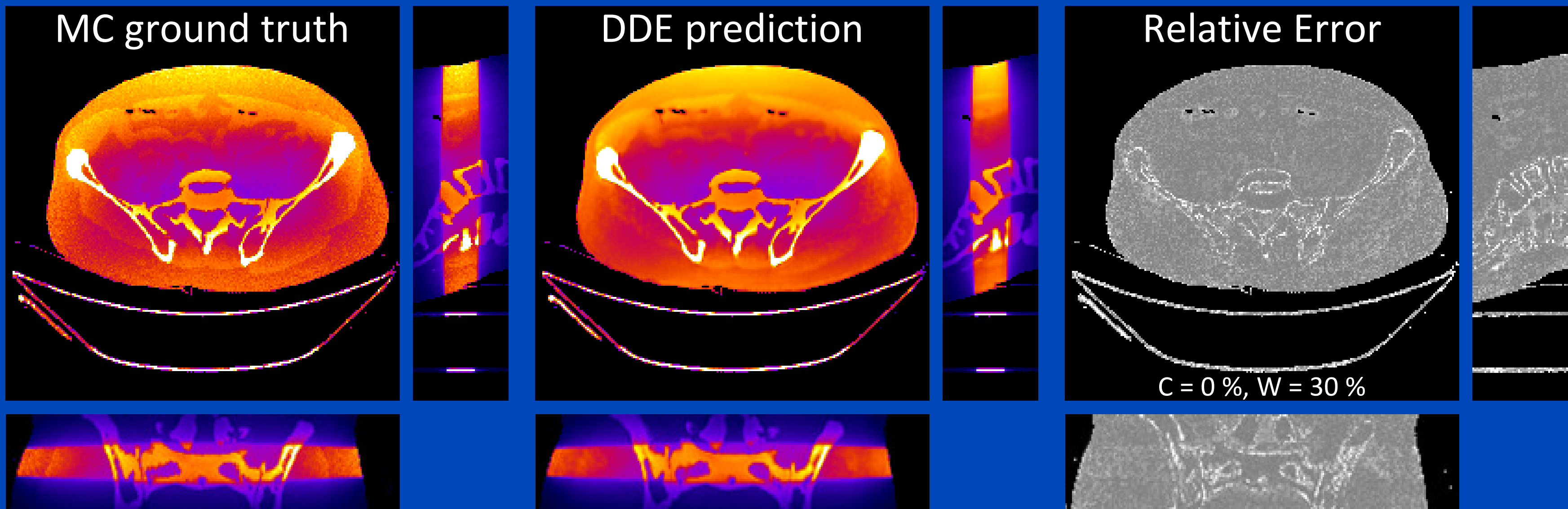
Deep Dose Estimation (DDE)



	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 30 h for 200 epochs, 720 samples, 48 slices per sample



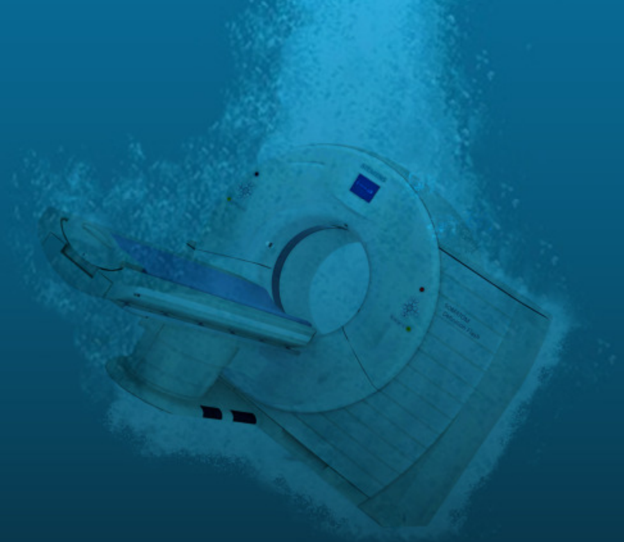
J. Maier, E. Eulig, S. Dorn, S. Sawall, and M. Kachelrieß. Real-time patient-specific CT dose estimation using a deep convolutional neural network. Proc. IEEE MIC 2018.

Conclusions on Deep Learning for CT Image Formation

- Machine learning will play a significant role in CT image formation.
- High potential for
  - Artifact correction
  - Noise and dose reduction
  - Real-time dose assessment (also for RT)
  - ...
- Care has to be taken
  - Underdetermined acquisition, e.g. sparse view or limited angle CT, require the net to make up information!
  - Nice looking images do not neccesarily represent the ground truth.
  - Data consistency layers may ensure that the information that is made up is consistent with the measured data.
  - ...

dkfz.

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.