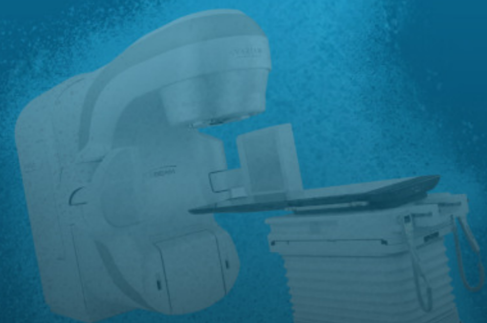
Deep Image Formation Algorithms for CT and CBCT



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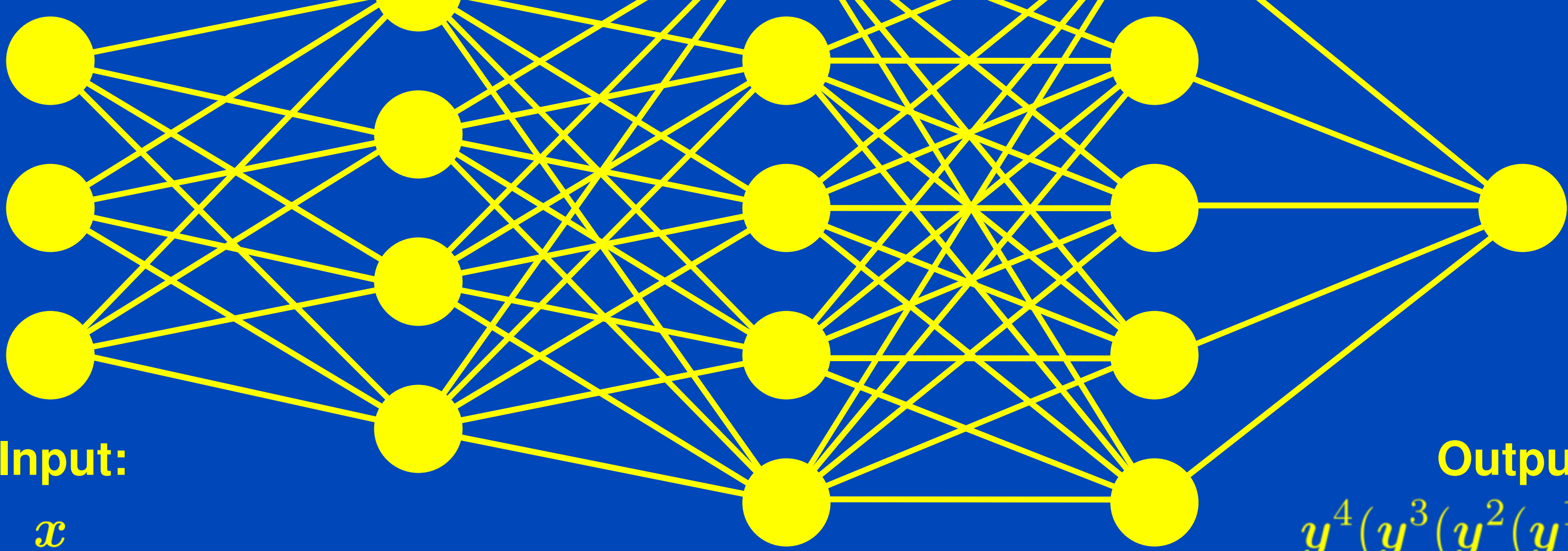
DEUTSCHES KREBSFORSCHUNGSZENTRUM IN DER HELMHOLTZ-GEMEINSCHAFT

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

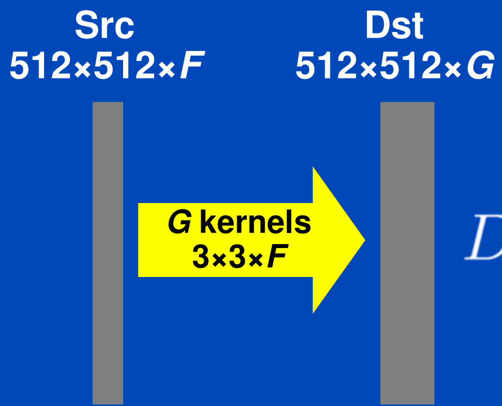
Input
e.g. 270×190×3 pixels
e.g.



$\boldsymbol{y}(\boldsymbol{x}) = \boldsymbol{f}(\boldsymbol{W}\cdot\boldsymbol{x}+\boldsymbol{b})$ with $\boldsymbol{f}(\boldsymbol{x}) = \big(f(x_1), f(x_2), \dots\big)$ point-wise scalar, e.g. $f(x) = x \vee 0 = \mathrm{ReLU}$

Convolutional Neural Network (CNN)

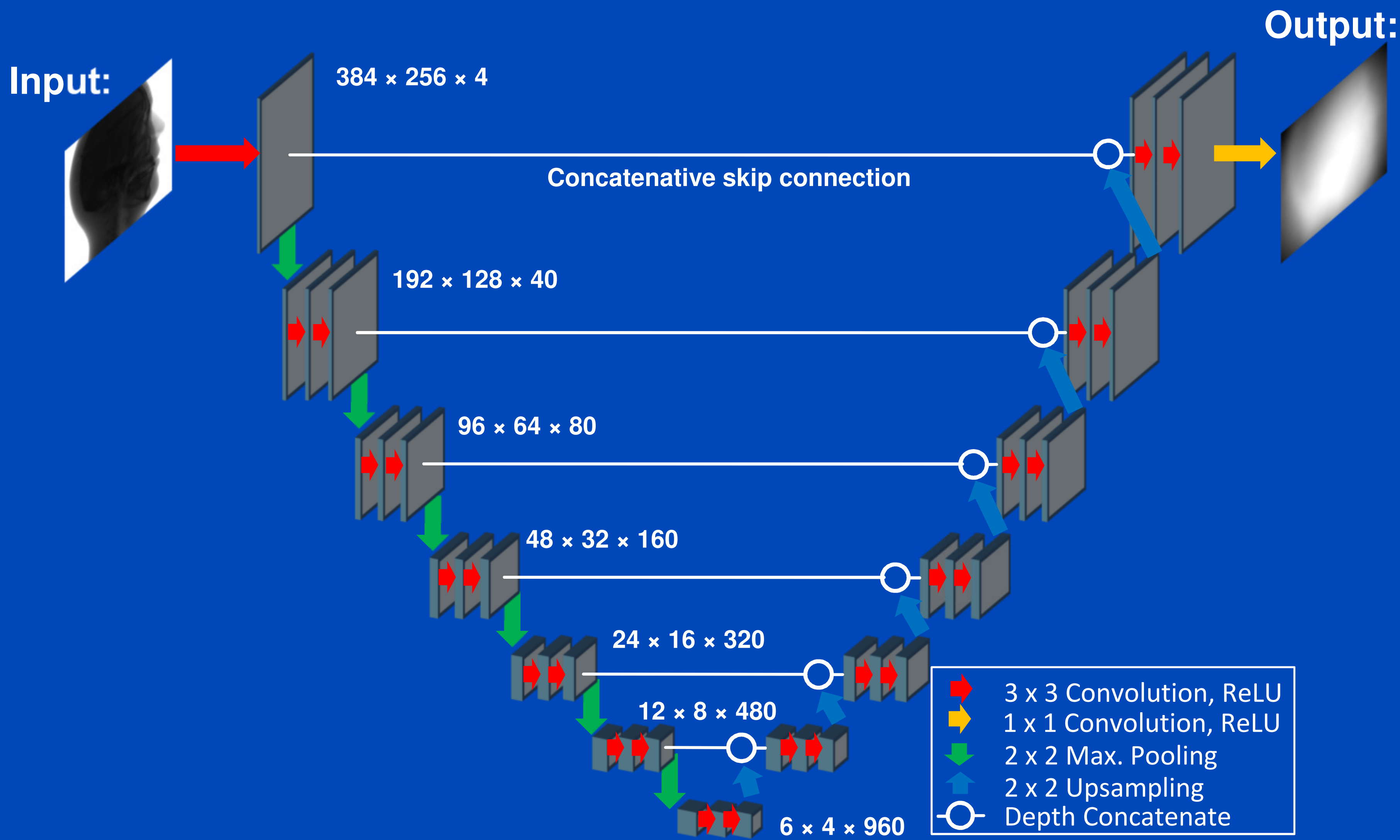
- Replace dense *W* in $y(x) = f(W \cdot x + b)$ by a sparse matrix *W* with sparsity being of convolutional type.
- CNNs consist (mainly) of convolutional layers.
- Convolutional layers are not fully connected.
- Convolutional layers are connected by small, say 3×3, convolution kernels whose entries 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[1]



[1]O. Ronneberger, P. Fischer, and T. Brox. U-net: Convolutional networks for biomedical image segmentation. Proc. MICCAI:234-241, 2015.

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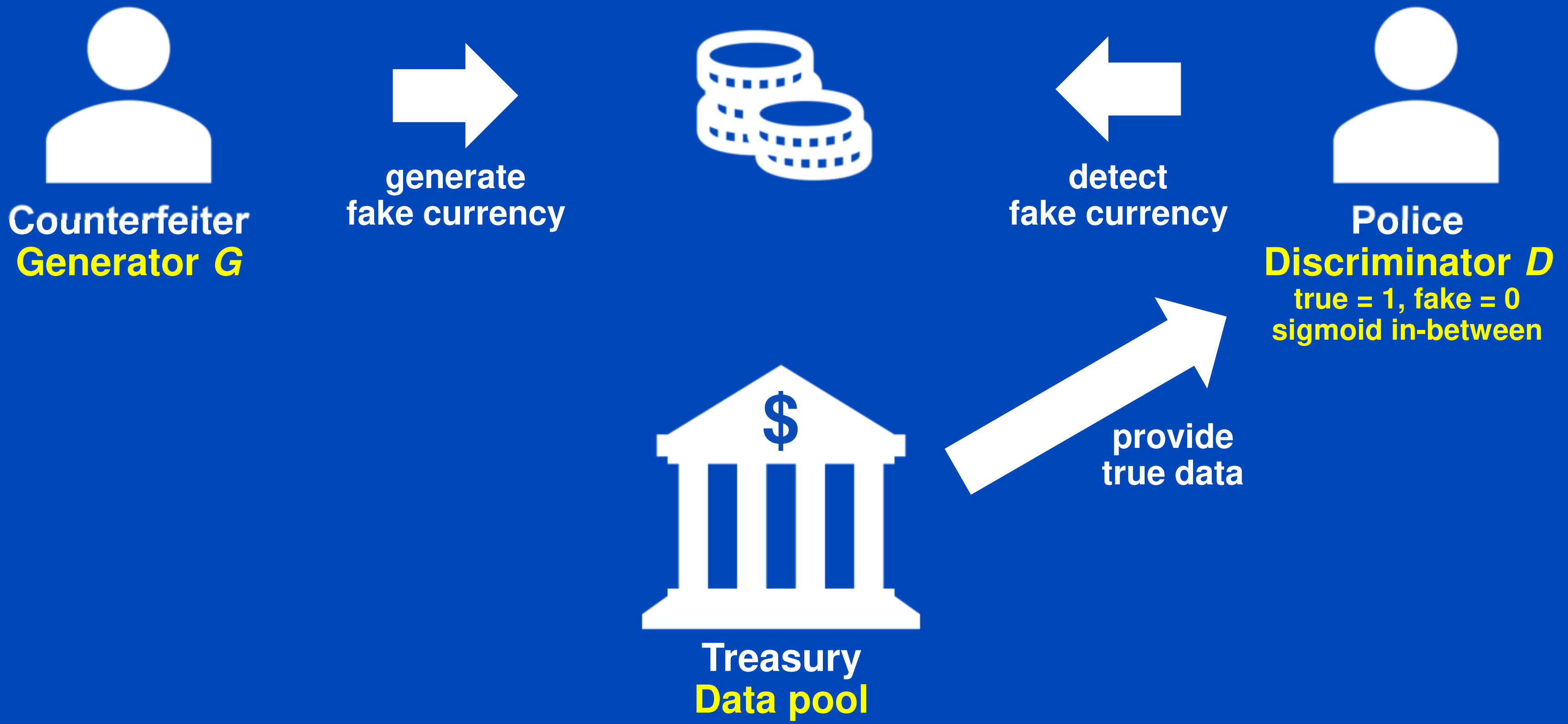
Generative Adversarial Network[1] (GAN)

- Useful, if no direct ground truth (GT) is available, the training data are unpaired, unsupervised learning



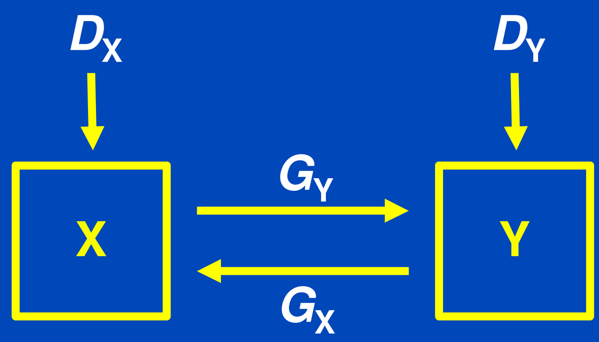
[1]Goodfellow et al. 2014

Generative Adversarial Network (GAN)

- **Typical loss function and minimax game:**

$$\min_G \max_D L(D,G) := \mathrm{E}_x \ln\big(1 - D(G(x))\big) + \mathrm{E}_y \ln D(y)$$

- **Conditional GAN[1]**
  - Conditinal GANs sample the generator input *x* not from a uniform distribution but from a conditional distribution, e.g. noisy CT images.
  - Need some measure to ensure similarity to input distribution (e.g. pixelwise loss added to the minimax loss function)
- **Cycle GAN[2]**
  - Two GANs (X $\rightarrow$ Y and Y $\rightarrow$ X)
  - Demand cyclic consistency, i.e. $x = G_X(G_Y(x))$ and $y = G_Y(G_X(x))$



[1]Isola et al. 2017
[2]Zhu et al., 2017

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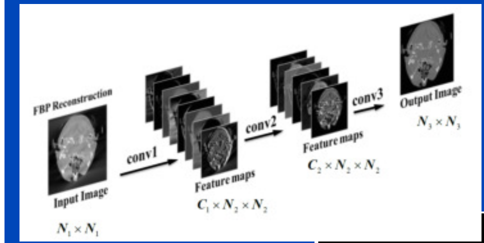
Outline

1. Making up data
2. Noise removal
3. Replacement of lengthy computations
4. Image reconstruction

Part 1:

Making up Data

Limited Angle Example



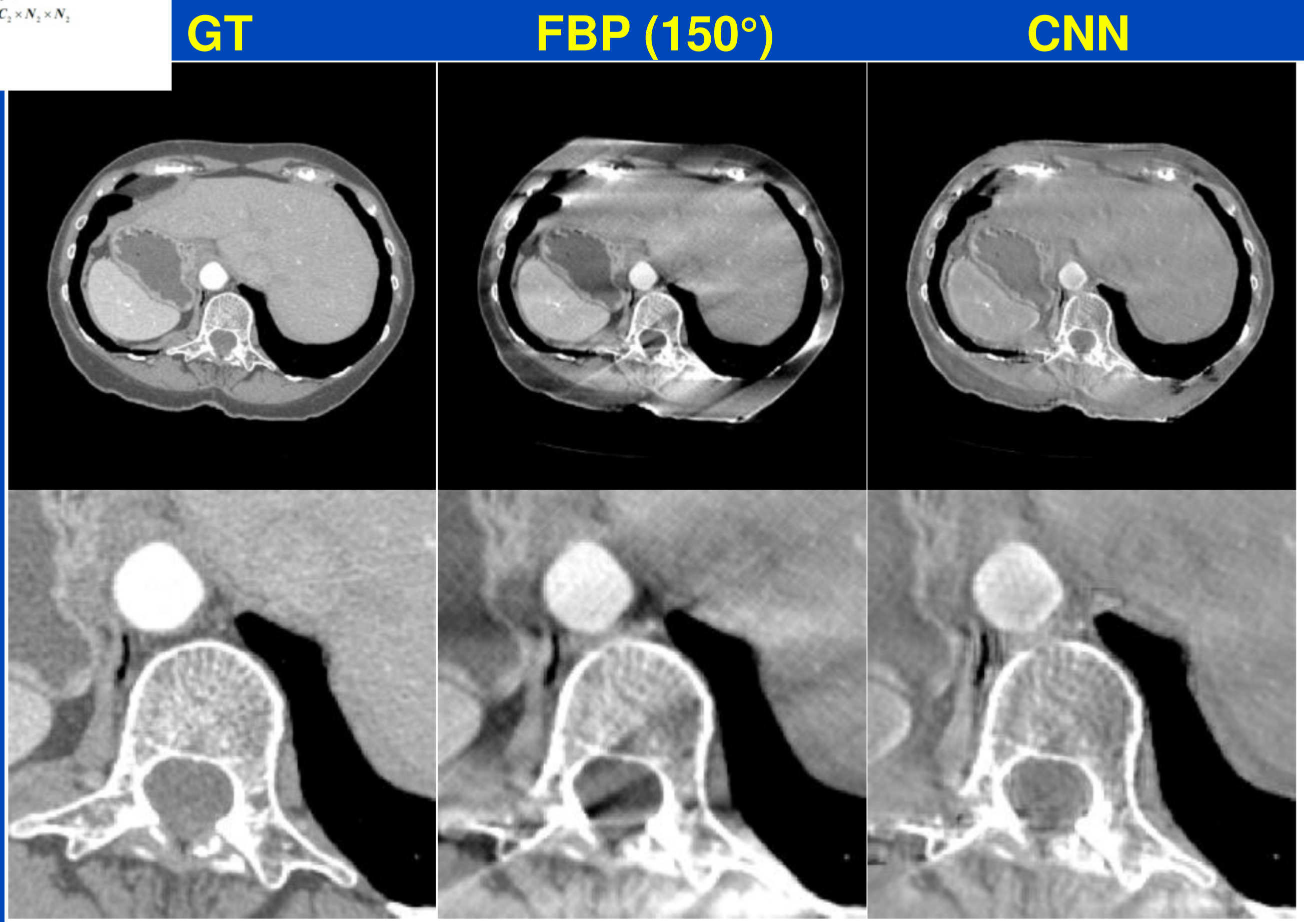
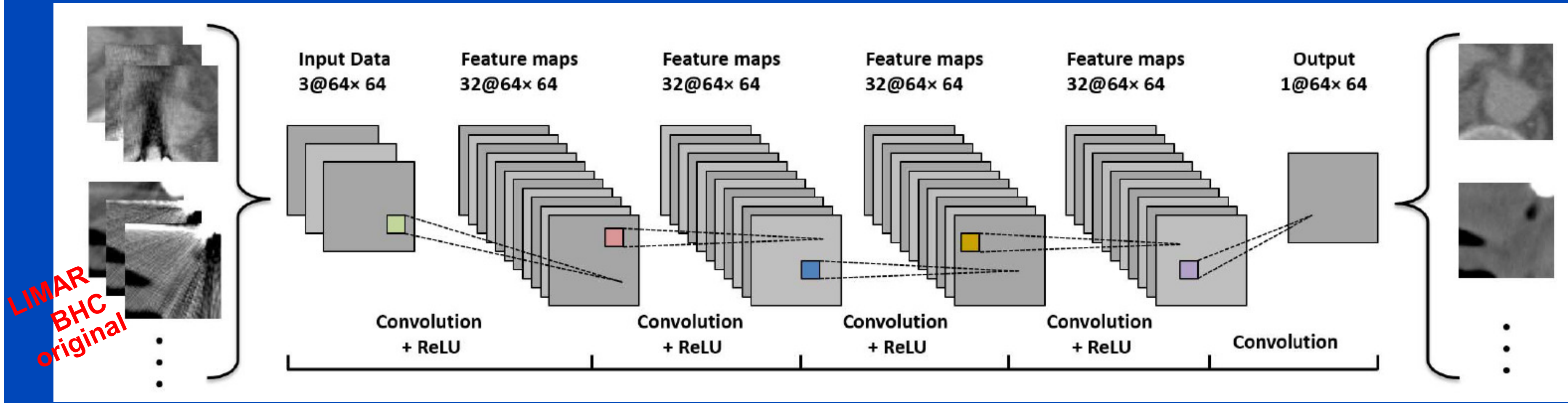


Image Prediction for Limited-Angle Tomography via Deep Learning with Convolutional Neural Network.
Hanming Zhang, Liang Li, Kai Qiao, Linyuan Wang, Bin Yan, Lei Li, Guoen Hu. arXiv 2016.

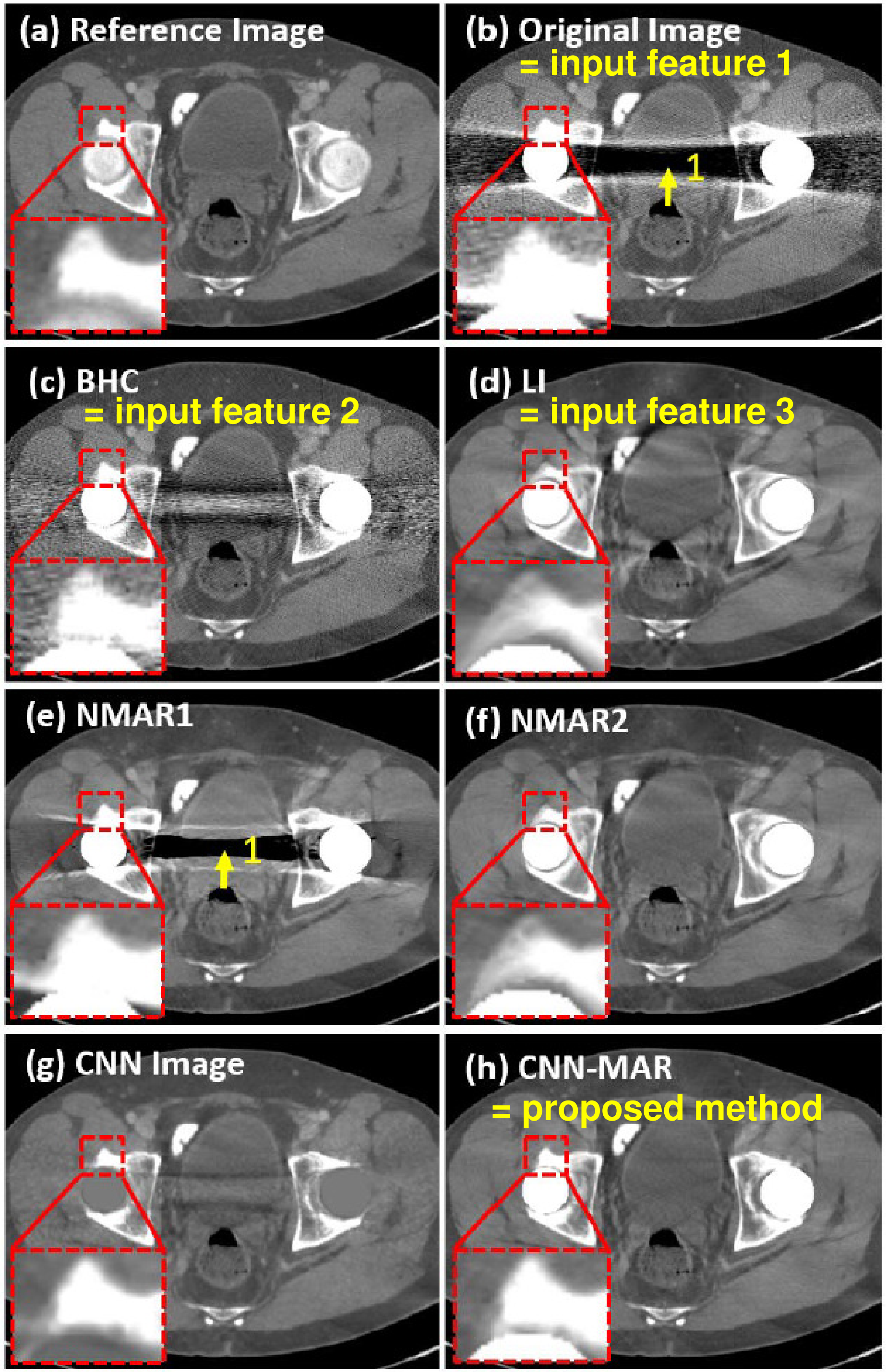
MAR Example

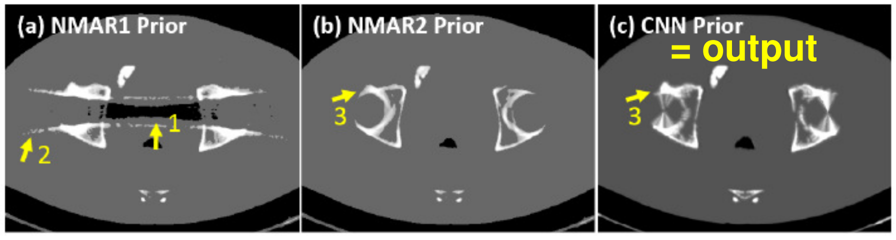
- Deep CNN-driven patch-based combination of the advantages of several MAR methods trained on simulated artifacts



- 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

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


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


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

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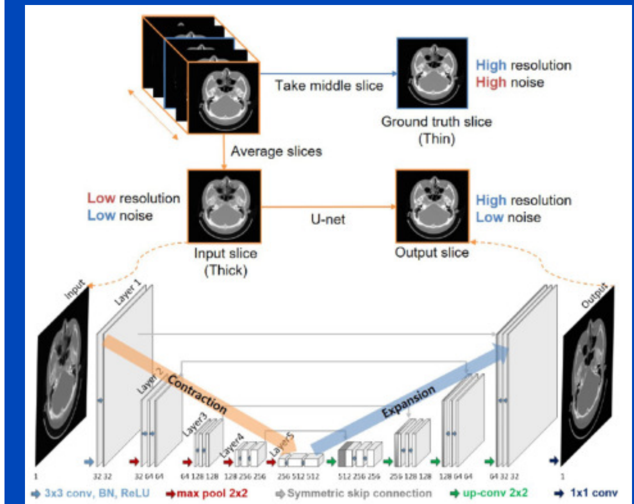
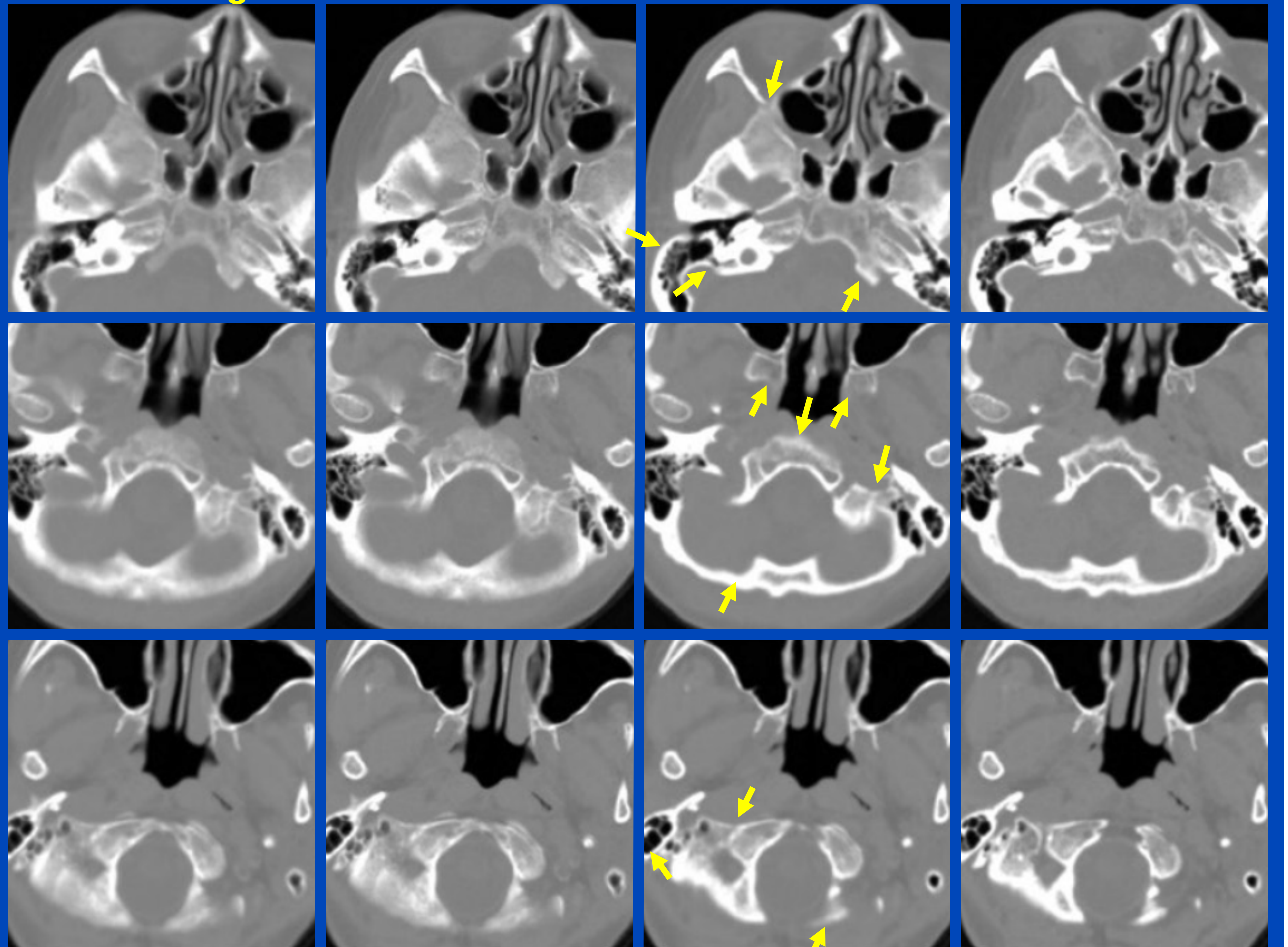
Resolution Improvement Example

- 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"

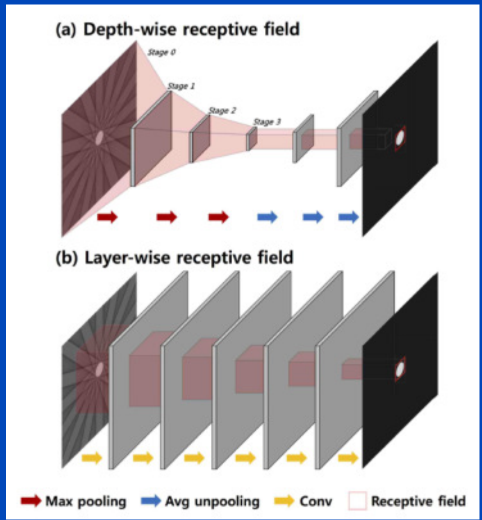


5 mm image | RL deconv. | U-net | 1 mm GT



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 Restoration Example



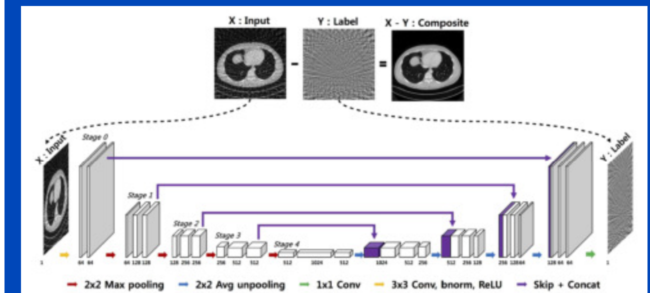
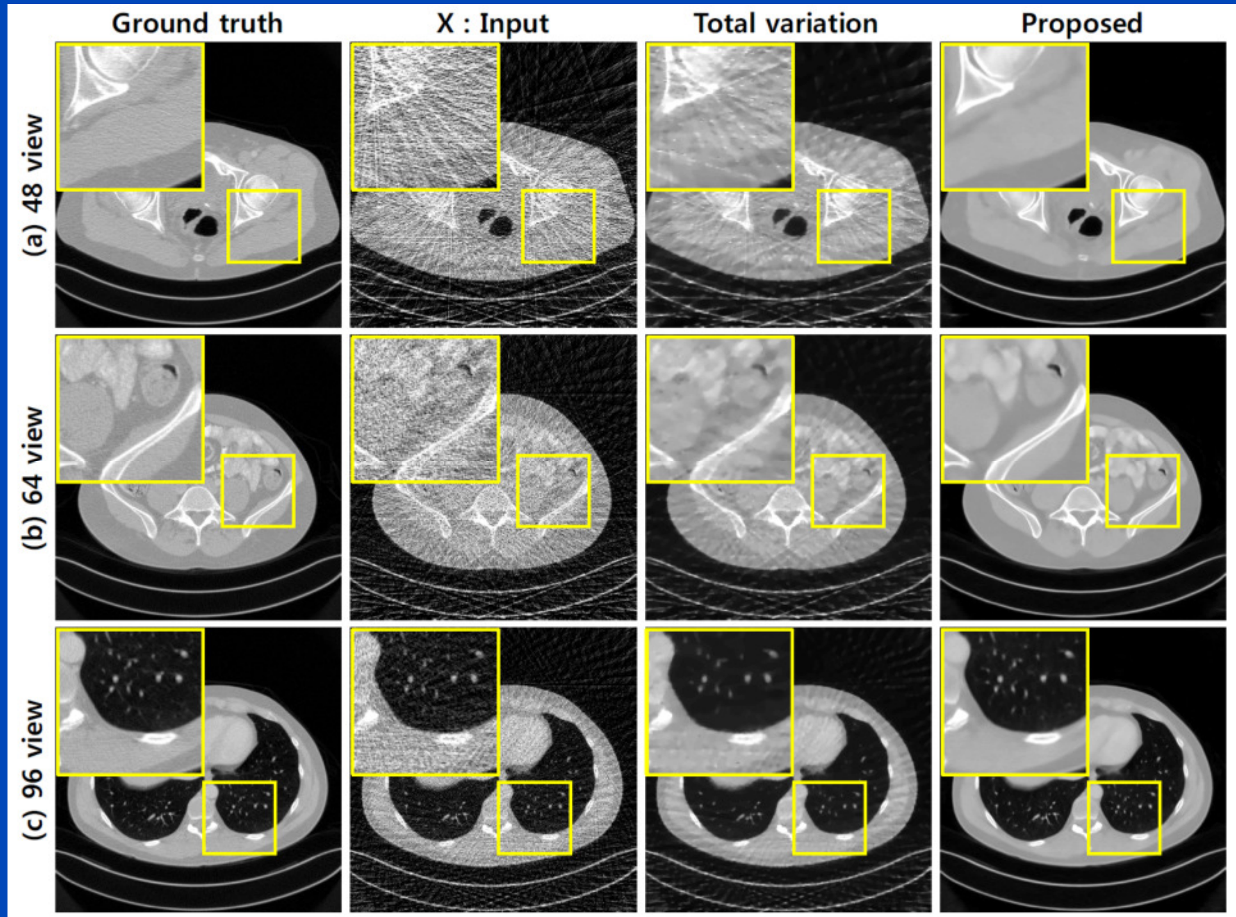
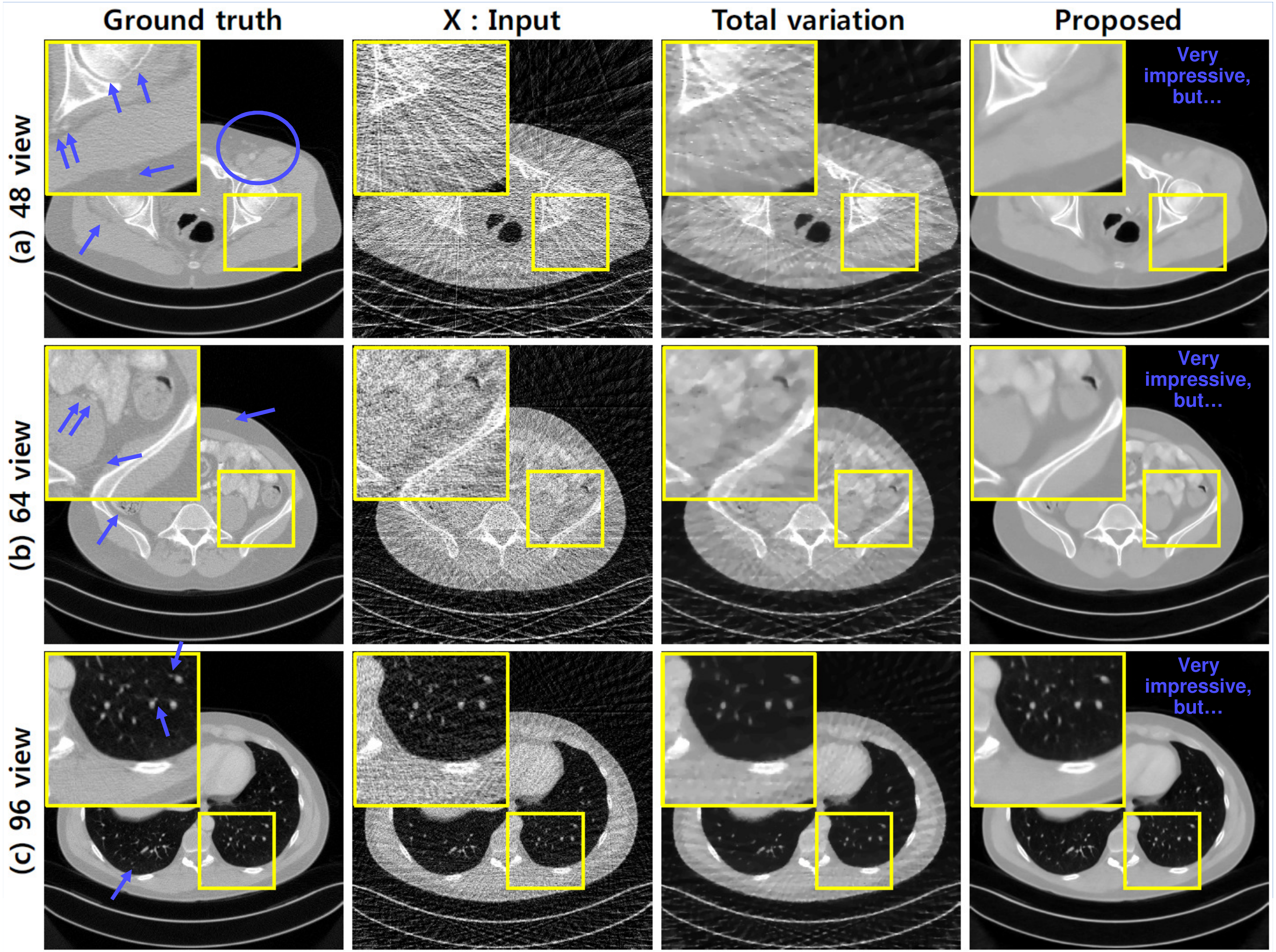


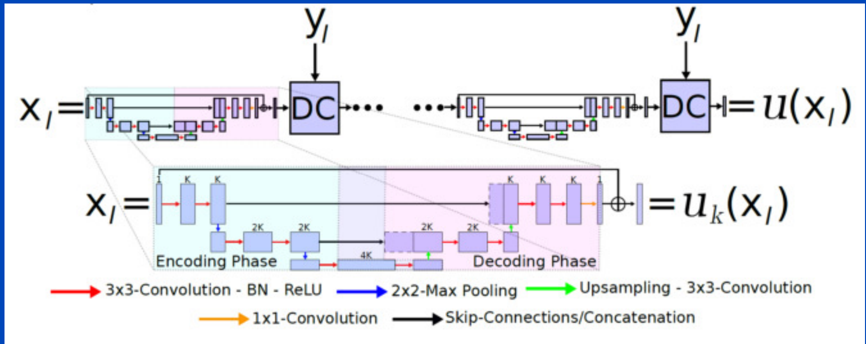
Figure 1. The proposed deep residual learning architecture for sparse view CT reconstruction.

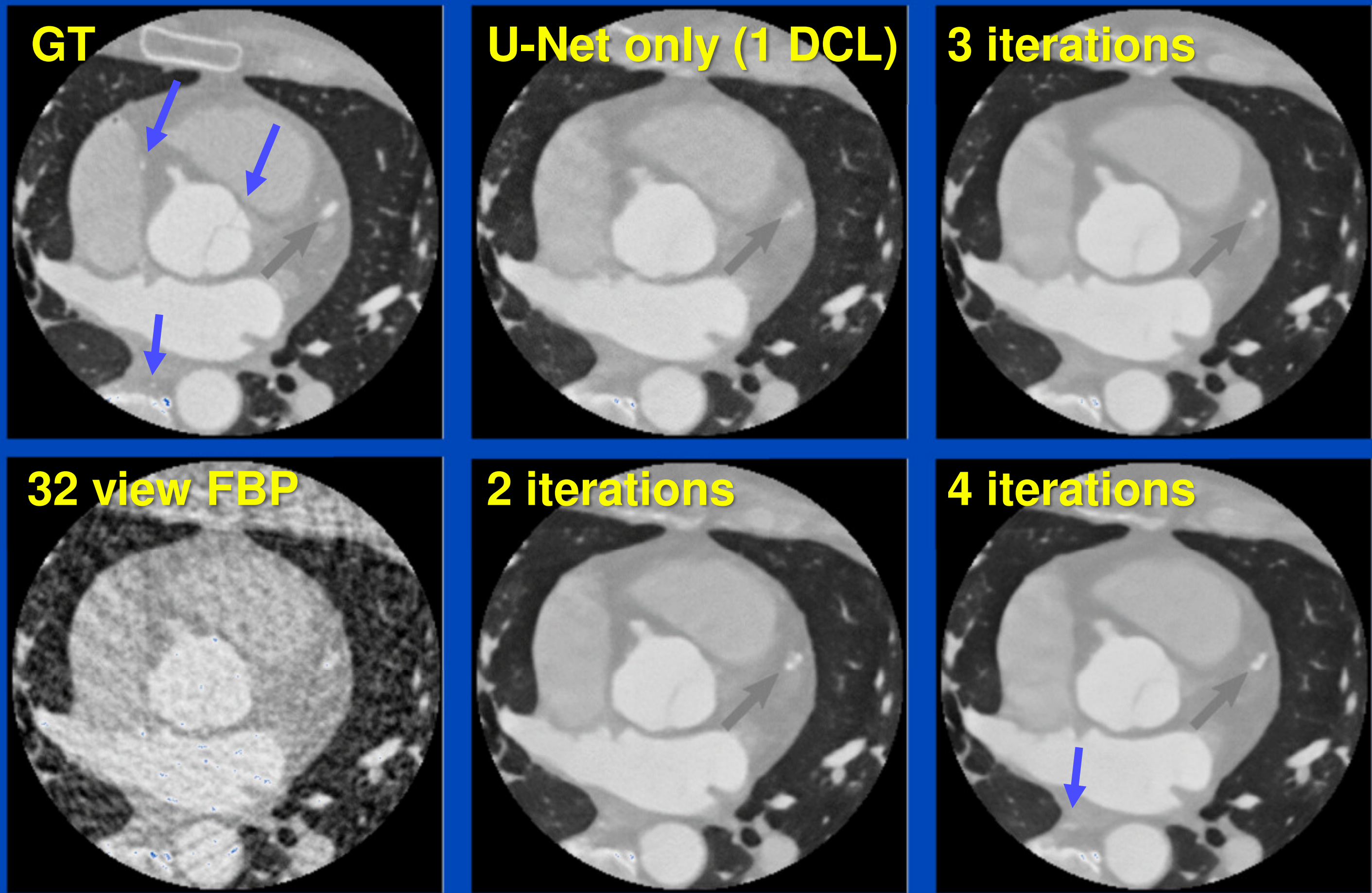


Yo Seob Han, Jaejun Yoo and Jong Chul Ye. Deep Residual Learning for Compressed Sensing CT Reconstruction via Persistent Homology Analysis. ArXiv 2016.


Ground truth
X : Input
Total variation
Proposed
(a) 48 view
(b) 64 view
(c) 96 view
Very impressive, but…
Very impressive, but…
Very impressive, but…

Sparse CT Recon with Data Consistency Layers (DCLs)





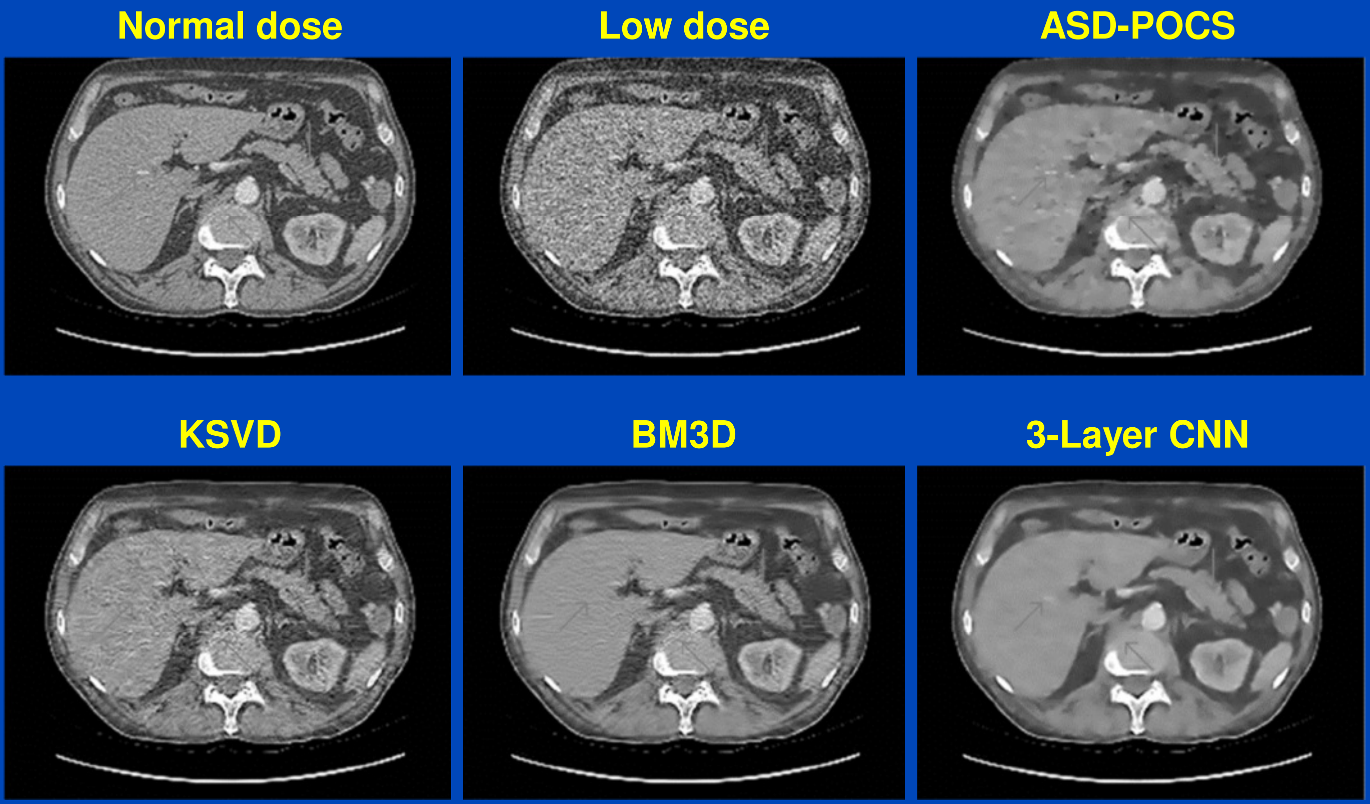
A. Kofler, M. Haltmeier, C. Kolbitsch, M. Kachelrieß, and M. Dewey. A U-Nets Cascade for Sparse View Computed Tomography, MICCAI 2018

Part 2:

Noise Removal

Noise Removal Example 1

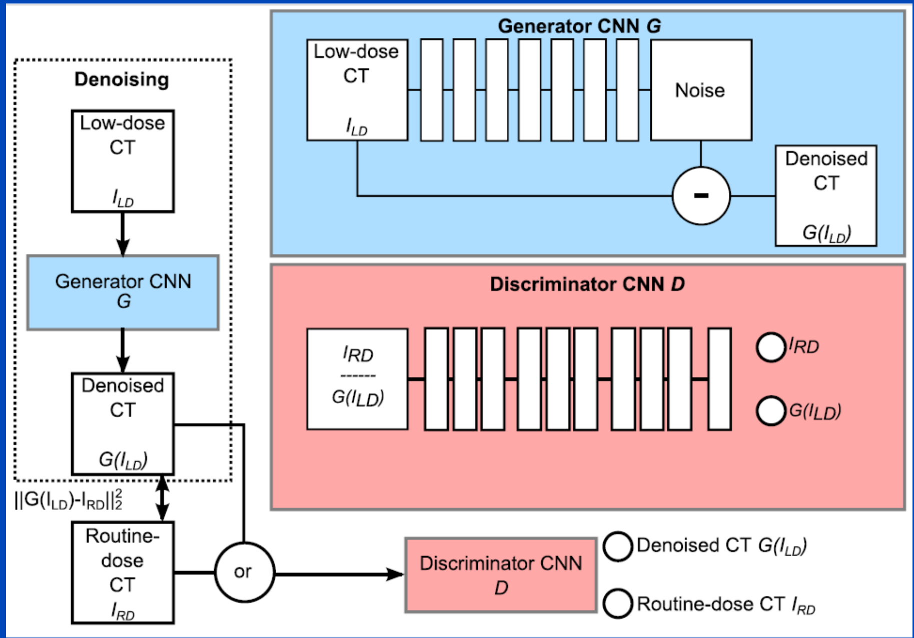
- 3-layer CNN uses low dose and corresponding normal dose image patches for training



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

- Task: Reduce noise from low dose CT images.
- A conditional generative adversarial networks (GAN) is used
- Generator *G*:
  - 3D CNN that operates on small cardiac CT sub volumes
  - Seven 3×3×3 convolutional layers yielding a receptive field of 15×15×15 voxels for each destination voxel
  - Depths (features) from 32 to 128
  - Batch norm only in the hidden layers
  - Subtracting skip connection
- Discriminator *D*:
  - Sees either routine dose image or a generator-denoised low dose image
  - Two 3×3×3 layers followed by several 3×3 layers with varying strides
  - Feedback from *D* prevents smoothing.
- Training:
  - Unenhanced (why?) patient data acquired with Philips Briliance iCT 256 at 120 kV.
  - Two scans (why?) per patient, one with 0.2 mSv and one with 0.9 mSv effective dose.



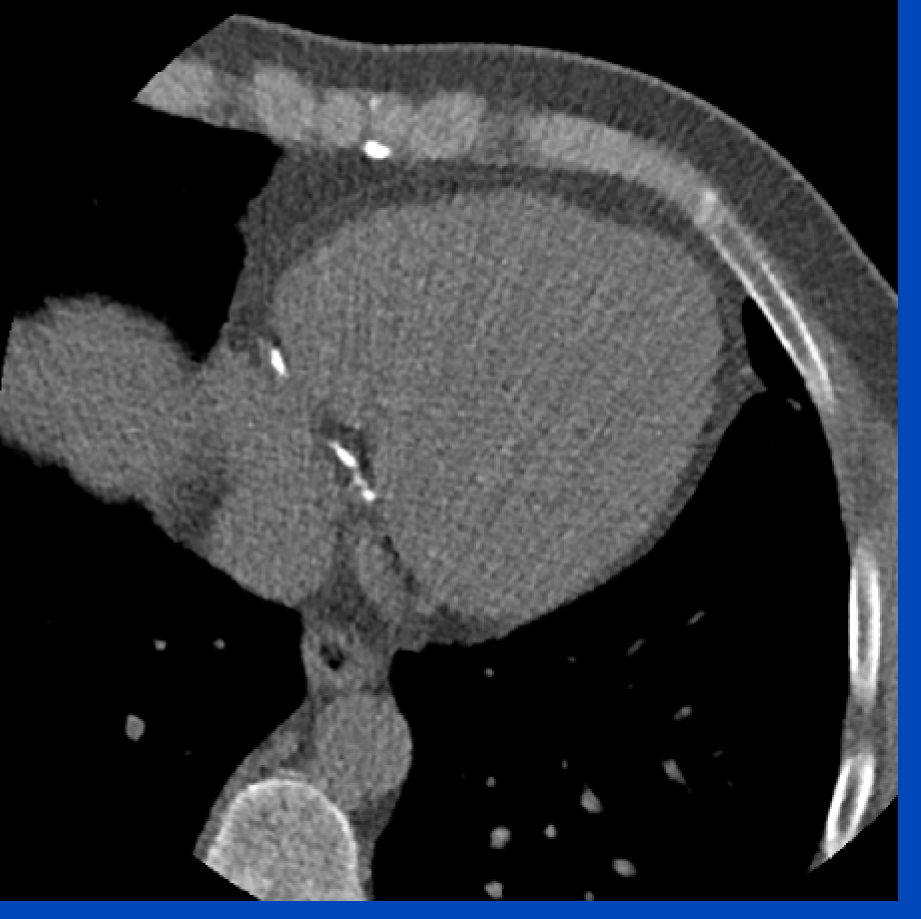
J. Wolterink, T. Leiner, M. Viergever, and I. Išgum. Generative Adversarial Networks for Noise Reduction in Low-Dose CT. IEEE TMI 36(12):2536-2544, Dec. 2017.

Noise Removal Example 2

Low dose image (0.2 mSv)

J. Wolterink, T. Leiner, M. Viergever, and I. Išgum. Generative Adversarial Networks for Noise Reduction in Low-Dose CT. IEEE TMI 36(12):2536-2544, Dec. 2017.

Noise Removal Example 2



iDose level 3 reconstruction (0.2 mSv)

J. Wolterink, T. Leiner, M. Viergever, and I. Išgum. Generative Adversarial Networks for Noise Reduction in Low-Dose CT. IEEE TMI 36(12):2536-2544, Dec. 2017.

Noise Removal Example 2

Denoised low dose image (0.2 mSv)

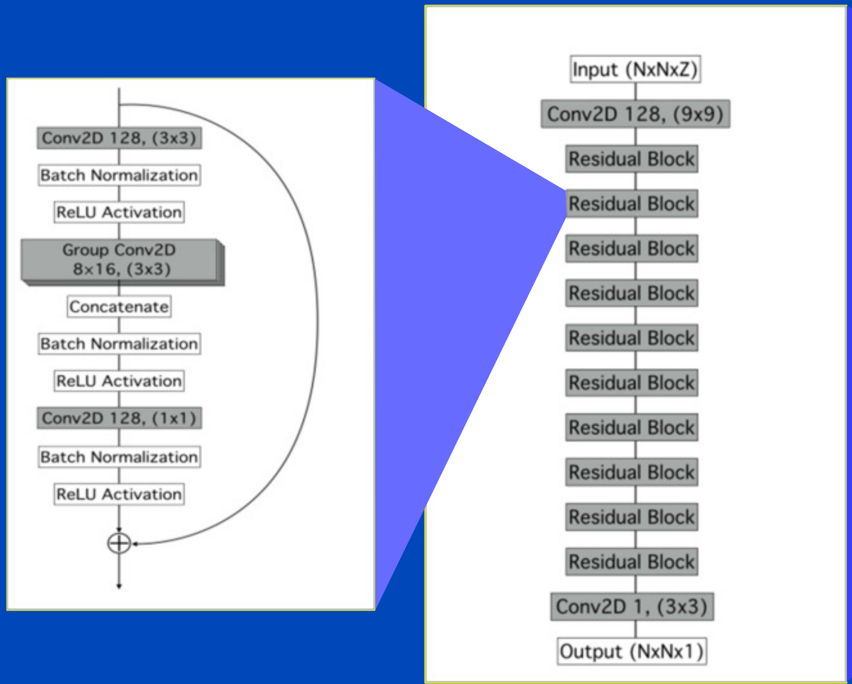
J. Wolterink, T. Leiner, M. Viergever, and I. Išgum. Generative Adversarial Networks for Noise Reduction in Low-Dose CT. IEEE TMI 36(12):2536-2544, Dec. 2017.

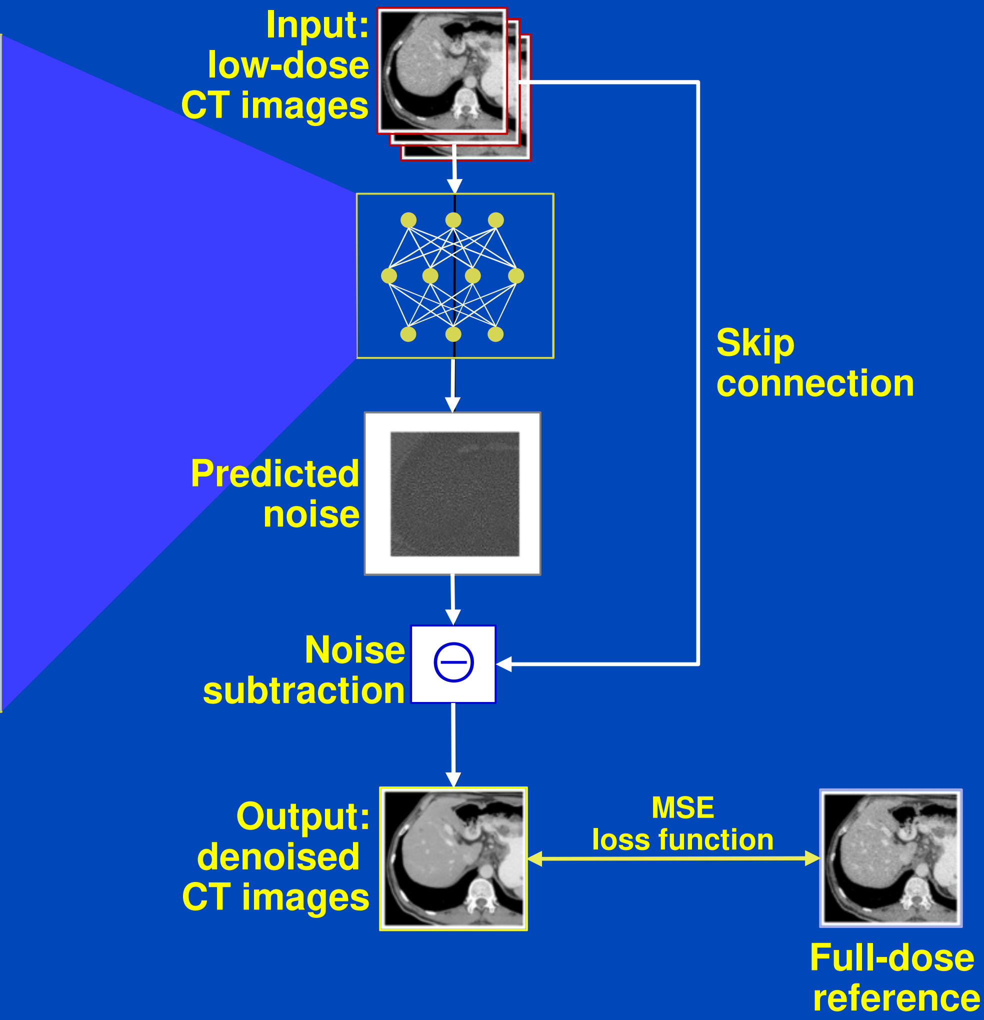
Noise Removal Example 2

Normal dose image (0.9 mSv)

J. Wolterink, T. Leiner, M. Viergever, and I. Išgum. Generative Adversarial Networks for Noise Reduction in Low-Dose CT. IEEE TMI 36(12):2536-2544, Dec. 2017.

Noise Removal Example 3

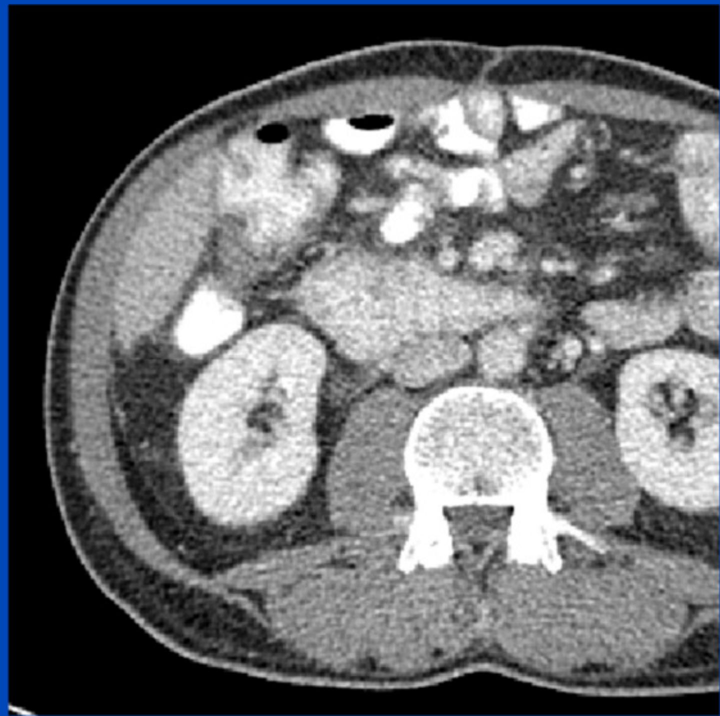




- Architecture based on state-of-the art networks for image classification (ResNet).
- 32 conv layers with skip connections
- About 2 million tunable parameters in total
- Input is arbitrarily-size stack of images, with a fixed number of adjacent slices in the channel/feature dimension.

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

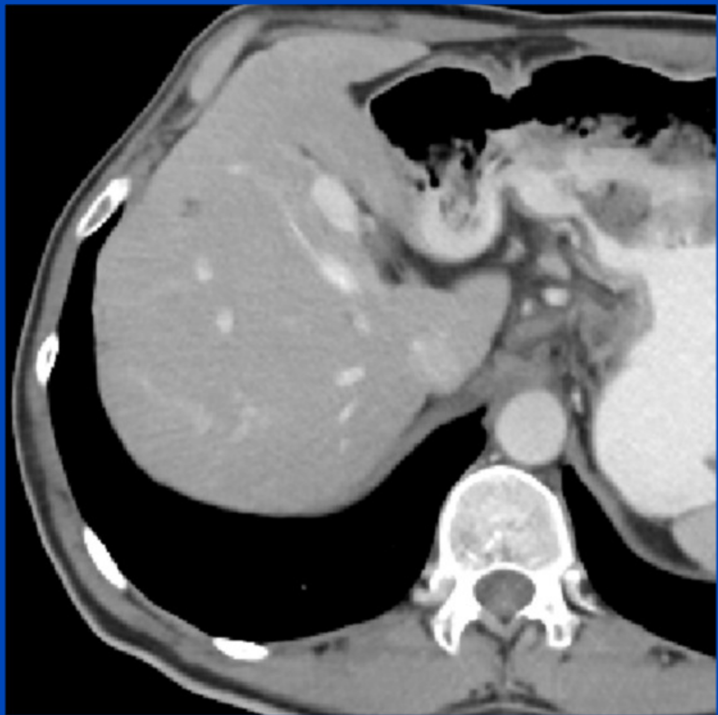
Noise Removal Example 3



Low dose images (1/4 of full dose)

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

Noise Removal Example 3



Denoised low dose

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

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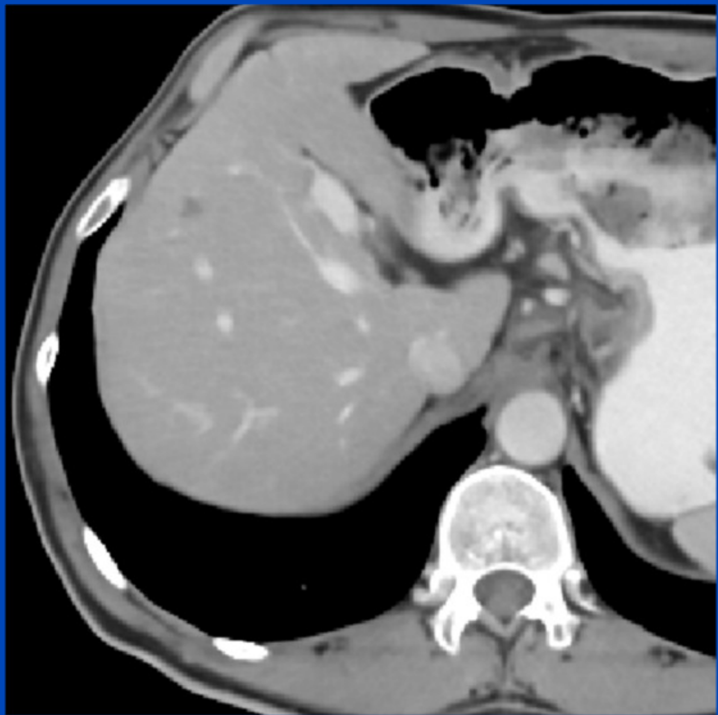
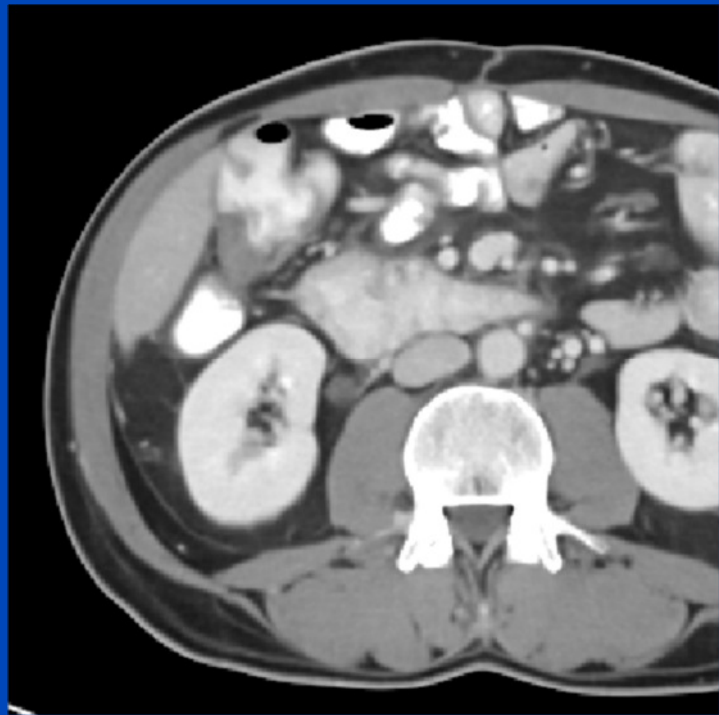
Noise Removal Example 3

Full dose

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

Noise Removal Example 3

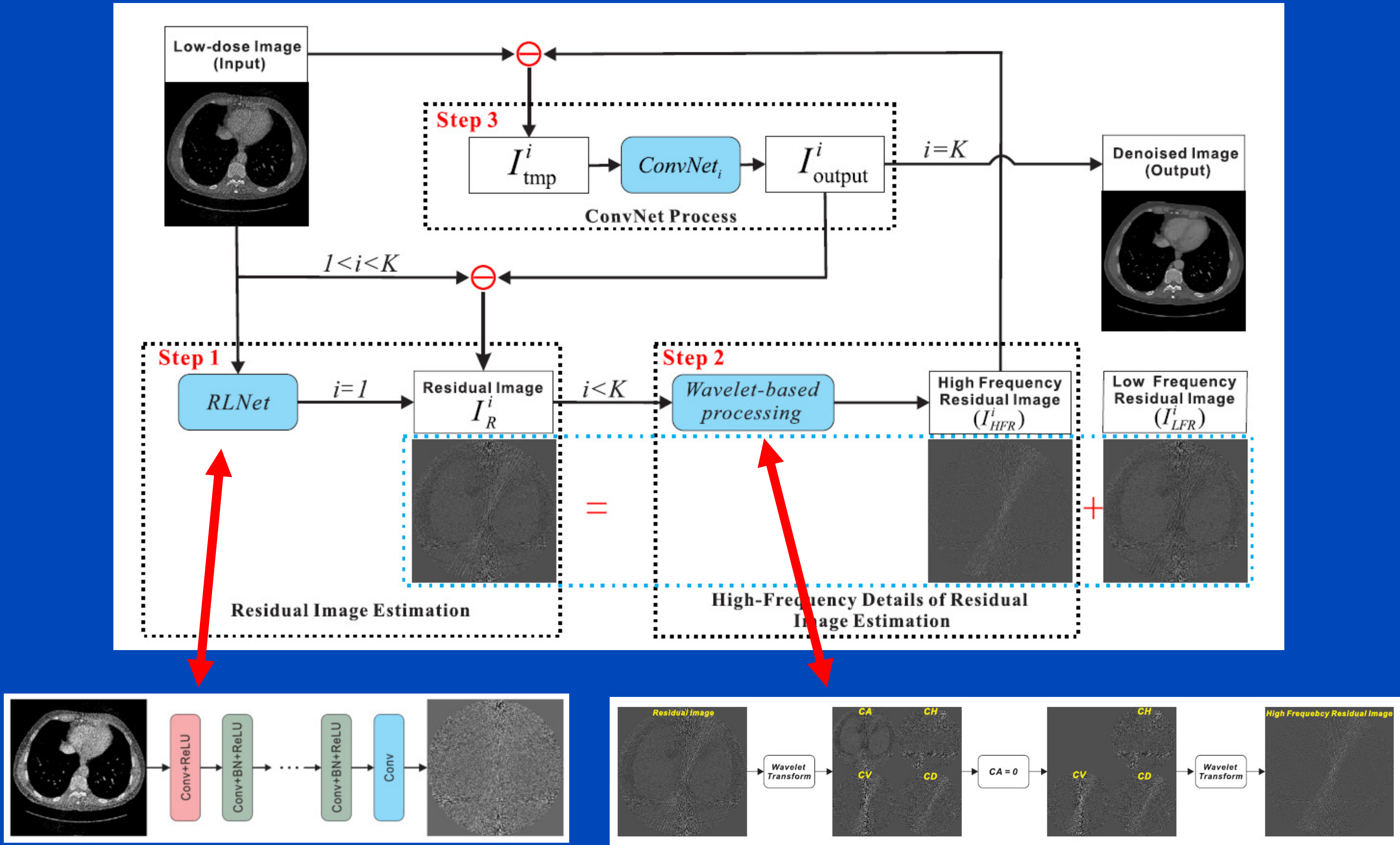




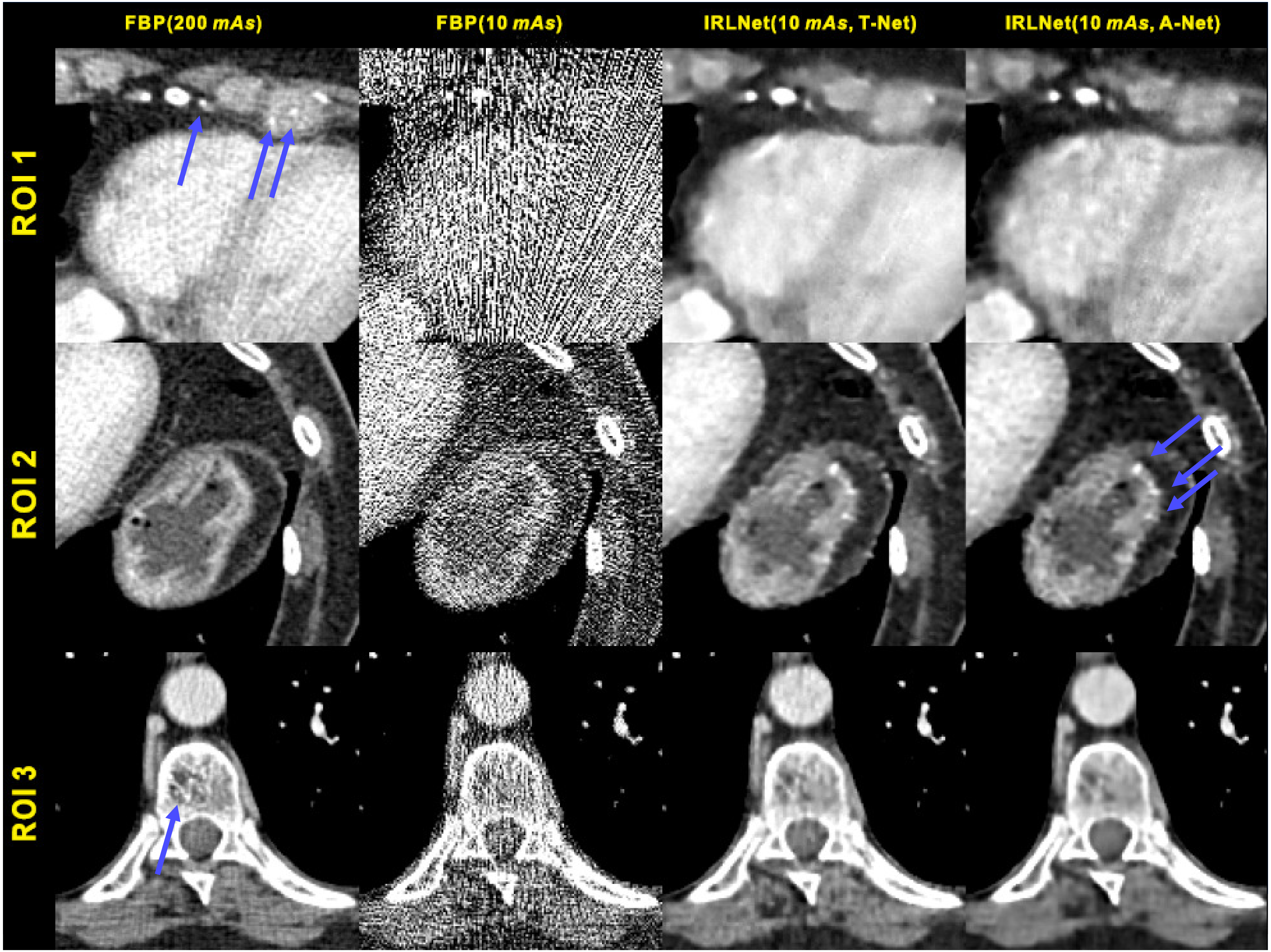
Denoised full dose

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

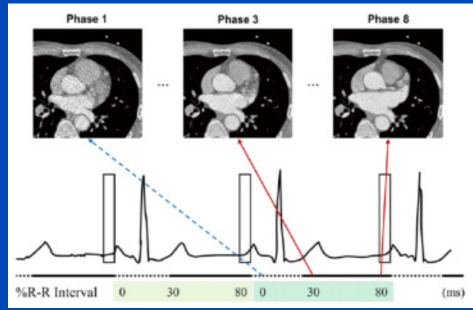
Noise Removal Example 4



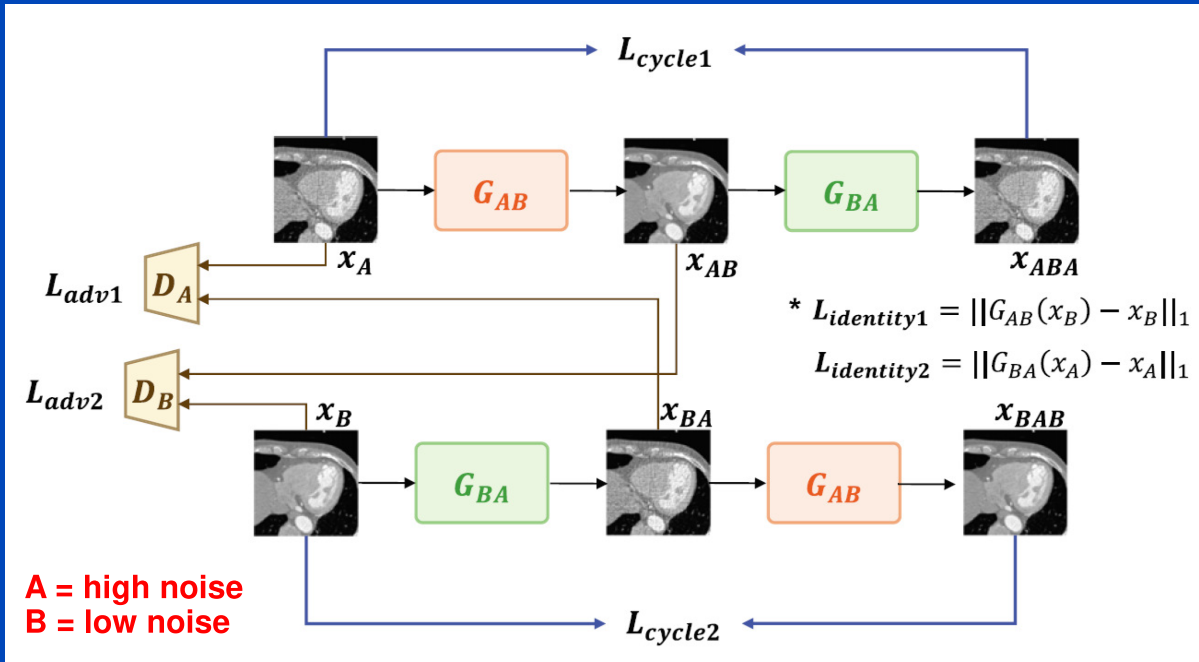
Y. Wang et al. Iterative quality enhancement via residual-artifact learning networks for low-dose CT. Phys. Med. Biol. 63:215004, 2018.


FBP(200 mAs)
FBP(10 mAs)
IRLNet(10 mAs, T-Net)
IRLNet(10 mAs, A-Net)
ROI 1
ROI 2
ROI 3

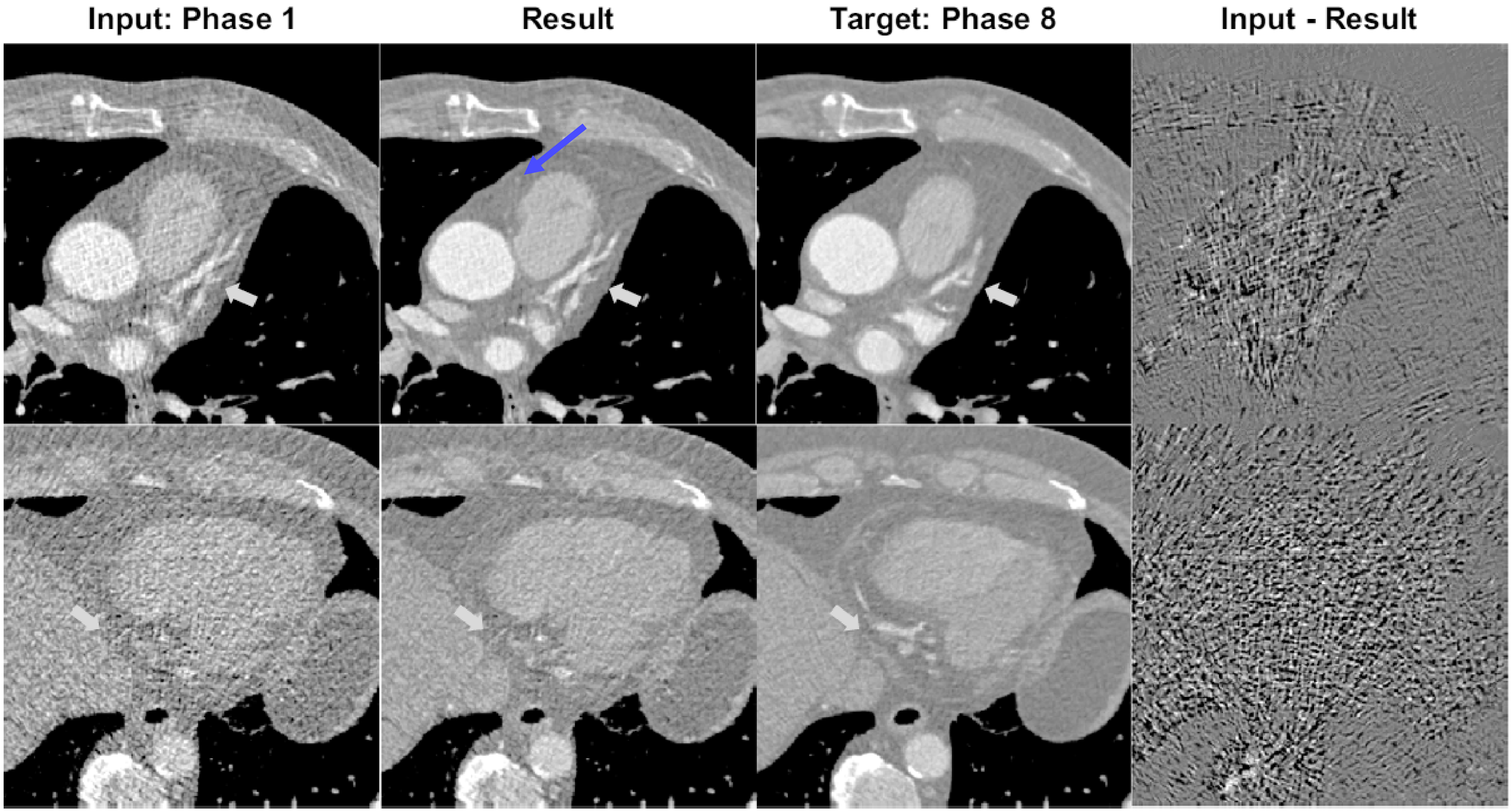
Noise Removal Example 5

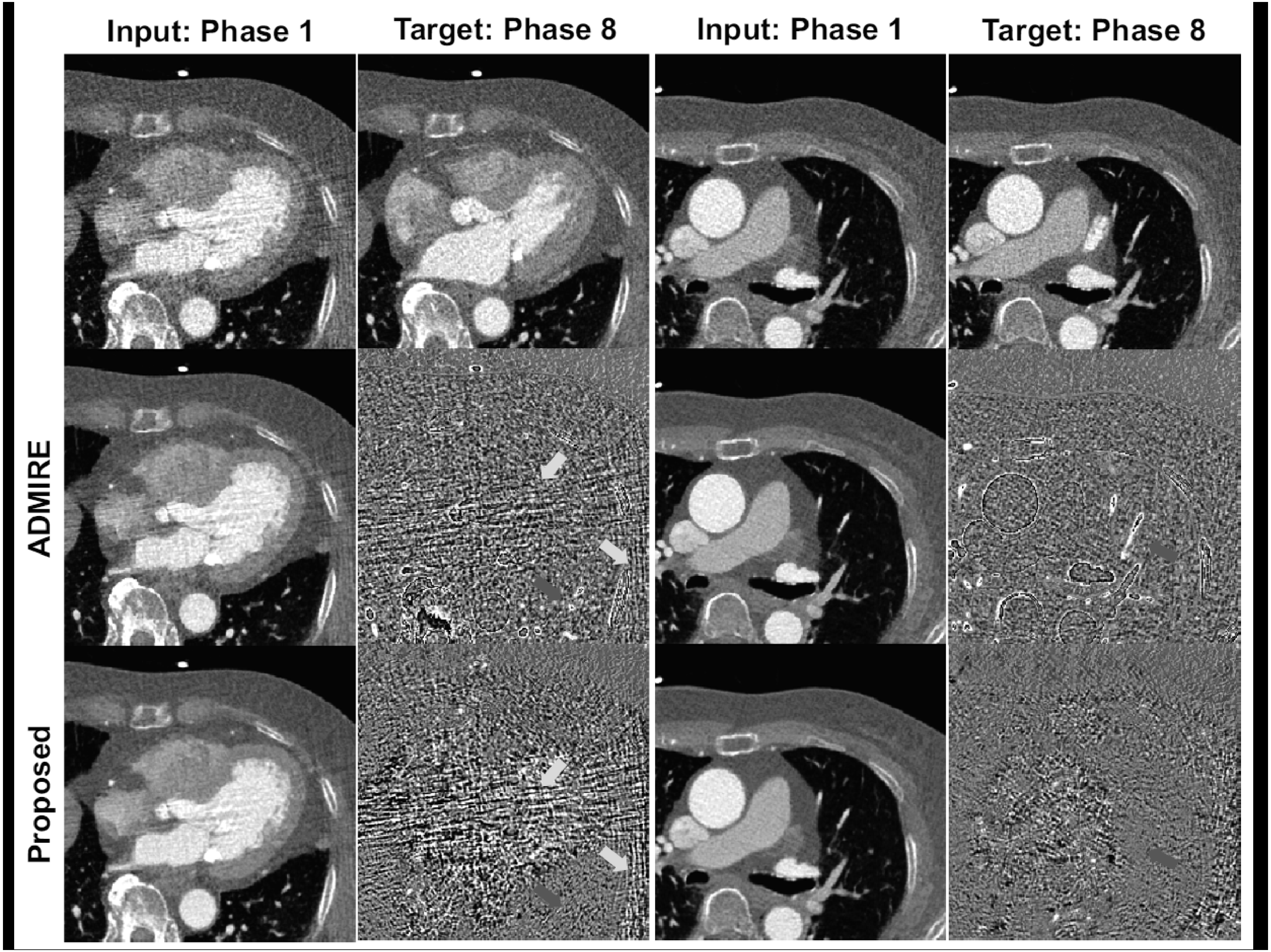


- ECG-based TCM yields cardiac phases with high noise.
- Train a cycle GAN that learns from the low noise phases to remove noise in the high noise phases.
- 50 patient cases used for training.
- Nice results!



E. Kang, J.C. Ye et al. Cycle-consistent adversarial denoising network for multiphase coronary CT angiography. Med. Phys. 46(2), February 2019.

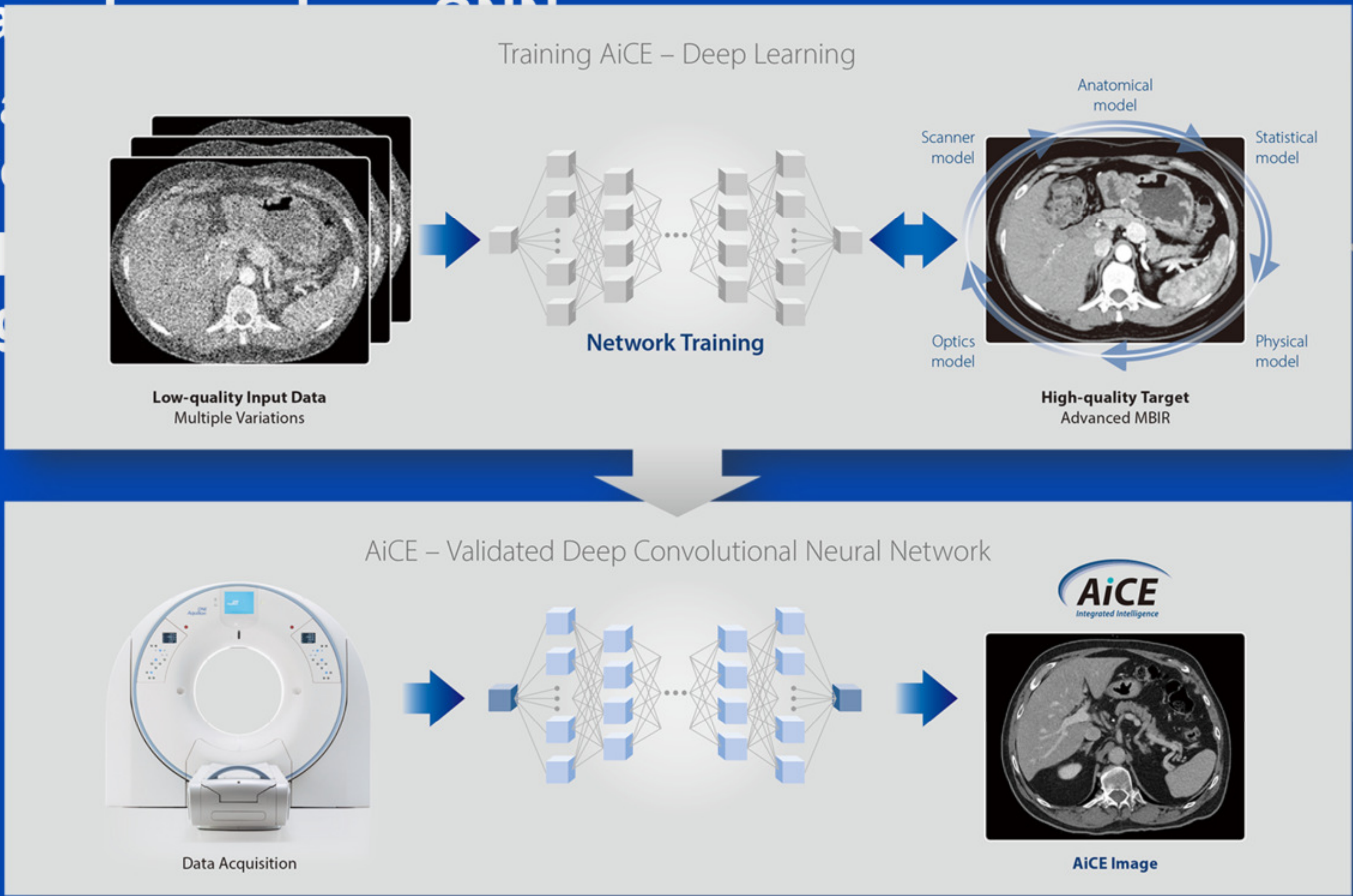

Input: Phase 1
Result
Target: Phase 8
Input - Result



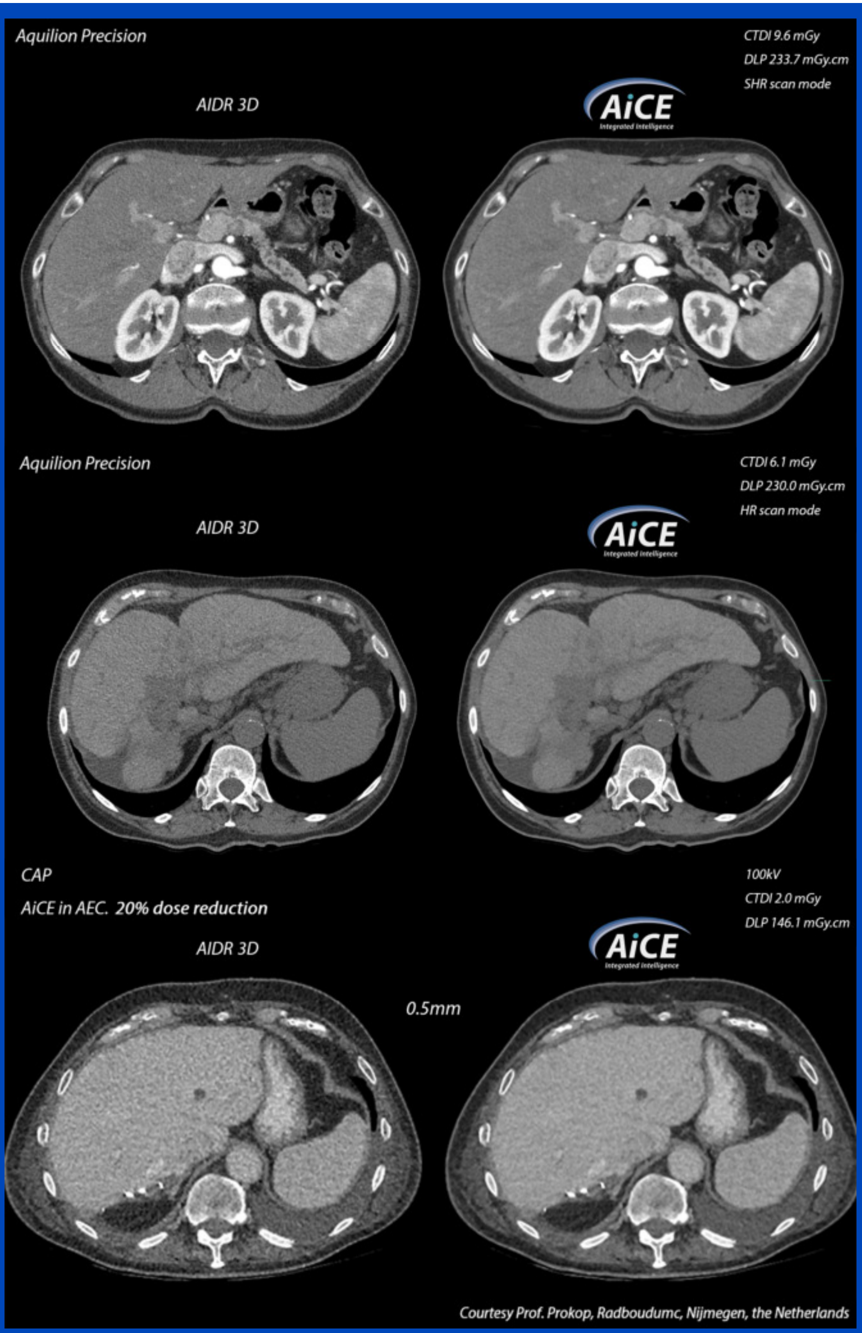
Input: Phase 1
Target: Phase 8
Input: Phase 1
Target: Phase 8
ADMIRE
Proposed

Noise Removal Example 6
Canon‘s AiCE

- Ba
- Tr pr
- Fl hi



MK1



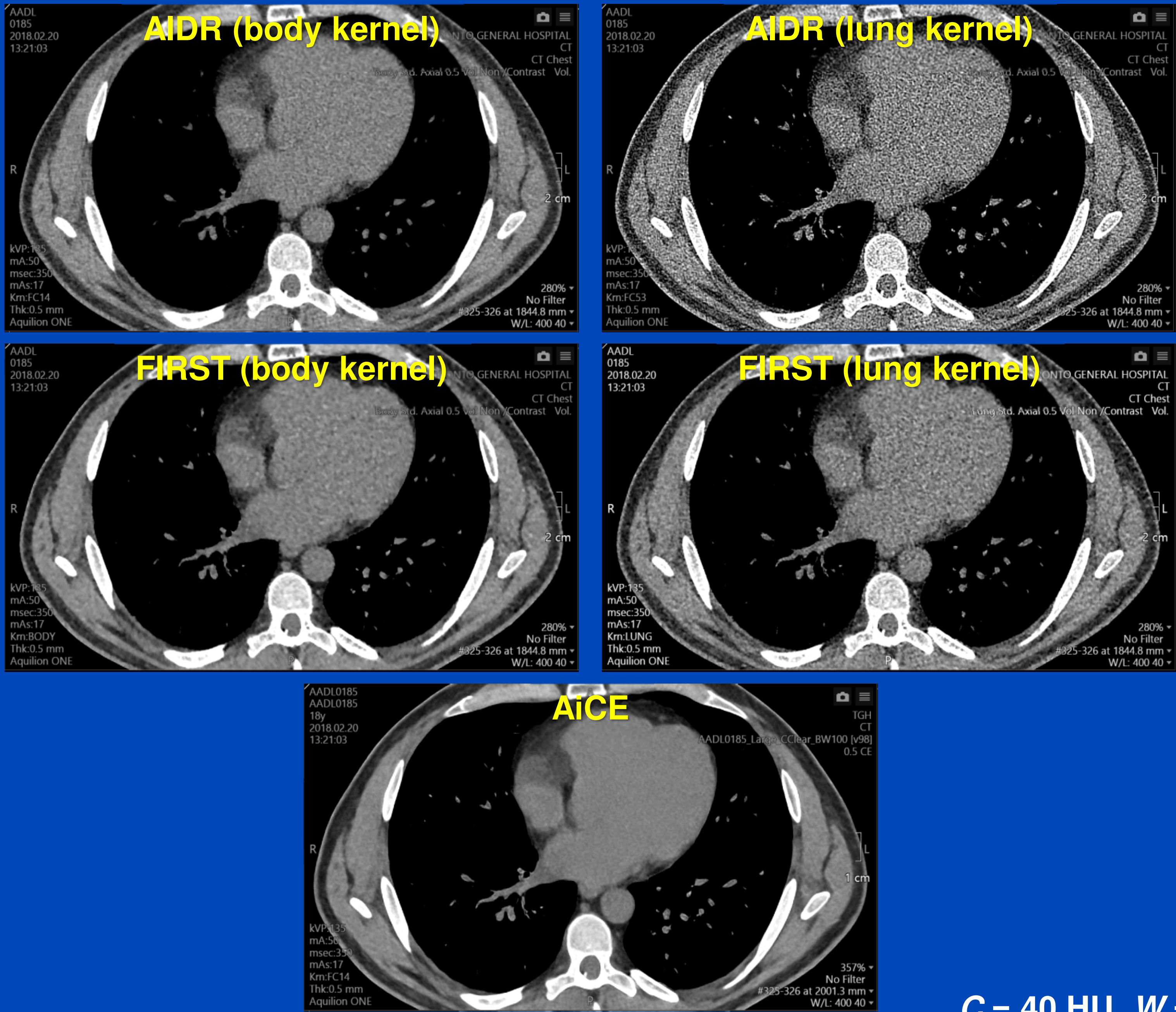
Images taken from https://global.medical.canon/products/computed-tomography/aice_dlr

Folie 37

MK1 S. Auch das PPT (bzw. PDF) DeepLearningReconstructionInThoracicCT_RSNA2018_PatrikRogallavon Patrick Roalla.

Laut Patrik wird AiCE auf FIRST-Daten trainiert. Diese sind aber nicht auf Low-Dose-Bilder angewendet, sondern auf High-Dose-Bilder. Weil Anwendung von FIRST auf Low-Dose-Bilder würde zu einer Glättung der Kanten führen.
Also macht man HigherDose=FIRST(HighDose) und AddNoise(HighDose)=LowDose und trainiert das Netz, so dass es LowDose in HigherDose umrechnen kann.

Angeblich werden sogar zwei unterschiedliche Rekons kombiniert: eine für Lunge, ein für Weichteile.
Prof. Dr. Marc Kachelrieß; 30.11.2018



C = 40 HU, W = 400 HU

Image courtesy of Dr. Patrik Rogalla, Toronto, Canada

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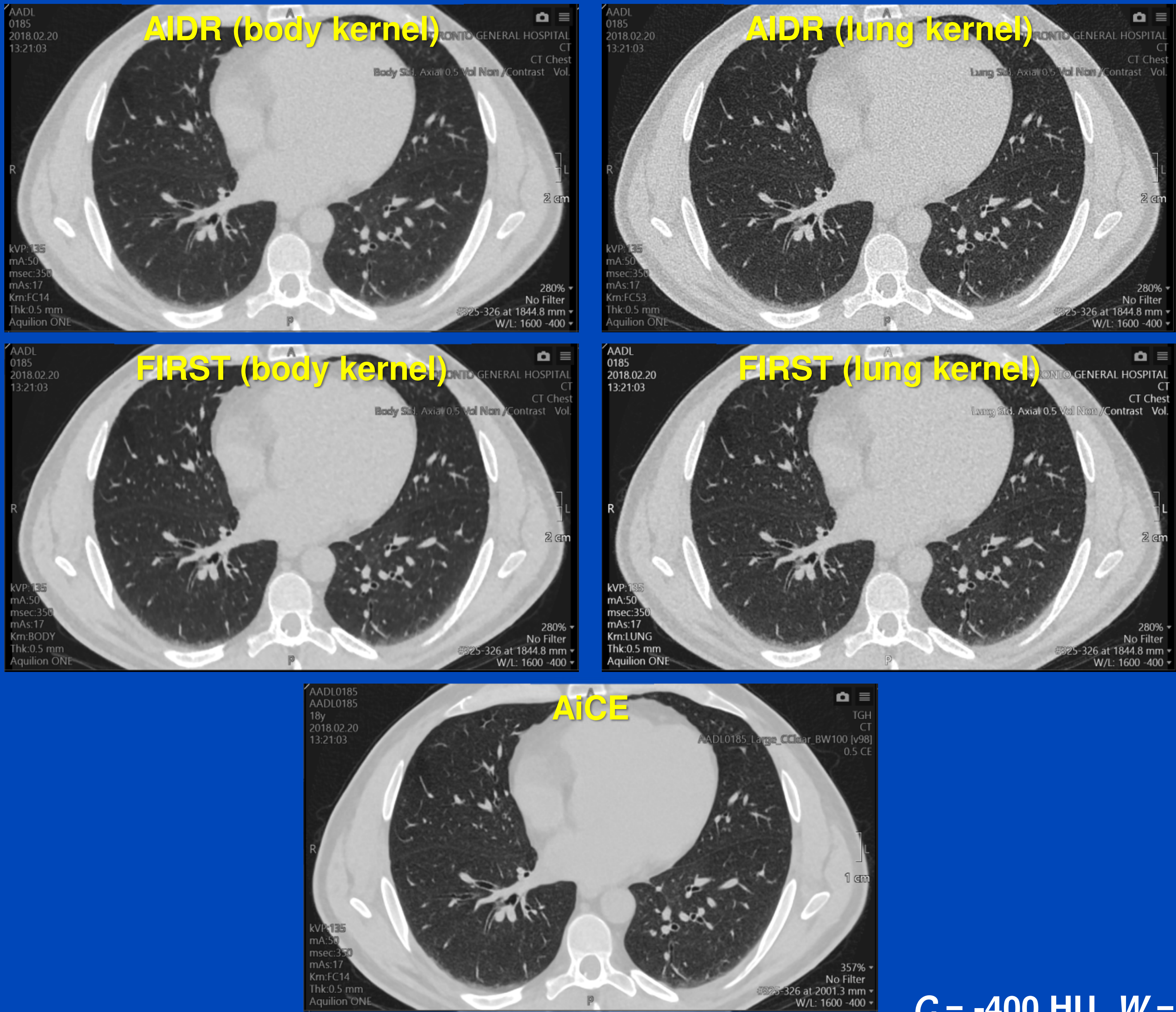
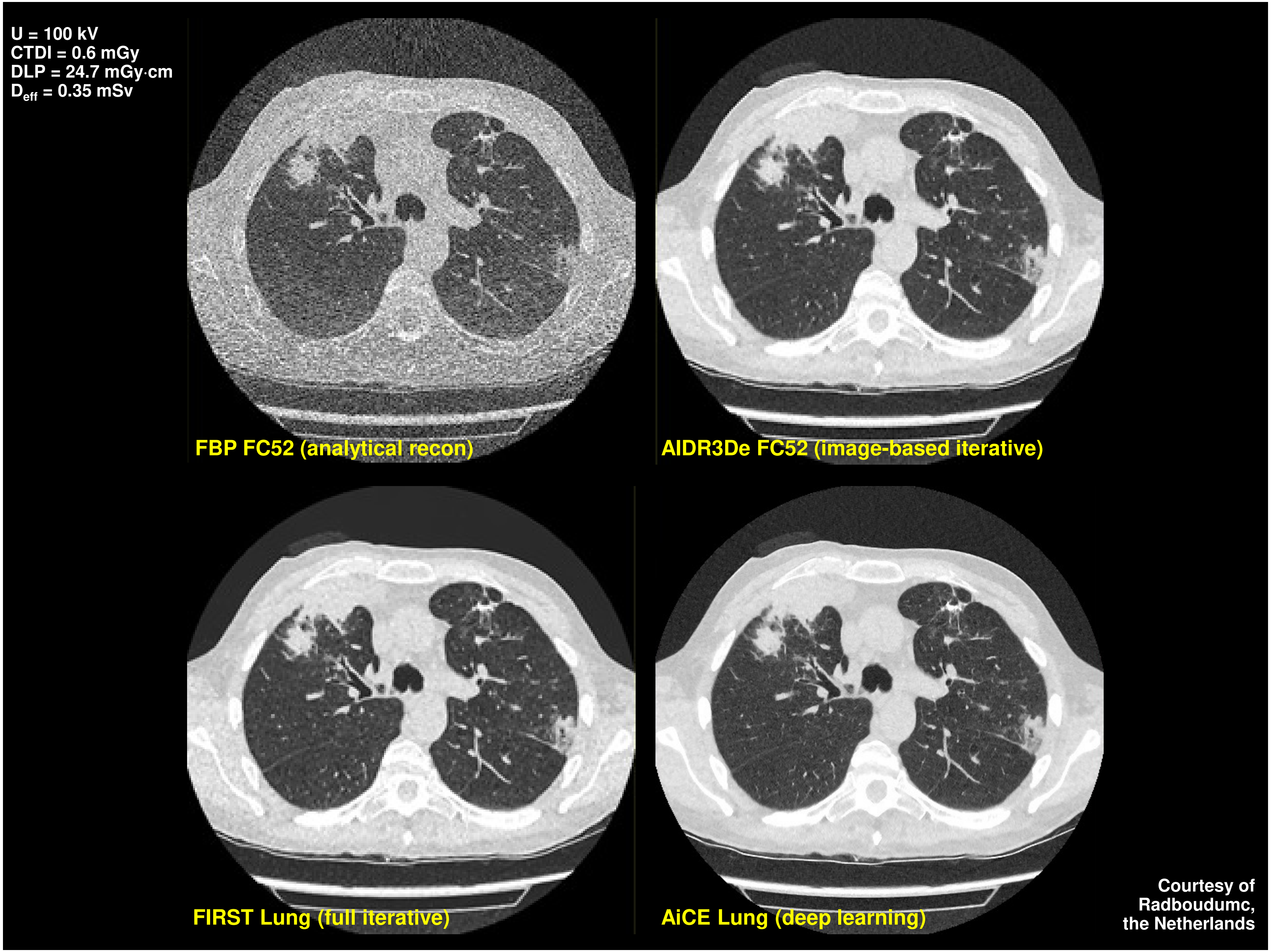


C = -400 HU, W = 1600 HU

Image courtesy of Dr. Patrik Rogalla, Toronto, Canada


U = 100 kV
CTDI = 0.6 mGy
DLP = 24.7 mGy·cm
D_{eff} = 0.35 mSv
FBP FC52 (analytical recon)
AIDR3De FC52 (image-based iterative)
FIRST Lung (full iterative)
AiCE Lung (deep learning)
Courtesy of
Radboudumc,
the Netherlands

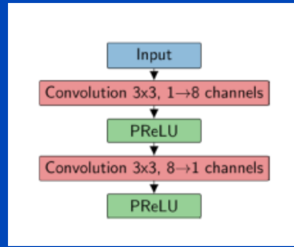
Part 3:

Replacement of Lengthy Computations

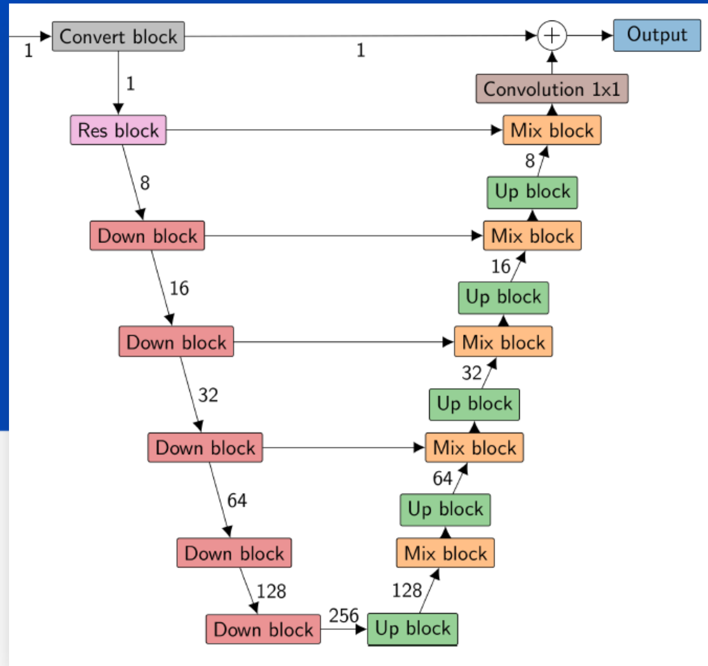
Empirical Shading Correction: ScatterNet

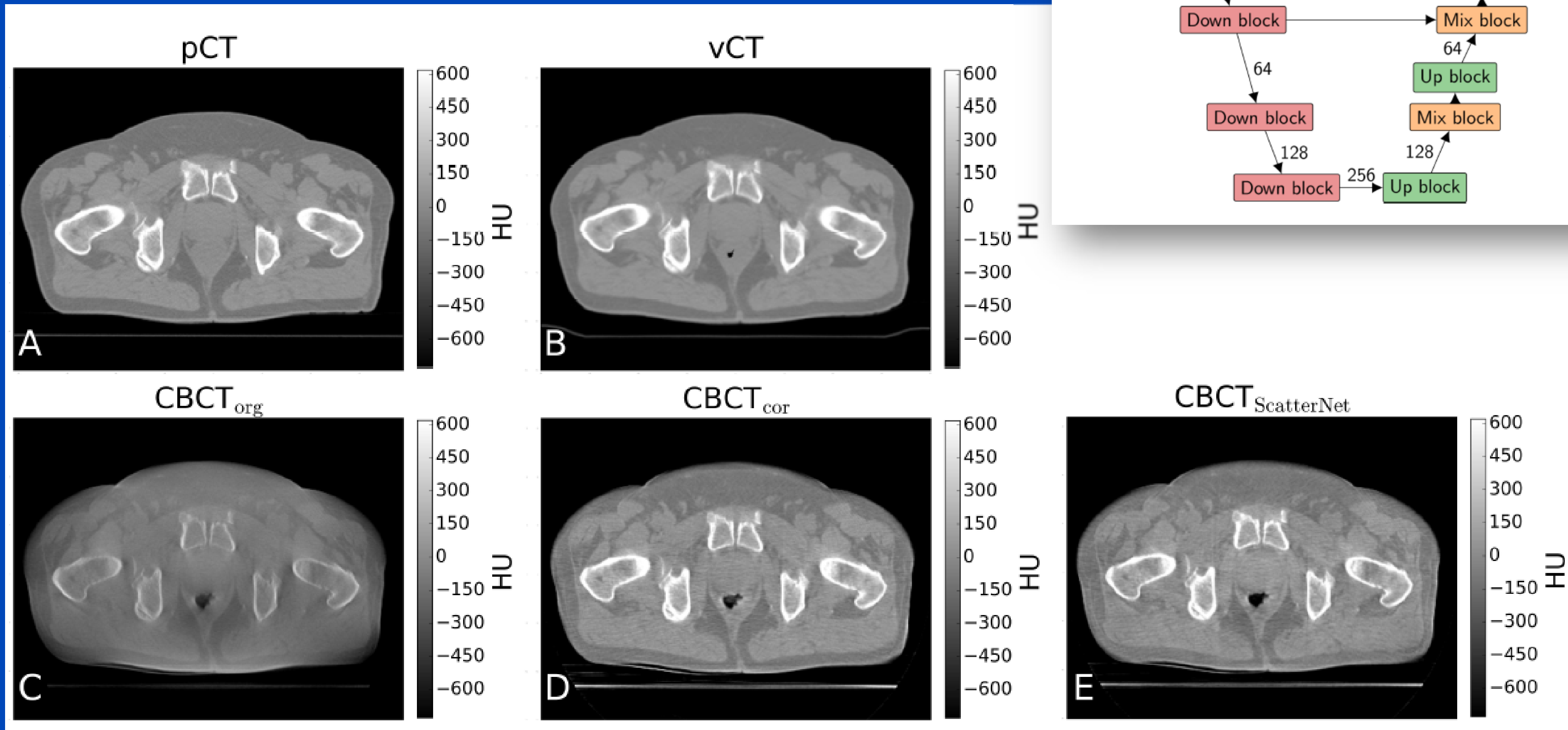
- Net to convert CBCT log (why?) rawdata into artifact-free data.
- Net architecture:
  - Small receptive field spectrum converter block adapts the attenuation values.
  - Residual U-Net then follows to account for scatter.
- Pixel-wise loss function comparing the corrected CBCT projections with those of the reference shading correction method.
- Reference shading correction method:
  - Use data from a clinical CT scan as an artifact-free prior.
  - Intensity domain frequency split between planning CT and CBCT:
    - » Deformably register planning CT onto CBCT and forward project and exponentiate to obtain "ideal" intensity data
    - » Scale CBCT intensities to match the prior CT intensities
    - » Corrected intensities = LP(forward proj. CT)+HP(scaled uncorr. CBCT)
- ScatterNet replaces the previous correction method and thus speeds up computation and does not make use of the planning CT.

Spectrum converter block



ScatterNet





D. Hansen, K. Parodi et al. ScatterNet: A convolutional neural network for cone-beam CT intensity correction, Med. Phys., Sep. 2018.

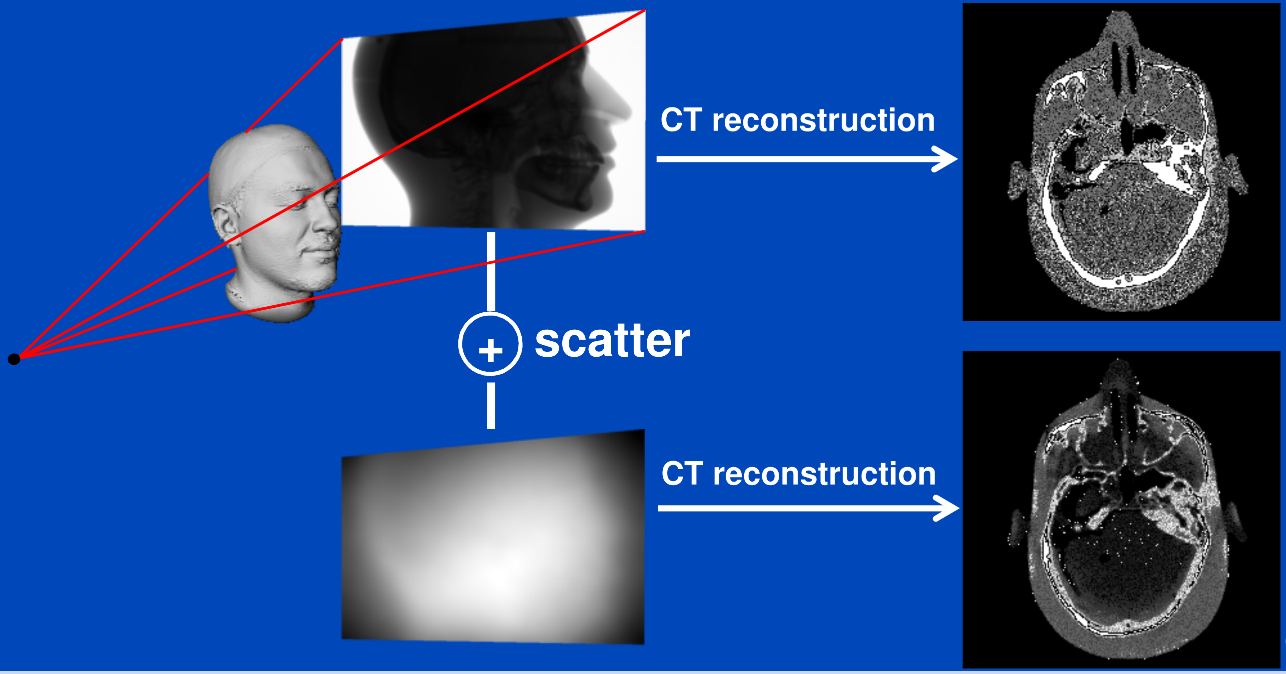
Deep Scatter Estimation

Motivation

- 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.

Primary intensity

CT image



C = 0 HU, W = 800 HU

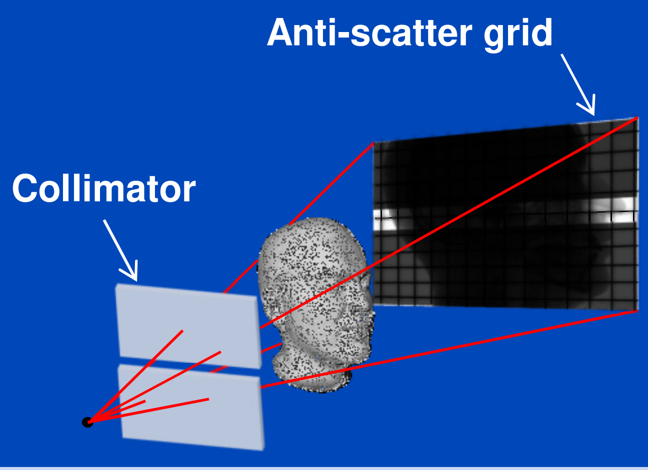
Scatter Correction

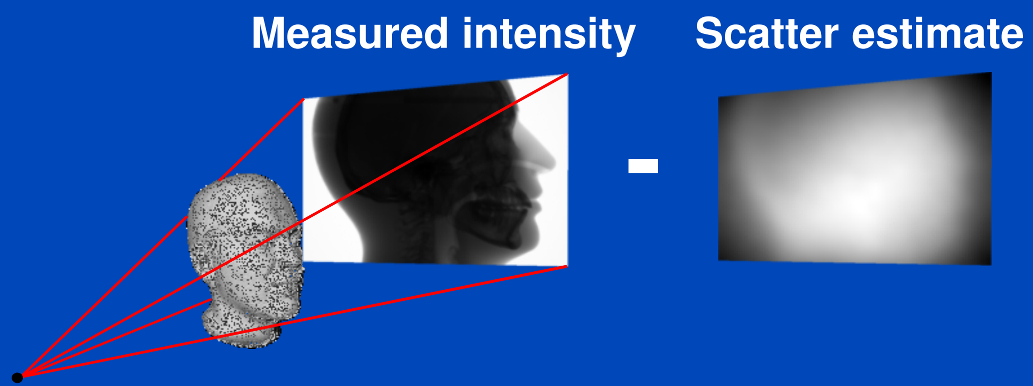
Scatter suppression

- Anti-scatter grids
- Collimators
- …

Scatter estimation

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

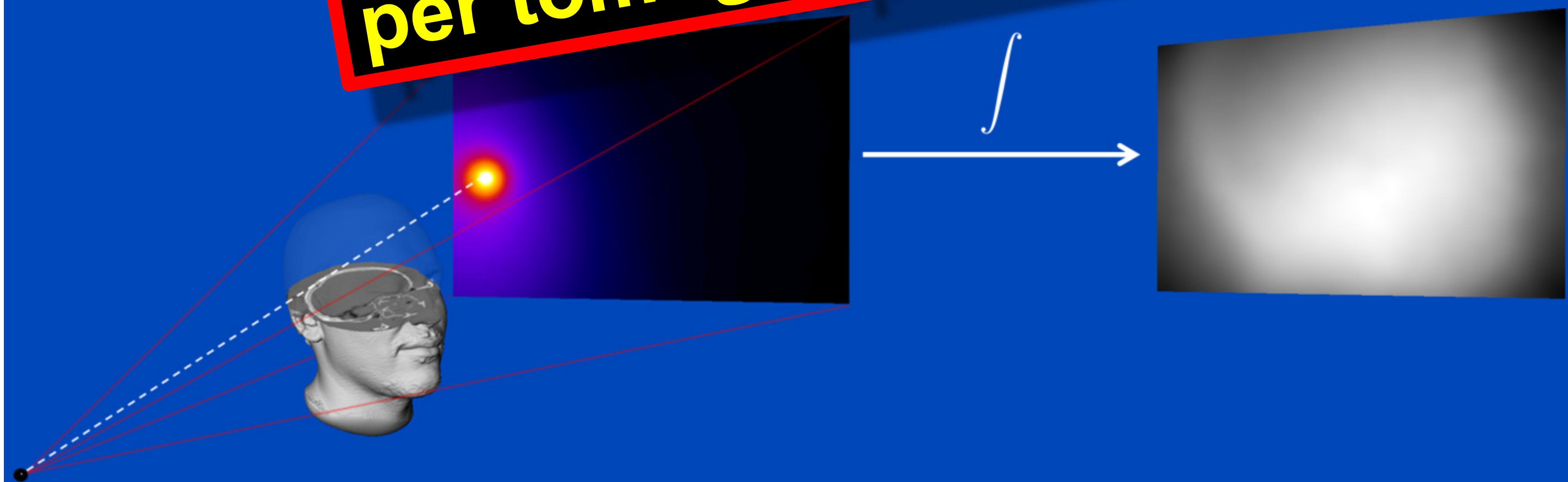




Monte Carlo Scatter Estimation

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

1 to 10 hours per tomographic data set

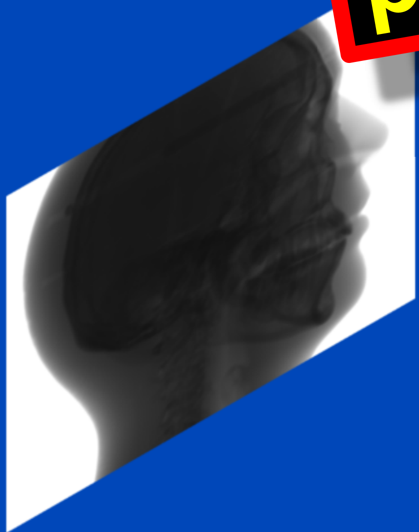


Deep Scatter Estimation (DSE)

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

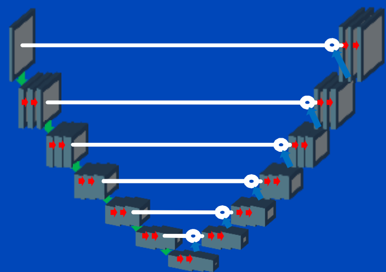
0.1 to 1 minute per tomographic data set

Input: $T(p)$

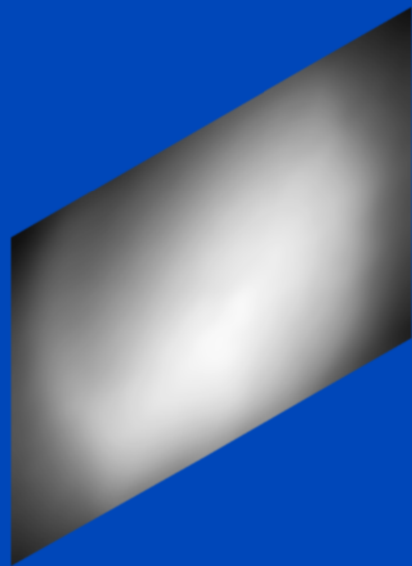


~~Monte Carlo~~

Convolutional neural network



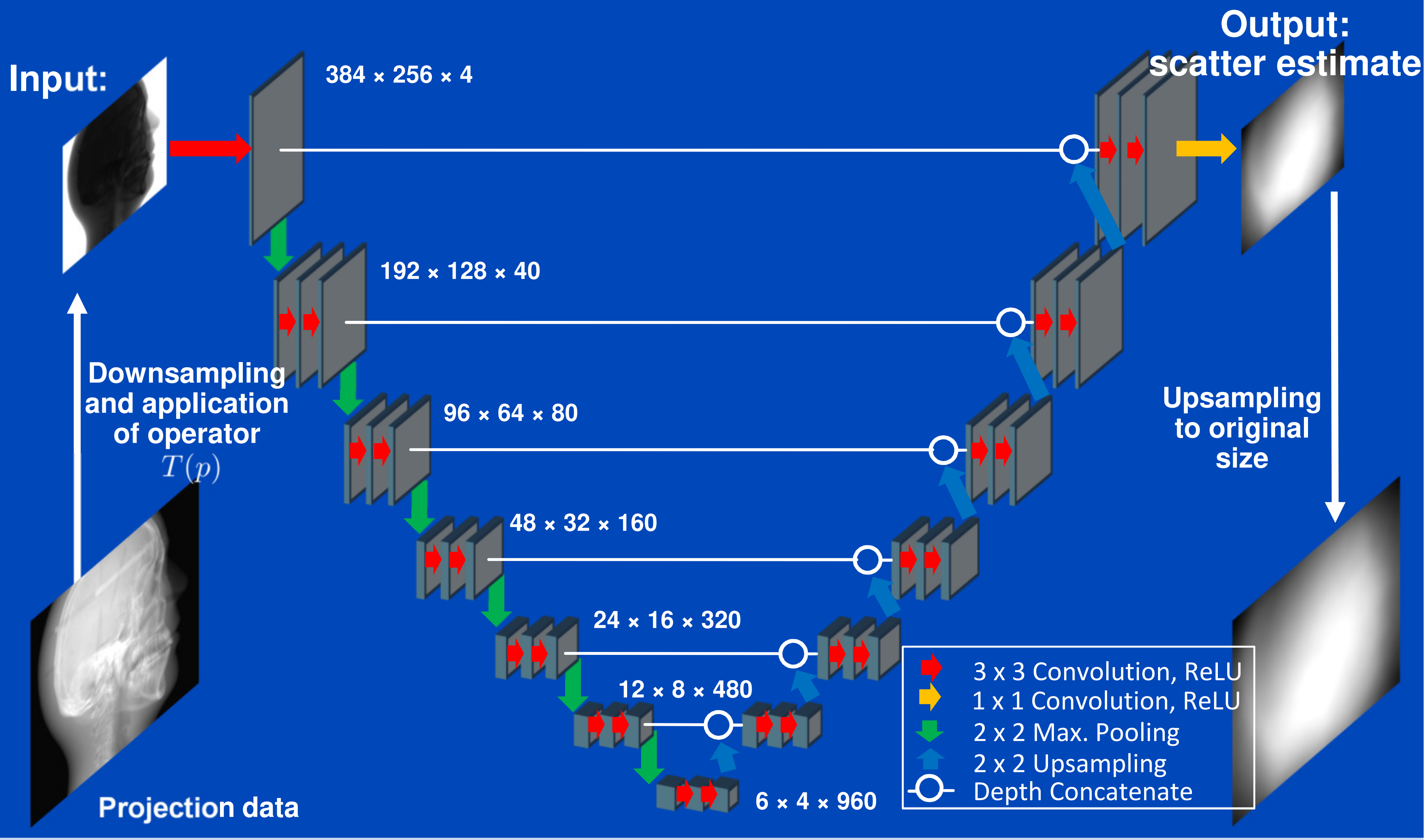
Scatter estimate



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

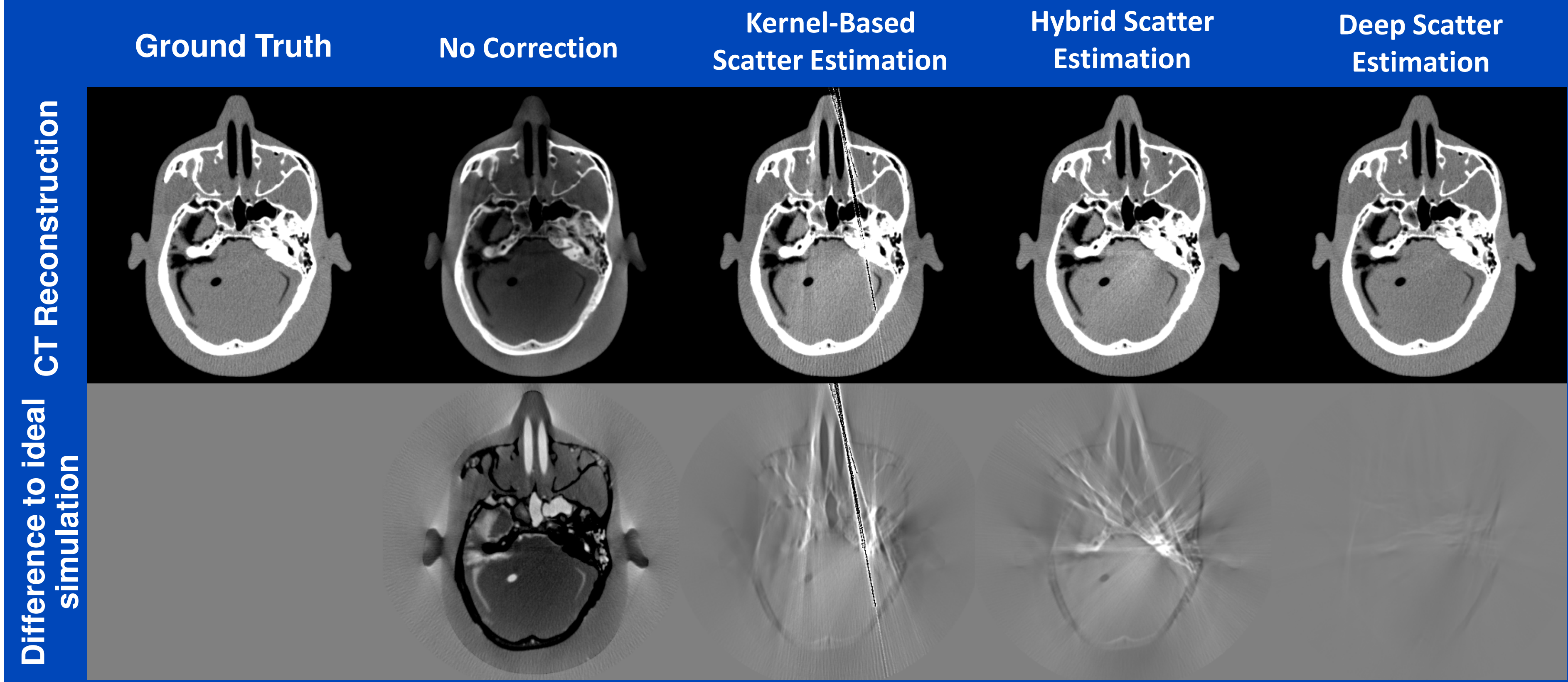
Deep Scatter Estimation

Network architecture & scatter estimation framework



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

Reconstructions of Simulated Data



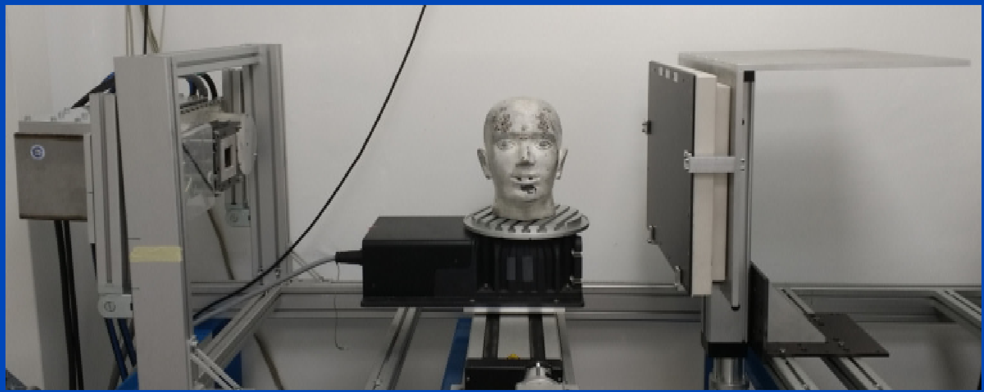
$C = 0$ HU, $W = 1000$ HU

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

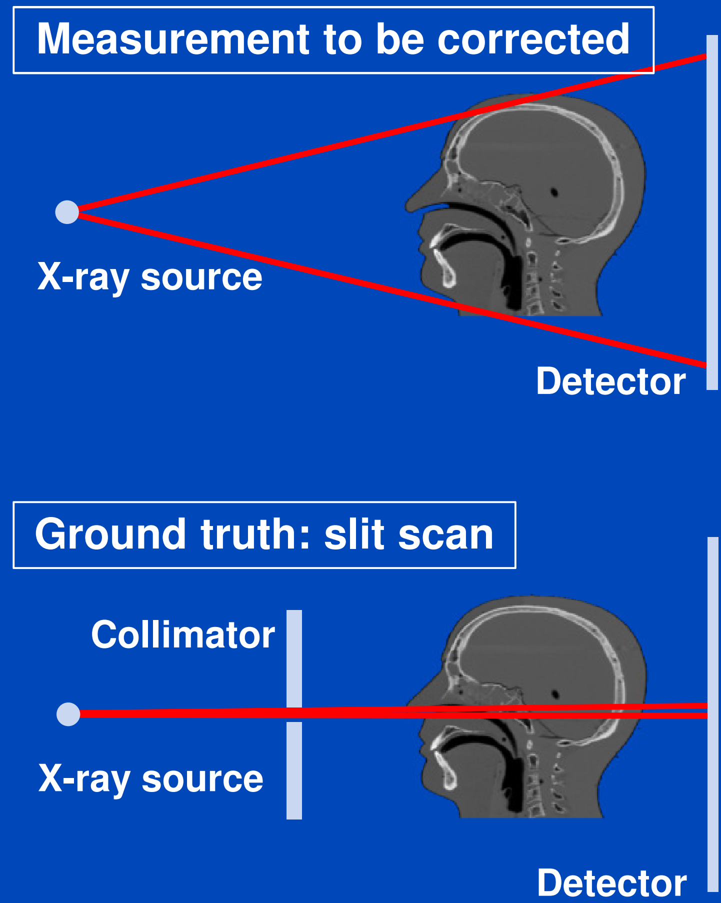
dkfz.

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

DKFZ table-top CT

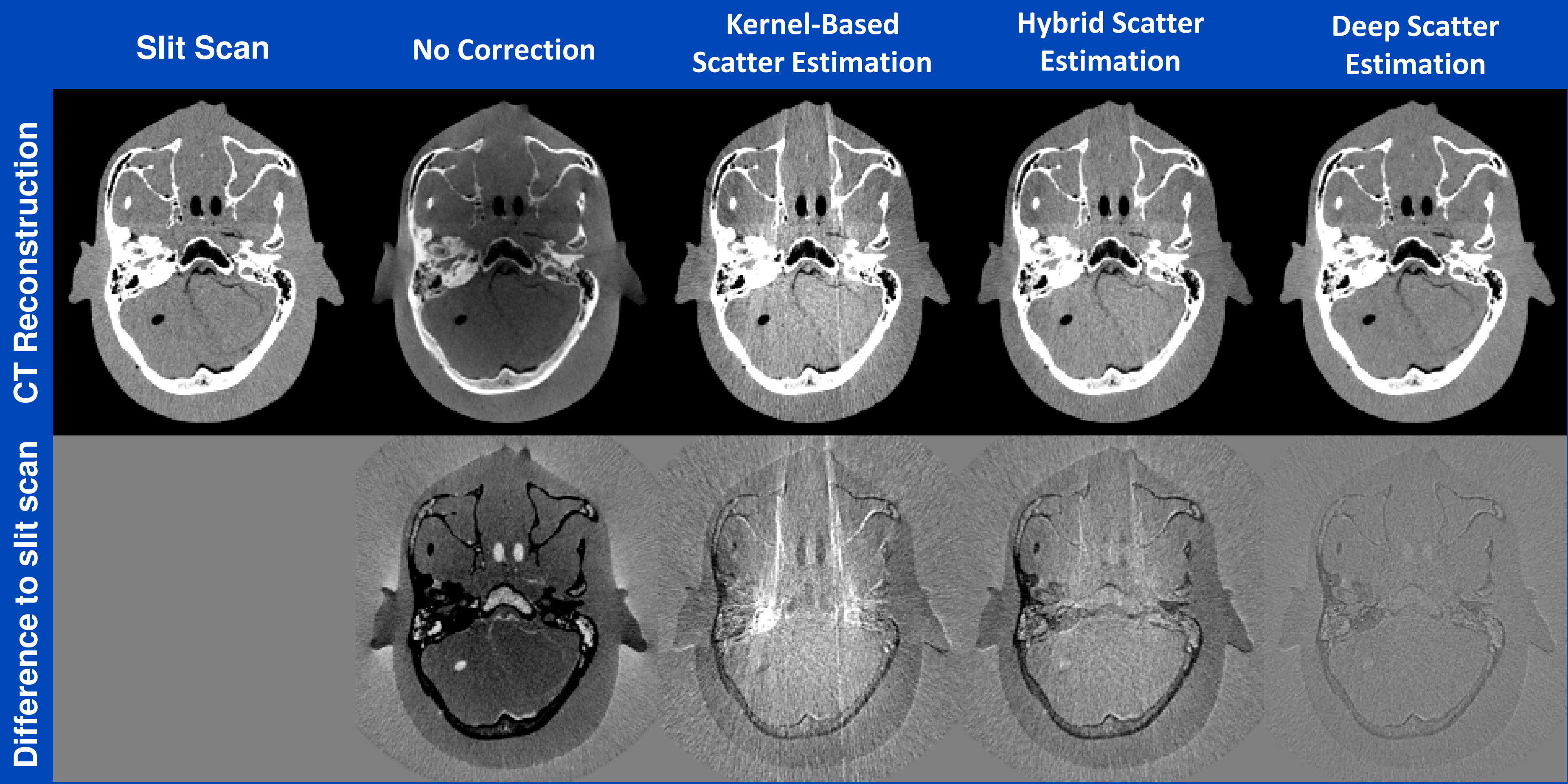


- Measurement of a head phantom at our in-house table-top CT.
- Slit scan measurement serves as ground truth.



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

Reconstructions of Measured Data

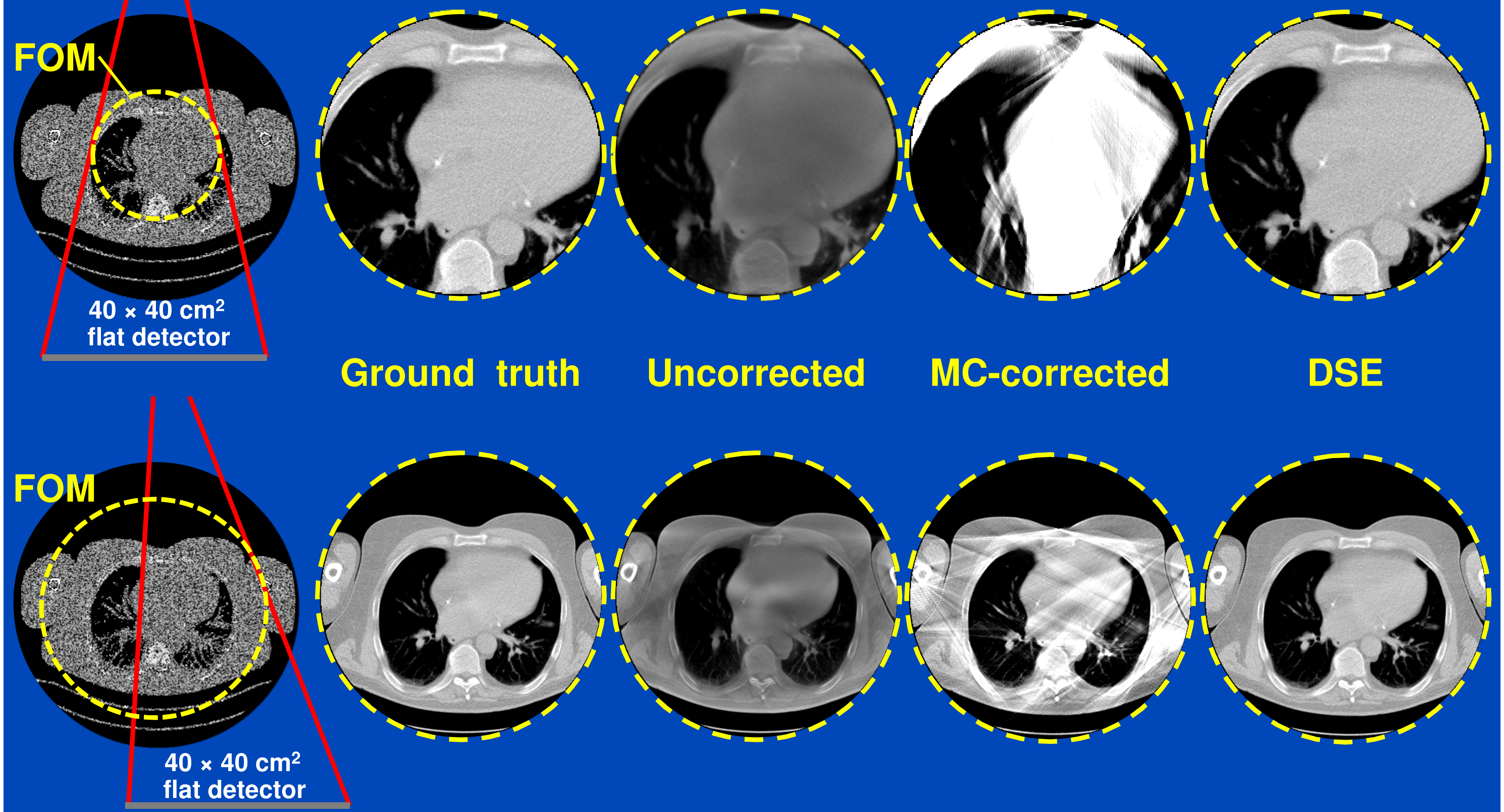


C = 0 HU, W = 1000 HU

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

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

Truncated DSE[1,2]



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

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

dkfz.

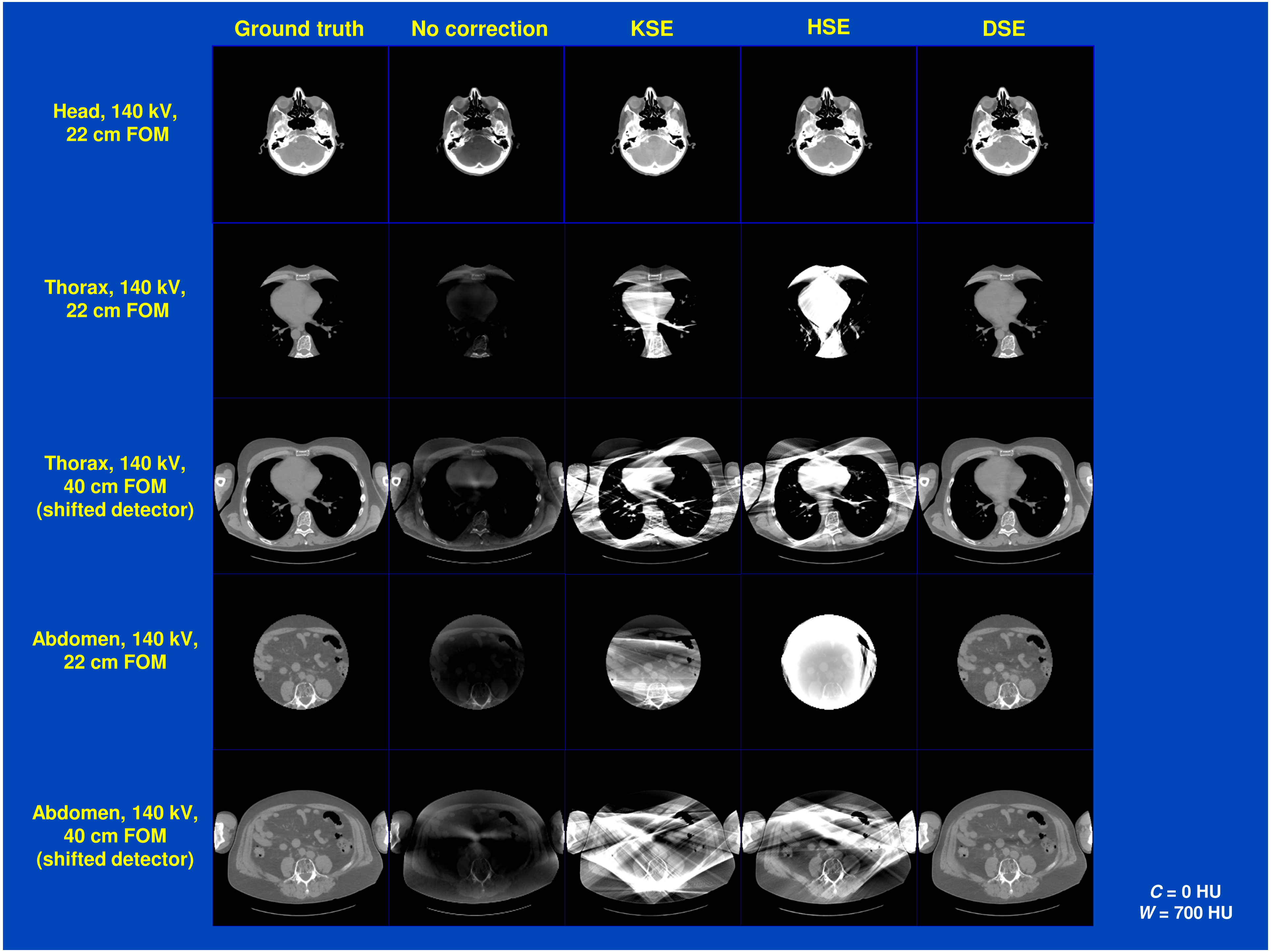
Does DSE Generalize to Different Anatomical Regions?

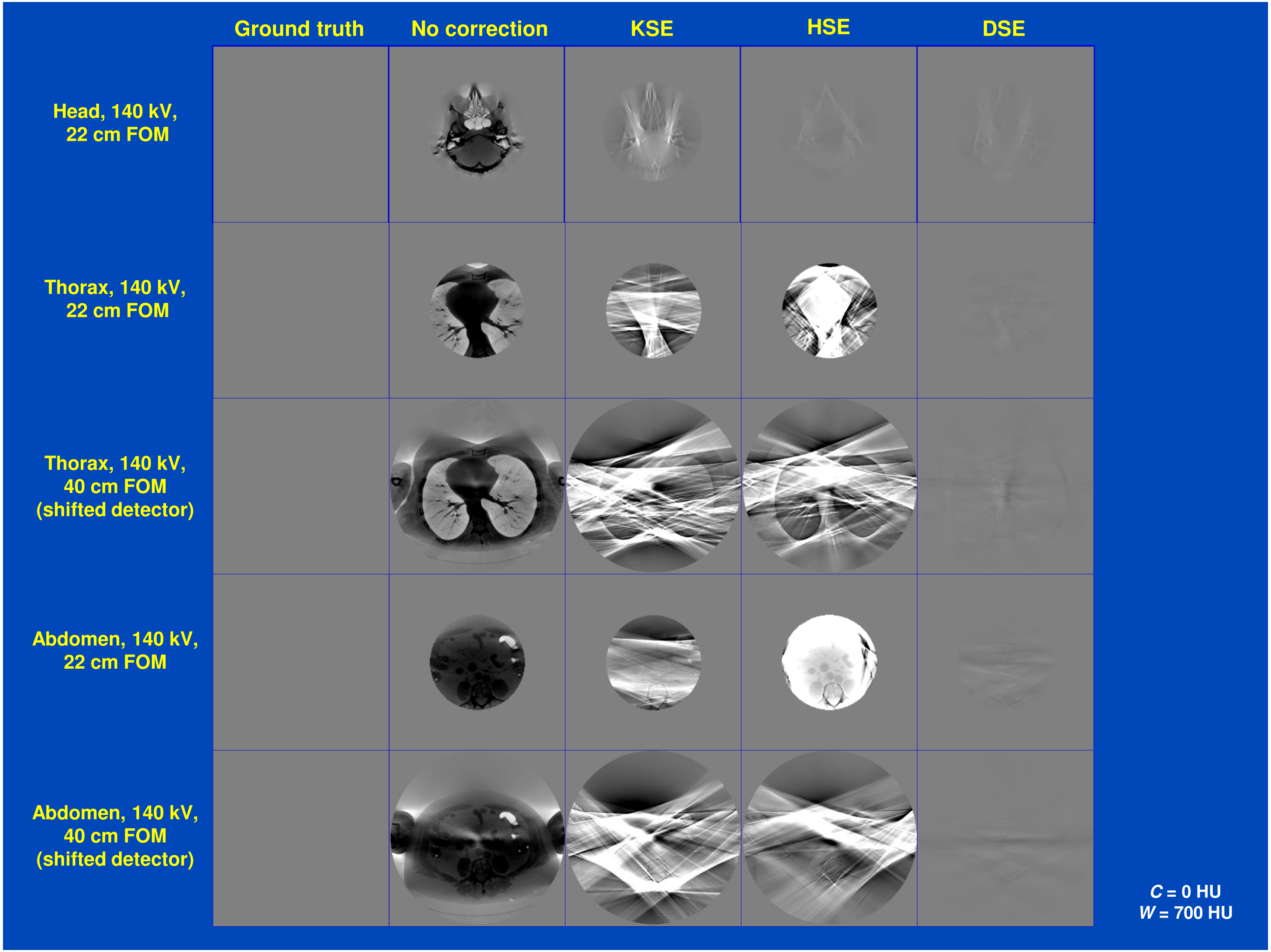
KSE	Head	Thorax	Abdomen
Head	14.5	26.8	32.5
Thorax	16.2	18.5	19.4
Abdomen	16.8	22.1	17.8
All data	14.9	20.5	19.3

DSE	Head	Thorax	Abdomen
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

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 40×30 cm flat detector.

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


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


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

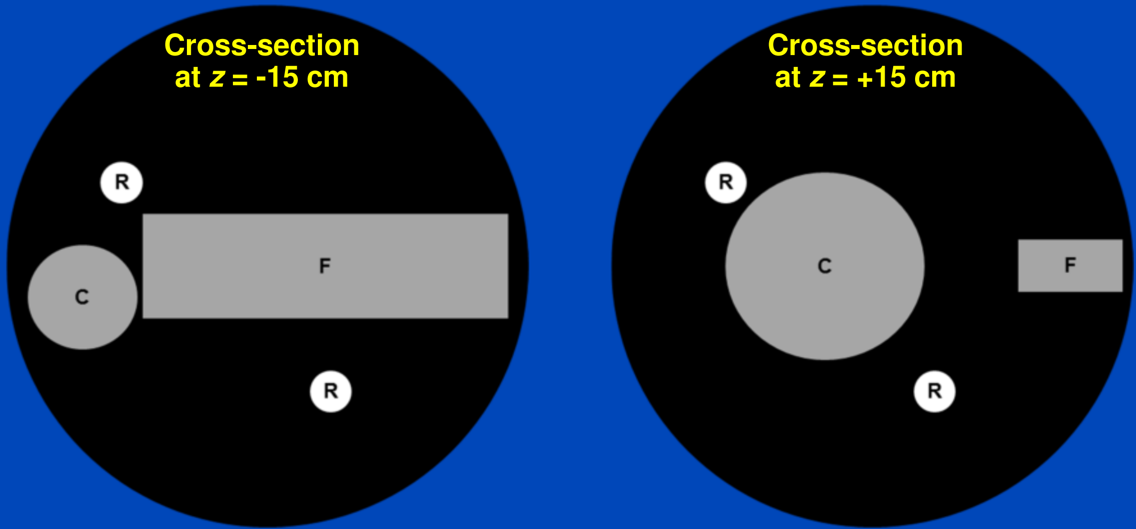
Conclusions on DSE

- 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.

dkfz.

DSE without Monte Carlo

Calibration Phantom (one configuration)



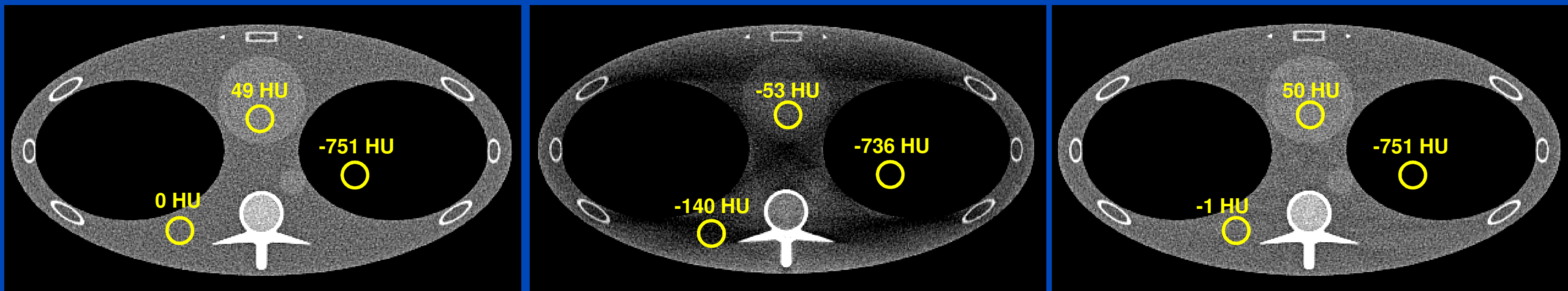
C = truncated PE cone
(diameter from 10 cm to 28 cm)

F = rectangular PE frustum
(from 35 cm × 10 cm to 10 cm × 5 cm)

R = Teflon rod
(4 cm diameter)

Calibration phantom measured in about 20 configurations (translate, tilt, shift, rotate) to collect sufficiently many data for the neural net to be able to reliably deduce primary from scatter.

Test Phantom (water precorrected)



Ground truth (no scatter) | Uncorrected (with scatter) | mbDSE-corrected

C = 0 HU, *W* = 500 HU

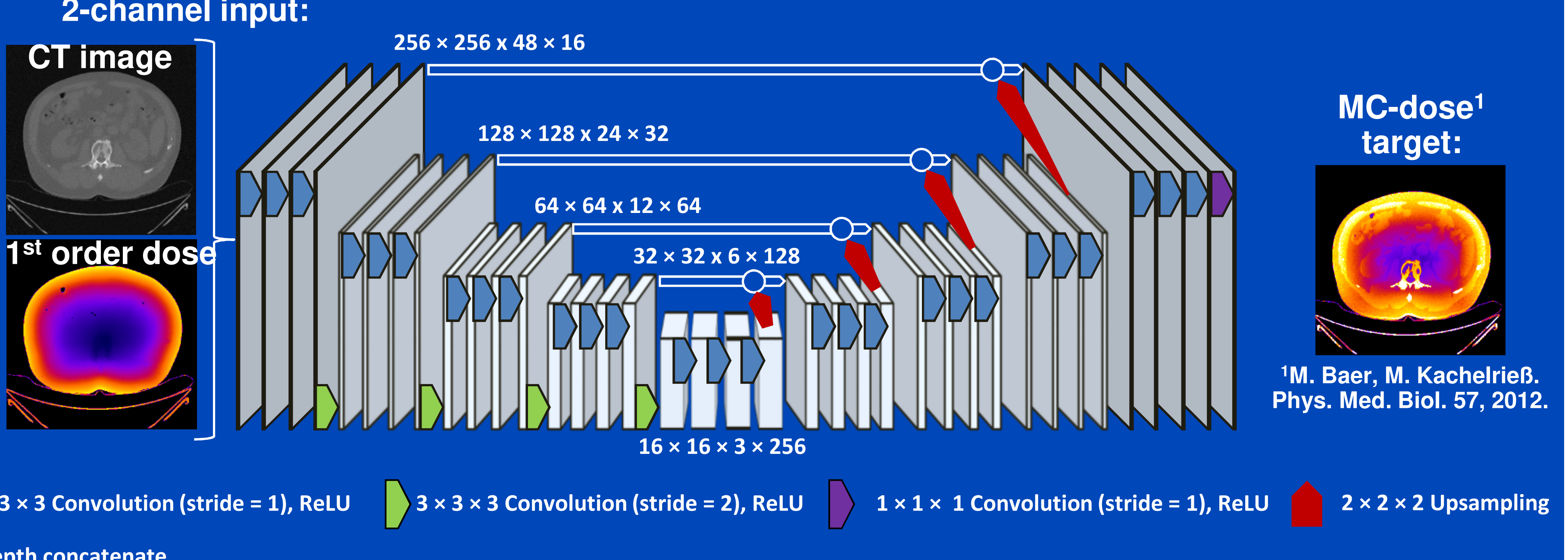
Estimation of Dose Distributions

- **Useful to study dose reduction techniques**
  - Tube current modulation
  - Prefiltration and shaped filtration
  - Tube voltage settings
  - ...
- **Useful to estimate patient dose**
  - Risk assessment requires segmentation of the organs (difficult)
  - Often semiantropomorphic patient models take over
  - The infamous k-factors that convert DLP into D_{eff} are derived this way, e.g. k_{chest} = 0.014 mSv/mGy/cm
  - ...
- **Could be useful for patient-specific CT scan protocol optimization**
- **However: Dose estimation does not work in real time!**

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

Deep Dose Estimation (DDE)

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



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

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

First-Order Dose Estimate

- DDE network needs information about the tube current, the tube voltage, shaped filters etc., which is encoded in the first-order dose estimate.
- First order dose-estimate in a voxel with volume V and mass *m* at position *r* :

$$D_{1^{\rm st}}(\boldsymbol{r}) = \frac{V}{m}\int \frac{d^2N}{d\Omega dE} \sum_{i=\rm PE,\ CS} P_{{\rm int},i}(\boldsymbol{r},E)E_{{\rm dep},i}(E)\,dE$$

Emission characteristic of the x-ray source (including shaped filters)

Interaction probability for photo effect (*i* = PE) and Compton scattering (*i* = CS)

Energy deposition by photo effect (*i* = PE) and Compton scattering (*i* = CS)

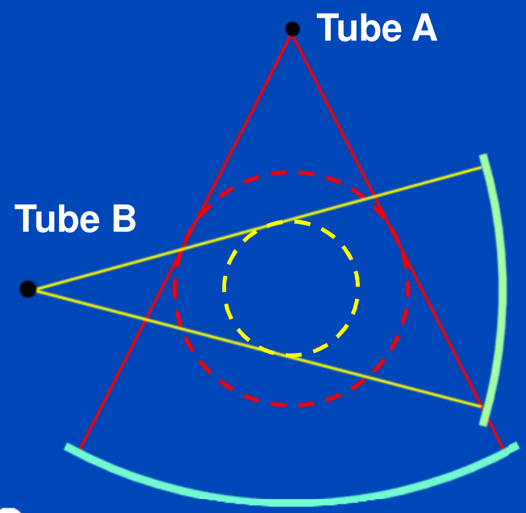
$$P_{\rm int,\ PE}(\boldsymbol{r},E) = \mu_{\rm PE}(\boldsymbol{r},E)\cdot e^{-\int_0^r \mu(r',E)dr'} \qquad E_{\rm dep,\ PE}(E) = E$$

$$P_{\rm int,\ CS}(\boldsymbol{r},E) = \mu_{\rm CS}(\boldsymbol{r},E)\cdot e^{-\int_0^r \mu(r',E)dr'} \qquad E_{\rm dep,\ CS}(E) = \int \frac{d\sigma}{d\Omega}(E)\Delta E_{\rm CS}(\vartheta)d\Omega$$

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

Training and Validation

- Simulation of 1440 circular dual-source CT scans (64×0.6 mm, FOM_A = 50 cm, FOM_B = 32 cm) of thorax, abdomen, and pelvis using 12 different patients.
- Simulation with and without bowtie.
- No data augmentation
- Reconstruction on a 512×512×96 grid with 1 mm voxel size, followed by 2×2×2 binning for dose estimation.

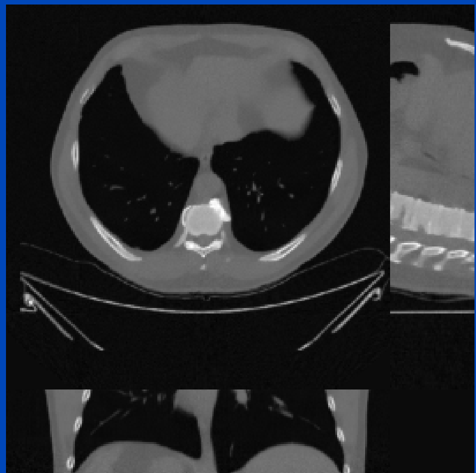


- 9 patients were used for training and 3 for testing.
- DDE was trained for 300 epochs on an Nvidia Quadro P6000 GPU using a mean absolute error pixel-wise loss, the Adam optimizer, and a batch size of 4.
- The same weights and biases were used for all cases.

Results

Thorax, tube A, 120 kV, with bowtie

CT image



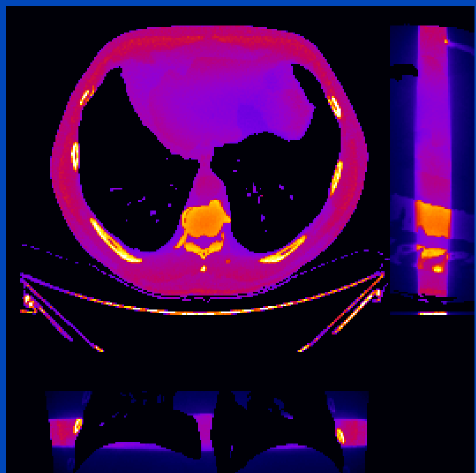
First order dose

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

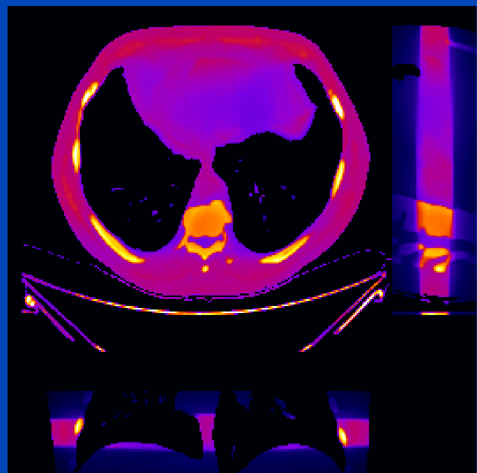
MC uses 16 CPU kernels
DDE uses one Nvidia Quadro P600 GPU

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

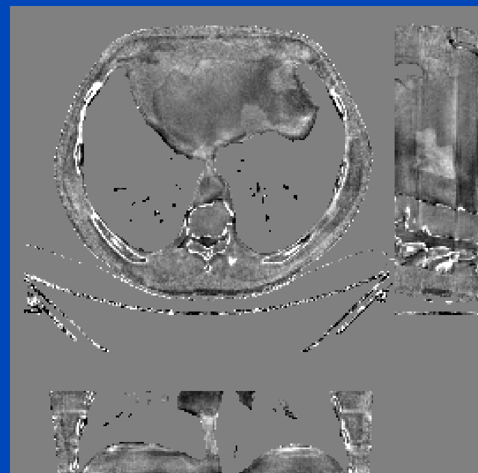
MC ground truth



DDE



Relative error



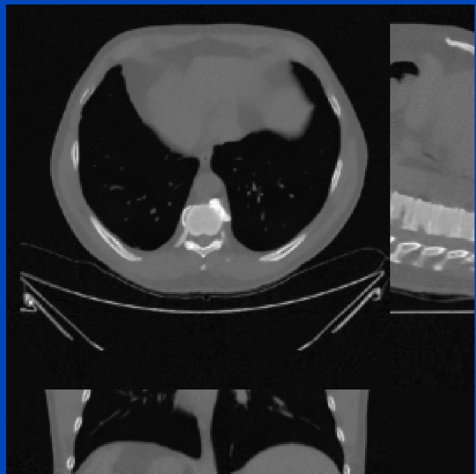
$C = 0\%$
$W = 40\%$

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

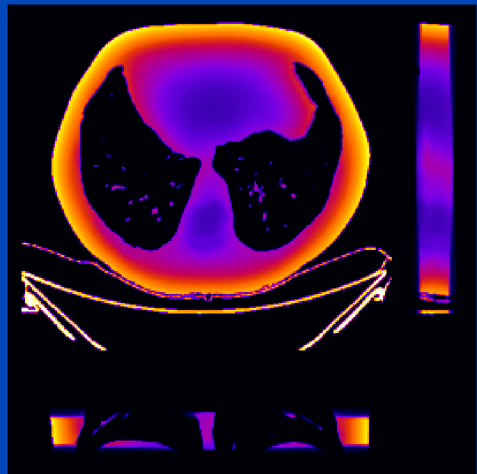
Results

Thorax, tube A, 120 kV, no bowtie

CT image



First order dose



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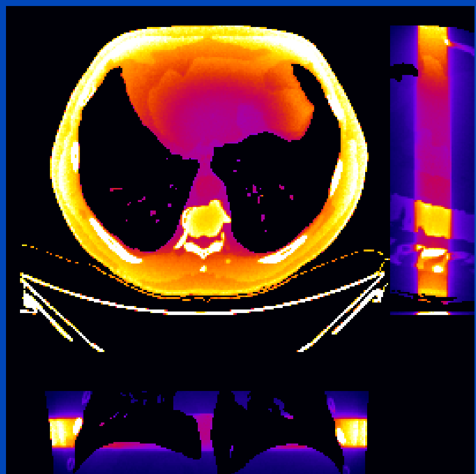
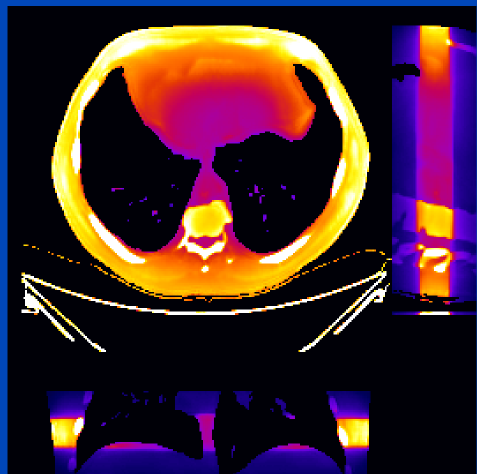
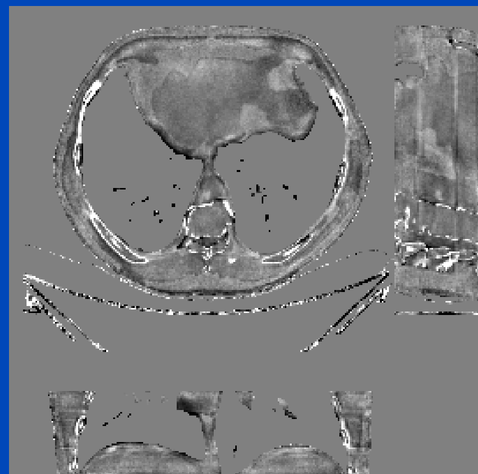
MC ground truth



DDE



Relative error



C = 0%
W = 40%

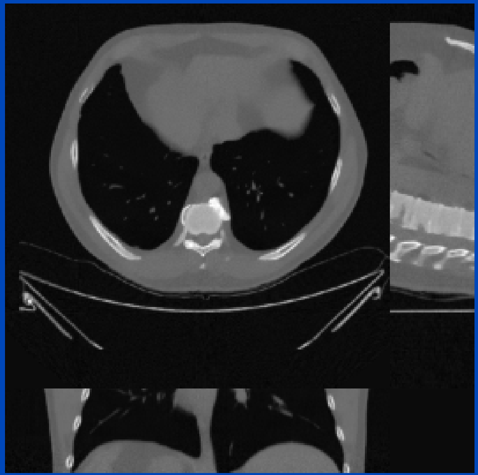
J. Maier, E. Eulig, S. Sawall, and M. Kachelrieß. Real-time patient-specific CT dose estimation using a deep convolutional neural network, Proc. IEEE MIC 2018 and ECR Book of Abstracts 2019. *Best Paper within Machine Learning at ECR 2019!*

dkfz.

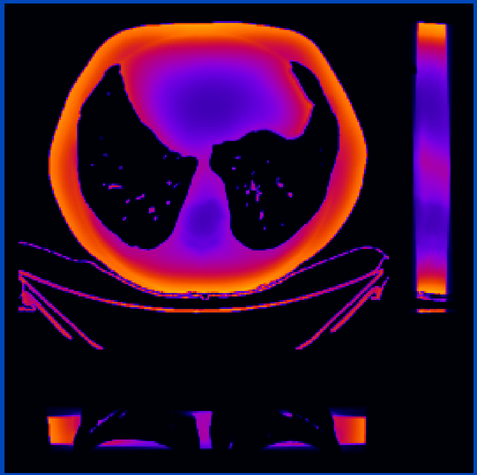
Results

Thorax, tube B, 120 kV, no bowtie

CT image



First order dose

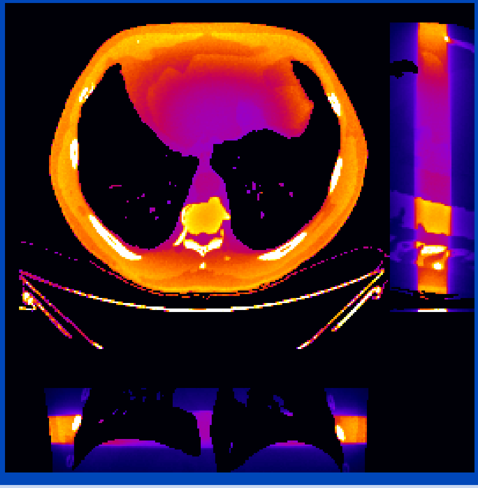


	MC	DDE
48 slices	1 h	0.25 s
whole body	20 h	5 s

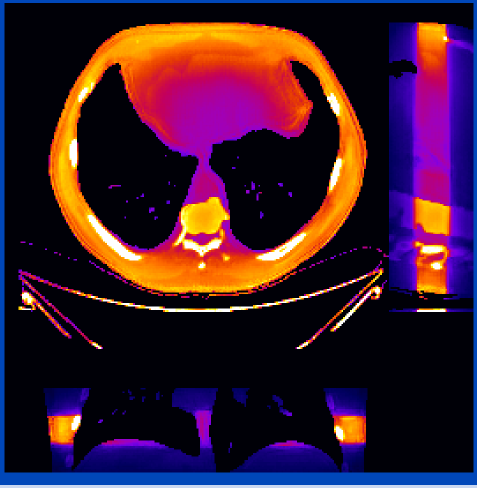
MC uses 16 CPU kernels
DDE uses one Nvidia Quadro P600 GPU

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

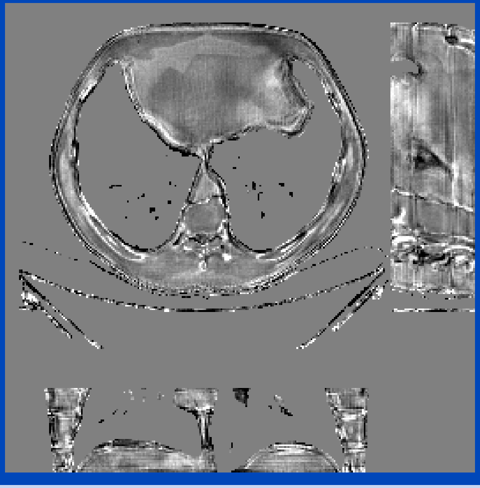
MC ground truth



DDE



Relative error



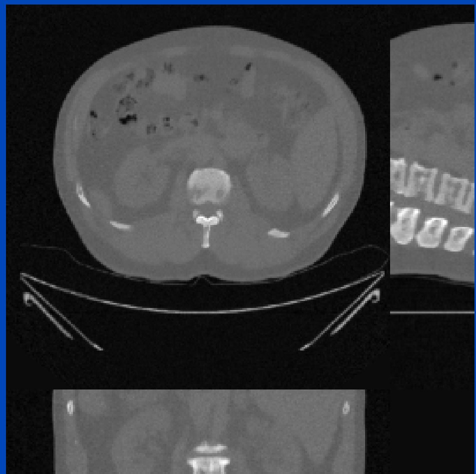
$C = 0\%$
$W = 40\%$

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

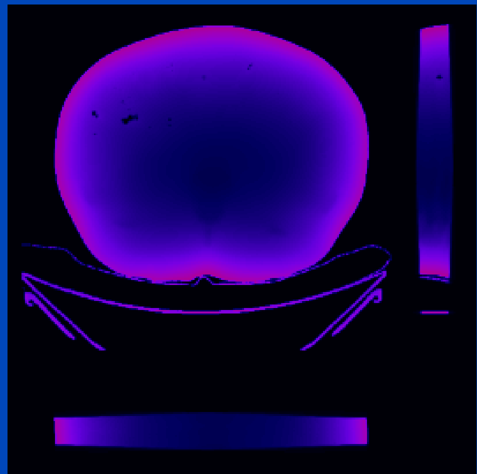
Results

Abdomen, tube A, 120 kV, with bowtie

CT image



First order dose



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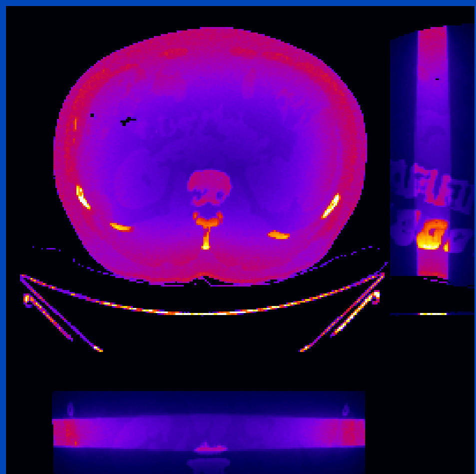
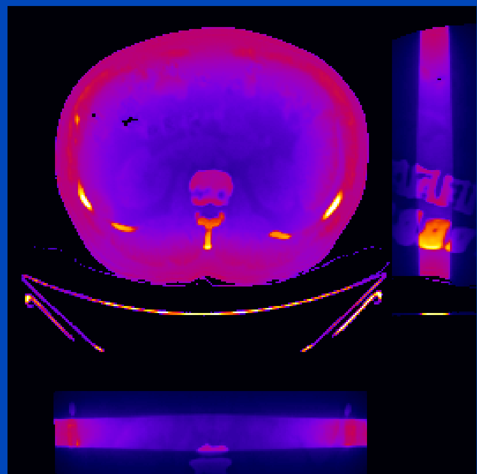
DDE uses one Nvidia Quadro P600 GPU

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

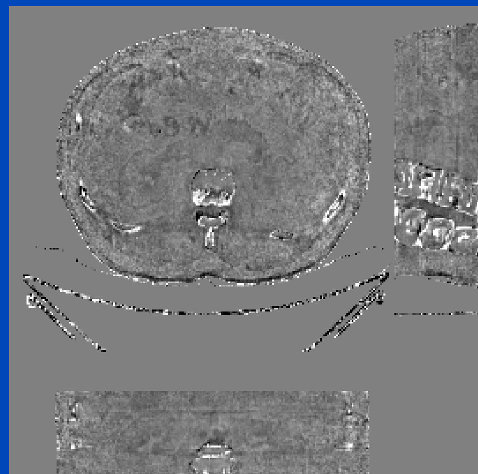
MC ground truth



DDE



Relative error



C = 0%
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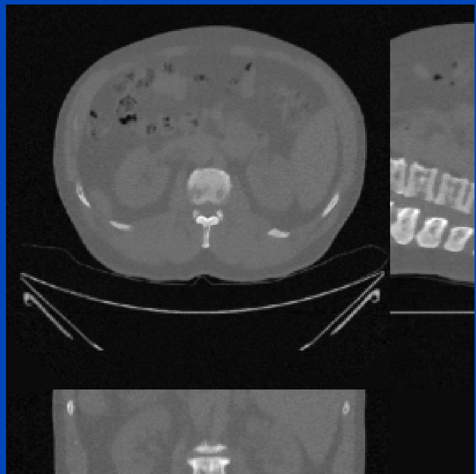
J. Maier, E. Eulig, S. Sawall, and M. Kachelrieß. Real-time patient-specific CT dose estimation using a deep convolutional neural network, Proc. IEEE MIC 2018 and ECR Book of Abstracts 2019. *Best Paper within Machine Learning at ECR 2019!*

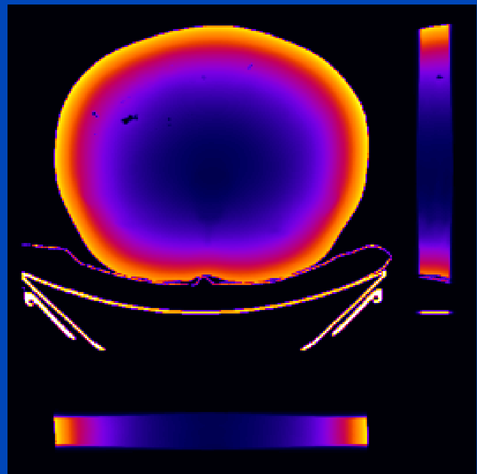
Results

Abdomen, tube A, 120 kV, no bowtie

CT image



First order dose



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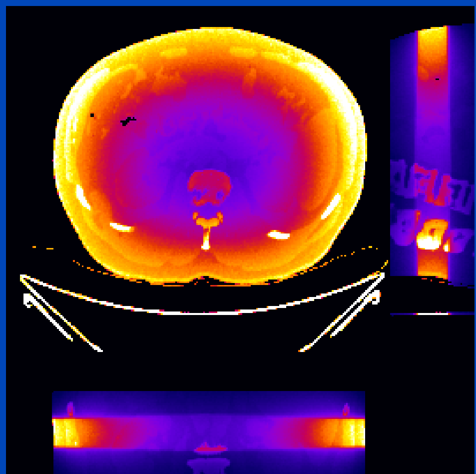
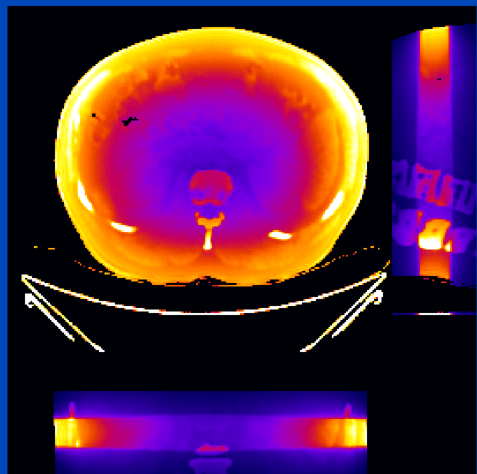
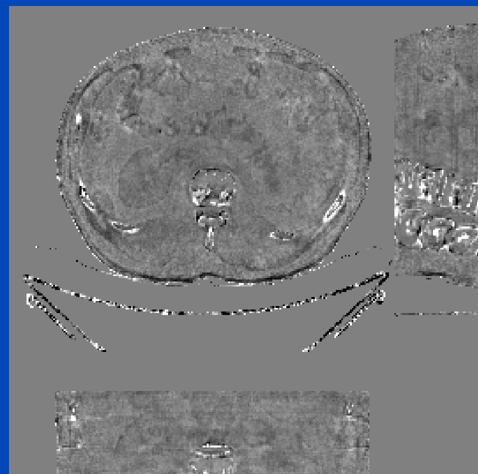
MC ground truth



DDE



Relative error



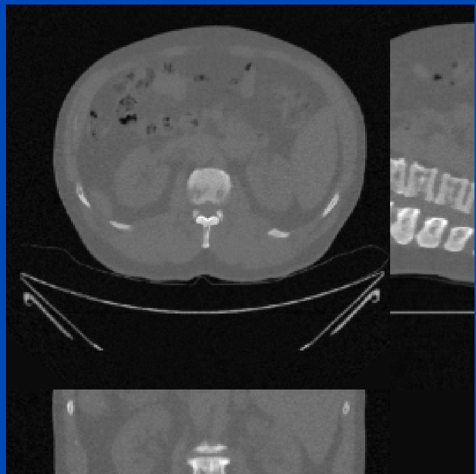
C = 0%
W = 40%

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

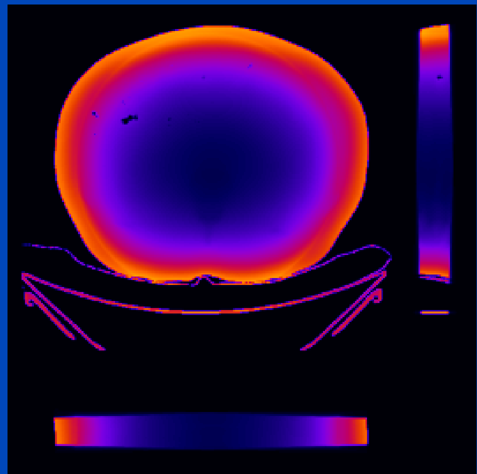
Results

Abdomen, tube B, 120 kV, no bowtie

CT image



First order dose

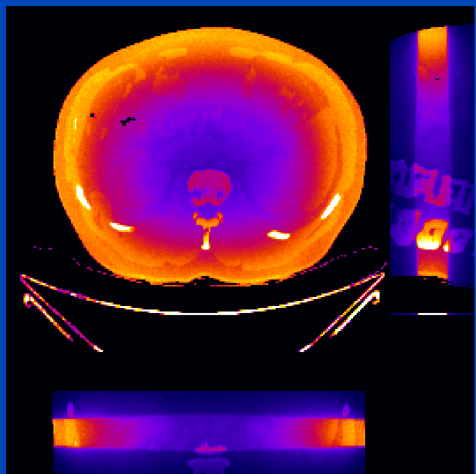


	MC	DDE
48 slices	1 h	0.25 s
whole body	20 h	5 s

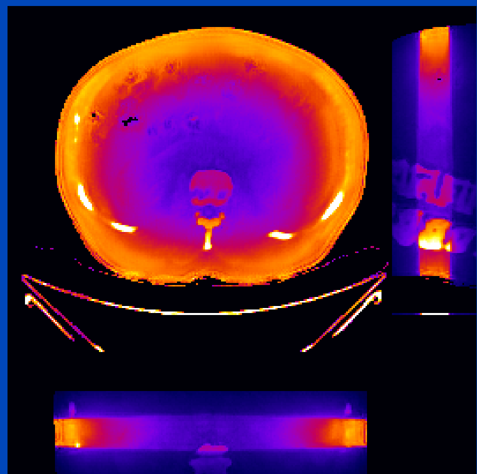
MC uses 16 CPU kernels
DDE uses one Nvidia Quadro P600 GPU

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

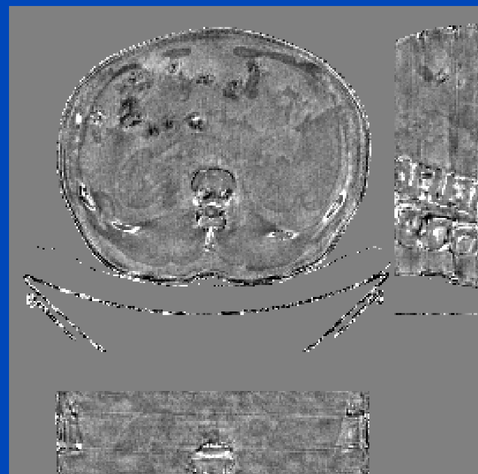
MC ground truth



DDE



Relative error



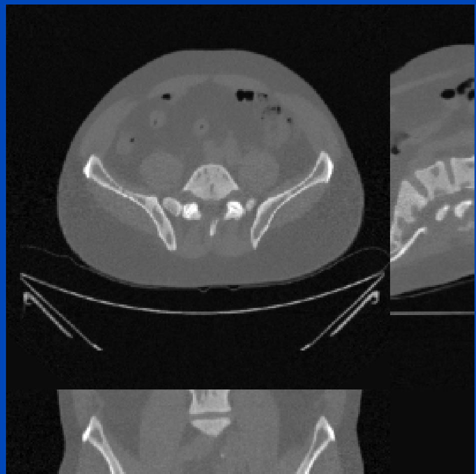
C = 0%
W = 40%

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

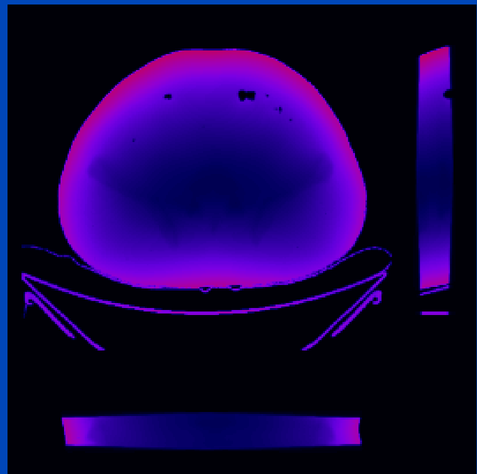
Results

Pelvis, tube A, 120 kV, with bowtie

CT image



First order dose



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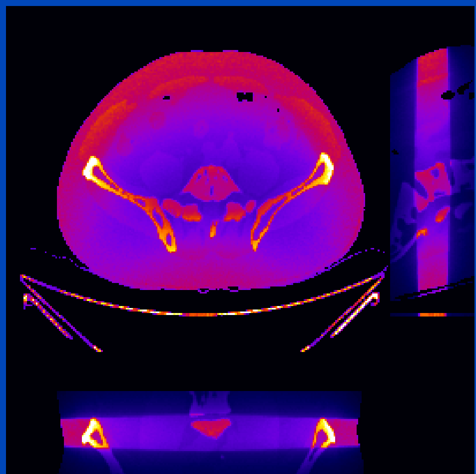
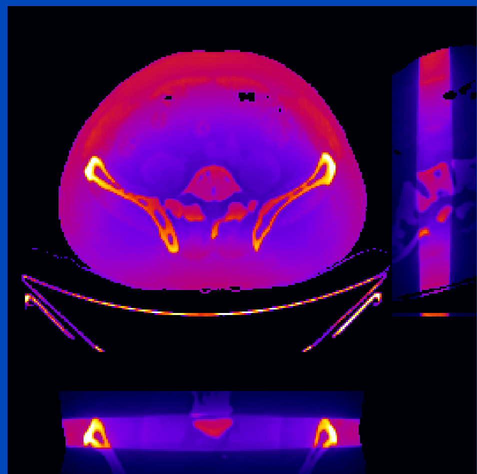
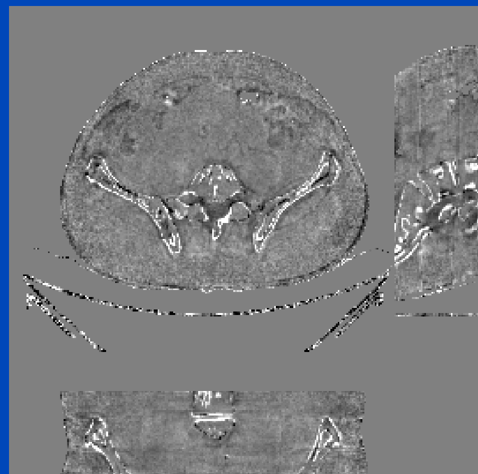


DDE



Relative error



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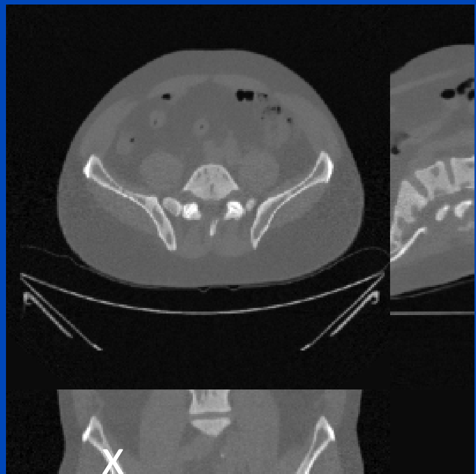
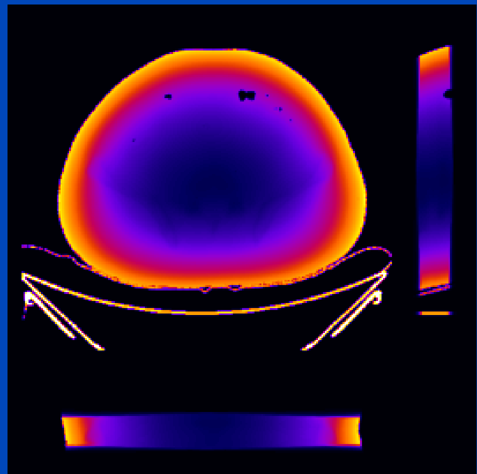
Results

Pelvis, tube A, 120 kV, no bowtie

CT image



First order dose



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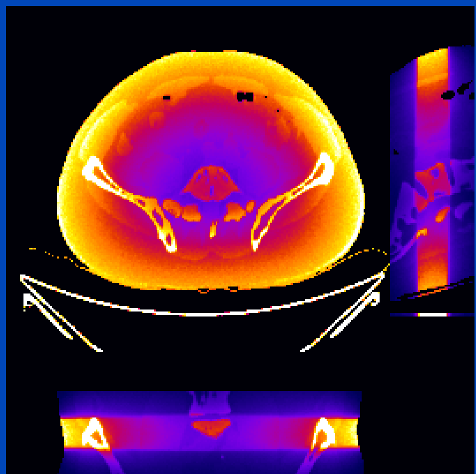
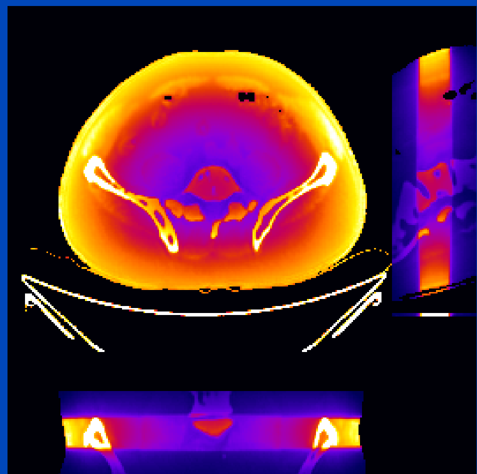
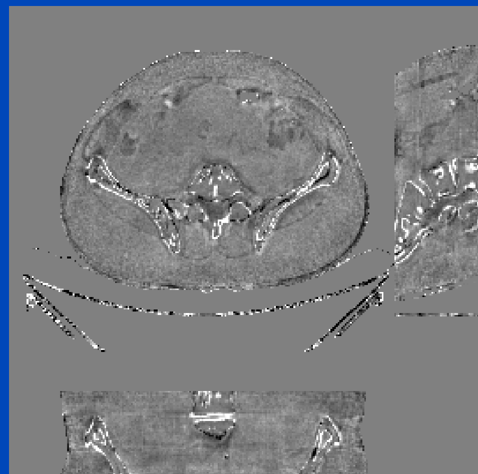


DDE



Relative error



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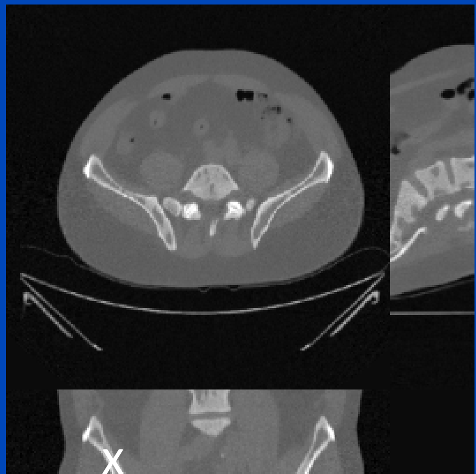
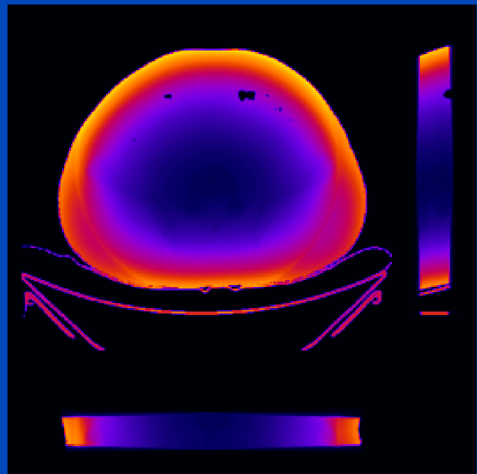
Results

Pelvis, tube B, 120 kV, no bowtie

CT image



First order dose



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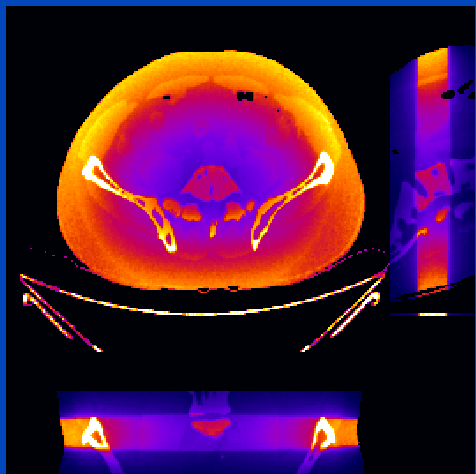
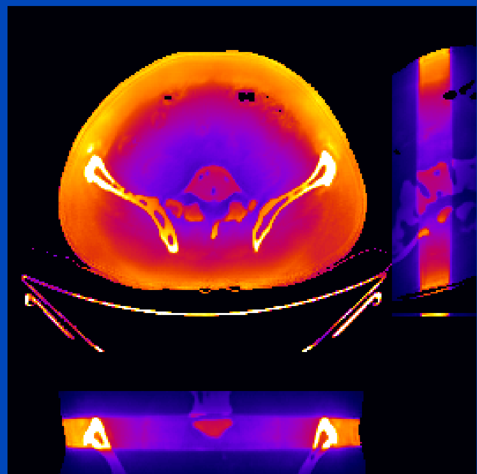
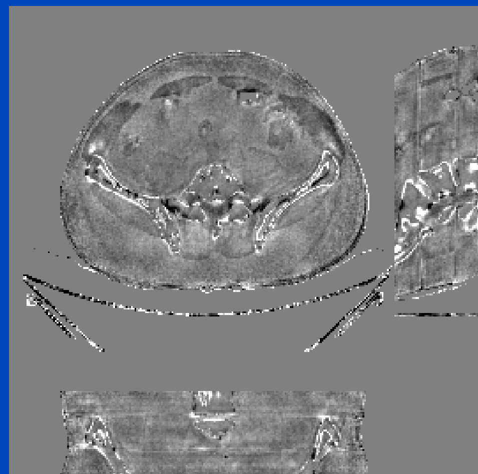


DDE



Relative error



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Conclusions on DDE

- DDE is able to derive dose estimates with almost similar accuracy as MC (average deviation: 4.6 %).
- DDE can provide accurate dose predictions
  - for sequence scans
  - for partial scans (less than 360°)
  - for spiral scans
  - for different tube voltages
  - for scans with and without bowtie filtration
  - for scans with tube current modulation
  - across anatomical regions
- In practice it may therefore be not necessary to perform separate training runs for these cases.
- Thus, accurate real-time patient dose estimation may become feasible with DDE.

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

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Part 4:

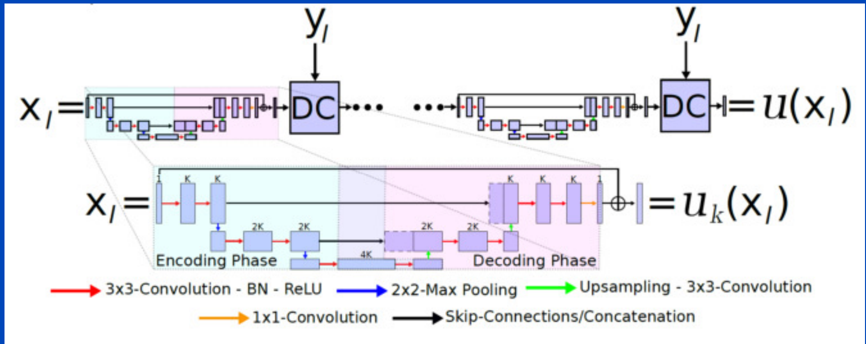
Image Reconstruction

Often “Just” Image Restoration

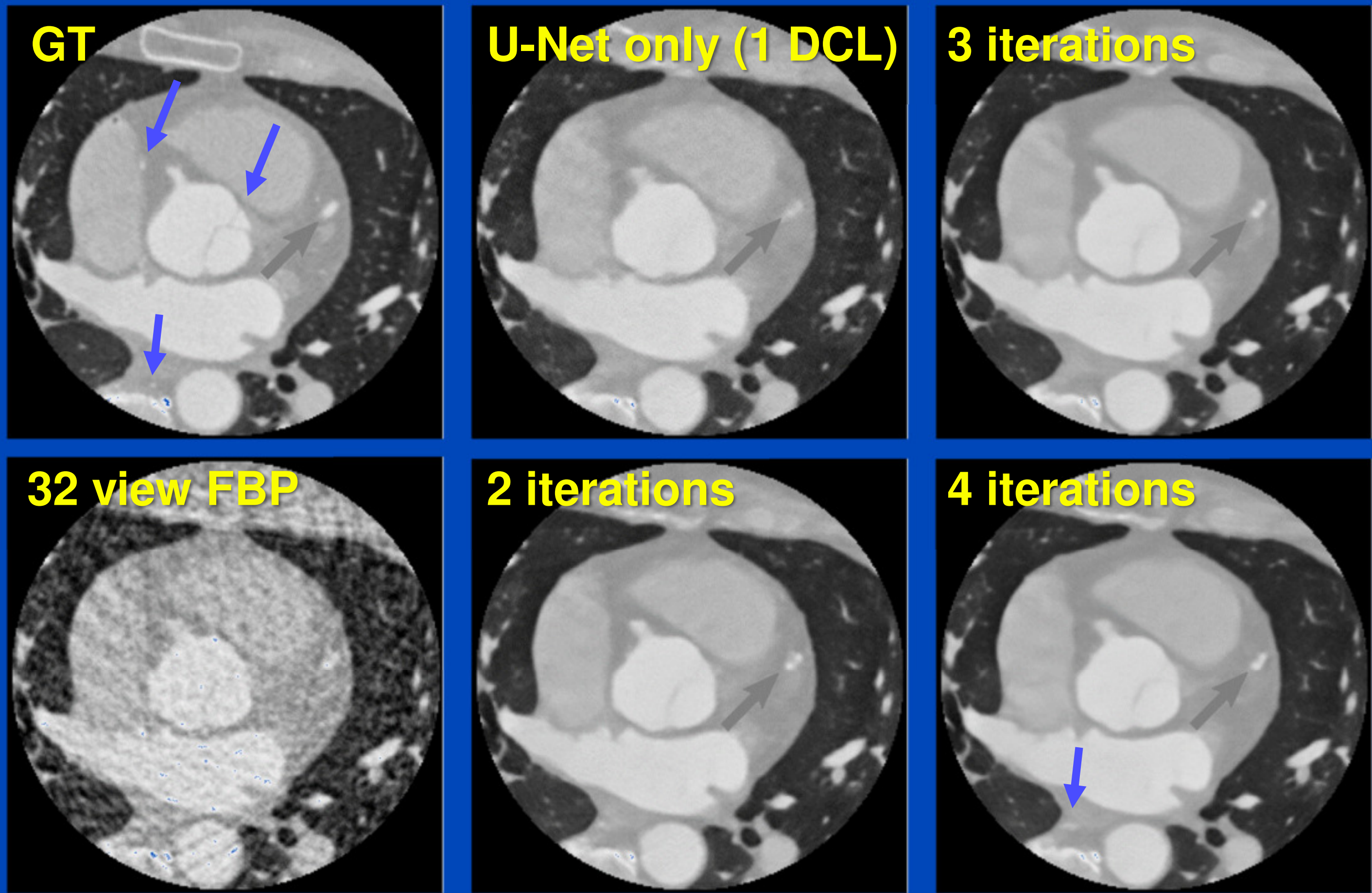
- Speeding up iterative reconstruction by training a CNN to convert an FBP image into an iterative image
  - Canon‘s AiCE algorithm
  - GE‘s True Fidelity algorithm
  - plus a few more algorithms proposed in the literature
- Noise reduction by training, e.g. a mapping from low dose to high dose images
  - many examples in the literature, some in this presentation
- Artifact reduction in image domain
  - many examples in the literature, one shown in this presentation
- …

Sometimes “Real” Image Reconstruction

- Networks employing data consistency layers
- Networks including backprojection layers
- Learning of backprojectors
- End-to-end training from sinogram to image
- Unrolled iterative reconstruction with learned priors
- …



Sparse CT Recon with Data Consistency Layers (DCLs)



A. Kofler, M. Haltmeier, C. Kolbitsch, M. Kachelrieß, and M. Dewey. A U-Nets Cascade for Sparse View Computed Tomography, MICCAI 2018

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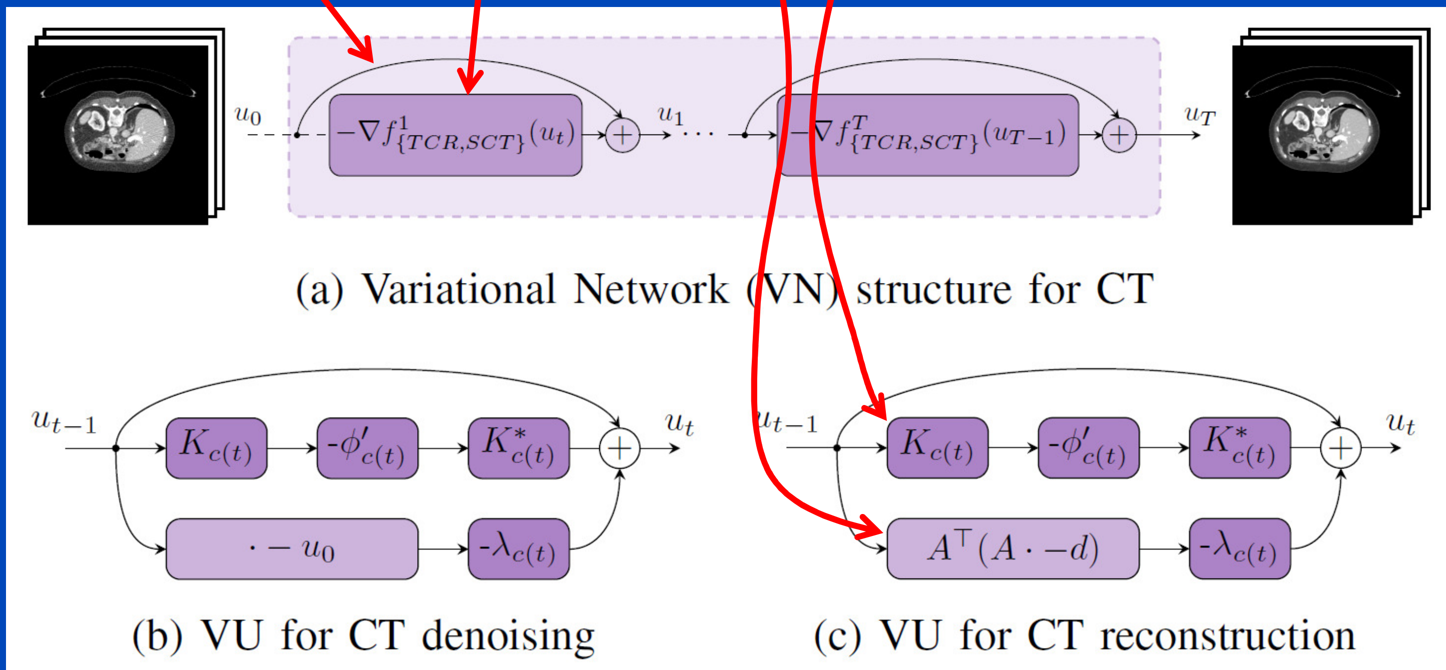
Variational Network-Based Image Reconstruction

$$C(\boldsymbol{f}) = \|\boldsymbol{X}\cdot\boldsymbol{f}-\boldsymbol{p}\|^2_{\boldsymbol{W}} + R(\boldsymbol{f})$$

$$\nabla C(\boldsymbol{f}) = \boldsymbol{X}^{\mathrm{T}}\cdot\boldsymbol{W}\cdot(\boldsymbol{X}\cdot\boldsymbol{f}-\boldsymbol{p}) + \nabla R(\boldsymbol{f})$$

$$\boldsymbol{f}^{(t+1)} = \boldsymbol{f}^{(t)} - \lambda\nabla C(\boldsymbol{f}^{(t)})$$

Highly simplified example. Varnets work for a much wider class of cost functions whose NN-based minimization is motivated by the primal dual approach.

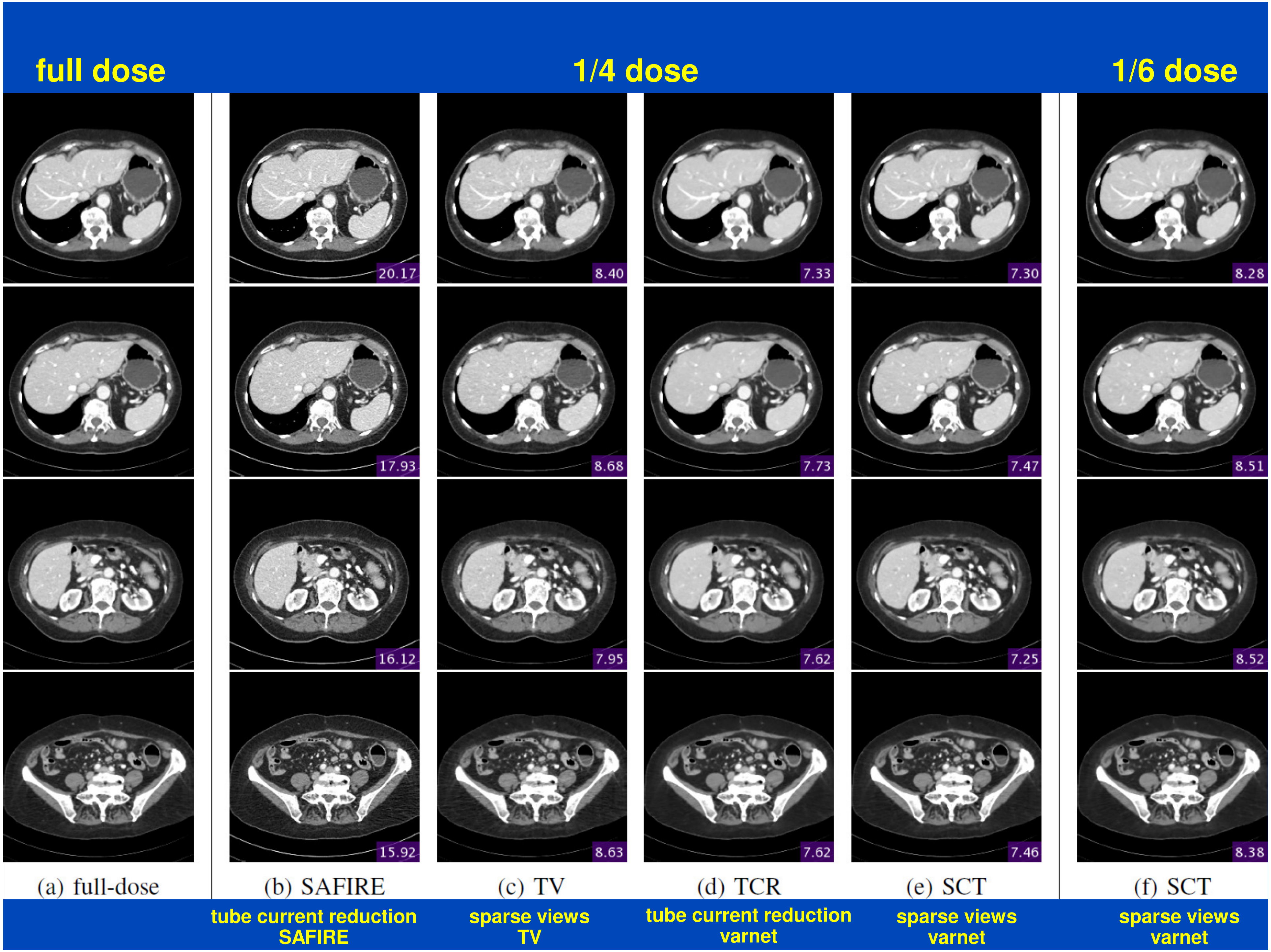


(a) Variational Network (VN) structure for CT

(b) VU for CT denoising

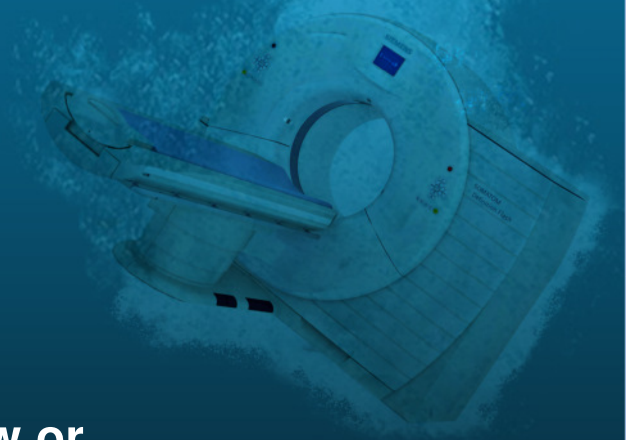
(c) VU for CT reconstruction

E. Kobler, R. Otazo et al. Variational network learning for low-dose CT. Proc. 5th CT-Meeting:430-434, 2018.


full dose
1/4 dose
1/6 dose
20.17
8.40
7.33
7.30
8.28
17.93
8.68
7.73
7.47
8.51
16.12
7.95
7.62
7.25
8.52
15.92
8.63
7.62
7.46
8.38
(a) full-dose
(b) SAFIRE
(c) TV
(d) TCR
(e) SCT
(f) SCT
tube current reduction
SAFIRE
sparse views
TV
tube current reduction
varnet
sparse views
varnet
sparse views
varnet

Conclusions on Deep CT

- Machine learning will play a significant role in CT optimization.
- 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 necessarily represent the ground truth.
  - Data consistency layers and variational networks with rawdata access may ensure that the information that is made up is consistent with the measured data.
  - ...



Thank You!

The 6th International Conference on

Image Formation in X-Ray Computed Tomography

Conference Chair: **Marc Kachelrieß**, German Cancer Research Center (DKFZ), Heidelberg, Germany

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

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

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