AI in CT Image Formation

Getting Ready and Tips for Researchers

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DEUTSCHES KREBSFORSCHUNGSZENTRUM IN DER HELMHOLTZ-GEMEINSCHAFT

Getting Ready

- **Wrong:**
  - **"The aim is to develop and train a neural network that solves problem XYZ."**
- **Even wronger:**
  - **"Problem XYZ is typically well solved with classical algorithms. I want to solve it with AI."**
- **Right:**
  - **"The aim is to solve problem XYZ."**
  - **"Literature shows *N* classical and *M* deep learning-based approaches solving XYZ.
The classical ones are inaccurate because XYZ is very complex.
The AI-based solutions are much more promising but hallucinate too much."**
  - **"Thus, we want to develop a new data-driven solution."**

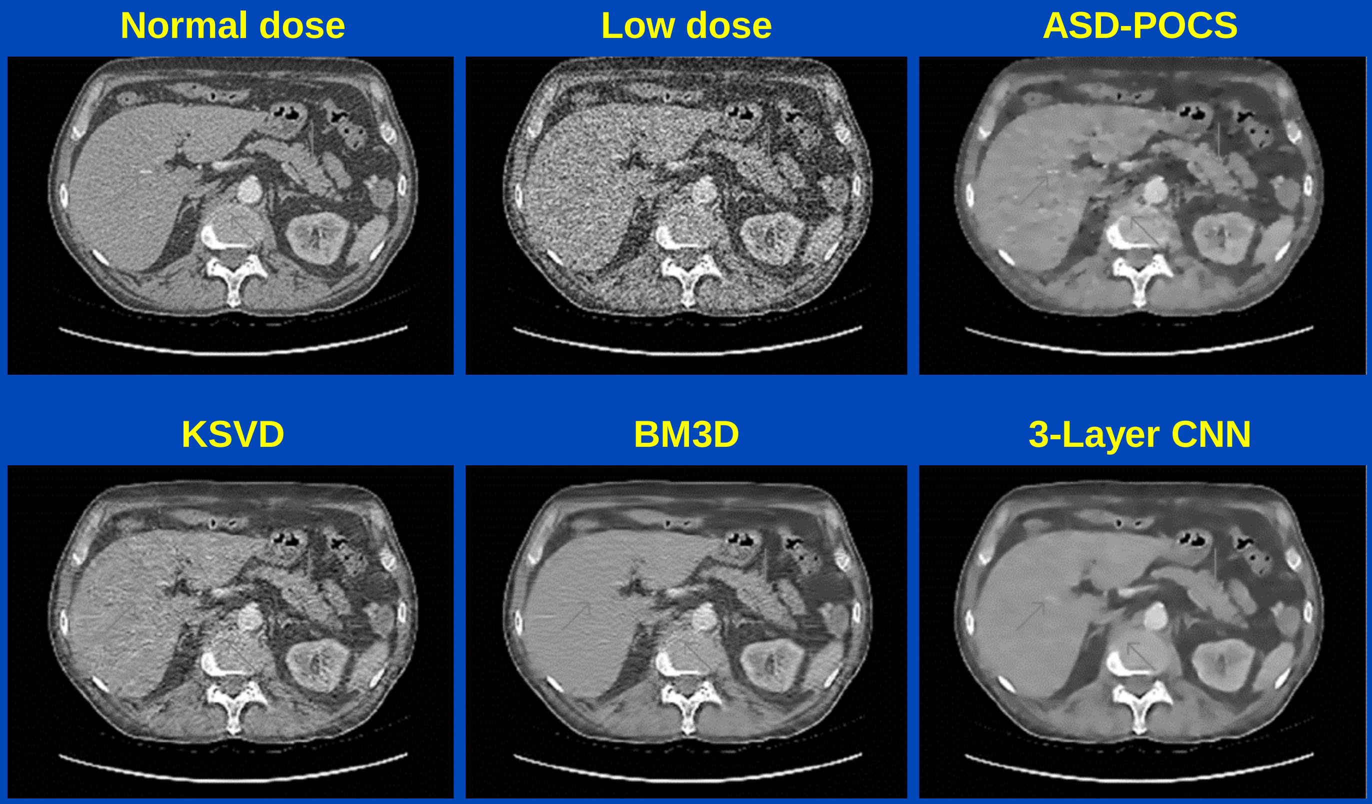
Also right:
Attend my refresher course "Basics of AI" tomorrow morning at 8:00 in room Saturn.

Important, but boring

NOISE REDUCTION

Negative Example

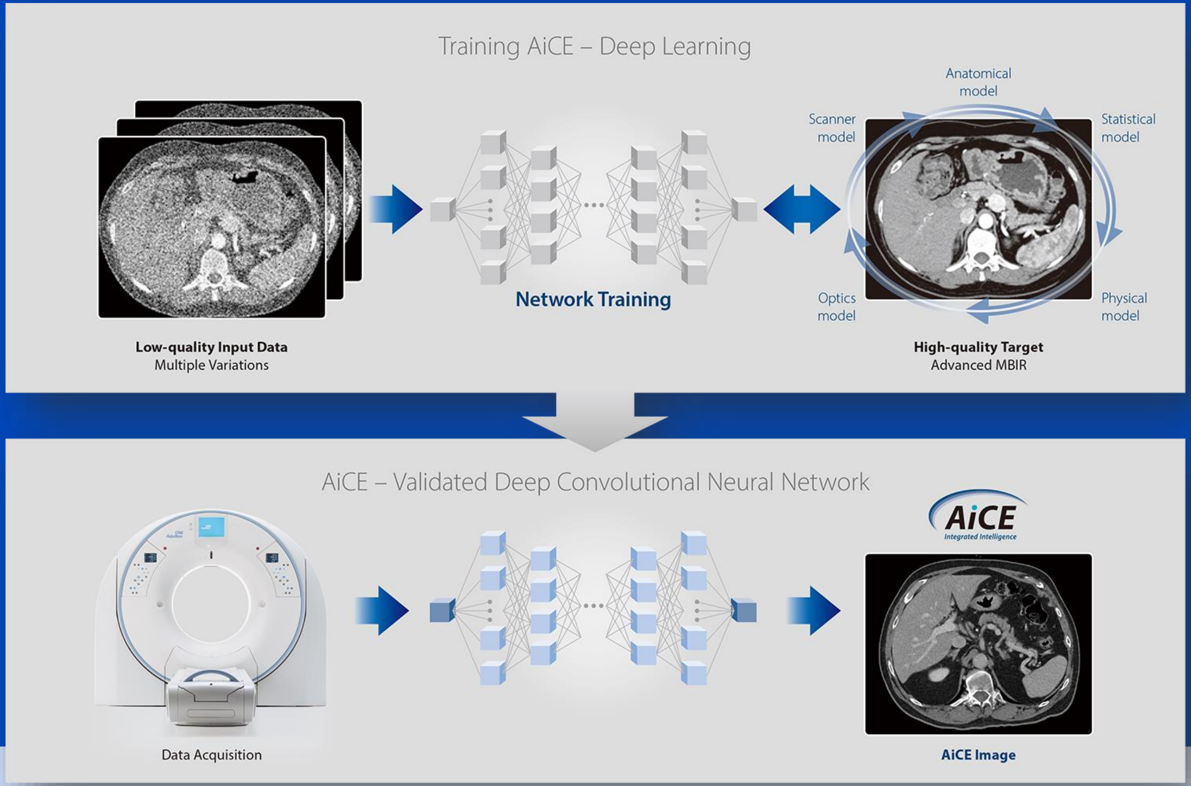
- 3-layer CNN uses low dose and corresponding normal dose image patches for training



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.

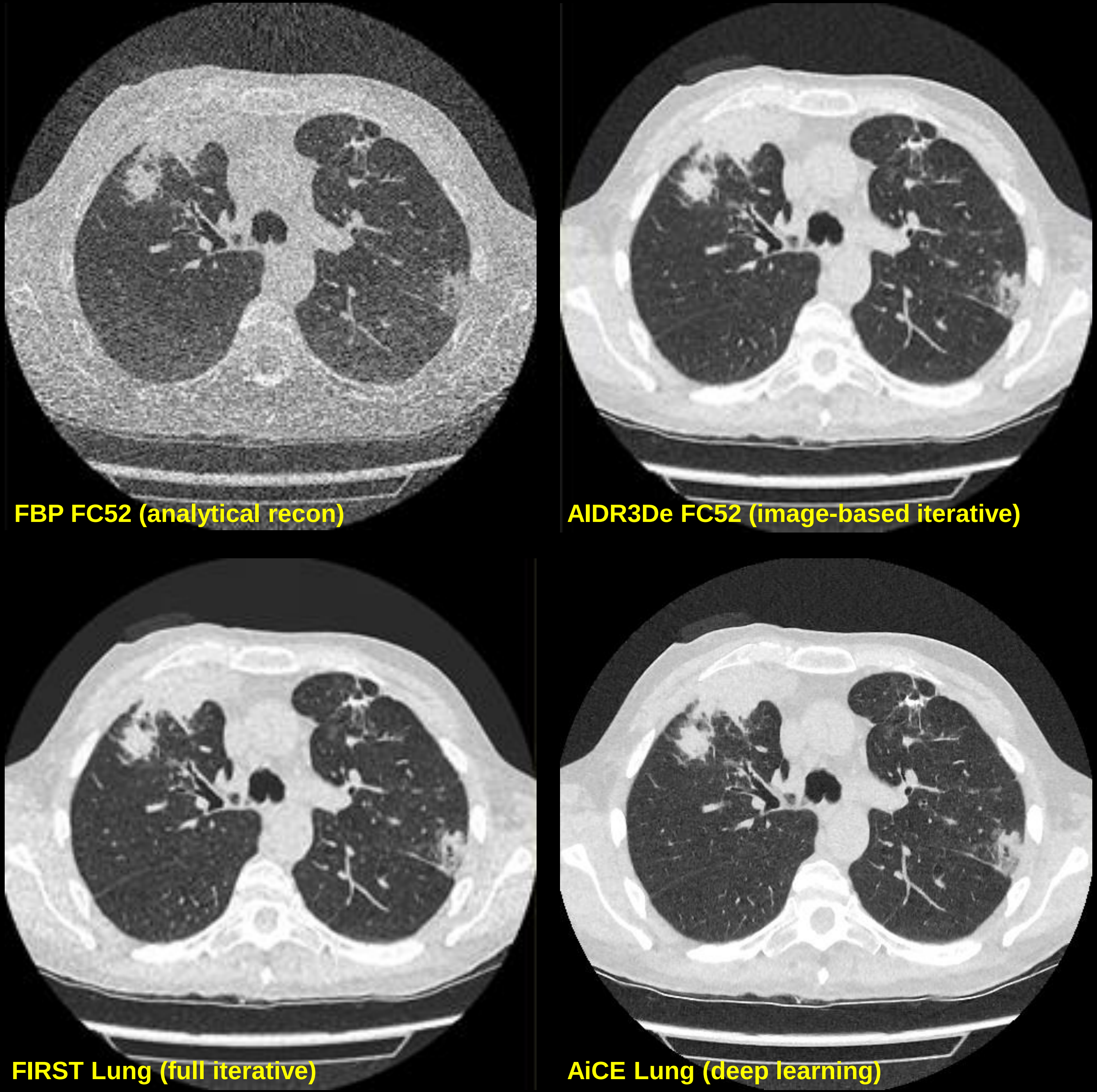
Noise Removal: Canon‘s AiCE

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



K. Boedeker. AiCE Deep Learning Reconstruction: Bringing the Power of Ultra High Resolution CT to Routine Imaging. Whitepaper, Canon, 2019.

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



Courtesy of
Radboudumc,
the Netherlands

CT Vendor-Based DL Denoising Algorithms

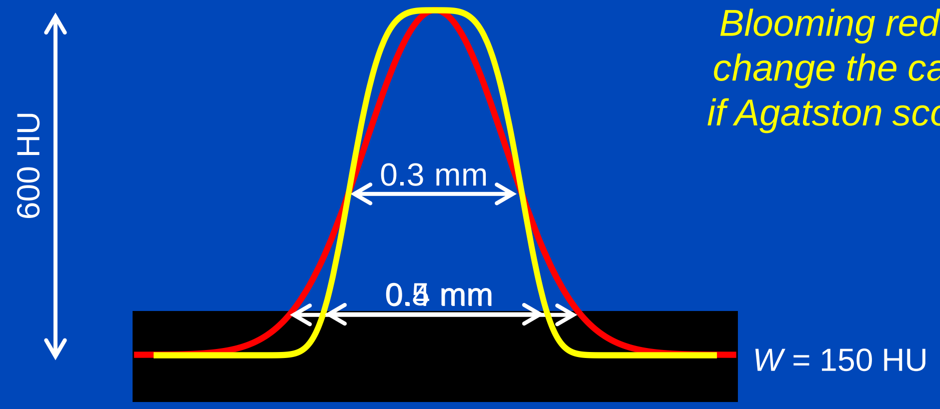
Name	Vendor	Source	Labels	Comments
AiCE	Canon	Low dose AIDR3D images (by noise injection)	FIRST reconstruction of normal dose data	
True Fidelity	GE	Low dose rawdata/images (by noise injection)	FBP reconstruction of normal/high dose data	Probably uses BP layer. Said to preserve noise texture.
Precise Image	Philips	Low dose images (by noise injection)	FBP reconstruction of normal dose data	
-	Siemens	-	-	
AIIR	United	Low dose sinograms (by noise injection?)	Iterative reconstruction of normal dose data	Neural network regularizes IR

Interesting, but misleading

SPATIAL RESOLUTION ENHANCEMENT

Canon PIQE

- Precise IQ Engine (PIQE).
- Trained on data from Canon's Precision high spatial resolution CT
- Converts images from Canon's standard spatial resolution scanners (e.g. Aquilion ONE / PRISM edition) to look like high spatial resolution images.



Warning:
Blooming reduction might change the calcium score, if Agatston scoring is used.

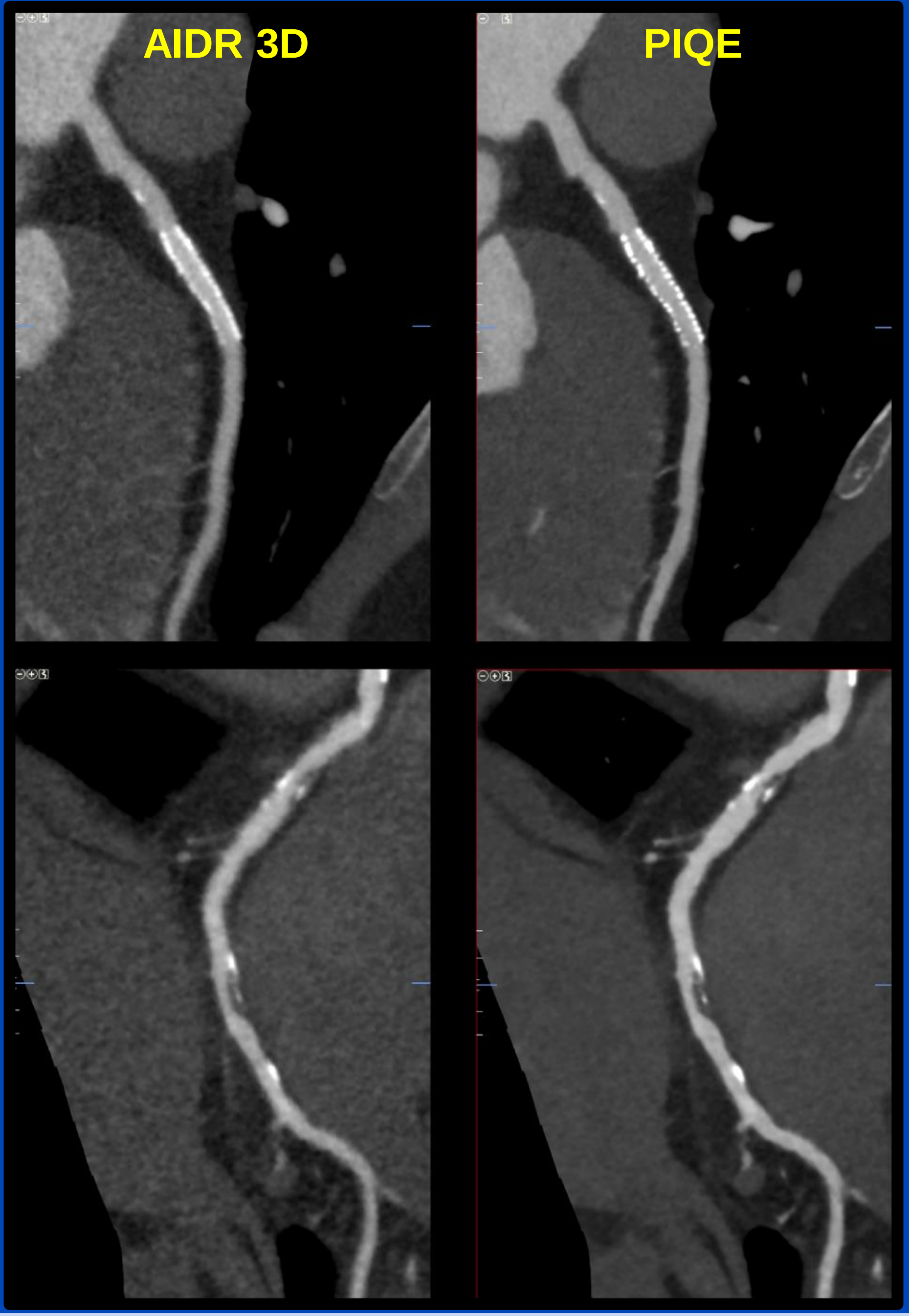


Image courtesy of Canon Medical Systems

Surprising, but well performing

SCATTER ESTIMATION - FAST PHYSICS

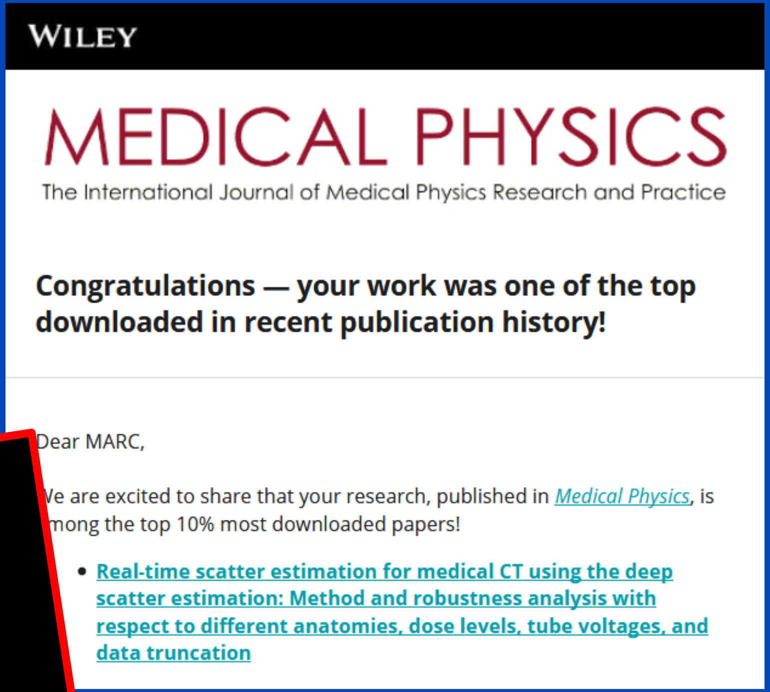
Deep Scatter Estimation (DSE)


TOP DOWNLOADED PAPER 2018-2019

CONGRATULATIONS TO

Marc Kachelriess

whose paper has been recognized as
one of the most read in


WILEY

MEDICAL PHYSICS

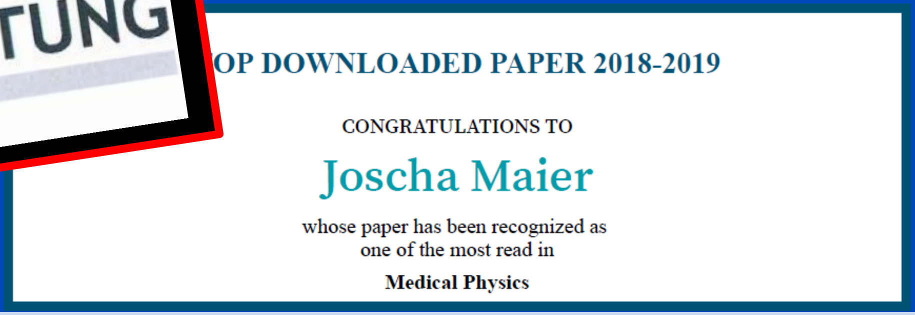
The International Journal of Medical Physics Research and Practice

Congratulations — your work was one of the top downloaded in recent publication history!

Dear MARC,

We are excited to share that your research, published in *Medical Physics*, is among the top 10% most downloaded papers!

- Real-time scatter estimation for medical CT using the deep scatter estimation: Method and robustness analysis with respect to different anatomies, dose levels, tube voltages, and data truncation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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.

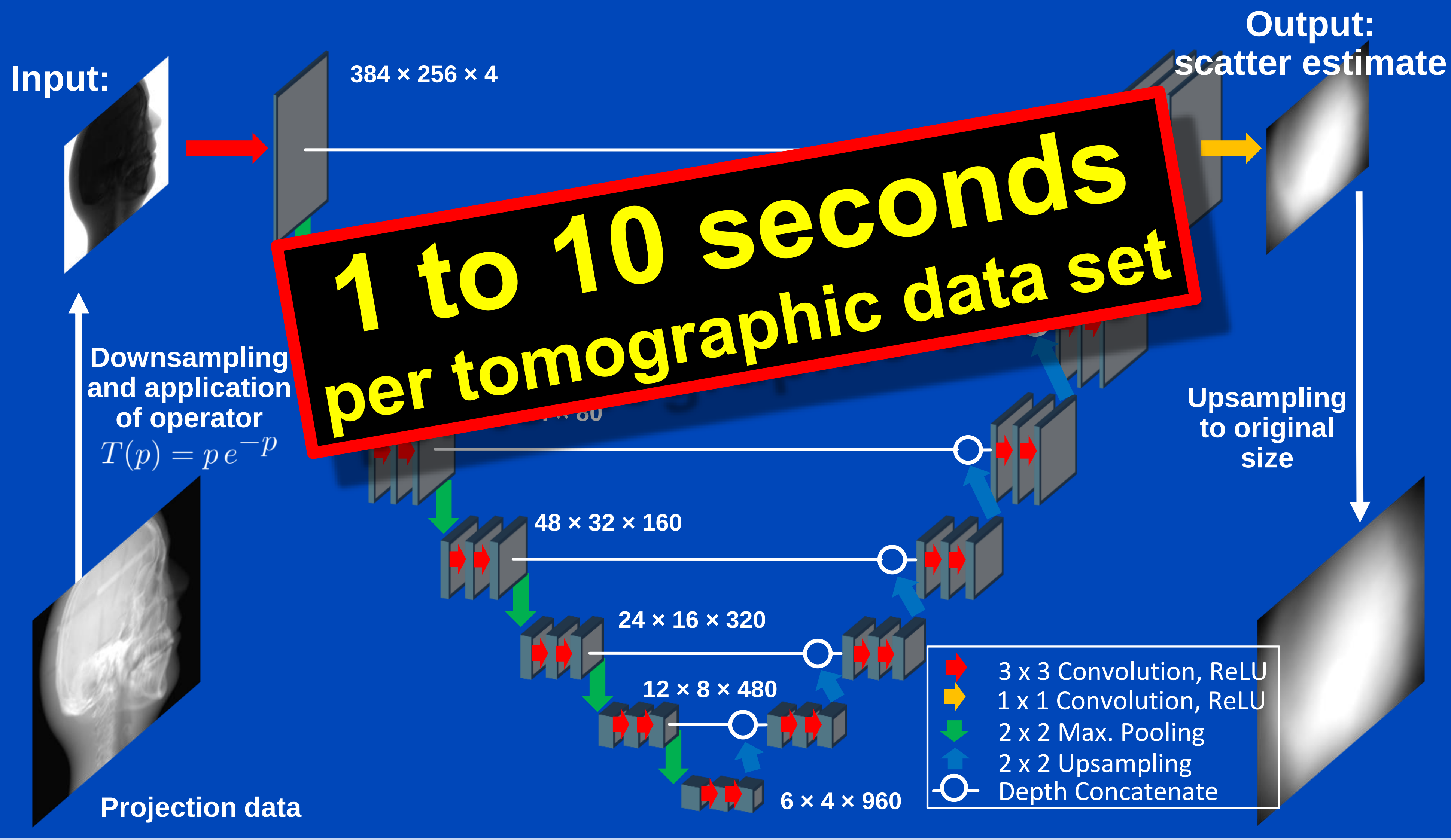
Monte Carlo Scatter Estimation

- Simulation of photon trajectories according to physical interaction probabilities.
- Simulating a large number of photon … approximates the actual scatter distrib…

1 to 10 hours
per tomographic data set

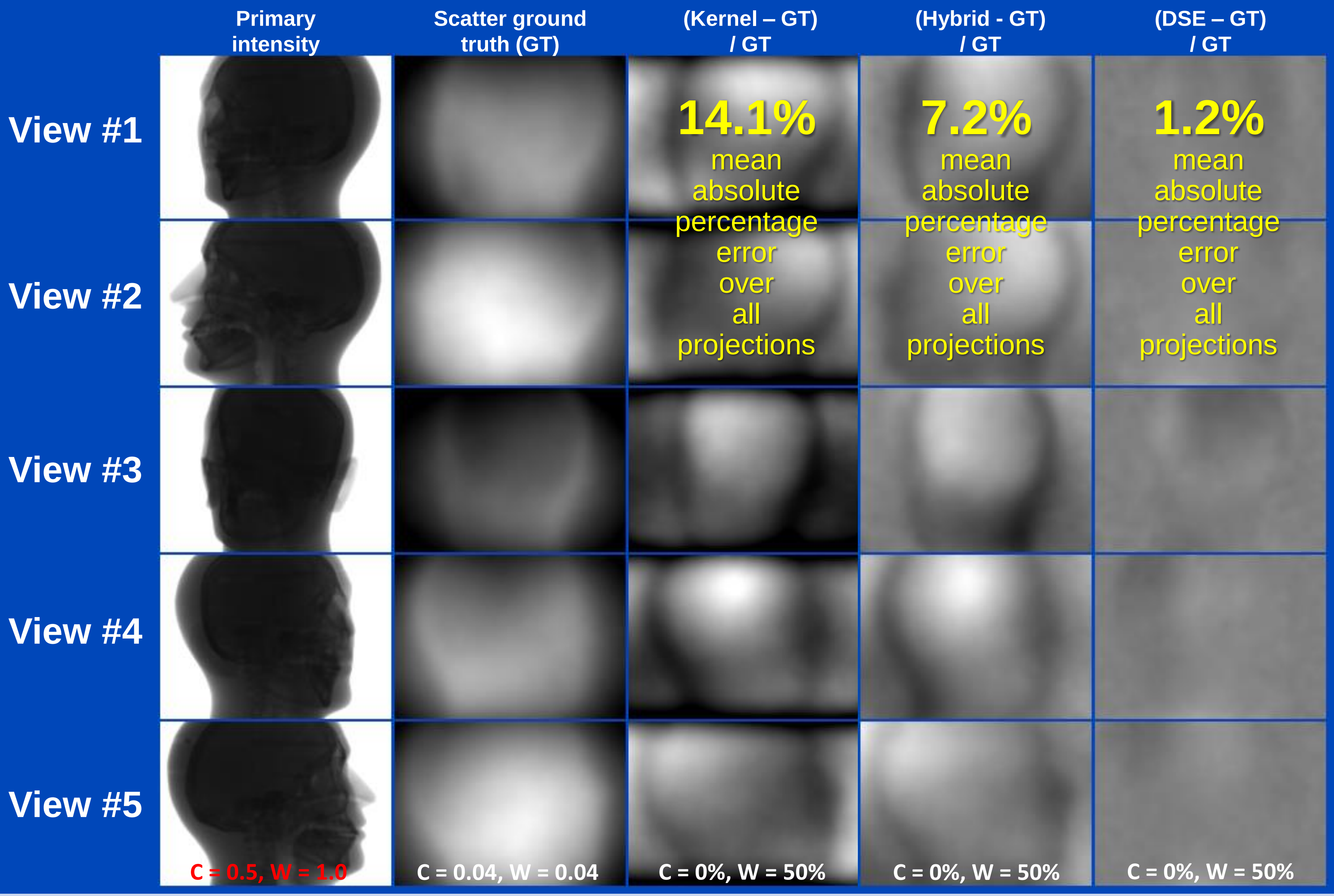
Deep Scatter Estimation

Network architecture & scatter estimation framework



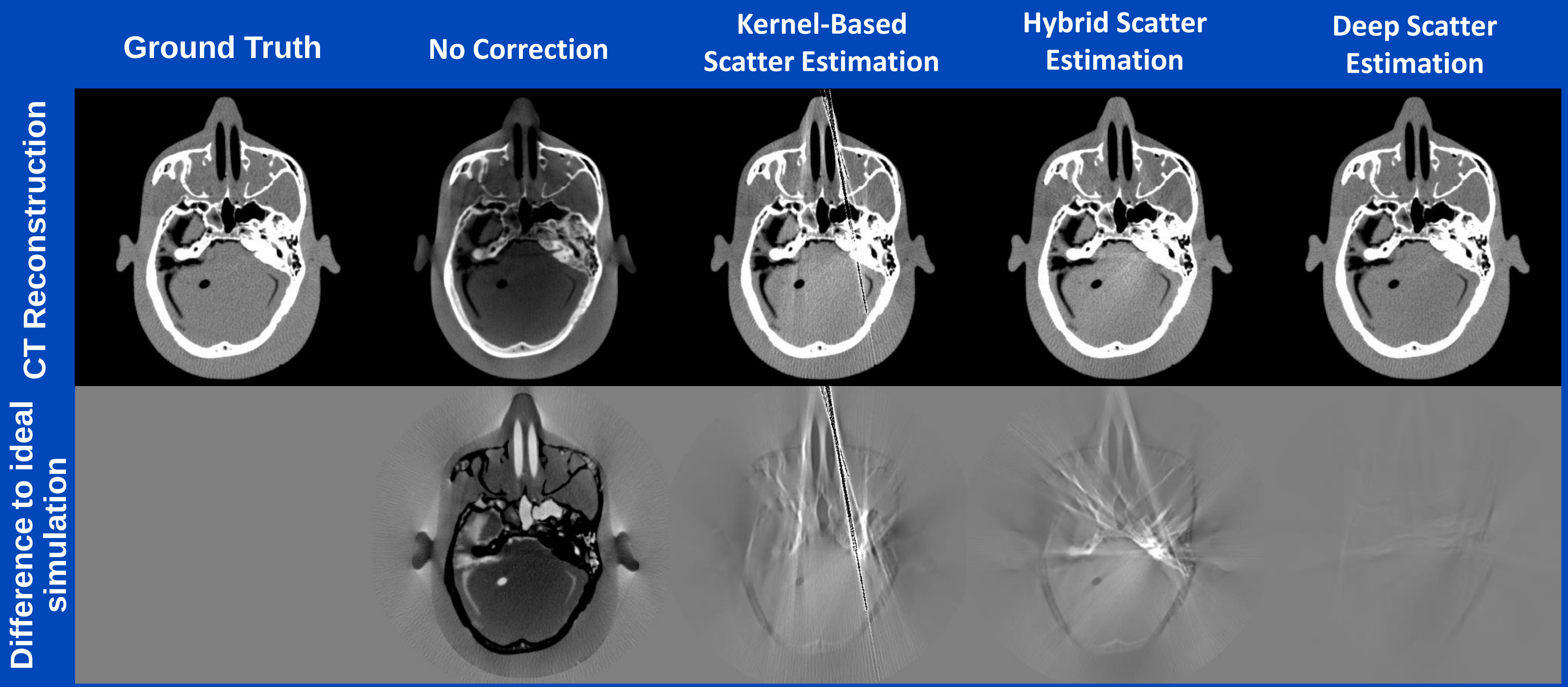
J. Maier, M. Kachelrieß et al. Deep scatter estimation (DSE). SPIE 2017 and Journal of Nondestructive Evaluation 37:57, July 2018.
J. Maier, M. Kachelrieß et al. Robustness of DSE. Med. Phys. 46(1):238-249, January 2019.

Results on Simulated Projection Data



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

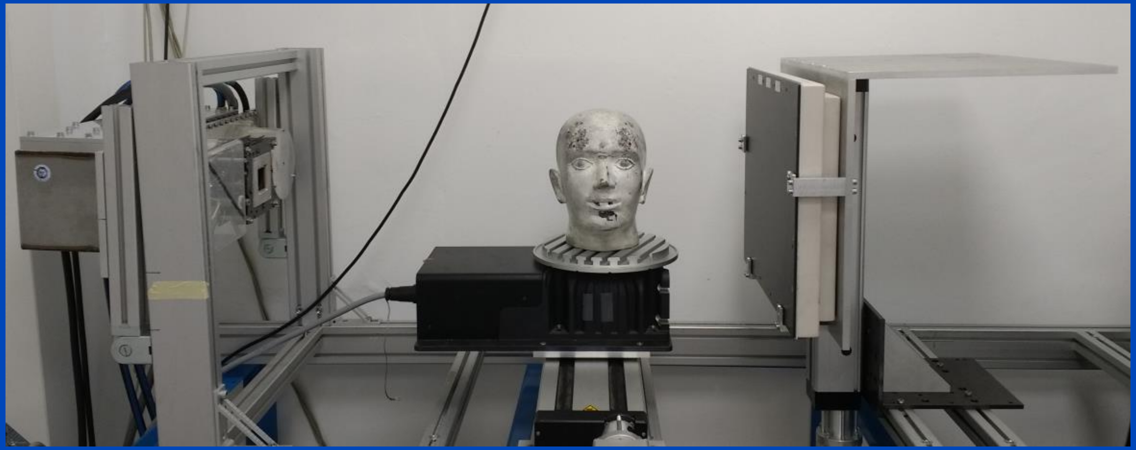
Reconstructions of Simulated Data



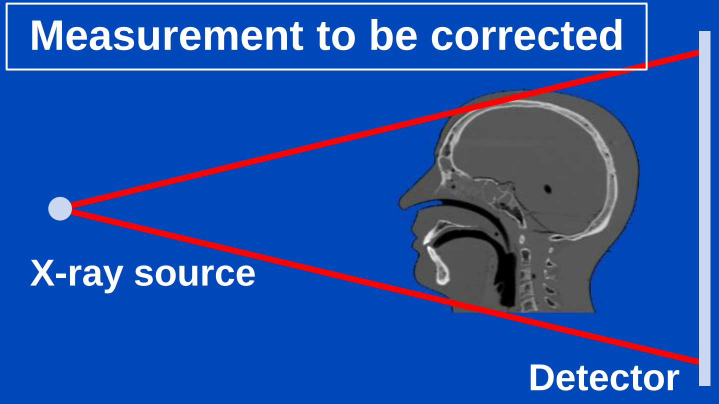
C = 0 HU, W = 1000 HU

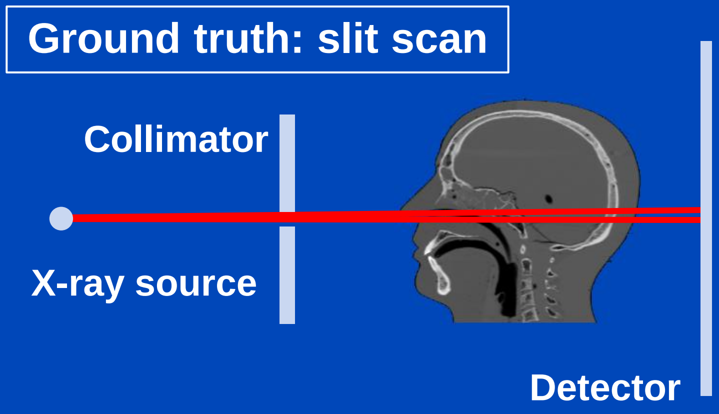
Testing of the DSE Network for Measured Data (120 kV)

DKFZ table-top CT



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





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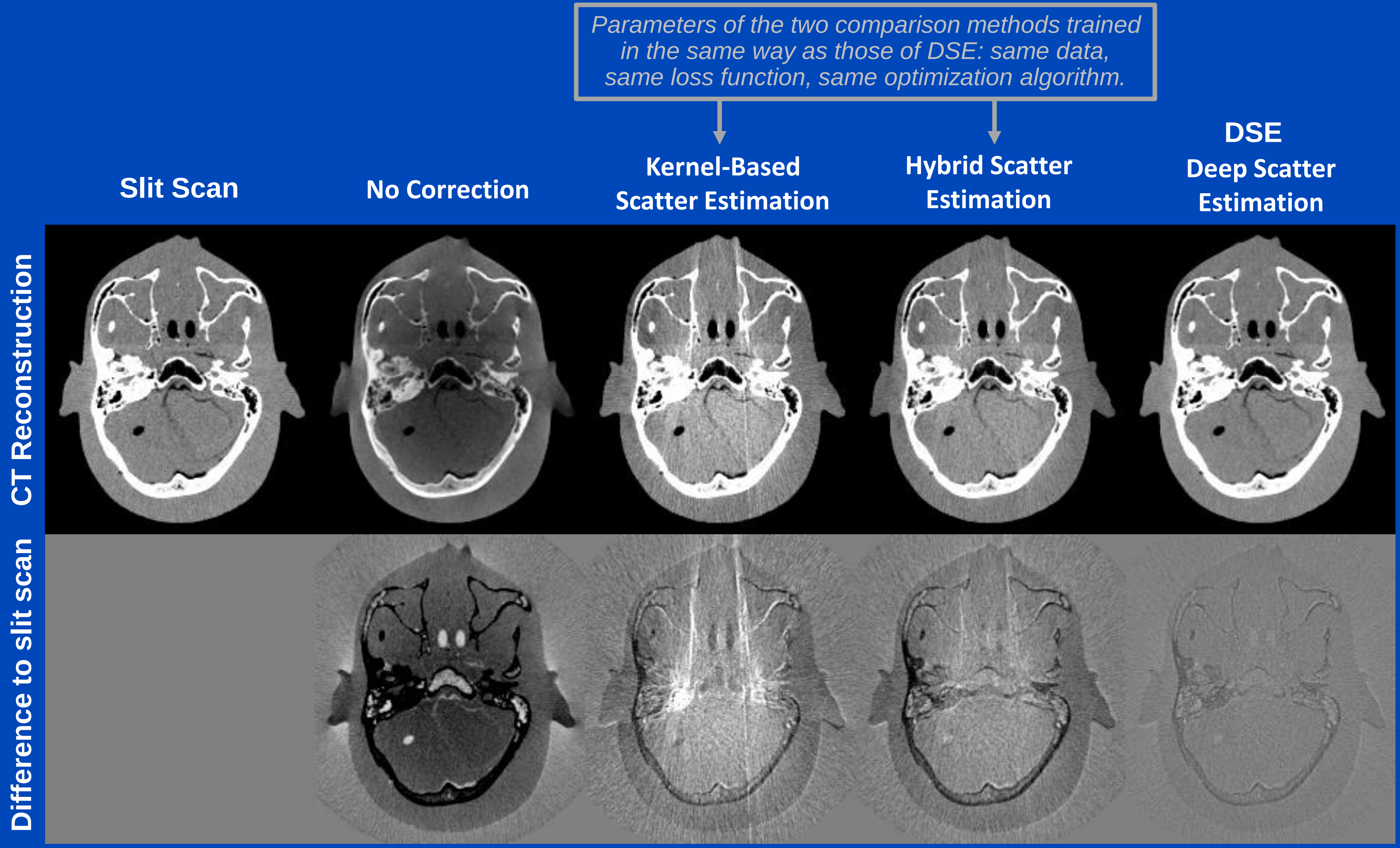
Reconstructions of Measured Data



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.

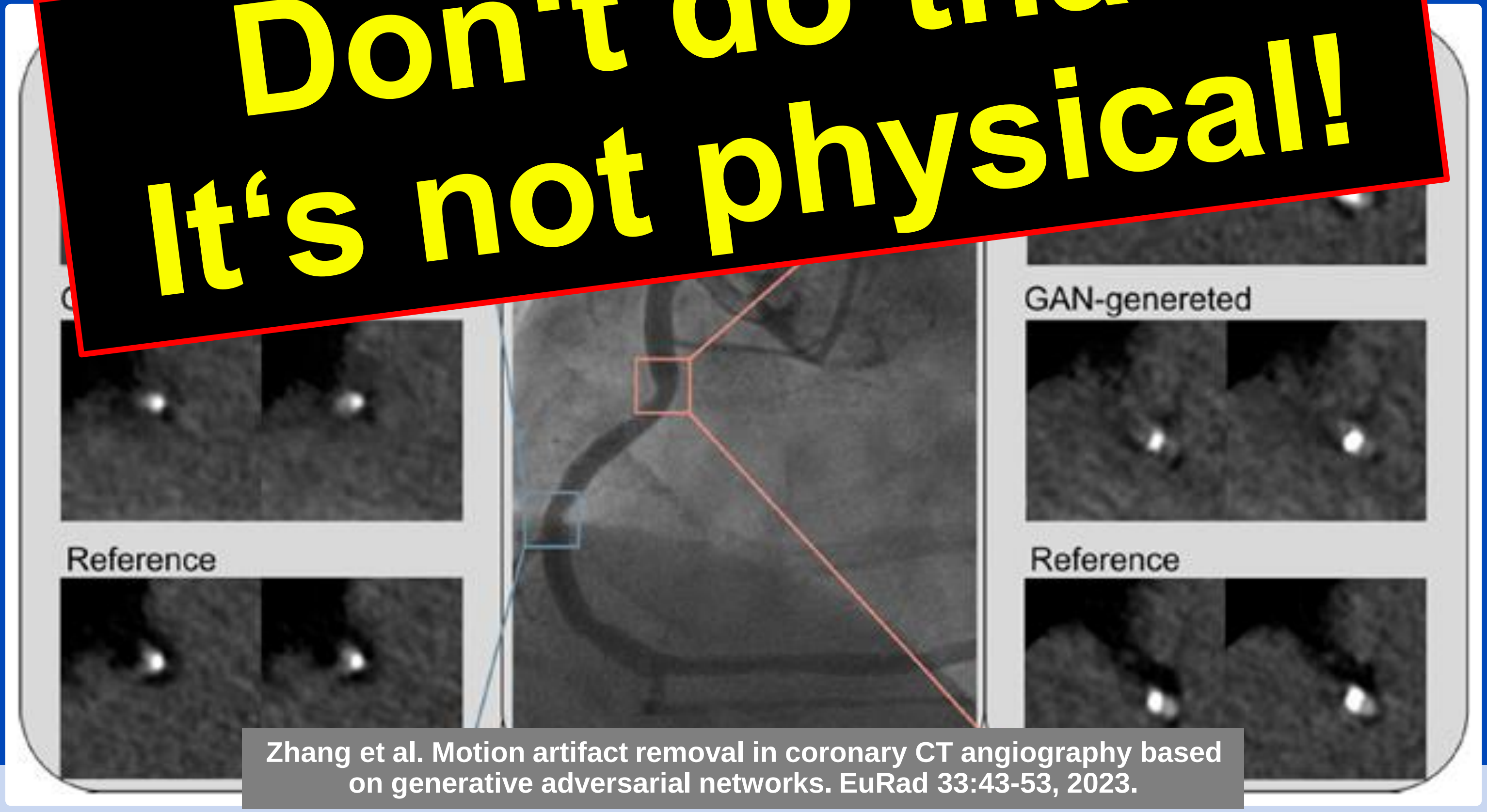
Challenging, but relevant

MOTION COMPENSATION

Deep Cosmetic Motion Artifact Reduction

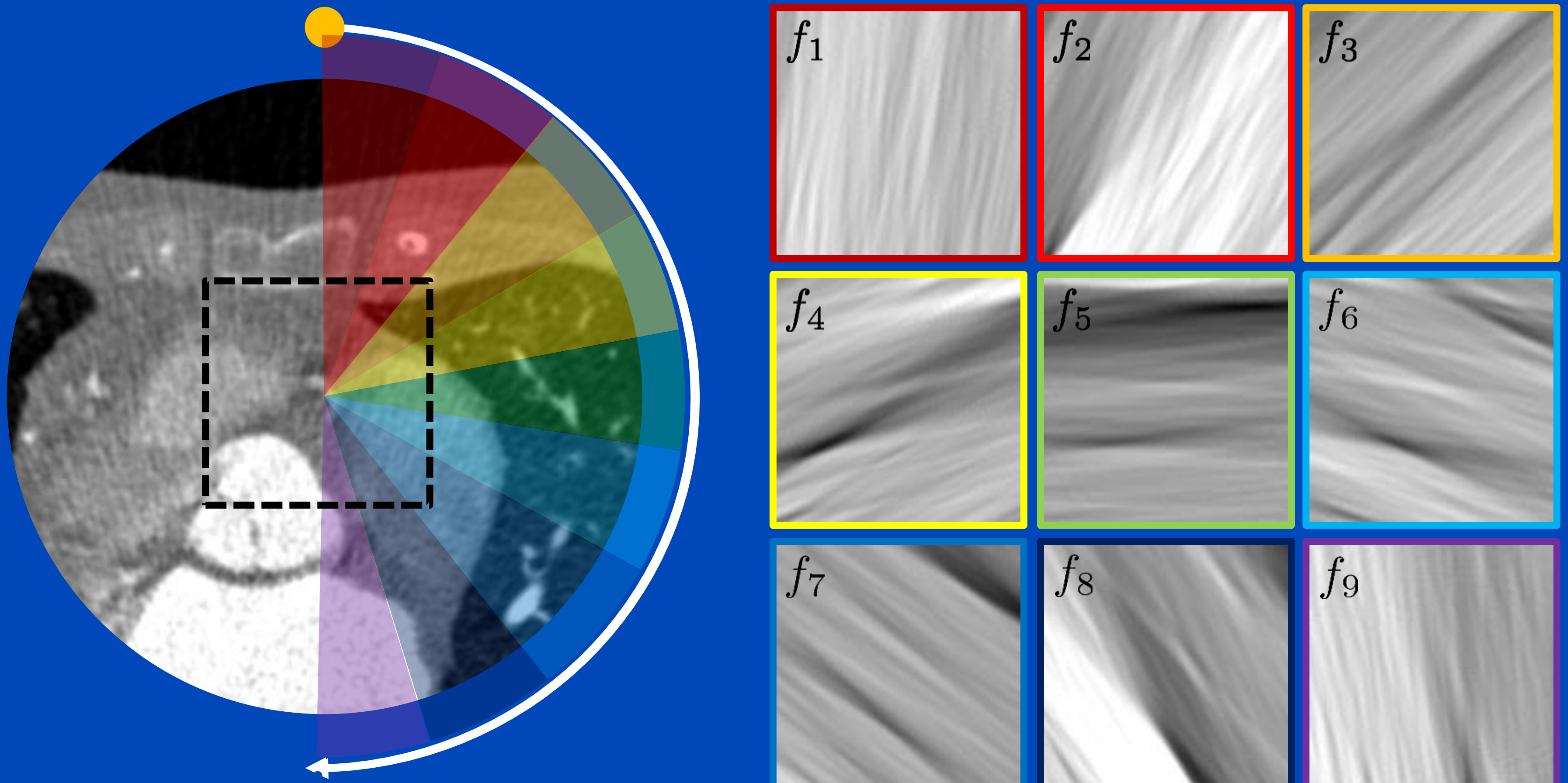
- Image-based correction
  = cosmetic correction
  = similar to pic beauty and others
- May not be the most confident

Don‘t do that!
It‘s not physical!



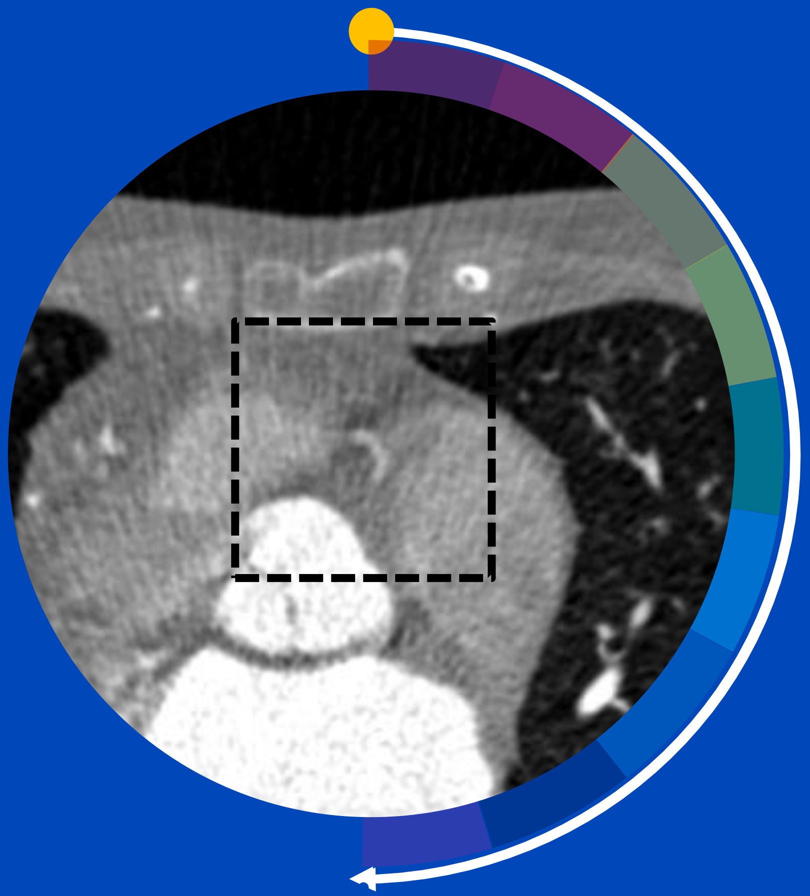
Zhang et al. Motion artifact removal in coronary CT angiography based on generative adversarial networks. EuRad 33:43-53, 2023.

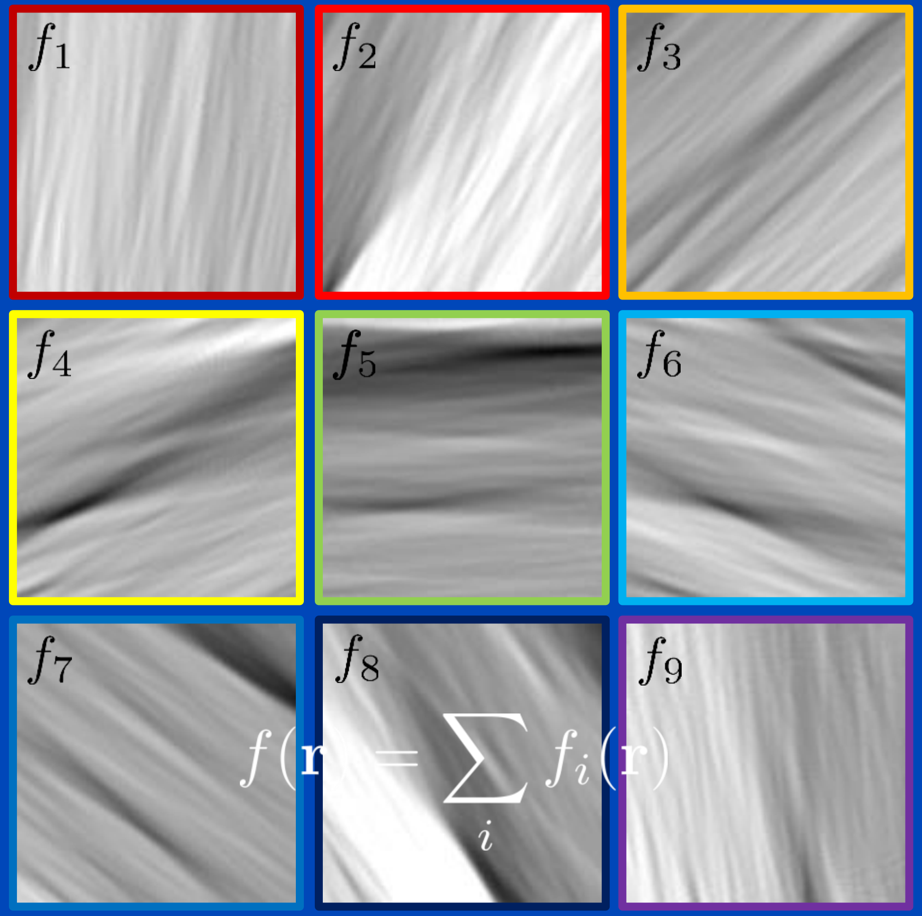
Partial Angle-Based Motion Compensation (PAMoCo)



Animated rotation time = 100 × real rotation time

Partial Angle-Based Motion Compensation (PAMoCo)





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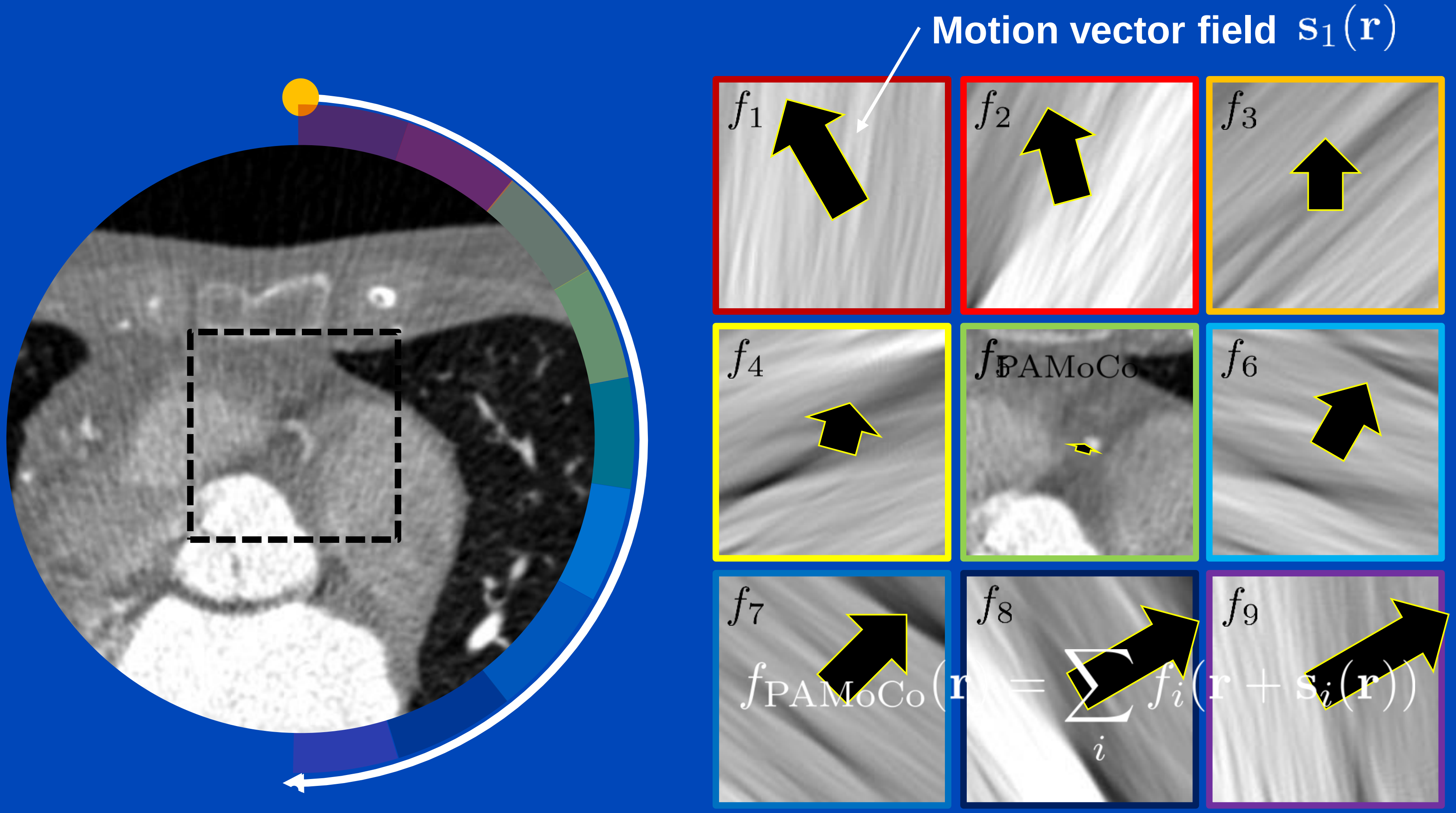


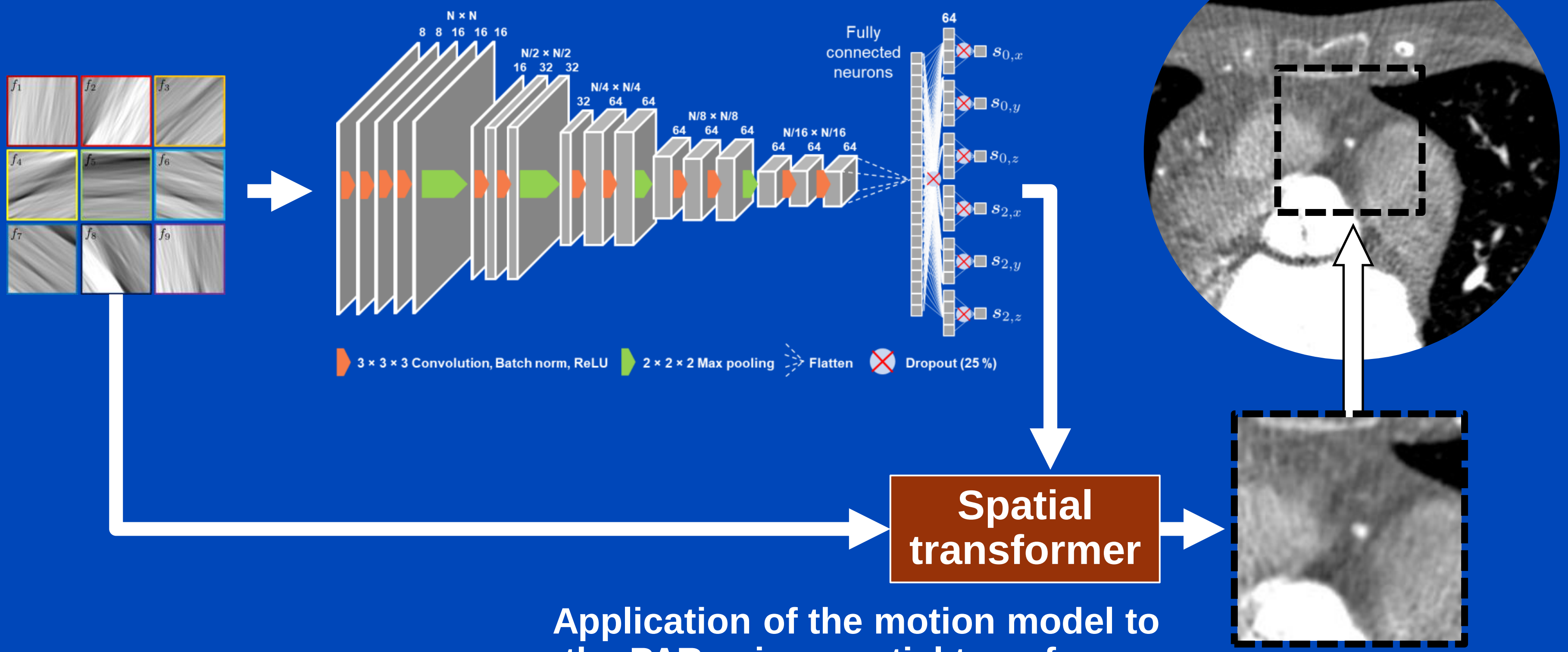
Apply motion vector fields (MVFs) to partial angle reconstructions

Deep Partial Angle-Based Motion Compensation (Deep PAMoCo)

PARs centered around coronary artery

Neural network to predict parameters of a motion model

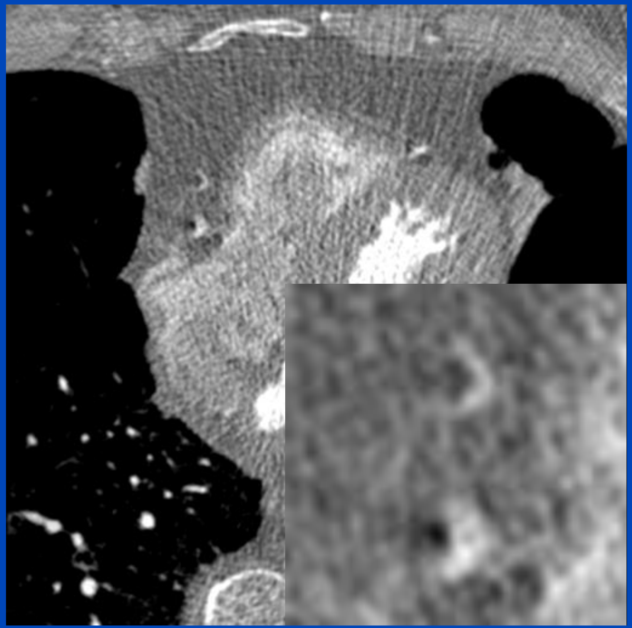
Reinsertion of patch into initial reconstruction

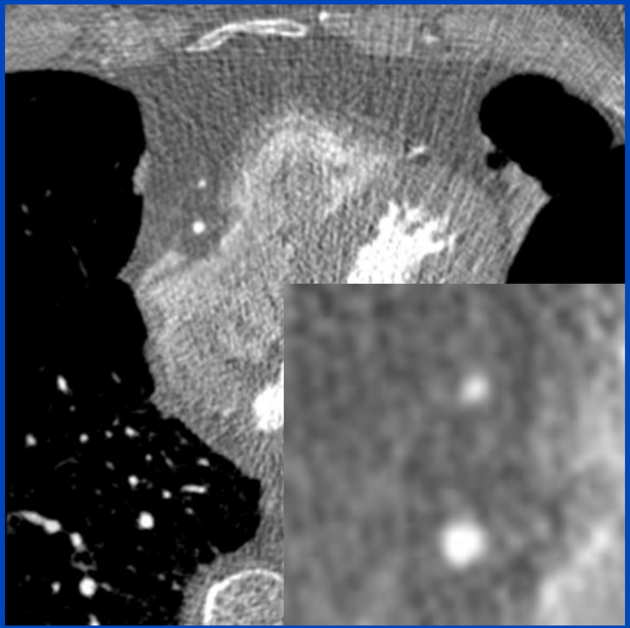


Application of the motion model to the PARs via a spatial transformer

J. Maier, S. Lebedev, J. Erath, E. Eulig, S. Sawall, E. Fournié, K. Stierstorfer, M. Lell, and M. Kachelrieß. Deep learning-based coronary artery motion estimation and compensation for short-scan cardiac CT. Med. Phys. 48(7):3559-3571, July 2021.

Patient 1



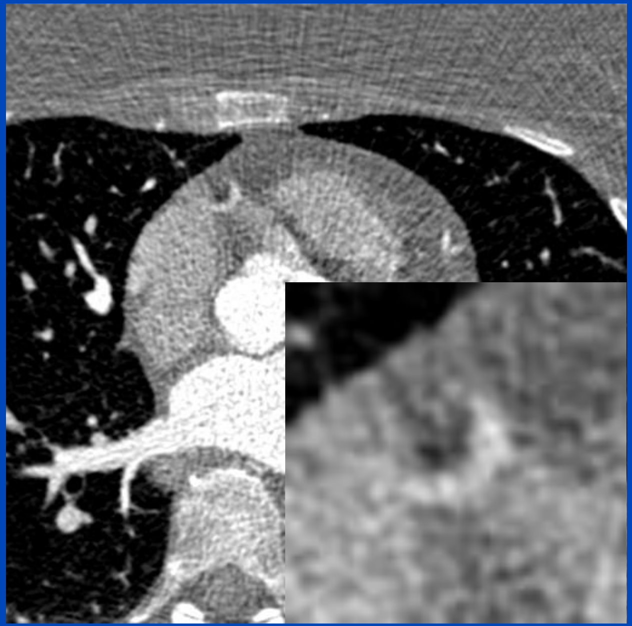


C = 0 HU, *W* = 1400 HU

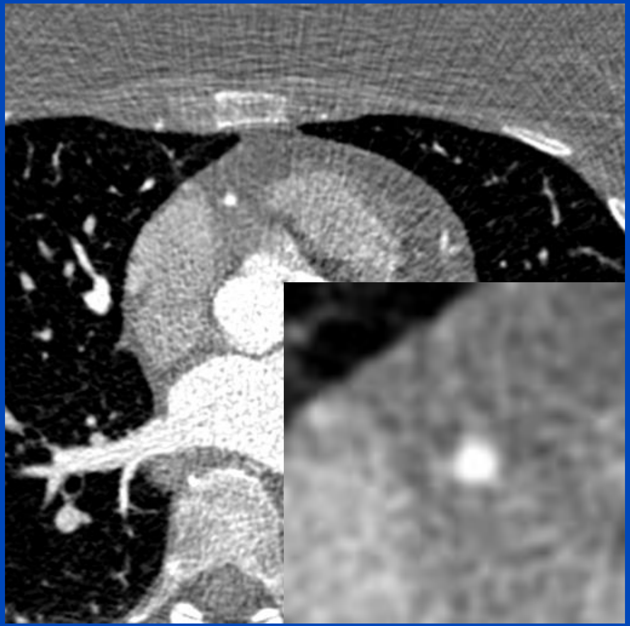
J. Maier, S. Lebedev, J. Erath, E. Eulig, S. Sawall, E. Fournié, K. Stierstorfer, M. Lell, and M. Kachelrieß. Deep learning-based coronary artery motion estimation and compensation for short-scan cardiac CT. Med. Phys. 48(7):3559-3571, July 2021.

Patient 2

Original



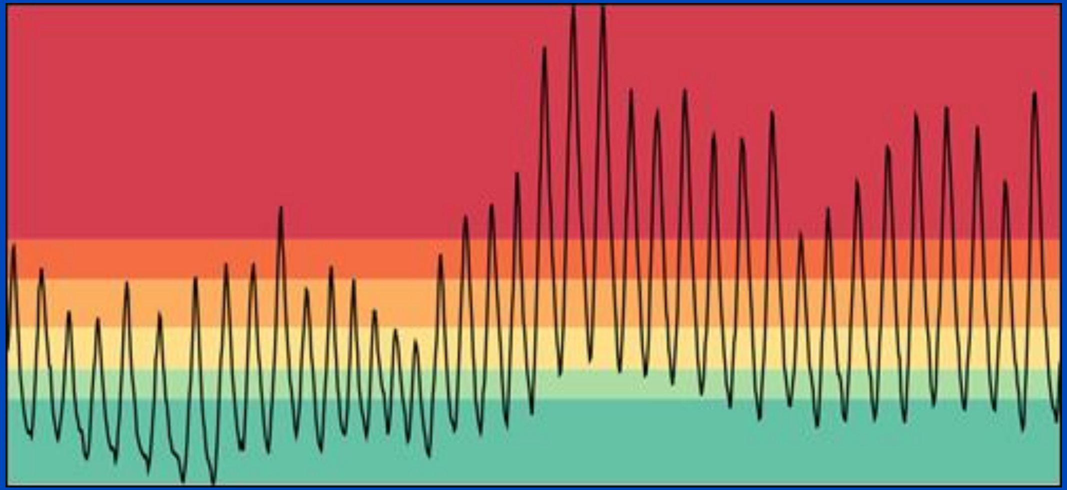
Deep PAMoCo

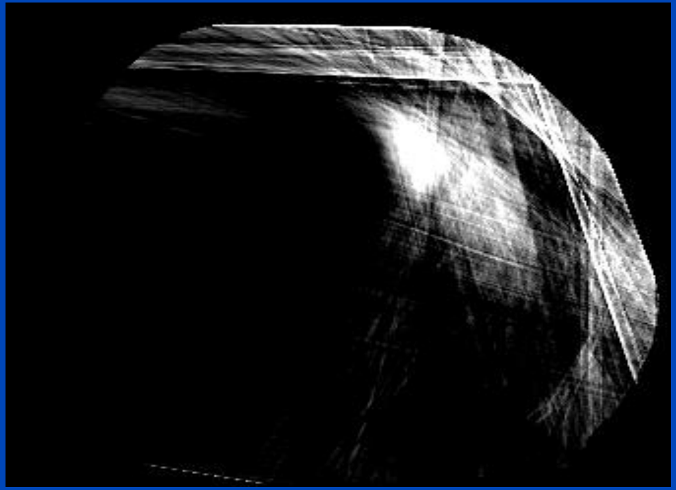


C = 0 HU, *W* = 1600 HU

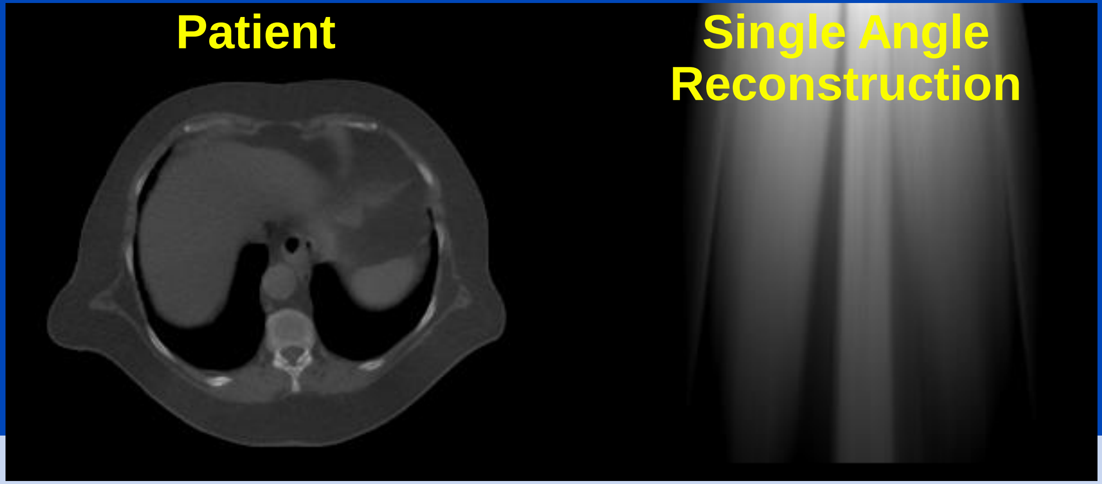
MoCo for CBCT (Slow Rotating CT)

- Gating does only work on regular breating. Otherwise:



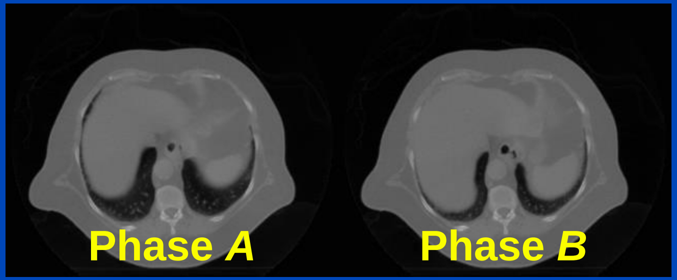


- Idea: Just use a single x-ray projection as a time point for motion estimation:



dkfz.

Training Workflow of Deep SAMoCo

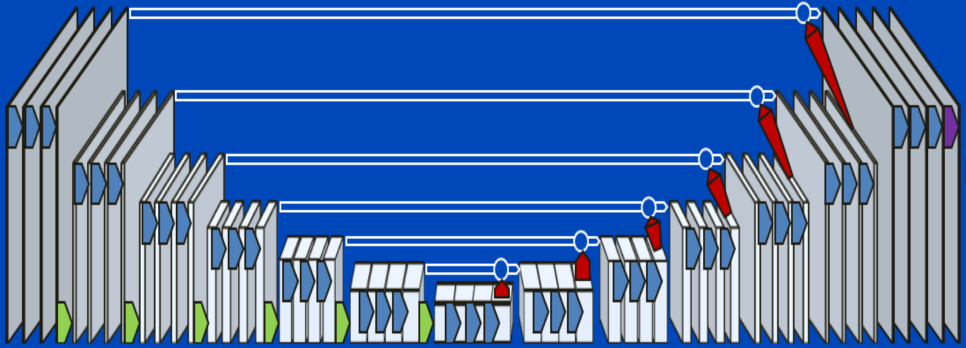


Random patient, random *A* and *B*

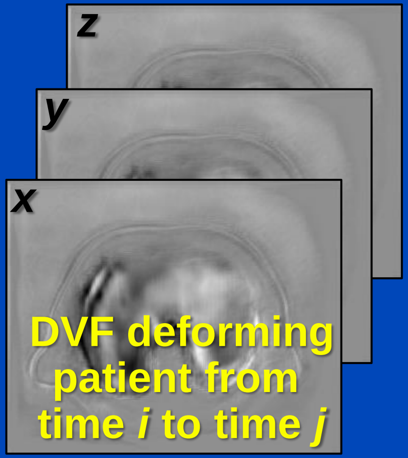
Randomly select
- projection *i* from *A*
- projection *j* from *B*
and backproject.

Calculate DVF from phase *A* to phase *B* (Demons, Deeds, VoxelMorph, …)

Network input



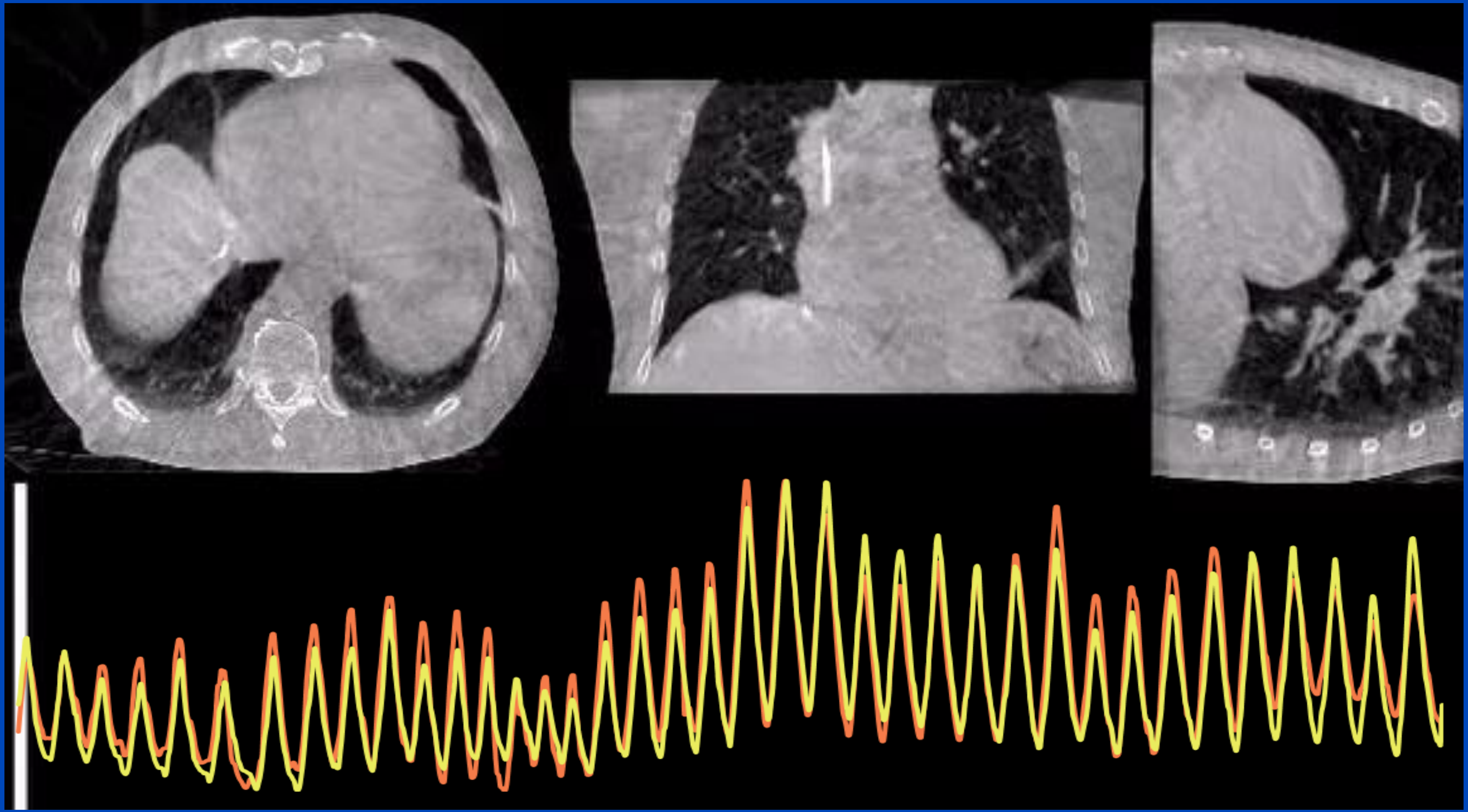
Network (modified U-Net)



Training labels

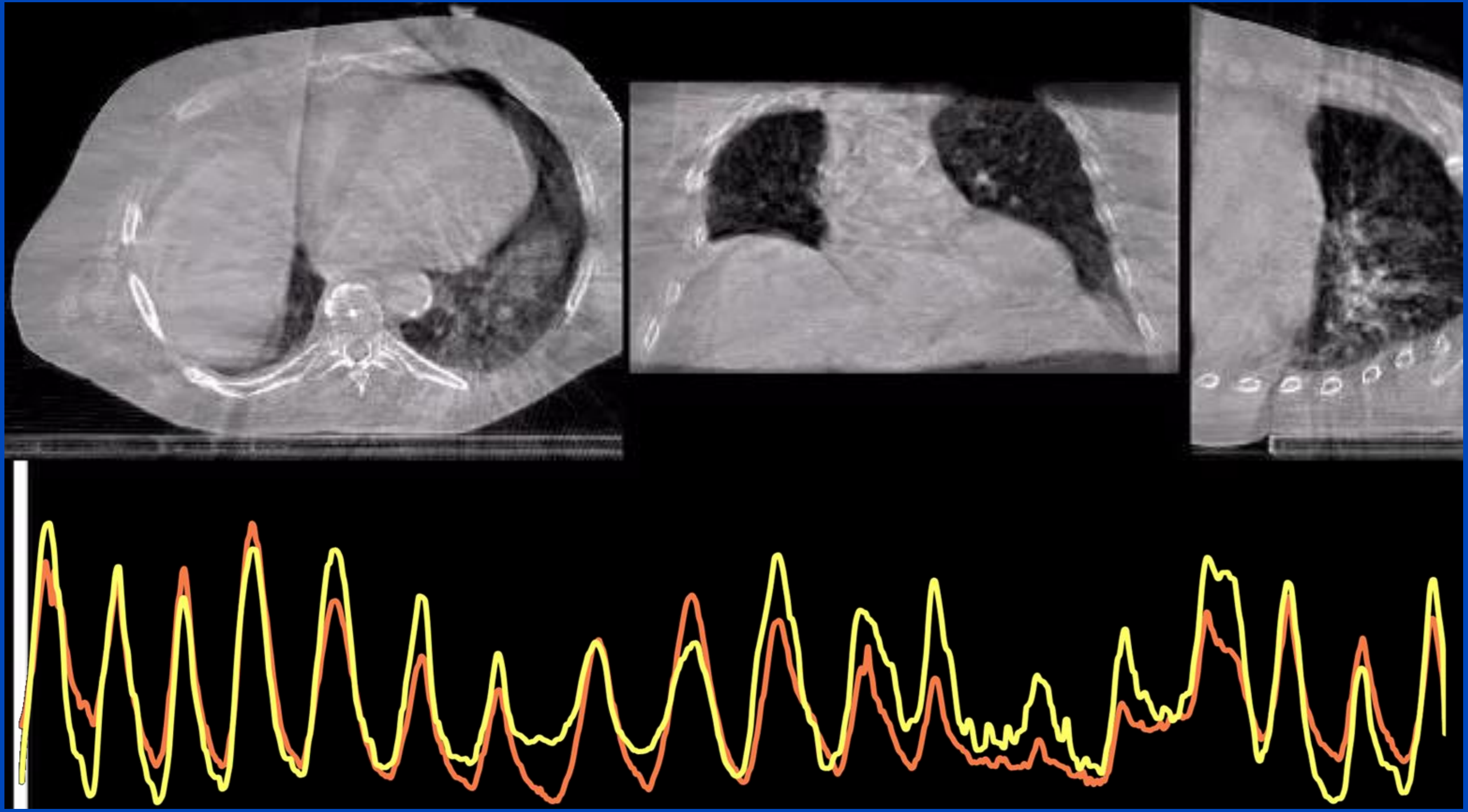
All images shown here are volumes of size 512^3.

VUMC_4DThorax

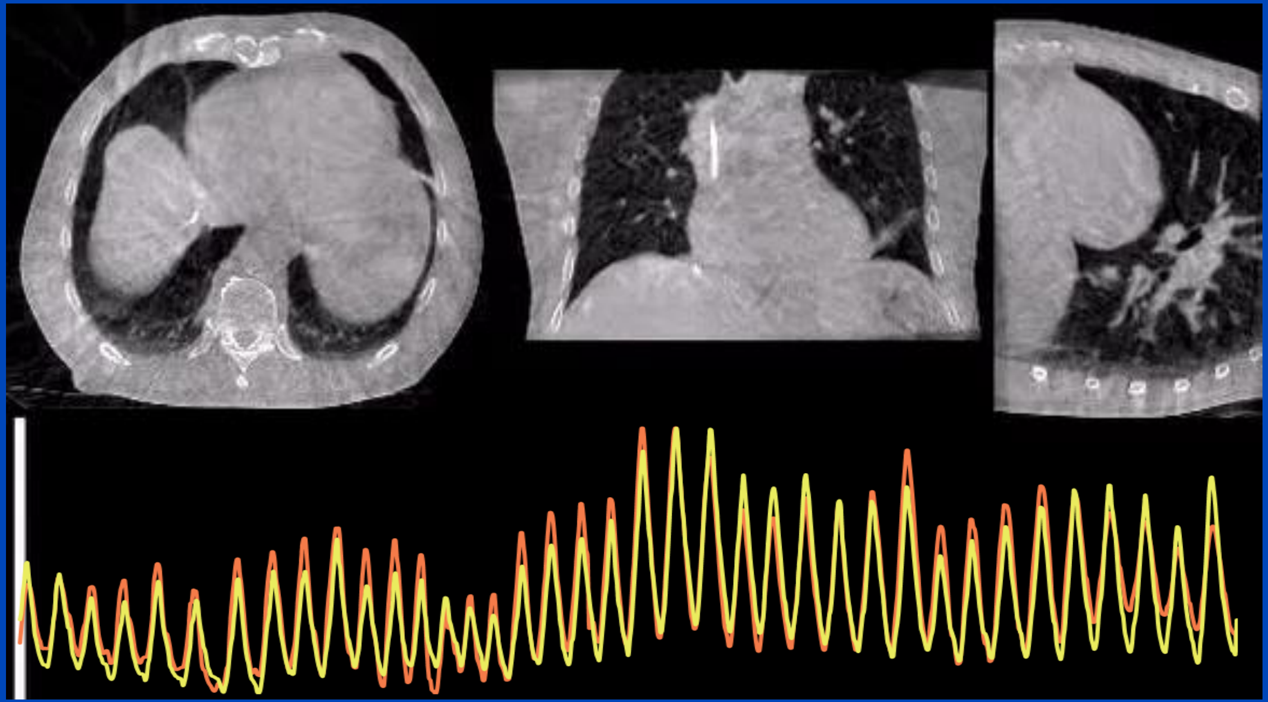


Red: RPM signal (external signal – not used for recon)
Yellow: Diaphragm motion (intrinsic signal – from PAMoCo recon)

MSK 1



Red: RPM signal (external signal – not used for recon)
Yellow: Diaphragm motion (intrinsic signal – from PAMoCo recon)



Imaging ($t < 0$)

Treatment ($t > 0$)

t

Lots of missing data

DETRUNCATION

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

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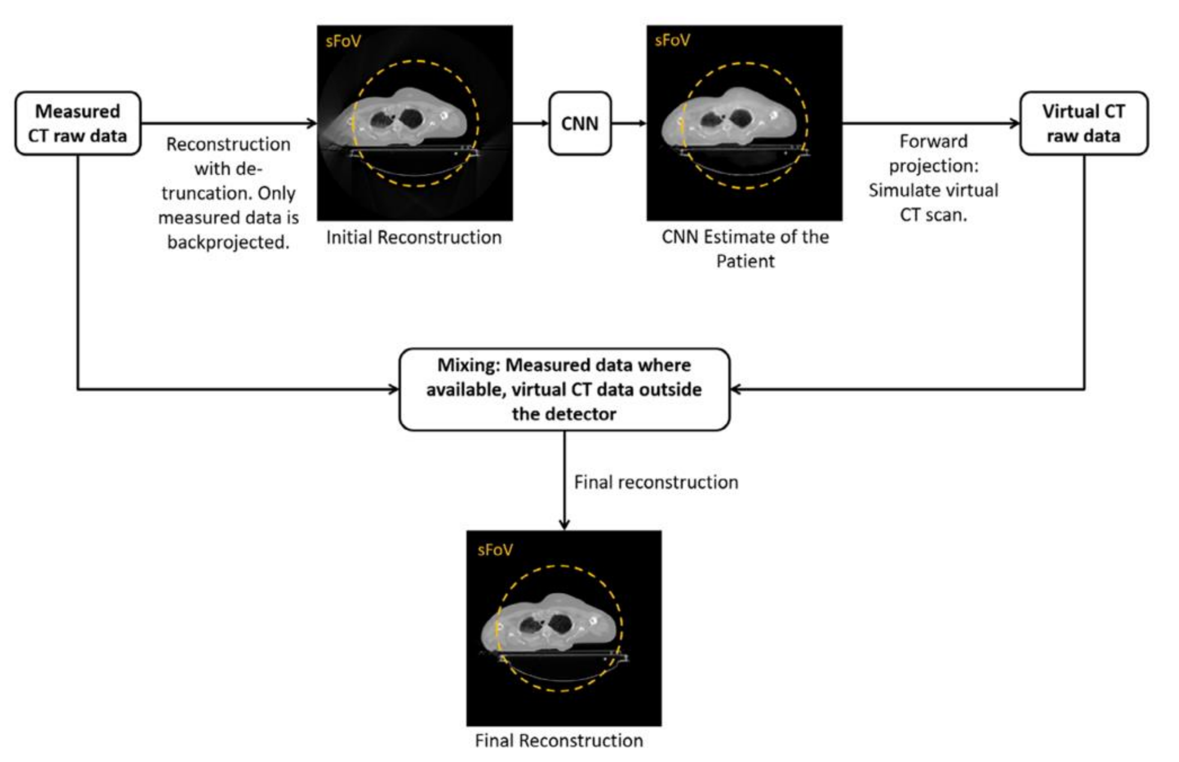
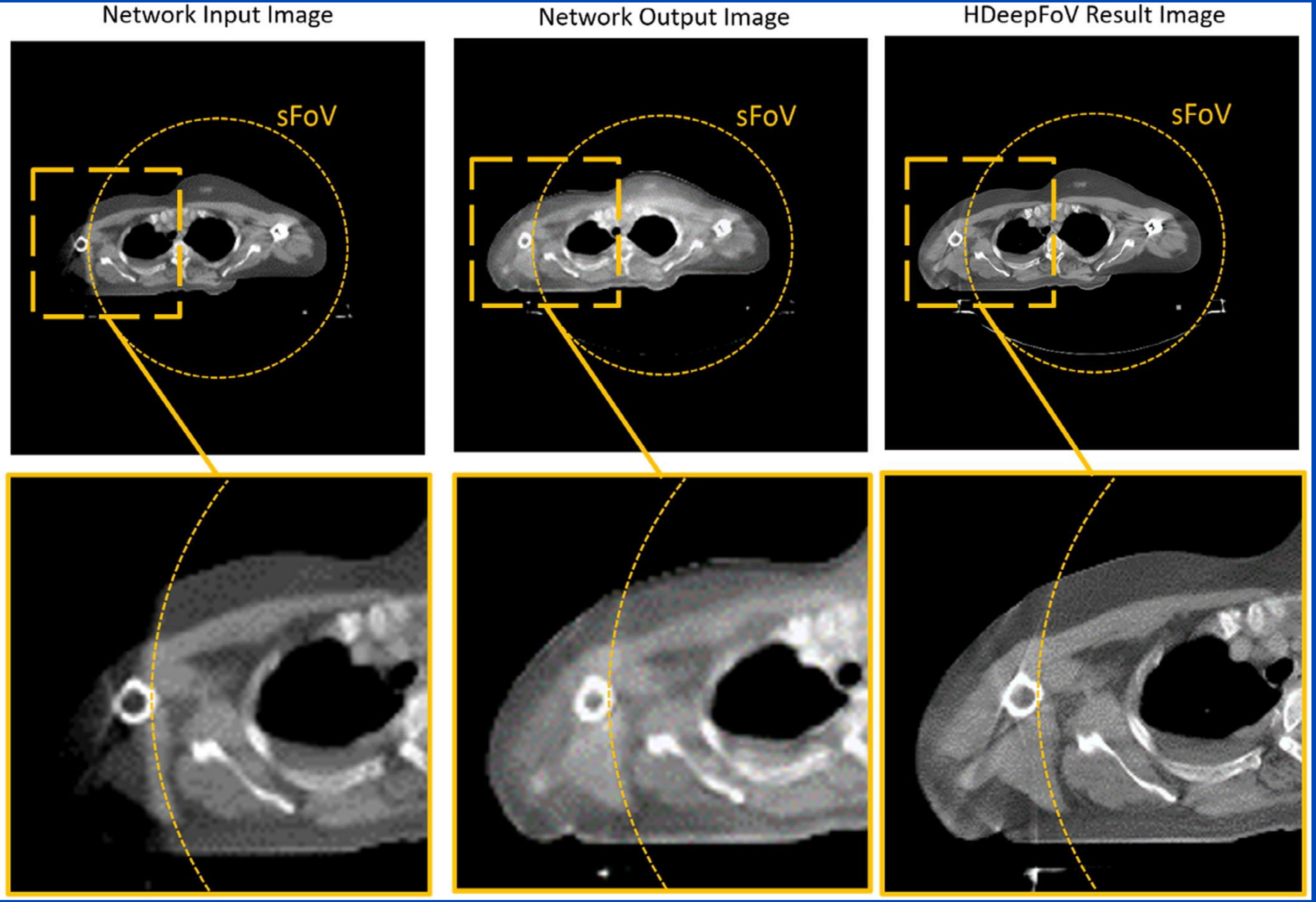


Fonseca, Gabriel Paiva, et al. "Evaluation of novel AI-based extended field-of-view CT reconstructions." *Medical Physics* (2021).



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

Latent Space Reconstruction and its Application to CT Detruncation: Latent Detruncation

Anton Kabelac, Elias Eulig, Joscha Maier, Michael Knaup, and Marc Kachelrieß

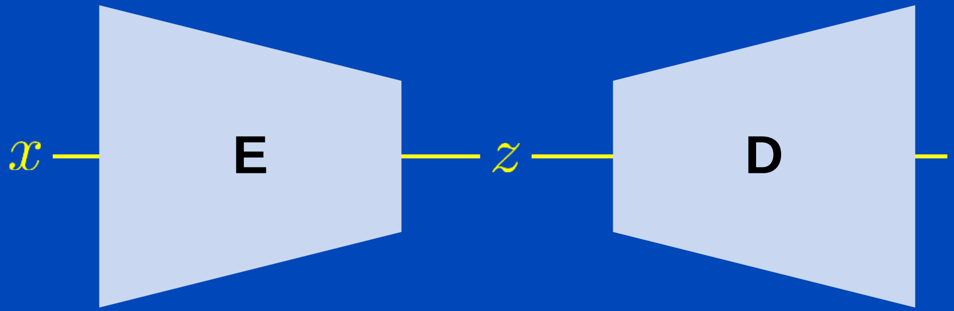
Abstract—**Truncation in CT occurs when parts of the patient laterally exceed the field of measurement (FOM). This is typically the case for obese patients in clinical CT and for most patients in CBCT unless CBCT uses a shifted detector or a very large detector. Conventional reconstruction algorithms (analytic, iterative, deep learning) will also suffer from severe truncation artifacts. Correcting for these artifacts within the FOM is easy, but providing a good reconstruction quality of the parts that lie outside the FOM is hard and has never been achieved, yet.**

In this work, we propose a novel deep learning-based approach called the latent space reconstruction (LSR). We apply LSR to the

(FOV) extension, have been proposed. Early techniques for the reconstruction of incomplete projection data primarily fall roughly into two groups. The first group is made up of data completion methods, like more or less simple extrapolation algorithms. Reference [1] used the size and slope of a water cylinder fitted into each projection to estimate suitable projection extension. Other studies used cosine fitting and elliptical extrapolation, sometimes combined with consistency conditions, to estimate a convex hull of the patient in order to

What is an Autoencoder?

- In and output domain are the same, here *x*.
- Bottleneck *z* enforces the encoder and decoder to do a good job.

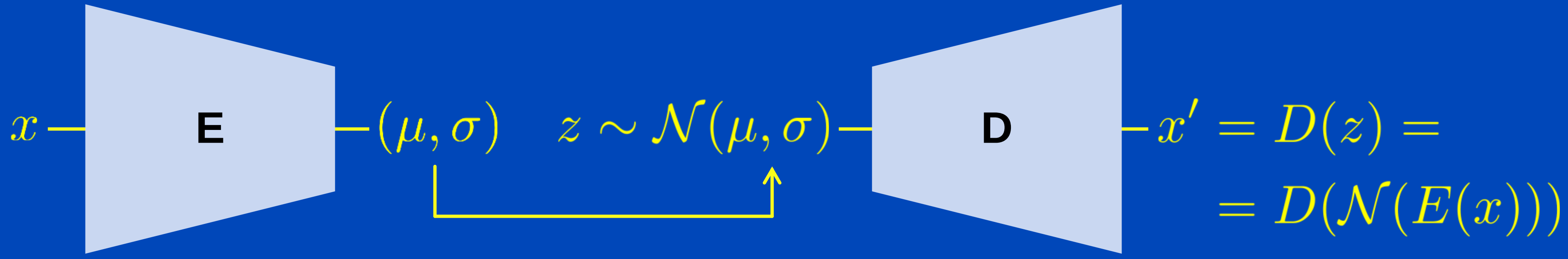


$$x' = D(z) = D(E(x))$$

- Examples:
  - Principal component analysis (linear autoencoder), lossless
  - PCA with dimensionality reduction (nonlinear due to clipping), lossy
  - Image compression and decoding, e.g. jpeg, lossy
- Latent space typically not interpretable.

What is a Variational Autoencoder?

- Make latent space regular.
- Allow to sample in latent space from a given distribution, here: normal distribution.



- The VAE is a generative model.
- It allows to generate new data by sampling new values from the normal distribution.

VAE Data & Training

- **Data:**
  - Clinical data acquired with a Siemens Somatom Force CT
  - 85 adult patient scans
  - 0.6 mm slice thickness and 0.69 to 0.98 mm axial voxel spacing
  - Randomly split into training, validation and testing (70:15:15)
- **Training:**
  - Trained for 150 epochs
  - Learning rate 0.001
  - Adam optimizer
  - Hybrid loss function consisting of VAE loss, perceptual loss and WGAN generator loss

$$L = L_{\text{pixel-wise}} + \beta\, L_{\text{Kullback–Leibler}} + \gamma\, L_{\text{perc}} + \delta\, L_{\text{WGAN}}$$

Coronal

Sagittal

LSR for Detruncation

- Train VAE on very many untruncated CT images f_n

$$\theta = \arg\min_\theta \sum_n \| D(\mathcal{N}(E(f_n(\boldsymbol{r})))) - f_n(\boldsymbol{r}) \|$$

- Find latent space point z to best match the truncated rawdata p

$$z = \arg\min_z \| \mathsf{X} D(z) - p \|_{15\,\mathrm{cm}}$$

- Forward project $D(z)$ and use the resulting rawdata to extrapolate the measured rawdata.
- Do a final image reconstruction of the detruncated sinogram.

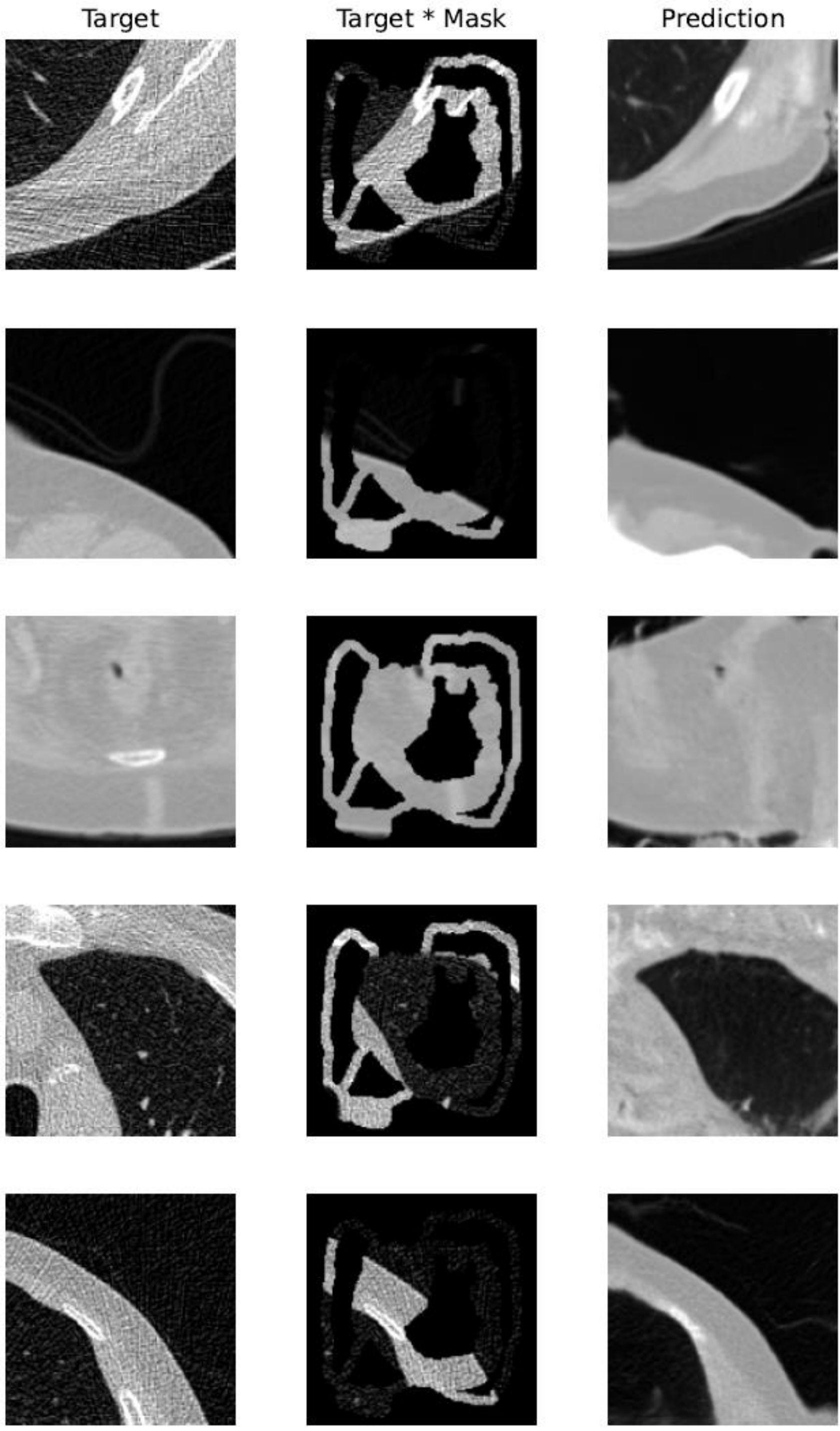
Image Domain Experiment

- **Purely image domain**
- **Hand-crafted mask**

- **Minimizing**

$$z = \arg\min_{z} \|D(z) - M(\boldsymbol{r}) f(\boldsymbol{r})\|$$

- **Results see rhs.**

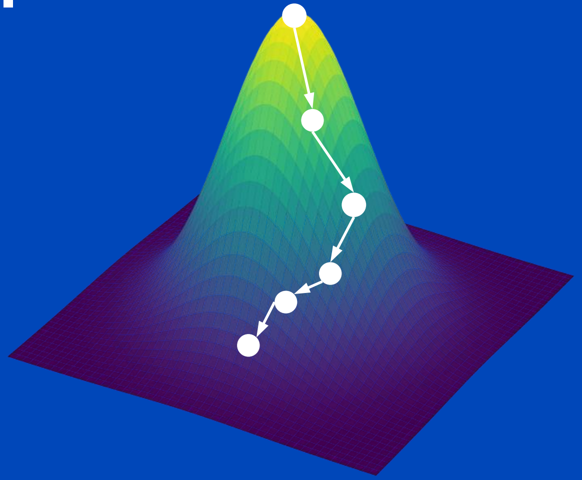


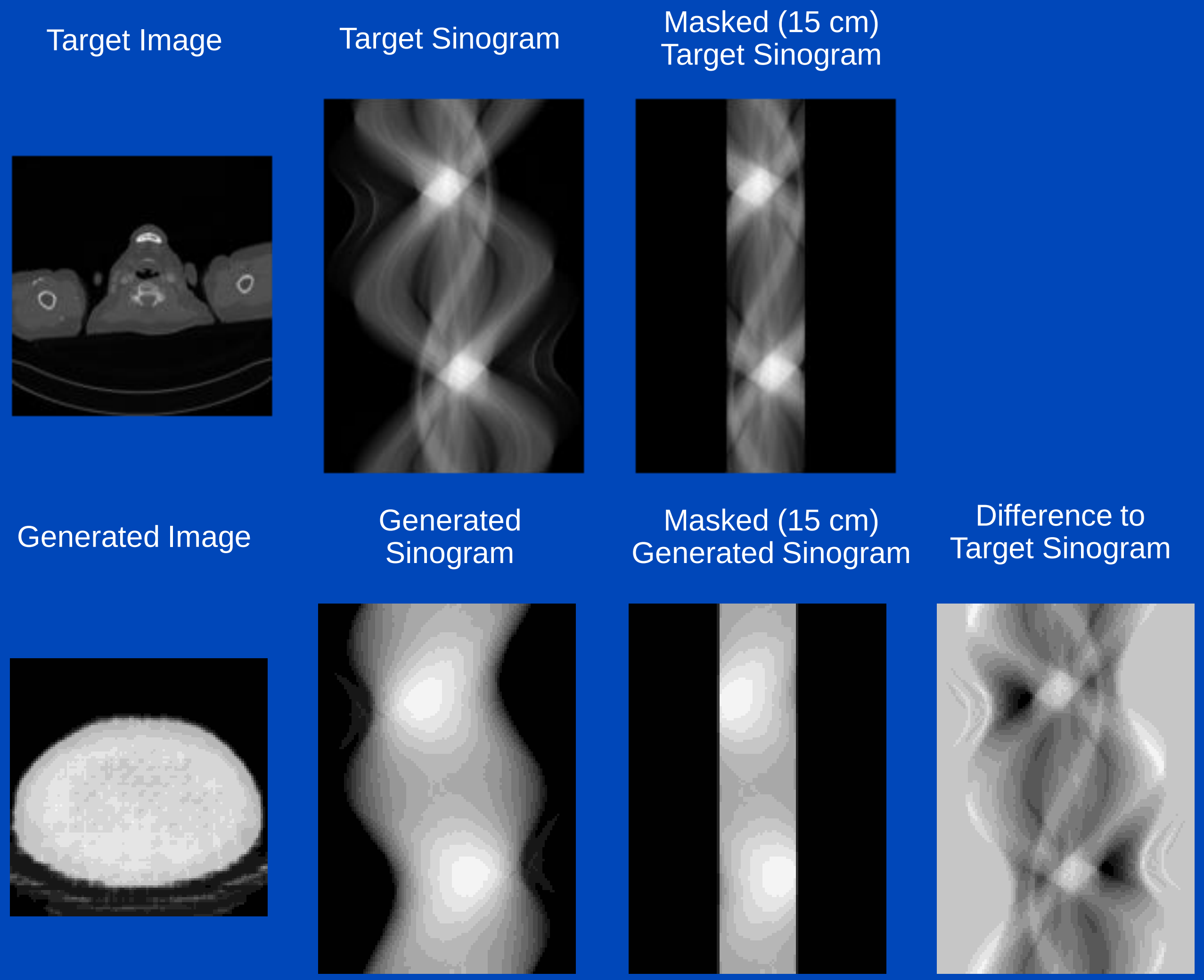
Search in Latent Space

- **Optimization of latent space vector in projection domain**

$$z = \arg\min_{z} \| X D(z) - p \|_{15\,\mathrm{cm}}$$

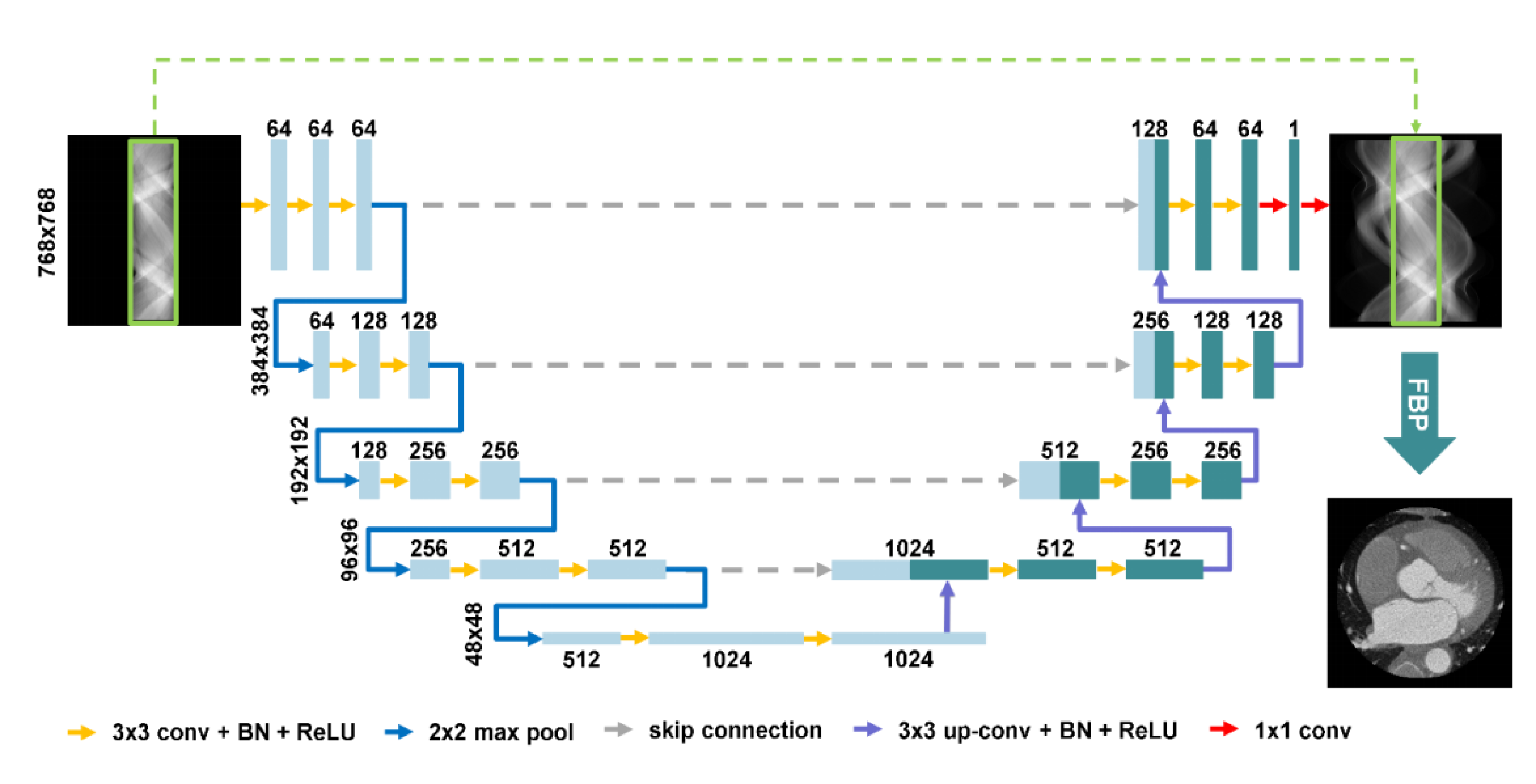
- **Video showing intermediate images of selected iteration steps.**





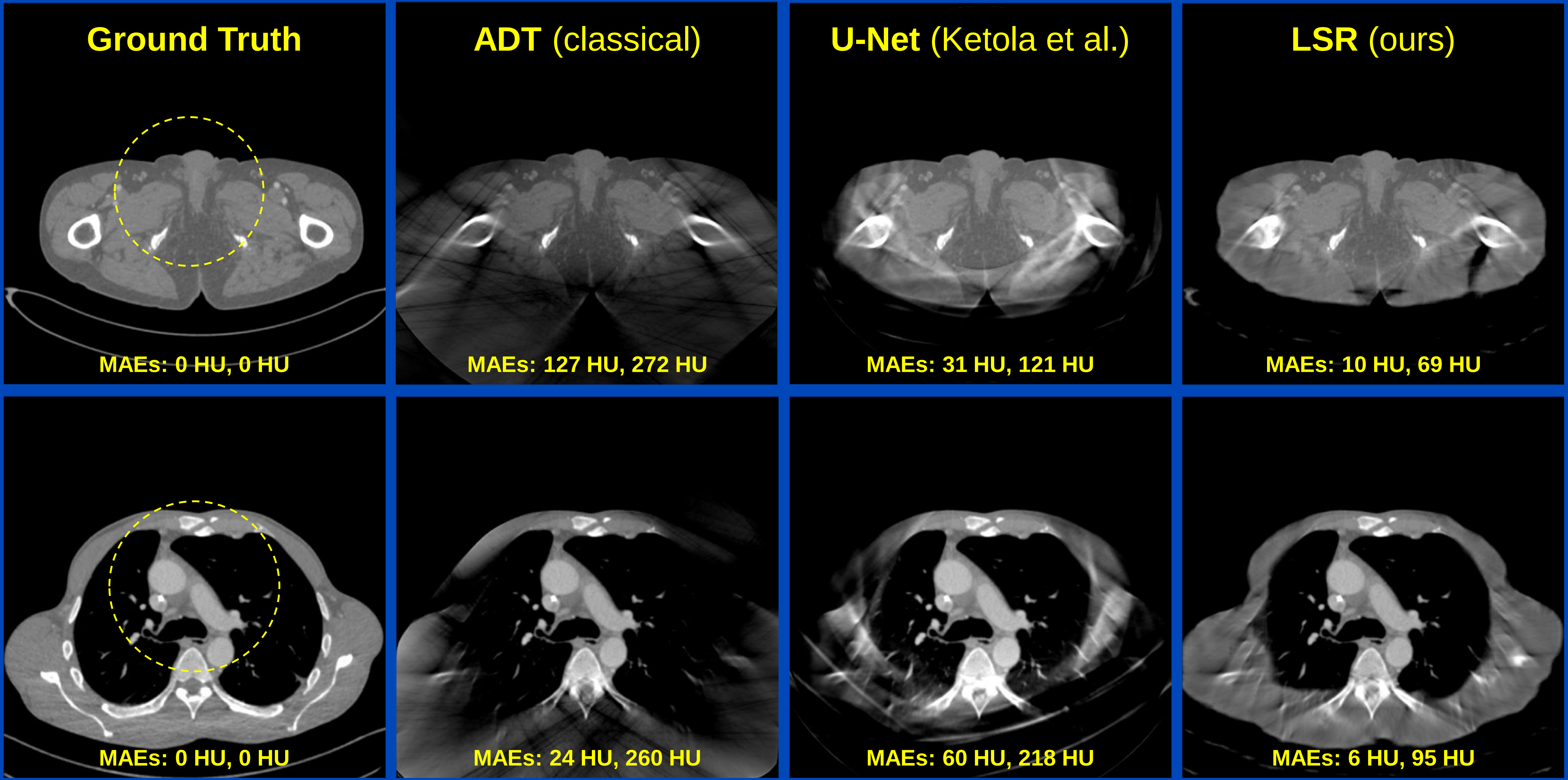
Reference Methods

U-Net-based Sinogram Extension



J. HJ. Ketola, et al., *Deep learning-based sinogram extension method for interior computed tomography*, *Medical Imaging: Physics of Medical Imaging*. Vol. 11595. International Society for Optics and Photonics (2021)

Results



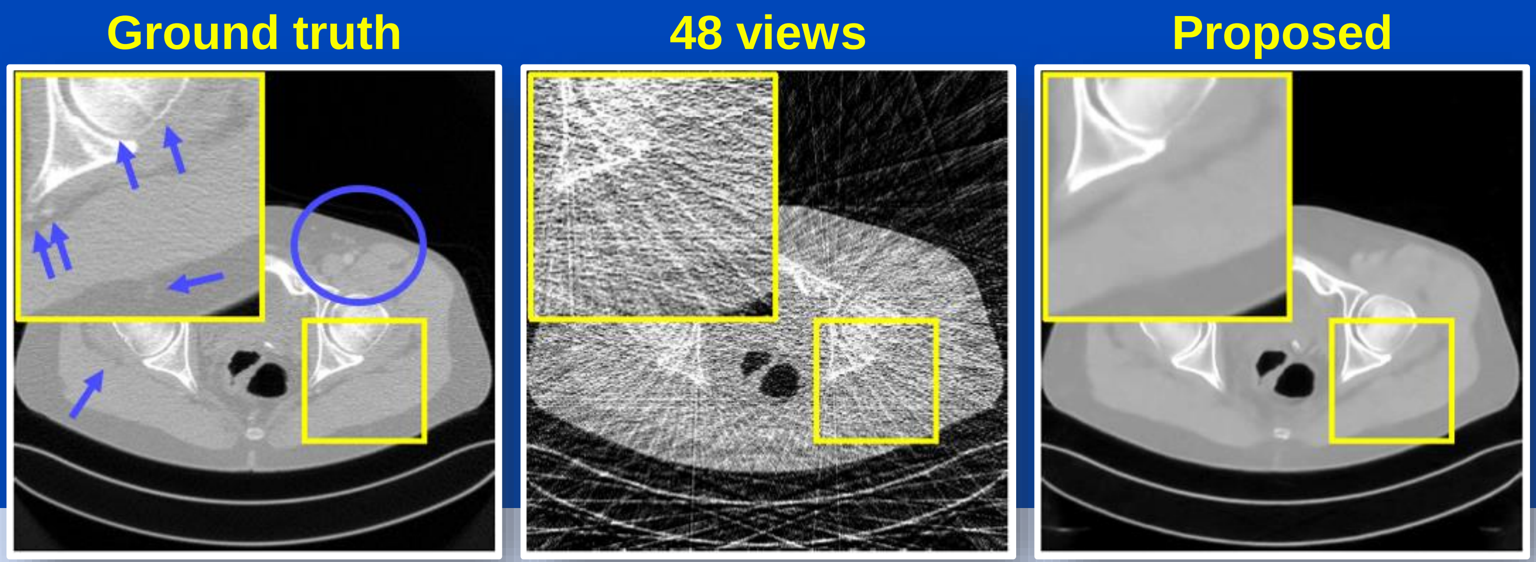
C = 50 HU, W = 1200 HU.

Tips for Researchers

- Do not feel pressed to invent new networks
  - Regard existing networks as a computational tool (such as, e.g., the Fourier transform).
  - Many existing networks are useful for other purposes than their original one.
  - Achtung: Some uninformed reviewers may reject your manuscript:
    - » R: “This network is not new. This is why I recommend rejection.”
    - » A: “Why should it be? Fourier transforms can also be used. They are far from being new!”
- Perform ablation studies
  - Change parameters of your network (e.g. size, depth, etc.)
  - Change training parameters (learning rate, batch size, dropout rate, etc.)
  - Change the amount of training data
- Existing solutions
  - Compare with prior approaches, also with non-AI ones, in particular with the gold standard
  - Optimize prior approaches with the same effort
    - » Same training data (also to fit the parameters of non-AI algorithms)
    - » Same loss function
    - » Same minimization algorithm

More Tips for Researchers

- Ensure all the data that have been acquired make it into the image.
- Do not exaggerate (e.g. noise reduction)
- Question whether the solution is really based on measured information or whether it is just nicely looking ($\rightarrow$ hallucinations)
- Unphysical but nicely looking:
  - Converting 80 kV images into 140 kV ones
  - Converting sparse view into full view images
  - Generating contrast-enhanced images from unenhanced ones
  - Removing motion artifacts from a cardiac CT image by editing the image
  - …



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

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).

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