Deep Learning-based Scatter Estimation for Time-of-Flight PET

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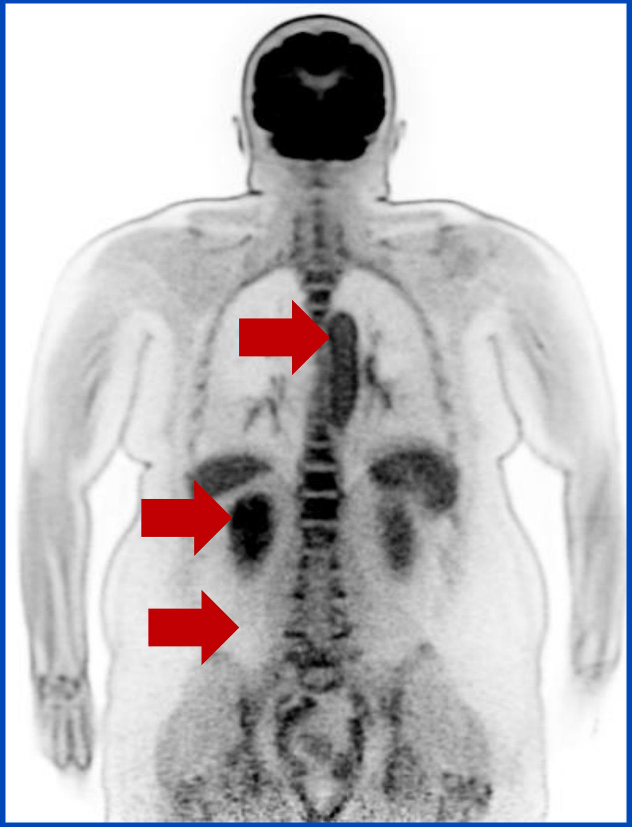
DEUTSCHES KREBSFORSCHUNGSZENTRUM IN DER HELMHOLTZ-GEMEINSCHAFT

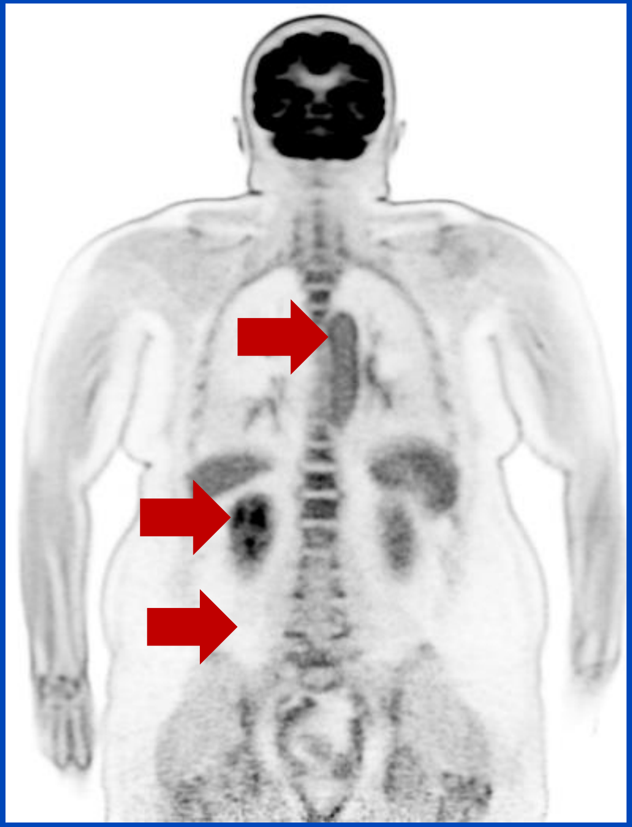
Motivation

- **Scatter is a major cause of image quality degradation in PET leading to:**
  - **Loss of contrast**
  - **Quantification bias**
  - **Image artifacts**
- **Scatter fraction in PET is often in the range of 30 - 40 %[1,2,3,4] for energies > ~420 keV.**
- **Precise scatter correction is crucial to maintain the diagnostic quality of the PET scan.**

No scatter correction



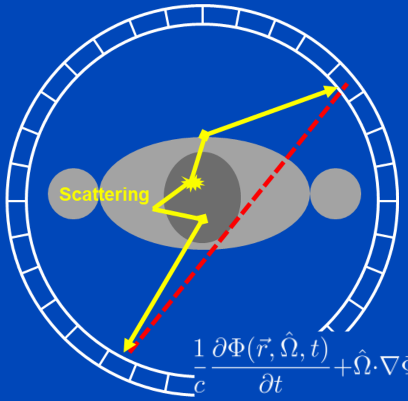
MC scatter correction



[1] V. Bettinardi et al., “Physical performance of the new hybrid PET/CT discovery-690”, *Med. Phys*. 38:5394–411, 2011
[2] S.Surti et al., “Performance of philips gemini TF PET/CT scanner with special consideration for its time-of-light imaging capabilities”, *J. Nucl. Med.* 48(3):471–80, 2007.
[3] J. van Sluis et al., “Performance characteristics of the digital biograph vision PET/CT system”, *J. Nucl. Med.* 60(7):1031–6, 2019.
[4] B. Spencer B et al., “Performance evaluation of the EXPLORER total-body PET/CT scanner based on NEMA NU-2 2018 standard with additional tests for extended geometry”, NSS/MIC 2019.

Scatter Estimation / Correction: Prior Work

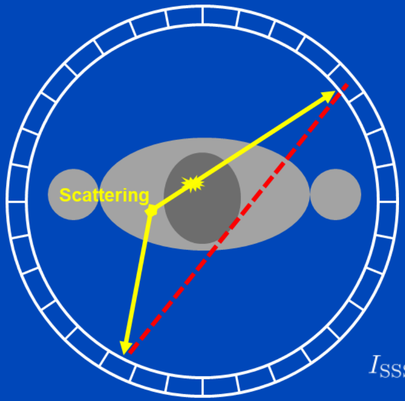
Gold standard: Monte Carlo Simulation[1]



Numerical solution of the Boltzmann transport equation using physics-based random sampling.

$$\frac{1}{c}\frac{\partial\Phi(\vec{r},\hat{\Omega},t)}{\partial t}+\hat{\Omega}\cdot\nabla\Phi(\vec{r},\hat{\Omega},t)+\mu(\vec{r},E)\Phi(\vec{r},\hat{\Omega},t)=\int_{4\pi}\frac{d\sigma(\hat{\Omega}'\to\hat{\Omega},E)}{d\Omega}\Phi(\vec{r},\hat{\Omega}',t)\,d\hat{\Omega}'+S(\vec{r},\hat{\Omega},t)$$

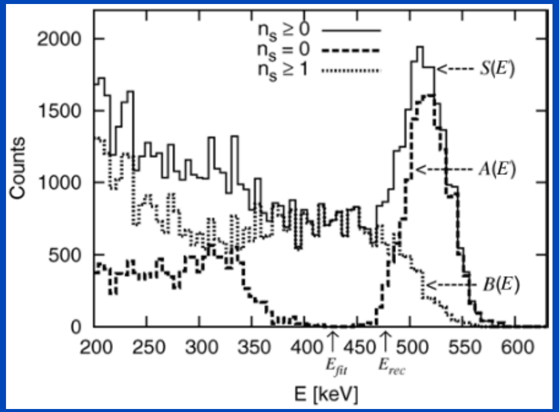
Single Scatter Simulation[2]



Analytic solution of the Boltzmann transport equation using single scatter approximation.

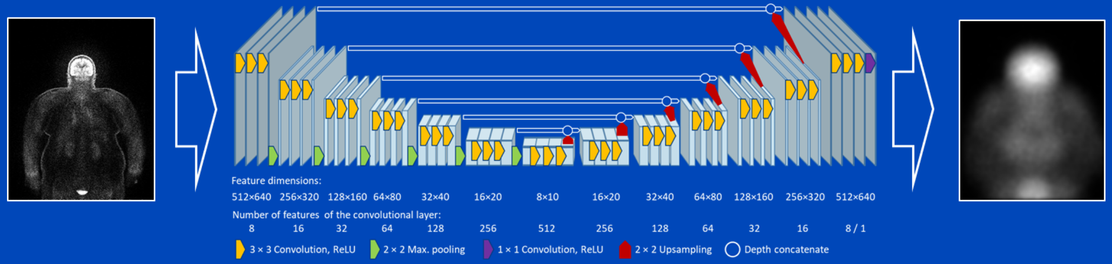
$$I_{\mathrm{SSS}}(\vec{r}_1,\vec{r}_2)=I_0\int_V d^3r'\,T(\vec{r}_1,\vec{r}')T(\vec{r}_2,\vec{r}')\,\mu_s(\vec{r}')\,P(\hat{\Omega}_1'\to\hat{\Omega}_1)P(\hat{\Omega}_2'\to\hat{\Omega}_2)$$

Energy-based Scatter Estimation[3]



Make use of the difference between the energy spectra of the unscattered and scattered photons.

Deep Learning-based Scatter Estimation[4]

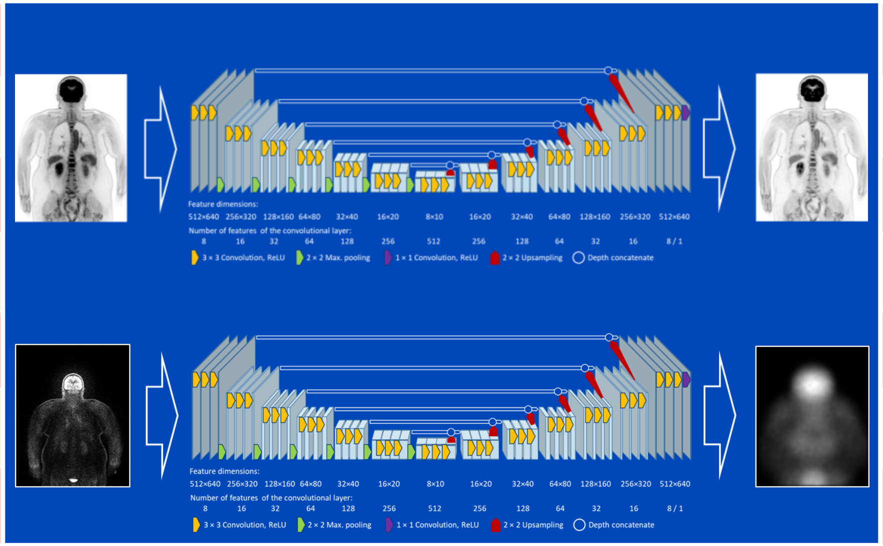


Train neural networks to correct for scatter / predict PET scatter distributions.

[1] H. Zaidi, "Relevance of accurate Monte Carlo modeling in nuclear medical imaging", *Med. Phys*. 26(4):574-608, 1999.
[2] J.M. Ollinger, "Model-based scatter correction for fully 3D PET", Phys. Med. Biol. 41(1), 153–176, 1996.
[3] L. M. Popescu et al. "PET energy-based scatter estimation and image reconstruction with energy-dependent corrections", *Phys. Med. Biol*. 51(11), 2919–2937, 2006.
[4] Y. Berker et al., "Deep Scatter Estimation in PET: Fast Scatter Correction Using a Convolutional Neural Network", NSS/MIC 2018.

Deep Learning-based Scatter Estimation / Correction

Domain	#	TOF	Training / Application
Image	3	Yes	Uncorrected Reconstruction → Scatter-corrected reconstruction
	4	No	Uncorrected Reconstruction → Scatter-corrected reconstruction
	5	No	Uncorrected Reconstruction → Scatter-corrected reconstruction
	6	Yes	Monte Carlo correction based on DL Reconstruction
Sinogram	1	No	Single scatter → MC, emission/attenuation data → MC
	2	No	Emission/attenuation data → Single scatter
	7	No	Emission/attenuation data → MC scatter



[1] H. Qian et al., “Deep Learning Models for PET Scatter Estimations”, *NSS/MIC* 2017.
[2] Y. Berker et al., “Deep Scatter Estimation in PET: Fast Scatter Correction Using a Convolutional Neural Network”, *NSS/MIC* 2018.
[3] J.Yang et al., “Joint correction of attenuation and scatter in image space using deep convolutional neural networks for dedicated brain 18F-FDG PET”, *Phys. Med. Biol*. 64(7), 2019.
[4] I. Shiri et al., “Deep-JASC: joint attenuation and scatter correction in whole-body 18F-FDG PET using a deep residual network”. EJNMMI 47(11), 2533–2548, 2020.
[5] S. Mostafapour et al., “Feasibility of Deep Learning-Guided Attenuation and Scatter Correction of Whole-Body 68Ga-PSMA PET Studies in the Image Domain”, . *Clin. Nucl. Med. 46*(8), 609–615, 2021
[6] K. Li et al., “Deep Learning Accelerates Accurate Scatter Correction with Histo-image in TOF PET/CT System”, *NSS/MIC* 2022
[7] B. Laurent et al, “PET scatter estimation using deep learning U-Net architecture”, *Phys. Med. Biol*. 68(6), 2023.

Sinogram Domain Scatter Estimation
What's New in this Work?

- Deep scatter estimation (DSE) for TOF PET scans:
  - Can DSE be generalized to different TOF bins?
  - Is there an advantage of processing all TOF bins simultaneously?
- Application to long axial FOV PET scanner:
  - Can DSE be generalized to highly oblique planes?

Whole-body TOF PET system.

Data Generation: Monte Carlo Simulation

Siemens Biograph Vision Quadra @ DKFZ

Whole-body TOF scans with two bed positions

Initial PET reconstruction + SSS

CT attenuation map

MC

List mode data

Rebinning

MC Scatter distribution

Data Generation: Monte Carlo Simulation

Siemens Biograph Vision Quadra @ DKFZ

Whole-body TOF scans with two bed positions

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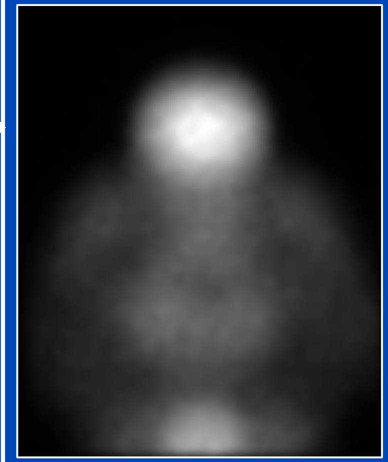
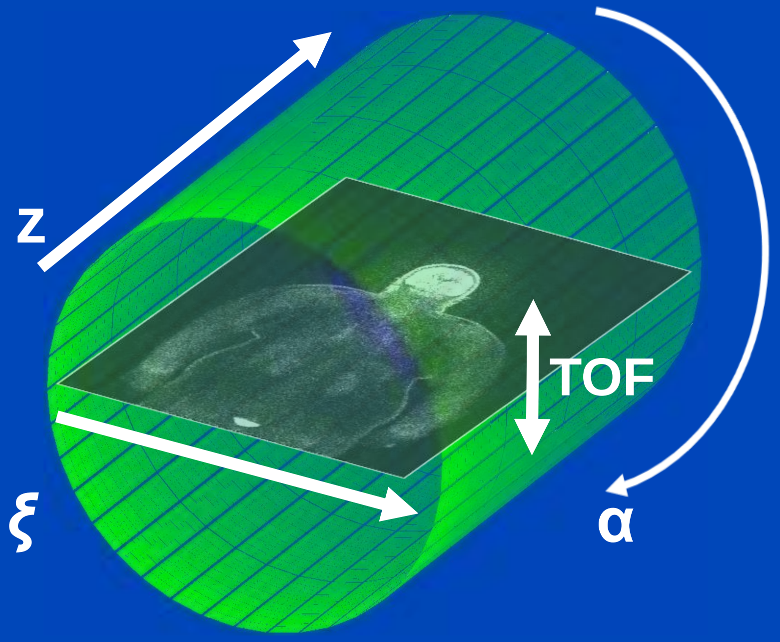
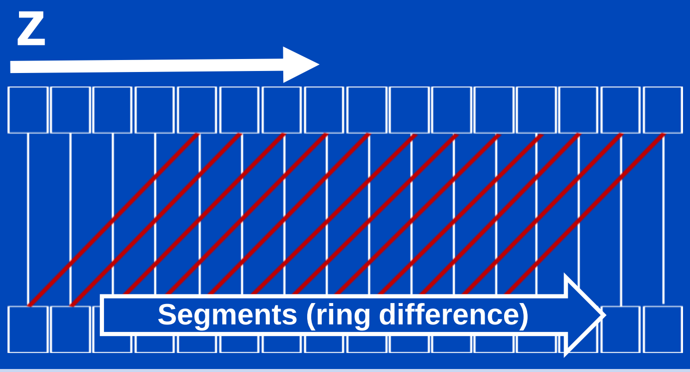


Aim: Replace this step by a neural network.

Data Representation

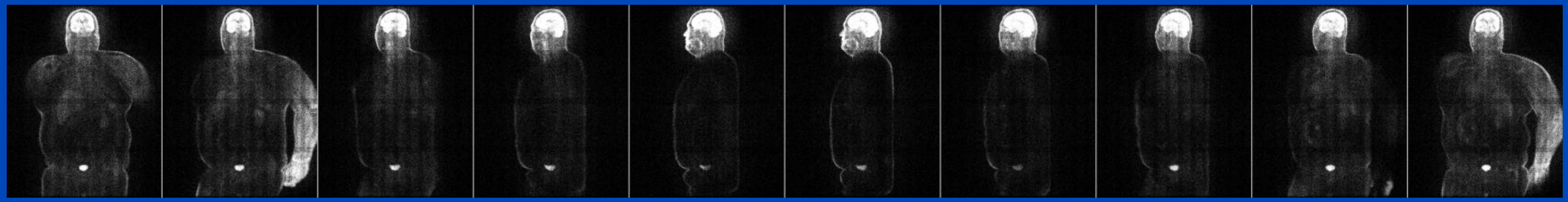
Emission data



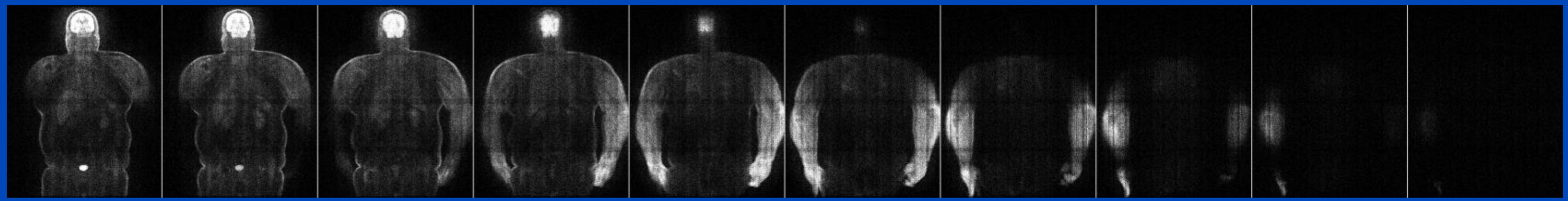


- All experiments shown in the following use 2D sub-sinograms in ξ-z-plane, i.e. for each plane we have:

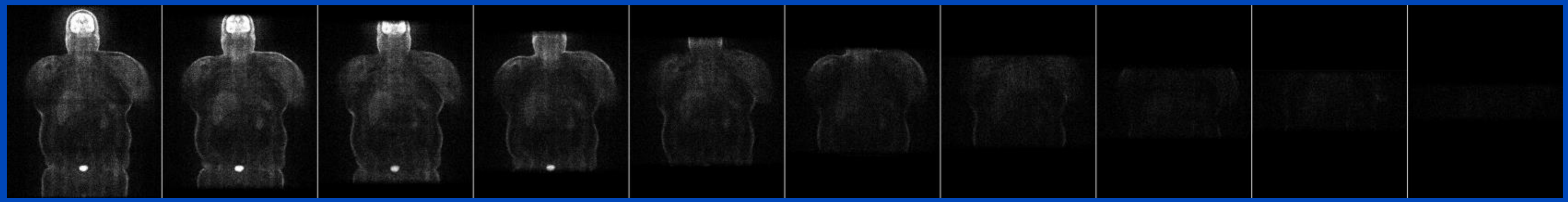
50 angles, 0°-180°, Δα = 3.6° (not all angles shown)



33 TOF bins, ΔTOF = 143 ps (not all TOF bins shown)



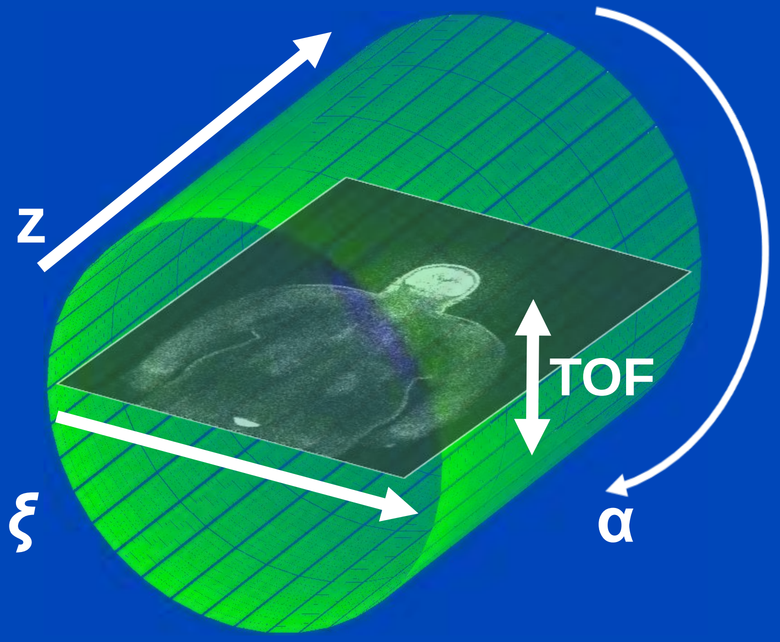
35 segments, Max. ring diff. = 322, axial compr. = 19 (not all shown)

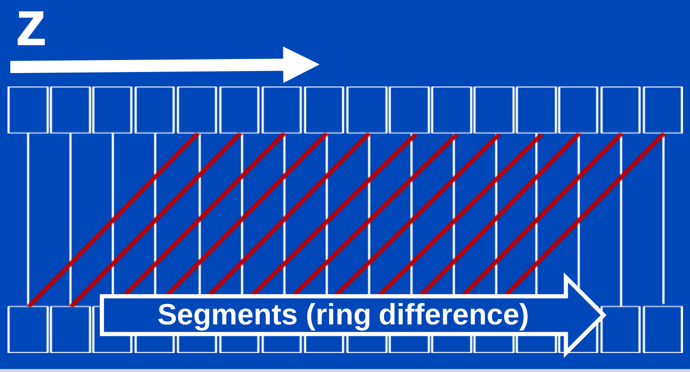


→ 57750 ξ-z-planes / scan

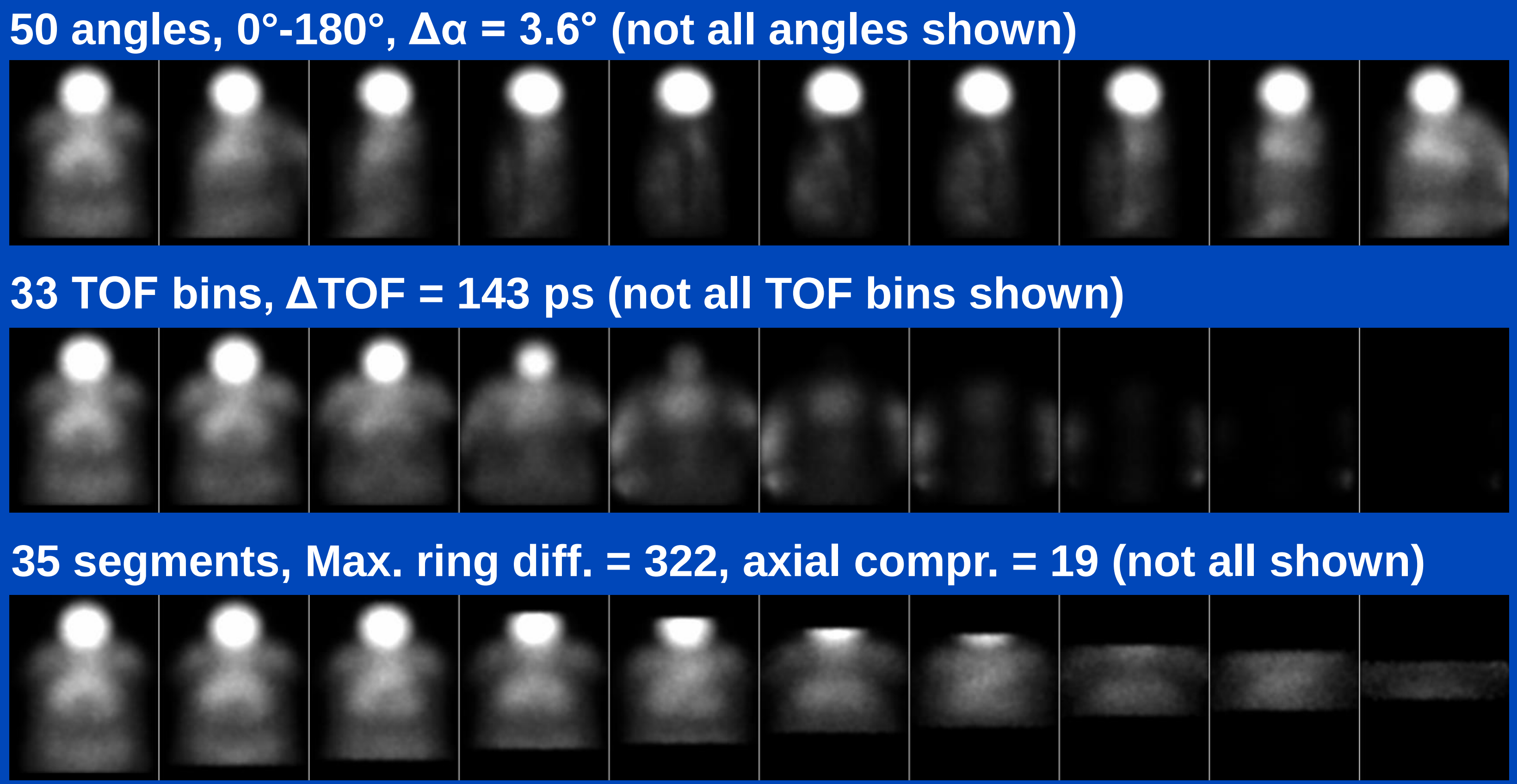
Data Representation

Scatter distributions





- All experiments shown in the following use 2D sub-sinograms in *ξ*-*z*-plane, i.e. for each plane we have:



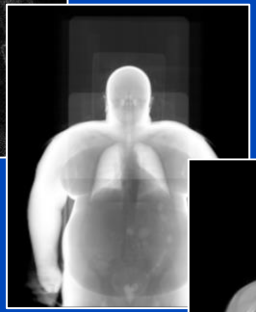
→ 57750 *ξ*-*z*-planes / scan

PET Deep Scatter Estimation

Realization #1: Each TOF bin as separate input

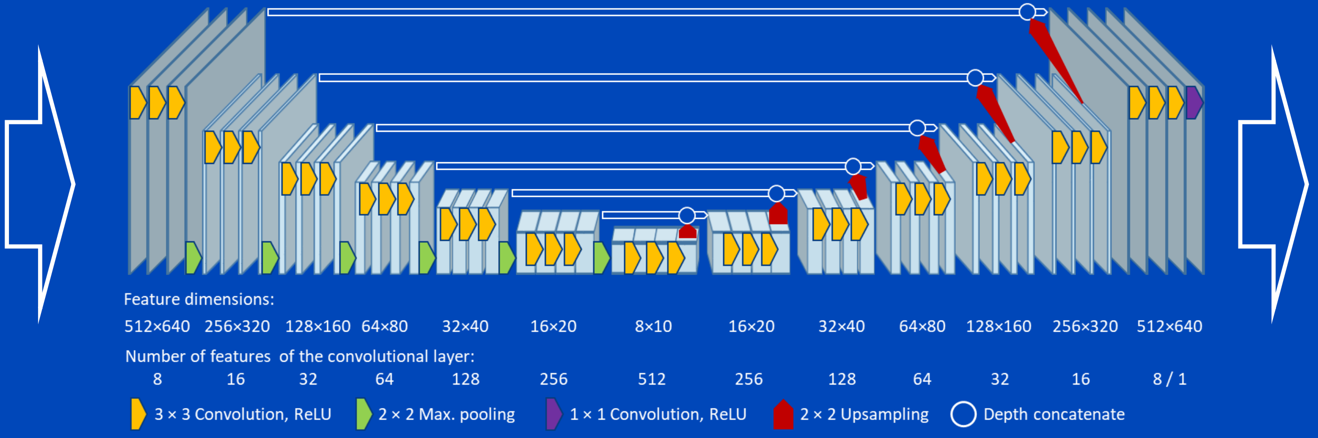
- Use measured activity (trues + scatter + randoms), pep-image, and attenuation image as 3-channel input to a U-net.
- Minimize MSE between prediction and the MC to optimize the network's weights
- Training on 50 patients / Testing on 6 patients.

Emission data (Trues + Scatter + Randoms)



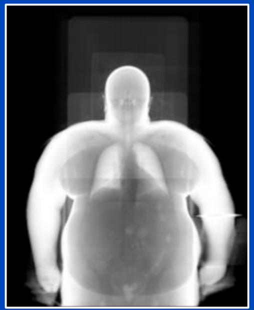
Pep-Image

Attenuation

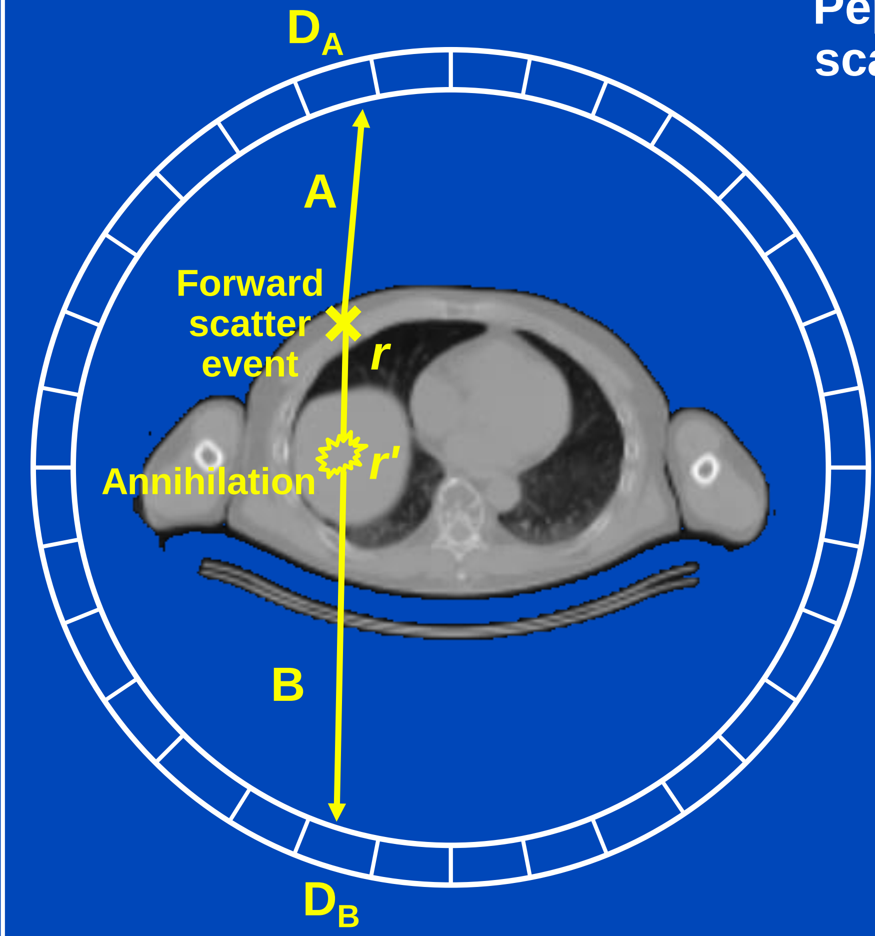


MC Scatter

Pep-Image



Pep-Image [1]



Pep = Approximation of single-scattering in forward direction.

$$
\begin{aligned}
&\text{Pep} = \\
&\text{Activity } A(r') \text{ at } r' \\
&\times \int \text{Probability of A being scattered} \\
&\times \text{Probability scattered A reaching } \mathrm{D_A} \\
&\times \text{Probability of B reaching } \mathrm{D_B}\ dr \\
&= A(r') \cdot p \cdot e^{-p} \\
&\text{with} \\
&p = \int_{D_A}^{D_B} \mu(r) dr
\end{aligned}
$$

[1] B. Ohnesorge et al., “Efficient correction for CT image artifacts caused by objects extending outside the scan field of view”, *Med. Phys. 27*(1), 39–46, 2000

PET Deep Scatter Estimation

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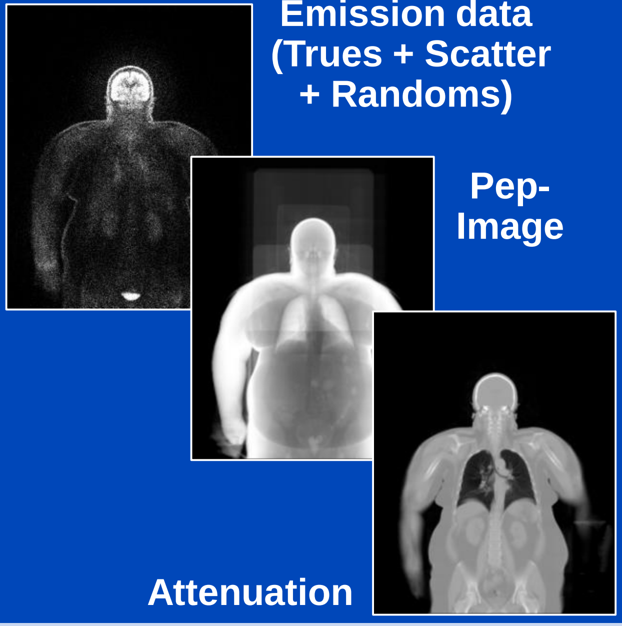
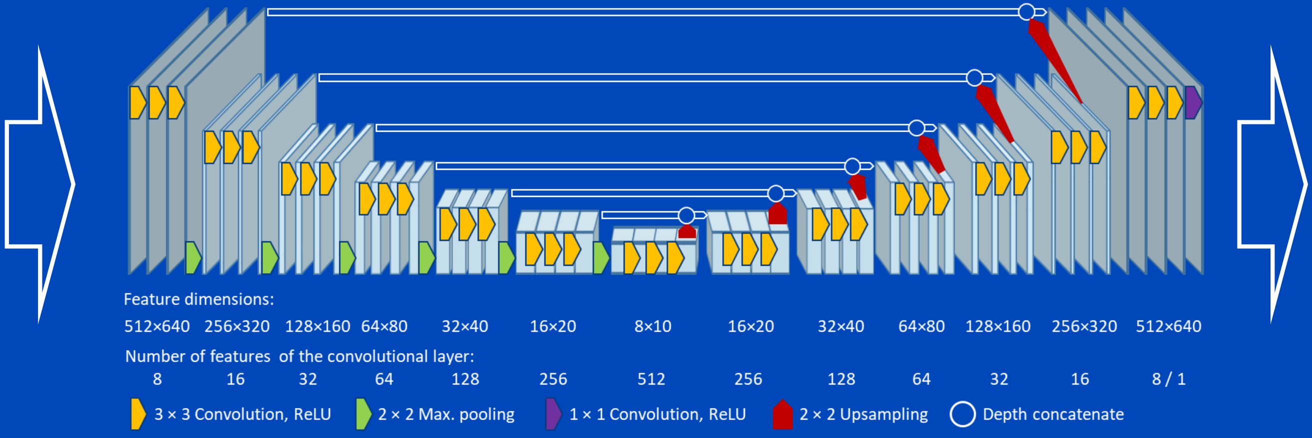


Emission data (Trues + Scatter + Randoms)

Pep-Image

Attenuation



MC Scatter

PET Deep Scatter Estimation

Realization #1: Each TOF bin as separate input

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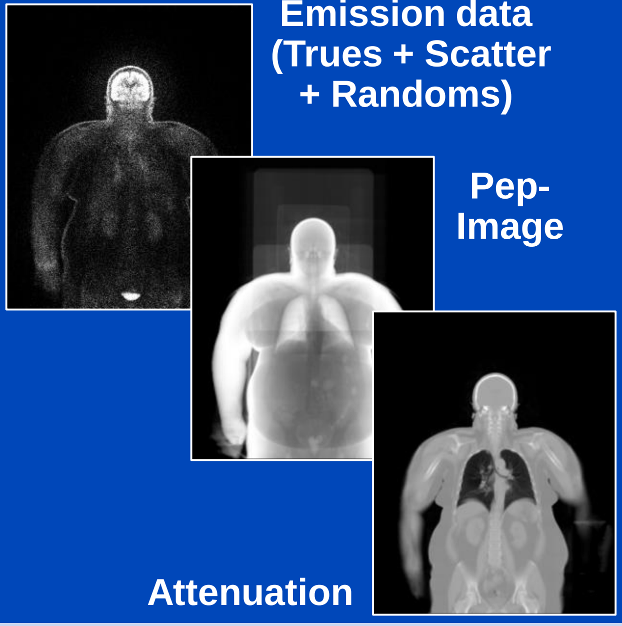
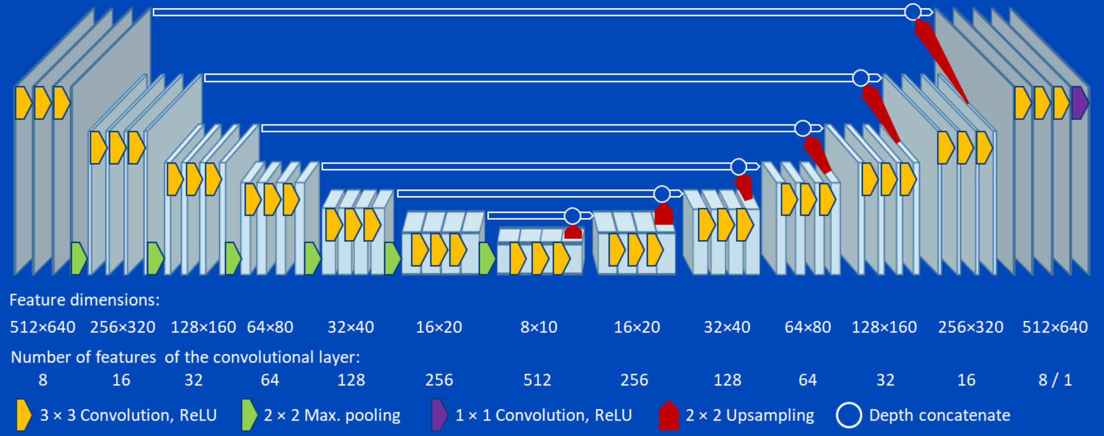
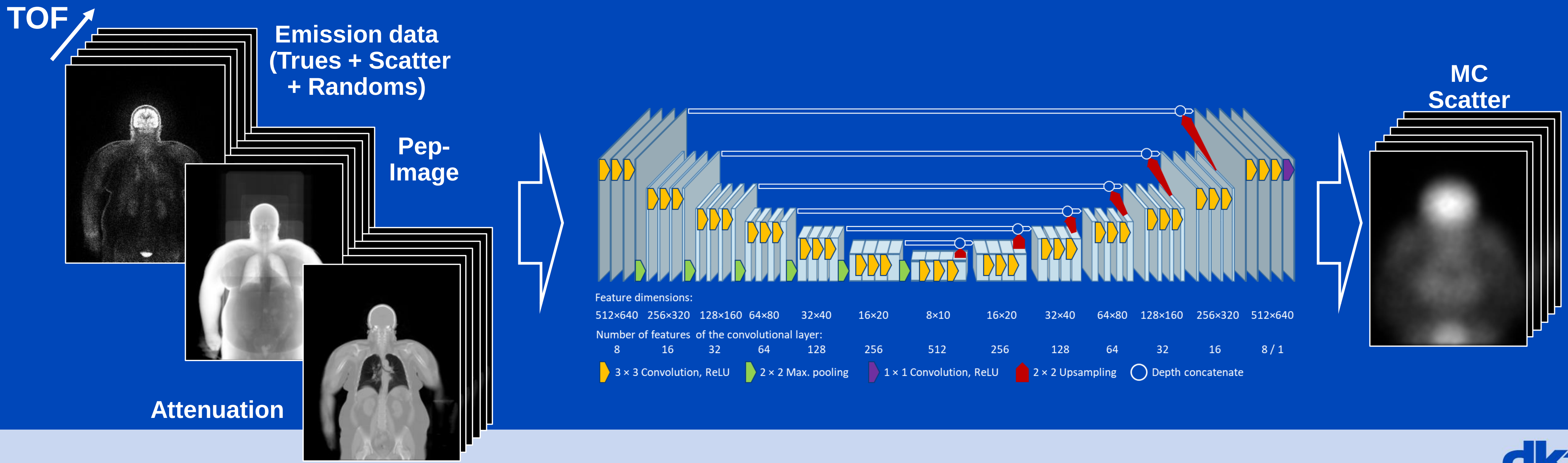




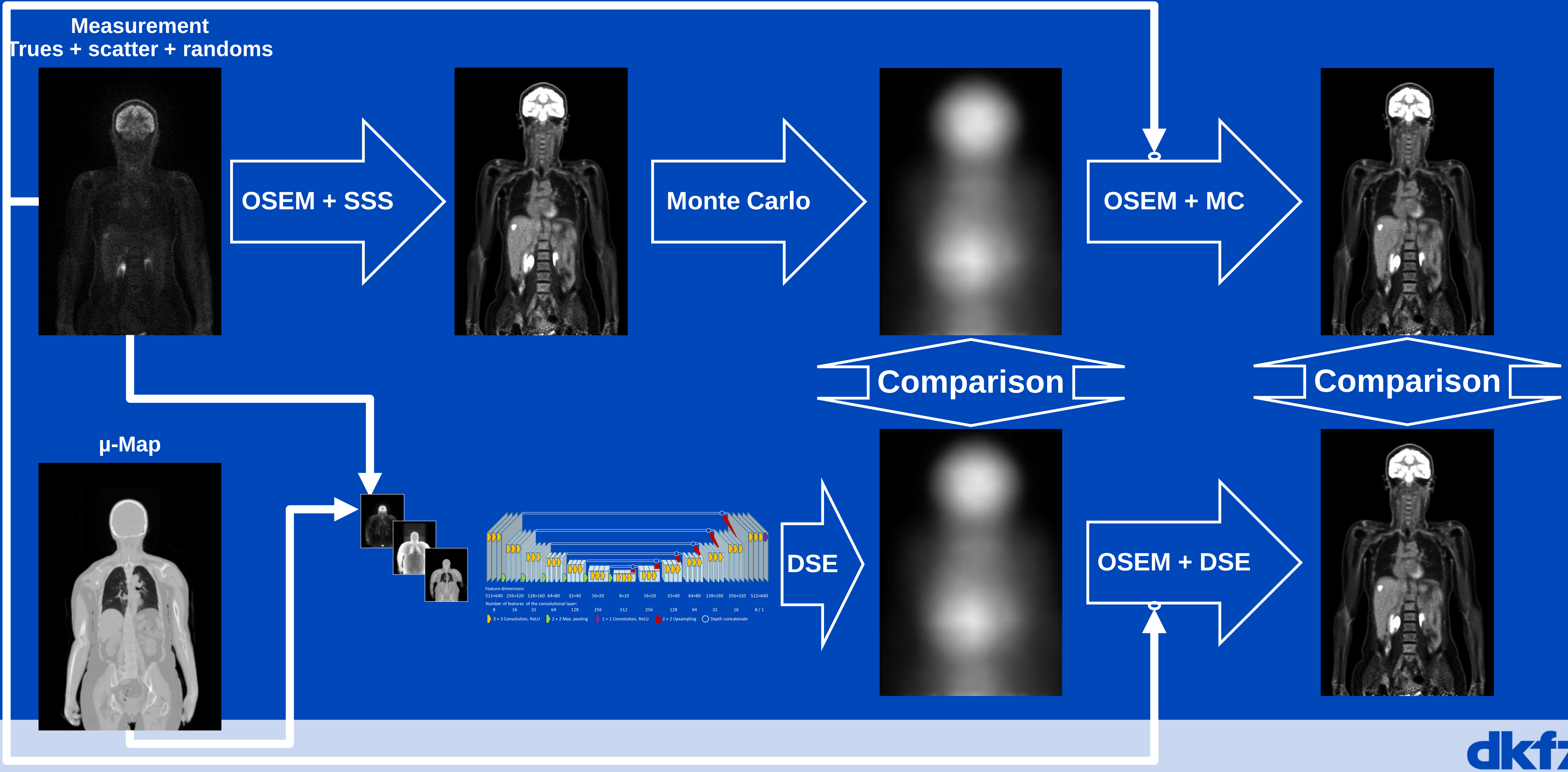
PET Deep Scatter Estimation

Realization #2: All TOF bins as multi-channel input

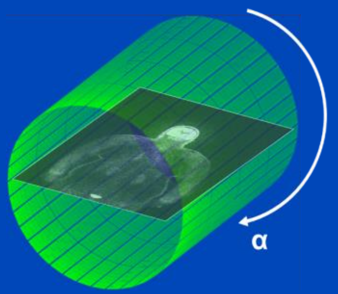
- Use measured activity (trues + scatter + randoms), pep-image, and attenuation of all TOF bins as multi-channel input.
- Minimize MSE between prediction and the MC to optimize the network's weights
- Training on 50 patients / Testing on 6 patients.



DSE Testing (6 Patients)



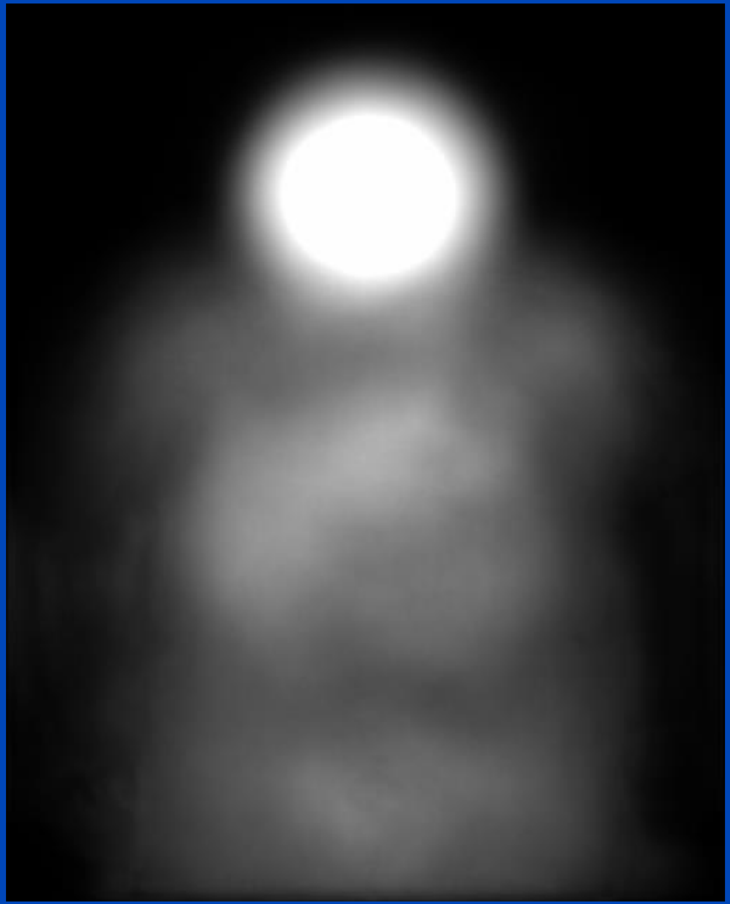
Results: TOF-bin 0, Segment 0, Angles 0 - 49



Monte Carlo Simulation

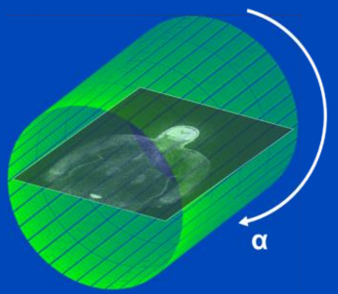
DSE #1 (single inputs)

DSE #2 (all TOF)

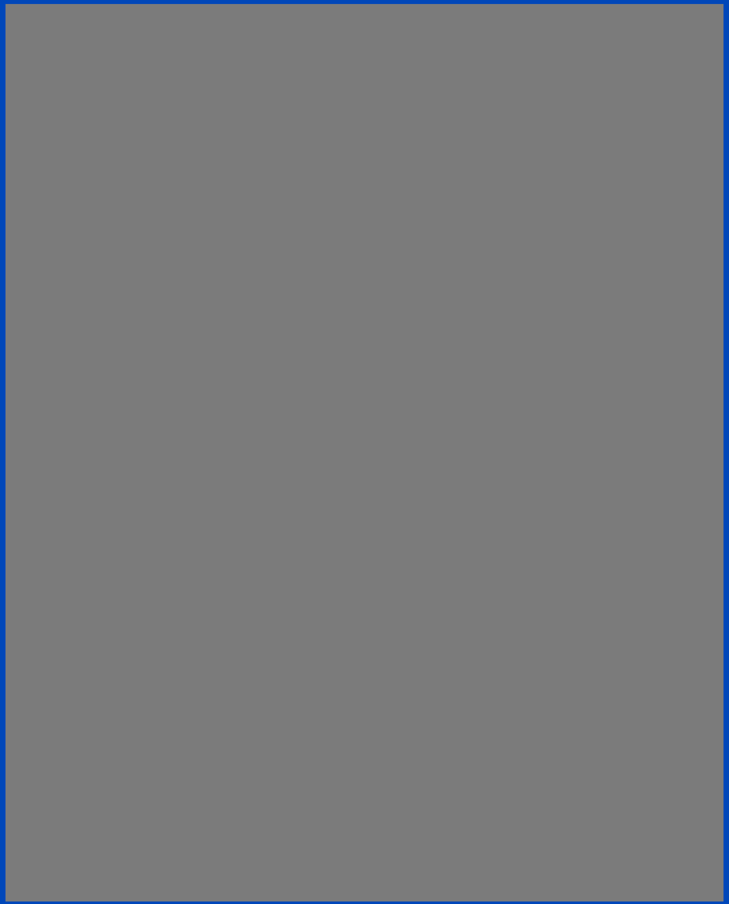


dkfz.

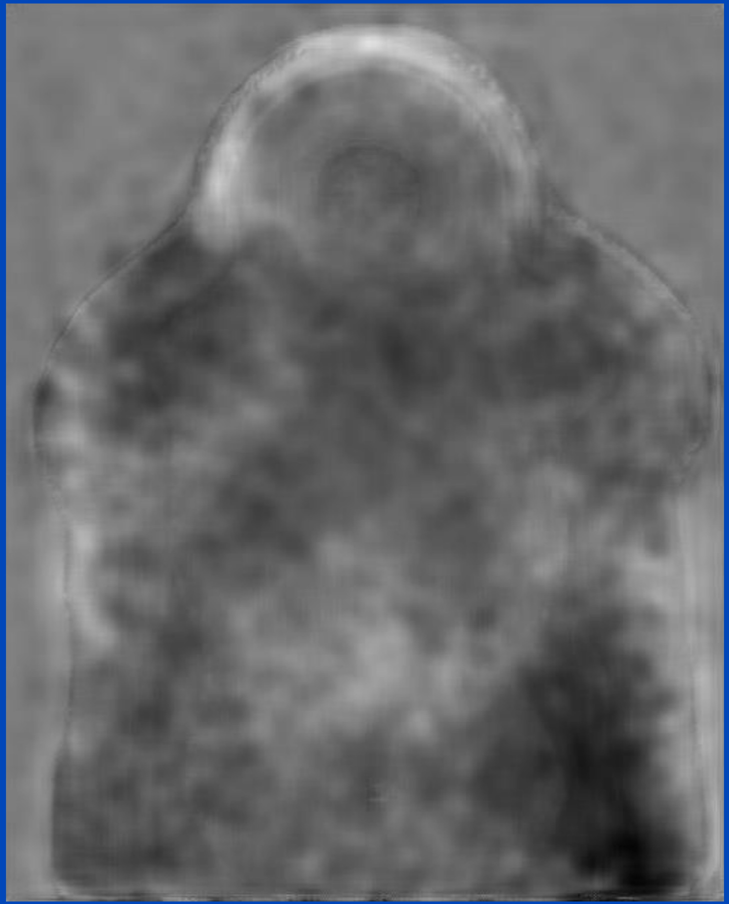
Results: TOF-bin 0, Segment 0, Angles 0 - 49



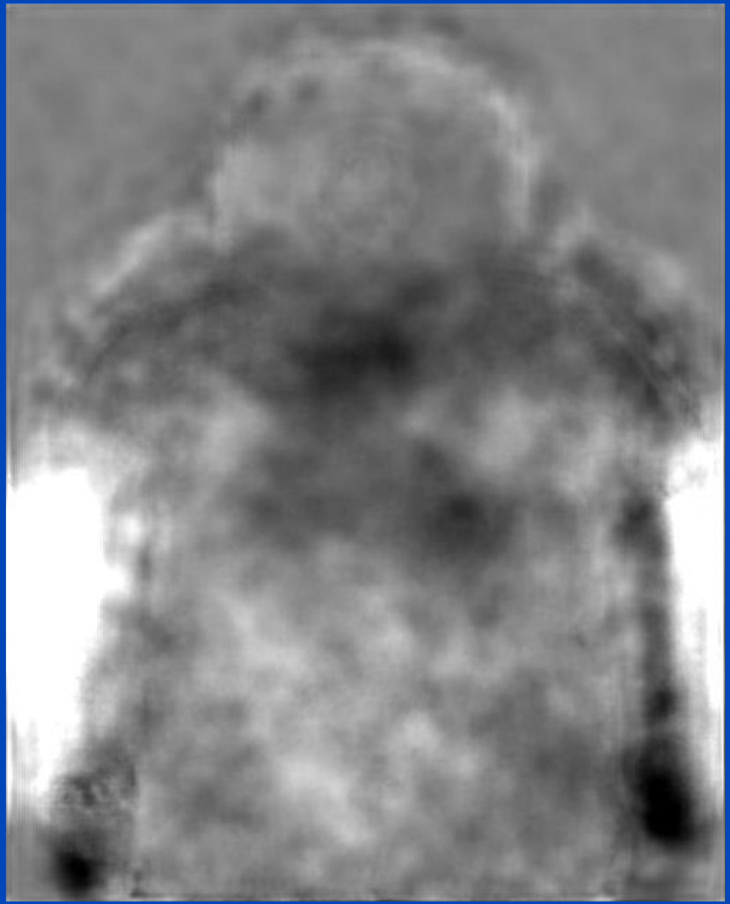
Monte Carlo Simulation



Relative error DSE #1

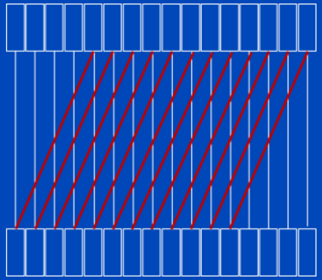


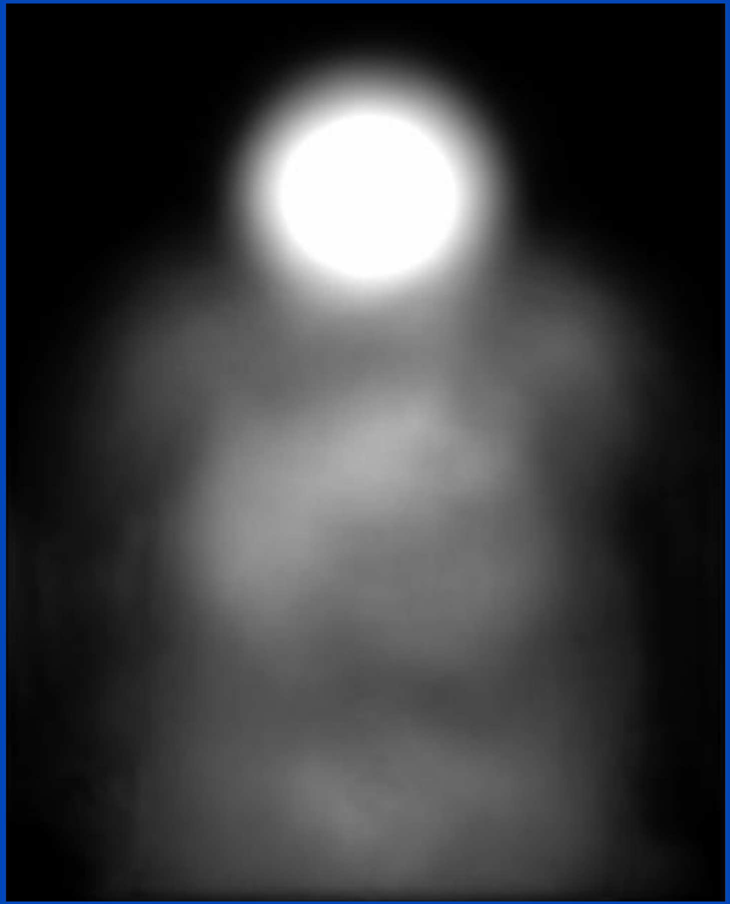
Relative error DSE #2



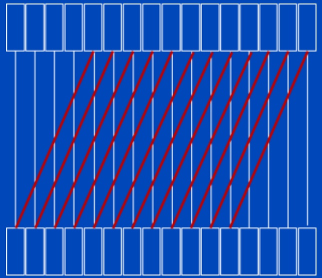
C = 0 %, W = 60 %

Results: TOF-bin 0, Segments 0 - 34, Angle 0

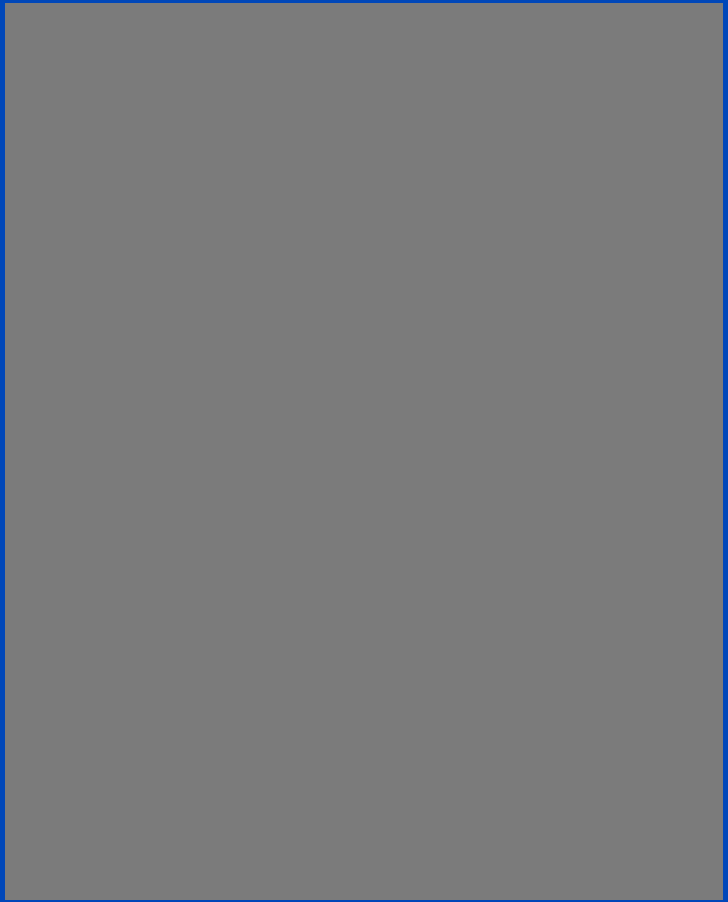


Monte Carlo Simulation	DSE #1 (single inputs)	DSE #2 (all TOF)
		

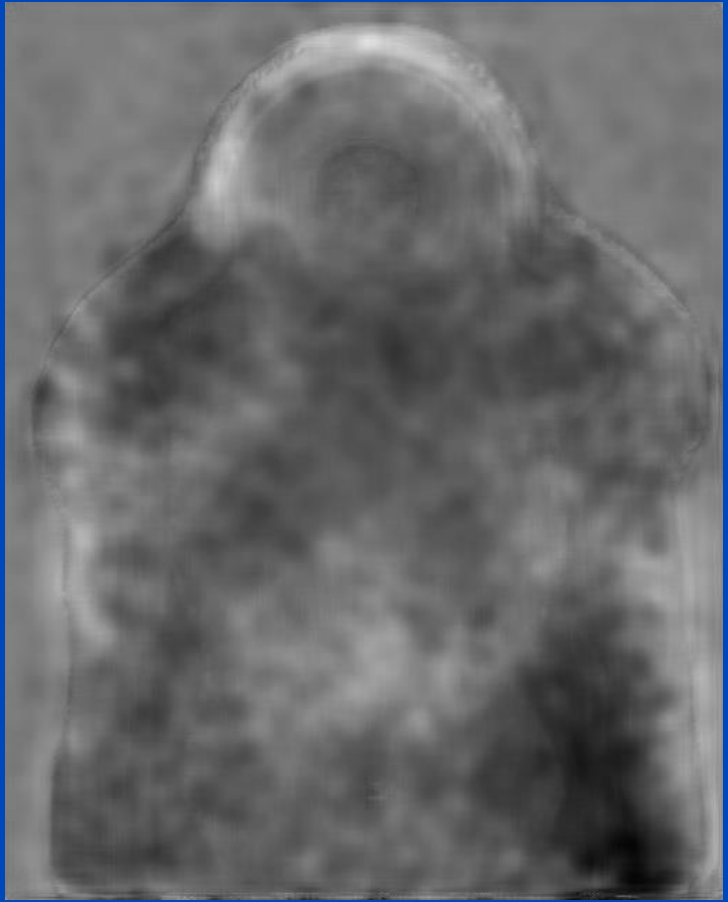
Results: TOF-bin 0, Segments 0 - 34, Angle 0



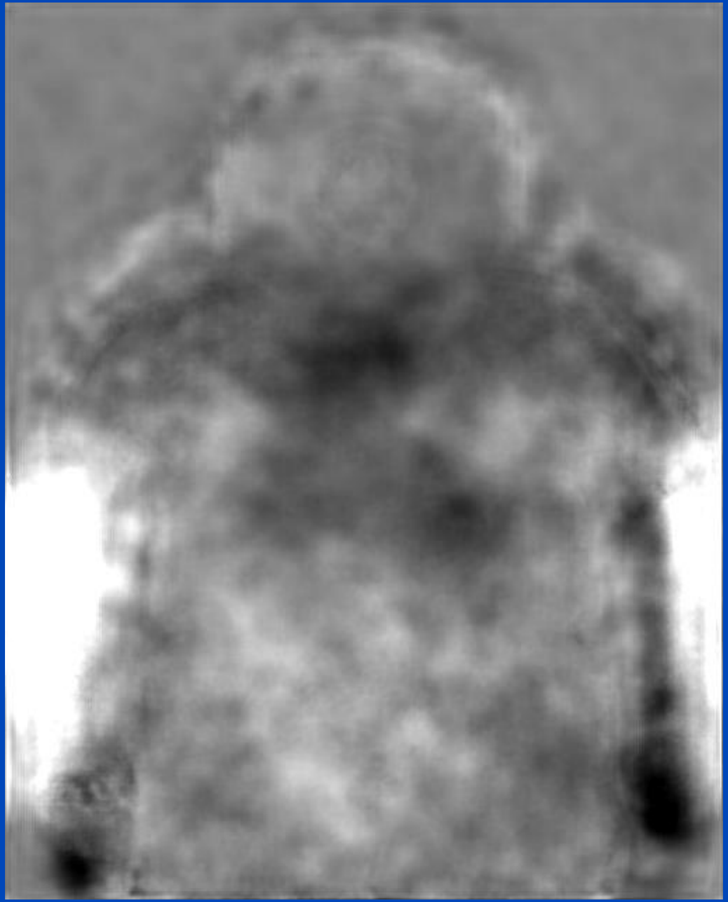
Monte Carlo Simulation



Relative error DSE #1

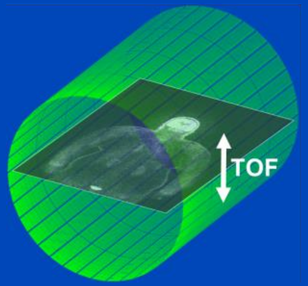


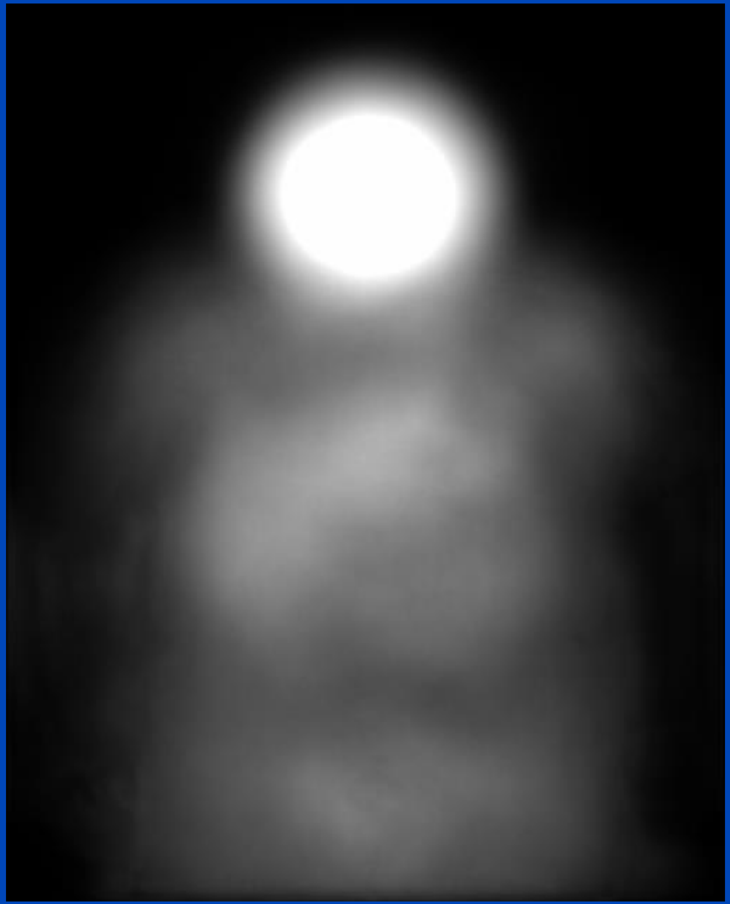
Relative error DSE #2



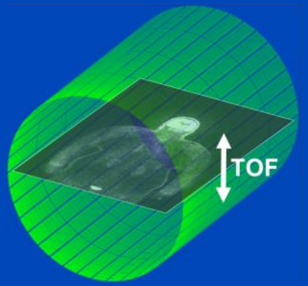
C = 0 %, W = 60 %

Results: TOF-bins 0 - 32, Segment 0, Angle 0

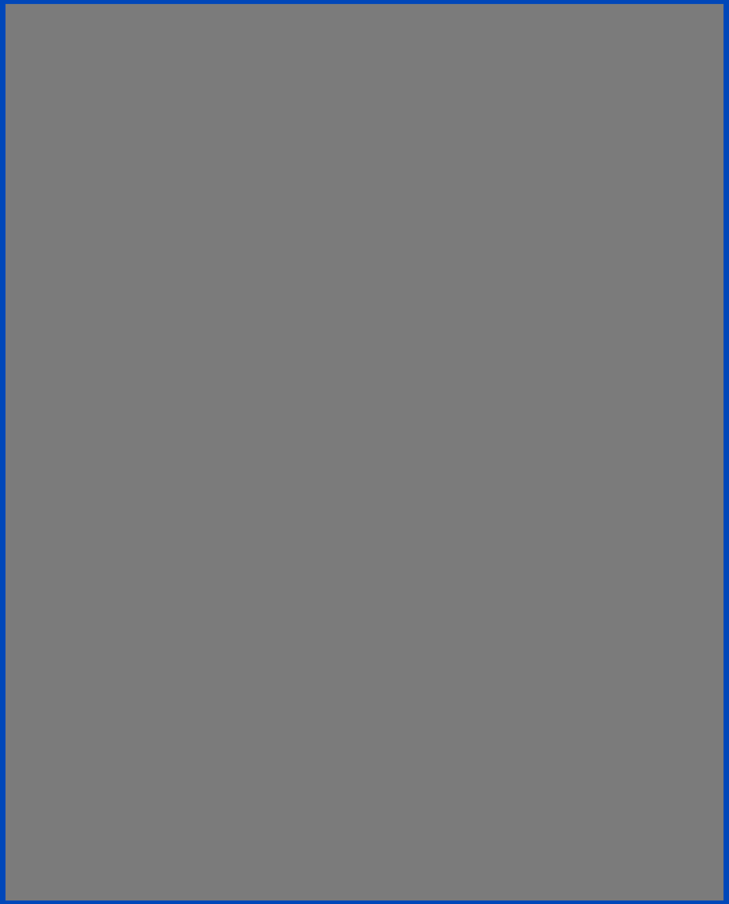


Monte Carlo Simulation	DSE #1 (single inputs)	DSE #2 (all TOF)
		

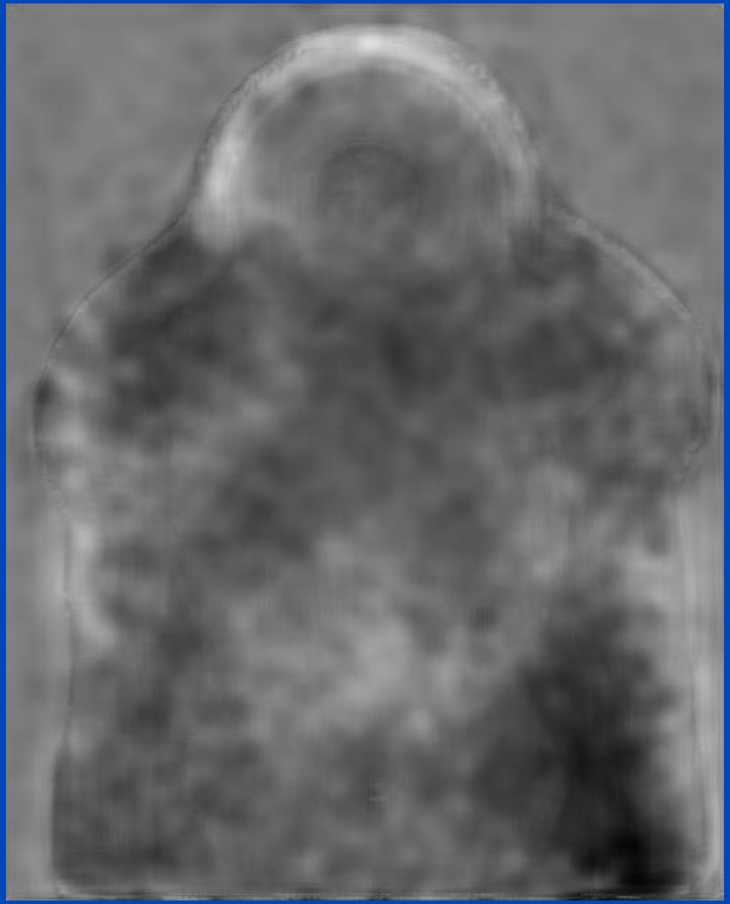
Results: TOF-bins 0 - 32, Segment 0, Angle 0



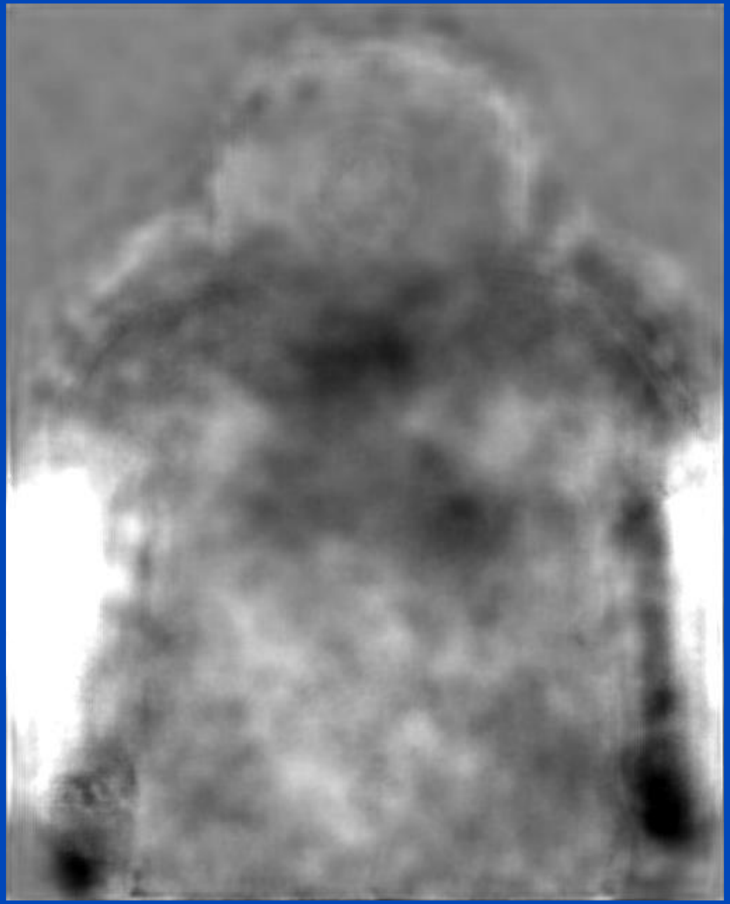
Monte Carlo Simulation



Relative error DSE #1

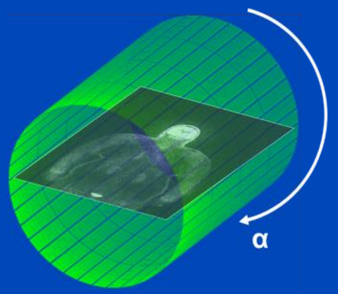


Relative error DSE #2

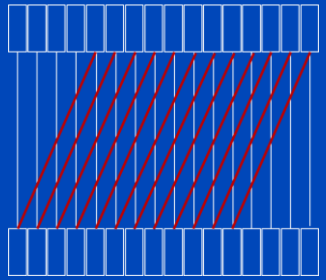


C = 0 %, W = 60 %

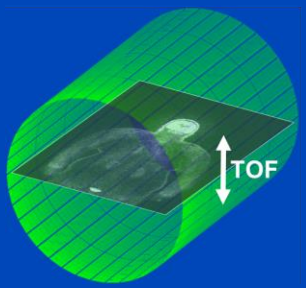
Evaluation for All Test Patients – Mean Absolute Percentage Error of Scatter Estimates



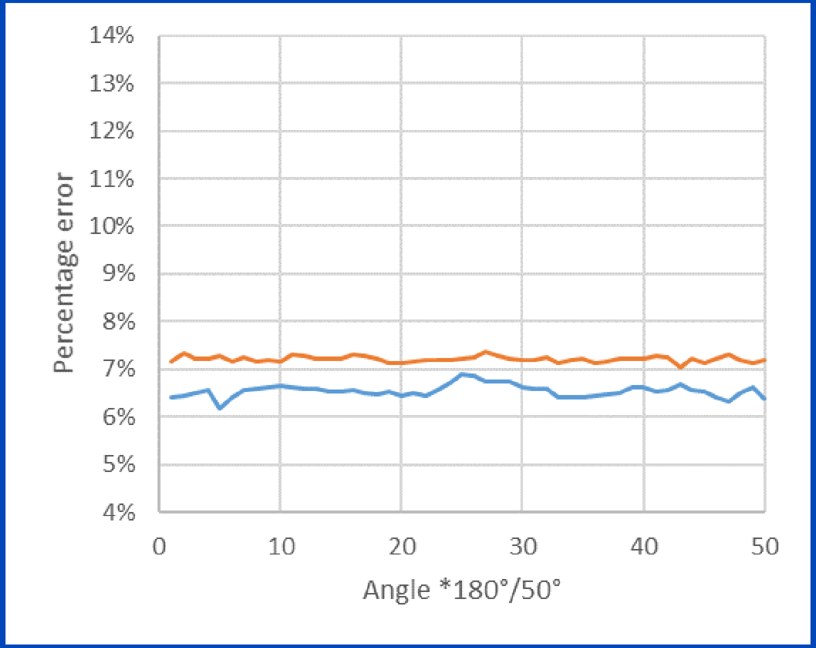
Angular dependence

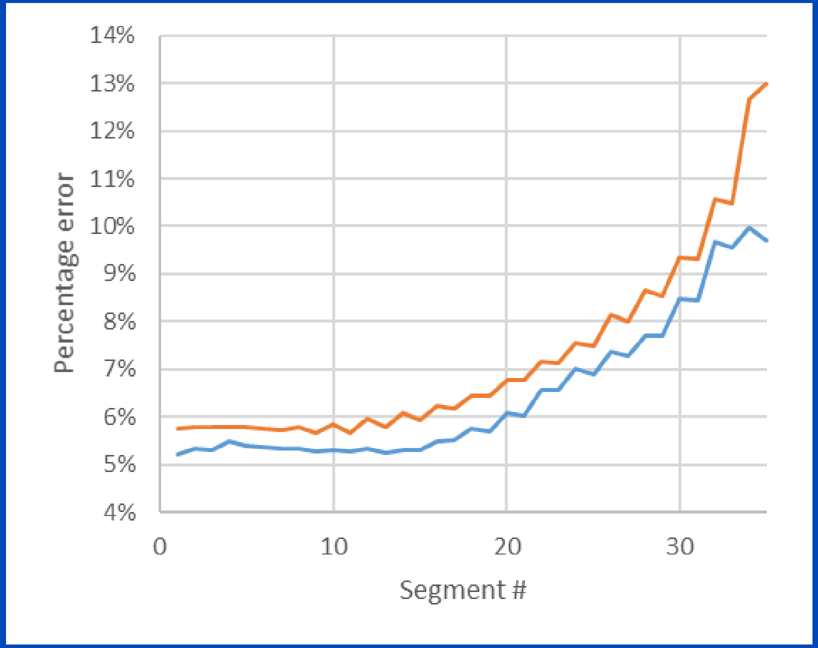


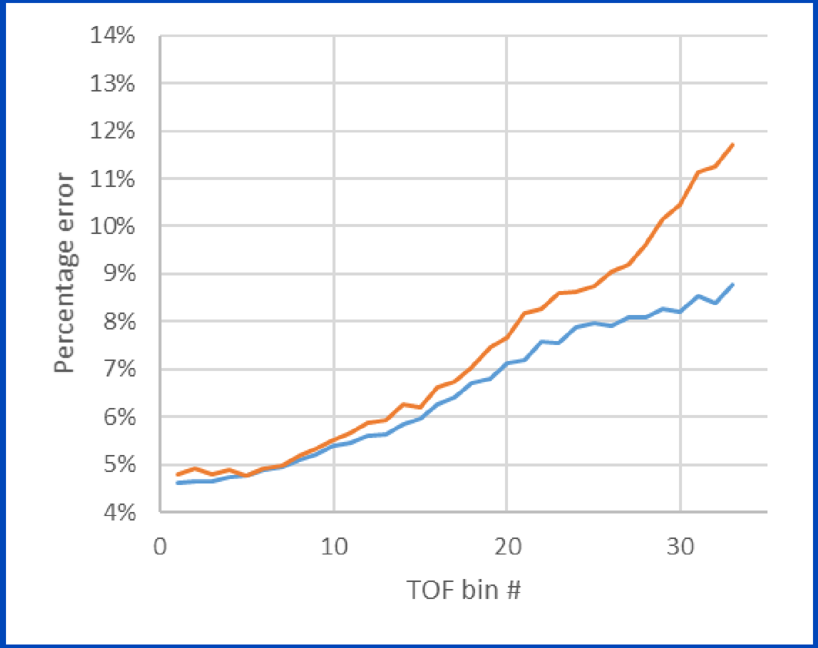
Segment dependence



TOF bin dependence





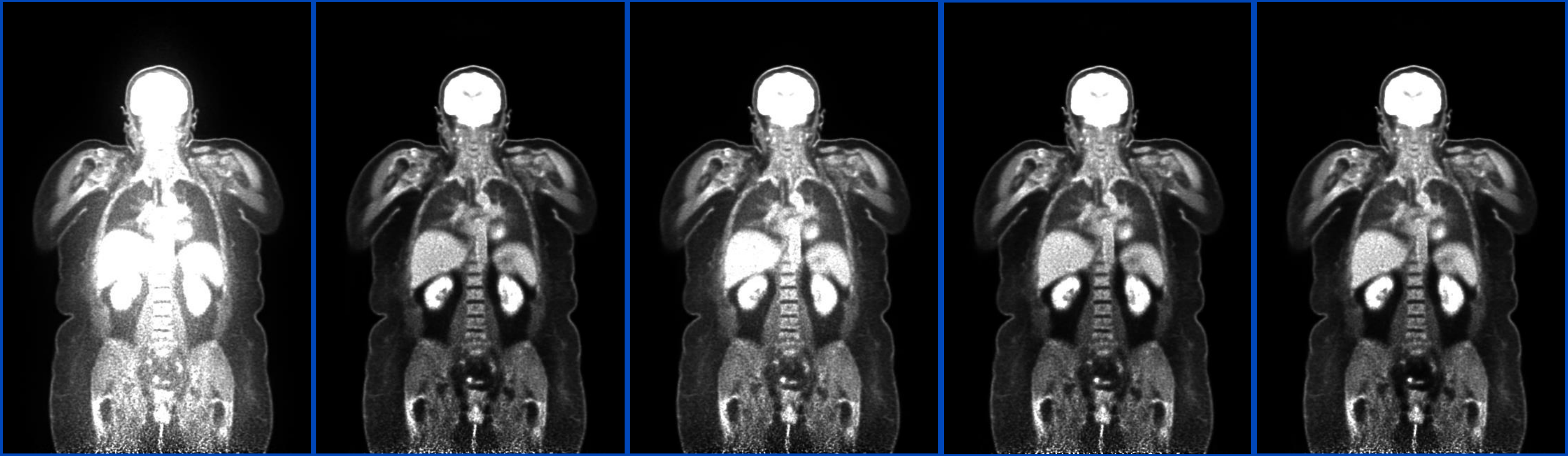


Single TOF bin   All TOF bins as channels

PET Reconstructions + Scatter Correction

Female patient, BMI = 43

No Correction	Monte Carlo (MC)	Siemens SSS	DSE #1	DSE #2

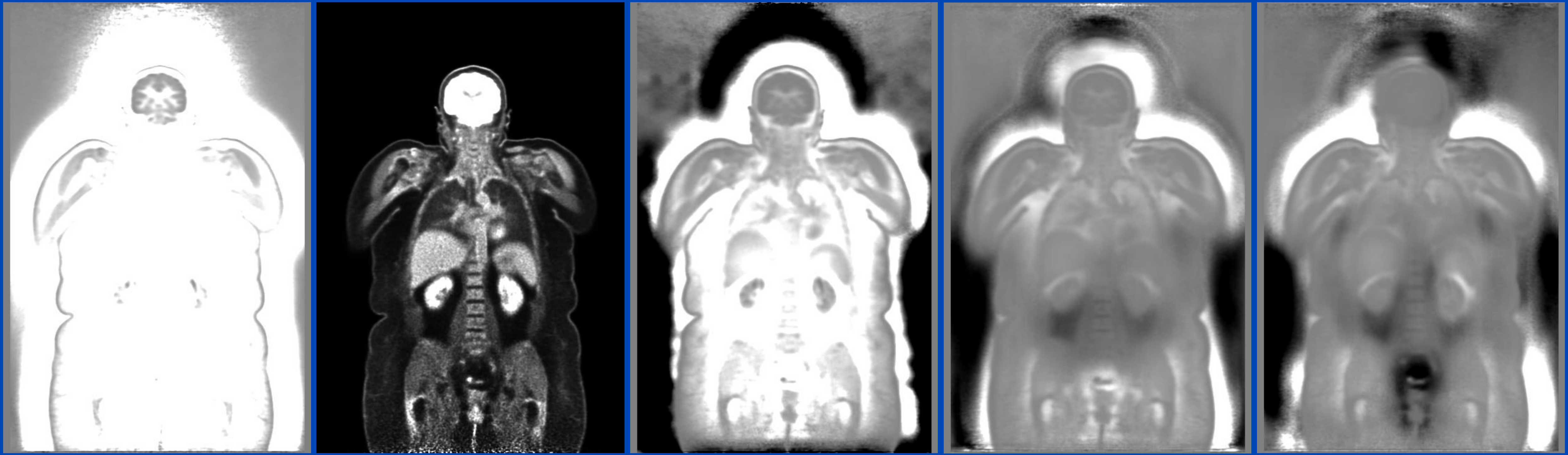


C = 2000, W = 4000

PET Reconstructions + Scatter Correction

Female patient, BMI = 43

(No Correction – MC)/MC | Monte Carlo (MC) | (Siemens SSS – MC)/MC | (DSE #1 – MC)/MC | (DSE #2 – MC)/MC



Avg: 140.7 % | Avg: 27.8 % | Avg: 6.5 % | Avg: 7.1 %

C = 0 %, *W* = 100 %

Conclusions

- DSE can reproduce Monte Carlo Scatter estimates with a mean absolute percentage error (MAPE) of about 6 % (SSS error: 23 %).
- Similar trends are observed for scatter-corrected reconstructions with a MAPE of 7 % for DSE and a MAPE of 28 % for SSS.
- A single DSE network can be trained to account for different TOF bins and different segments, however, with a slightly reduced accuracy for higher TOF values and highly oblique planes.
- No advantage of processing all TOF bins at once as different input channels to the network.
- Runtime: 5 ms per sample (520 x 645), 5 min per data set (~ runtime of SSS).

Thank You!

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

Job opportunities through DKFZ's international PhD or Postdoctoral Fellowship programs (www.dkfz.de), or directly through Prof. Dr. Marc Kachelrieß (marc.kachelriess@dkfz.de).

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