Deep Bowtie and Patient Scatter Correction Applied to Clinical Photon-Counting CT

Lukas Hennemann[1,2,3], Julien Erath[1,2], Andreas Heinkele[1,2,3], Joscha Maier[1], Eric Fournié[2], Martin Petersilka[2], Karl Stierstorfer[2], and Marc Kachelrieß[1,3]

[1]German Cancer Research Center (DKFZ), Heidelberg, Germany
[2]Siemens Healthineers, Forchheim, Germany
[3]Ruprecht-Karls-Universität, Heidelberg, Germany
www.dkfz.de/ct

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Motivation

- **Several artifacts may impair CT image quality**
  - Noise
  - Motion
  - Metal
  - Scatter
  - ….
- **This work focuses on deep learning-based scatter correction**

Scatter correction

- Statistical approaches
  - Image-based (MC, Boltzmann transport)
- Analytical approaches
  - Image-based (MC, Boltzmann transport)
  - Projection-based (pep model[3])
- Deep learning-based (e.g. DSE[1,2])
- Measurement-based

[1] J. Maier, M. Kachelrieß et al. "Robustness of DSE", Med. Phys. 46(1):238-249, January 2019.
[2] J. Maier, M. Kachelrieß et al. "Deep Scatter Estimation (DSE)", SPIE 2018 and J. of Nondest. Eval. 37:57, July 2018.
[3] B. Ohnesorge, K. Klingenbeck-Regn et al. "Efficient object scatter correction algorithm for third and fourth generation CT scanners" *European Radiology* 9, 563–569 (Mar. 1999)
[4] E. P. Rührnschopf, K. Klingenbeck „A general framework and review of scatter correction methods in x-ray cone-beam computerized tomography. Part 1: Scatter compensation approaches" *Medical Physics* 38, 4296–4311 (June 2011)

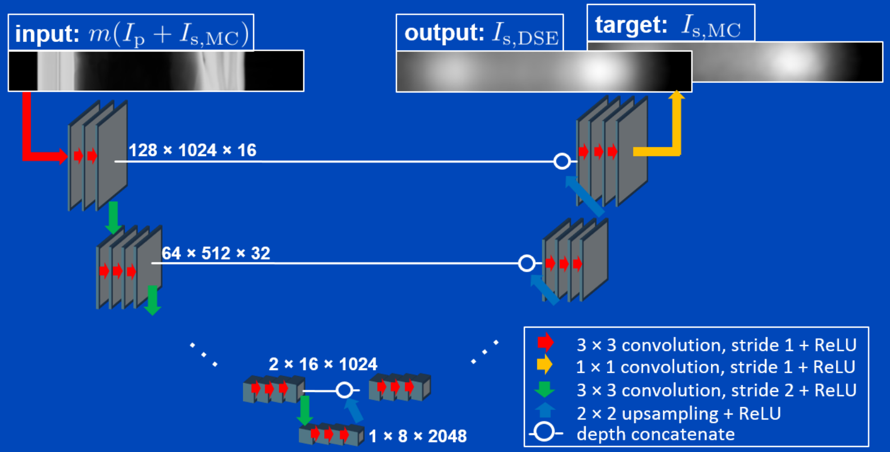
Prior Work

- Deep neural networks are powerful tools to reduce object scatter artifacts.[1-5]
- The deep scatter estimation (DSE) outperforms other techniques.[1-5]
- DSE can also be trained with measured data and is real-time capable.[1,2,5]
- DSE also shows great potential for cross-scatter correction.[4,5]

Scatter profile from Monte Carlo simulation
Time: 65 s per projection = 14 h per circle scan

Scatter prediction from deep scatter estimation
Time: 6.7 ms per projection = 8 s per circle scan

| DSE - MC | MAPE = 2.5 %



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Current limitations:

Bowtie scatter estimation has not been incorporated in previous work.

Aim: To obtain information on whether it is possible to estimate object/patient and bowtie scatter simultaneously with the DSE, or whether a separate estimation is necessary.

[1]J. Maier, M. Kachelrieß et al. “Deep Scatter Estimation (DSE)“, SPIE 2018 and J. of Nondest. Eval. 37:57, July 2018.
[2]J. Maier, M. Kachelrieß et al. “Robustness of DSE“, Med. Phys. 46(1):238-249, January 2019.
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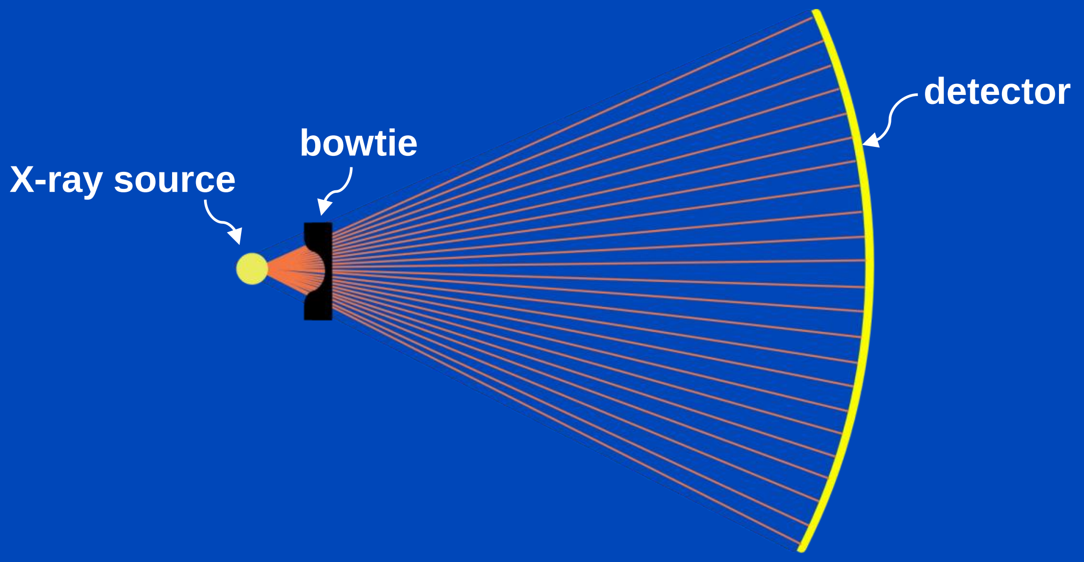
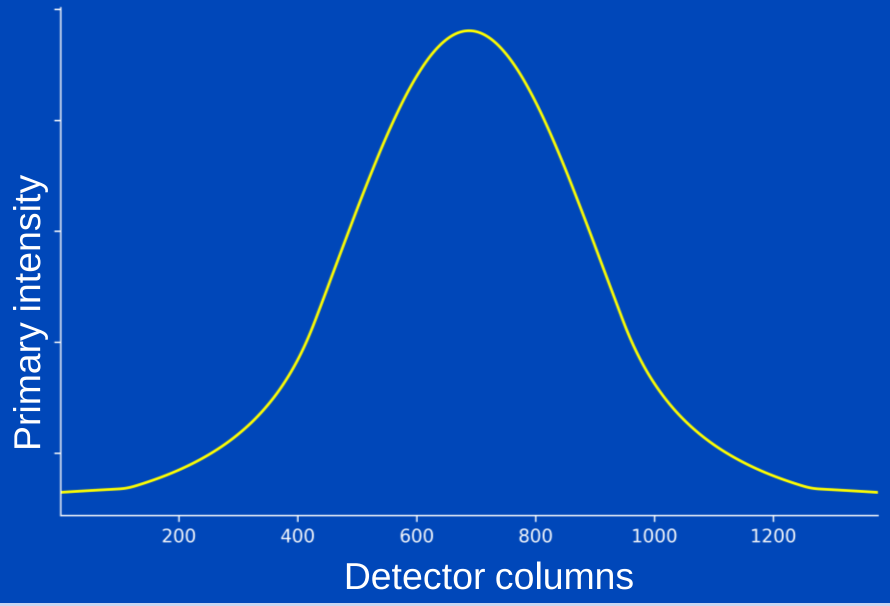
Bowtie Filter

- Scattered radiation can originate not only from patients or scanned objects but also from other elements in the beam path, such as bowtie or shape filters.
- Bowtie filters are used to modulate the X-ray beam intensity depending on the beam position. The aim is to optimize the dose distribution and improve image quality at the same time.
- Unlike other prefilters, bowtie filters are inhomogeneous in the φ-direction, which leads to a position-dependent attenuation and thus to different scatter to primary ratios, which directly correlate with errors in the reconstructed images.





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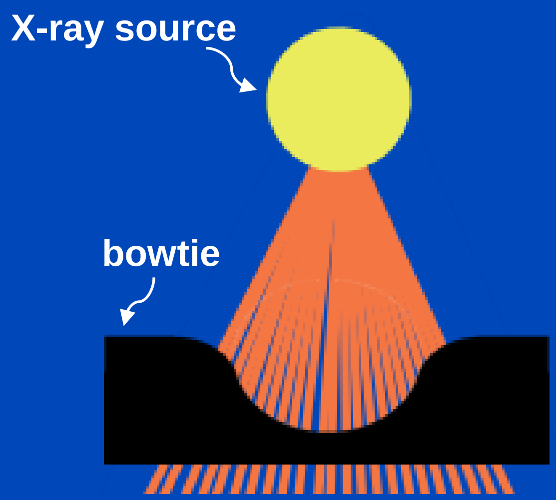
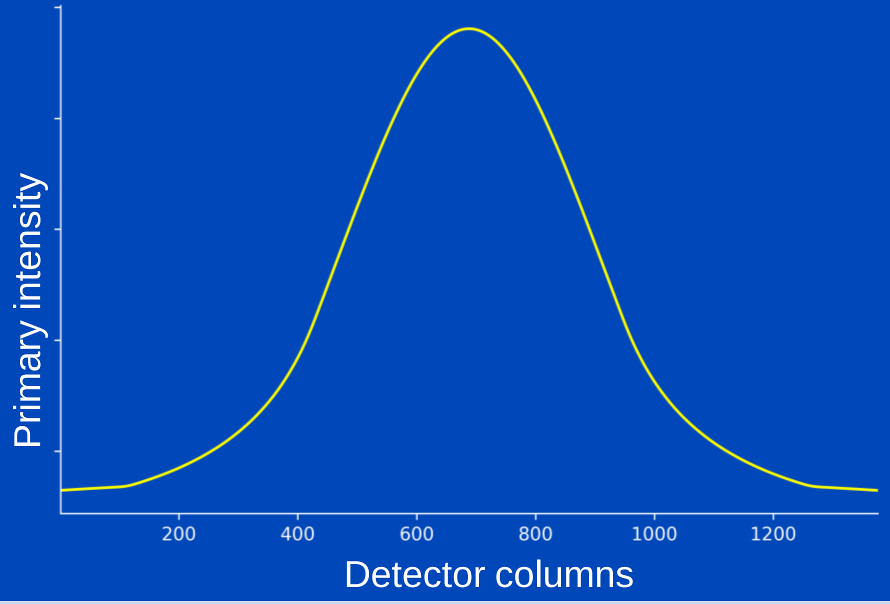
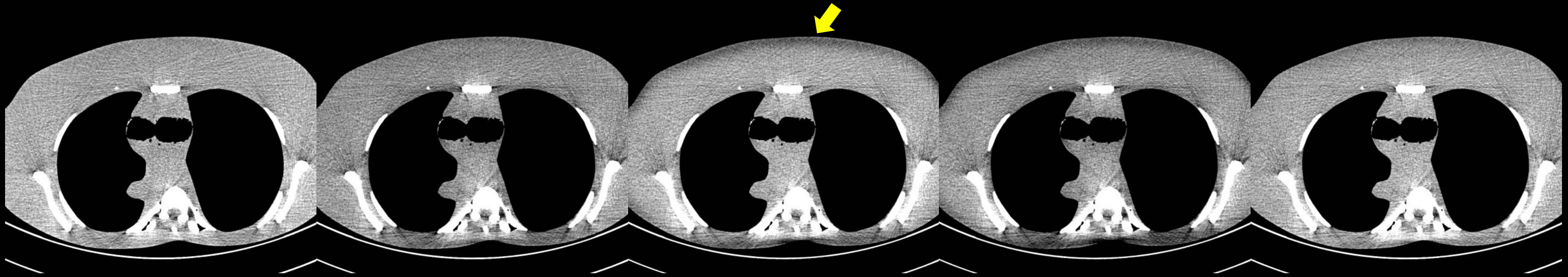




Scatter Artifacts in Image Domain – Measurements

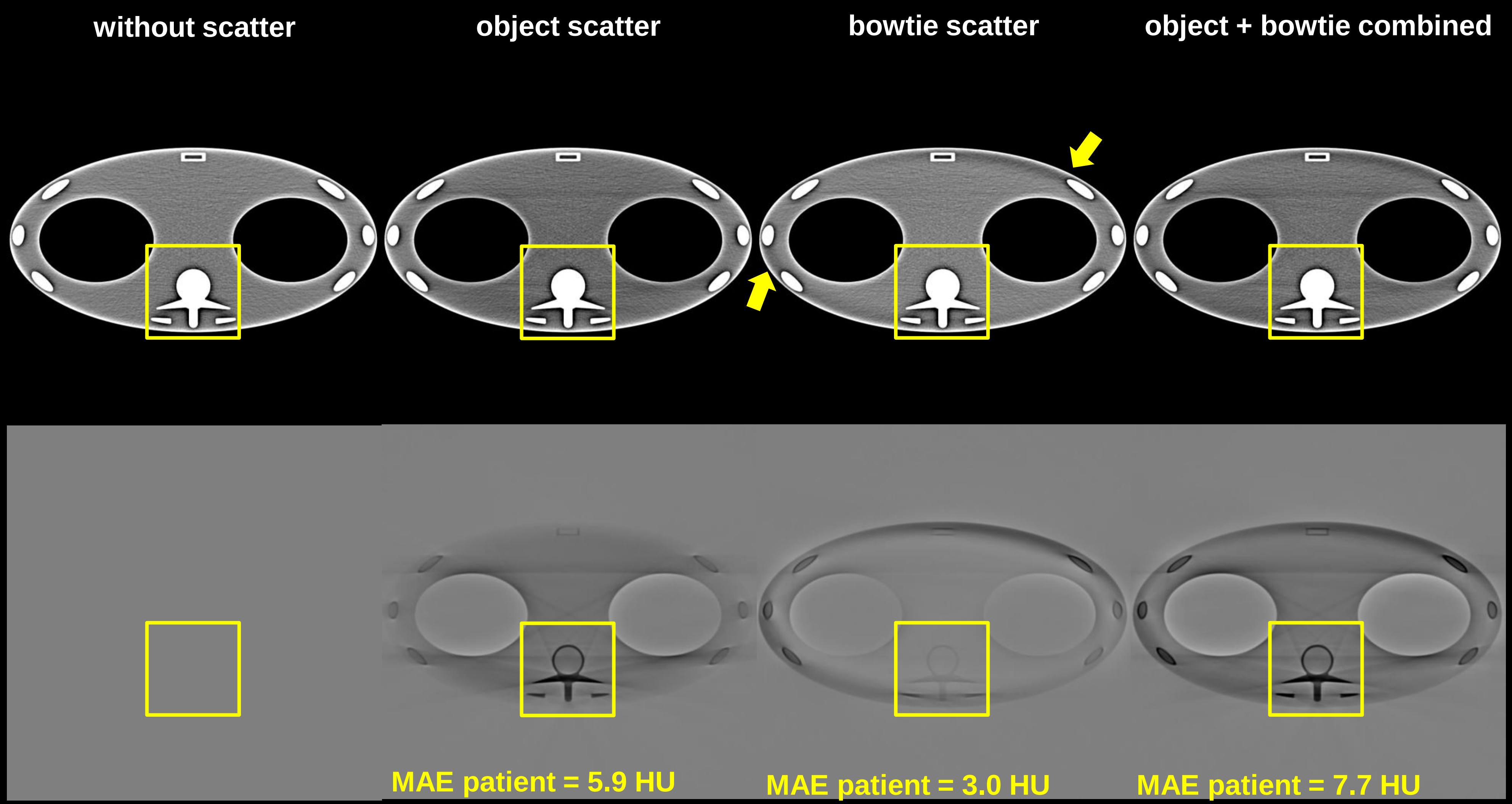
without scatter	object scatter	bowtie scatter	object + bowtie combined	PEP approach scatter correction



slit scan	only bowtie scatter correction active!	only object scatter correction active!	no scatter correction active!	object and bowtie scatter correction active!

FOV 350 mm, Qr40f kernel, FBP reconstruction, C = 20 HU, W = 100 HU

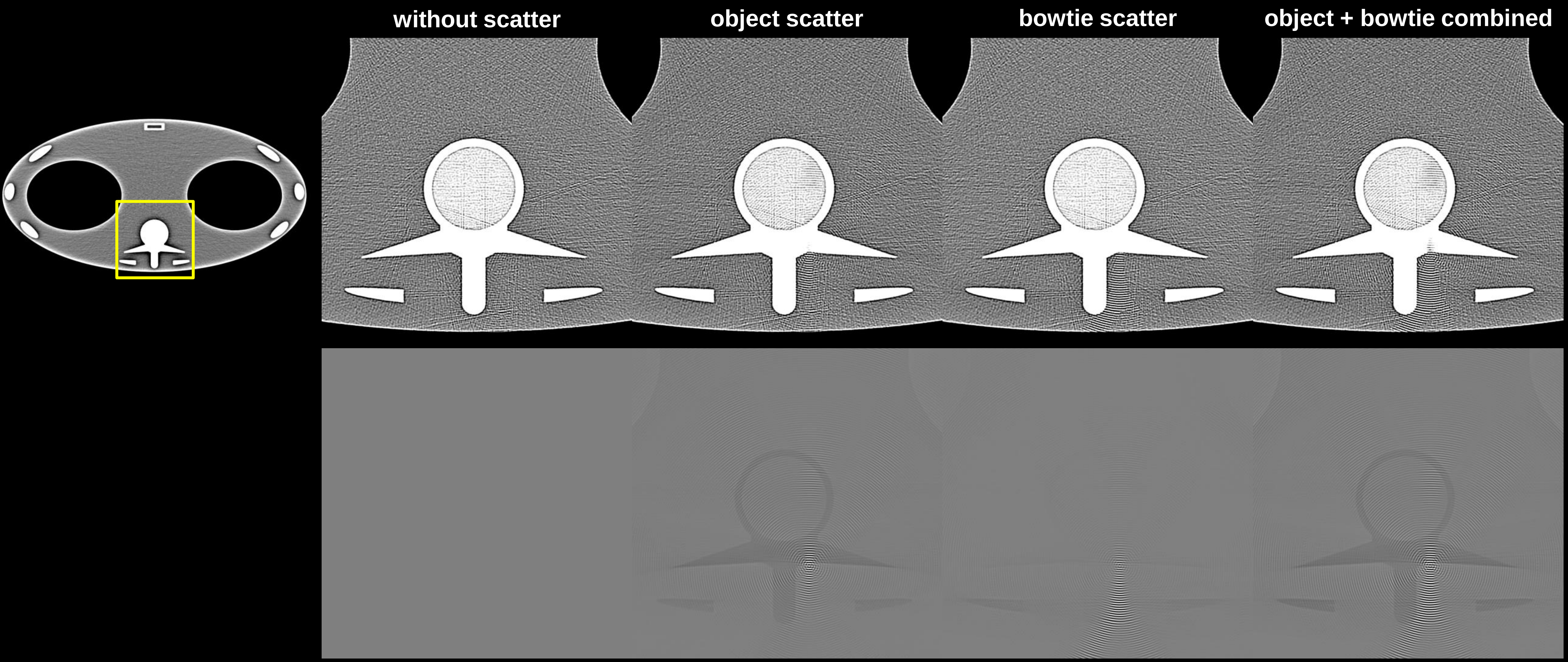
Scatter Artifacts in Image Domain – Low Energy



FOV 370 mm, Br40f kernel, FBP

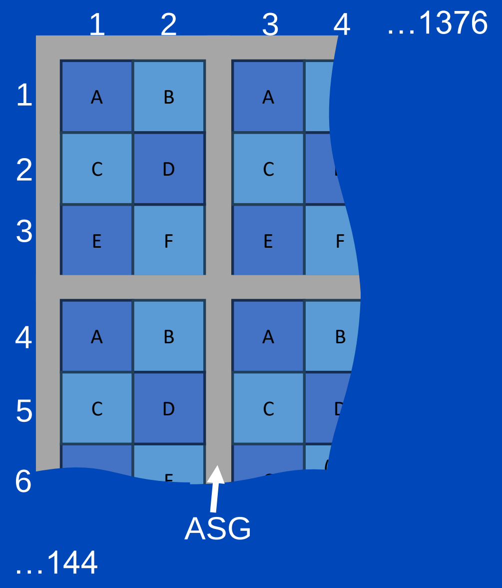
Images: *C* = 0 HU, *W* = 100 HU. Difference images: *C* = 0 HU, *W* = 100 HU.

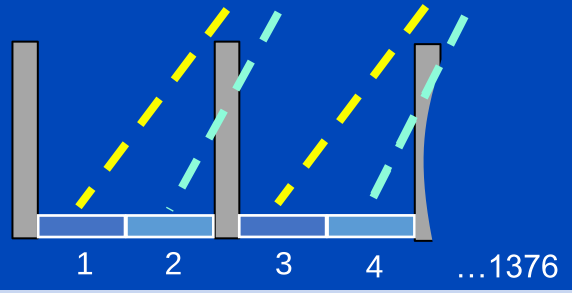
Scatter Artifacts in Image Domain – Low Energy

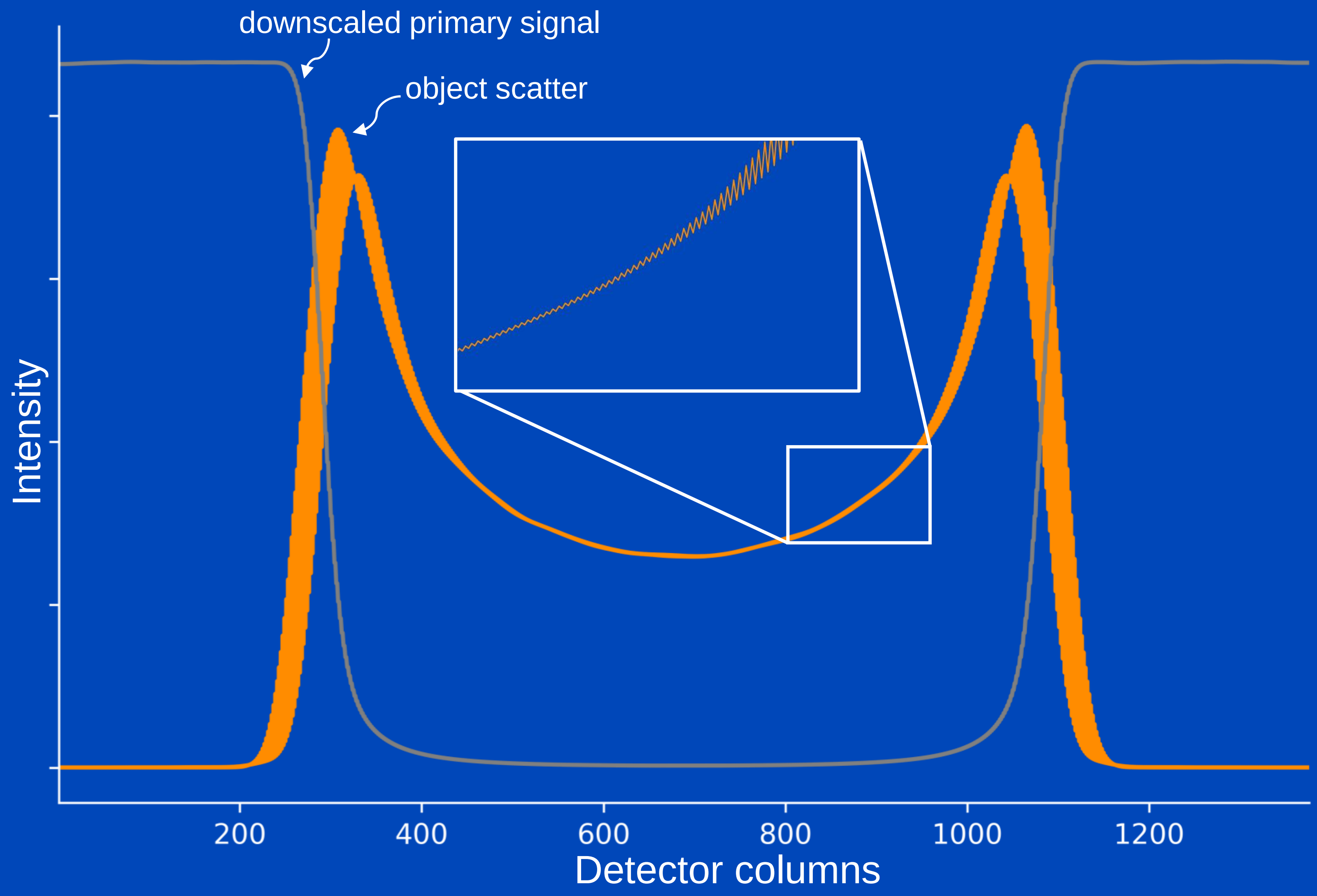


Reconstruction: FOV 100 mm, Br72f kernel, reconstructed images *C* = 0 HU, *W* = 400 HU
difference images *C* = 0 HU, *W* = 200 HU

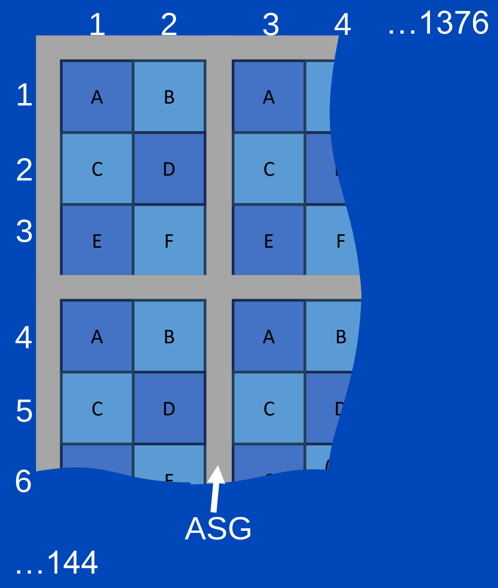
Object Scatter for Coarse Anti-Scatter Grid (ASG)

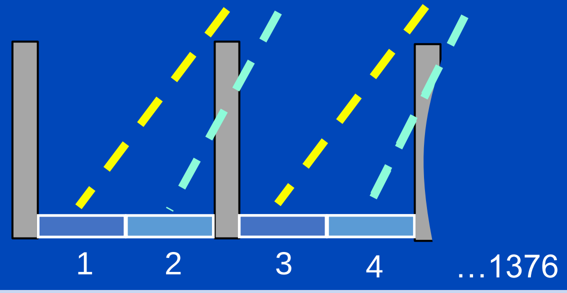


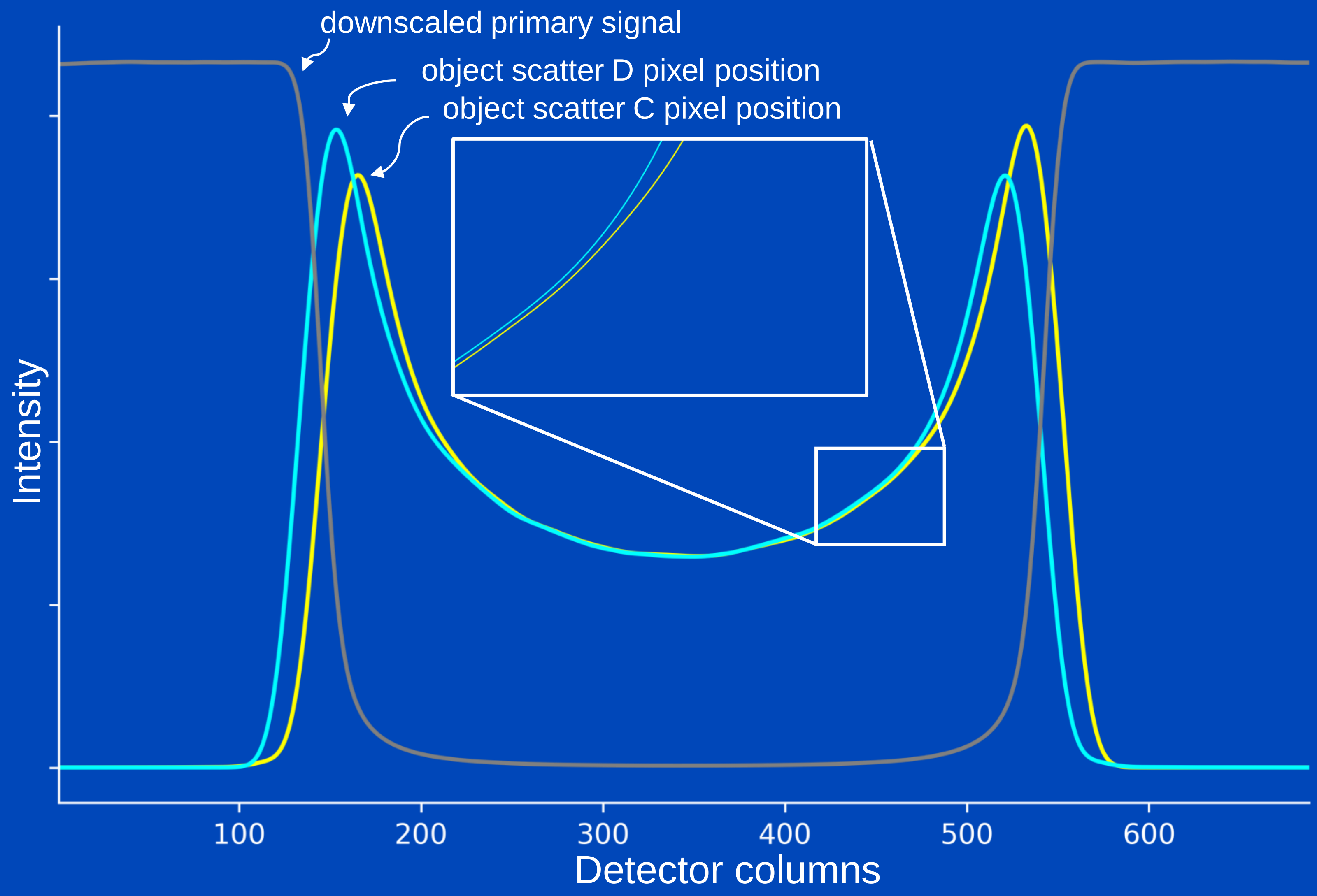




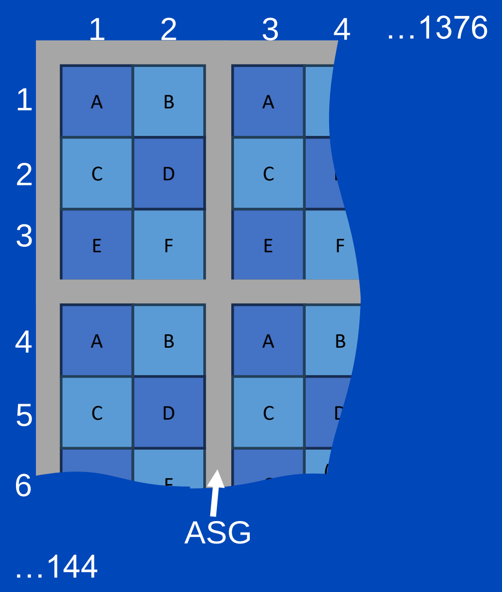
Object Scatter
Split into C/D Pixel Position within ASG

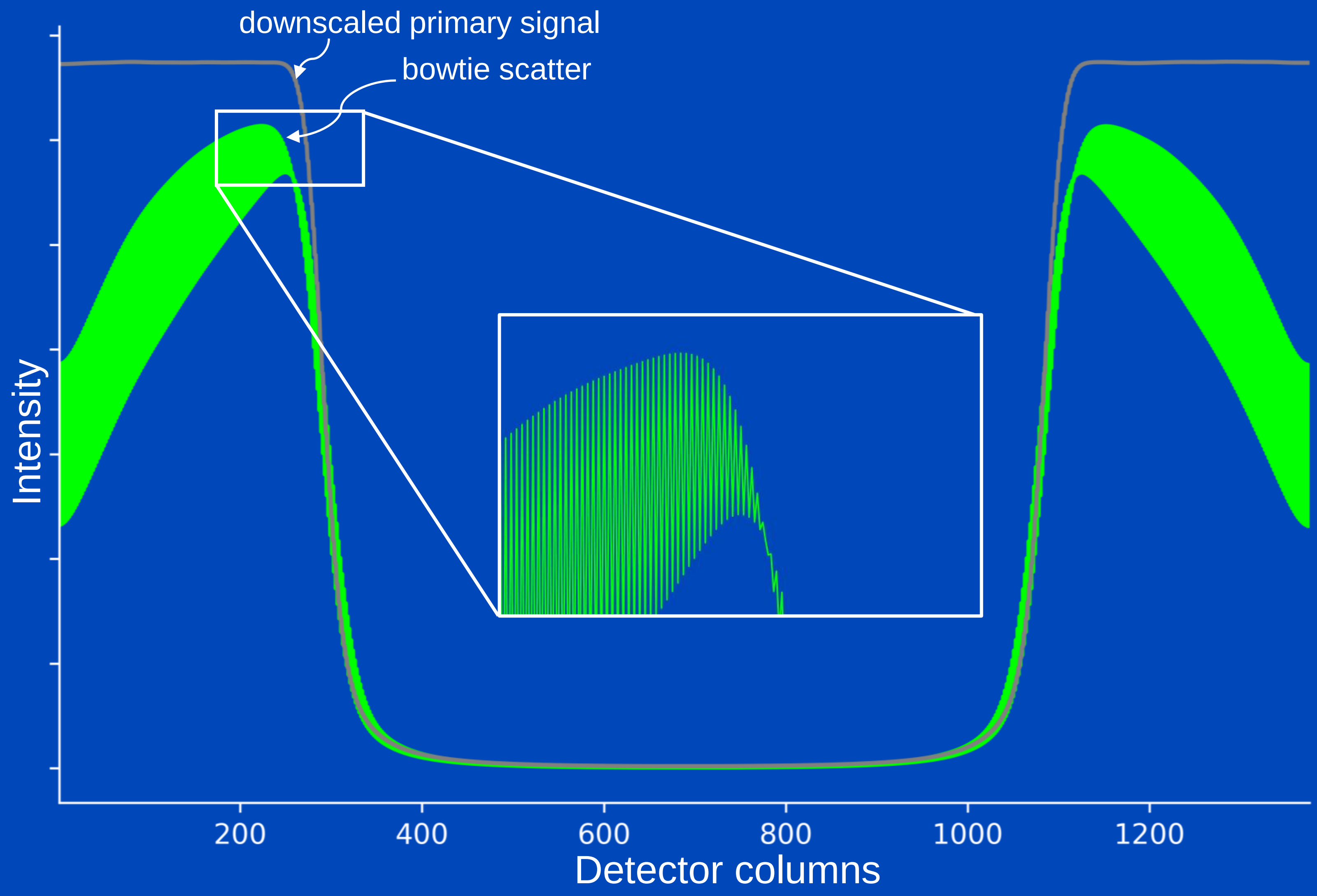


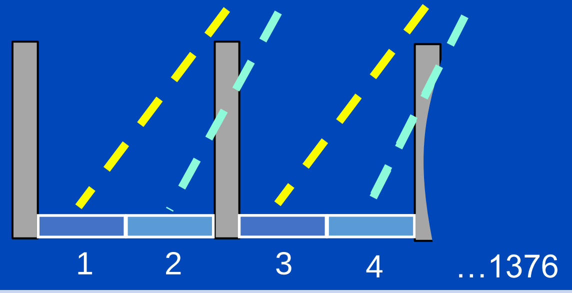




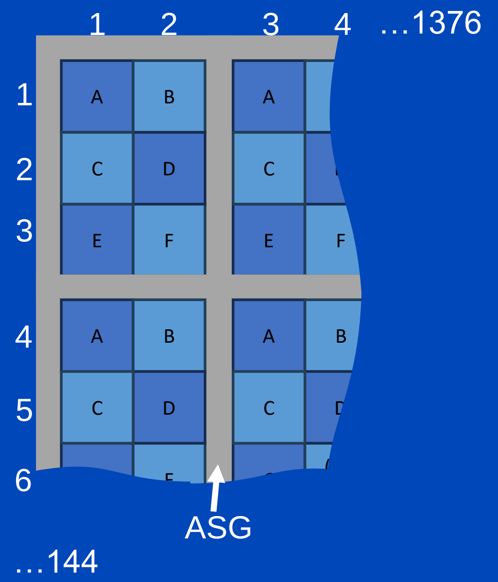
Bowtie Scatter (Attenuated by Object) for Coarse ASG

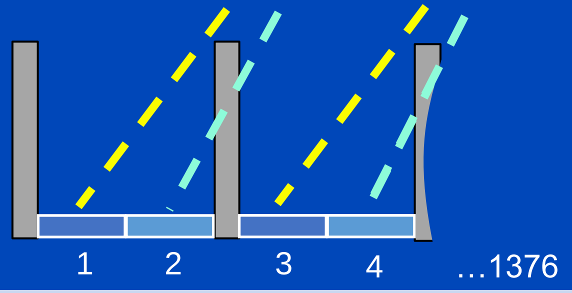


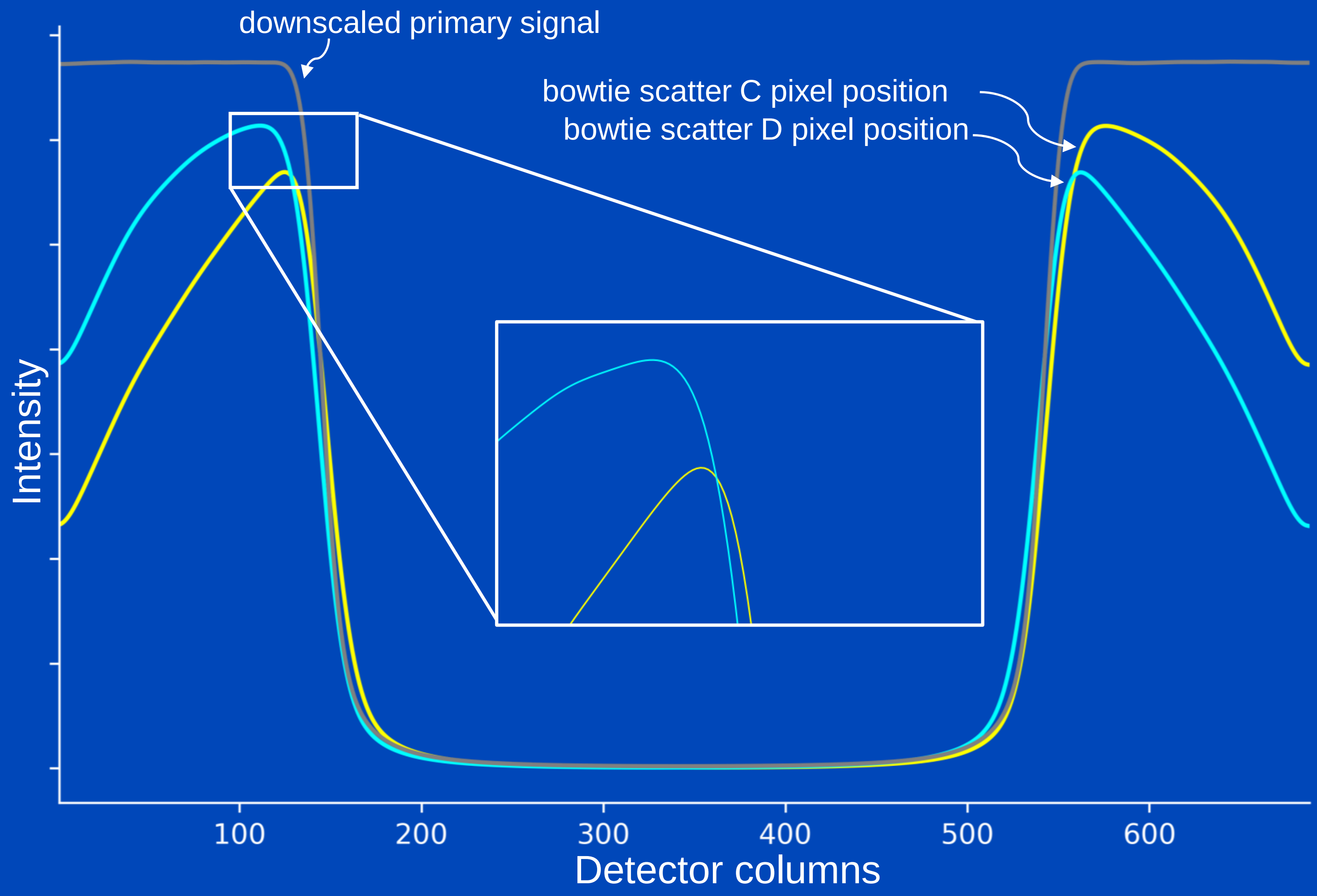




Bowtie Scatter (Attenuated by Object) Split into C/D Pixel Position within ASG







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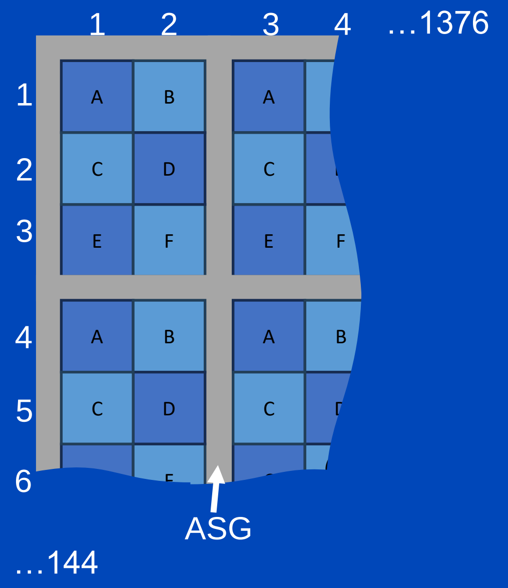
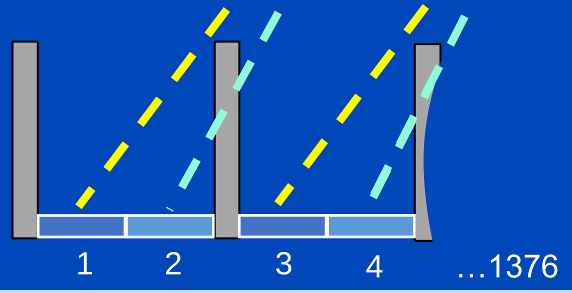
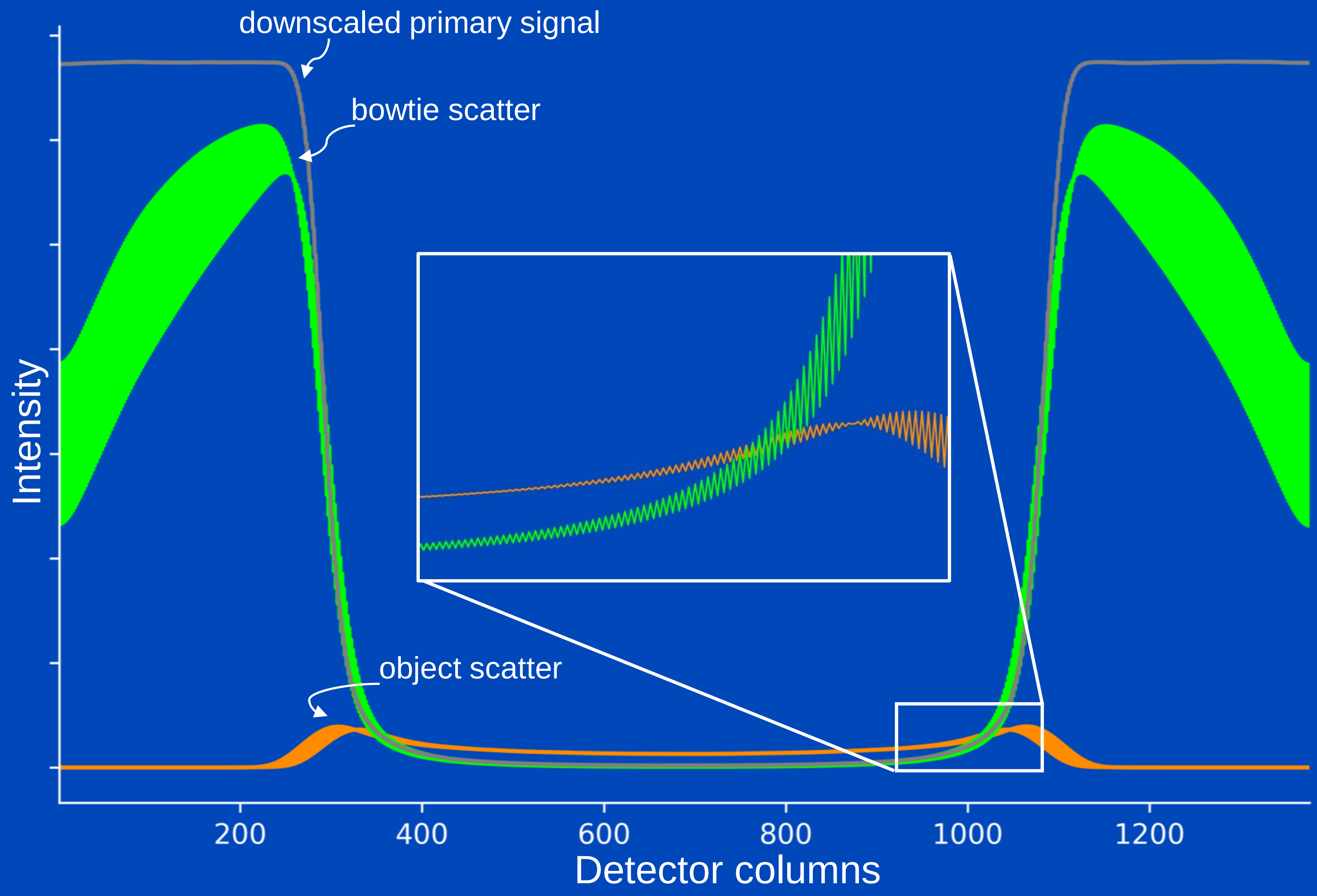
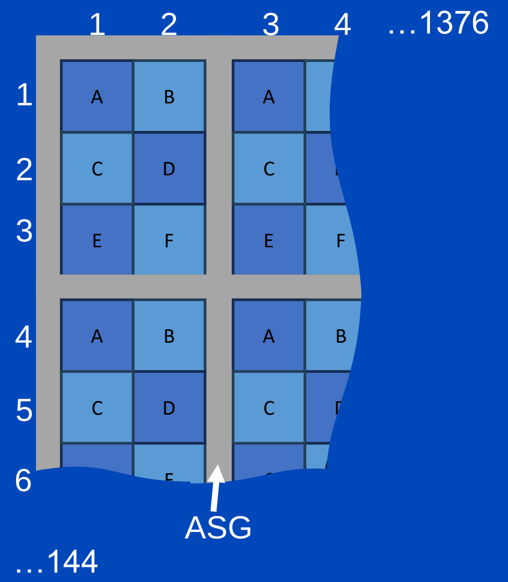
Scatter for Coarse ASG

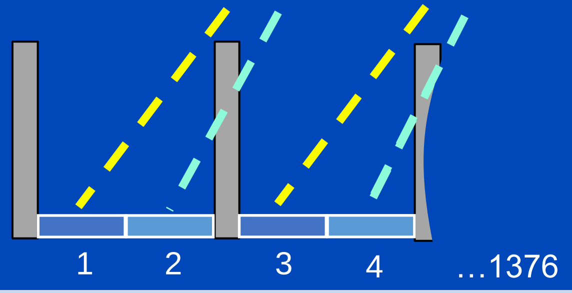


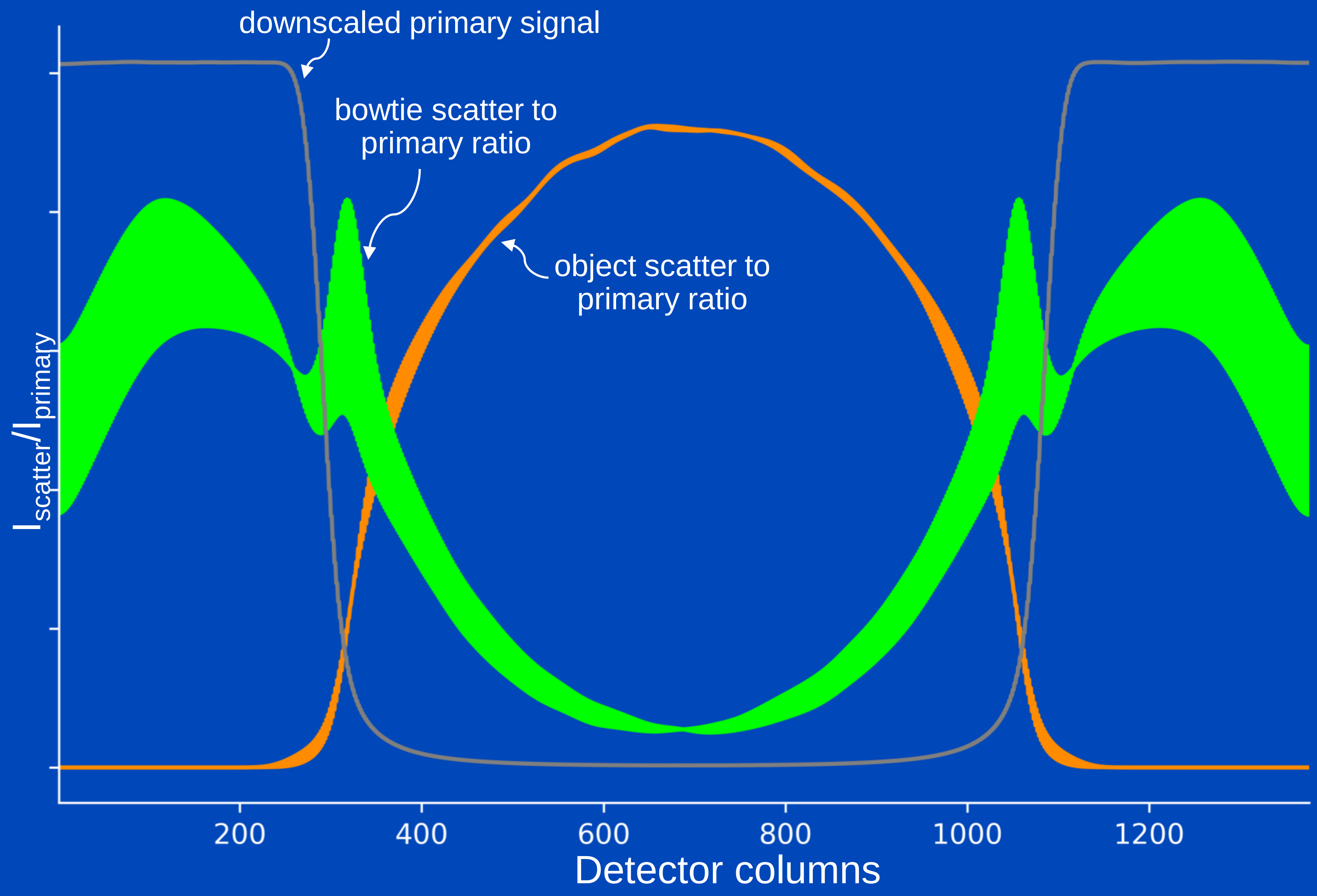




Scatter to Primary Ratio for Coarse ASG







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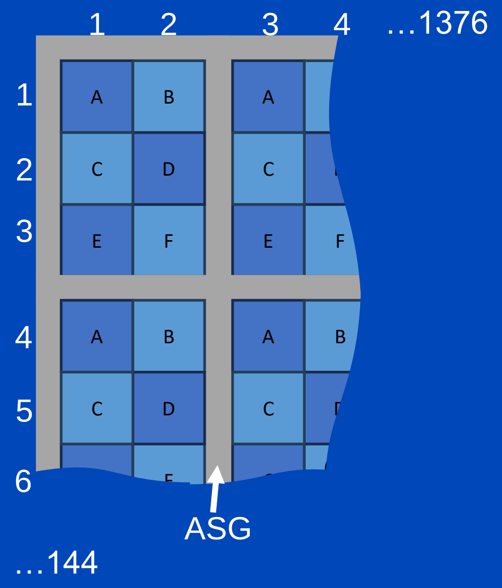

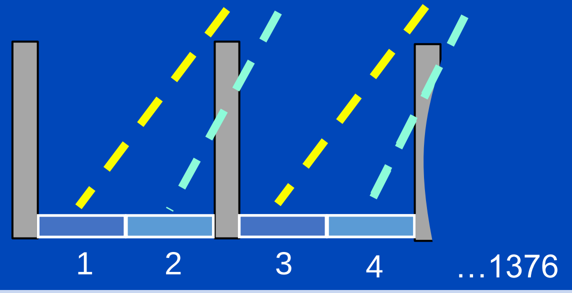

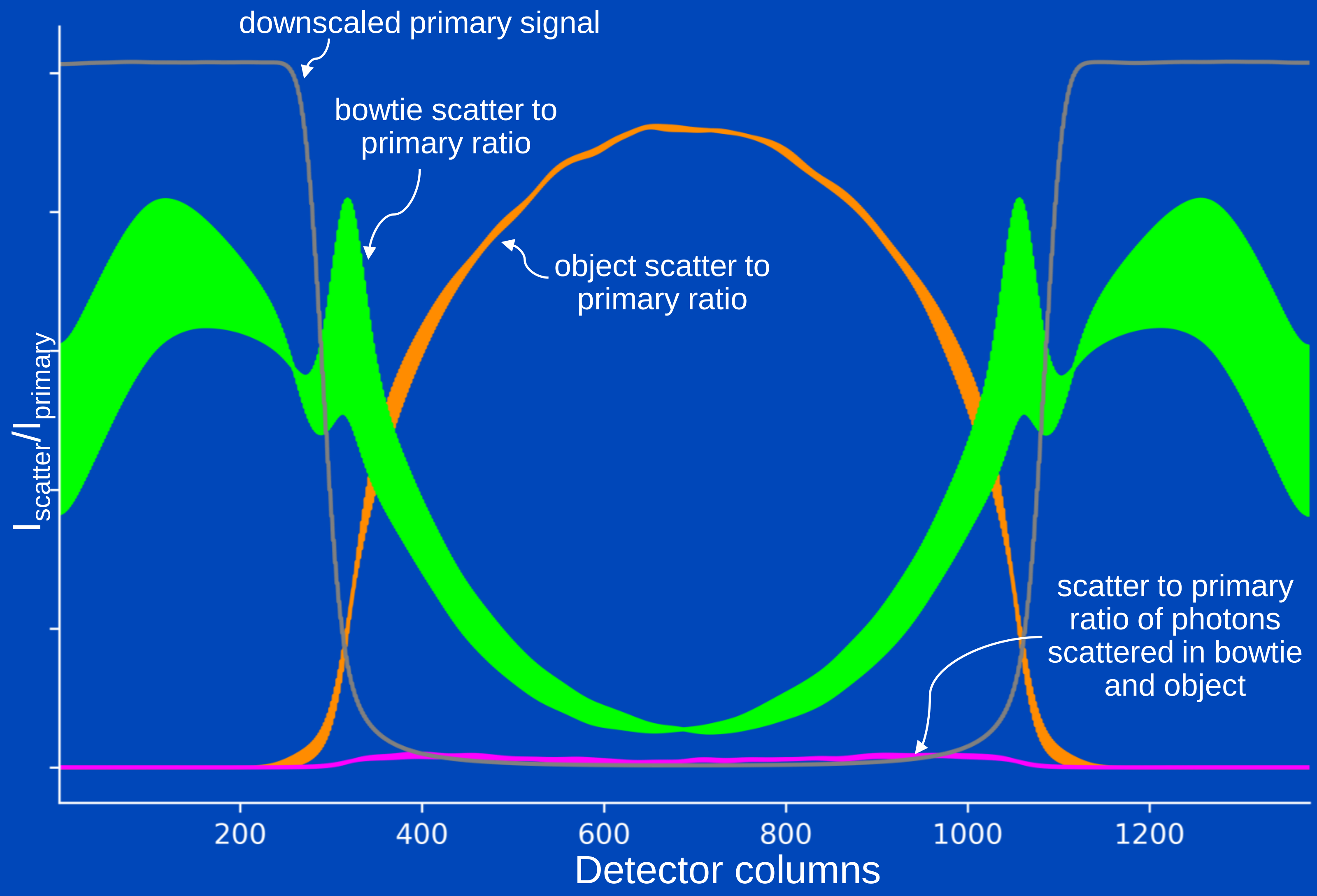

Deep Scatter Estimation (DSE)

- Deep scatter estimation[1-5] outperforms other scatter estimation techniques[1,2,4,5] and shows great potential for cross-scatter correction[4,5] and real-time scatter estimation.[1,2,5]
- Training parameters:
  - Input:

$$p = -\ln\left(\frac{I_{\text{primary}}}{I_0} + \frac{I_{\text{object scatter}}}{I_0} + \frac{I_{\text{bowtie scatter}}}{I_0}\right)$$

  - Addition of varying noise in projection domain (corresponds to approx. 10 to 100 HU in image domain) during training to further improve robustness
  - Loss function: SPMAPE (scatter-to-primary weighted MAPE)
  - Output, which one is better?

combined $\boxed{\frac{I_{\text{object scatter}}}{I_0} + \frac{I_{\text{bowtie scatter}}}{I_0}}$ separately $\boxed{\frac{I_{\text{object scatter}}}{I_0}}, \boxed{\frac{I_{\text{bowtie scatter}}}{I_0}}$

[1]J. Maier, M. Kachelrieß et al. "Deep Scatter Estimation (DSE)", SPIE 2018 and J. of Nondest. Eval. 37:57, July 2018.
[2]J. Maier, M. Kachelrieß et al. "Robustness of DSE", Med. Phys. 46(1):238-249, January 2019.
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Data Set

- Monte Carlo-simulated data corresponding to the photon-counting CT scanner NAEOTOM Alpha.Prime (Siemens Healthineers)
- 100 different thorax, head (both FORBILD[1,2]) and cylindrical/elliptical 30 cm water phantoms
  - Different phantom sizes (uniformly distributed scaling from 0.7 to 1.3)
  - Different phantom positions (uniformly distributed from -5 cm to 5 cm)
  - One projection simulated every 5°
- This resulted in 72 projections per 360° scan, which corresponds to a total number of data pairs (primary and scatter object/bowtie) of 7200.
- Training, validation and test split is 70:20:10.
- Simulation of a coarse ASG with detector dimensions of 1376 × 144 pixels
- Four different energy thresholds 20 keV, 55 keV, 70 keV and 90 keV (values available at the scanner) for 140 kV tube voltage.
- Networks are trained with 20 keV threshold data only.

[1]M. Kachelrieß "The FORBILD CT–simulation phantoms," Proc. of the 1999 Int. Meeting on Fully 3D Image Reconstruction, p. 383 (1999).
[2]www.dkfz.de/ct

UNet Architecture DSE

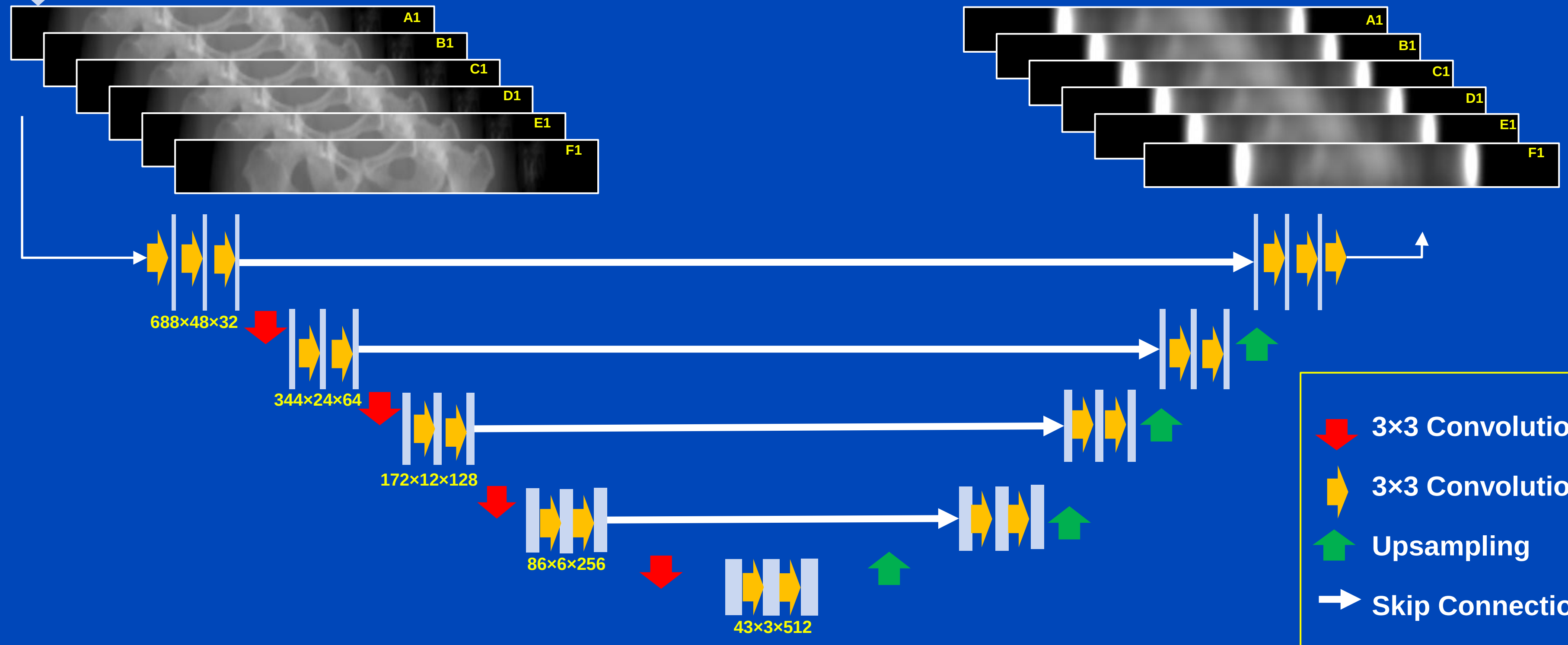
Detector dimension 1376×144

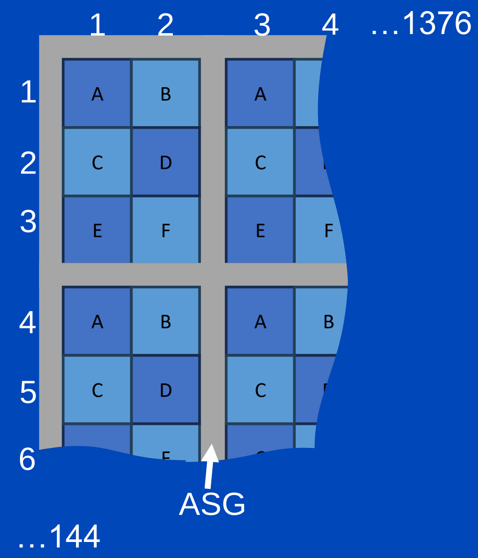
Each channel corresponds to a different pixel position between the lamellae of the ASG

merging 6 pixel positions

Input: 6 channels
(1 energy threshold × 6 pixel positions)
Dimension: 688×48

Output: 6 channels





3×3 Convolution, Stride 2

3×3 Convolution, Stride 1

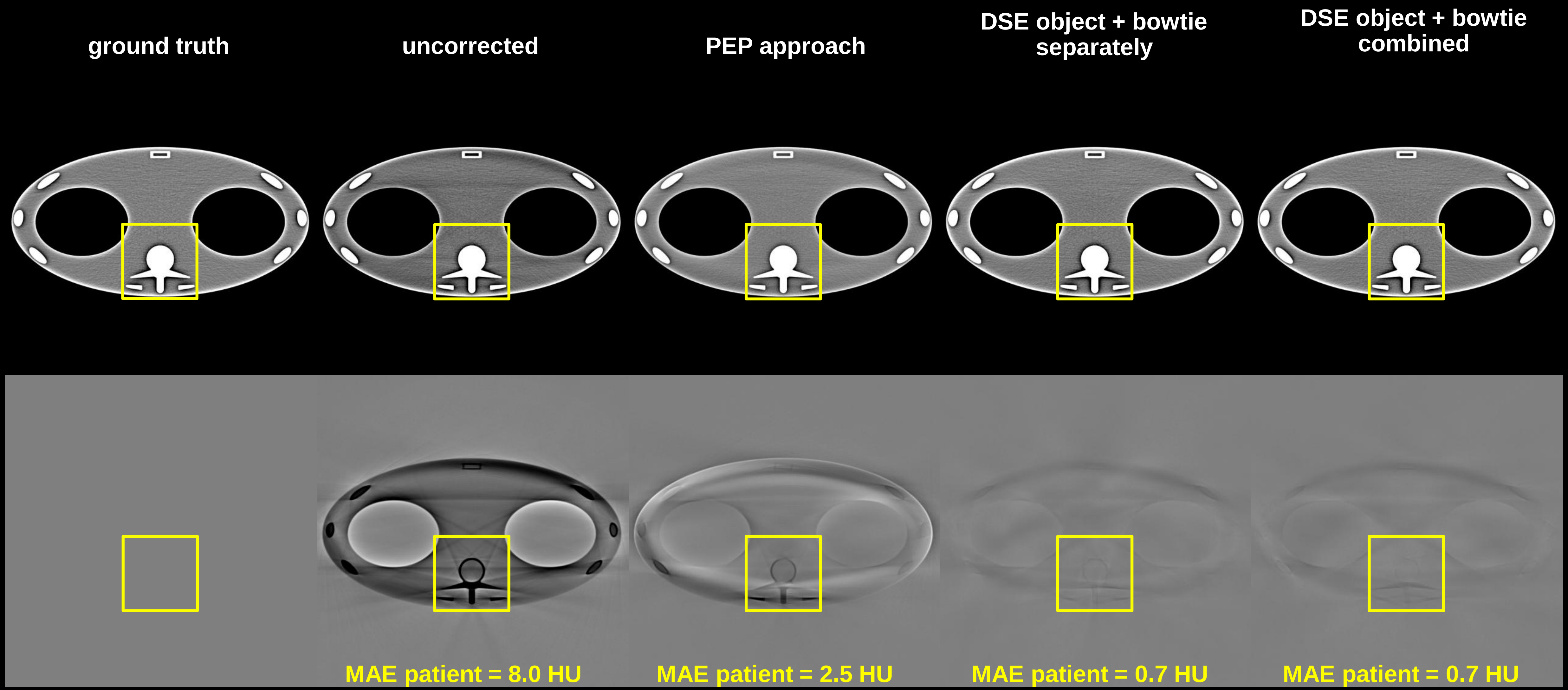
Upsampling

Skip Connection

- Number of network parameters: 8,631,724

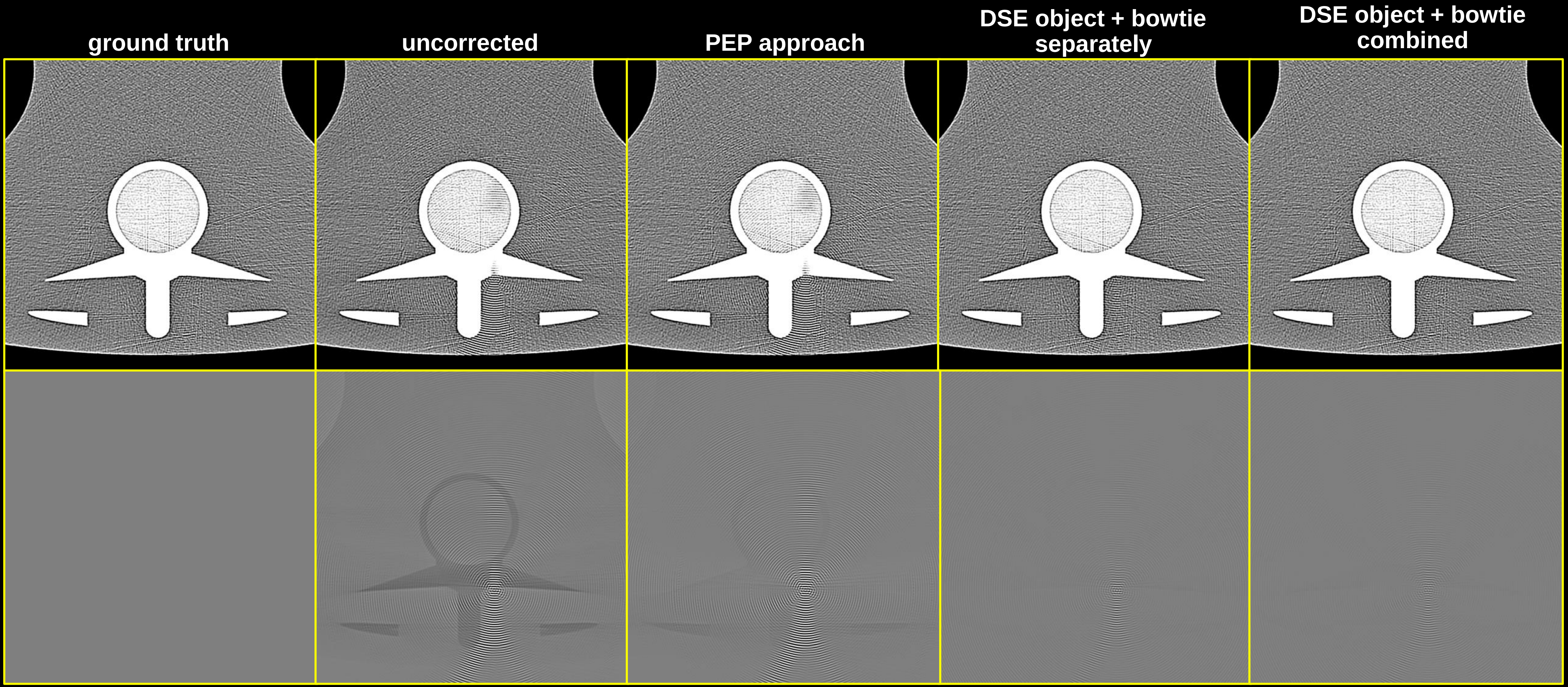
RESULTS

Reconstructions Low Energy - Thorax



Reconstruction: FOV 370 mm, Br40f kernel, reconstructed images C = 0 HU, W = 150 HU
difference images C = 0 HU, W = 50 HU

Reconstructions Low Energy - Thorax



Reconstruction: FOV 100 mm, Br72f kernel, reconstructed images *C* = 0 HU, *W* = 400 HU
difference images *C* = 0 HU, *W* = 200 HU

Conclusions

- Bowtie scatter
  - appears mostly at the edge of the scanned objects.
  - leads to visible artifacts and shading.
- DSE is able to reduce scatter artifacts caused by bowtie and object.
- High-frequency scatter artifacts caused by the coarse ASG are significantly reduced.
- Separate estimation of bowtie and object scatter not necessary.
  - For the test data set the separately trained DSE reduce the MAE by 7.0 HU (from 8.1 HU to 1.1 HU) compared to the uncorrected MC-simulated images.
  - DSE trained on bowtie and object scatter combined performs slightly better with a reduction in the MAE of around 7.2 HU (from 8.1 HU uncorrected to 0.9 HU DSE-corrected).
- Next step: apply to real measurements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