Latent Space Reconstruction (LSR) and its Application to CT Detruncation

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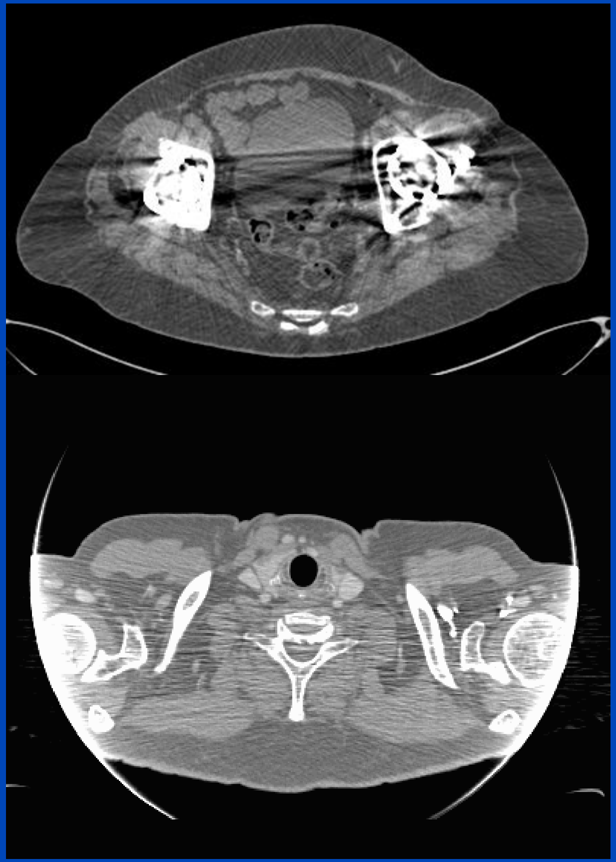
DEUTSCHES
KREBSFORSCHUNGSZENTRUM
IN DER HELMHOLTZ-GEMEINSCHAFT

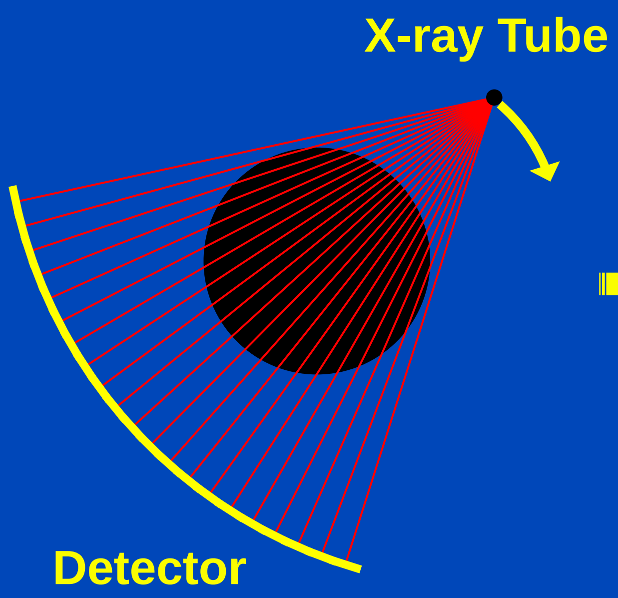
Introduction

- High quality images can be reconstructed, if the reconstruction problem is well-posed.
- In practice, that depends on
  - Sufficient projections
  - Complete and “noise-free” data
  - …
- CT examples for missing data
  - Limited angle
  - Metal artifacts
  - Sparseness artifacts
  - Truncation (lateral, longitudinal, …)
  - …

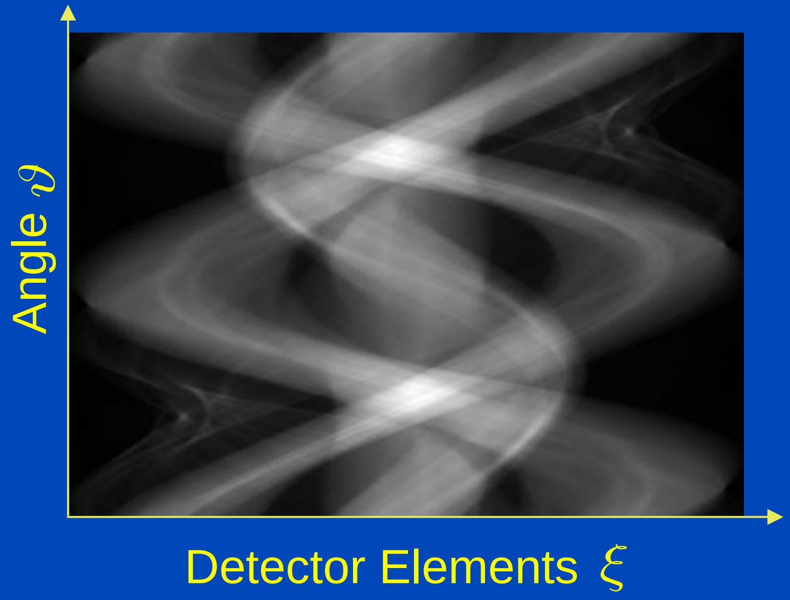


Introduction

Truncation in CT

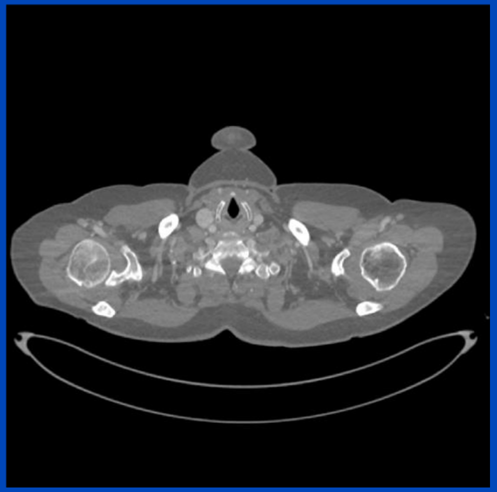


Projection Data p
or Sinogram



FBP

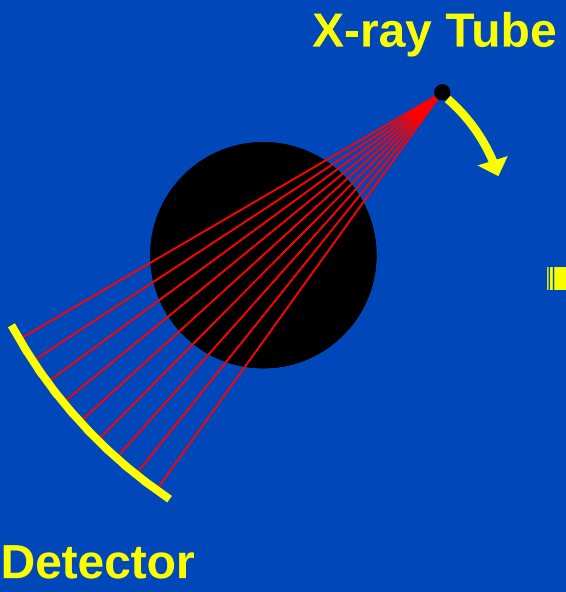
Image f



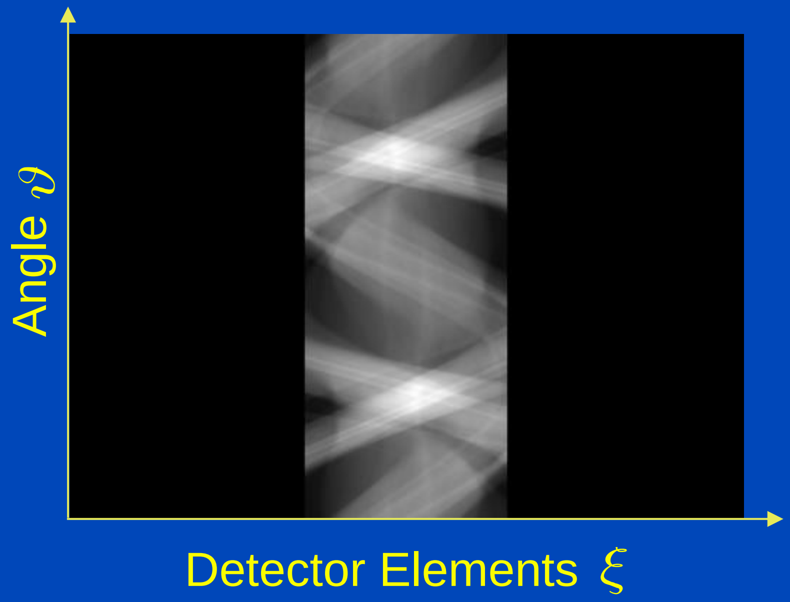
C = 50 HU, W = 1400 HU

Introduction

Truncation in CT

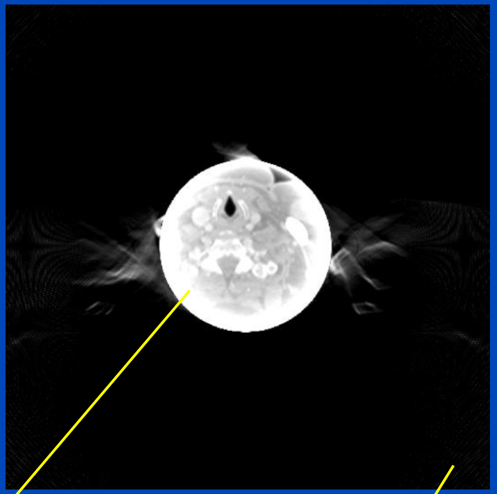


Truncated
Sinogram



FBP

Truncated
Image f



Truncation Problem 1: cupping artifacts inside the FOM

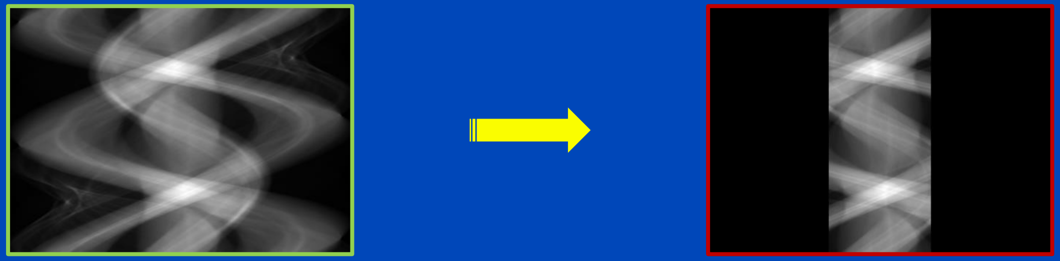
Truncation Problem 2: reconstruction outside the FOM

C = 50 HU, W = 1400 HU

Introduction

Truncation in CT

- Truncation examples from clinical practice include:
  - Obese patients
  - Patients that are not centered
  - Using C-arm systems
- Inspired by the FOM of C-arm systems, we simulated truncation to a FOM of 15 cm
- Truncation was simulated by zeroing the outermost left and right detector channels



What is a Variational Autoencoder?

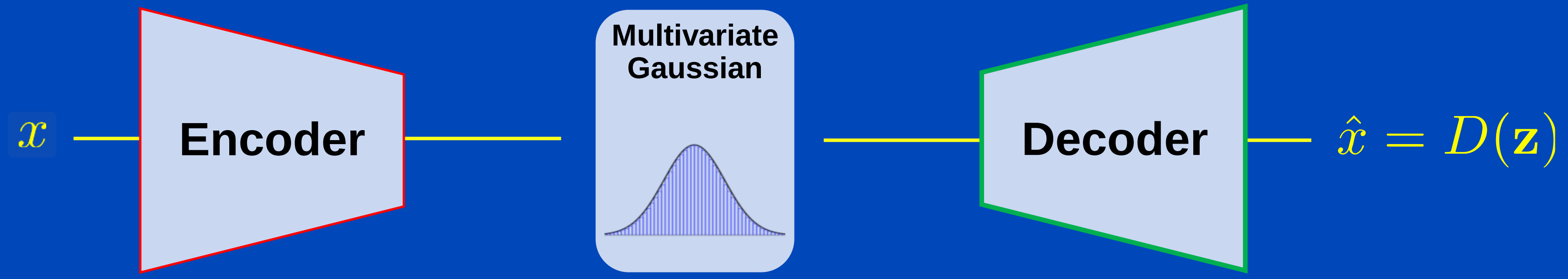
- **Input and output domain are the same, here *x*.**
- **Encoder *E* maps input onto a normal distribution.**

$$E(x) = \mathcal{N}(\mu(x), \sigma^2(x))$$

- **A point *z* in latent space corresponds to the parameters of a normal distribution.**

$$\mathbf{z} \sim \mathcal{N}(\mu(x), \sigma^2(x))$$

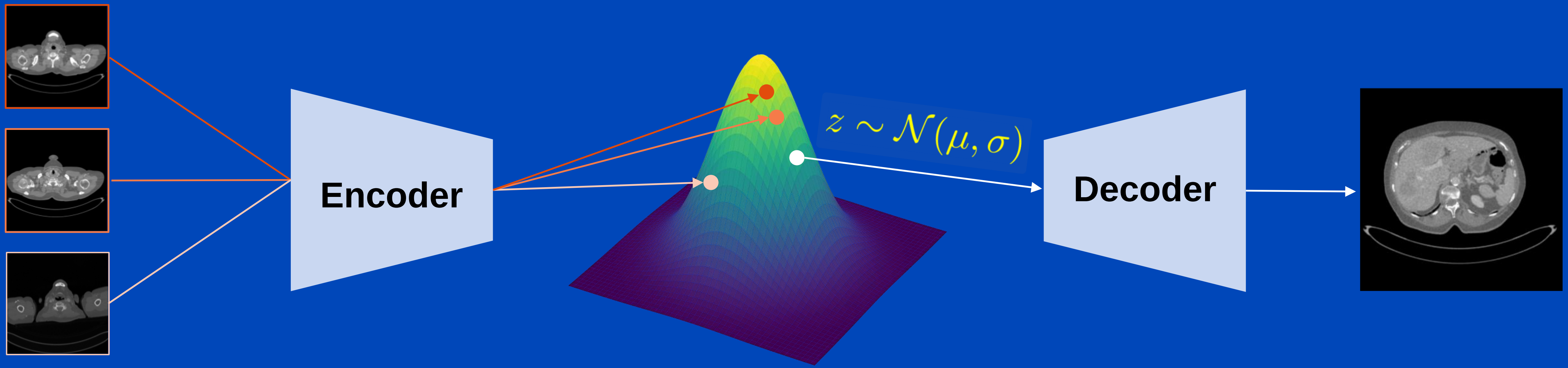
- **Decoder *D* maps latent space vector onto output.**



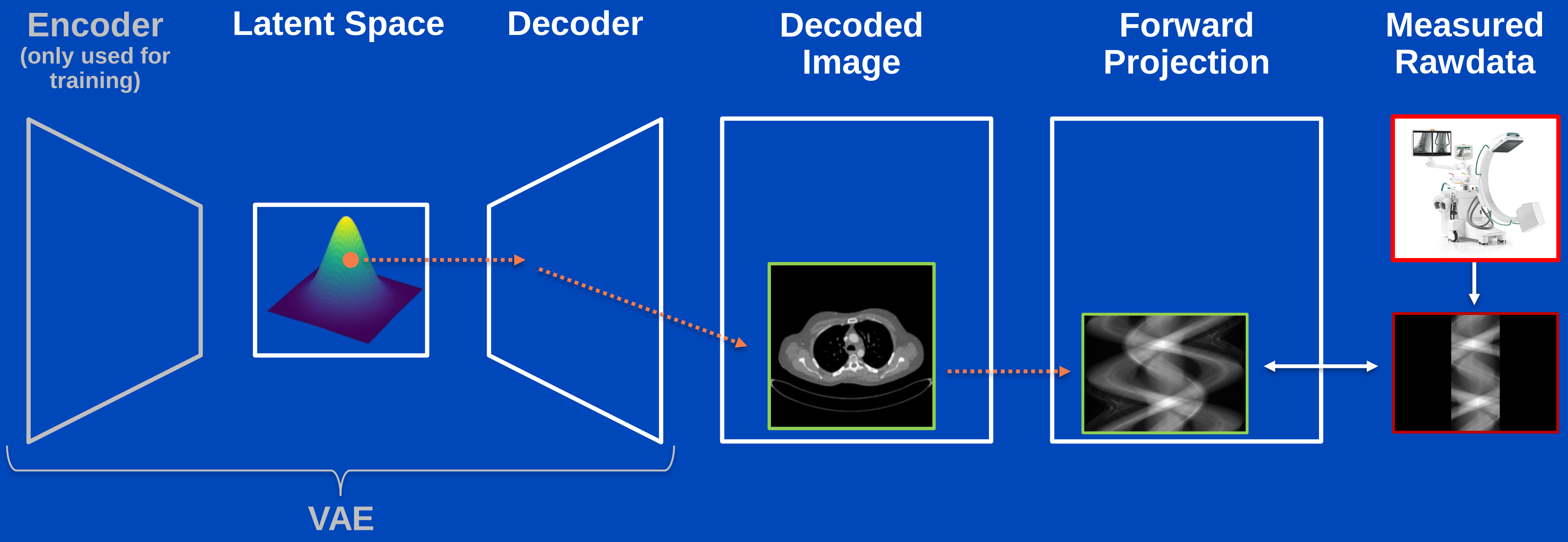
Sampling from a VAE
Why use a continouse Latent Space?

- The VAE is a generative model.
- It allows to generate new data by sampling points from the continuous latent space.

$$f(\mathbf{z}|\boldsymbol{\mu}, \boldsymbol{\Sigma}) = \frac{1}{(2\pi)^{k/2}|\boldsymbol{\Sigma}|^{1/2}} \exp\left(-\frac{1}{2}(\mathbf{z}-\boldsymbol{\mu})^T \boldsymbol{\Sigma}^{-1}(\mathbf{z}-\boldsymbol{\mu})\right)$$



Main Idea
Latent Space Reconstruction (LSR)



Main Idea

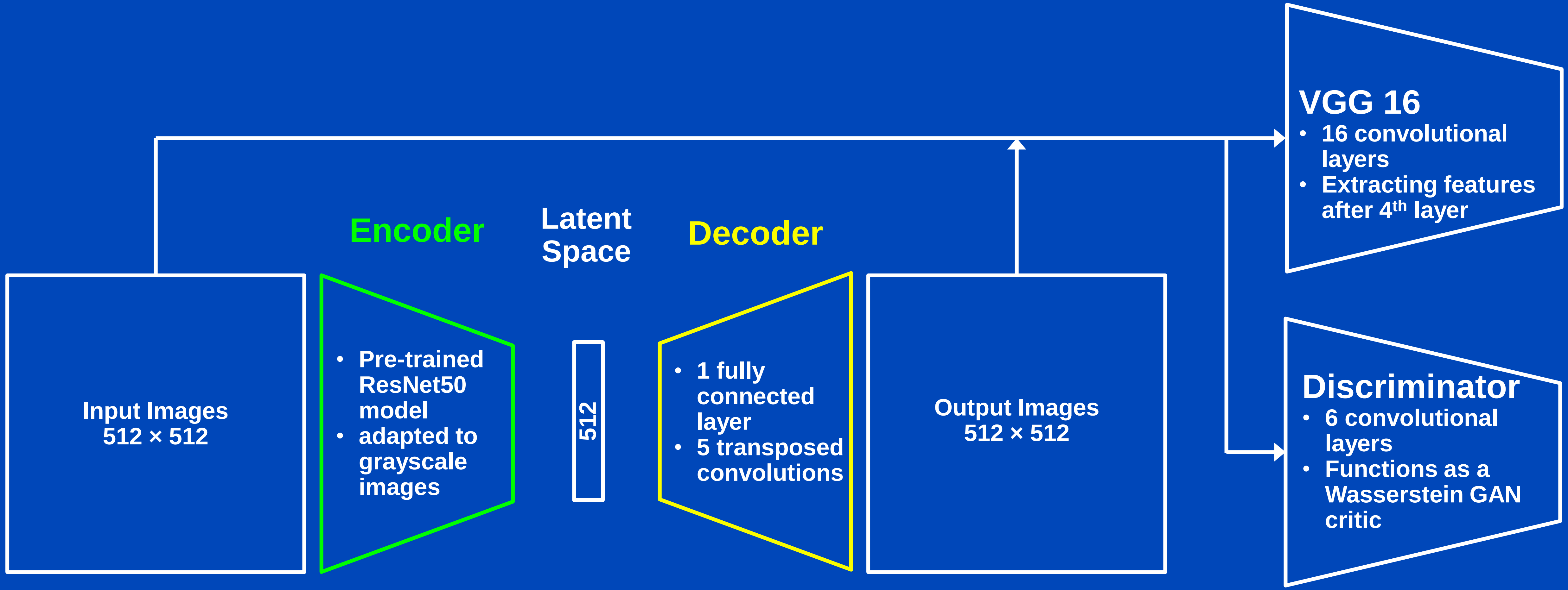
Latent Space Reconstruction (LSR)

1. Train VAE on untruncated CT images f_n
2. Find latent space point z to best match the truncated rawdata p

$$z = \arg\min_z \|\mathrm{X}D(z) - p\|$$

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

Our VAE



Input Images
512 × 512
Encoder
Pre-trained ResNet50 model
adapted to grayscale images
Latent Space
512
Decoder
1 fully connected layer
5 transposed convolutions
Output Images
512 × 512
VGG 16
16 convolutional layers
Extracting features after 4th layer
Discriminator
6 convolutional layers
Functions as a Wasserstein GAN critic

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

Coronal

Sagittal

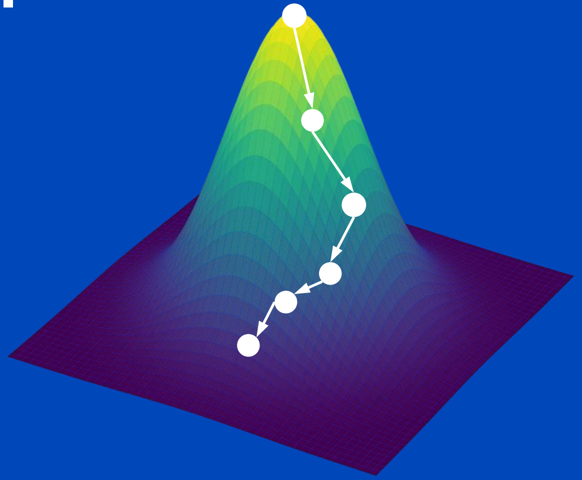
$$L = L_{\text{pixel-wise}} + \beta \cdot L_{\text{Kullback–Leibler}} + \gamma \cdot L_{\text{perc}} + \delta \cdot L_{\text{WGAN}}$$

Search in Latent Space

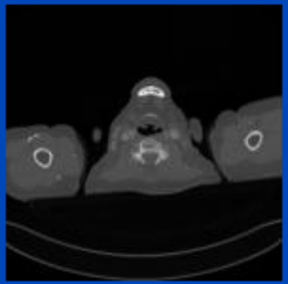
- **Optimization of latent space vector in projection domain**

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

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

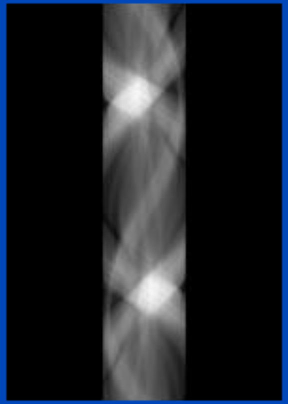


Target Image

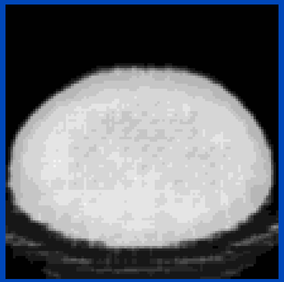


Target Sinogram

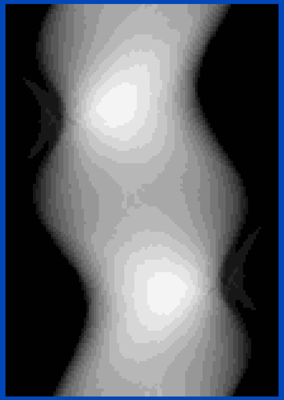
Masked (15 cm)
Target Sinogram



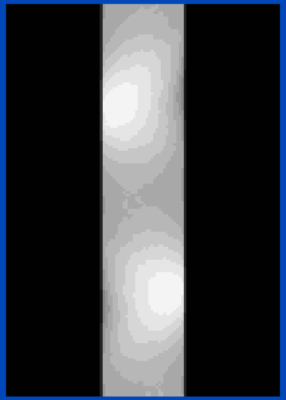
Generated Image



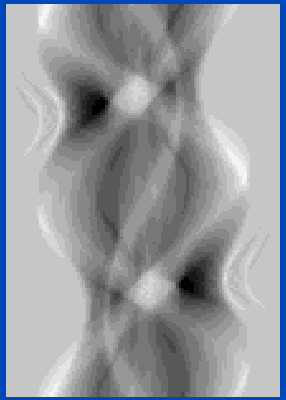
Generated
Sinogram



Masked (15 cm)
Generated Sinogram

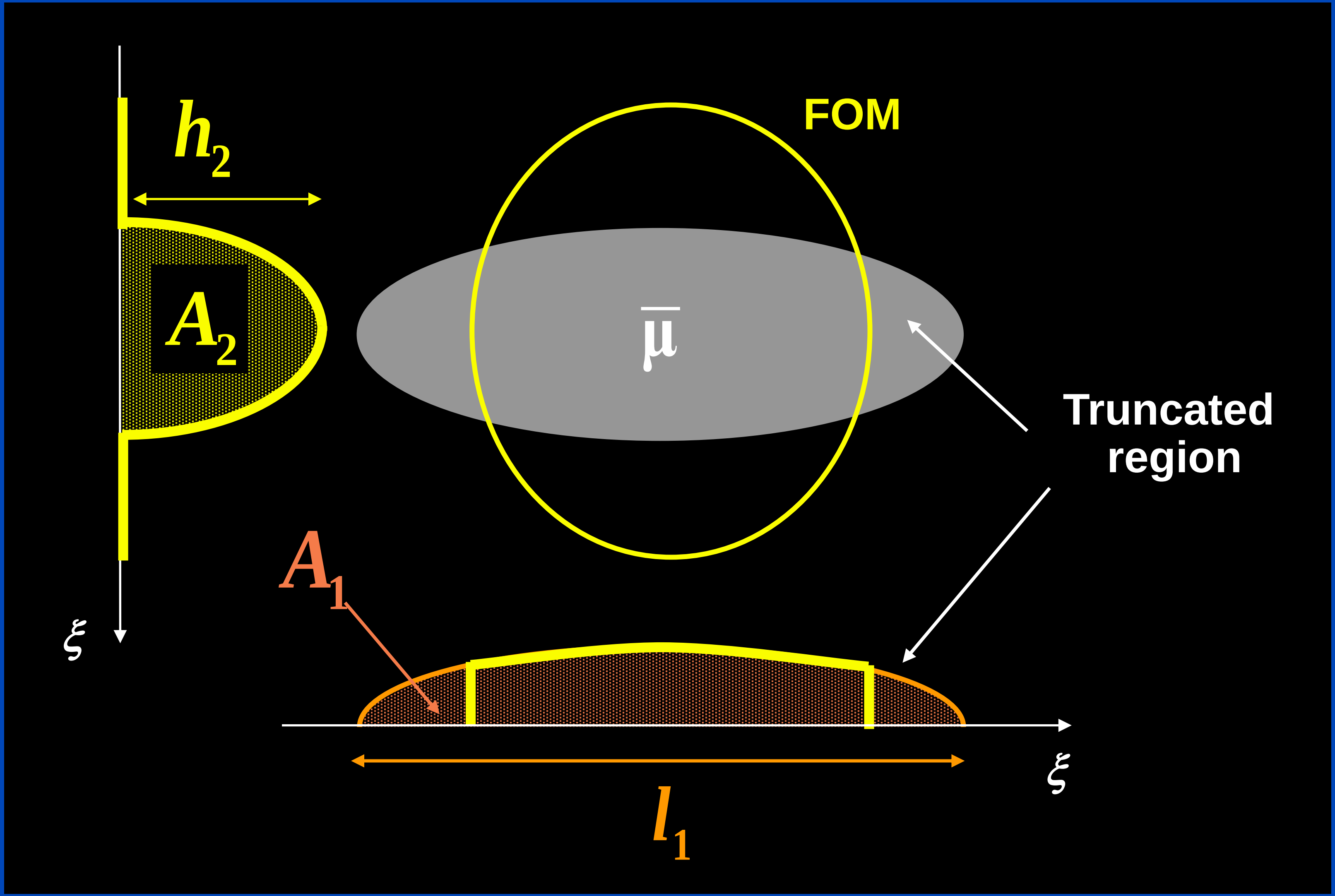


Difference to
Target Sinogram



Reference Methods

Adaptive Detruncation (ADT)



smooth extrapolation

$$\sqrt{a\xi^2 + b\xi + c}$$

data consistency

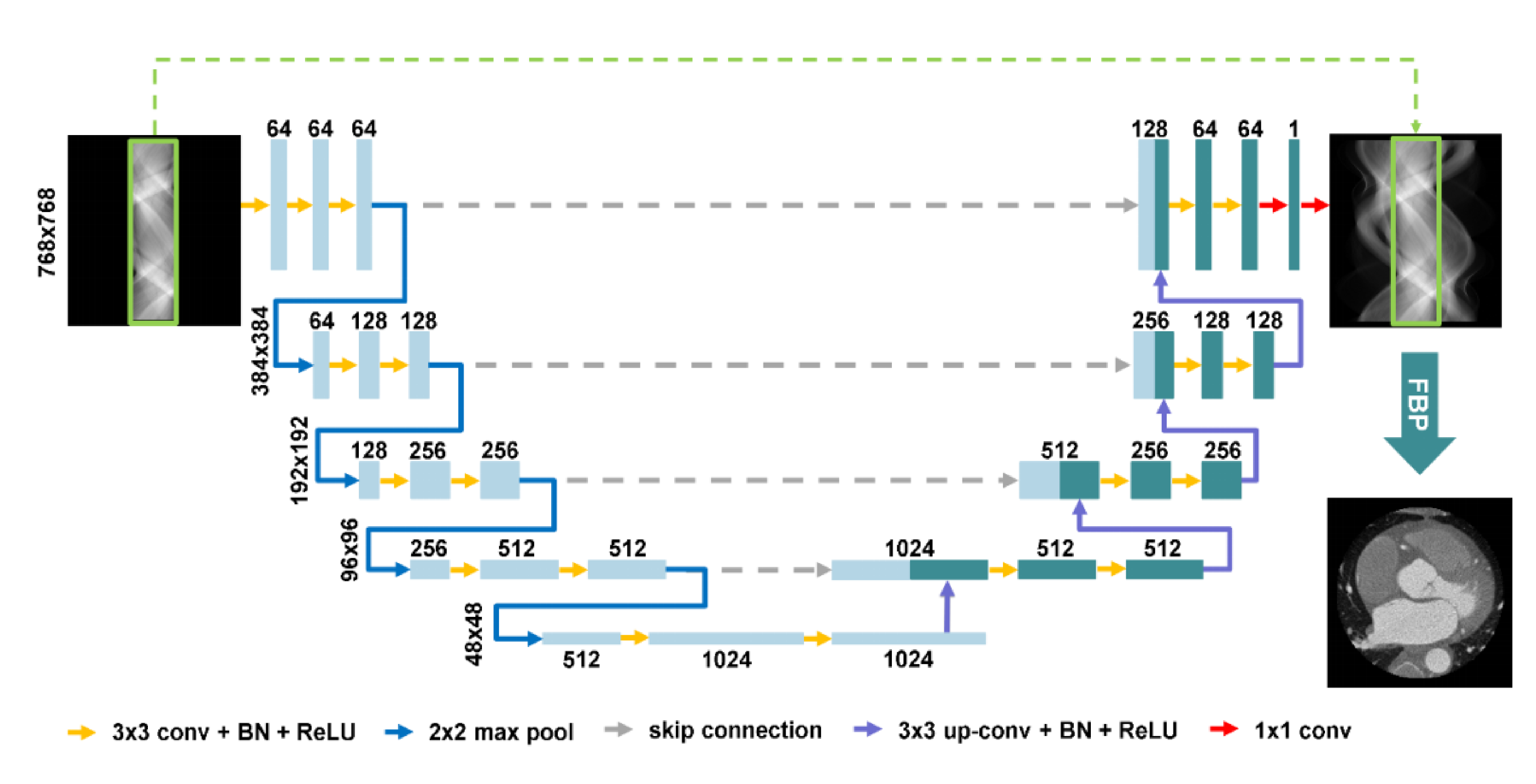
$$l_1 = h_2/\bar{\mu}$$

$$A_1 = A_2$$

K. Sourbelle, M. Kachelrieß and W.A. Kalender, *Reconstruction from truncated projections in CT using adaptive detruncation,* Eur Radiol 15:1008–1014 (2005)

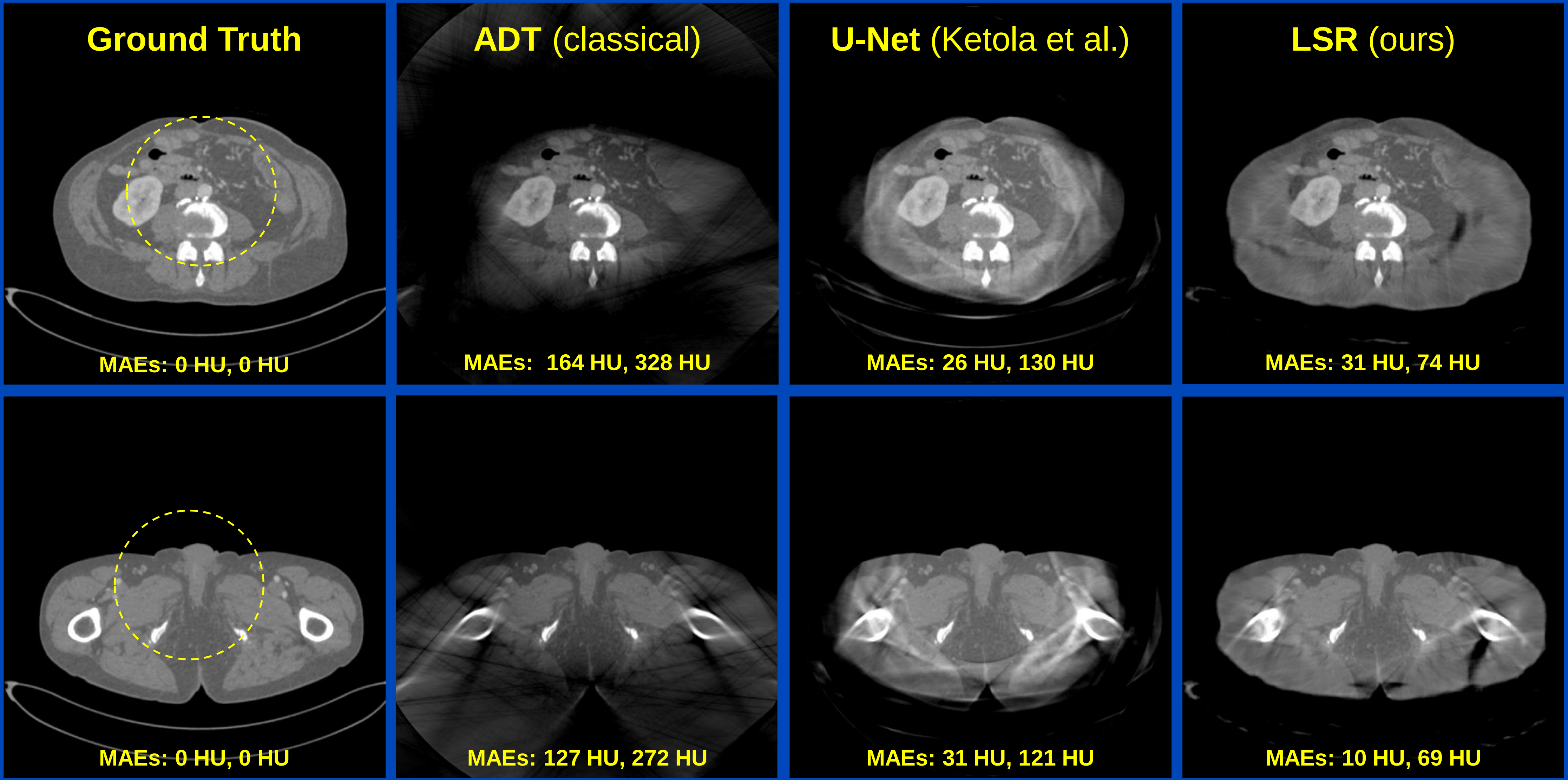
Reference Methods

U-Net based Sinogram Extension



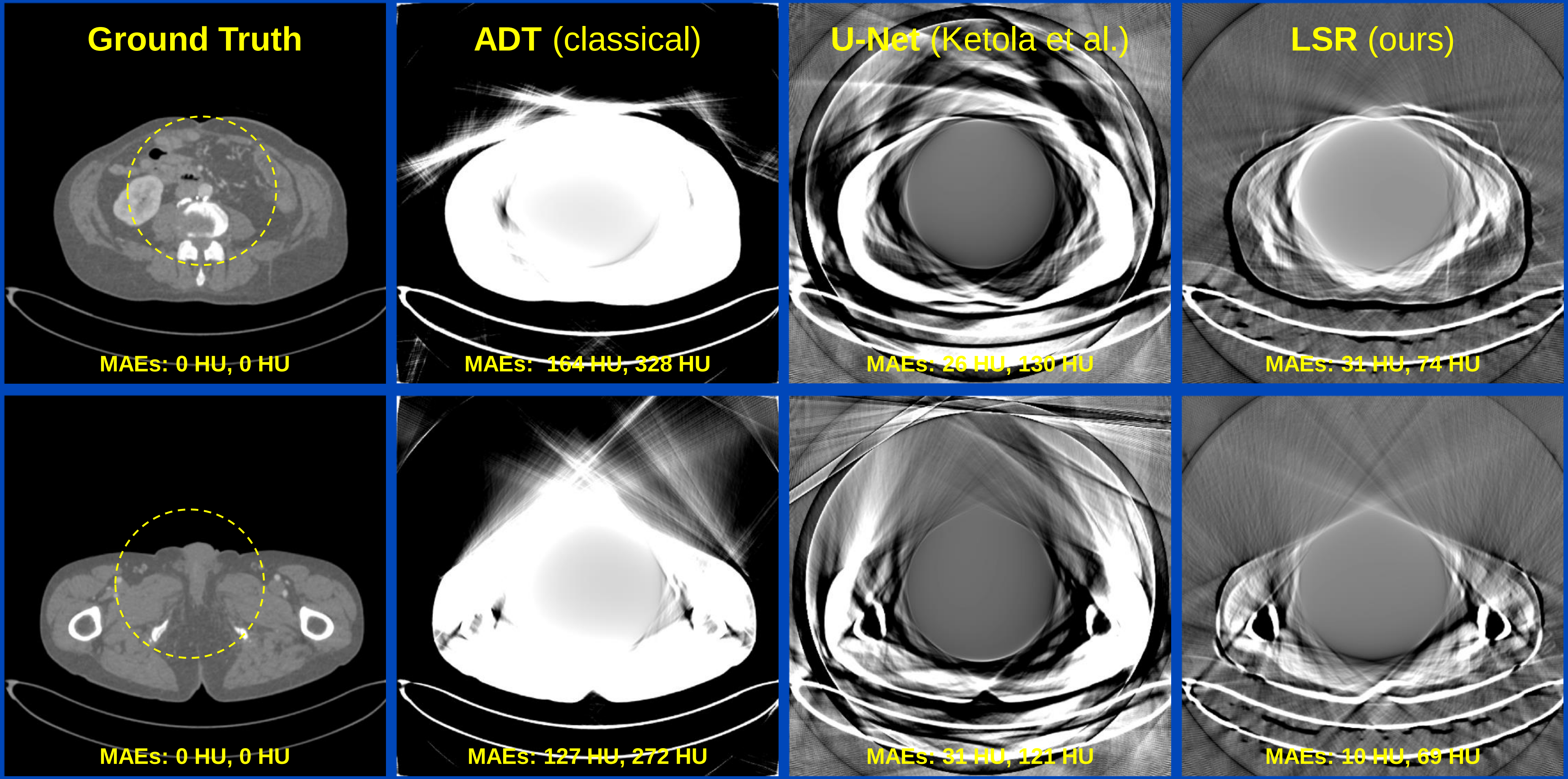
J. HJ. Ketola, et al., *Deep learning-based sinogram extension method for interior computed tomography*, *Medical Imaging: Physics of Medical Imaging*. Vol. 11595. International Society for Optics and Photonics (2021)

Results



C = 50 HU, *W* = 1200 HU.

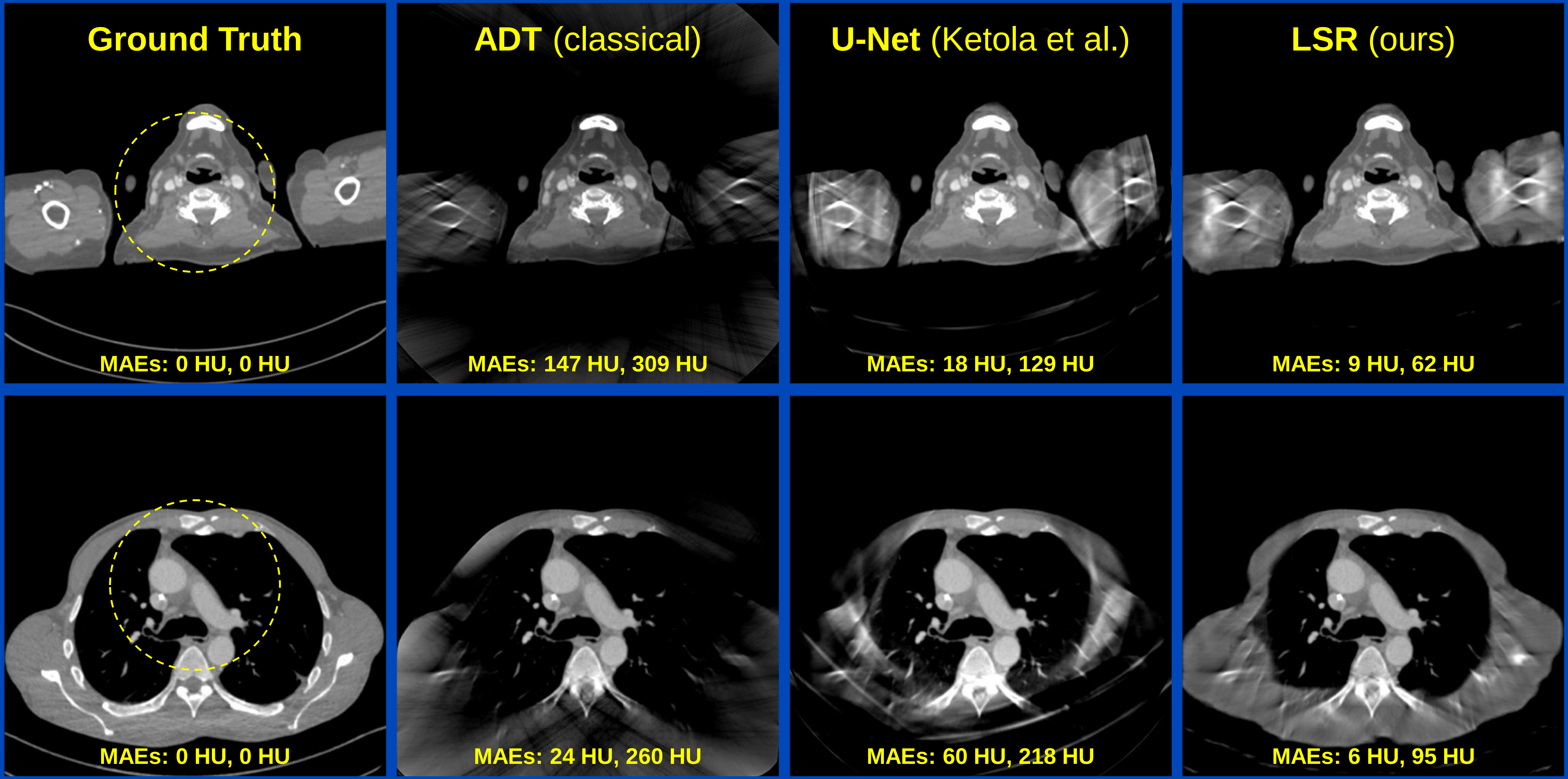
Differences to Ground Truth



Images: C = 50 HU, W = 1200 HU. Difference Images: C = 0 HU, W = 300 HU.

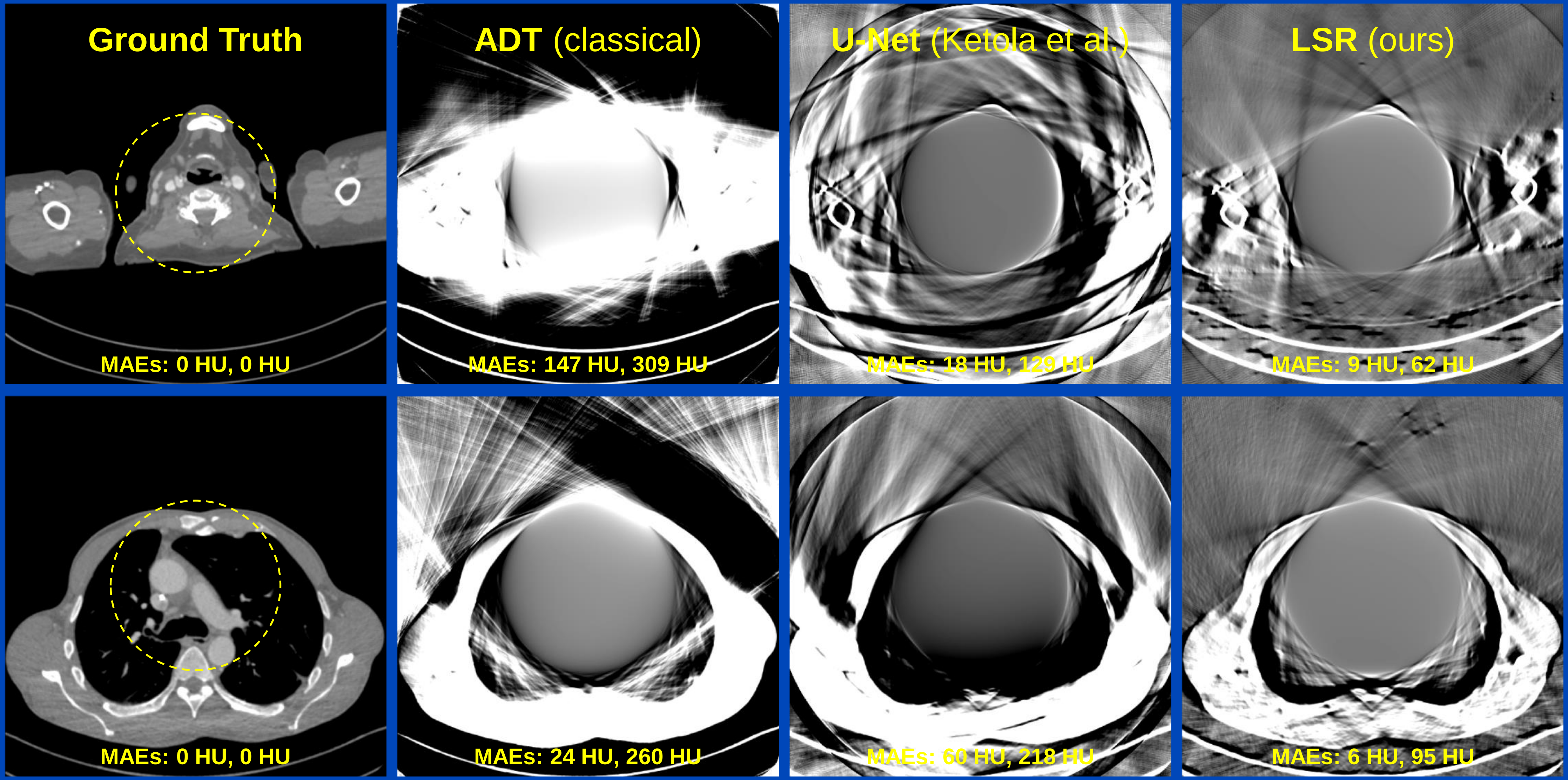
dkfz.

Results



C = 50 HU, W = 1200 HU.

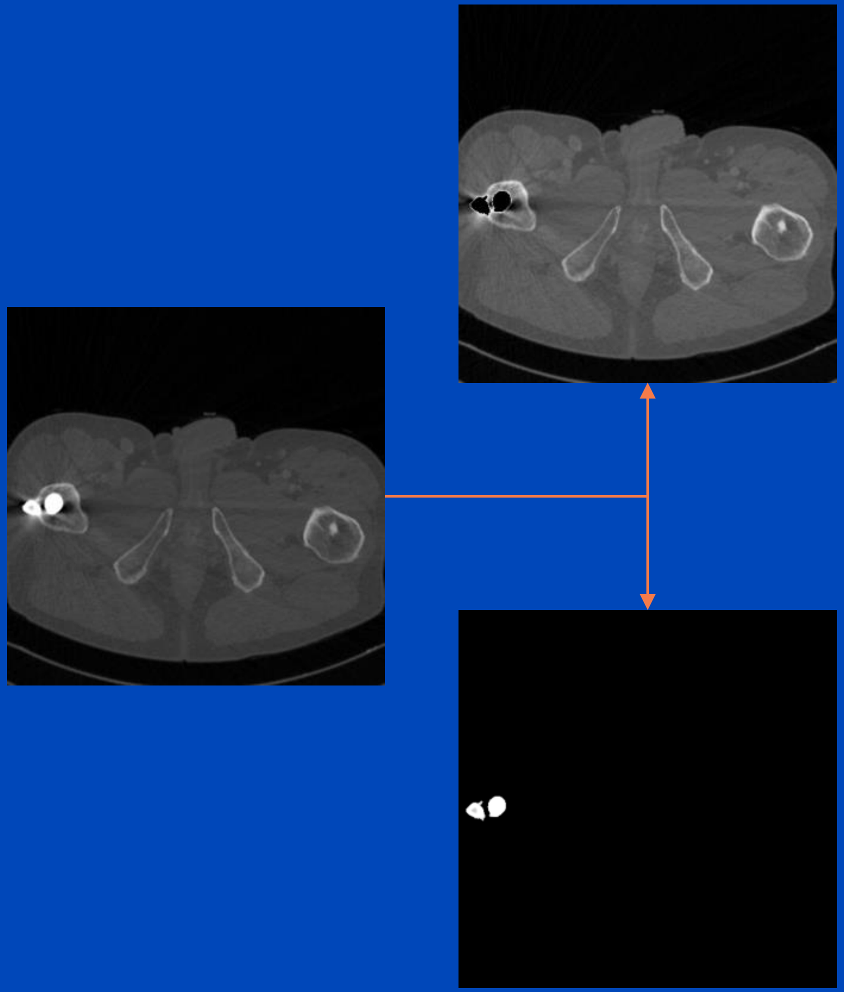
Differences to Ground Truth



Images: C = 50 HU, W = 1200 HU. Difference Images: C = 0 HU, W = 300 HU.

Conclusion & Outlook

- LSR has proven to be a capable tool for the truncation problem in CT
- Next: tackle other ill-posed problems like metal artifact reduction



Thank You!

- This presentation will soon be available at www.dkfz.de/ct.
- Job opportunities through DKFZ's international PhD or Postdoctoral Fellowship programs (marc.kachelriess@dkfz.de).
- Parts of the reconstruction software were provided by RayConStruct® GmbH, Nürnberg, Germany.

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