RIDL: Row Interpolation with Deep Learning

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Motivation:

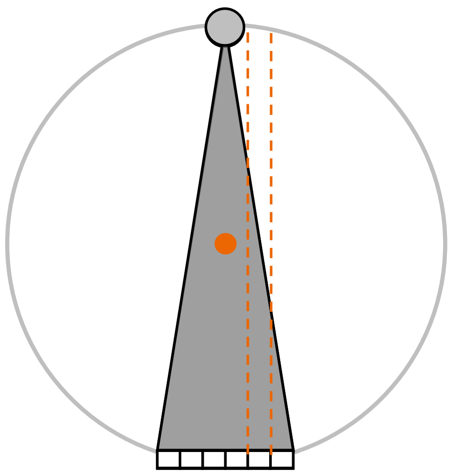
- Correct sampling needs to fulfill the Nyquist theorem: at least two sample points should be recorded per FWHM of the detector point spread function (PSF).

➢ Requiring at least two samples per detector pixel

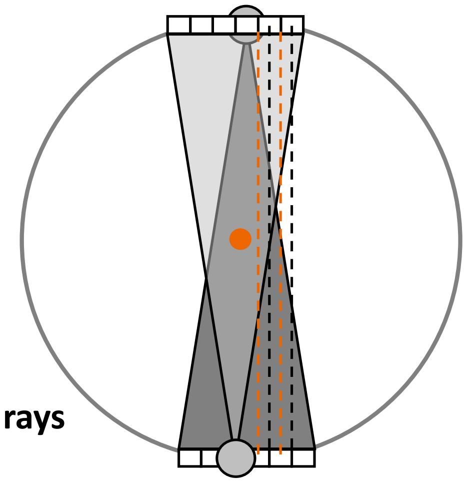
- This condition is not given in real CT setup, as the spacing of detector sample centers is slightly larger than the active width of the detector pixels.

➢ Quarter detector offset (QDO) is used to fulfill the Nyquist theorem by mounting the detector array shifted by one quarter of detector sampling distance in x-y-plane.

Without ¼ shift



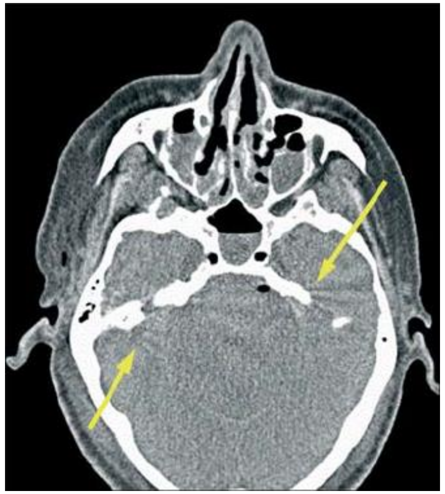
With ¼ shift



opposing rays interlace

Motivation:
Spiral CT and Windmill Artifacts

- During backprojection in multislice spiral CT, an interpolation is performed between adjacent detector rows.
- Inadequate longitudinal sampling leads to so-called windmill artifacts .
- Characterized by streaks diverging from a focal high-density structure.
- Streaks appear to rotate while scrolling through the affected slices.



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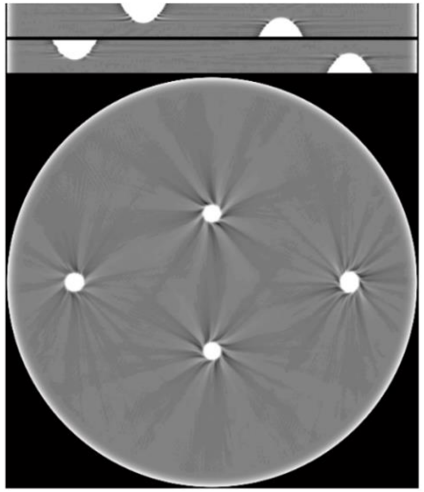
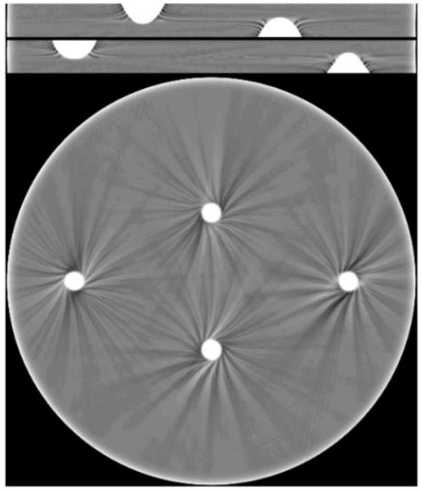
Pitch: 0.5



Pitch: 1.0



1: B. Ohnesorge, T. Flohr, H. C. Becker, A. Knez and M. Reiser. “Multi-slice CT Technology”. Multi-slice CT in Cardiac Imaging, 2007, PP. 41-69

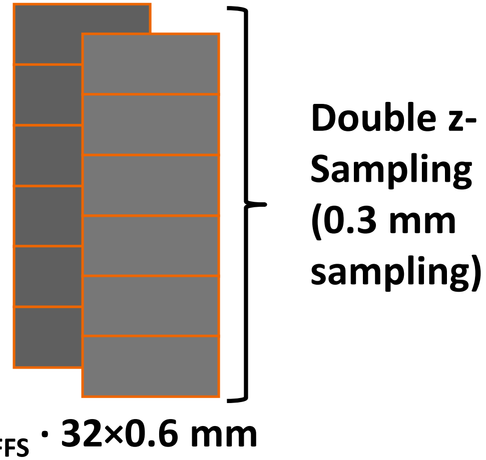
Motivation:
Spiral CT and Windmill Artifacts

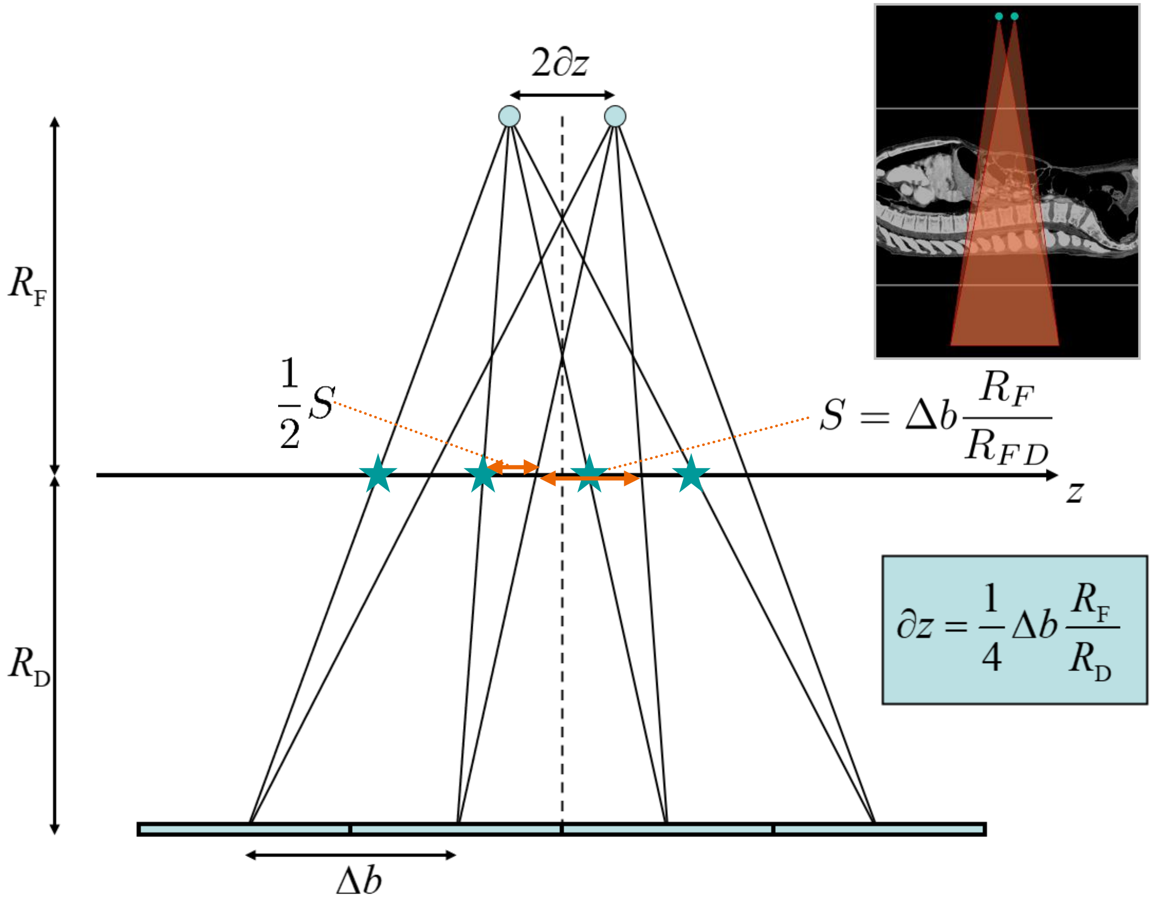
Without zFFS

With zFFS

Motivation:
Z-Flying Focal Spot (zFFS)

- **Z-flying focal spot (zFFS) uses a periodic motion of the focal spot in longitudinal direction.**
- **Two subsequent readings are slightly shifted in z-direction to achieve a doubled sampling distance in the iso-center.**





$$\partial z = \frac{1}{4} \Delta b \frac{R_F}{R_D}$$

1

1: M. Kachelrieß, M. Knaup, C. Penßel and W. A. Kalender. "Flying Focal Spot (FFS) in Cone-Beam CT". In: IEEE Transactions on Nuclear Science, June 2006, Vol. 52, No. 3, PP. 1238-1247

Motivation:

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Disadvantages of zFFS:

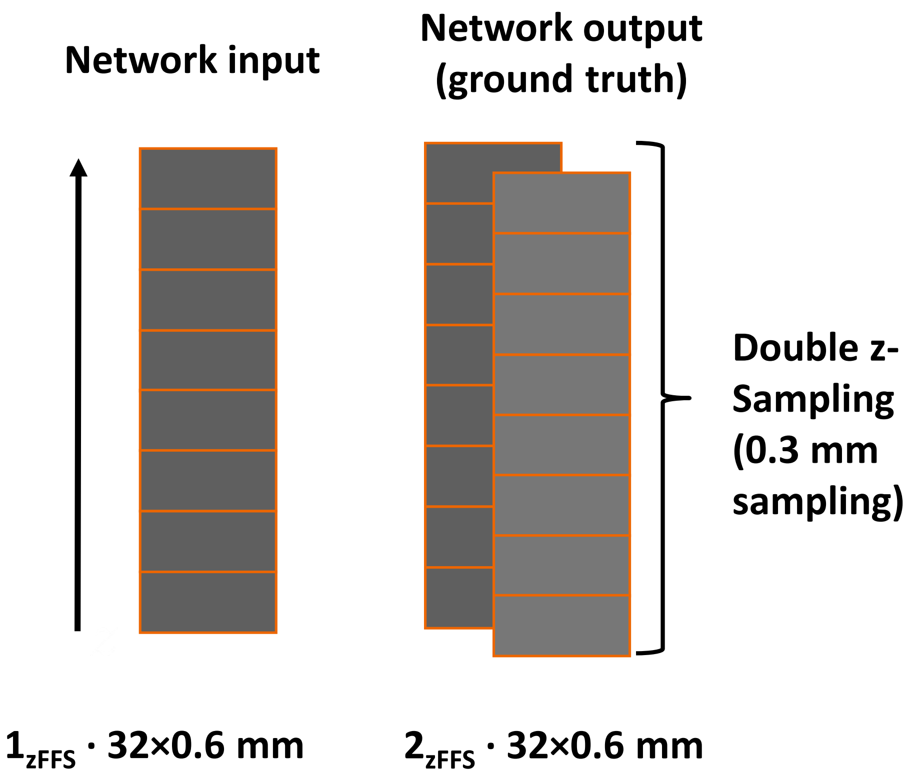
- **High technical effort and therefore expensive.**
- **No application in CT systems that lack the technical requirements.**
- **More readings required, which may prevent switching in the fastest scan mode.**

- **Is a neural network able to interpolate between detector rows in z-direction to achieve a higher sampling?**
- **Is this approach able to outperform a linear interpolation of the detector rows?**

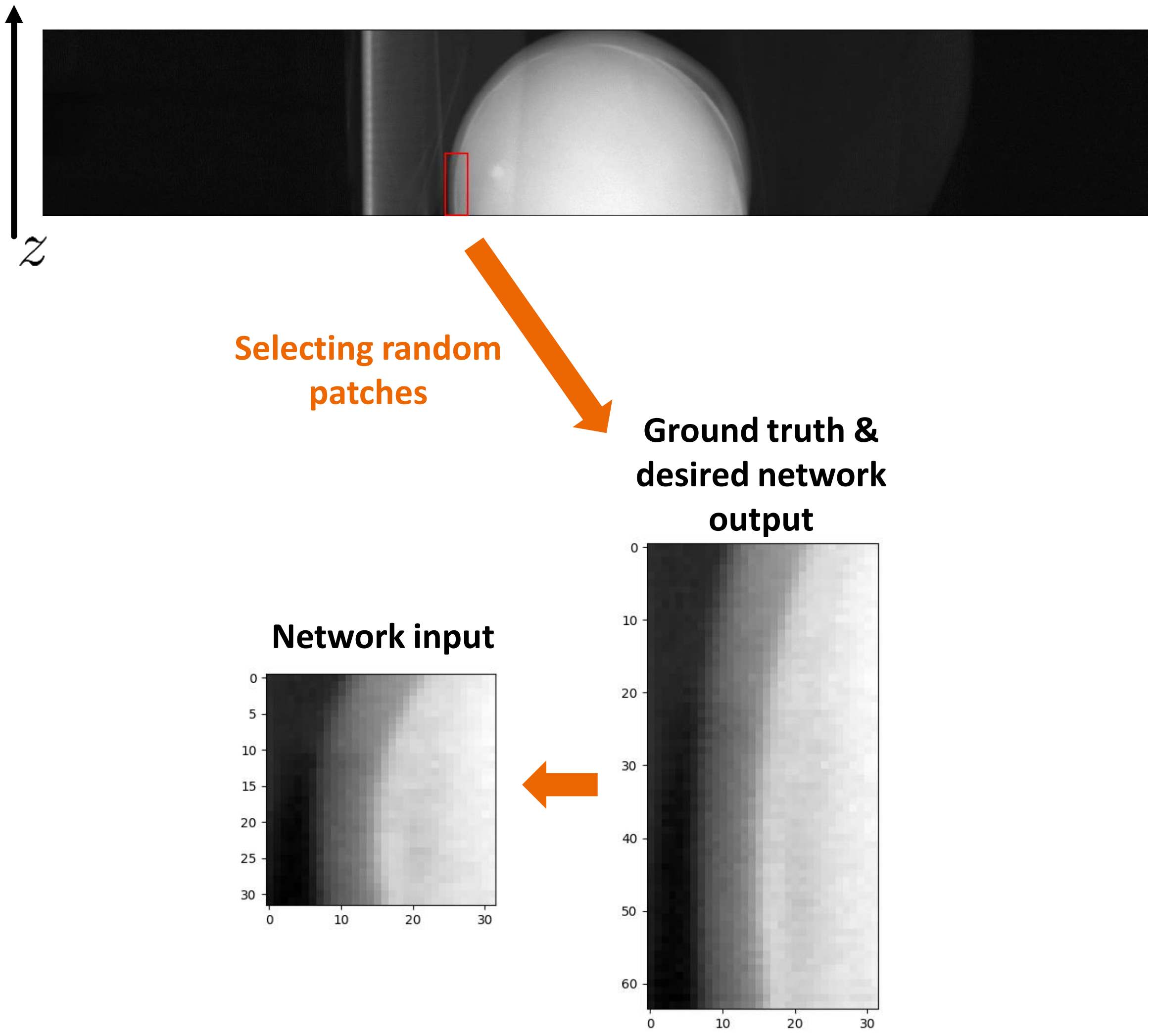
Methods

Concept

- **Train a neural network that learns to generate interpolated rows by supervised learning.**
- **Divide projection data (detector readouts) in alternative rows.**
- **Every second row of a certain projection is used as network input .**
- **Projection image containing all zFFS-generated rows is set as network ground truth.**

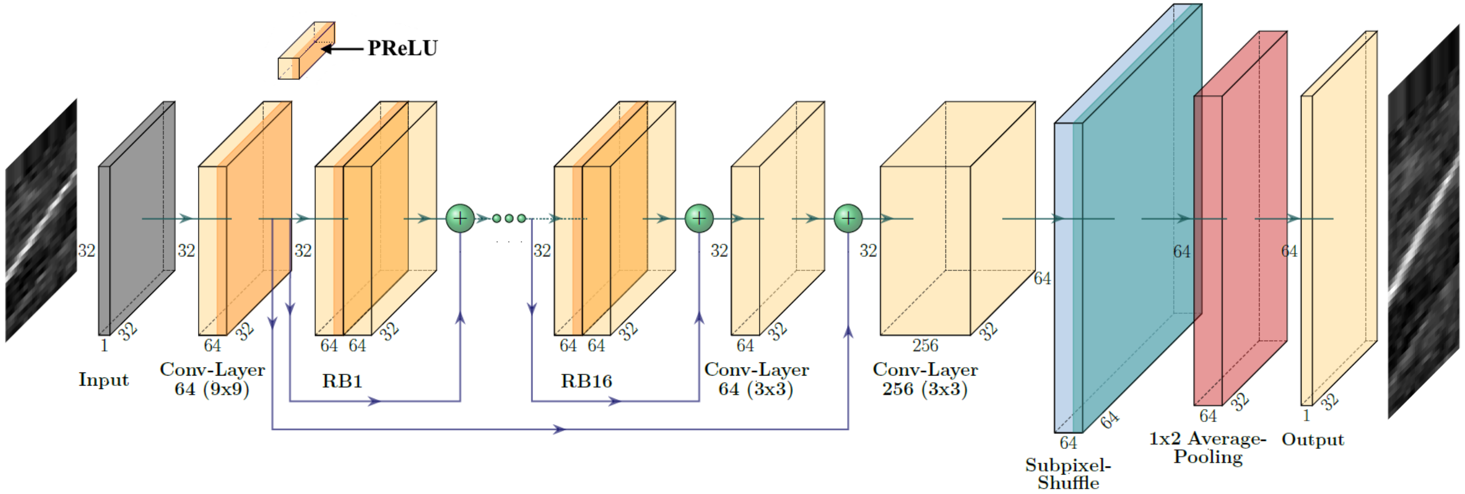


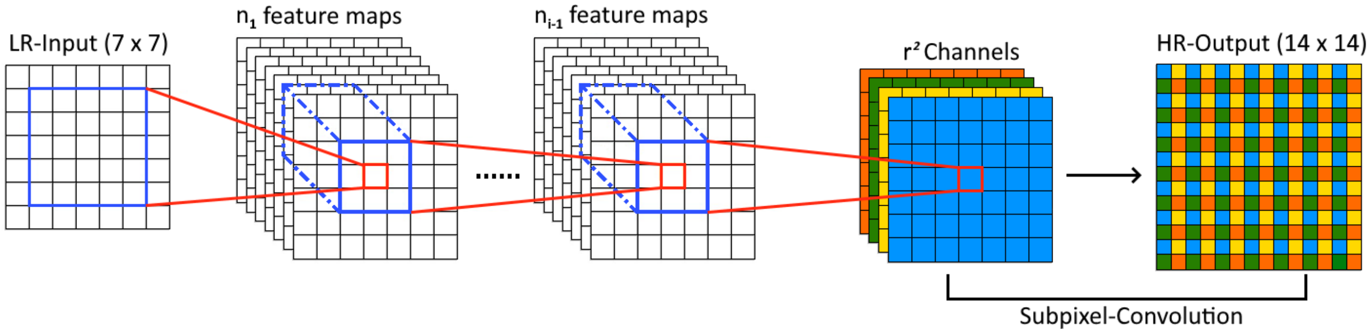
Data Preparation: Training and Testing Data



- 29 clinical CT scans of different body regions from various Siemens CT systems (0.6 mm slice thickness)
- Split into two disjoint subsets: training (23 scans) and testing data (6 scans)
- Projection data acquisition after the rebinning
- Selecting random projection data patches (64×32) and globally normalize value range to [0,1]

Network Architecture: RIDL-SRResNet





2

- Network application in the field of super-resolution (Ledig et al.[1])
- 64×32 patches
- Input: 32×32, Output: 64×32
- 1,377,921 trainable parameters
- Upscaling of the input image LR feature maps by using a subpixel convolution (Shi et al.[2])

1: C. Ledig, L. Theis, F. Huszár, et al. "Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network". In: Computer Vision and Pattern Recognition, July 2017, PP. 105–114.

2: W. Shi, J. Caballero, F. Huszár, et al. "Real-Time Single Image and Video Super-Resolution Using an Efficient Sub-Pixel Convolutional Neural Network". In: 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). 2016, PP. 1874–1883

Training Details

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- **Training: 500,000 pairs of patches from training data**
- **Testing: 125,000 pairs from testing data**
- **ADAM optimizer; initial learning rate: 1×10^{-5} ; halved once the validation error could not be minimized after 25 epochs; early-stopping regularization after 100 epochs**
- **Loss function proposed in[1]:**

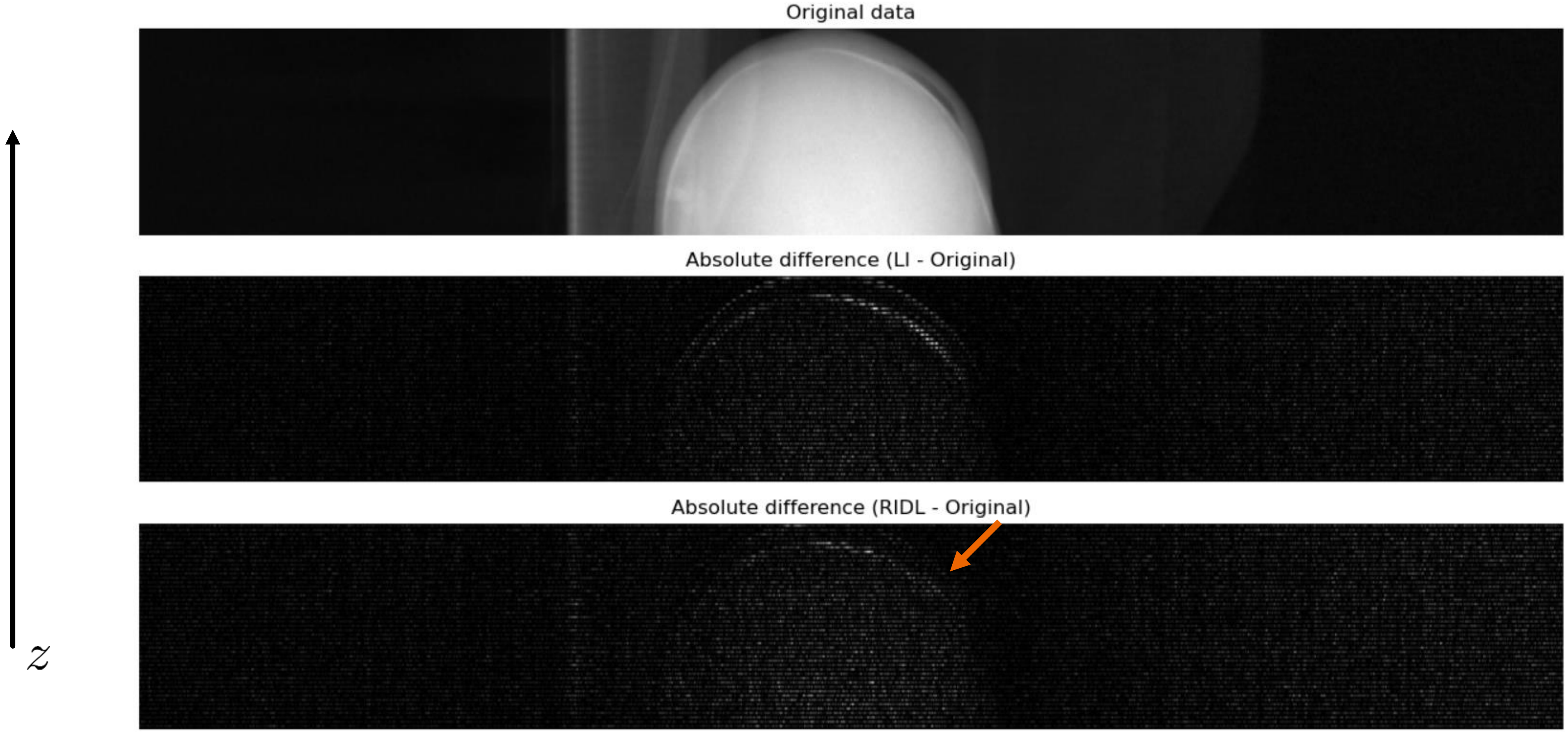
$$L_{\text{comb}}(y,\hat{y}) = \alpha \cdot (1 - L_{\text{MS-SSIM}}(y,\hat{y})) + (1-\alpha) \cdot L_{\text{MAE}}(y,\hat{y})$$

- **α = 0.84, empirically determined**

1: Z. Zhao, et al. “Loss Functions for Image Restoration With Neural Networks”. In: 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). 2016, PP. 1874–1883

Results

Results in Projection Domain



ID	Loss function	$\mathrm{MSE}(y, \hat{y})$	$\overline{\mathrm{MSE}}(y, \hat{y})$
LI	-	$2.352 \cdot 10^{-4}$	$6.306 \cdot 10^{-4} \pm 5.310 \cdot 10^{-4}$
RIDL	L_{comb}	$\mathbf{1.976 \cdot 10^{-4}}$	$\mathbf{5.626 \cdot 10^{-4} \pm 4.718 \cdot 10^{-4}}$

Results in Image Domain

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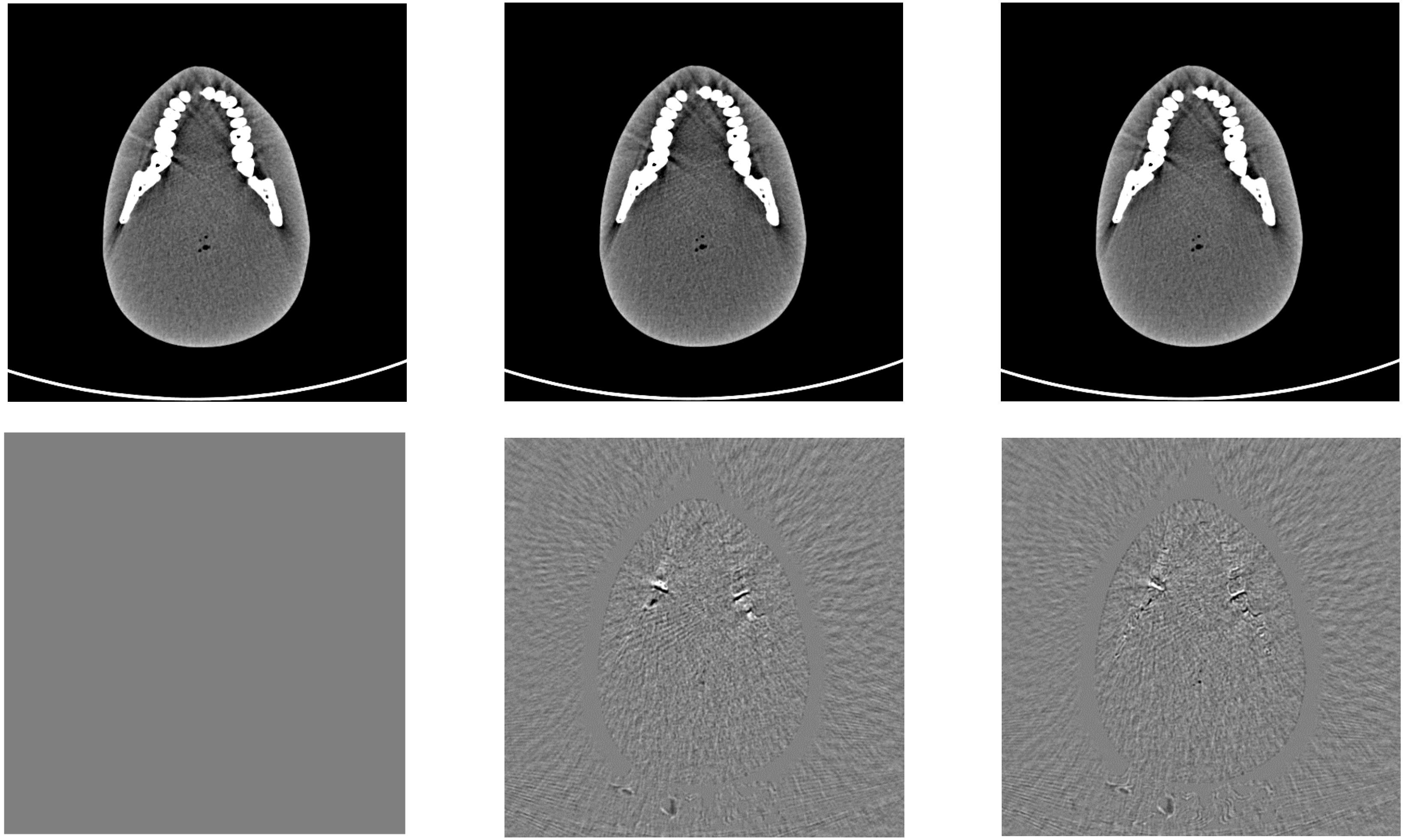
Ground truth with zFFS | **Linear interpolation (LI)** | **RIDL**

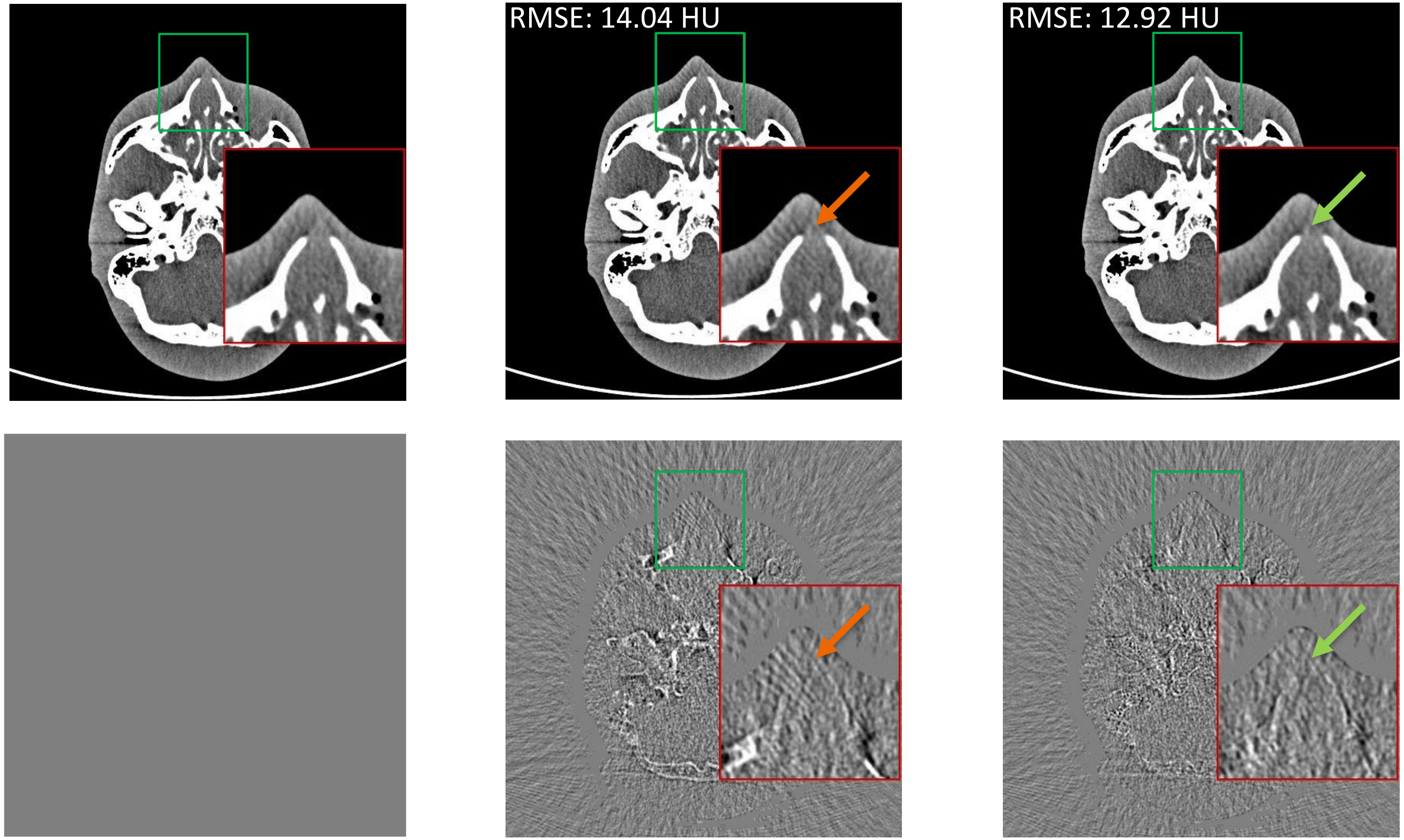


C = 60 HU
W = 360 HU

C = 0 HU
W = 150 HU

Results in Image Domain:
Slice No. 74

Ground truth with zFFS | Linear interpolation (LI) | RIDL

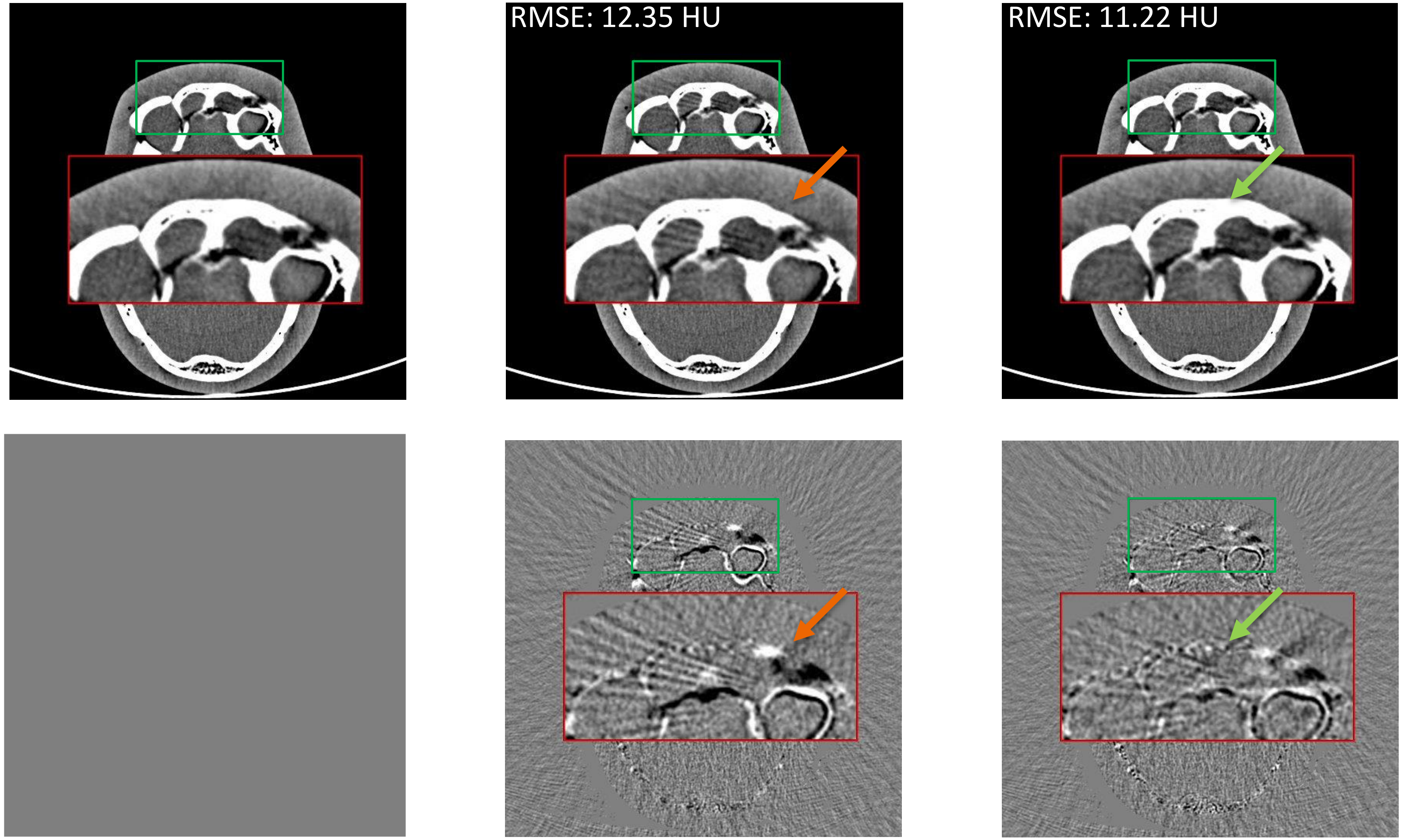


C = 60 HU
W = 360 HU

C = 0 HU
W = 150 HU

Results in Image Domain: Slice No. 125

Ground truth with zFFS | **Linear interpolation (LI)** | **RIDL**



C = 60 HU
W = 360 HU

C = 0 HU
W = 150 HU

Conclusion

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- **Row interpolation with RIDL network can achieve better results than linear interpolation.**
- **Results can be considered a proof of concept: a neural network can meet the requirements of increasing the sampling of projection data.**
- **Positive impact on the prevention of windmill artifacts in spiral CT reconstruction.**

Outlook and Future Ideas

- Compare RIDL network results to more advanced interpolation algorithms.
- Further adjustment of critical network parameters.
- Investigate other architectures and try to simplify the network.
- Improvement of training and test data.

Thank you
for your attention!

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