Deep Learning-Based Detector Row Upsampling to Reduce Windmill Artifacts in Diagnostic Spiral CT

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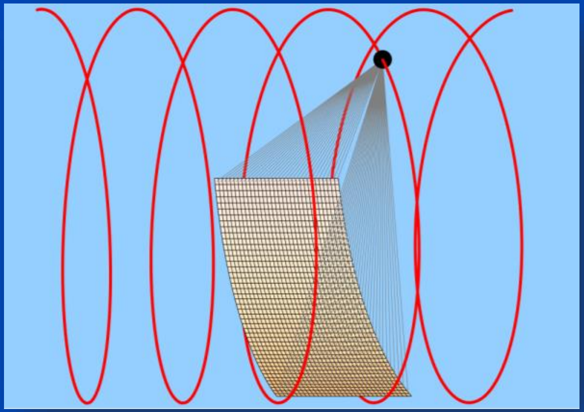
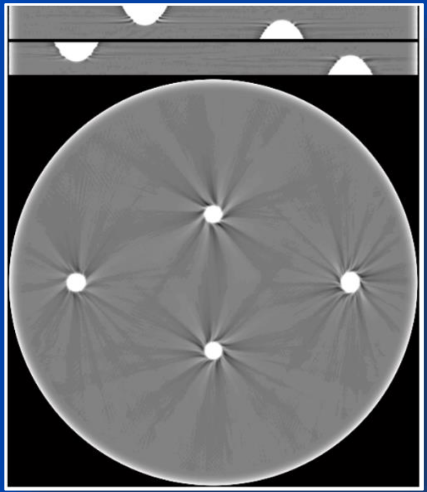
Windmill Artifacts in Spiral CT

- Interpolation between adjacent detector rows is performed during backprojection in multislice spiral CT.
- Not satisfying the Nyquist criterion due to longitudinal undersampling leads to the so-called windmill artifacts.
- They are characterized by streaks diverging from a focal high-density structure.

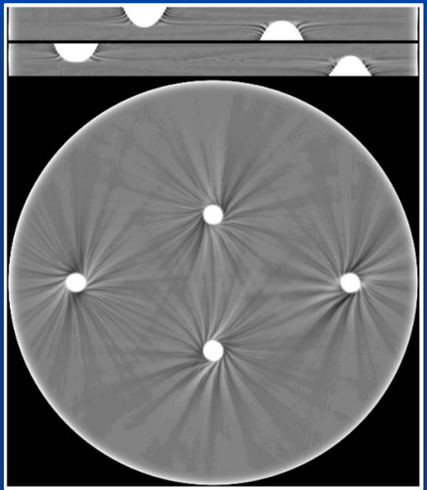


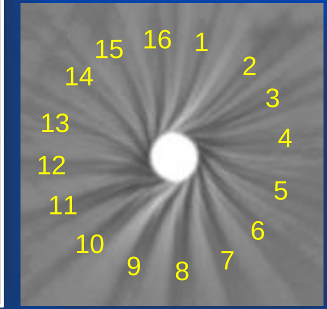
C = 0 HU, *W* = 200 HU
(32×0.6 mm)

Pitch: 0.5



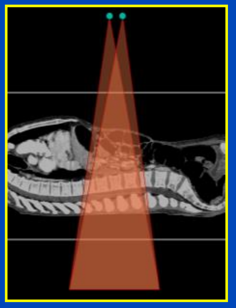
Pitch: 1.0





Reconstructions of a phantom scanned with a Siemens Somatom Sensation 16 CT system (16×0.75 mm)

z-Flying Focal Spot (zFFS)

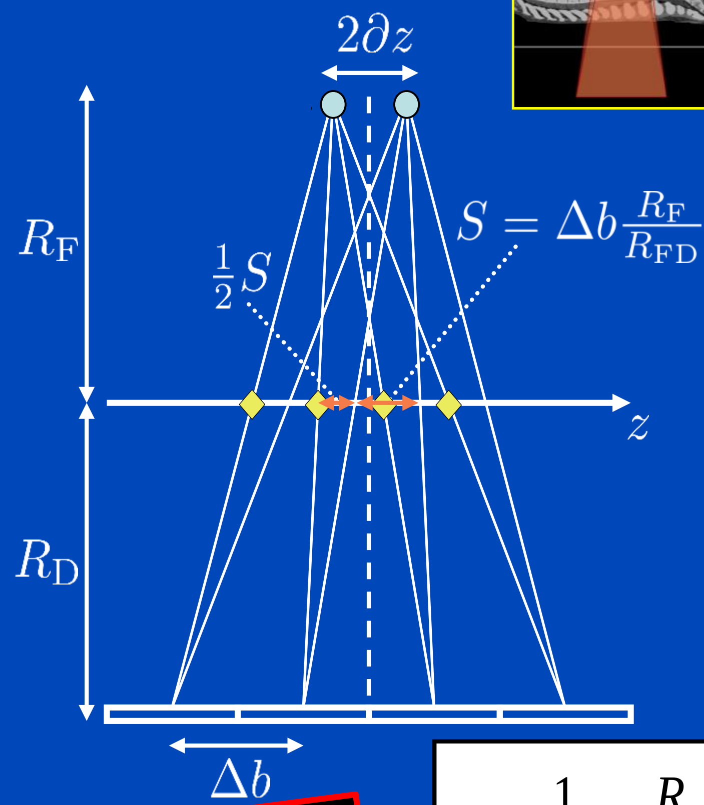


- **Two subsequent readings are slightly shifted in z-direction to achieve doubled sampling distance in the isocenter[1].**

Without zFFS
collimation: 96×0.6 mm

With zFFS
collimation: $2_{\mathrm{zFFS}} \cdot 96\times0.6$ mm

C **= 60 HU,** ***W*** **= 360 HU; reconstructed slice width 0.75 mm**



$$\partial z = \frac{1}{4}\Delta b \frac{R_{\mathrm{F}}}{R_{\mathrm{D}}}$$

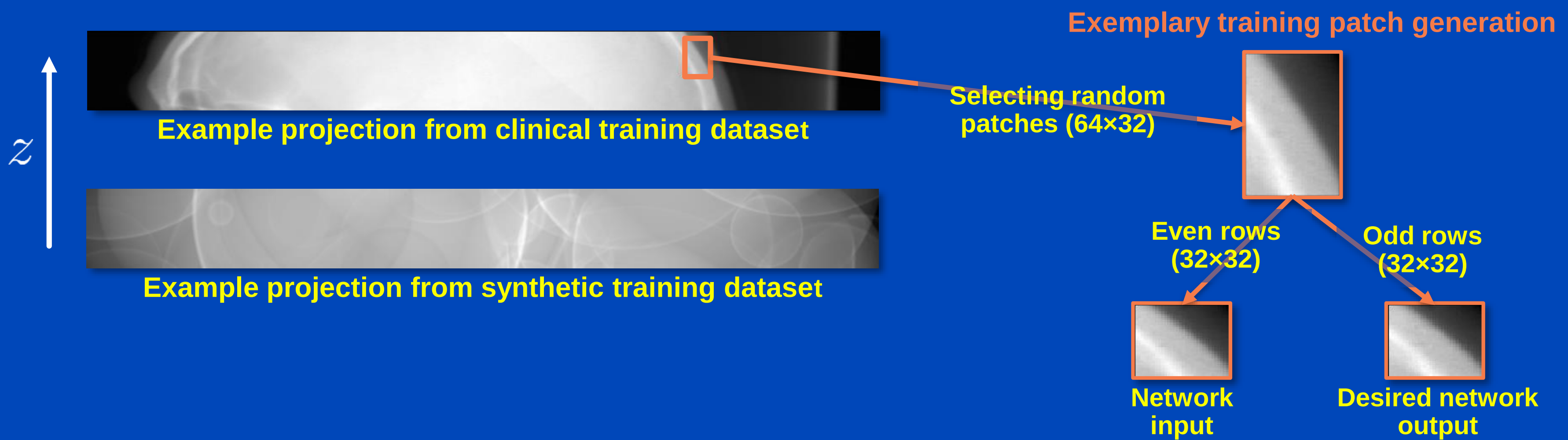
- **zFFS provided only in high-end CT scanners and may prevent the fastest scan mode.**

Aim: Provide a software-based approach that upsamples the projection data like the zFFS.

[1]M. Kachelrieß, M. Knaup, C. Penßel and W. A. Kalender. "Flying Focal Spot (FFS) in Cone-Beam CT". IEEE Transactions on Nuclear Science, 52(3):1238-1247, June 2006

Row Interpolation with Deep Learning (RIDL)

- **CNN trained to predict upsampled rows for a given input.**
- **Previously presented network architecture[1] was further simplified.**
- **An experimental synthetic dataset was provided[2].**
- **Training two separate RIDL-CNN networks:**
  - **Clinical dataset consisting of projection data from patient scans acquired with zFFS.**
  - **Synthetic dataset consisting of simulated noise-free projection data of spherical shells.**
- **Value range of synthetic data linearly scaled to range of clinical data.**

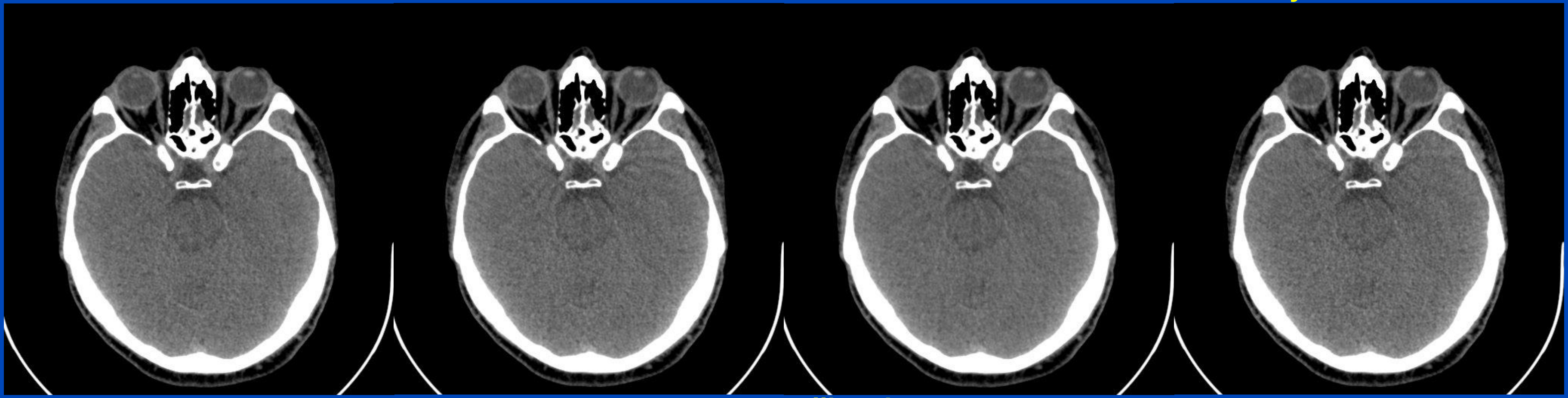


[1] J. Magonov, M. Kachelrieß, E. Fournié, K. Stierstorfer, T. Buzug, and M. Stille, "Row Interpolation in Spiral CT with Deep Learning". In: 16th International Meeting on Fully 3D Image Reconstruction in Radiology and Nuclear Medicine, Oct. 2021, PP. 376-380

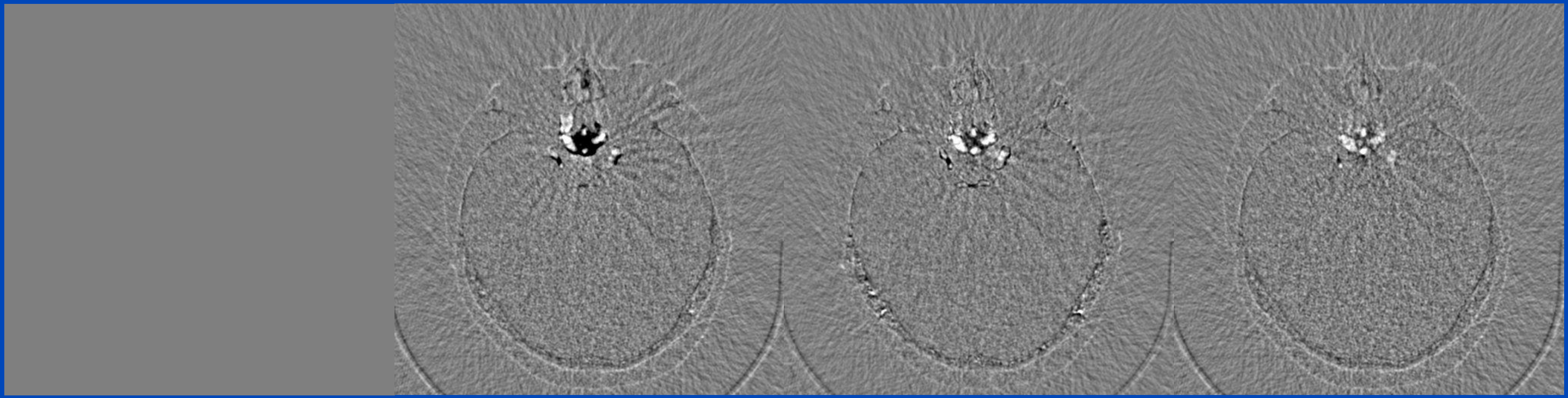
[2] J. Magonov, J. Erath, J. Maier, E. Fournié, K. Stierstorfer and M. Kachelrieß, "Deep Learning-Based Detector Row Upsampling for Clinical Spiral CT". In: CT Meeting, June 2022

Comparison of Windmill Artifact Reduction

Ground truth with zFFS	Without zFFS	RIDL-CNN trained with clinical dataset	RIDL-CNN trained with synthetic dataset



C = 60 HU, *W* = 260 HU; collimation: 64×0.6 mm; reconstructed slice width 0.6 mm



C = 0 HU, *W* = 100 HU

Difference images to a WFBP of corresponding projection data with zFFS.

Comparison of Windmill Artifact Reduction

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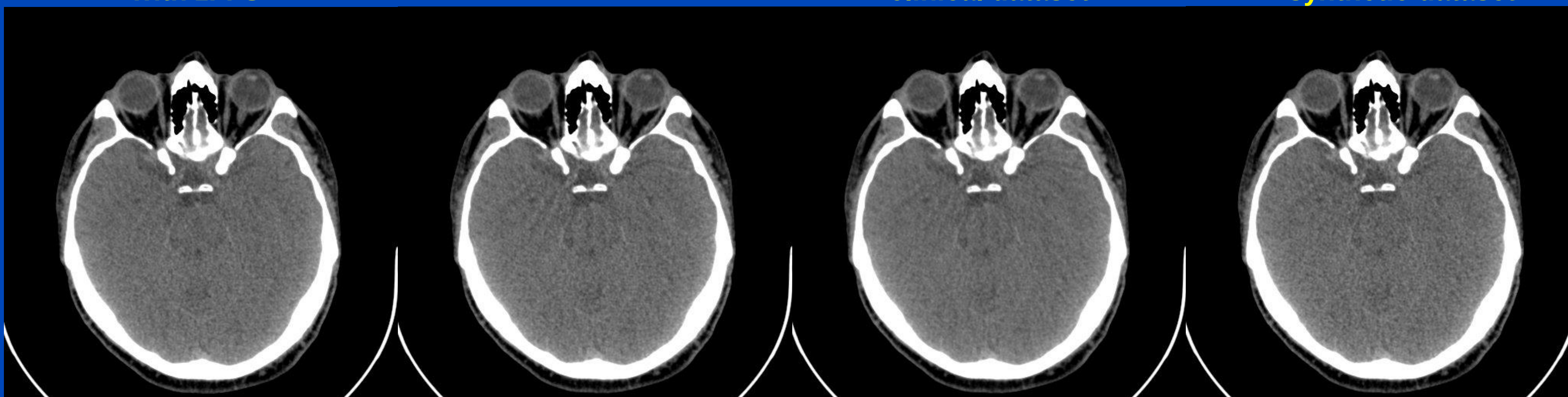

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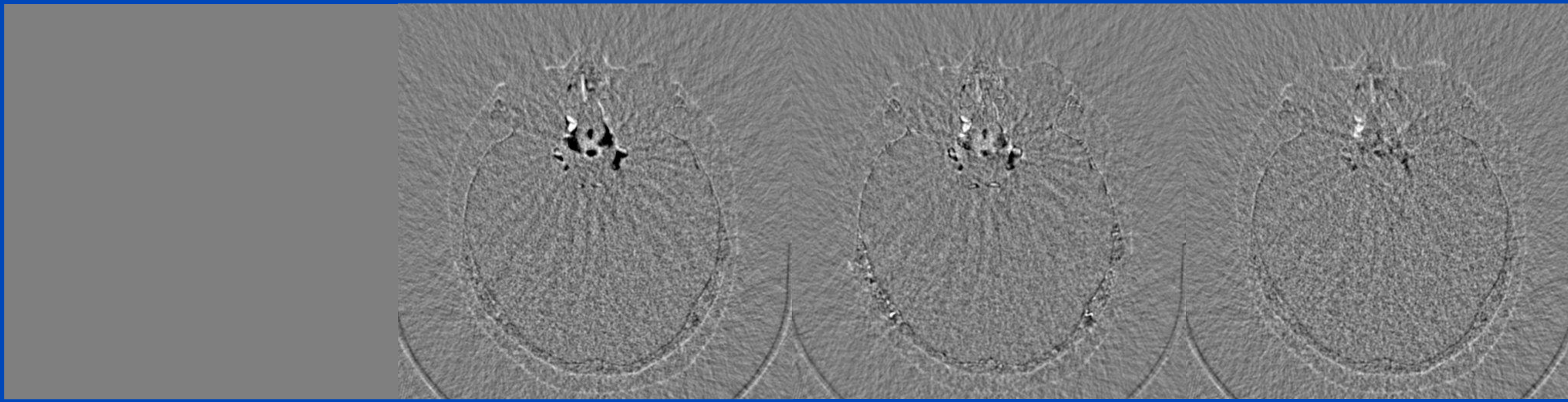

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Difference images to a WFBP of corresponding projection data with zFFS.

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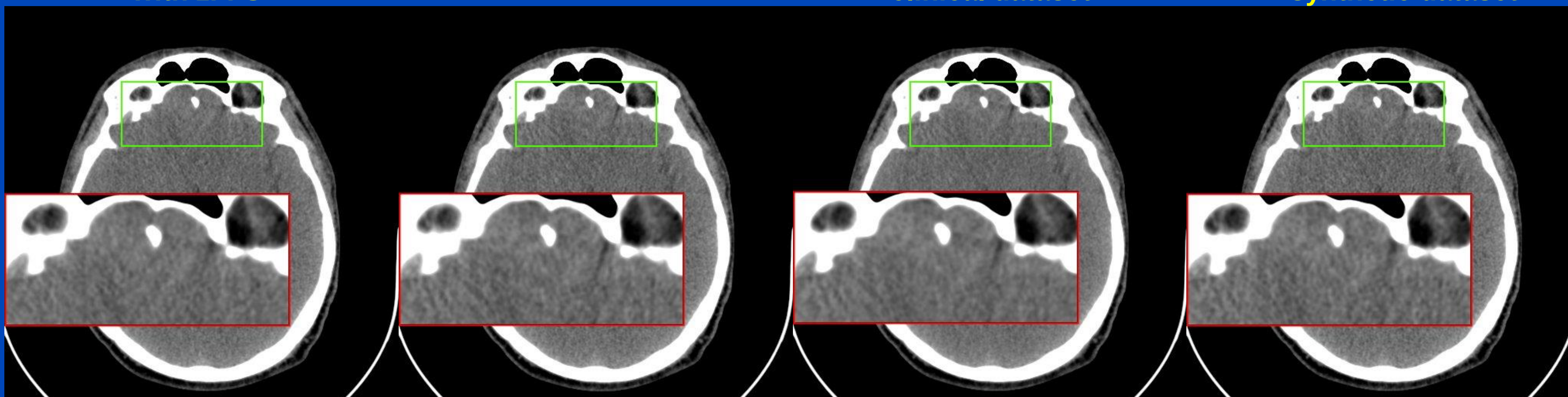

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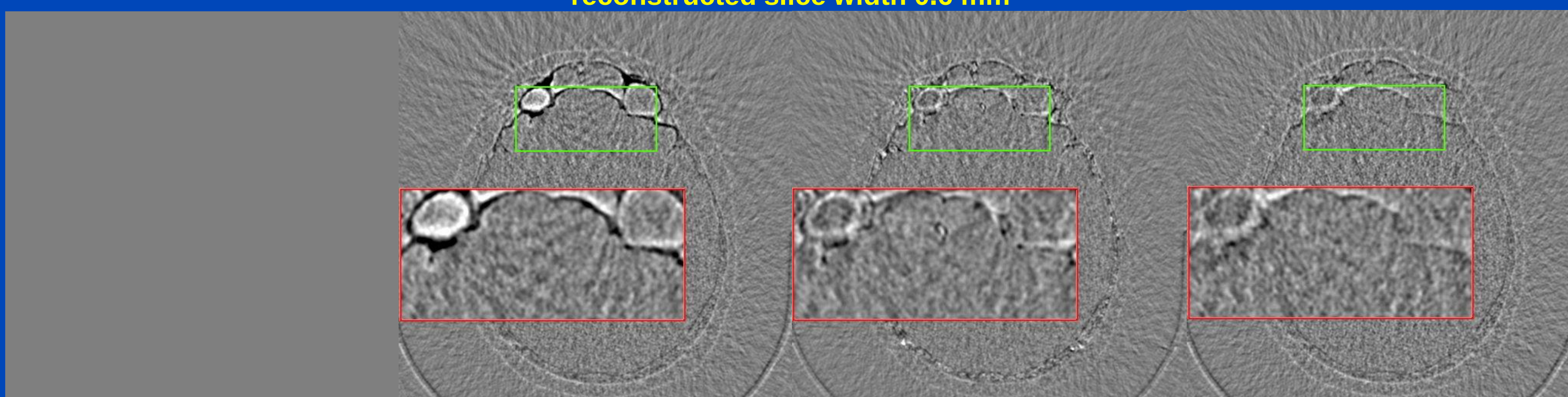

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Difference images to a WFBP of corresponding projection data with zFFS.

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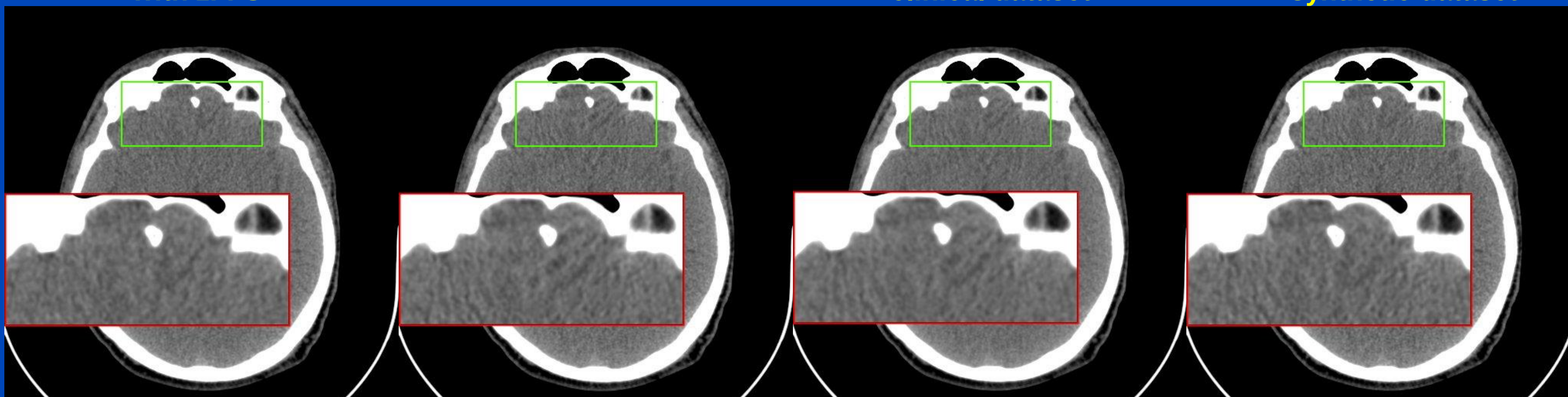
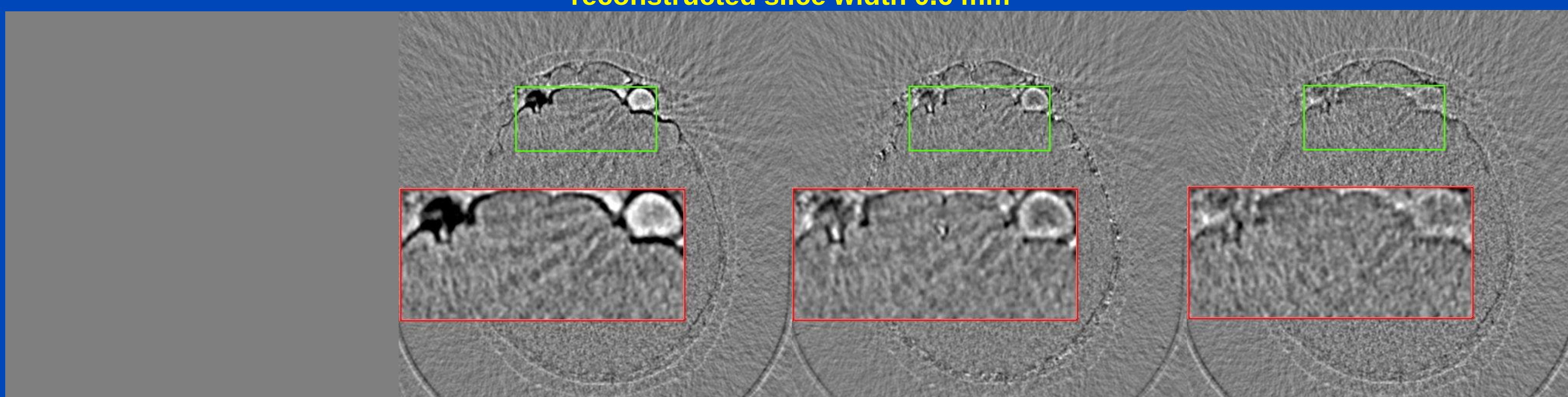


C = 60 HU, *W* = 260 HU; collimation: 64×0.6 mm;
reconstructed slice width 0.6 mm



C = 0 HU, *W* = 100 HU

Difference images to a WFBP of corresponding projection data with zFFS.

Comparison of Windmill Artifact Reduction

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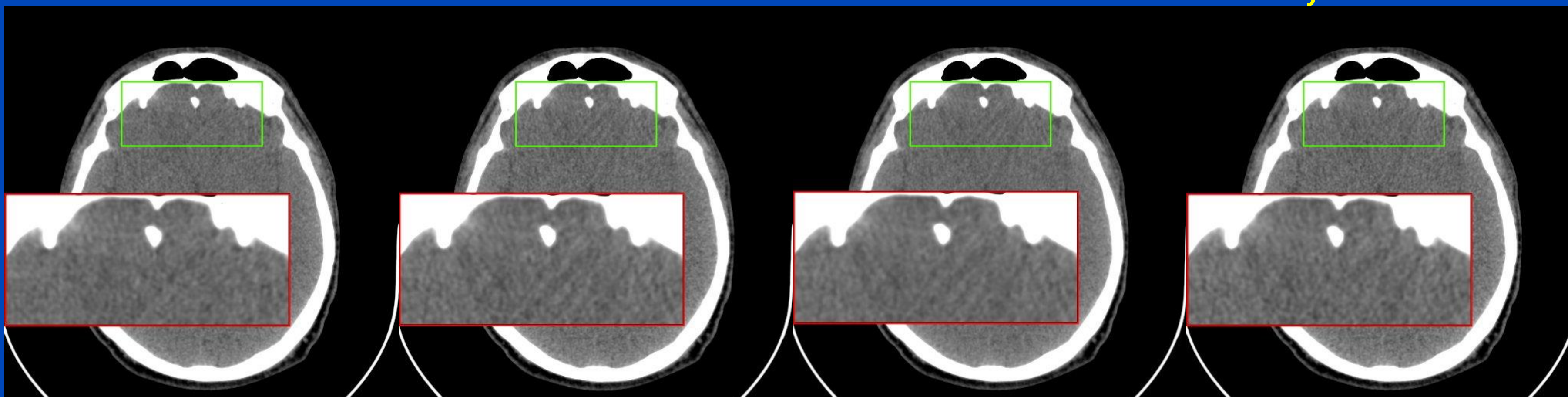
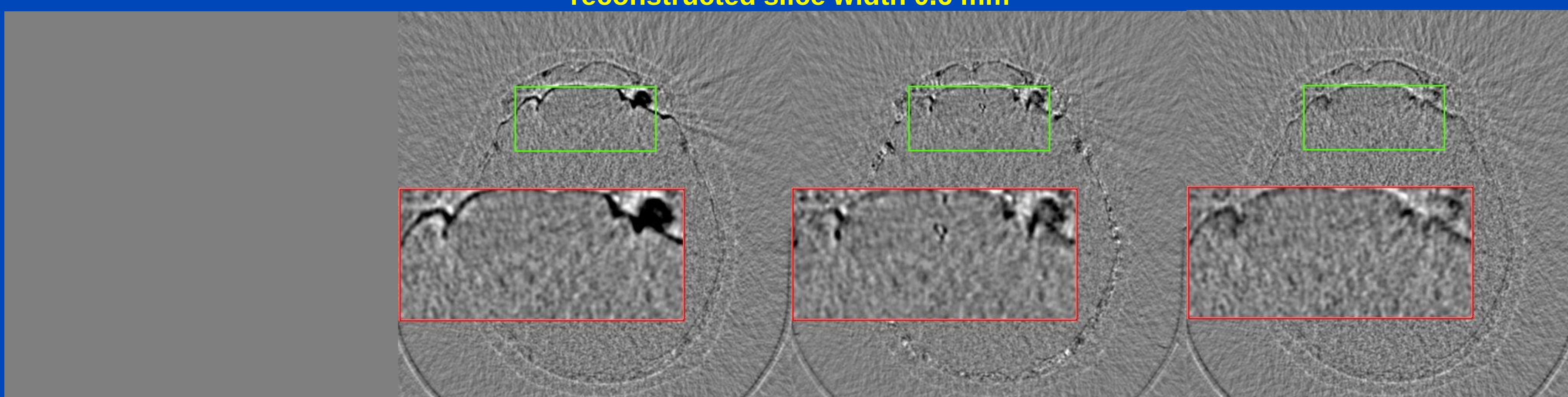


C = 60 HU, *W* = 260 HU; collimation: 64×0.6 mm; reconstructed slice width 0.6 mm



C = 0 HU, *W* = 100 HU

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Difference images to a WFBP of corresponding projection data with zFFS.

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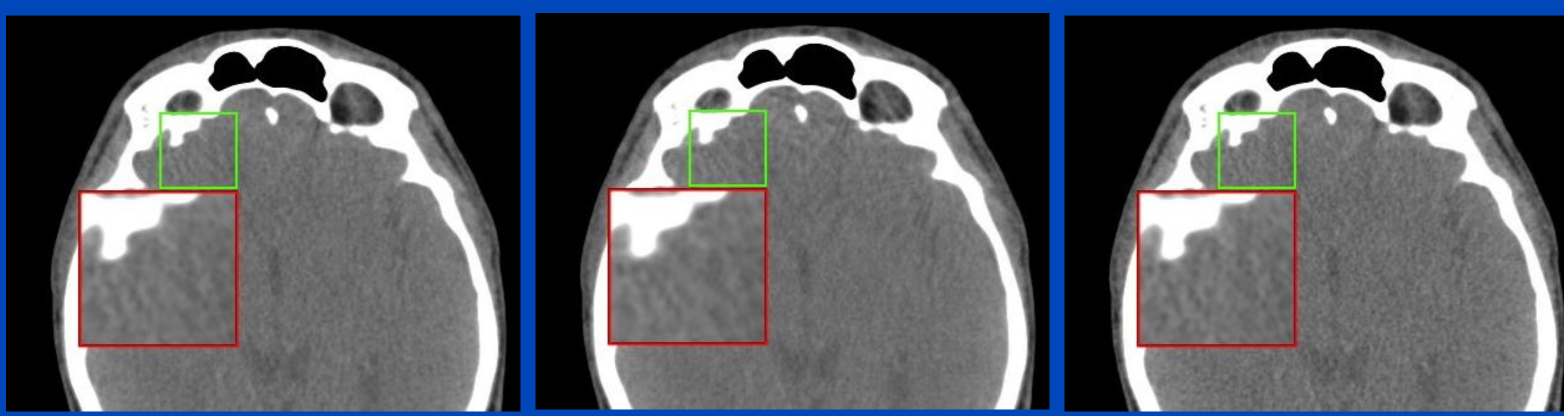
Conclusions

- **RIDL significantly reduces windmill artifacts.**
- **However, it cannot outperform zFFS.**
- **But it does not require special hardware.**
- **Training with noise-free synthetic data leads to superior performance!**
  - **This can, probably, be attributed to noise in the clinical data.**
  - **Further evaluation to be performed with more patient scans.**



RIDL trained on: noisy clinical data | noisy synthetic data | noise-free synthetic data

Thank You!

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