Data Consistent Artifact Reduction for Limited Angle Tomography with Deep Learning Prior

Yixing Huang, Alexander Preuhs, Günter Lauritsch, Michael Manhart,
Xiaolin Huang, and Andreas Maier

Outline

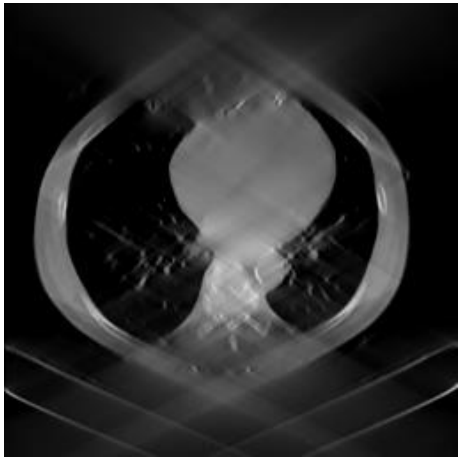
- Introduction
- Data Consistent Artifact Reduction (DCAR)
- Experimental Setup and Results
- Conclusion

Introduction

Limited angle tomography

- Reconstruction from data acquired in an insufficient angular range
- C-arm systems: restriction from other system parts or external obstacles
- Artifacts occur due to missing data, typically in the form of streaks

Siemens Arts zee Multipurpose system



120º reconstruction

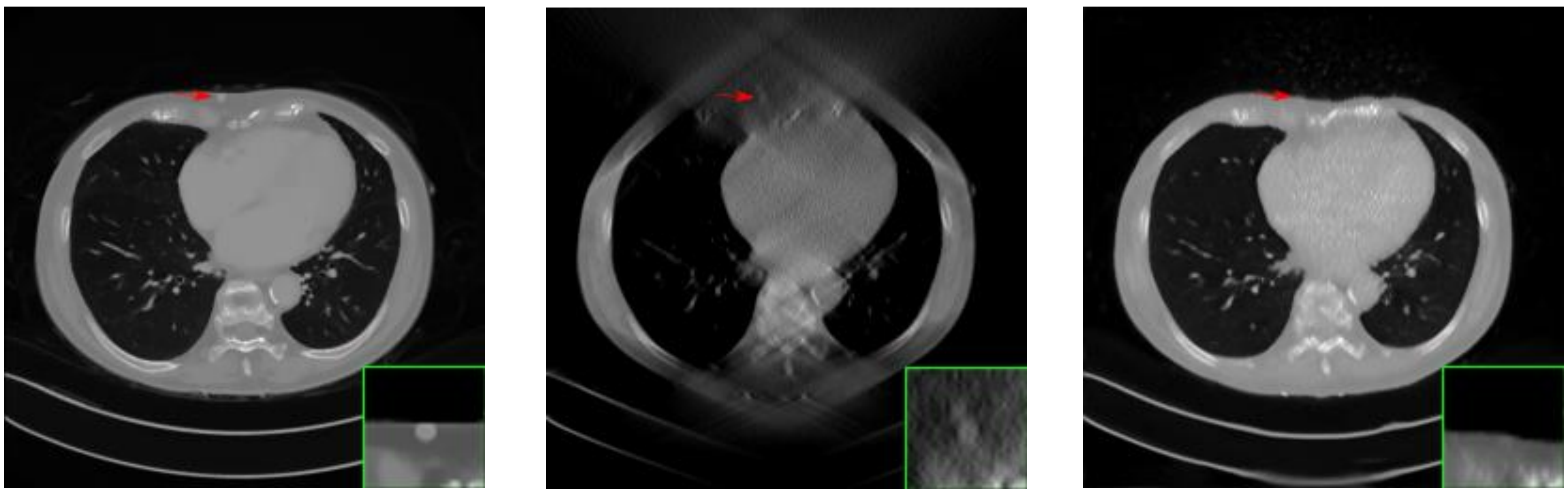
Artifact reduction methods

- Extrapolation methods [1]: do not work for complex objects
- Iterative reconstruction with compressed sensing [2]: do not work for super short scans
- Conventional machine learning [3]: may introduce new artifacts
- Deep learning [4-8]: state of the art, effective, but not robust

1. Y. Huang et al., “Restoration of missing data in limited angle tomography based on Helgason-Ludwig consistency conditions”, *Biomed. Phys. & Eng. Express*, 2017
2. Y. Huang et al., “Scale-space anisotropic total variation for limited angle tomography”, *IEEE Trans. Radiat. Plasma Med. Sci.,* 2018
3. Y. Huang et al., “Traditional machine learning for limited angle tomography”, *Int. J. Comput. Assist. Radiol. Surg.,* 2019
4. T. Würfl et al., “Deep learning computed tomography”, *Proc. MICCAI*, 2016
5. J. Gu and J. C. Ye, “Multi-scale wavelet domain residual learning for limited-angle CT reconstruction”, *Proc. Fully3D*, 2017
6. Y. Huang et al., “Some investigations on robustness of deep learning in deep learning”, *Proc. MICCAI*, 2018
7. T. Würfl et al., “Deep learning computed tomography: Learning projection-domain weights from image domain in limited angle problems”, *IEEE Trans. Med. Imaging*, 2018
8. T. A. Bubba et al., “Learning the invisible: a hybrid deep learning-shearlet framework for limited angle computed tomography”, *Inverse Probl.*, 2019

Robustness of deep learning

- Cannot reliably generalize to unseen data (insufficient training data)
- Sensitive to noise or adversarial perturbations [1]



reference | FBP reconstruction | U-Net reconstruction

1. Y. Huang et al., "Some investigations on robustness of deep learning in deep learning", *Proc. MICCAI*, 2018

Improve deep learning robustness

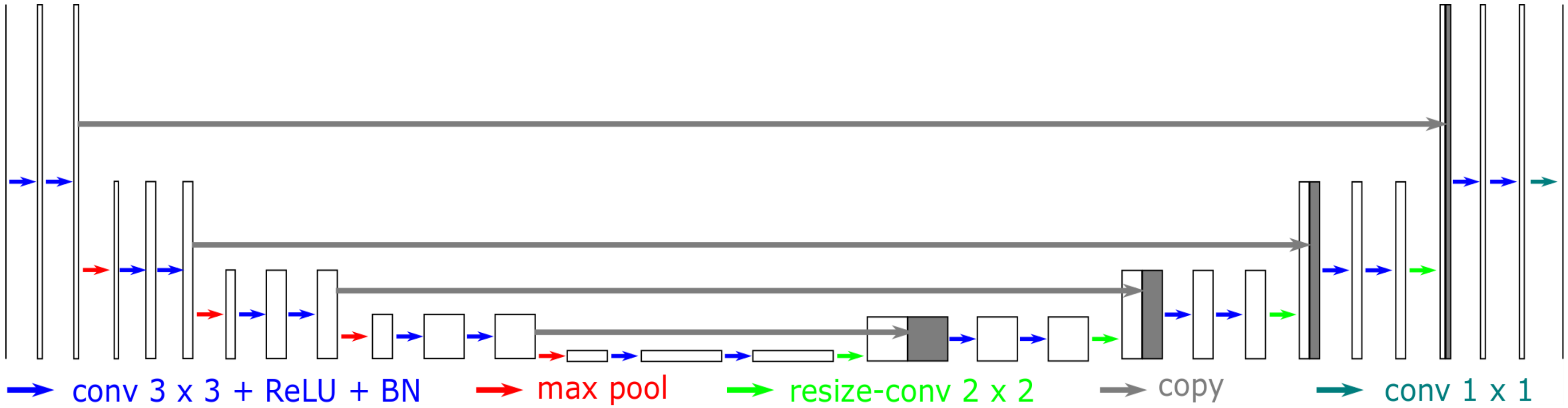
- Combine deep learning with conventional methods
  a. Build neural networks from known operators [1-3]
  b. Post-process deep learning reconstruction by conventional methods

1. A. Maier et al., "Learning with known operators reduces maximum training error bounds", Nat. Mach. Intell., 2019
2. T. Würfl et al., "Deep learning computed tomography: Learning projection-domain weights from image domain in limited angle problems", *IEEE Trans. Med. Imaging*, 2018
3. A. Kofler et al., "A U-Nets cascade for sparse view computed tomography", *Proc. MICCAI MLMIR*, 2018

Data Consistent Artifact Reduction (DCAR)

The U-Net

- The state-of-the-art U-Net [1,2] as post-processing for artifact reduction in image domain
- Image-to-image prediction has no direct connection to projection domain
- Incorrect structures occur



The U-Net architecture

1. O. Ronneberger et al., “U-Net: Convolutional networks for biomedical image segmentation”, *Proc. MICCAI*, 2015
2. J. Gu and J. C. Ye, “Multi-scale wavelet domain residual learning for limited-angle CT reconstruction”, *Proc. Fully3D*, 2017

Data consistent artifact reduction (DCAR)

- Data fidelity of measured data

$$\|\boldsymbol{A}_m \boldsymbol{f} - \boldsymbol{p}_m\| < e_1$$

where $\boldsymbol{p}_m$ denotes the measured projection data, $\boldsymbol{A}_m$ denotes the corresponding system matrix, $\boldsymbol{f}$ is the image to reconstruct, and e_1 is a parameter for error tolerance.

- Data fidelity of unmeasured data

$$\|\boldsymbol{A}_u \boldsymbol{f} - \boldsymbol{A}_u \boldsymbol{f}_{\mathrm{U-Net}}\| = \|\boldsymbol{A}_u (\boldsymbol{f} - \boldsymbol{f}_{\mathrm{U-Net}})\| < e_2$$

where $\boldsymbol{p}_u$ denotes the unmeasured projection data, $\boldsymbol{A}_u$ denotes the corresponding system matrix, $\boldsymbol{f}_{\mathrm{U-Net}}$ is the U-Net reconstruction, and e_2 is another parameter for error tolerance.

- $\boldsymbol{A}_m$ and $\boldsymbol{A}_u$ form a short scan

Data consistent artifact reduction (DCAR)

- Regularization by iterative reweighted total variation (wTV) [1] to further reduce artifacts due to the error tolerance of e_1 and e_2

$$\left\|\boldsymbol{f}^{(n)}\right\|_{\mathrm{wTV}} = \sum_{x,y,z} \boldsymbol{w}_{x,y,z}^{(n)} \left\|\mathcal{D}\boldsymbol{f}_{x,y,z}^{(n)}\right\|$$

$$\boldsymbol{w}_{x,y,z}^{(n)} = \frac{1}{\left\|\mathcal{D}\boldsymbol{f}_{x,y,z}^{(n)}\right\| + \epsilon}$$

- Overall objective function for DCAR:

$$\min_{\boldsymbol{f}} \left\|\boldsymbol{f}^{(n)}\right\|_{\mathrm{wTV}} \text{ subject to } \begin{cases} \|\boldsymbol{A}_m\boldsymbol{f} - \boldsymbol{p}_m\| < e_1 \\ \left\|\boldsymbol{A}_u(\boldsymbol{f} - \boldsymbol{f}_{\mathrm{U-Net}})\right\| < e_2 \\ \boldsymbol{f}^{(0)} = \boldsymbol{f}_{\mathrm{U-Net}} \end{cases}$$

1. Y. Huang et al., “Scale-space anisotropic total variation for limited angle tomography”, *IEEE Trans. Radiat. Plasma Med. Sci.*, 2018

Experimental Setup and Results

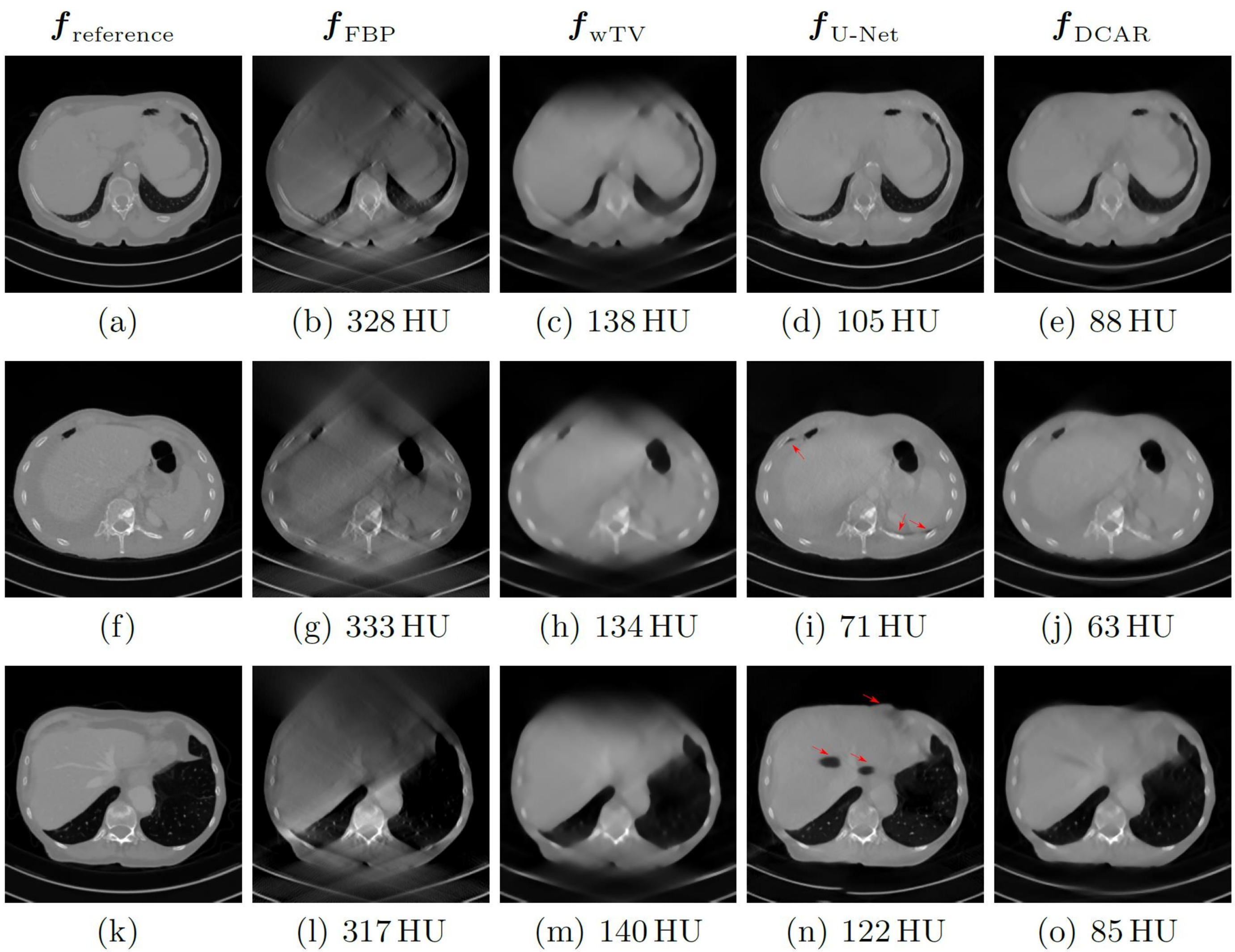
Experimental Setup

- 120º cone-beam limited angle tomography without and with Poisson
- 16 patients for training (25 slices from each patient) and 1 for test
- Reconstruction parameters:

  e_1= 0.001 (0.01), e_2= 0.5, ϵ = 5 HU, 100 iterations…

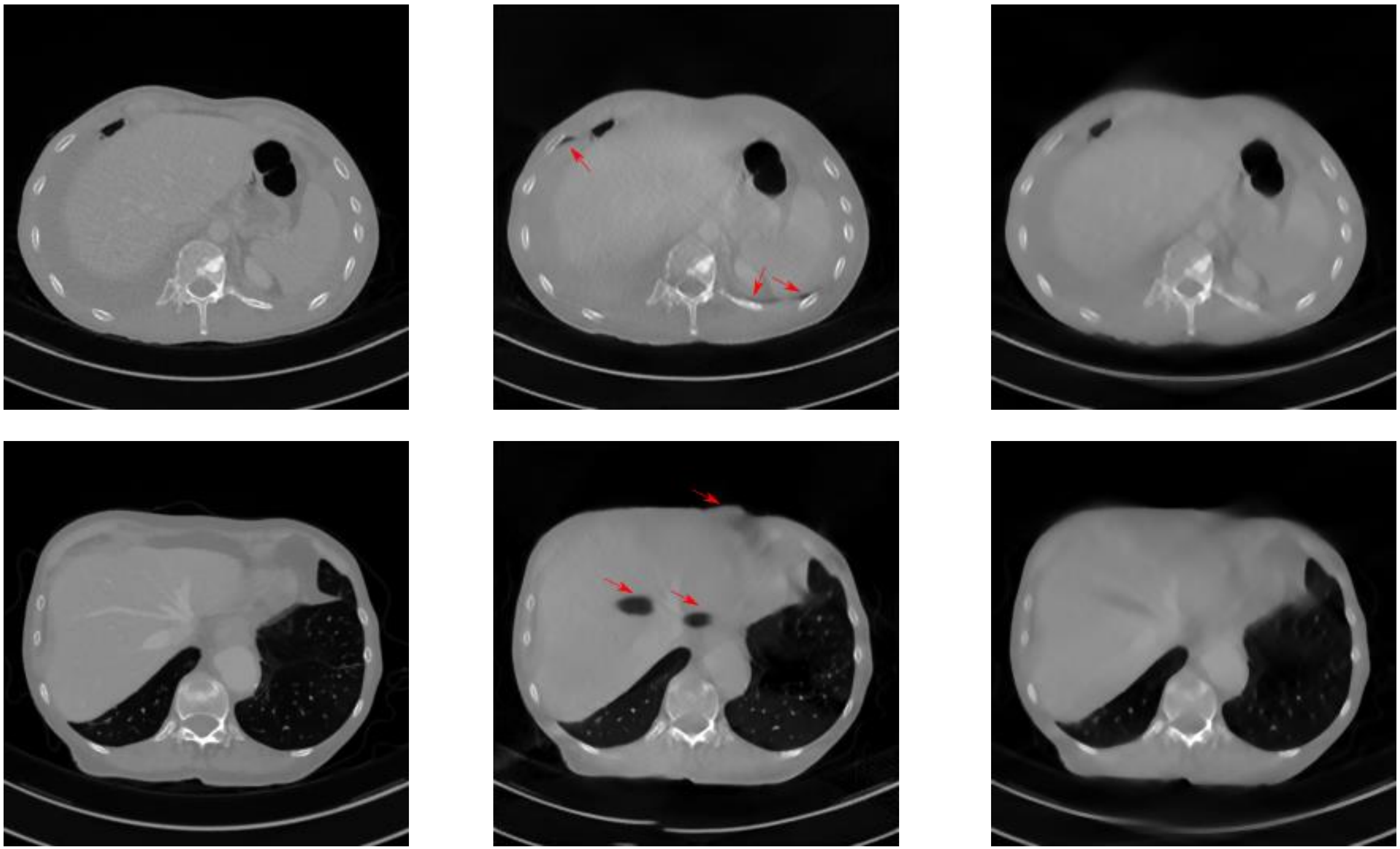
Parameter	Value
Scan angular range	$120^\circ (210^\circ)$
Start angle	$30^\circ (0^\circ)$
End Angle	$150^\circ (210^\circ)$
Angular step	1°
Source-to-detector distance	1200.0 mm
Source-to-isocenter distance	600.0 mm
Detector size	620×480
Detector pixel size	$1.0\,\text{mm} \times 1.0\,\text{mm}$
Image size	$256 \times 256 \times 256$
Image pixel size	$1.25\,\text{mm} \times 1.25\,\text{mm} \times 1.0\,\text{mm}$

Noise-free case results

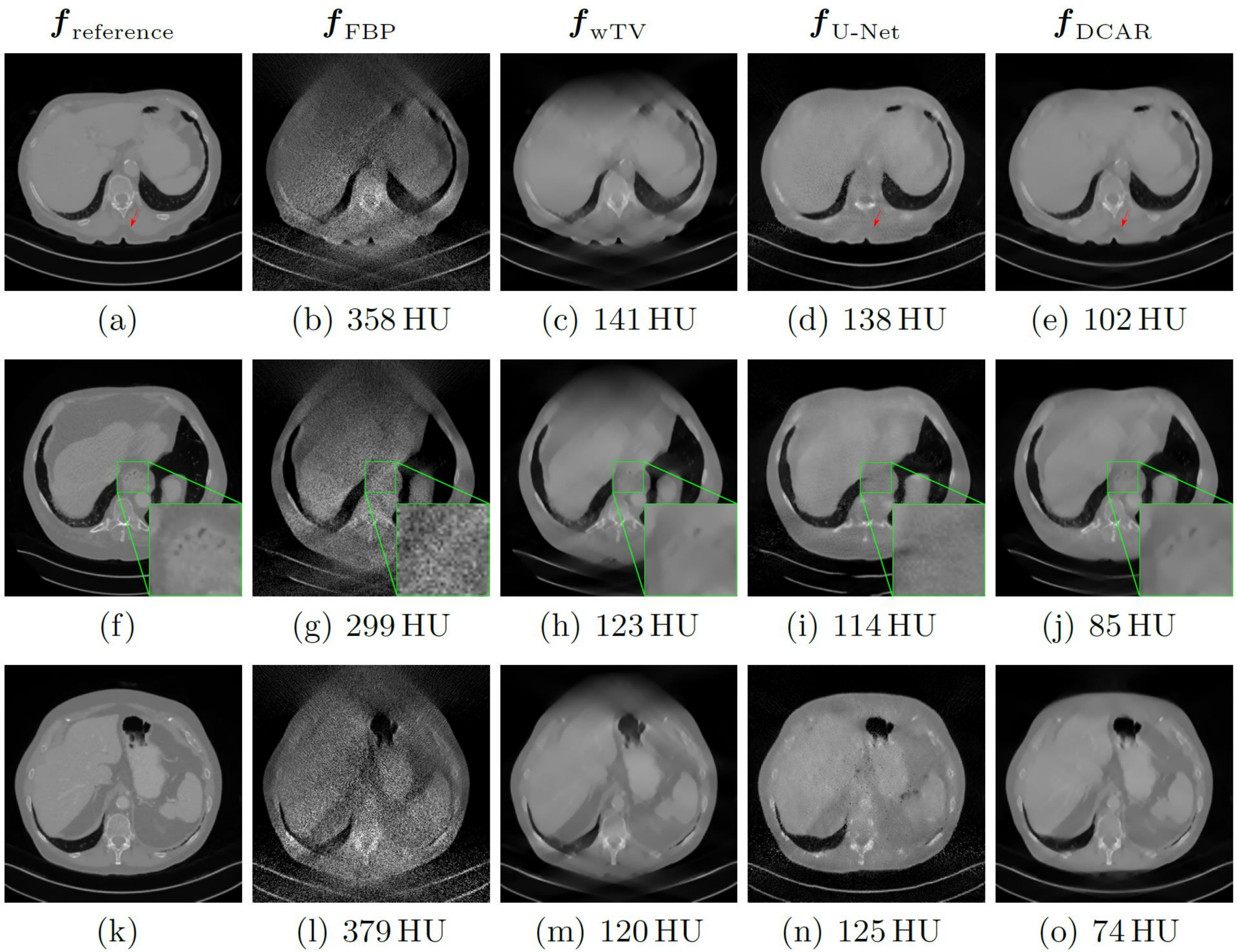


Noise-free case results

$f_{\text{reference}}$ $f_{\text{U-Net}}$ f_{DCAR}



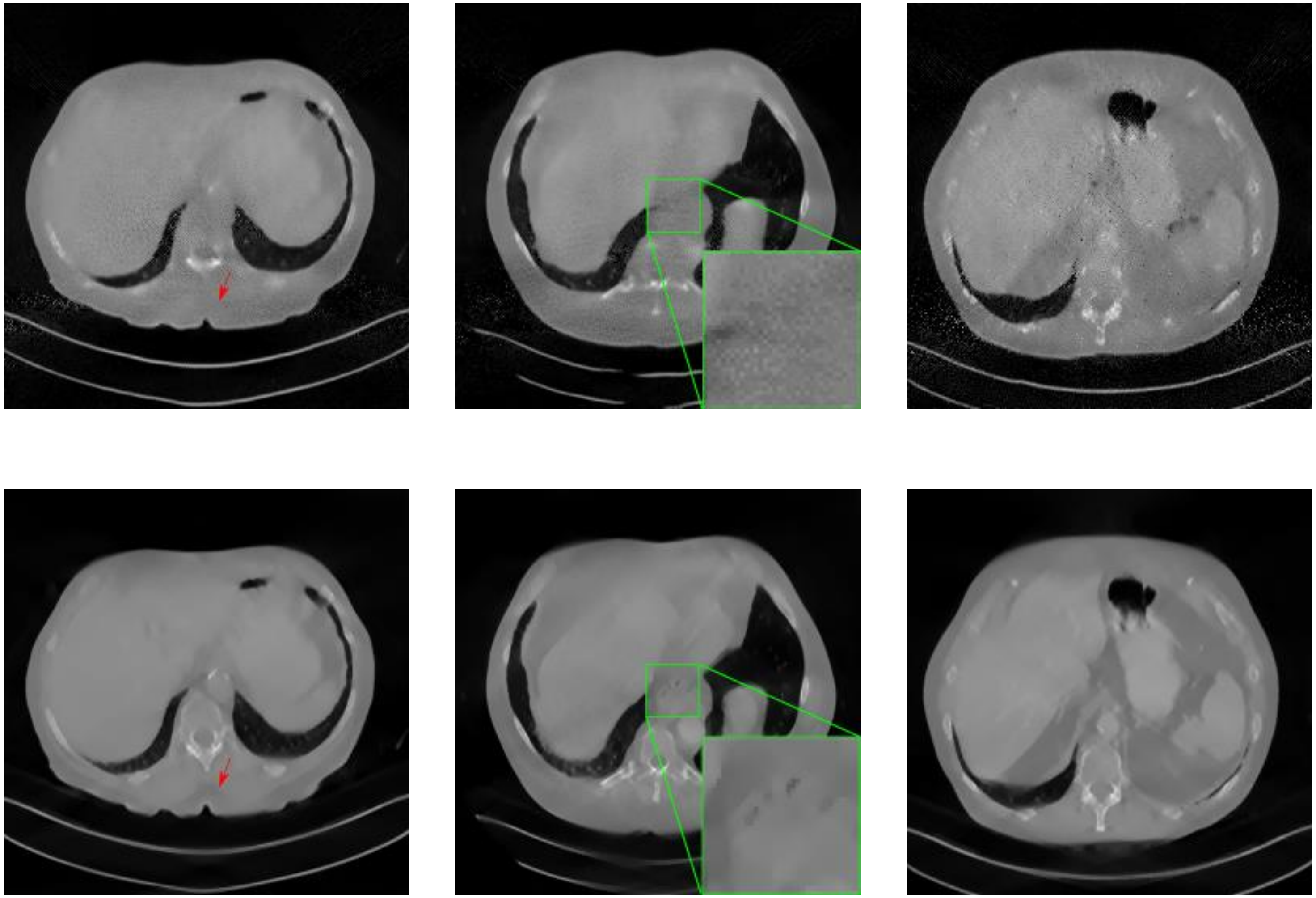
Noisy case results



Noisy case results

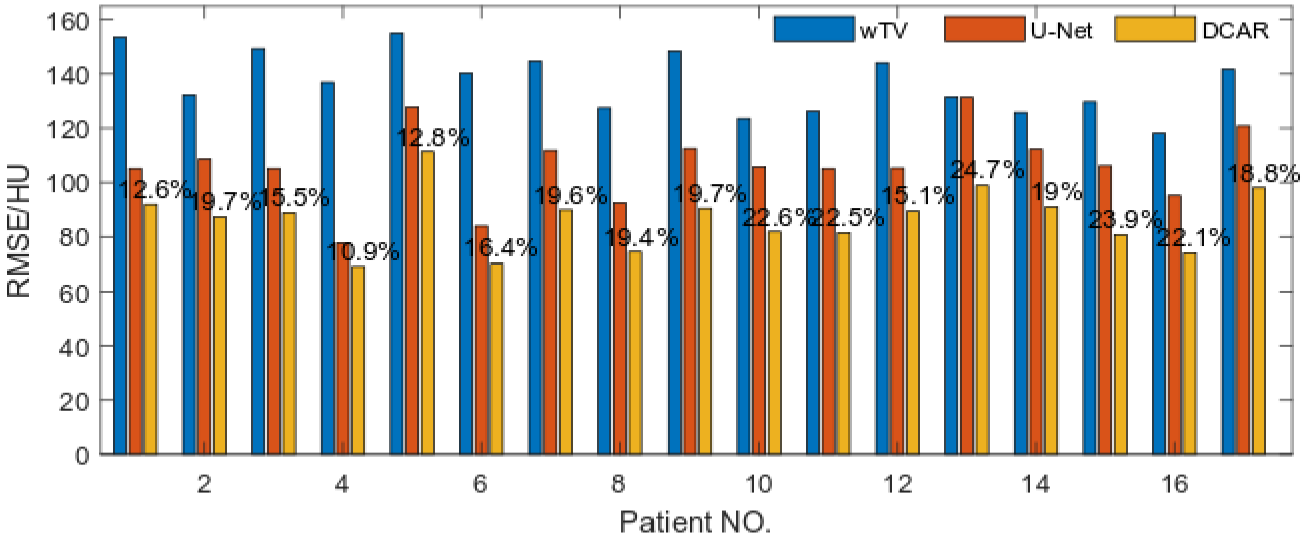
$f_{\mathrm{U-Net}}$

f_{DCAR}

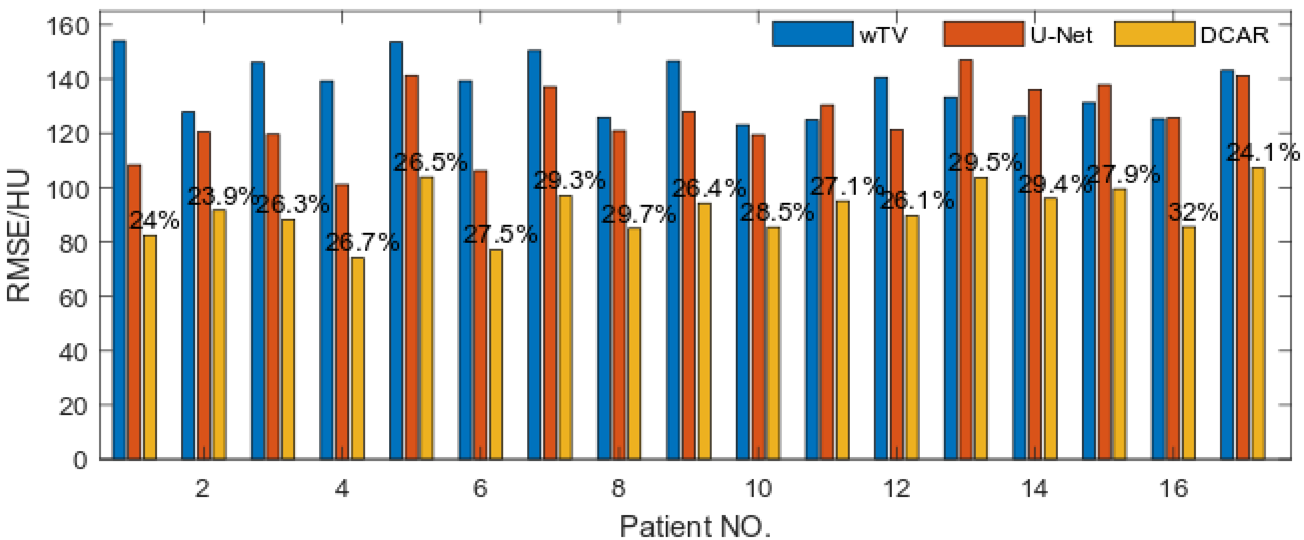


Leave-one-out cross-validation

Noise-free



Noisy



Conclusion

Conclusion

- DCAR utilizes deep learning reconstruction as prior for missing data
- DCAR combines the benefits of wTV and the U-Net
- Tags: hybrid, deep learning prior, post-processing

Thank you!

yixing.yh.huang@fau.de