DeepRAR: A CNN-Based Approach for CT and CBCT Ring Artifact Reduction

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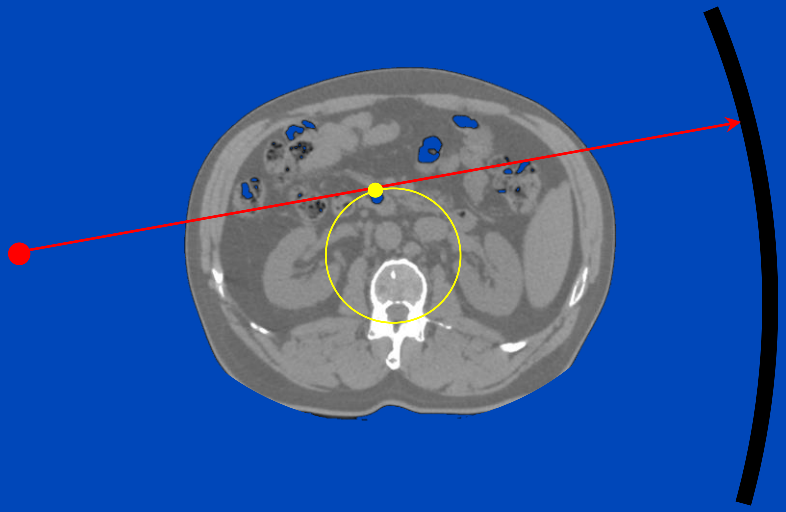
DEUTSCHES KREBSFORSCHUNGSZENTRUM IN DER HELMHOLTZ-GEMEINSCHAFT

Motivation and Background

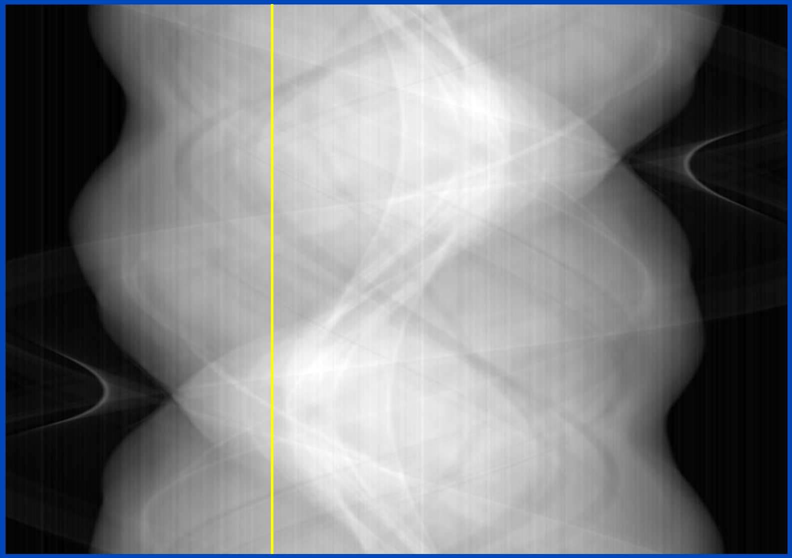
- Every X-ray detector exhibits systematic measurement deviations due to transmission errors of the detector pixels.
- The reason for such transmission errors are manifold, they may for instance be caused by
  - different dark currents of the photodiodes.
  - irregularities in the detector material (scintillator or semiconductor).
  - deviations of the channel sizes.
  - general differences in signal conversion and amplification processes of an X-ray signal into an electric current.
- These transmission errors, besides stochastic deviations, result in signal height differences between detector pixels, even if they are exposed to the same X-ray intensity.

Motivation and Background –
Ring Artifacts in CT Images

- If deviations of the signal heights are not compensated, artifacts occur in the reconstructed CT images.
- These artifacts appear in the form of rings in the reconstructed volume for circular trajectories.



Projection data acquisition



Sinogram

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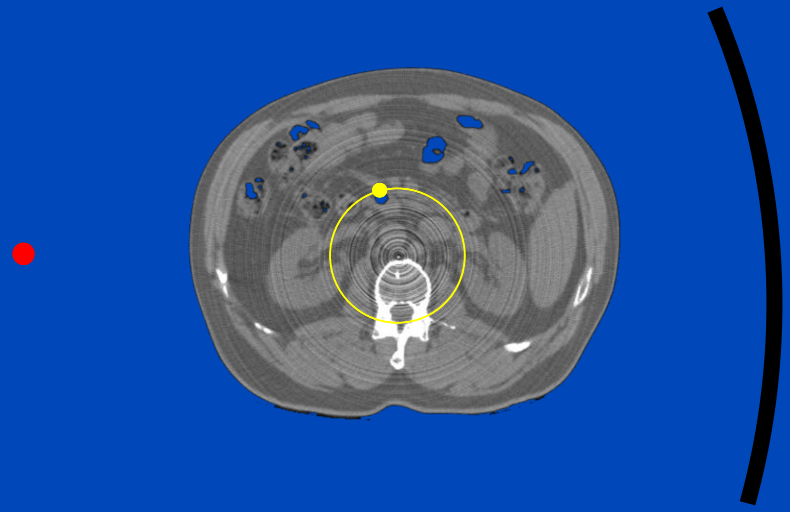
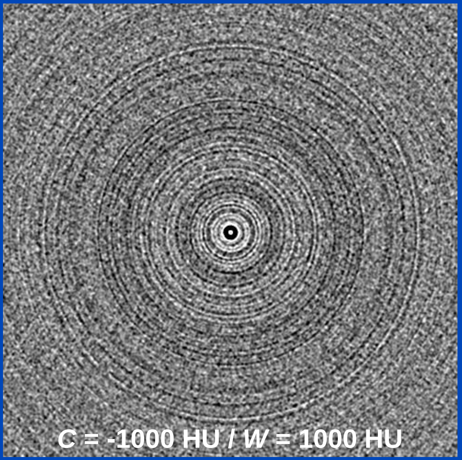
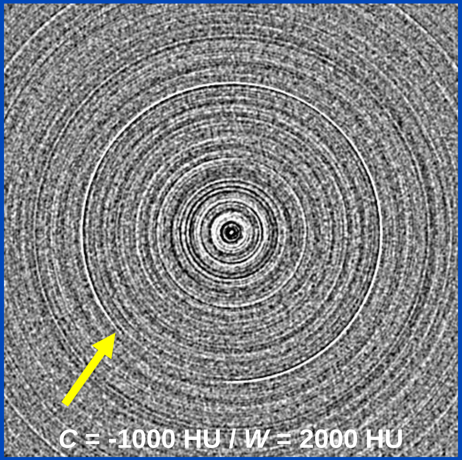


Reconstructed volume

Motivation and Background –
Further Characteristics of Ring Artifacts

- The width of the rings may vary due to the point-spread function (PSF) of the detector and the frequency of the disturbance.
- The intensity of ring artifacts is decreasing for increasing distances to the center of rotation.
- **Partial ring artifacts** may also occur, due to
  - a stochastical behaviour of the aforementioned effects.
  - spiral CT trajectories.

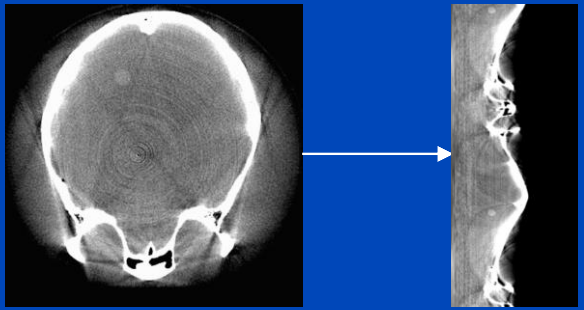




Two exemplary CT images of an air measurement with a CBCT setup.
(Partial) Ring artifacts of different frequencies and intensities may occur.

Methods for Ring Artifact Reduction

- **Properly calibrated flat field corrections**
  - » Schmidgunst et al. (2007), Medical Physics
- **Rawdata-based methods:**
  - – extract and remove lines from sinograms by filter operations
    - » Anas et al. (2010), Phys. Med. Biol.
    - » Kim et al. (2014), Optics Express
    - » Clark et al. (2017), PloS one
    - » Ours (after Clark et al. but lowpass acting on 2D intensity projections instead of log-sinograms)
  - – learning-based algorithms
    - » Nauwynck et al. (2020), CT Meeting
    - » Fang et al. (2020), IEEE Access
- **Image-based methods:**
  - – resampling on a polar grid and extract and remove lines by filter operations
    - » Syjbers et al. (2004), Phys. Med. Biol.
    - » Kyriakou et al. (2009), Phys. Med. Biol.
    - » Prell et al. (2009), Phys. Med. Biol.
  - – learning-based algorithms
    - » Lv et al. (2020), IEEE Access
    - » Chao et al. (2020), Phys. Med. Biol.
    - » Fang et al. (2020), IEEE Access



Polar grid resampling example from Prell et al.

Aim

- To reduce ring and partial ring artifacts using a convolutional neural network (CNN) in image domain without the necessity of resampling to another coordinate system.

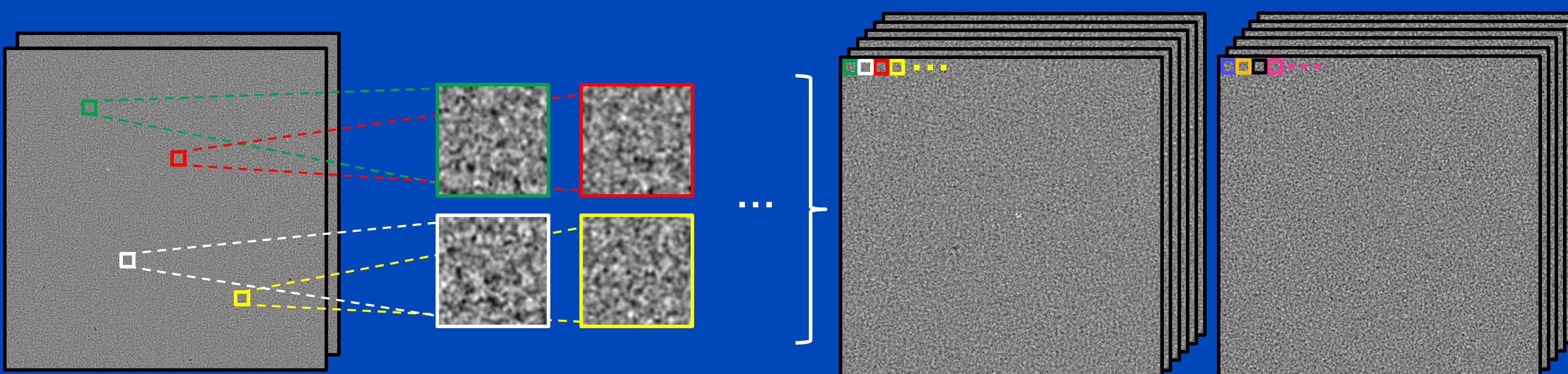
- Such a solution would be beneficial because
  - the availability of rawdata is not required.
  - no resampling to another coordinate system, e.g. a polar grid, is required.
  - no fine-tuning of correction parameters (e.g. filter parameters) is required.

Material and Methods

- Training and validation of the neural network were performed on simulated datasets and supervised learning was used.
  - For testing, both simulated data and measured photon counting (PC) micro CT data were used.
- Artifact-free diagnostic CT volumes were forward projected in a CBCT geometry (R_{FD} = 1080 mm).
  - Thorax and abdomen data were used for training (R_F = 620 mm).
  - Head data were used for validation and testing (R_F = 855 mm).
- Ring artifacts were simulated by adding random gains *g* and offsets *o* to the true signal *T*:

$$M(\alpha, u, v) = g(\alpha, u, v)\, T(\alpha, u, v) + o(\alpha, u, v)$$

  - The reconstruction $X^{-1}(-\ln(M))$ thus contains ring artifacts.
- For a realistic simulation of *g* and *o*, patches from CBCT flat field images were randomly sampled and combined:



Flat field images | Flat field images patches | Gain “projections” *g* | Offset “projections” *o*

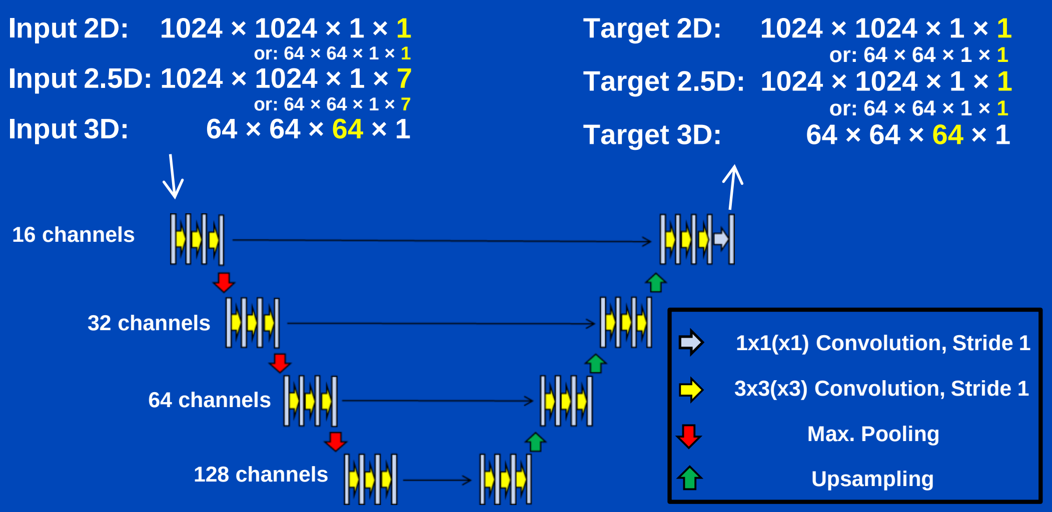
Material and Methods

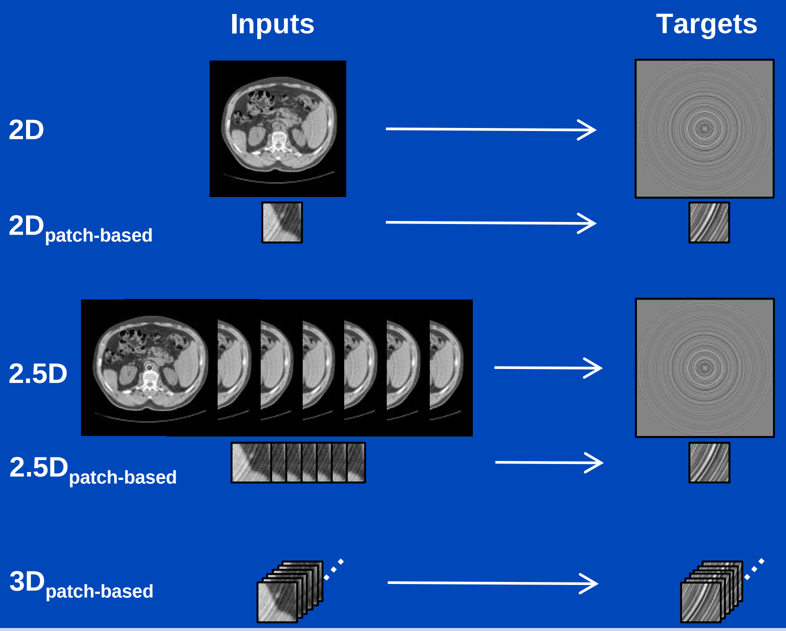
$$M(\alpha, u, v) = g(\alpha, u, v)\, T(\alpha, u, v) + o(\alpha, u, v)$$

- Weights were randomly assigned to each gain and offset projection to model different artifact strengths.
- A subset of pixels (1 to 10 percent per CT dataset) changes its behaviour once or multiple times during a scan (at some α) to model temporal signal deviations leading to partial rings.
- Different levels of Poisson noise were added to each dataset.
  - Photon numbers varied from N_P=500k to N_P=2.5M photons per pixel (unattenuated)
- A total of 18944 CT images were simulated with and without ring artifacts.
  - 65% Training data (abdomen and thorax CT images)
  - 25% Validation data (head CT images)
  - 10% Test data (head CT images)

Network Architectures

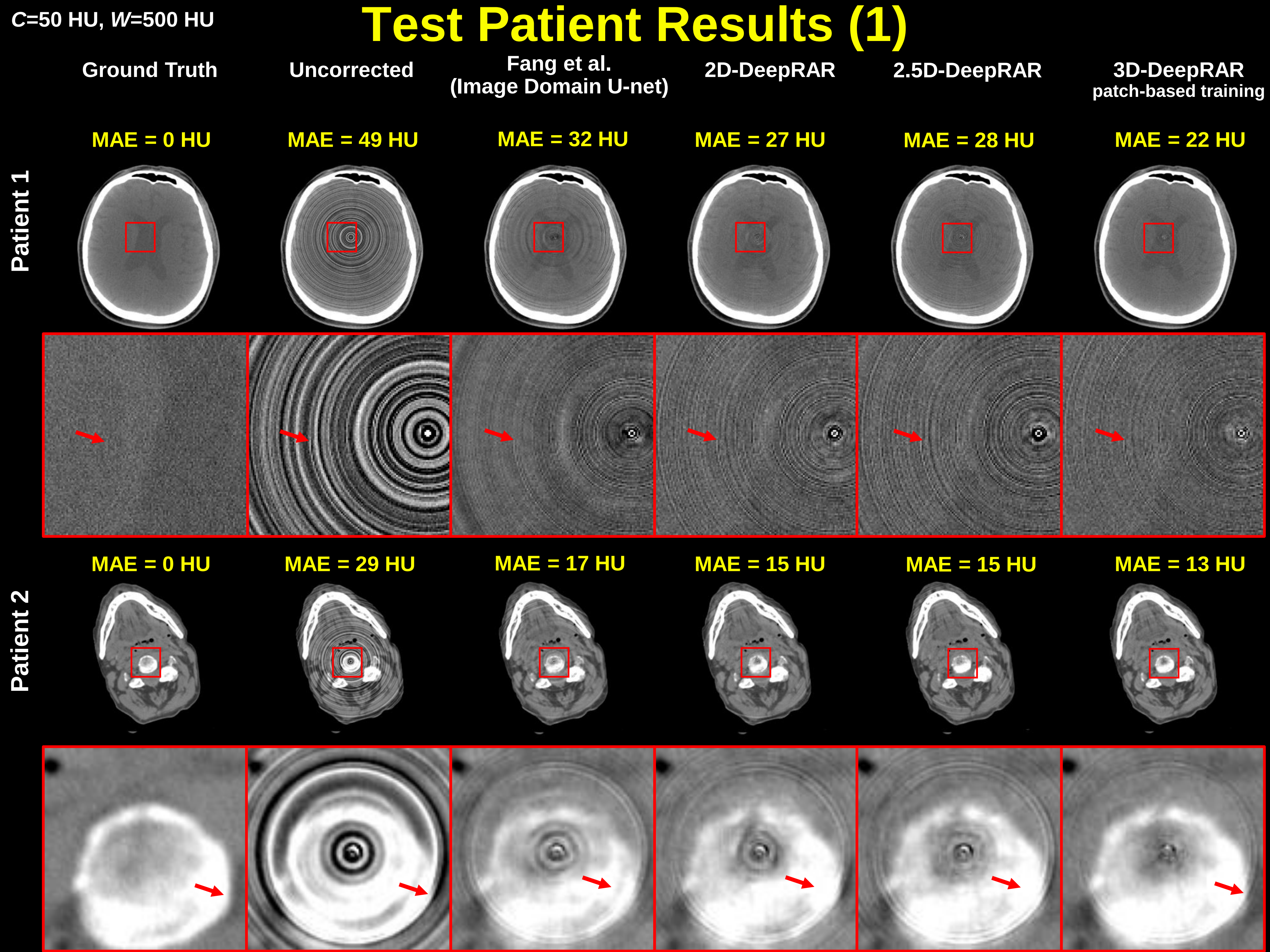
- Three different network architectures were tested.
  - The cartesian image domain U-Net[1] (2D) of Fang et al.[2] was implemented as reference method.
- All DeepRAR networks have the basis structure of an U-Net[1], differing in their dimensionality:
  - 2D network using 2D convolutions with a single CT image (or patch) as input
  - 2.5D network using 2D convolutions with three adjacent CT images (or patches) as inputs
  - 3D network using 3D convolutions with a stack of CT image patches as input
- Each network estimates the residual, thus image (patches) containing ring artifacts only.



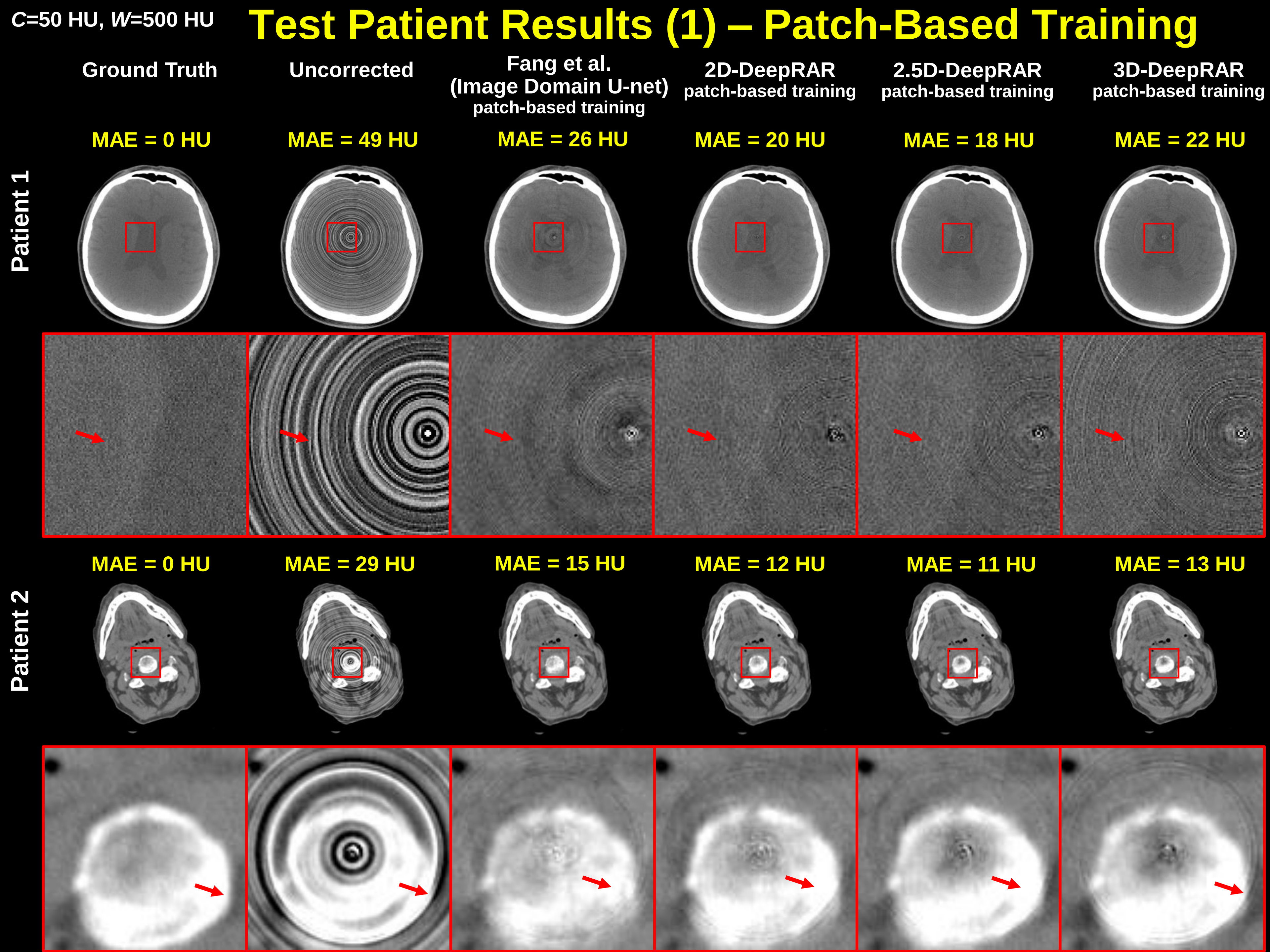


[1]Ronneberger et al., *U-net: CNNs for biomedical image segmentation*, Conference on Medical image computing […], 2015
[2]Fang et al., *Removing Ring Artefacts for PC Detectors Using Neural Networks in Different Domains*, IEEE Access, 2020

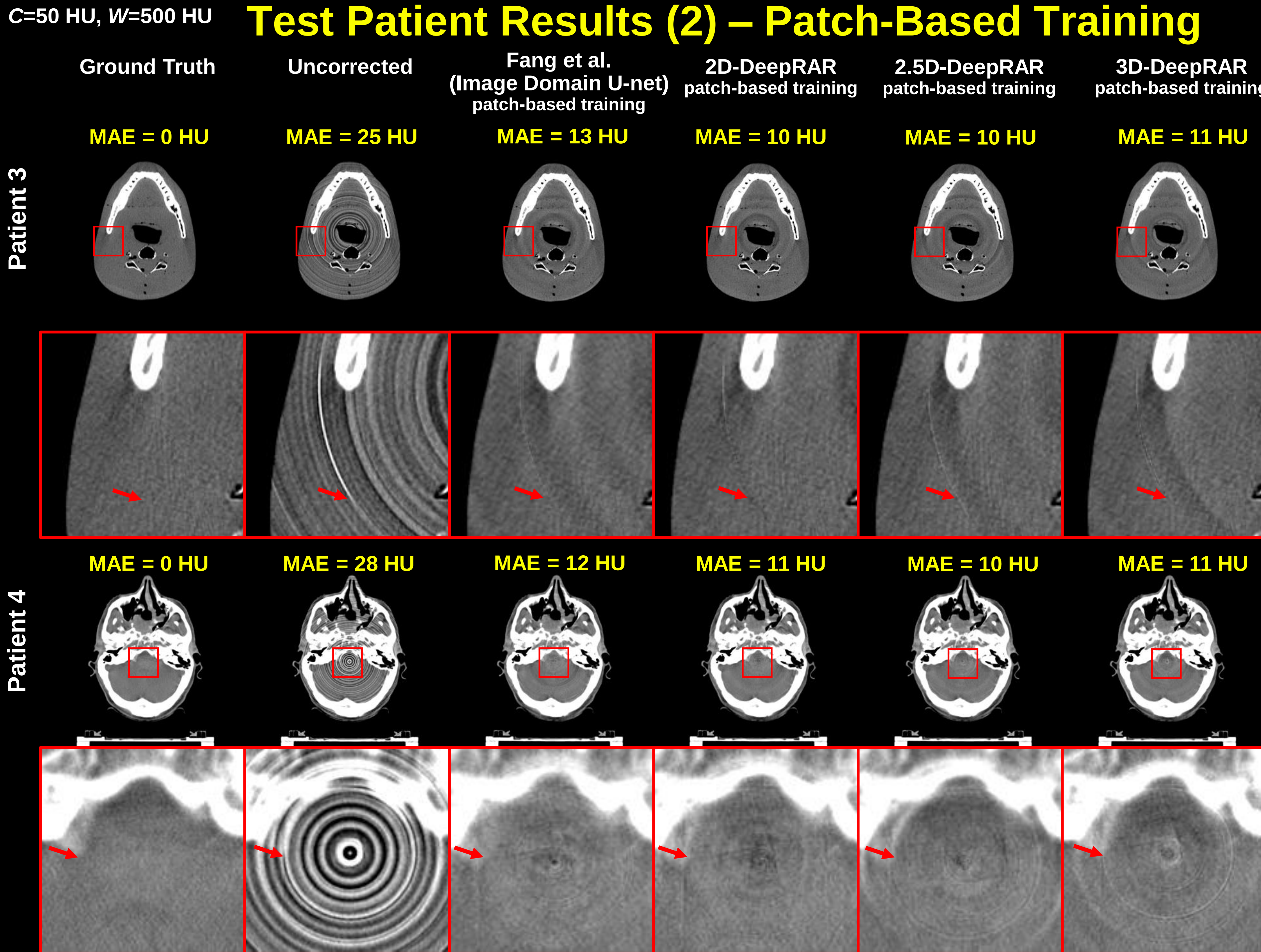
Test Patient Results (1)



Test Patient Results (1) – Patch-Based Training

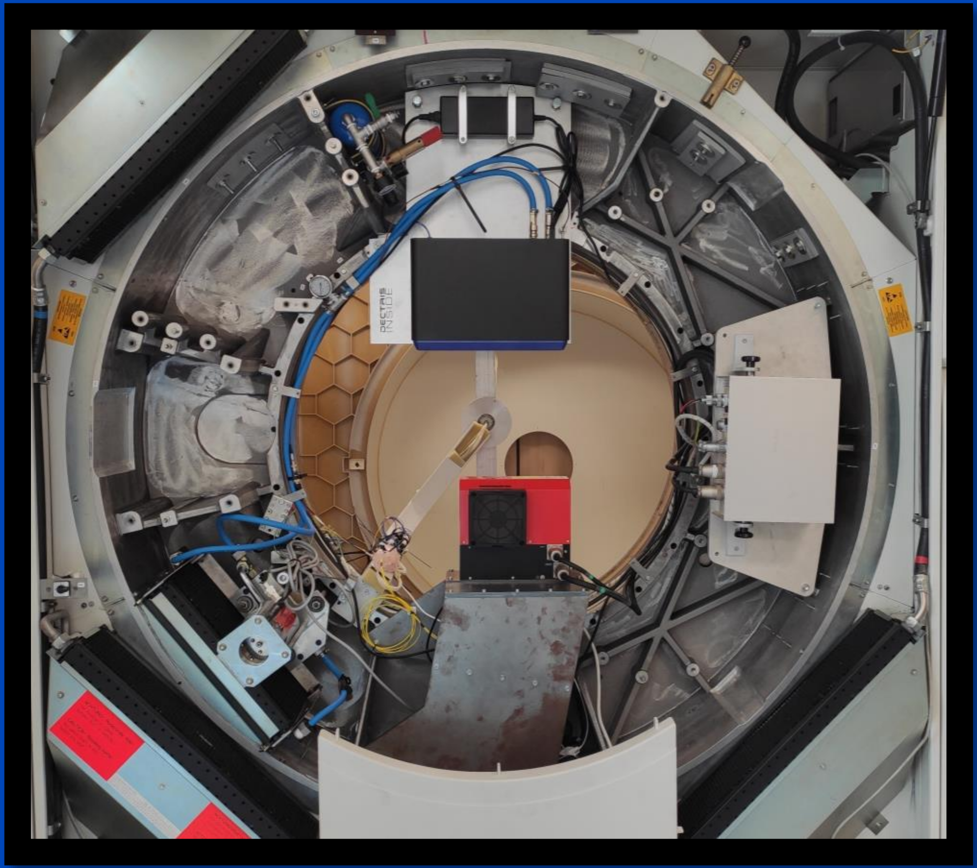


Test Patient Results (2) – Patch-Based Training



Experimental Setup

- DeepRAR was also tested on micro-CT data from our experimental gantry[3].
- CT system equipped with
  - Hamamatsu microfocus X-ray tube
  - Dectris Säntis photon counting detector
- Due to dynamic polarization of the sensor material, PCCT is particularly susceptible to ring artifacts[4]!
- Scanning parameters for mouse measurements:
  - Tube voltage: 90 kV
  - Tube current: 556 µA
  - Prefiltration: none
  - Frame rate: 65 Hz
  - Projections per rotation: 656
  - Rotations: 6 (60.5 s)
  - Energy threshold: 20 keV



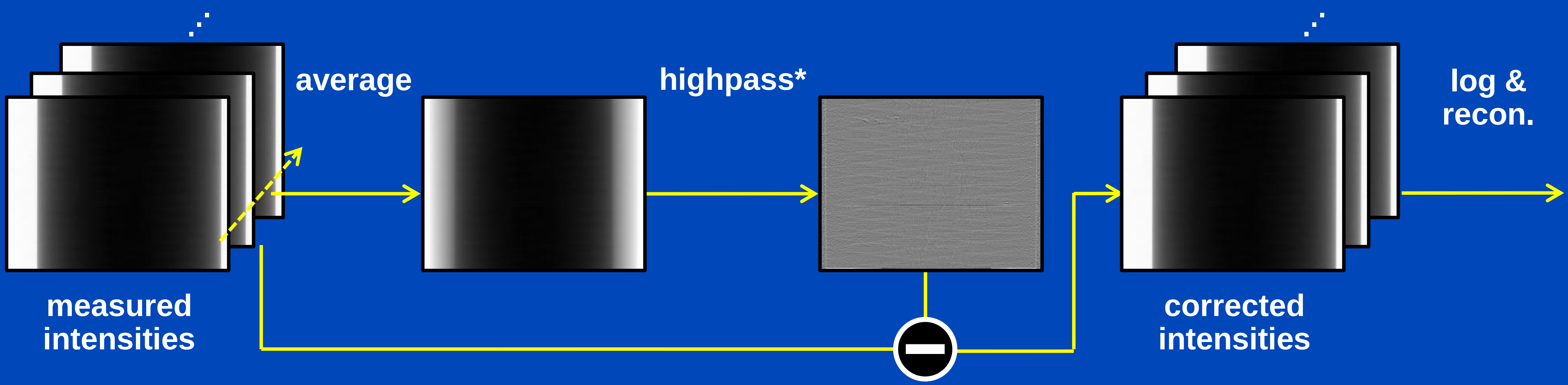
Experimental gantry located at the DKFZ

[3] Sawall, Kachelrieß et al., *Coronary micro-computed tomography angiography in mice*, Sci. Rep., Volume 10, Nr. 16866, 2020
[4] Szeles et al., *CdZnTe semiconductor detectors for spectroscopic X-ray im.*, IEEE Trans. on Nuc. Sc., Volume 55, Nr. 1, 2008

dkfz.

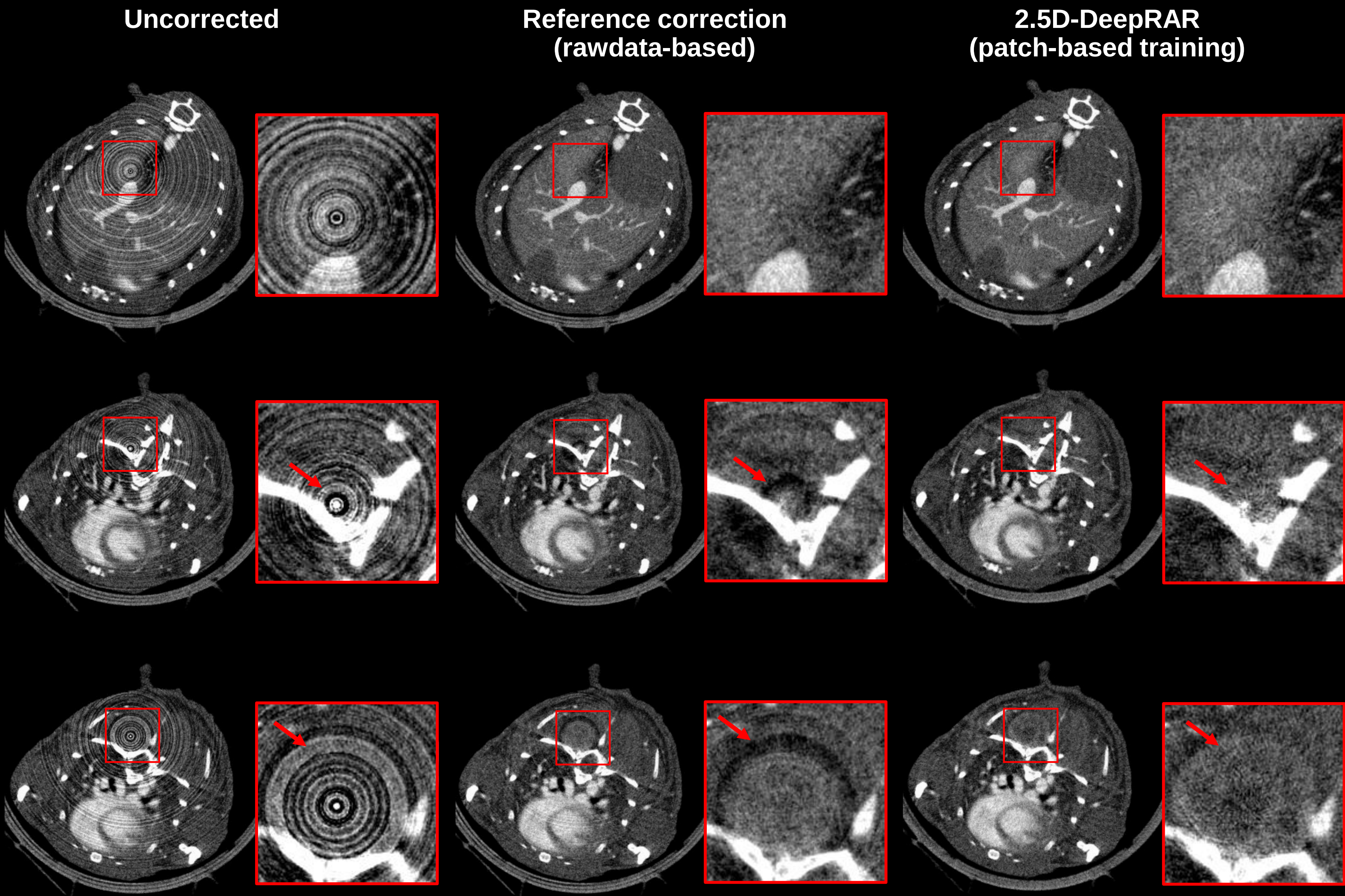
Reference Method: Rawdata-based RAR

- A ring artifact correction with 2.5D-DeepRAR is compared to a rawdata-based RAR method inspired by Clark et al.[5]
- The correction steps of this method include:
  - Averaging the projection images in intensity domain
  - Apply a 2D median filter* to the average image
  - Subtract the lowpass filtered image from the average projection → approximation of ring artifacts
  - Subtract the ring artifact "projection" from measured intensities, take the logarithm and reconstruct the data



[5]Clark et al., *Hybrid spectral CT reconstruction*, PloS one, Volume 12, Nr. 7, 2017
*The filter parameters must be carefully set to remove all artifacts and not create new ones.

Results: Measured PC Micro CT Data



C=500 HU, *W*=1500 HU

Conclusions

- Ring and partial ring artifacts could be reduced with all of the tested networks.
- DeepRAR is able to improve image quality, which was shown in simulations and measured PC micro CT data.
  - Parameter optimization or a resampling, e.g. on a polar grid, can thus be avoided.
- Training based on image patches has proven to be beneficial.
  - This is probably because the likelihood of overfitting to the anatomies used for training may be reduced, leading to a better generalizability of a so trained network.
- 2.5D-DeepRAR yields the best results for the simulated and measured test data.
  - Using a 2.5D architecture may be beneficial for the ring artifact reduction task.
  - The CNN probably benefits from information of adjacent slices about the artifacts it intends to correct.
- Some problems remain a challenge, particularly
  - Ring artifacts of very low frequency
  - Very strong ring artifacts, e.g. at the center of rotation

Thank You!

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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).

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