Coronary Artery Motion Compensation for Short-Scan Cardiac CT Using a Spatial Transformer Network

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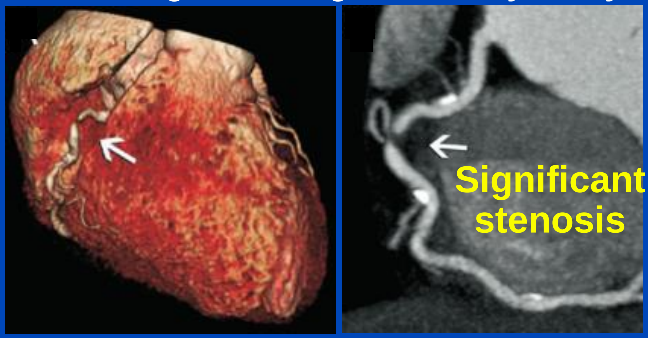
DEUTSCHES KREBSFORSCHUNGSZENTRUM IN DER HELMHOLTZ-GEMEINSCHAFT

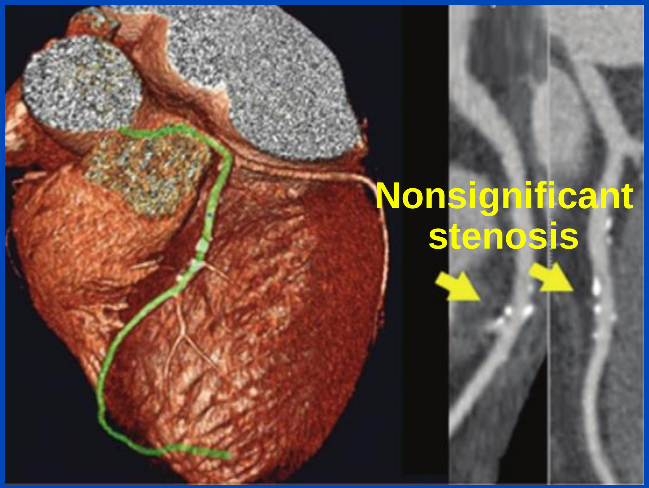
Motivation

- Cardiac CT imaging is routinely used for the diagnosis of cardiovascular diseases, especially those related to coronary arteries.
- Imaging of coronary arteries places high demands on the spatial and temporal resolution of the CT reconstruction.
- Motion artifacts may impair the diagnostic value of the CT examination.

CTCA image of the right coronary artery[1]



CTCA image of the left coronary artery[2]



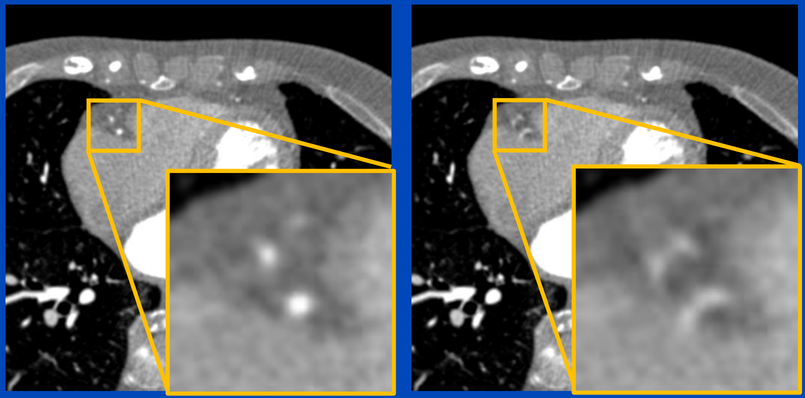
[1] W. B. Meijboom et al., "64-Slice Computed Tomography Coronary Angiography in Patients With High, Intermediate, or Low Pretest Probability of Significant Coronary Artery Disease", J. Am. Coll. Cardiol. 50 (15): 1469–1475 (2007).
[2] R. Leta et al., "Ruling Out Coronary Artery Disease with Noninvasive Coronary Multidetector CT Angiography before Noncoronary Cardiovascular Surgery", Heart 258 (2) (2011).

Motivation

- For the right coronary artery (RCA) mean velocities between 35 mm/s and 70 mm/s have been measured [1,2].

	Single source CT	Dual source CT
Rotation time	~ 0.3 s	~ 0.3 s
Temporal resolution (180° + fan)	~ 0.15 s	~ 0.075 s
Max. displacement	10.5 mm	5.25 mm

Simulation without / with motion

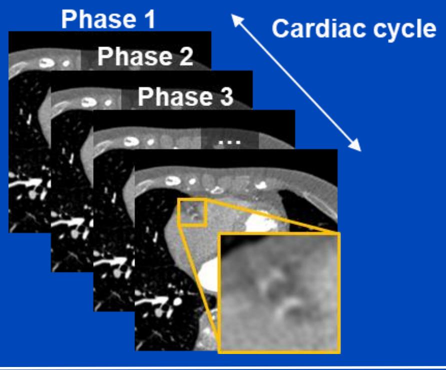


→ **Motion compensation to reduce motion artifacts**

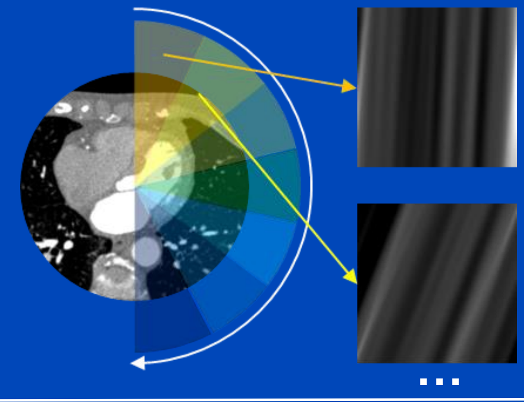
[1] Husmann et al., "Coronary Artery Motion and Cardiac Phases: Dependency on Heart Rate - Implications for CT Image Reconstruction", Radiology, Vol. 245, Nov 2007.
[2] Achenbach et al., "In-plane coronary arterial motion velocity: measurement with electron-beam CT", Radiology, Vol. 216, Aug 2000.

Prior Work

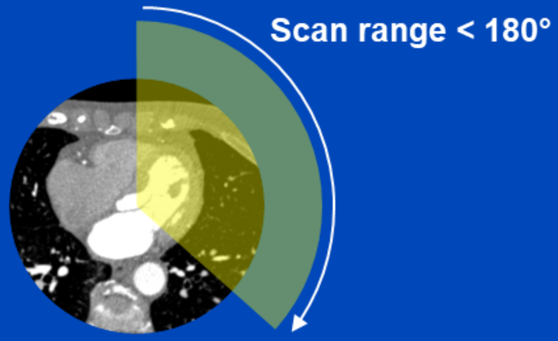
Multi-phase / registration-based approaches[1,2,3,4]



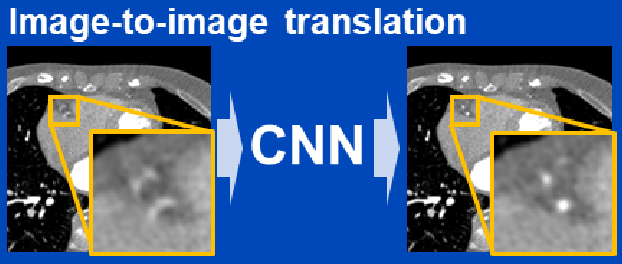
Partial angle-based approaches[7,8.9]



Limited angle approaches[5,6]



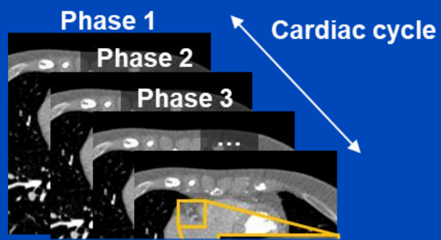
Deep learning-based approaches[10,11]



[1] U. Van Stevendaal et al., “A motion-compensated scheme for helical cone-beam reconstruction in cardiac CT angiography”, Med. Phys. 35 (7): 3239–3251 (2008).
[2] A. Isola et al., “Fully automatic nonrigid registration-based local motion estimation for motion-corrected iterative cardiac CT reconstruction”, Med. Phys. 37 (3): 1093–1109 (2010).
[3] R. Bhagalia et al., “Nonrigid registration-based coronary artery motion correction for cardiac computed tomography”, Med. Phys. 39 (7): 4245–4254 (2012).
[4] Q. Tang et al., “A fully four-dimensional, iterative motion estimation and compensation method for cardiac CT”, Med. Phys. 39 (7): 4291–4305 (2012).
[5] J. Tang et al., “Temporal resolution improvement in cardiac CT using PICCS (TRI-PICCS): Performance studies”, Med. Phys. 37 (8): 4377–4388 (2010).
[6] H. Schöndube et al., “Evaluation of a novel CT image reconstruction algorithm with enhanced temporal resolution”, SPIE 2011: 7961: 79611N (2011).
[7] S. Kim et al., “Cardiac motion correction based on partial angle reconstructed images in x-ray CT”, Med. Phys. 42 (5): 2560–2571 (2015).
[8] J. Hahn et al., “Motion compensation in the region of the coronary arteries based on partial angle reconstructions from short-scan CT data”, Med. Phys. 44 (11): 5795–5813 (2017).
[9] S. Kim et al., “Cardiac motion correction for helical CT scan with an ordinary pitch”, IEEE TMI 37 (7): 1587–1596 (2018).
[10] T. Lossau et al., “Motion estimation and correction in cardiac CT angiography images using convolutional neural networks”, Comput. Med. Imag. Grap. 76: 101640 (2019).
[11] S. Jung et al., “Deep learning cross-phase style transfer for motion artifact correction in coronary computed tomography angiography”, IEEE Access 8: 81849–81863 (2020).

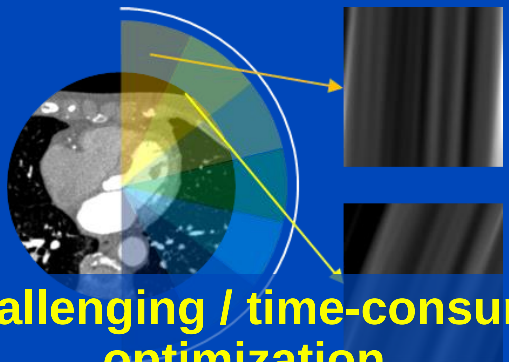
Limitations

Multi-phase / registration-based approaches[1,2,3,4]



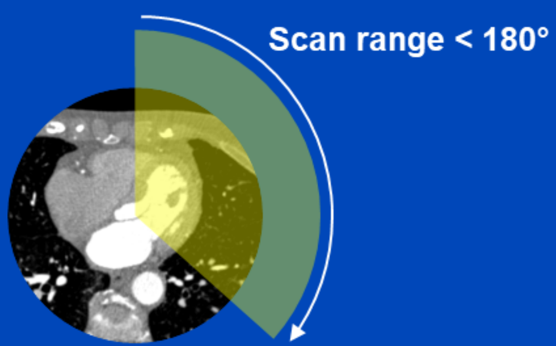
→ Not optimal in terms of x-ray dose since several phases are required

Partial angle-based approaches[7,8,9]



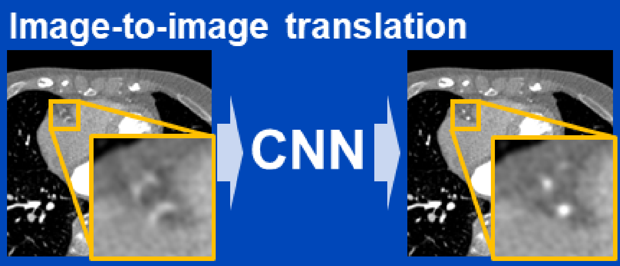
→ Challenging / time-consuming optimization

Limited angle approaches[5,6]



→ Limited capability to improve temporal resolution

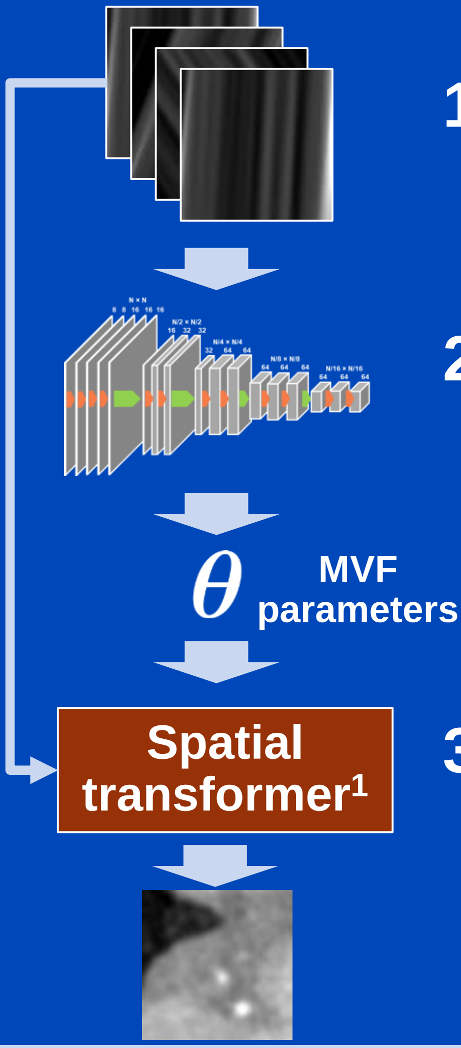
Deep learning-based approaches[10,11]



→ Image-to-image translation may alter the shape of the coronary arteries

Deep Partial Angle-Based Motion Compensation (Deep PAMoCo)

Basic idea

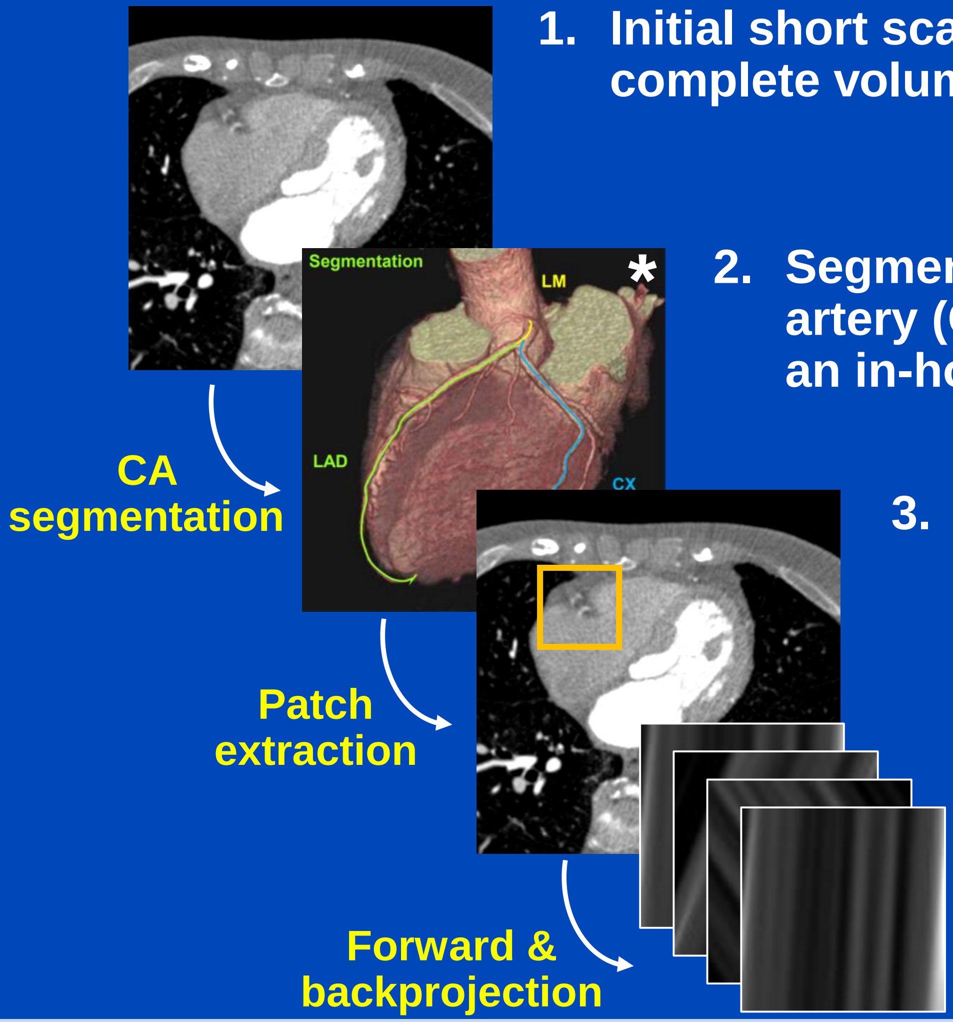


1. Use partial angle reconstructions (PARs) as input to a neural network.
2. Train neural network to predict the parameters of a motion model that maps all PARs to the same motion state.
3. Use a spatial transformer[1] that applies the motion model to the PARs to enable an end-to-end training.

[1] M. Jaderberg et al., "Spatial transformer networks", NIPS 2015: 2017–2025 (2015).

Deep PAMoCo

Generation of partial angle reconstructions



1. Initial short scan reconstruction of the complete volume.
2. Segmentation of one of the main coronary artery (CA) branches (RCA, LM, LAD, CX) by an in-house algorithm.
3. Extraction of 128 × 128 patches centered at the coronary artery.
4. Forward projection and reconstruction of 25 (non-overlapping) angular segments on a 128 × 128 × 15 voxel grid.

*Data courtesy of Dr. Stephan Achenbach

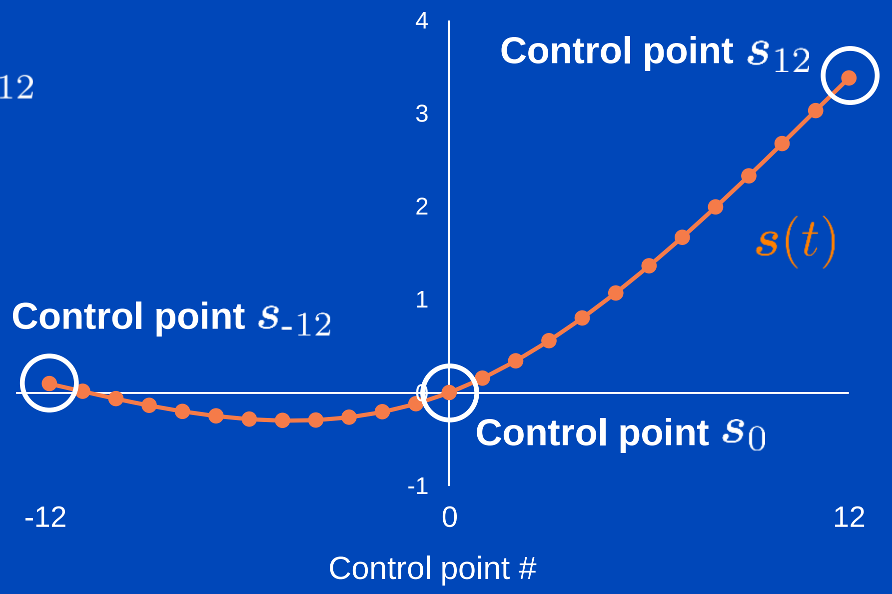
Deep PAMoCo

Motion model

- **The PAR $f_p(\boldsymbol{r}, t_i)$ corresponding to the time point t_i is transformed by a global translation $\boldsymbol{s}(t_i)$:**

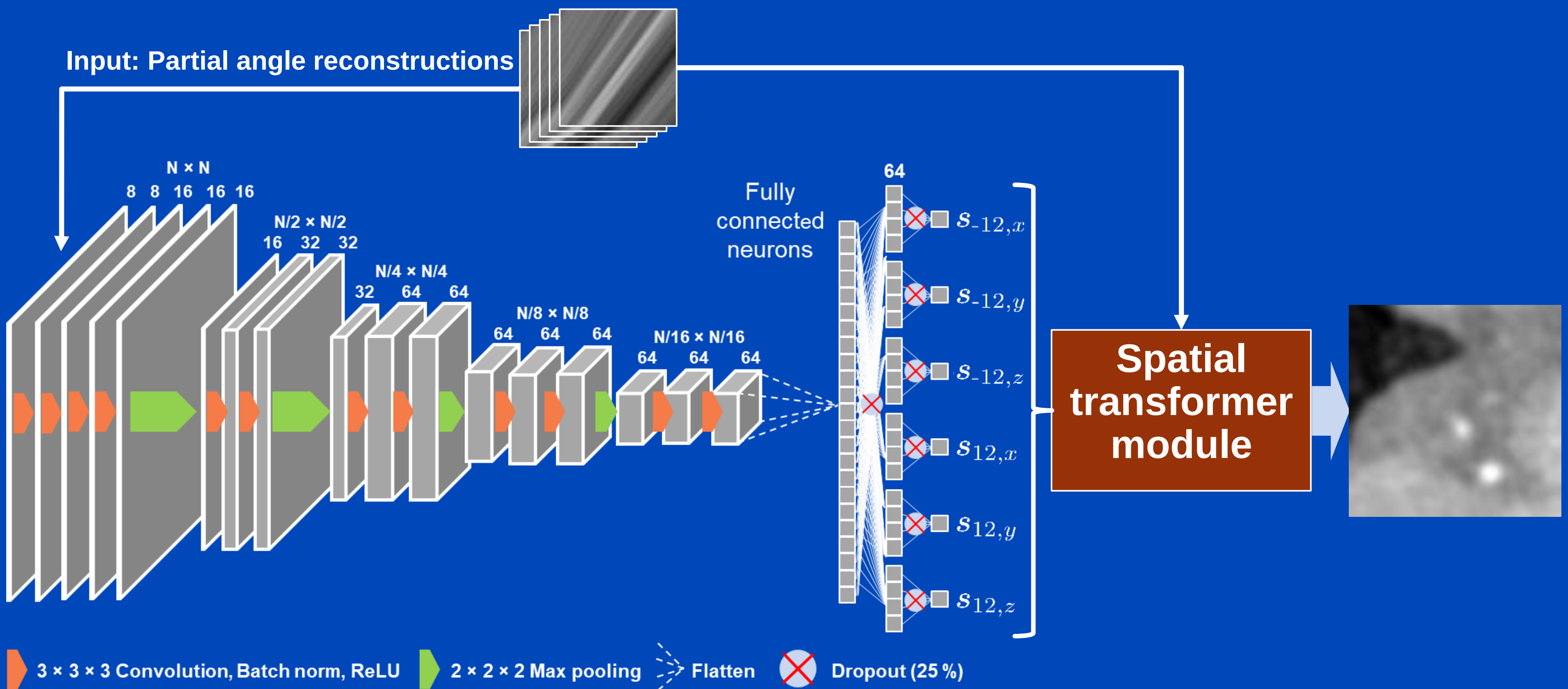
$$f_p'(\boldsymbol{r}, t_i) = f_p(\boldsymbol{r} + \boldsymbol{s}(t_i), t_i)$$

- **The temporal dependency of $\boldsymbol{s}(t)$ is modeled as a spline with 3 control points.**
  - **Motion is modeled by 3D displacement vectors $\boldsymbol{s}_{-12}, \boldsymbol{s}_0, \boldsymbol{s}_{12}$**
  - **The center point is always set to zero: $\boldsymbol{s}_0 = 0$**
  - **Any other displacement vector is derived by cubic spline interpolation**
  - **Thus, coronary artery motion is modeled by 6 parameters, i.e. the 3 coordinates of $\boldsymbol{s}_{-12}$ and $\boldsymbol{s}_{12}$**



Deep PAMoCo

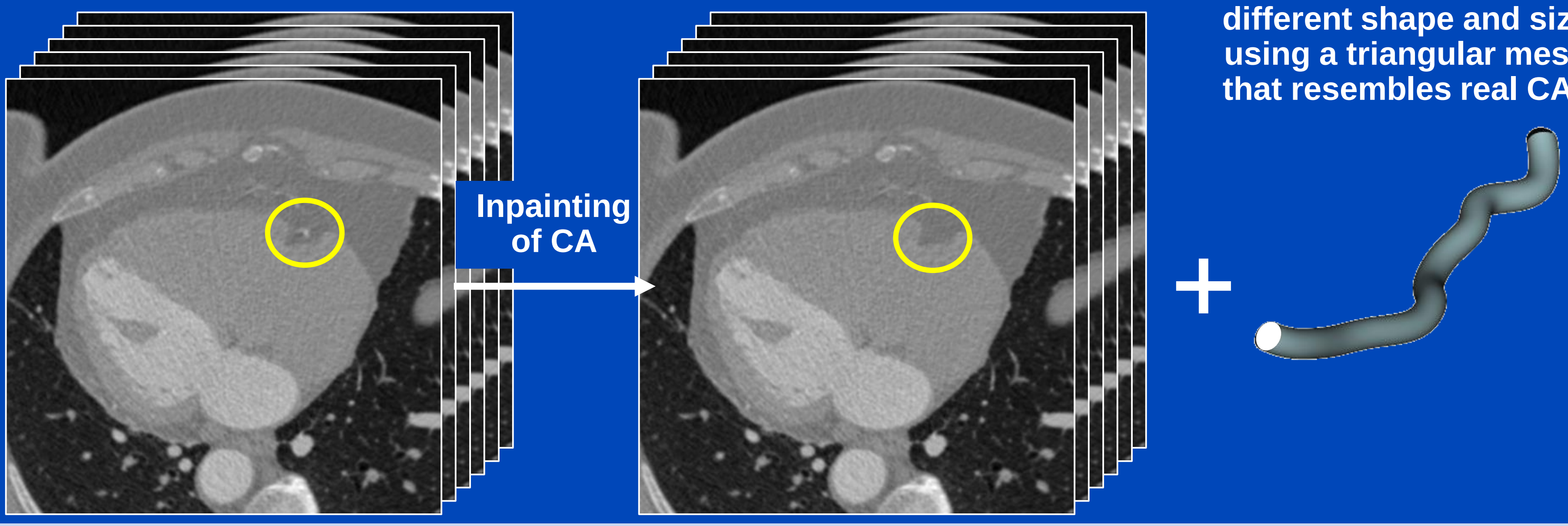
Network architecture



Training Data Generation

Generation of prior images

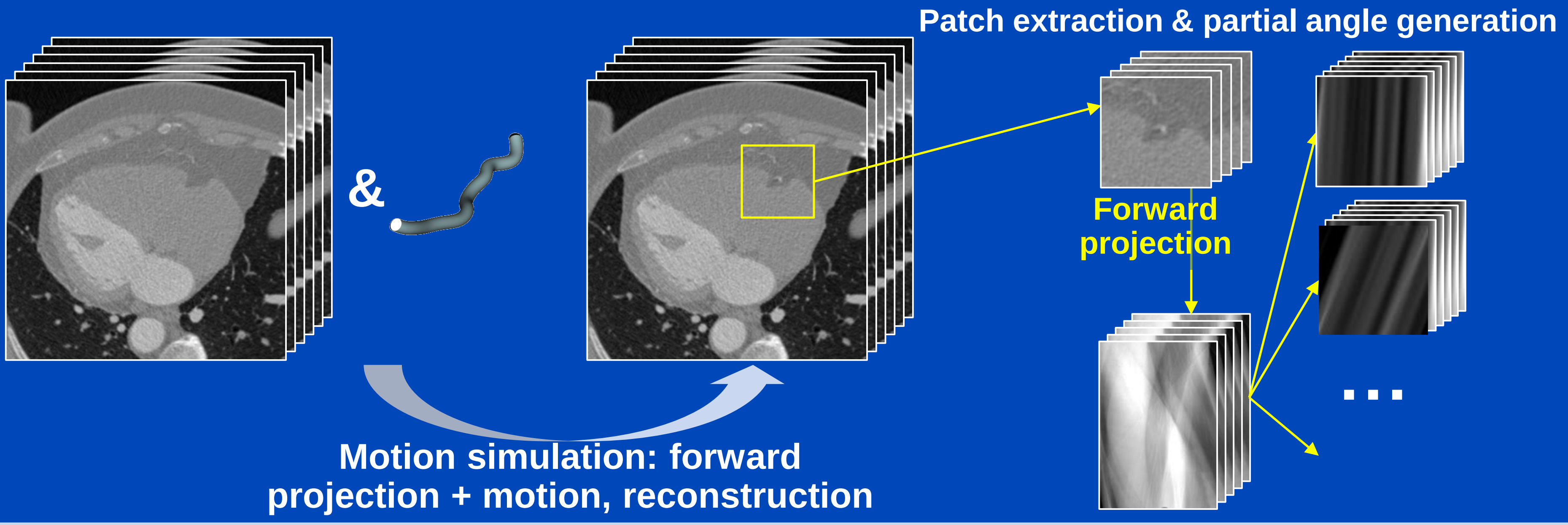
- Removal of coronary artery (CA) / stent from CT reconstructions.
- Reinsertion of simulated CAs based on a triangular mesh of different shaped CAs.
- In total 25 different patients were used. CAs were inserted at different locations.



Training Data Generation

Generation of partial angle images

- 3D global motion vector fields (MVF) are generated using a cubic spline interpolation between 3 random vectors.
- Motion is simulated by shifting the geometry vectors during forward projection according to the MVF.
- Here, the maximum velocity was set to 70 mm/s.



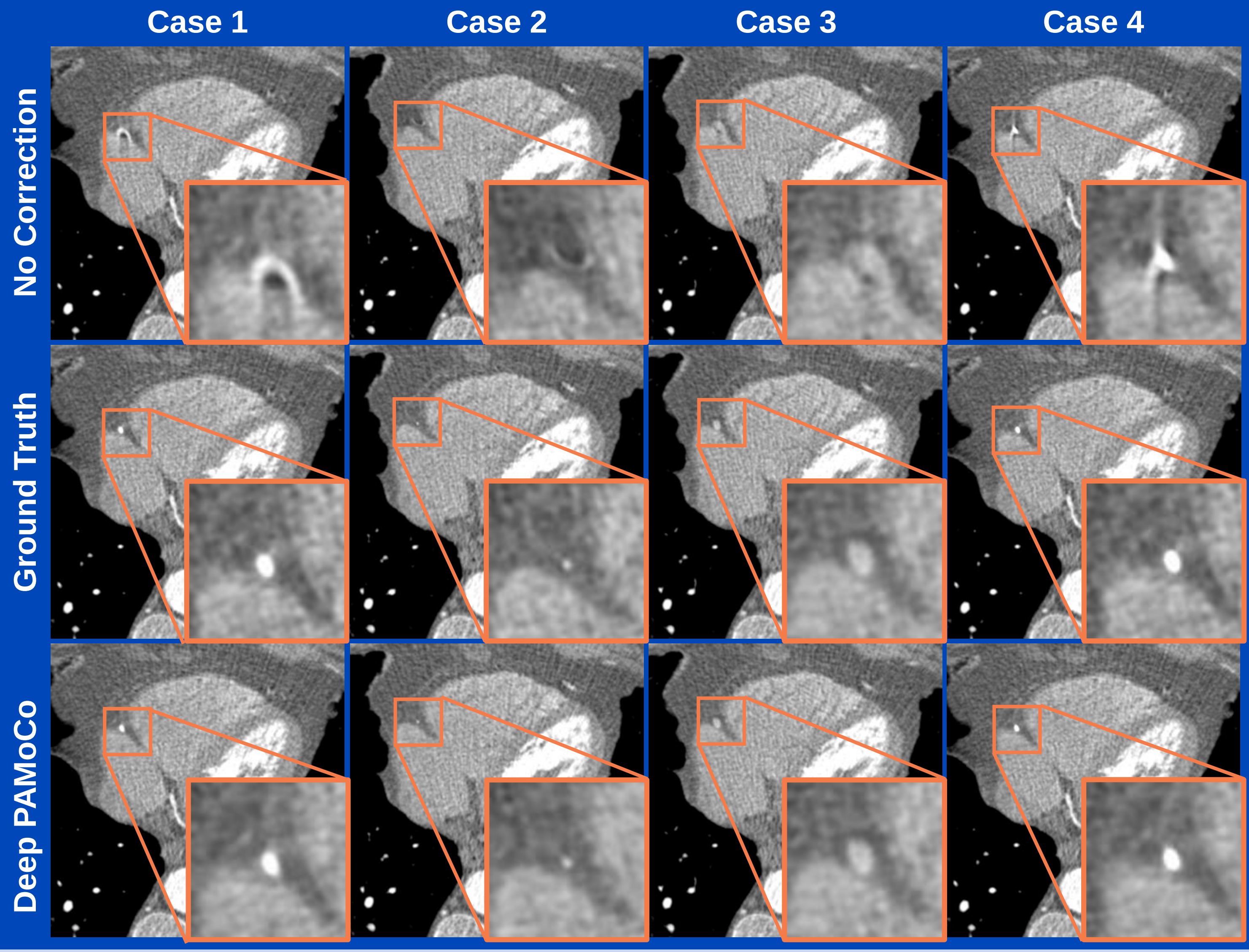
Training & Evaluation

- 100 000 CT scans were simulated with random motion patterns and different shaped coronary arteries.
- For each case a ground truth image without motion was simulated.
- The samples were split into 80 % training data and 20 % testing data.
- The network was trained for 100 epochs using an Adam optimizer and the mean squared error between the prediction and the ground truth as loss function.
- The performance of the deep PAMoCo was also tested for real cardiac CT scans performed at a Siemens Somatom AS+.
- Motion-compensated images are compared against a conventional PAMoCo approach[1] that transforms the partial angle reconstructions such that the image entropy of the final images is minimized.

[1] J. Hahn et al., "Motion compensation in the region of the coronary arteries based on partial angle reconstructions from short-scan CT data", Med. Phys. 44 (11): 5795–5813 (2017).

Results

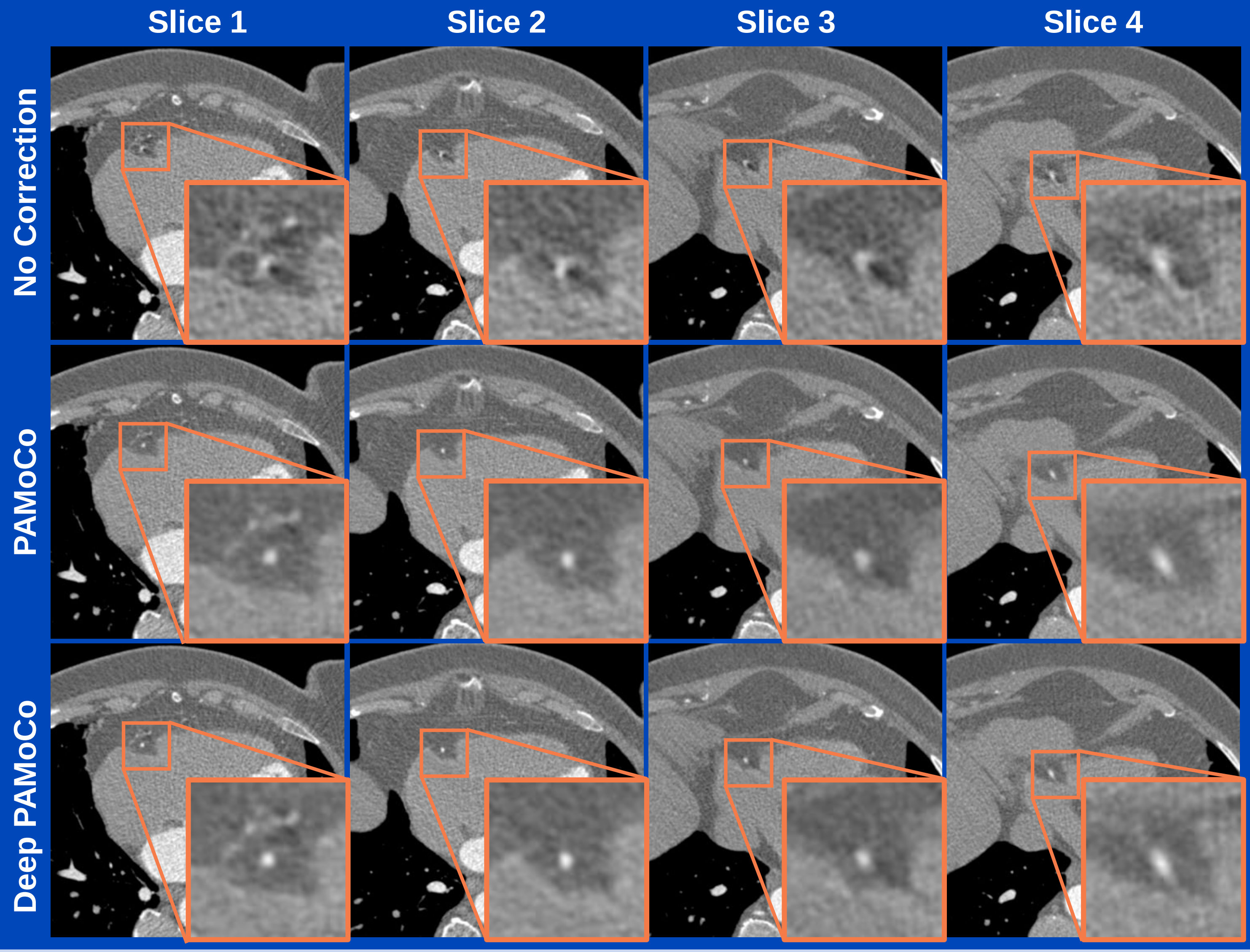
Simulated data



C = 1000 HU, W = 1000 HU

Results

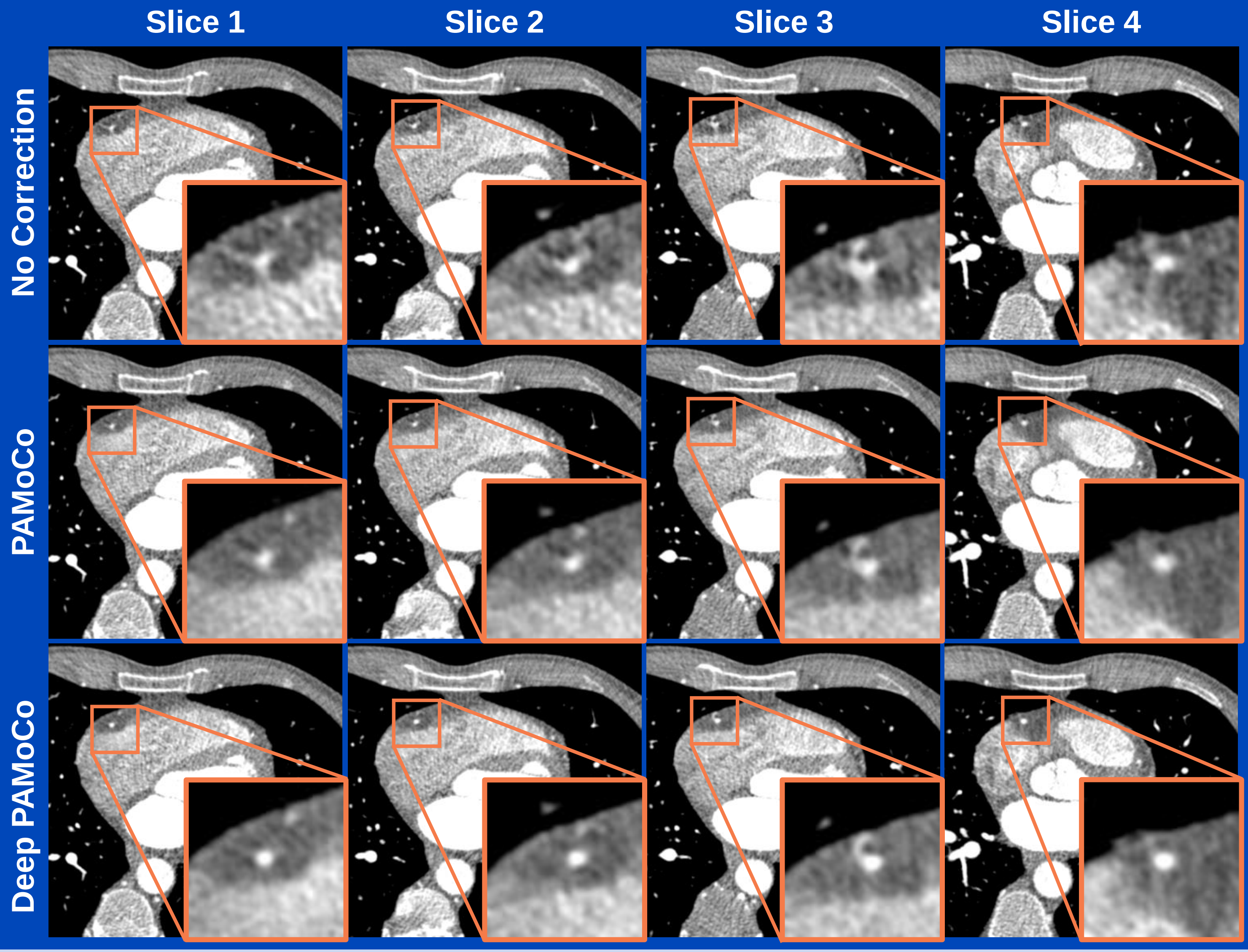
Measurements, patient 1



C = 1000 HU, W = 1000 HU

Results

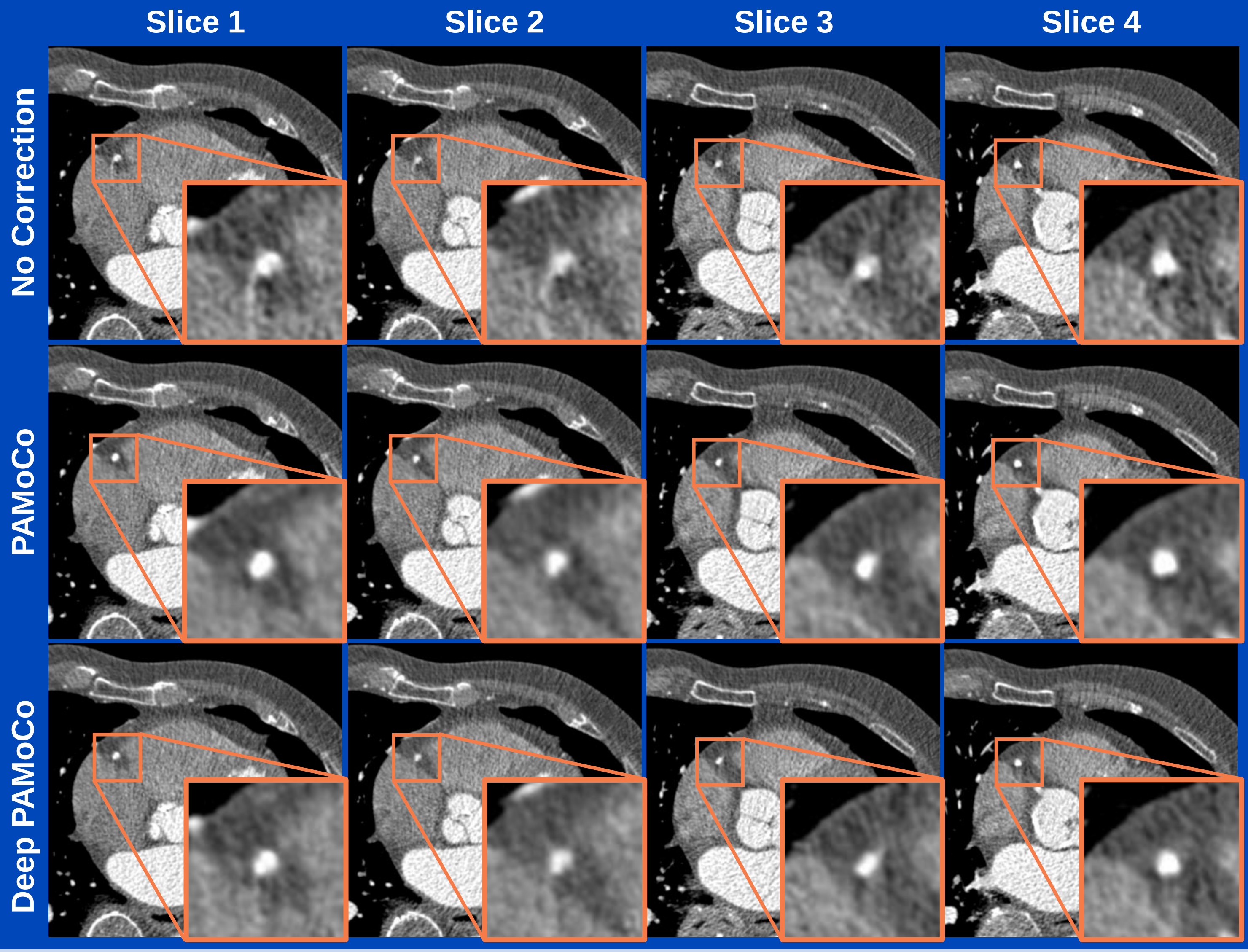
Measurements, patient 2



C = 1000 HU, W = 1000 HU

Results

Measurements, patient 3



C = 1100 HU, W = 1000 HU

Conclusions

- The deep PAMoCo enables an end-to-end training of coronary artery motion compensation using a 3D neural network.
- Neural network trained on simulated data also applies to measurements.
- In any case, motion artifacts could be reduced efficiently.
- The quality of the motion-compensated reconstructions is similar to conventional PAMoCo approach but can be applied in almost real-time (~ 1 s for a complete cardiac CT scan).

Thank You!

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