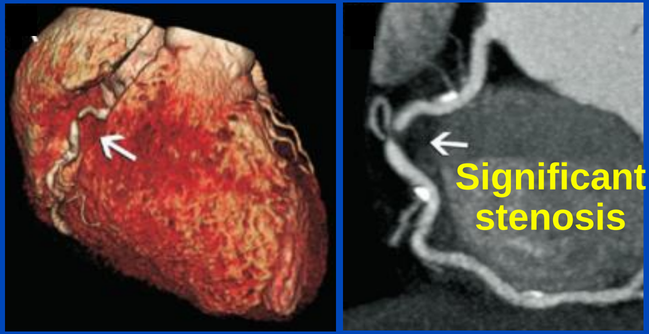
Deep Learning-Based Partial Angle Motion Compensation for the Entire Heart

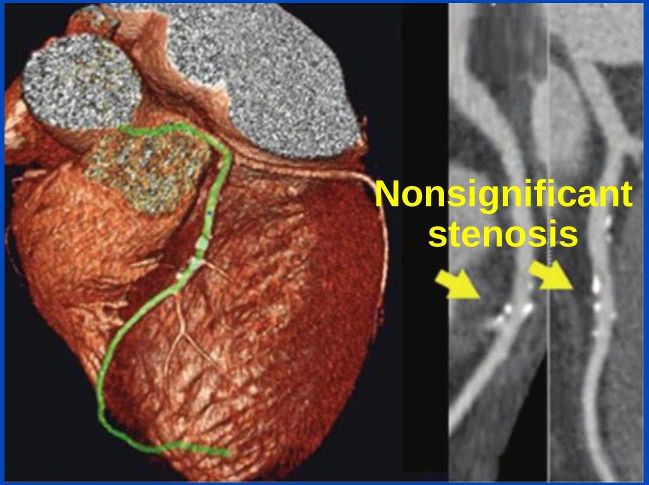
Ou Li, Joscha Maier, and Marc Kachelrieß
German Cancer Research Center (DKFZ)
Heidelberg, Germany
www.dkfz.de/ct

Motivation

- In cardiac CT, the imaging of small and fast moving vessels places high demands on the spatial and temporal resolution.
- Displacements of $d \approx \frac{T_{\mathrm{rot}}}{2}\,\bar{v} \approx 125\ \mathrm{ms} \cdot 50\,\frac{\mathrm{mm}}{\mathrm{s}} = 6.25\ \mathrm{mm}$ are possible according to RCA velocity measurements[1-4].
- Standard cardiac reconstruction might have an insufficient temporal resolution introducing strong motion artifacts.



CTCA image of the right coronary artery[5]



CTCA image of the left coronary artery[6]

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[1] Achenbach et al. In-plane coronary arterial motion velocity: measurement with electron-beam CT. Radiology, Vol. 216, Aug 2000.

[2] Vembar et al. A dynamic approach to identifying desired physiological phases for cardiac imaging using multislice spiral CT. Med. Phys. 30, Jul 2003.

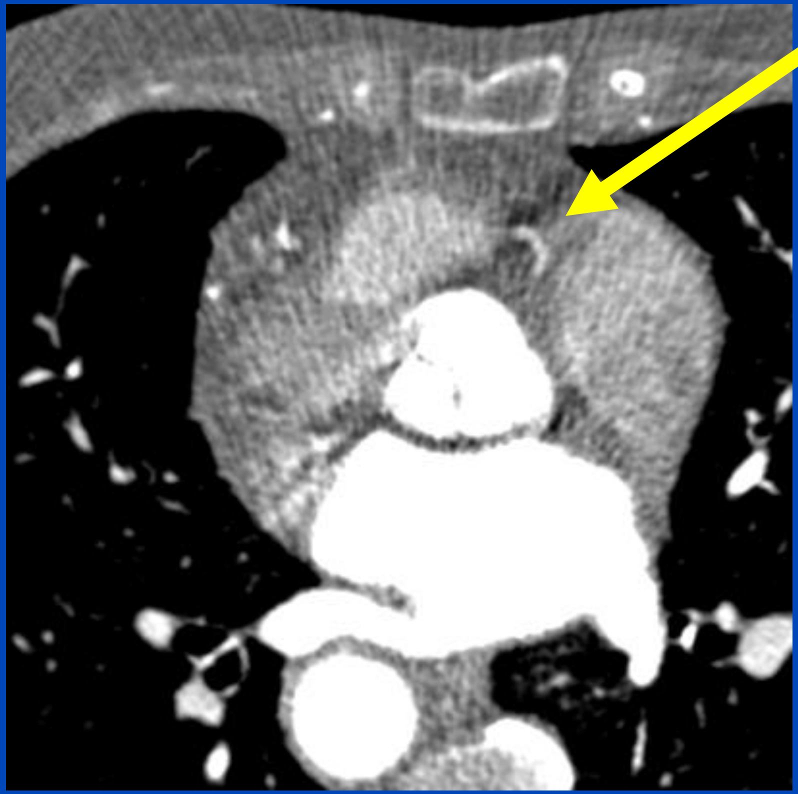
[3] Shechter et al. Displacement and velocity of the coronary arteries: Cardiac and respiratory motion. IEEE TMI 25(3): 369-375, Mar 2006.

[4] Husmann et al. Coronary artery motion and cardiac phases: Dependency on heart rate - Implications for CT image reconstruction. Radiology 245, Nov 2007.

[5] 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.

[6] R. Leta et al., “Ruling out coronary artery disease with noninvasive coronary multidetector CT angiography before noncoronary cardiovascular surgery”, Heart 258(2), 2011.

Motivation



C = 0 HU, *W* = 1200 HU

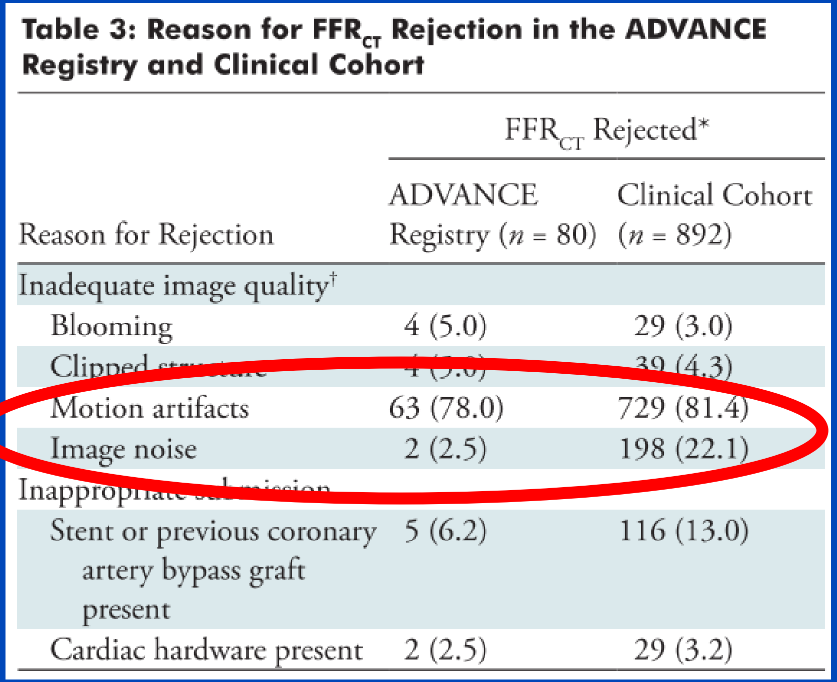


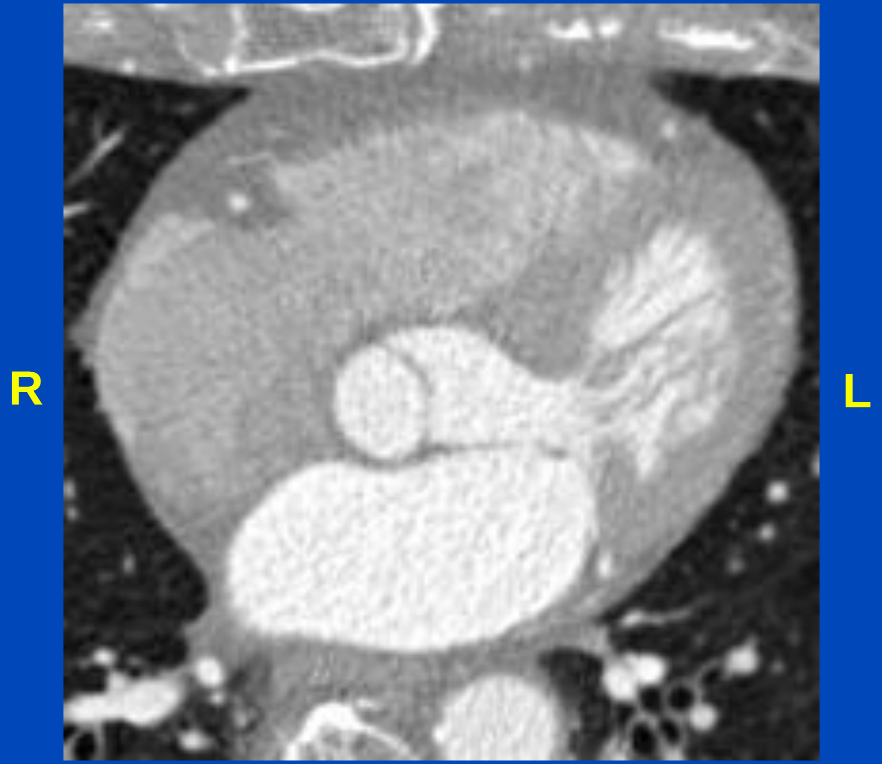
Table 3: Reason for FFR_{CT} Rejection in the ADVANCE Registry and Clinical Cohort

	FFR_{CT} Rejected*	
Reason for Rejection	ADVANCE Registry (*n* = 80)	Clinical Cohort (*n* = 892)
Inadequate image quality†		
Blooming	4 (5.0)	29 (3.0)
Clipped structure	4 (5.0)	39 (4.3)
Motion artifacts	63 (78.0)	729 (81.4)
Image noise	2 (2.5)	198 (22.1)
Inappropriate submission		
Stent or previous coronary artery bypass graft present	5 (6.2)	116 (13.0)
Cardiac hardware present	2 (2.5)	29 (3.2)

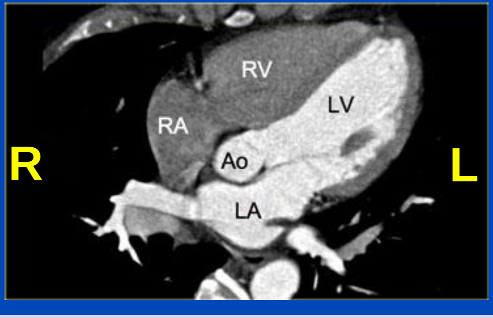
The rejection rate was 892 of 10 416 cases submitted

G. Pontone et al., “Determinants of rejection rate for coronary CT angiography fractional flow reserve analysis”, *Radiology*, *292*(3):597–605, 2019

No Motion Artifacts



With Motion Artifacts



Labeled five chamber view of the heart [1]

C = 0 HU, *W* = 1000 HU

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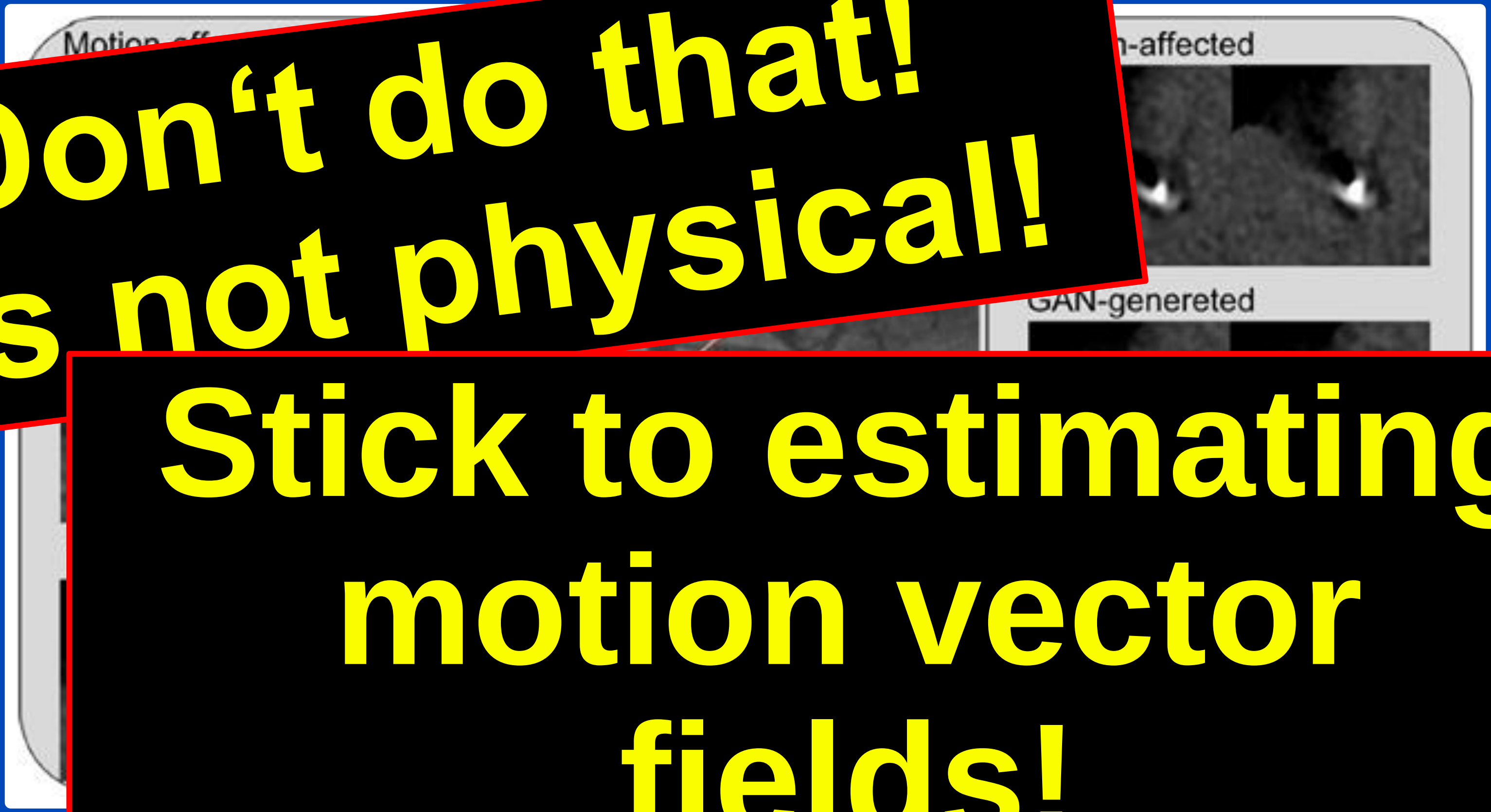
[1] Benoit Desjardins and Ella A. Kazerooni. ECG-gated cardiac CT: a review. AJR 182:993-1010, 2004

Deep Cosmetic Motion Artifact Reduction

- Image-based correction = cosmetic correction
- May not be the most confident way to go

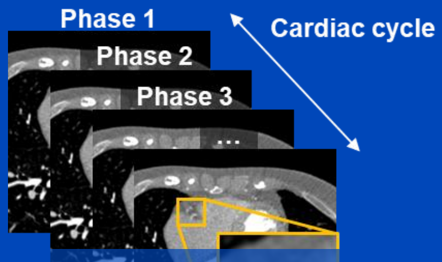


Don‘t do that!
It‘s not physical!

Stick to estimating motion vector fields!

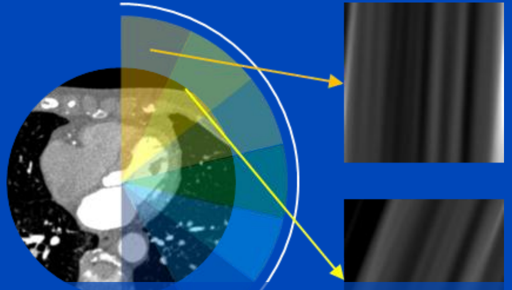
Cardiac MoCo Strategies

Multi-phase / registration-based approaches[1-4]



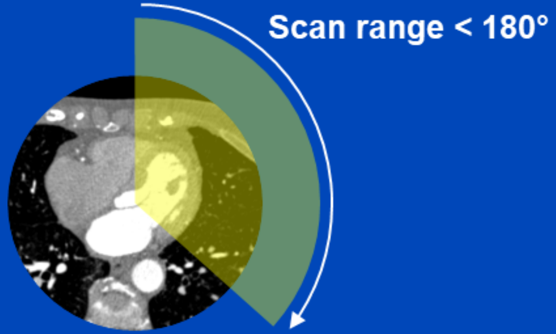
→ Not optimal in terms of x-ray dose since several phases are required

Partial angle-based approaches[7-9, 12]



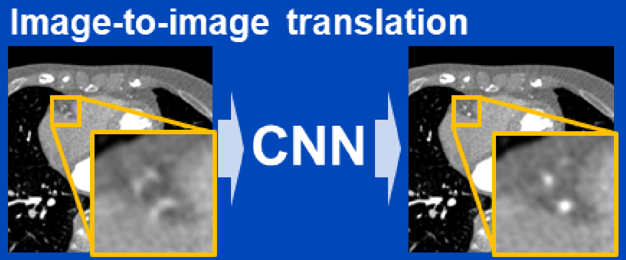
→ Current applications limited to coronary artery…

Limited angle approaches[5, 6]



→ Limited capability to improve temporal resolution

Deep learning image-based approaches[10, 11]



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

→ Purely cosmetic and non-physical

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[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, M. Kachelrieß 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).

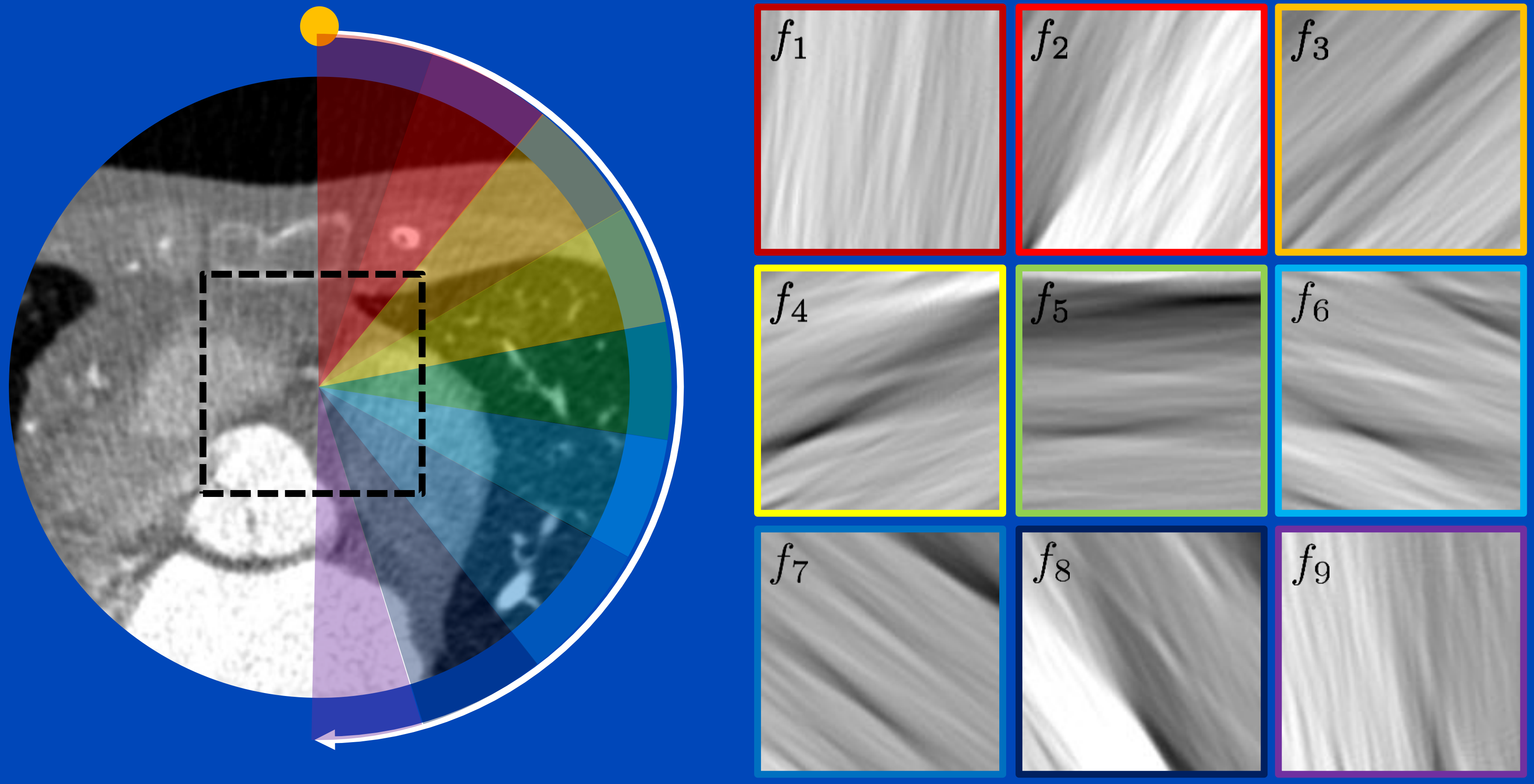
[9] S. Kim et al., “Cardiac motion correction for helical CT scan with an ordinary pitch”, IEEE TMI 37 (7): 1587–1596 (2018).

[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).

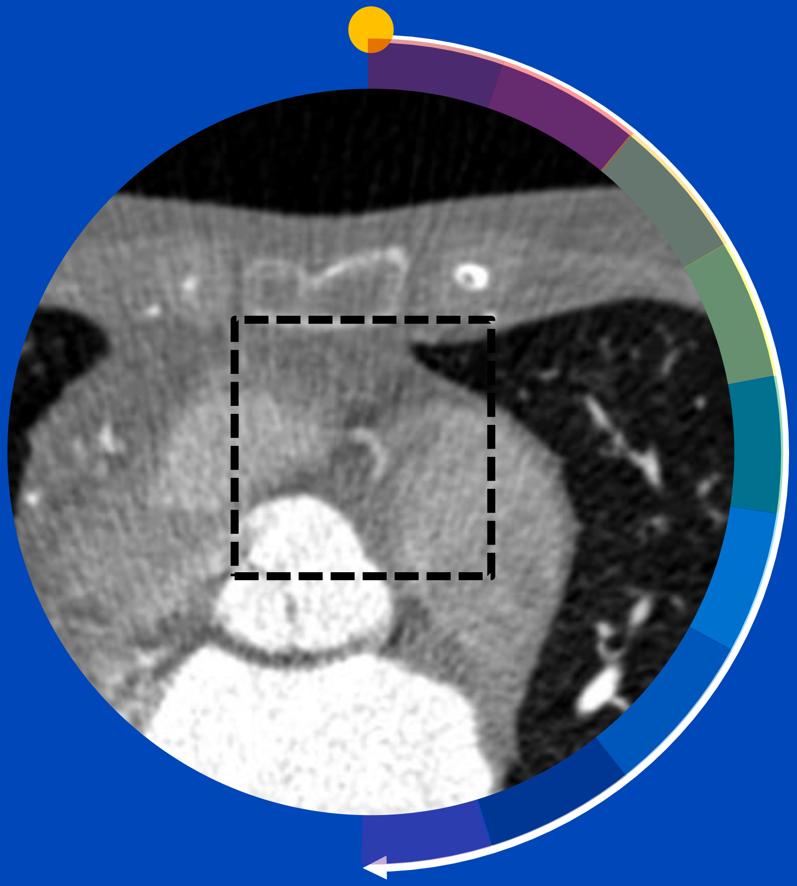
[12] J. Maier, S. Lebedev, J. Erath, E. Eulig, S. Sawall, E. Fournié, K. Stierstorfer, M. Lell, and M. Kachelrieß. Deep learning-based coronary artery motion estimation and compensation for short-scan cardiac CT. Med. Phys. 48(7):3559-3571, July 2021.

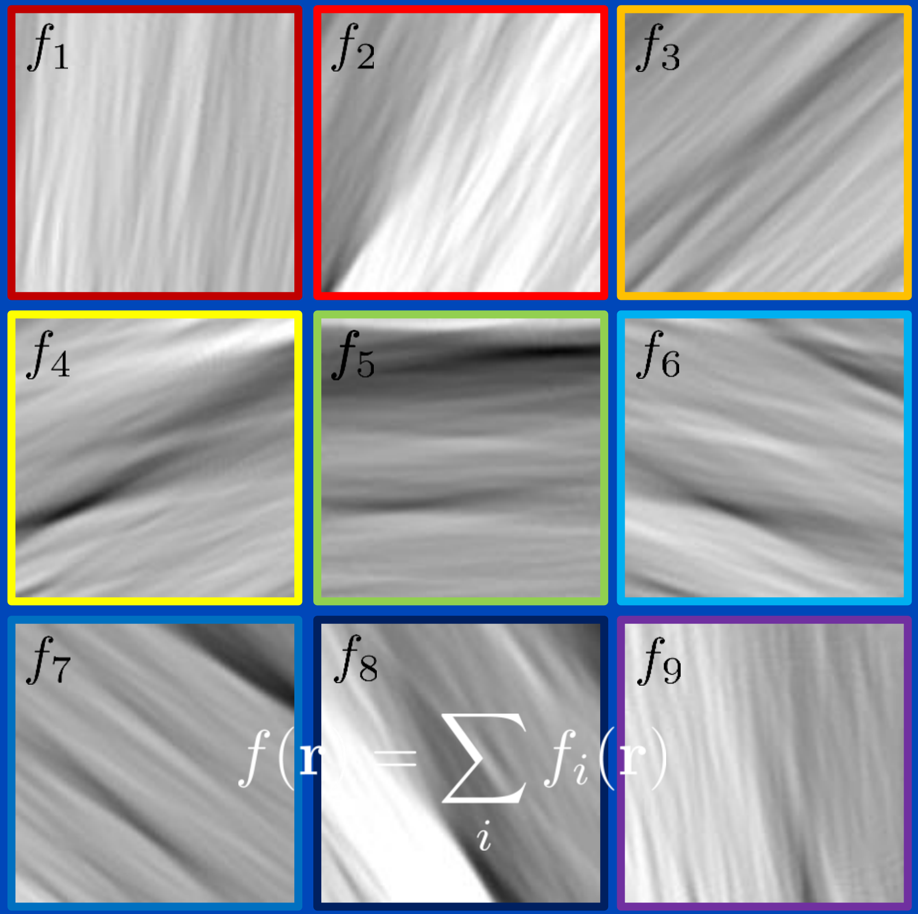
Partial Angle-Based Motion Compensation (PAMoCo)



Animated rotation time = 100 × real rotation time

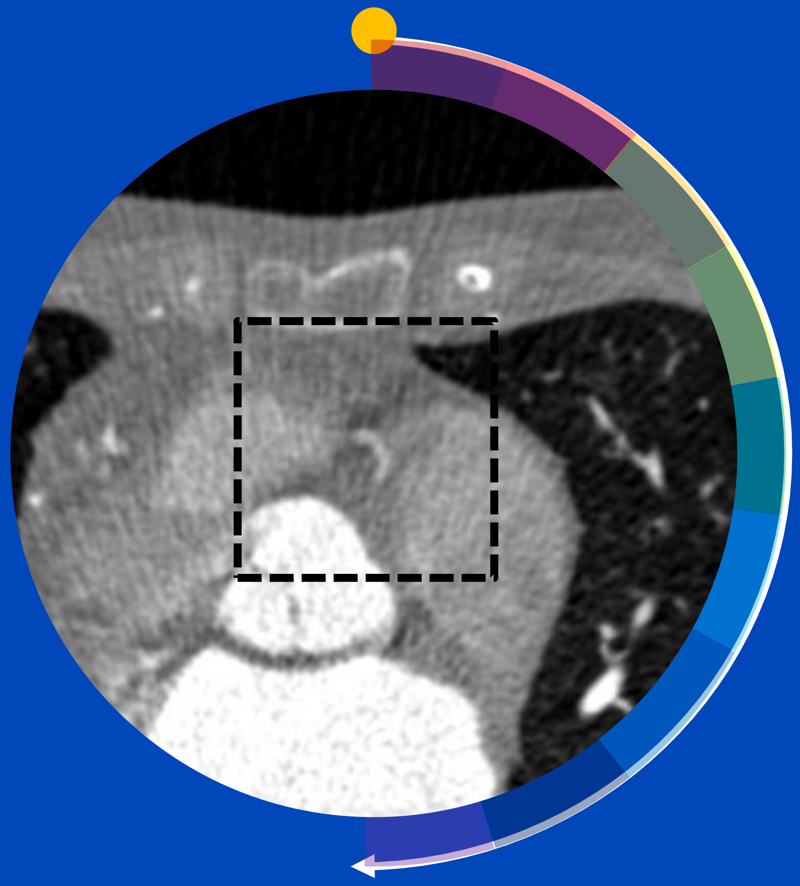
Partial Angle-Based Motion Compensation (PAMoCo)



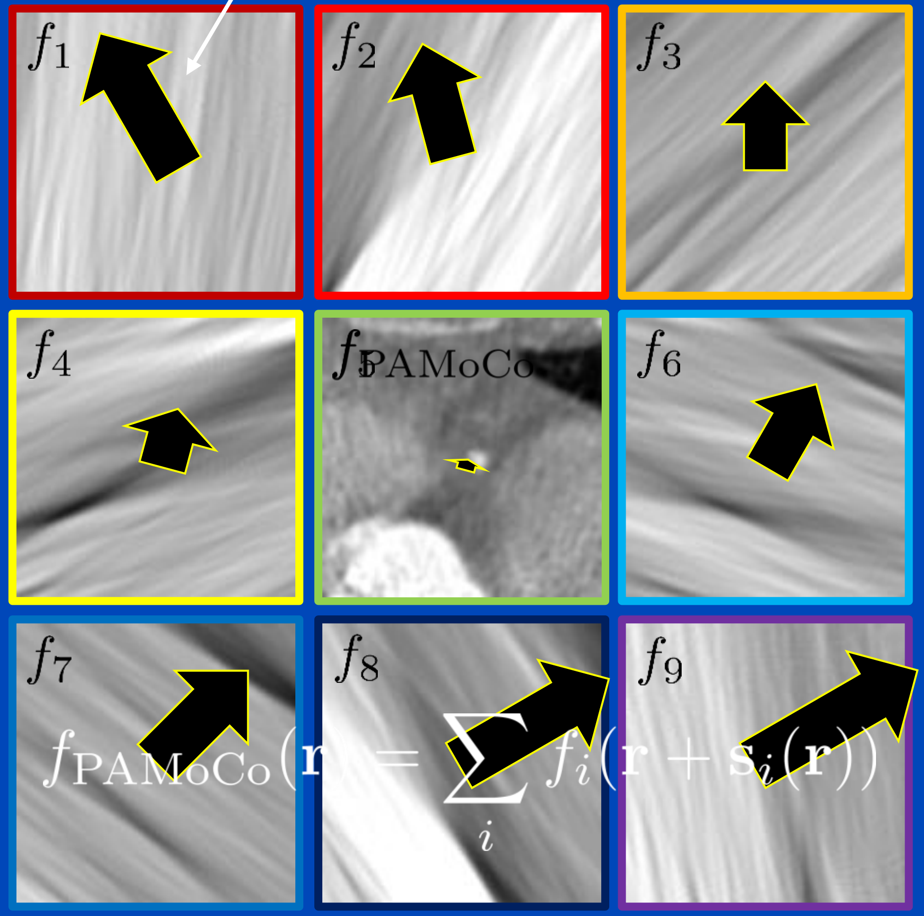


$$f(\mathbf{r}) = \sum_i f_i(\mathbf{r})$$

Partial Angle-Based Motion Compensation (PAMoCo)



Motion vector field $\mathbf{s}_1(\mathbf{r})$

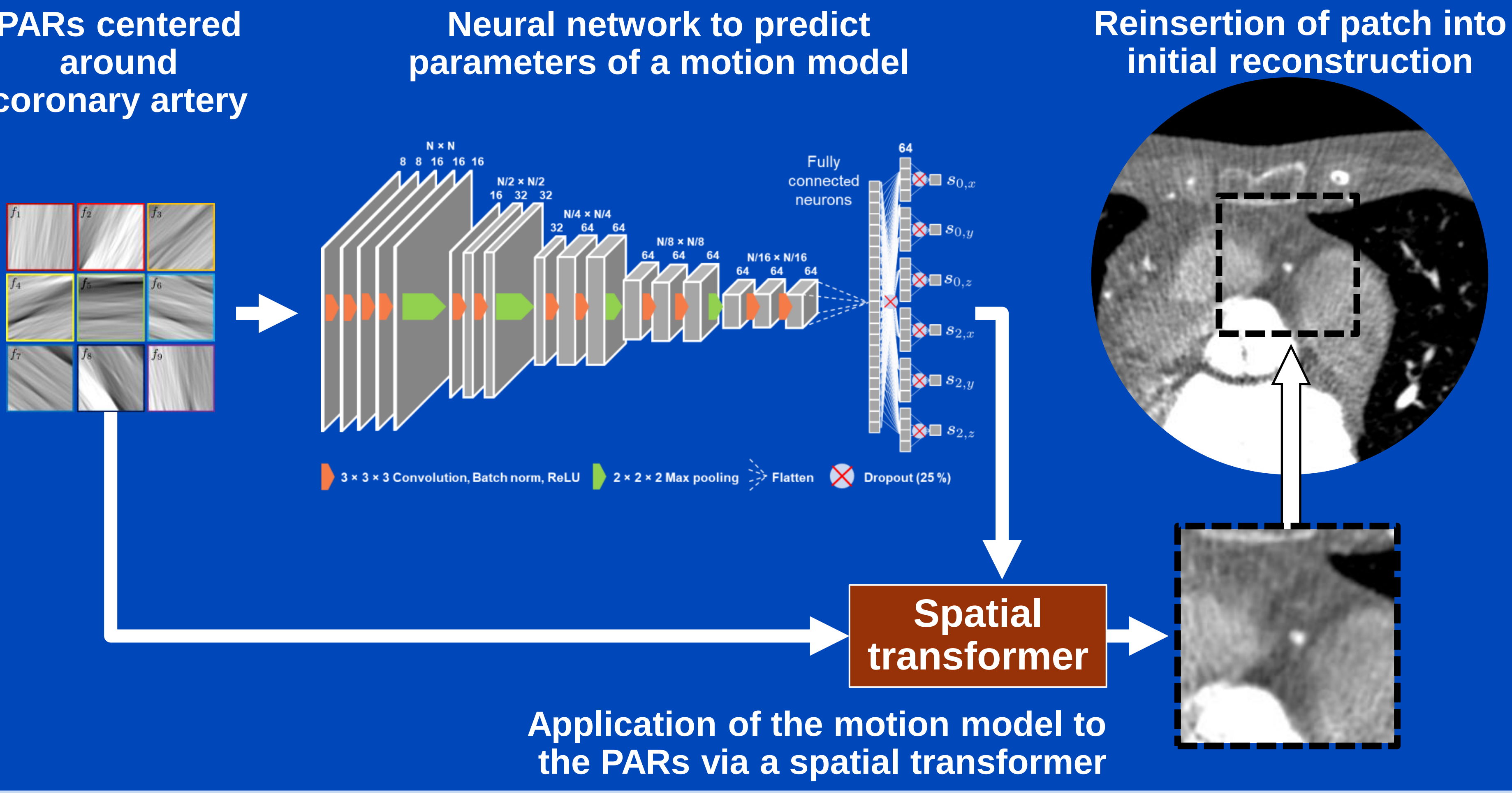


$$f_{\text{PAMoCo}}(\mathbf{r}) = \sum_i f_i(\mathbf{r} + \mathbf{s}_i(\mathbf{r}))$$

Apply motion vector fields (MVFs) to partial angle reconstructions

Deep PAMoCo

with fully connected final layers



PARs centered around coronary artery

Neural network to predict parameters of a motion model

Reinsertion of patch into initial reconstruction

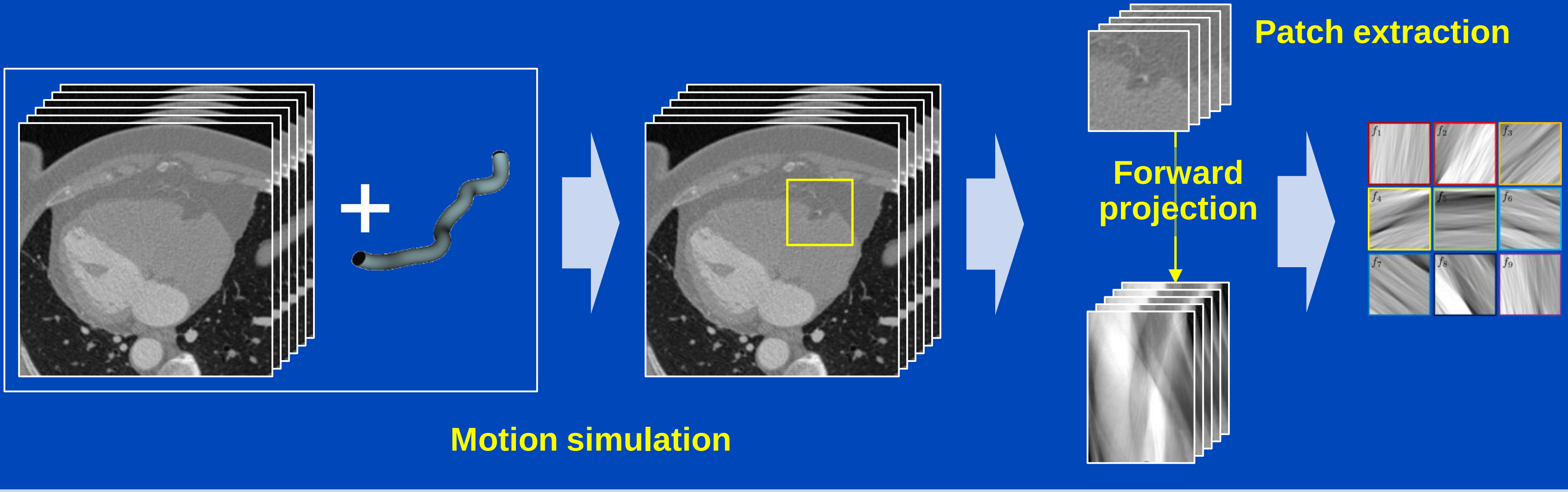
Spatial transformer

Application of the motion model to the PARs via a spatial transformer

J. Maier, S. Lebedev, J. Erath, E. Eulig, S. Sawall, E. Fournié, K. Stierstorfer, M. Lell, and M. Kachelrieß. Deep learning-based coronary artery motion estimation and compensation for short-scan cardiac CT. Med. Phys. 48(7):3559-3571, July 2021.

Training Data Generation

- Removal of coronary arteries from real CT reconstructions.
- Insertion of artificial coronary arteries with different shape, size, and contrast.
- Simulation of CT scans with coronary artery motion.


Patch extraction

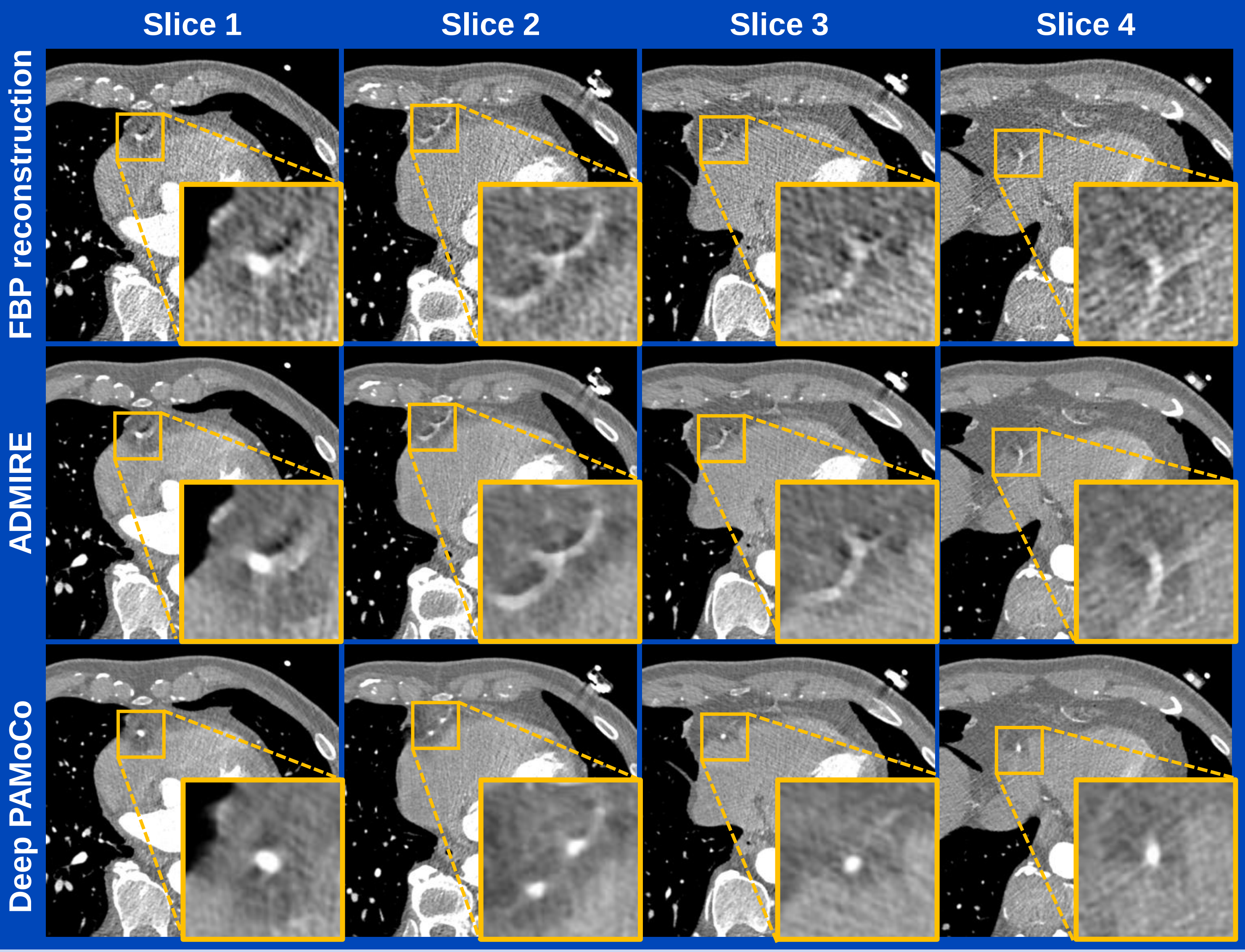
Forward projection

Motion simulation

J. Maier, S. Lebedev, J. Erath, E. Eulig, S. Sawall, E. Fournié, K. Stierstorfer, M. Lell, and M. Kachelrieß. Deep learning-based coronary artery motion estimation and compensation for short-scan cardiac CT. Med. Phys. 48(7):3559-3571, July 2021.

Results

Measurements at a Siemens Somatom AS, patient 1

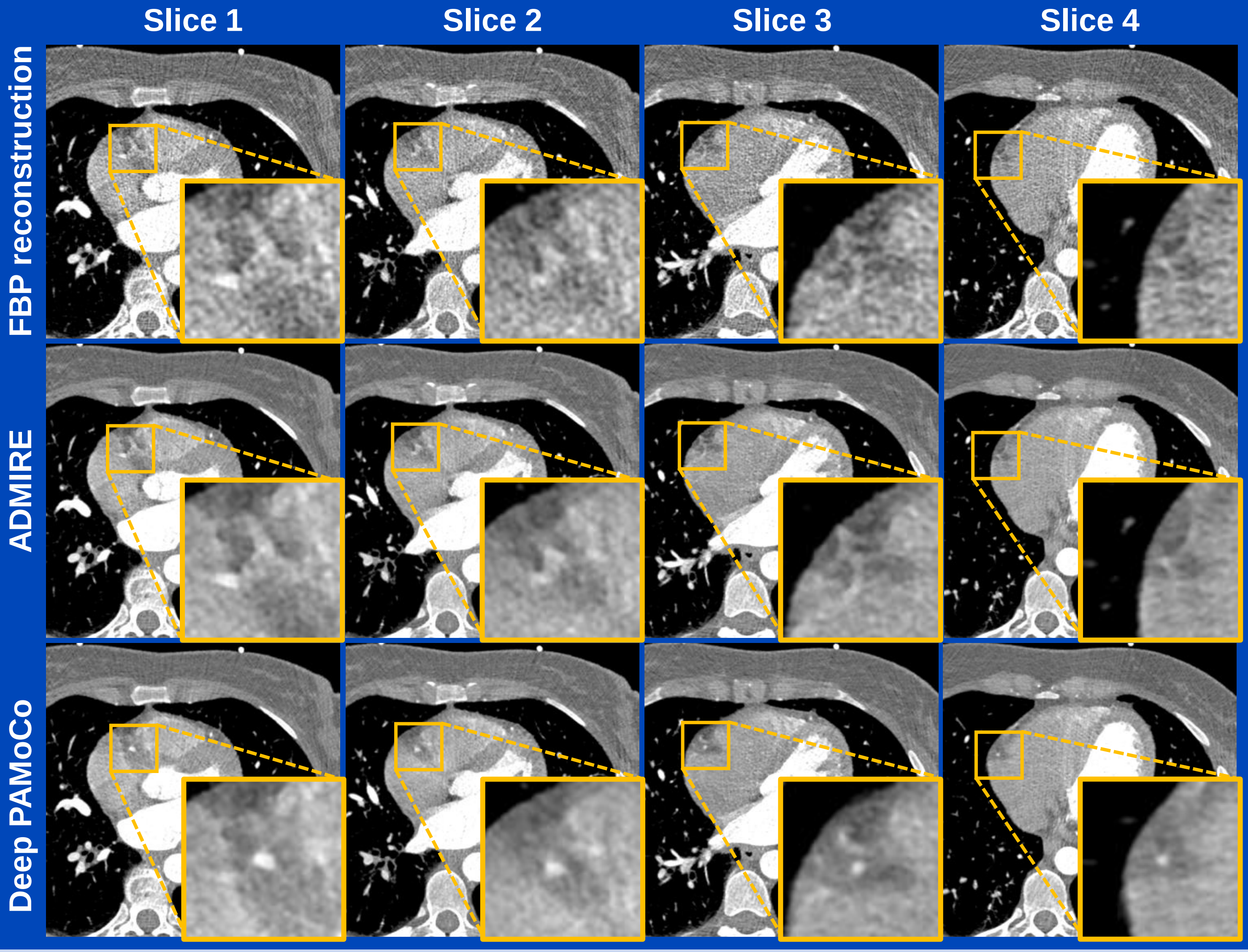


C = 0 HU, *W* = 1200 HU

J. Maier, S. Lebedev, J. Erath, E. Eulig, S. Sawall, E. Fournié, K. Stierstorfer, M. Lell, and M. Kachelrieß. Deep learning-based coronary artery motion estimation and compensation for short-scan cardiac CT. Med. Phys. 48(7):3559-3571, July 2021.

Results

Measurements at a Siemens Somatom AS, patient 2

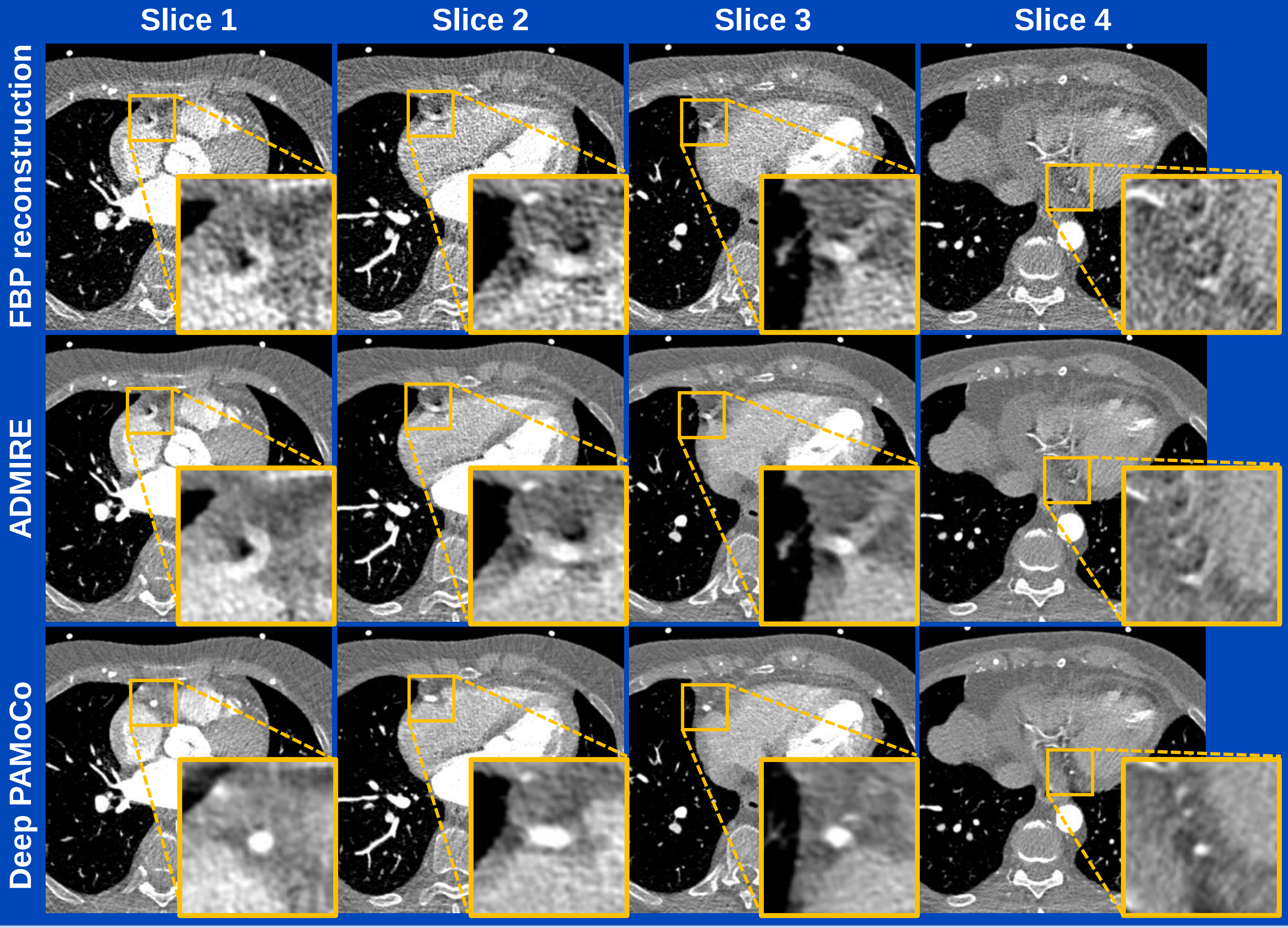


C = 0 HU, *W* = 1200 HU

J. Maier, S. Lebedev, J. Erath, E. Eulig, S. Sawall, E. Fournié, K. Stierstorfer, M. Lell, and M. Kachelrieß. Deep learning-based coronary artery motion estimation and compensation for short-scan cardiac CT. Med. Phys. 48(7):3559-3571, July 2021.

Results

Measurements at a Siemens Somatom AS, patient 3

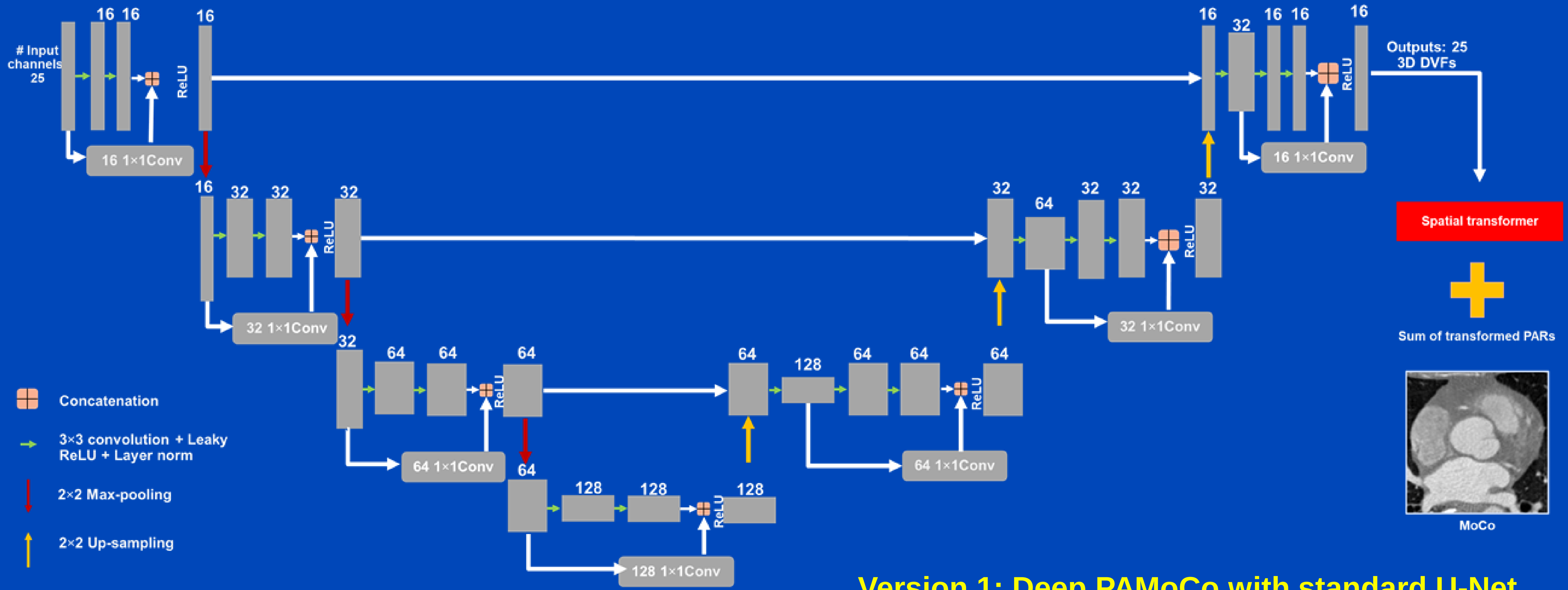


C = 0 HU, *W* = 1400 HU

J. Maier, S. Lebedev, J. Erath, E. Eulig, S. Sawall, E. Fournié, K. Stierstorfer, M. Lell, and M. Kachelrieß. Deep learning-based coronary artery motion estimation and compensation for short-scan cardiac CT. Med. Phys. 48(7):3559-3571, July 2021.

Deep PAMoCo with Standard or Residual U-Net

New Network Architecture for the Whole Heart

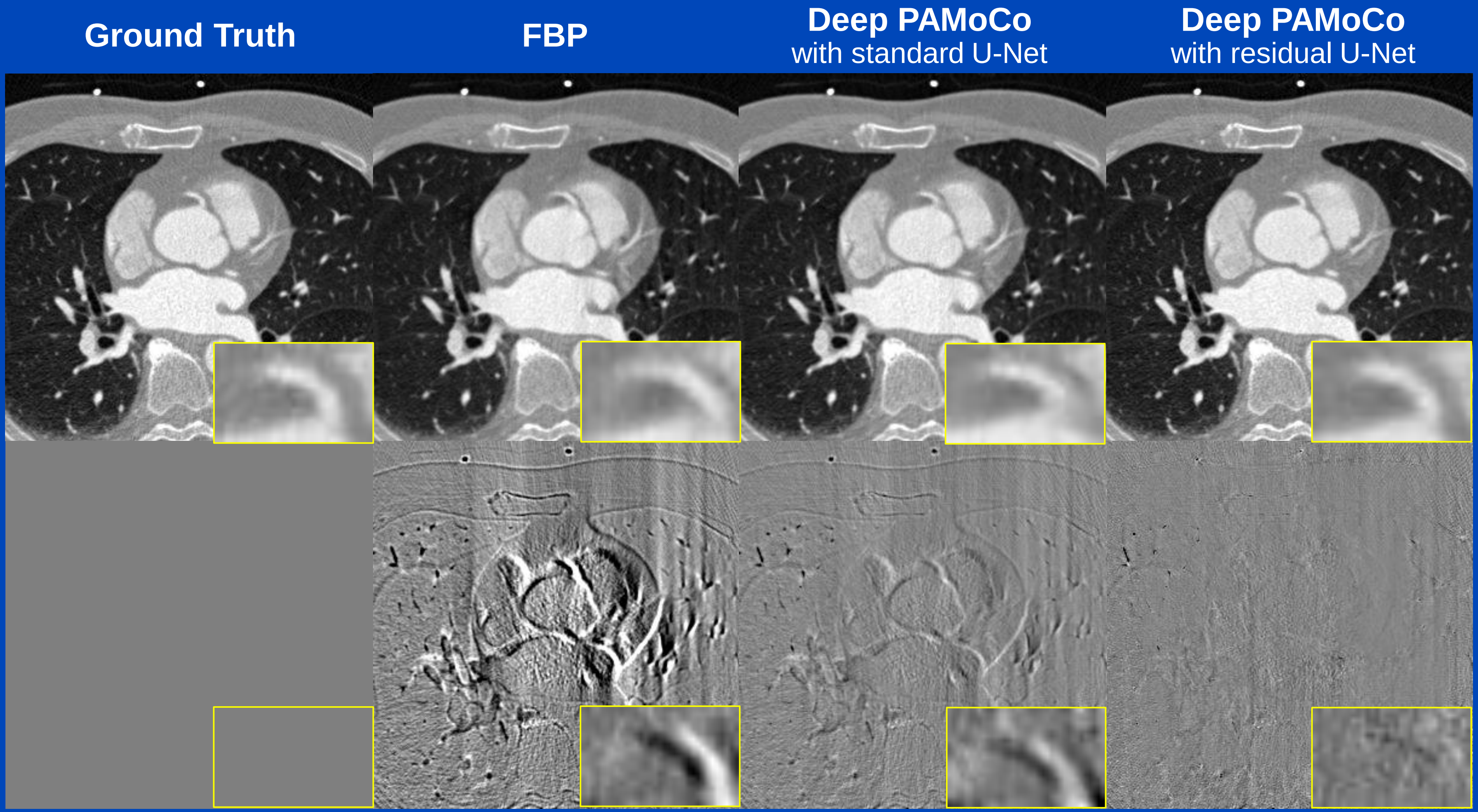


Version 1: Deep PAMoCo with standard U-Net
Version 2: Deep PAMoCo with residual U-Net

Training Data and Training

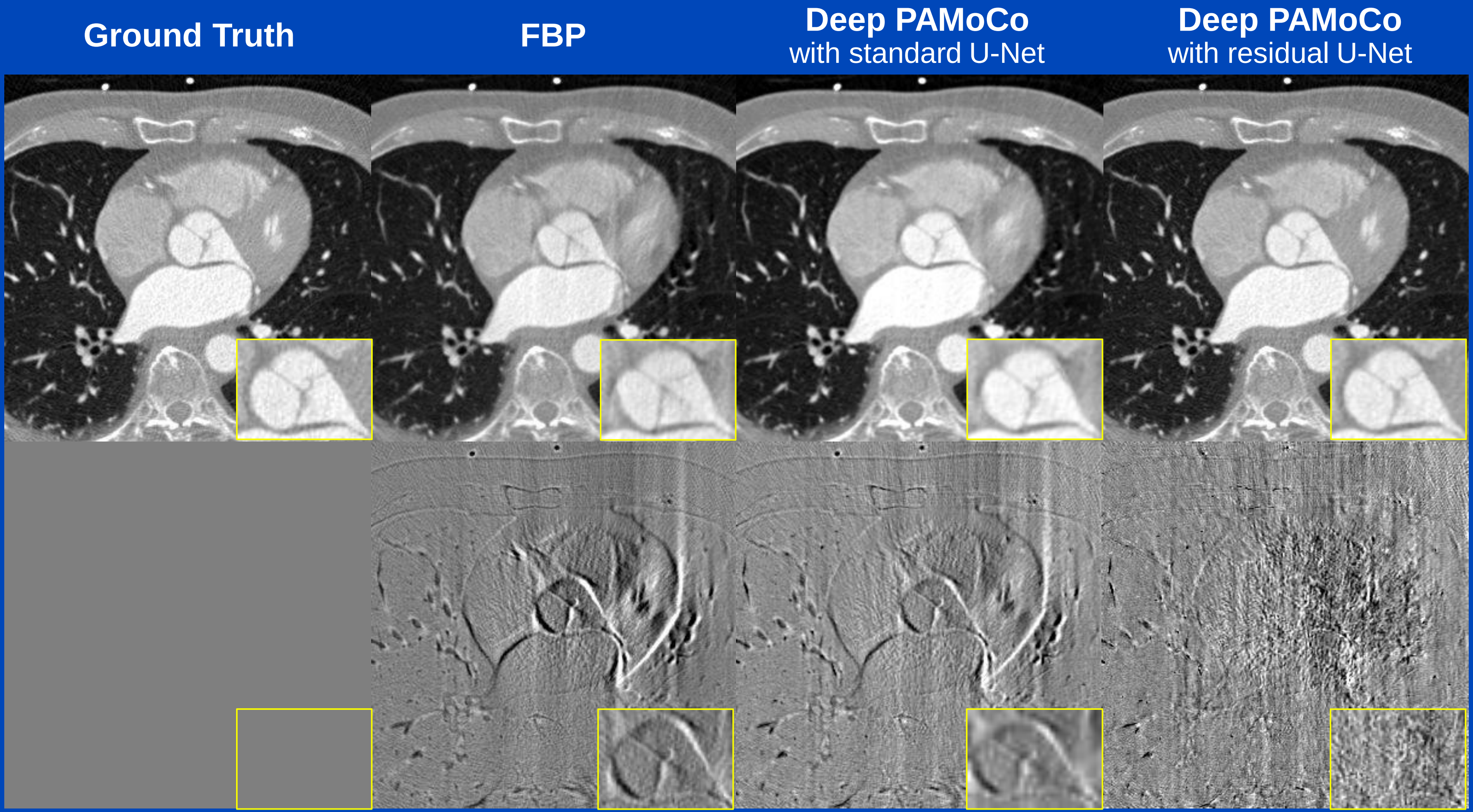
- Cardiac patient data sets (from different sources) to obtain DVFs
  - Systolic cardiac phase
  - Diastolic cardiac phase
  - VoxelMorph to find the DVF between the two phases
- Divide DVF into N_{180} = 600 sub-DVFs for simulation
  - Adopted linear motion due to the short time duration between two phases
- Deform patient volumes using the sub-DVFs and forward project them
  - Each projection corresponds to a different motion state
- Divide the 180° sinogram into 25 partial angle sinograms (7.2° each)
  - Each partial angle sinogram comprises 24 motion states.
  - The 25 sinograms correspond to the time steps -12, -11, …, 0, … +11, +12.
- Reconstruct each of the partial angle sinograms with FBP to obtain PARs.
- Deep PAMoco estimates 1 DVF for each of the 25 PARs, applies the spatial transformer, then sums.
  - Volume loss (VolLoss) weighted MSE: The reconstruction of the time step 0 is used as label.
- Training for 230 epochs
  - Adam optimizer was used with scheduled learning rate starting at 10^{-3}.

Patient 1



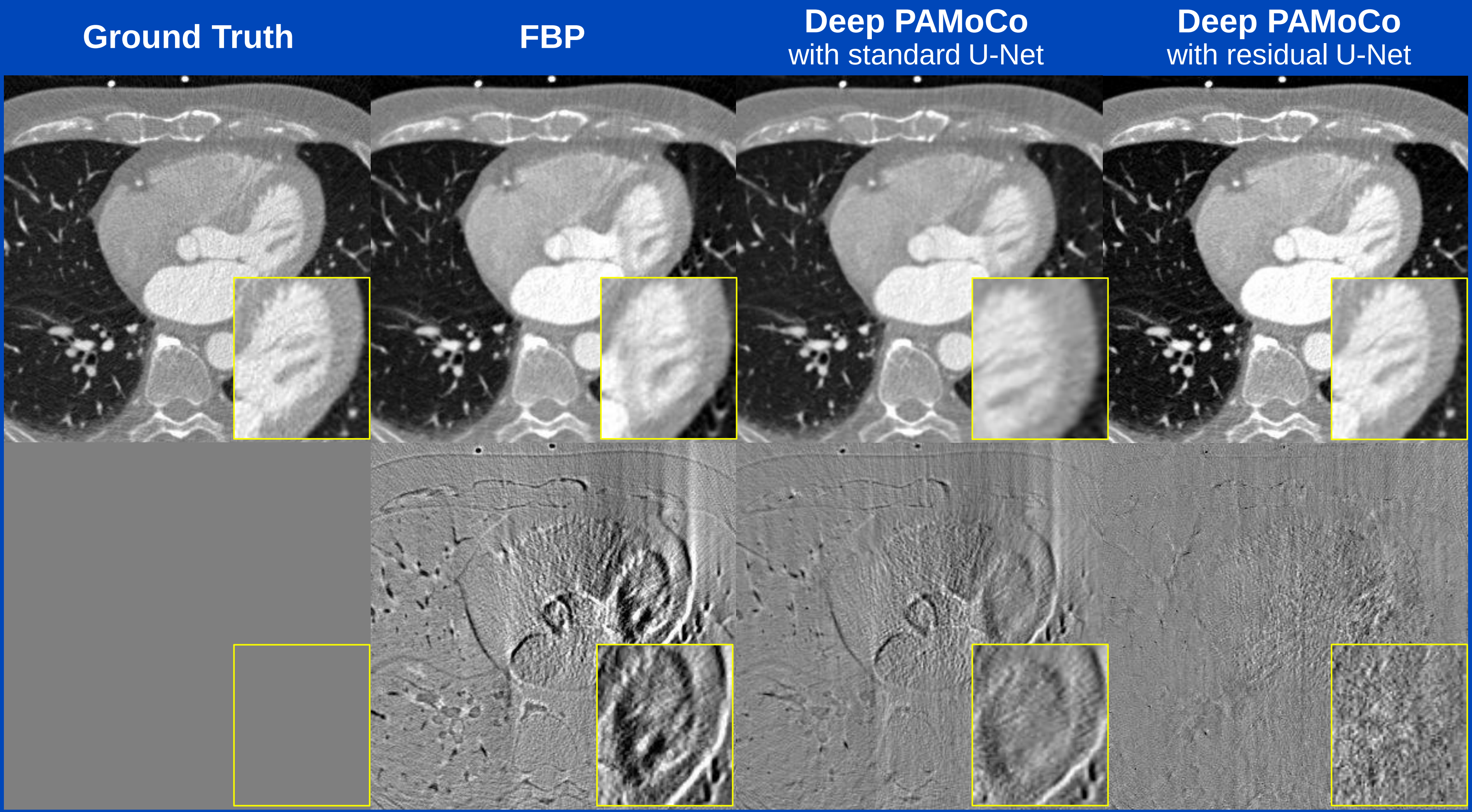
Images *C* = 0 HU, *W* = 1000 HU. Difference images: *C* = 0 HU, *W* = 100 HU.

Patient 2



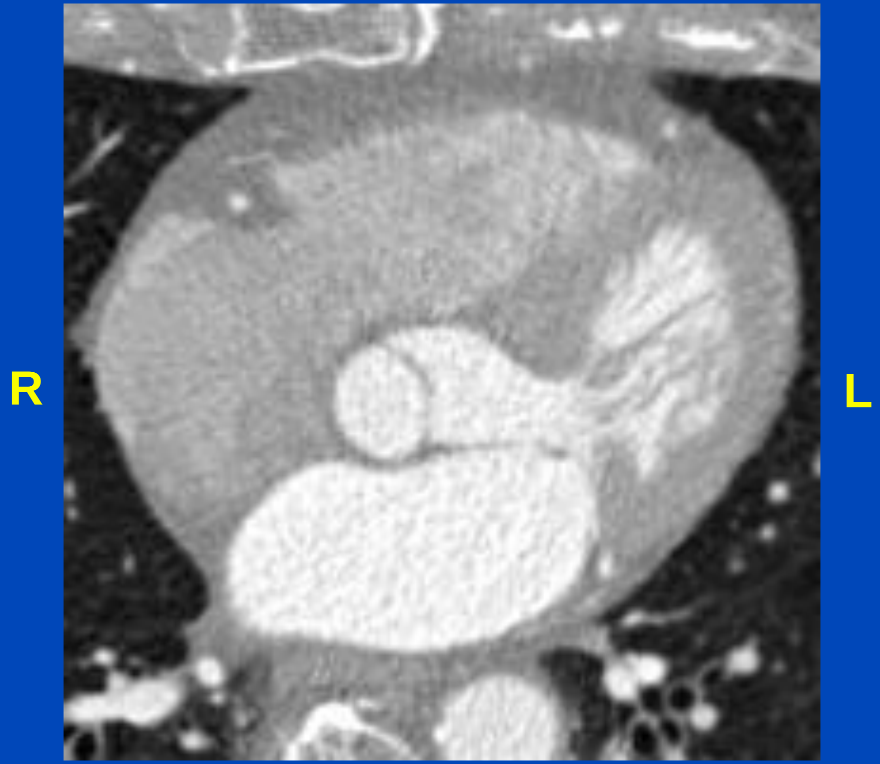
Images *C* = 0 HU, *W* = 1000 HU. Difference images: *C* = 0 HU, *W* = 100 HU.

Patient 3

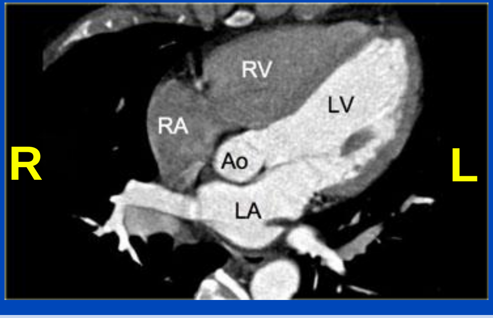


Images *C* = 0 HU, *W* = 1000 HU. Difference images: *C* = 0 HU, *W* = 100 HU.

No Motion Artifacts



Deep PAMoCo



Labeled five chamber view of the heart [1]

$C = 0$ HU, $W = 1000$ HU

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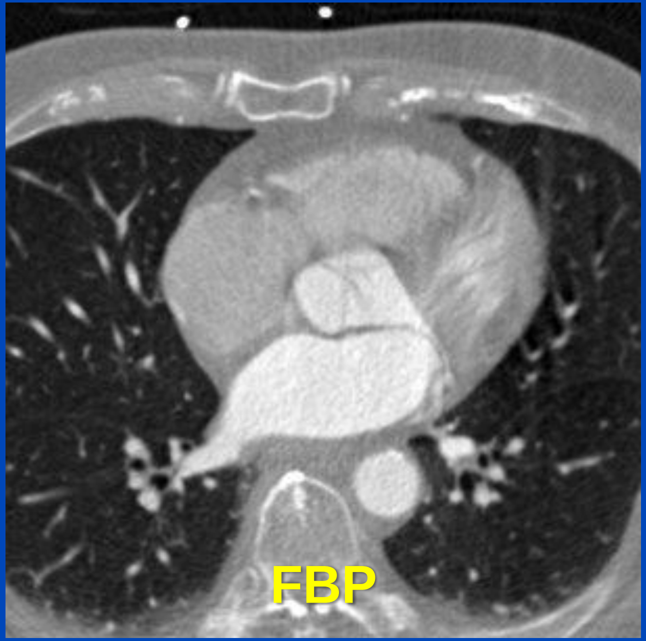
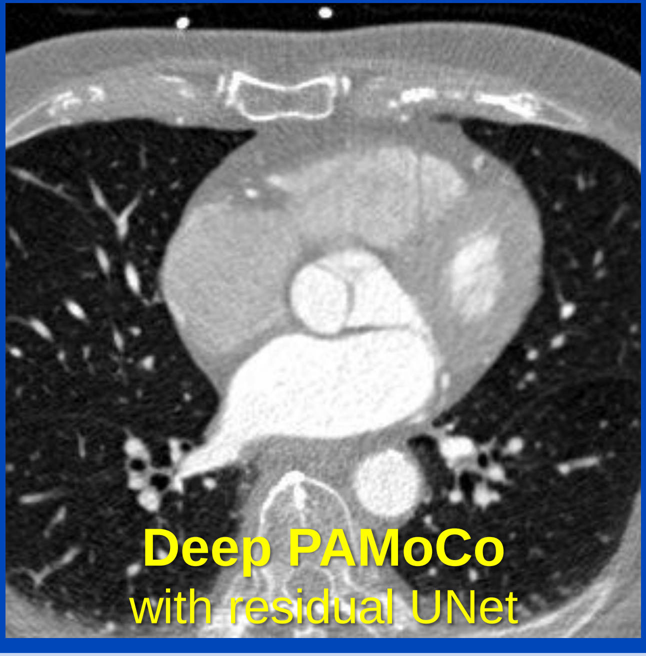
[1] Benoit Desjardins and Ella A. Kazerooni. ECG-gated cardiac CT: a review. AJR 182:993-1010, 2004

Discussion and Conclusions

- Motion artifacts in the heart were mostly removed.
- Mitigated the need for segmentation of coronary arteries
- Deep PAMoCo with the residual U-Net was able to improve the entire heart MAE by 74.4% from FBP and by 53.3% from the standard U-Net.
  - Ventricle: 61.2% improvement from FBP
  - Aortic valve: 75.2% improvement from FBP
- Limitations:
  - Motion simulation not yet realistic enough
  - Not applied to real patient data, yet
  - Only single-source energy-integrating CT considered so far

(MAE values)	**FBP**	**Deep PAMoCo** std. U-Net	**Deep PAMoCo** res. U-Net
Whole heart	32.7 HU	17.9 HU	8.4 HU
Ventricle	43.2 HU	36.3 HU	16.8 HU
Aortic valve	27.6 HU	10.7 HU	6.9 HU





Thank You!

- This presentation will soon be available at www.dkfz.de/ct.
- Job opportunities through marc.kachelriess@dkfz.de or through DKFZ’s PhD program.
- Parts of the reconstruction software were provided by RayConStruct® GmbH, Nürnberg, Germany.

Low dose CT benchmark:

github.com/eeulig/ldct-benchmark

E. Eulig, B. Ommer, and M. Kachelrieß. Benchmarking deep learning-based low-dose CT image denoising algorithms. Med. Phys. 51(12):8776-8788, December 2024.