Raw Data Consistent Cone-beam CT Motion Compensation with Single View Temporal Resolution

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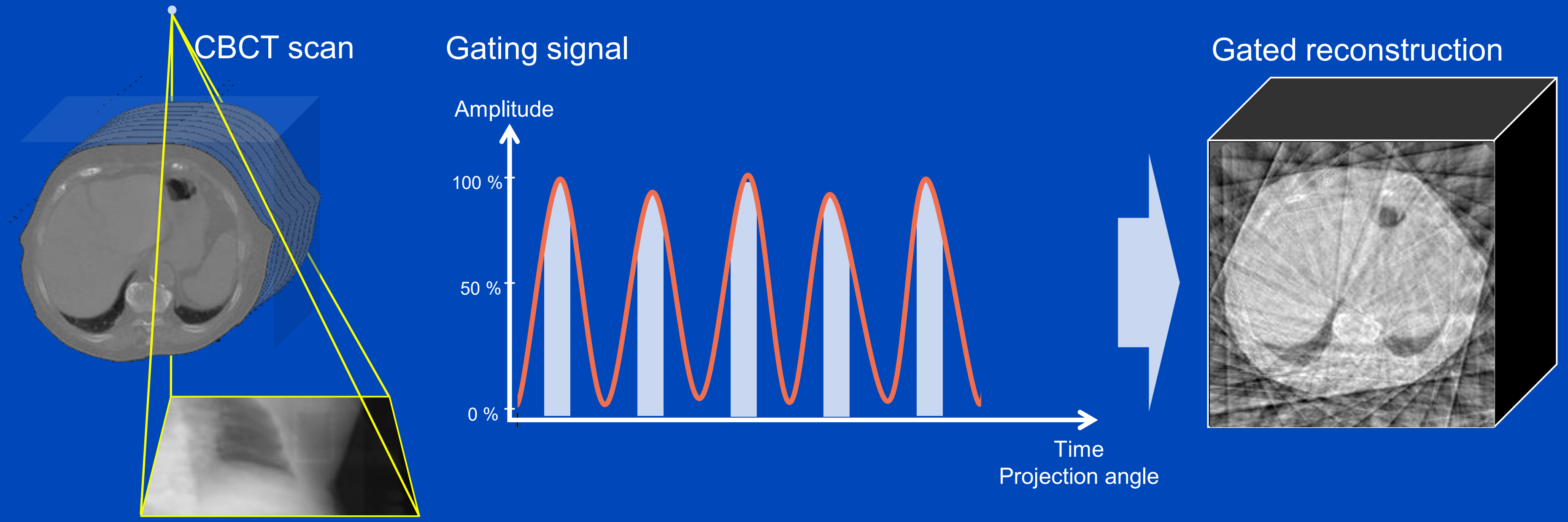
Motion in CBCT

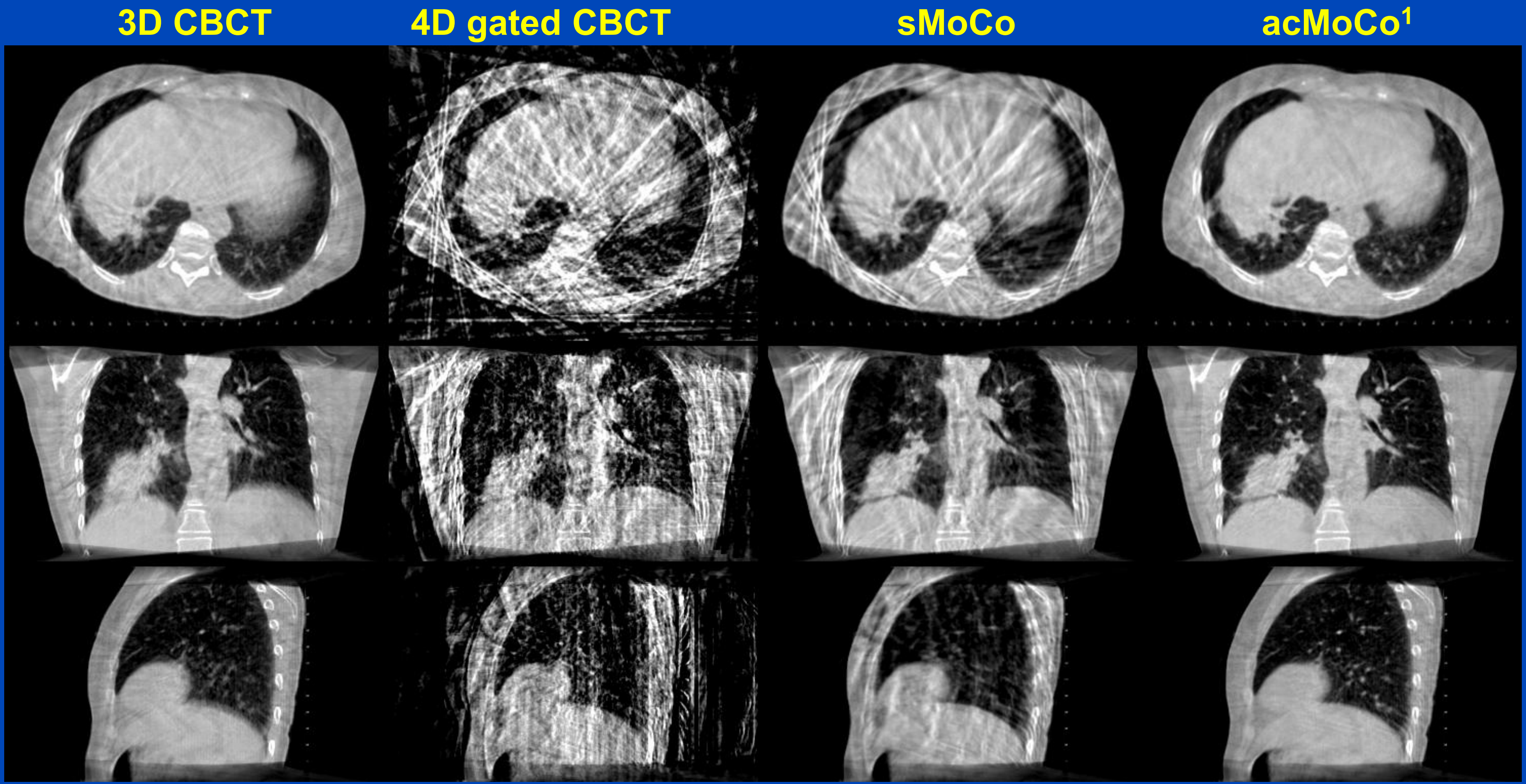
Gating-based strategies:



Drawbacks:

- requires gating signal,
- assumes periodic motion,
- has low temporal resolution,
- fails with irregular breathing,
- poor image quality,
- fails with short acquisition time

Examples for CBCT Motion Compensation



Drawbacks:

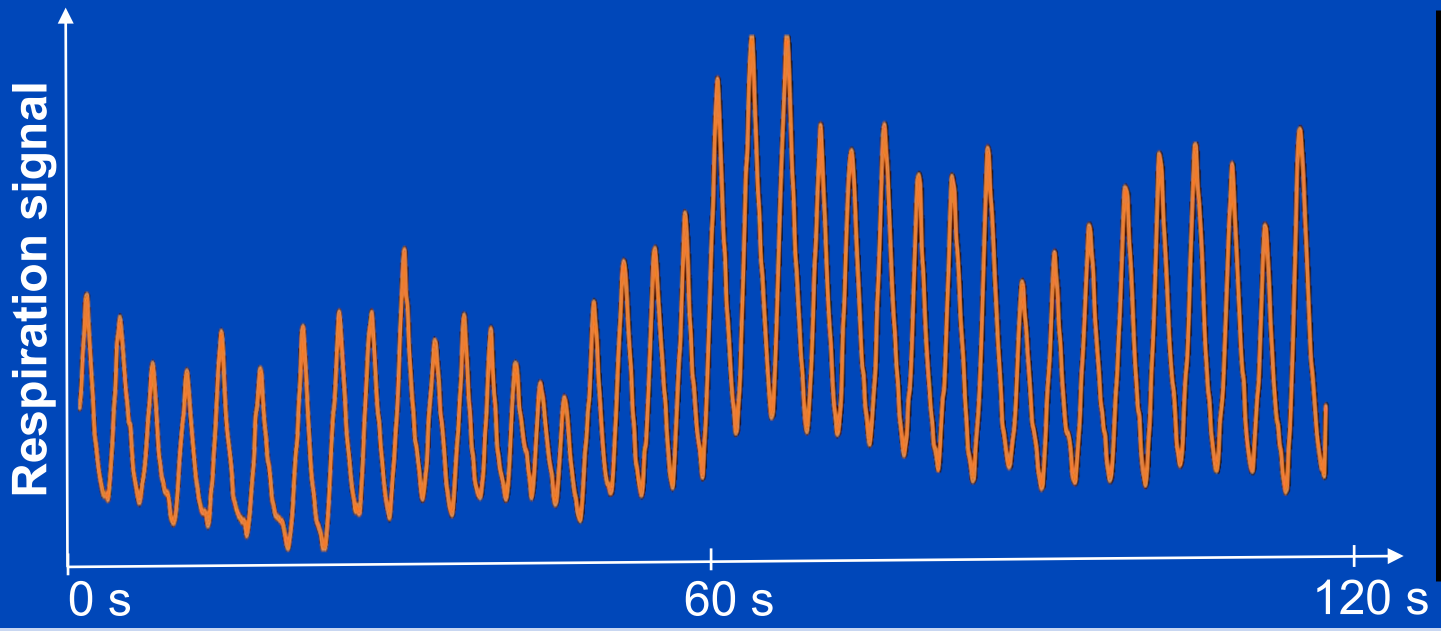
- requires gating signal,
- assumes periodic motion,
- has low temporal resolution,
- fails with irregular breathing,
- ~~poor image quality,~~
- fails with short acquisition time

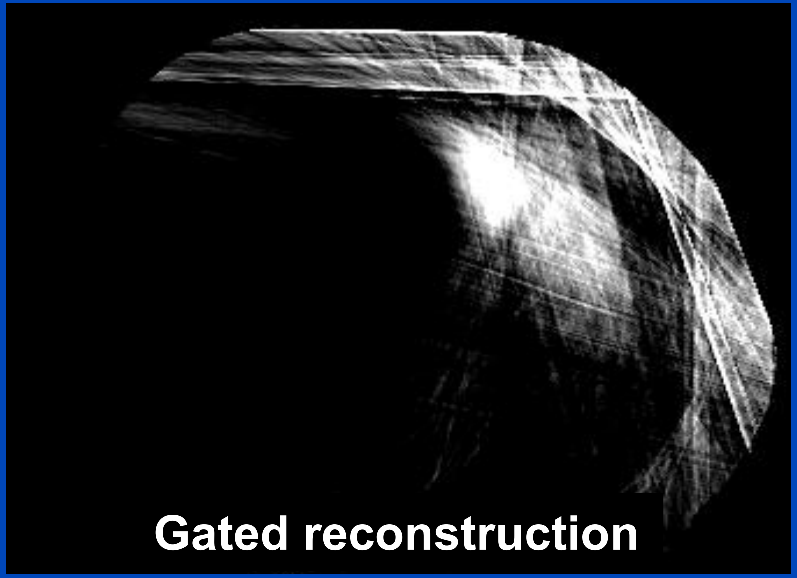
[1]M. Brehm, P. Paysan, M. Oelhafen, P. Kunz, M. Kachelrieß, "Self-adapting cyclic registration for motion-compensated cone-beam CT in image-guided radiation therapy", Medical Physics 39 (12): 7603–7618 (2012).

Irregular Motion Patterns

Irregular motion patterns may lead to:

- Poor image quality of gated reconstructions.
- Poor temporal resolution of gated reconstructions.
- Failure of current motion compensation approaches.

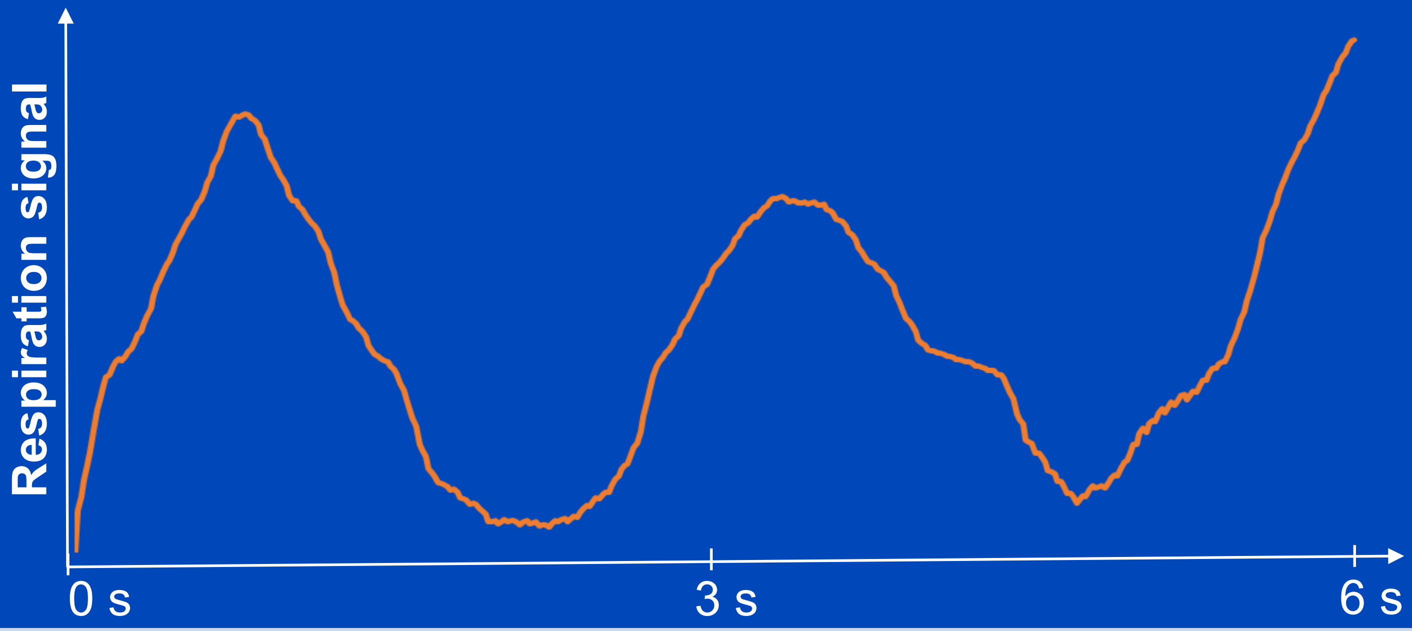


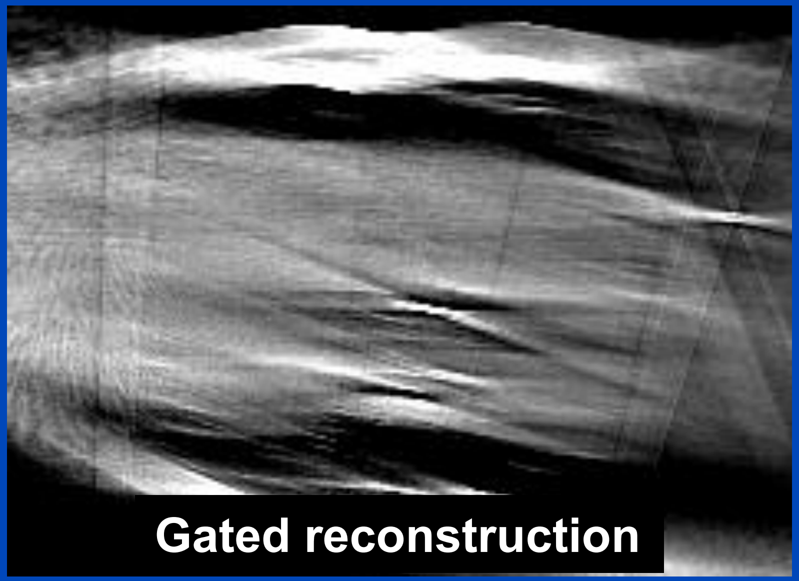


Scans with Short Acquisition Time

Scans with short acquisition may lead to:

- Poor image quality of gated reconstructions.
- Poor temporal resolution of gated reconstructions.
- Failure of current motion compensation approaches.





Aims

- Aim #1: Gating-free motion compensation that can be applied to arbitrary scan protocols and arbitrary motion patterns.

→Deep single-angle motion compensation (deep SAMoCo)[1]

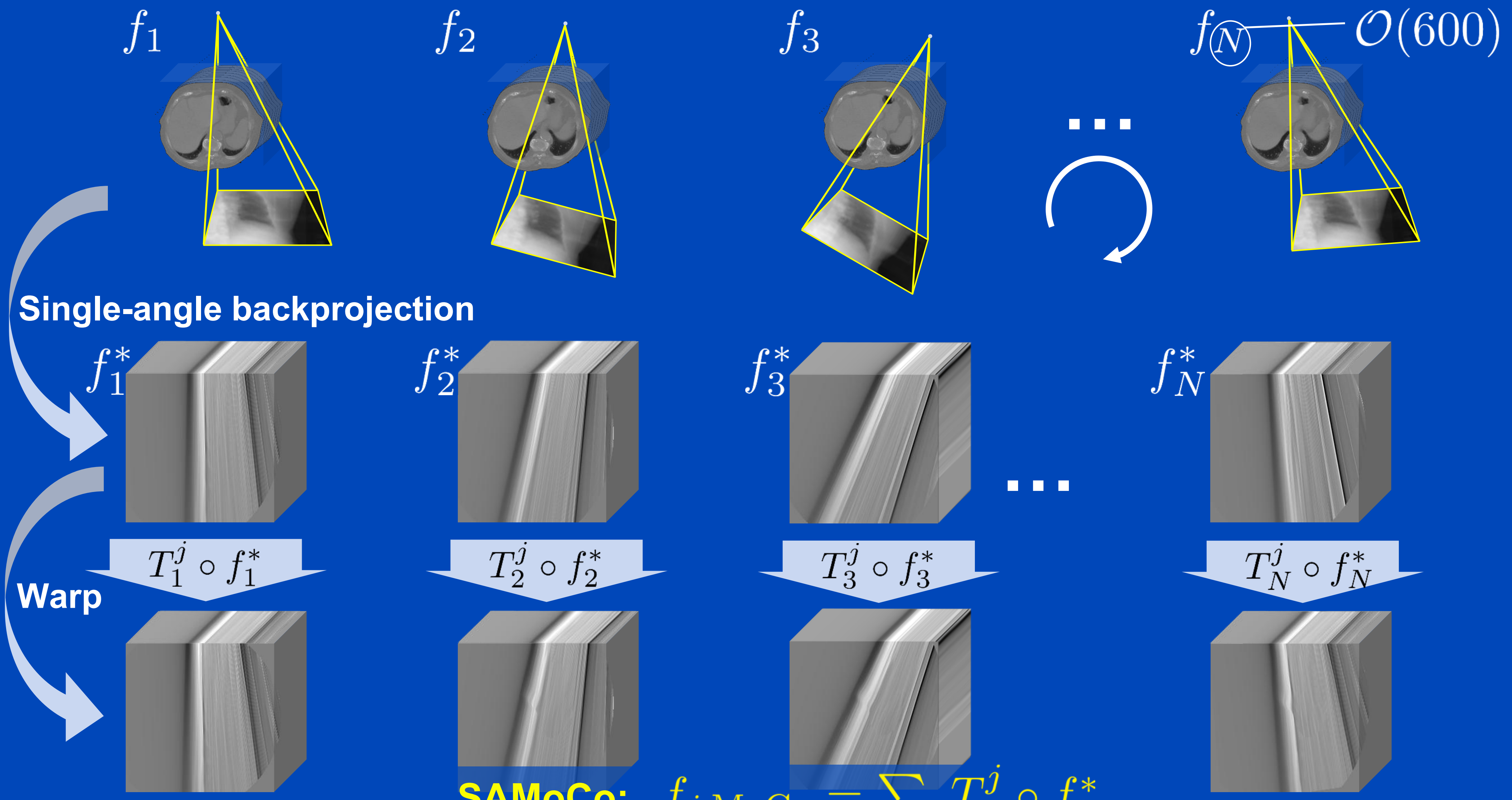
- Aim #2: Ensure final motion compensation is consistent with the acquired raw data.

→ Deep raw data consistent SAMoCo (deep rcSAMoCo)

[1]J. Maier, S. Sawall, M. Arheit, P. Paysan, M. Kachelrieß, "Deep Learning-Based Cone-Beam CT Motion Compensation with Single-View Temporal Resolution", Med. Phys. 2025

Single-angle Motion Compensation (SAMoCo)

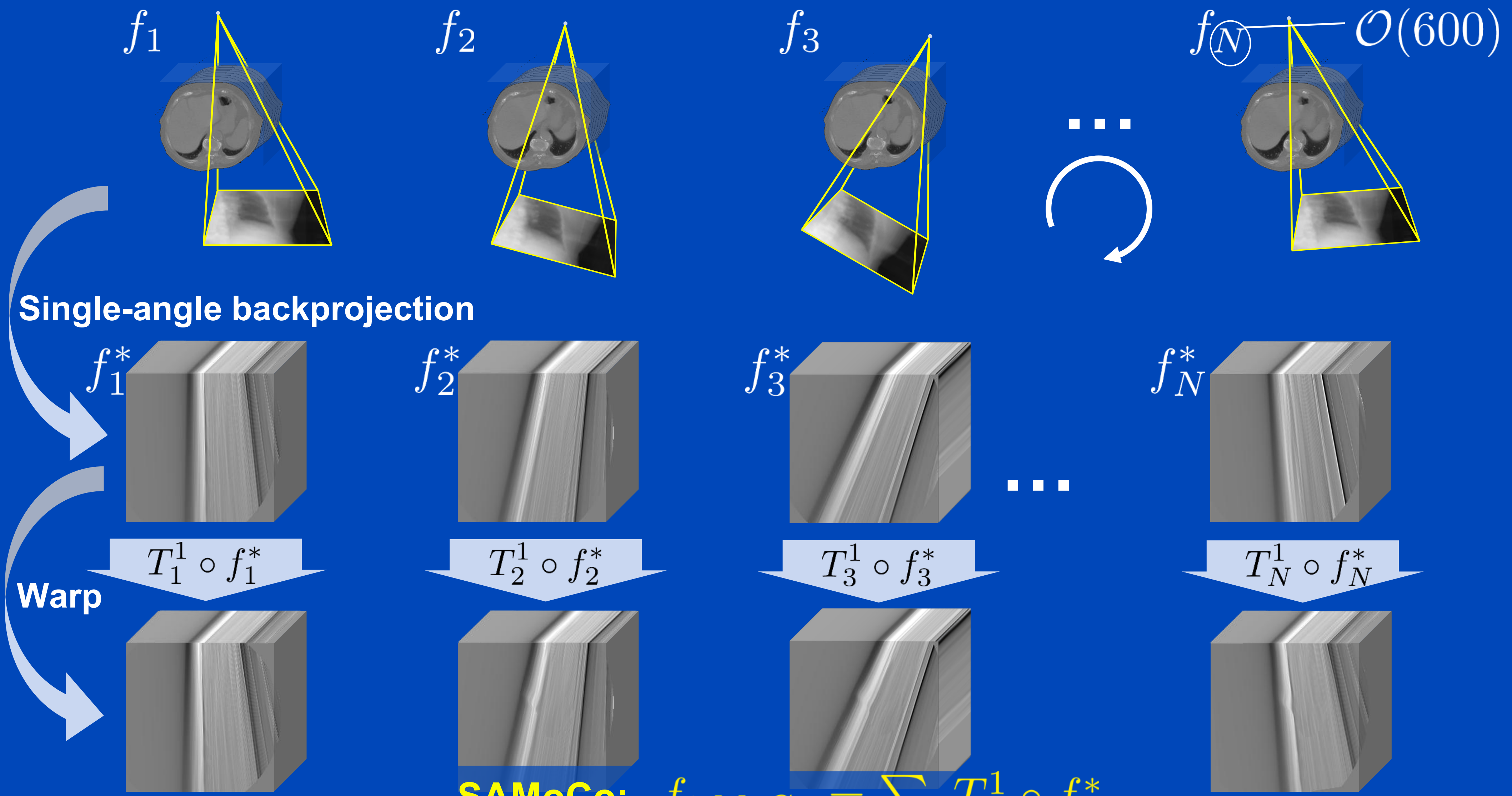
Basic Principle



SAMoCo: $f_{j,\mathrm{MoCo}} = \sum_i T_i^j \circ f_i^*$

SAMoCo of Motion State 1

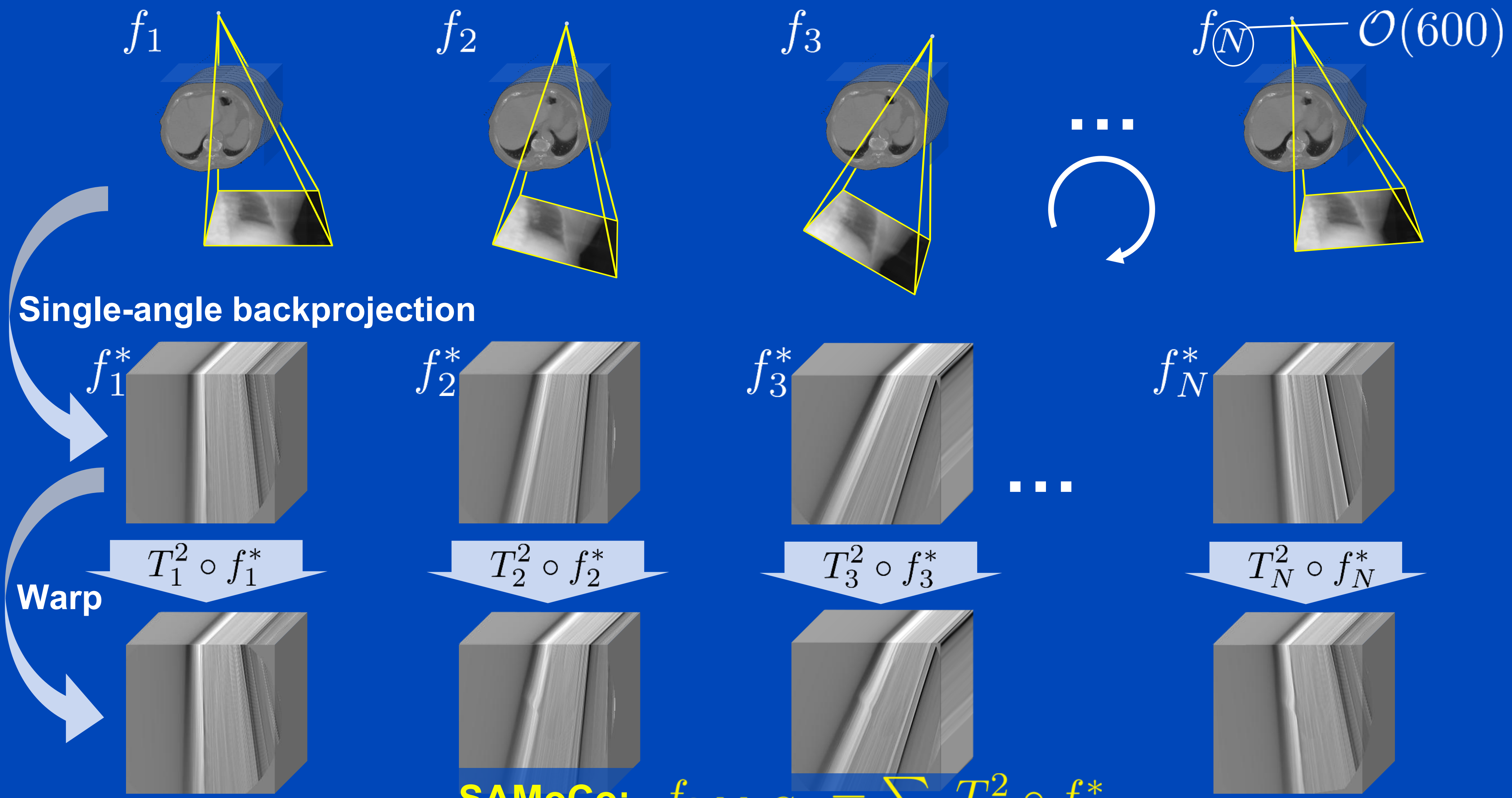
Basic Principle



SAMoCo: $f_{1,\mathrm{MoCo}} = \sum_i T_i^1 \circ f_i^*$

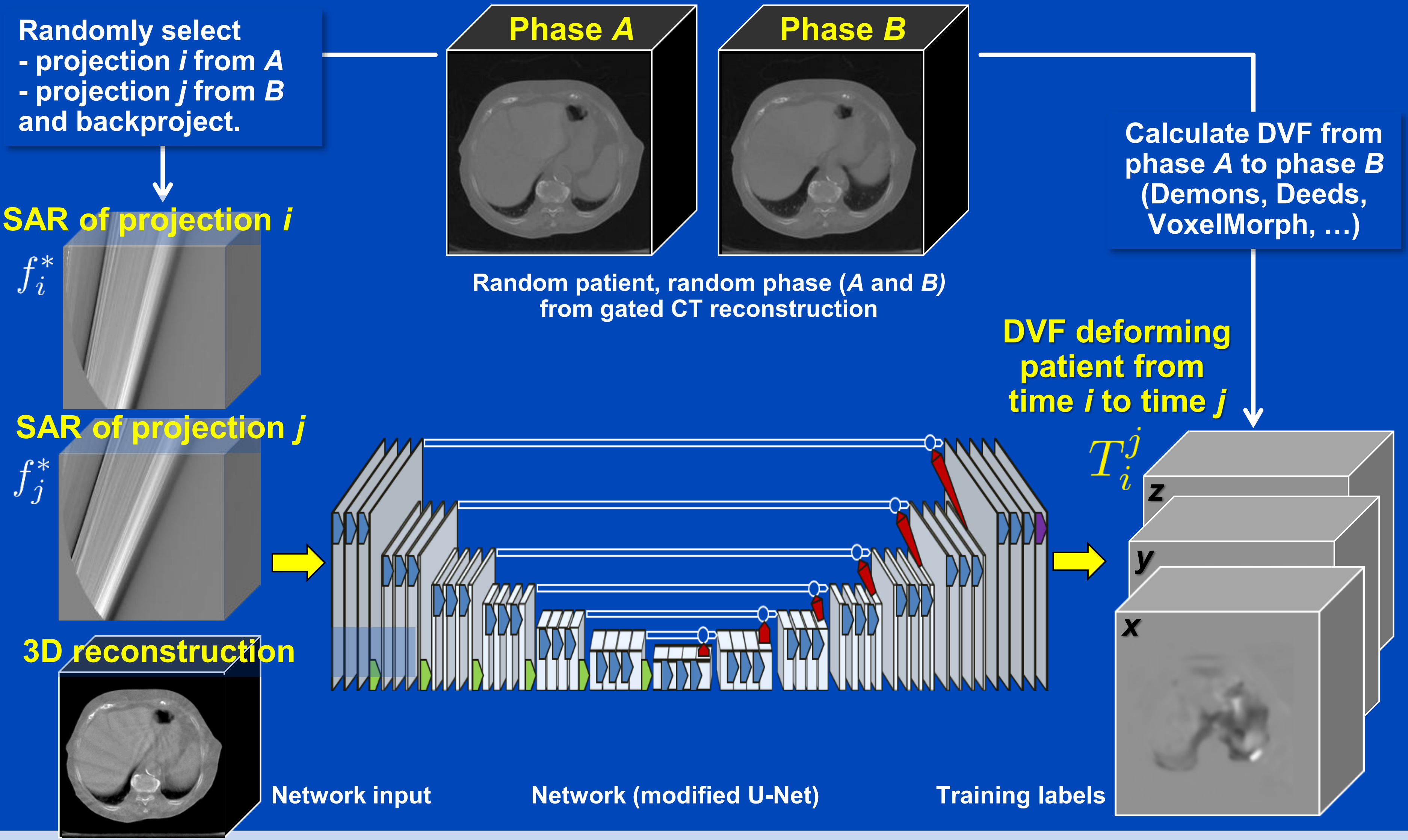
SAMoCo of Motion State 2

Basic Principle

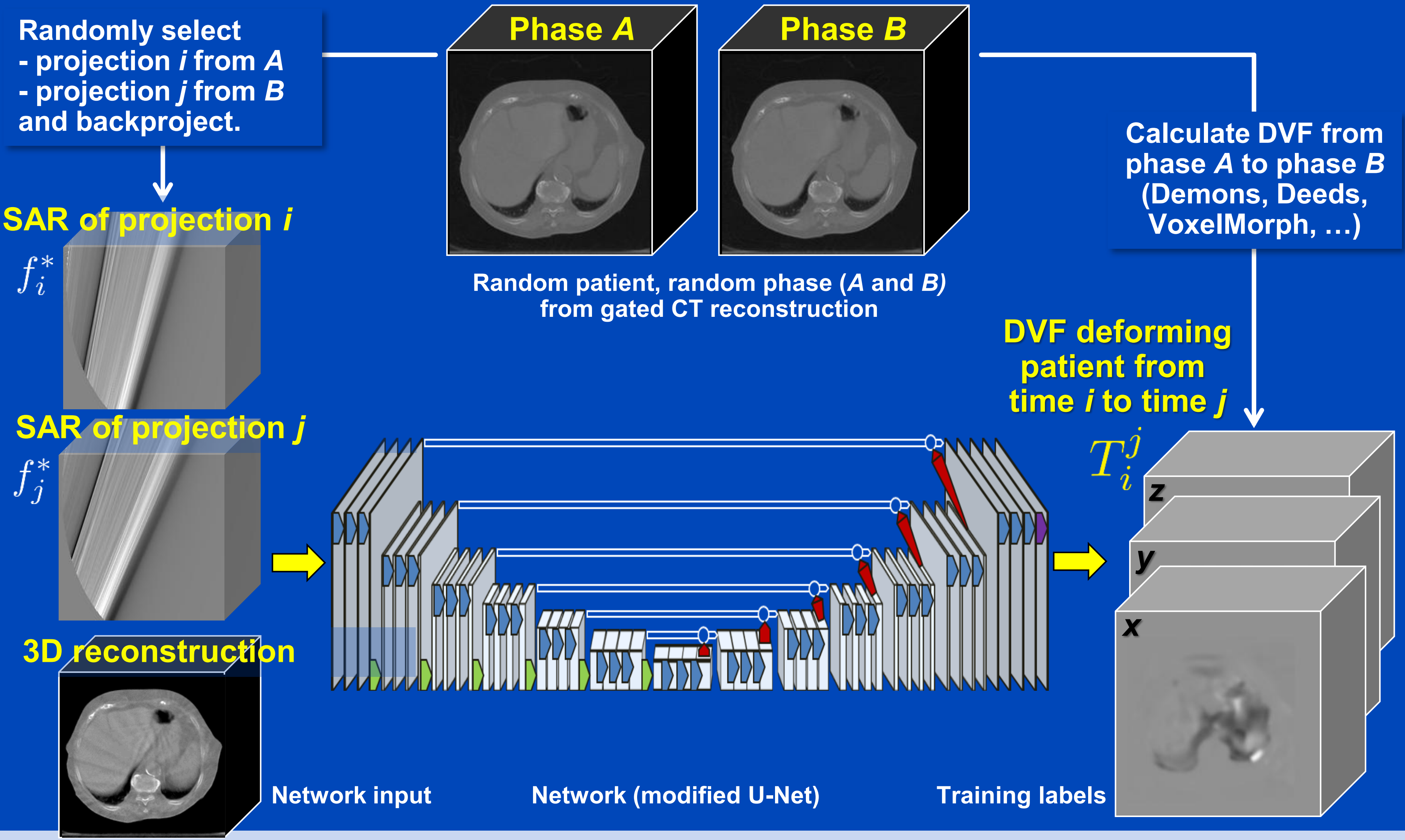


SAMoCo: $f_{2,\mathrm{MoCo}} = \sum_i T_i^2 \circ f_i^*$

Learning to Predict Deformation Vector Fields

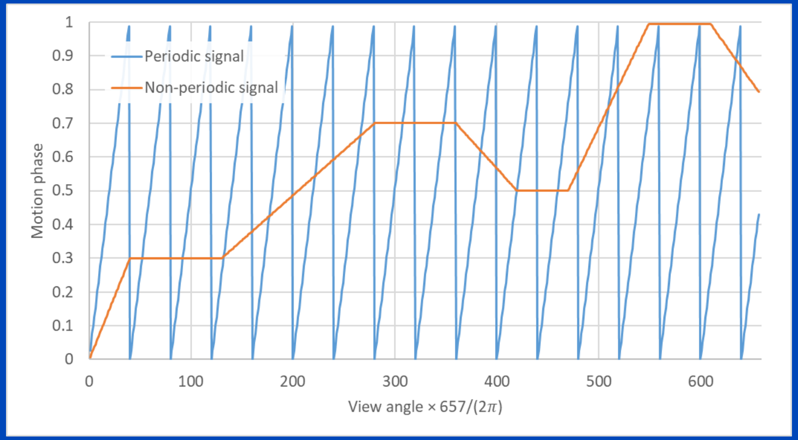


Learning to Predict Deformation Vector Fields

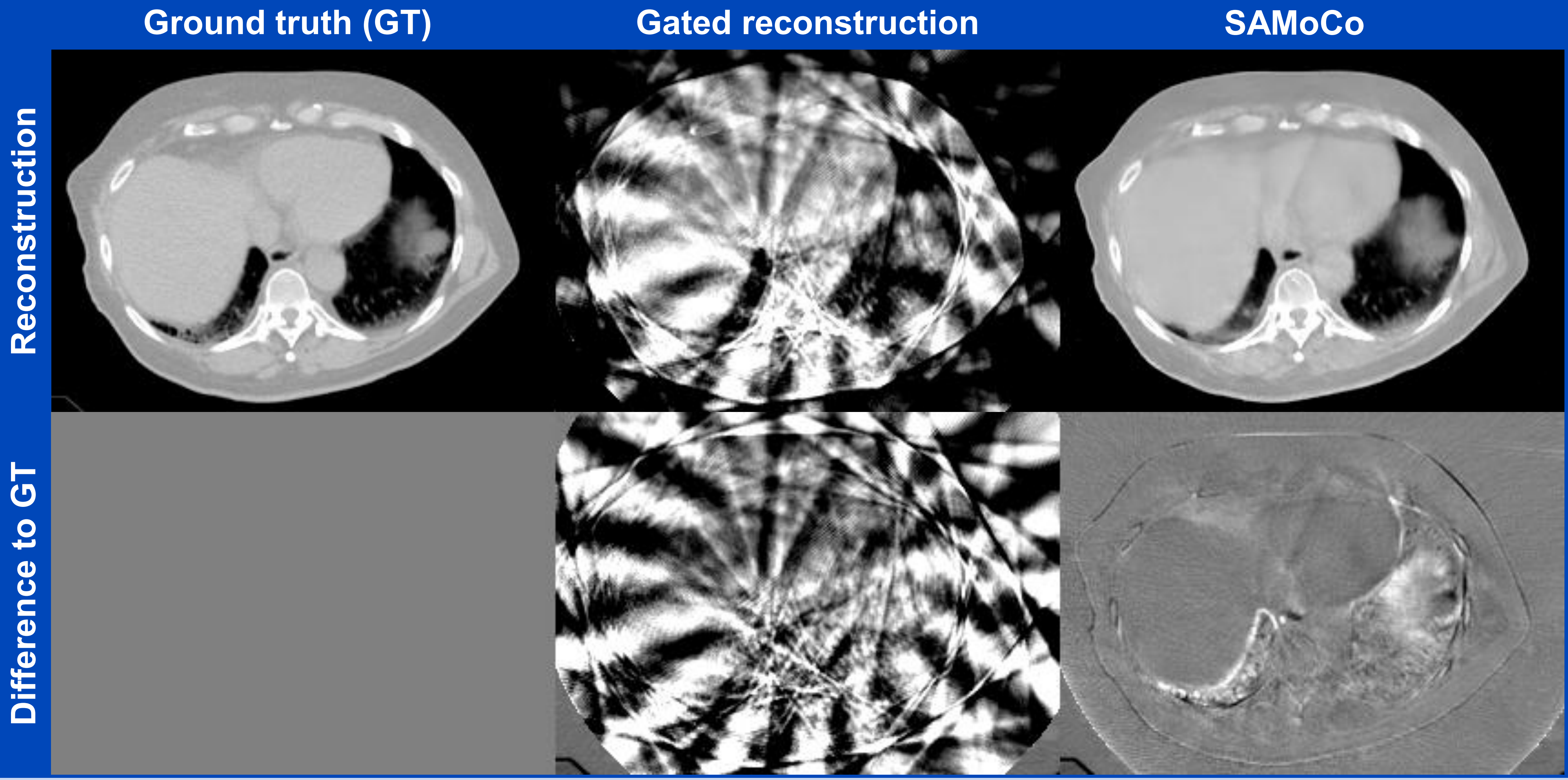


Training / Testing Details

- Training using gated CT reconstruction (high temporal resolution, no motion artifacts)
  - Gated CT reconstructions of 84 patients.
  - Simulation of CBCT (shifted-detector) single-angle reconstructions with random motion state and random projection angle.
  - Training of the network for 500 epochs using the MSE between prediction and ground truth DVF as loss function.
- Testing:
  - Simulated shifted-detector CBCT scans with periodic and highly non-periodic motion (rotation time: 60 s, 657 views / 360°).
  - Real-measurements of a Varian TrueBeam CBCT system.

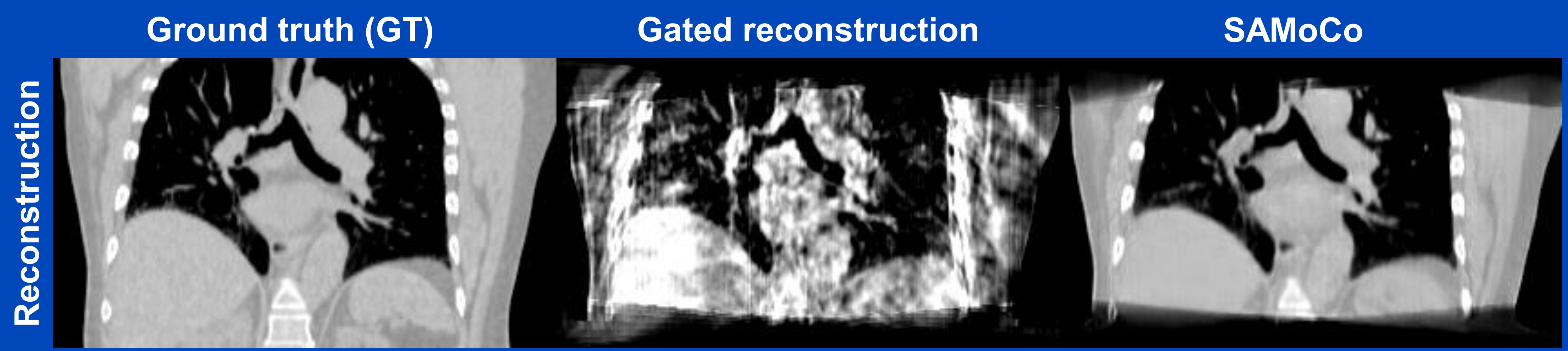


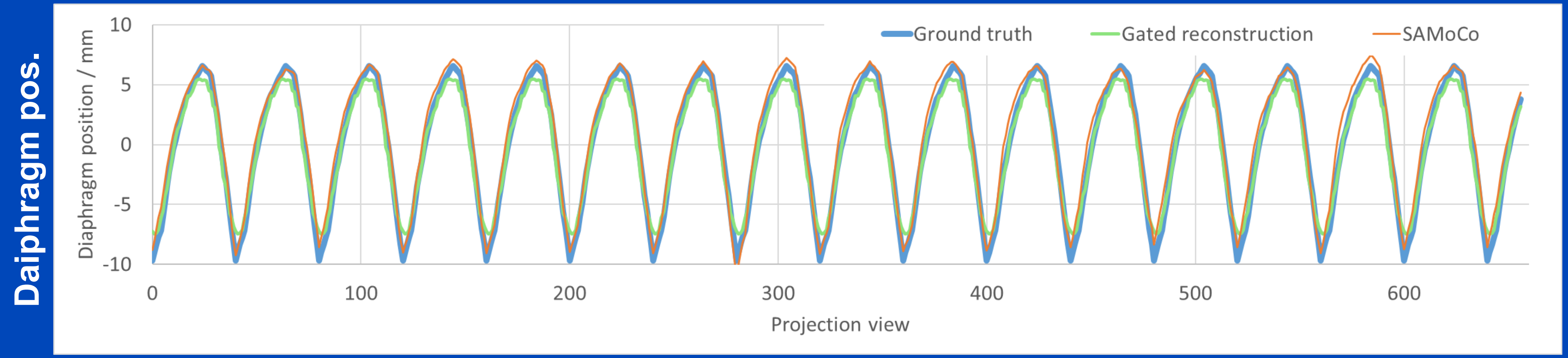
Results: Periodic Simulation, Test Patient #1



Top: *C* = -200 HU, *W* = 1000 HU, bottom: *C* = 0 HU, *W* = 600 HU

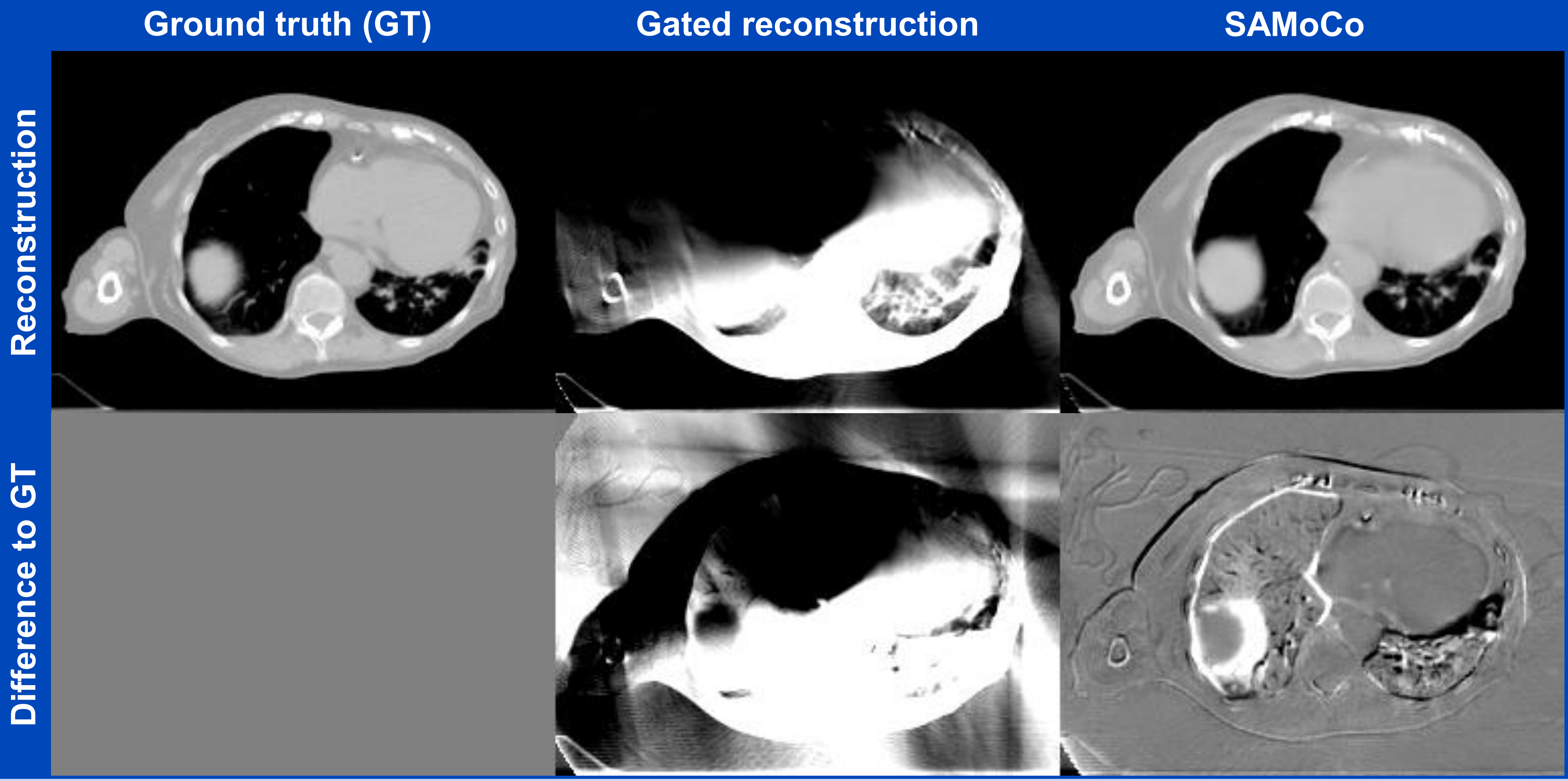
Results: Periodic Simulation, Test Patient #1





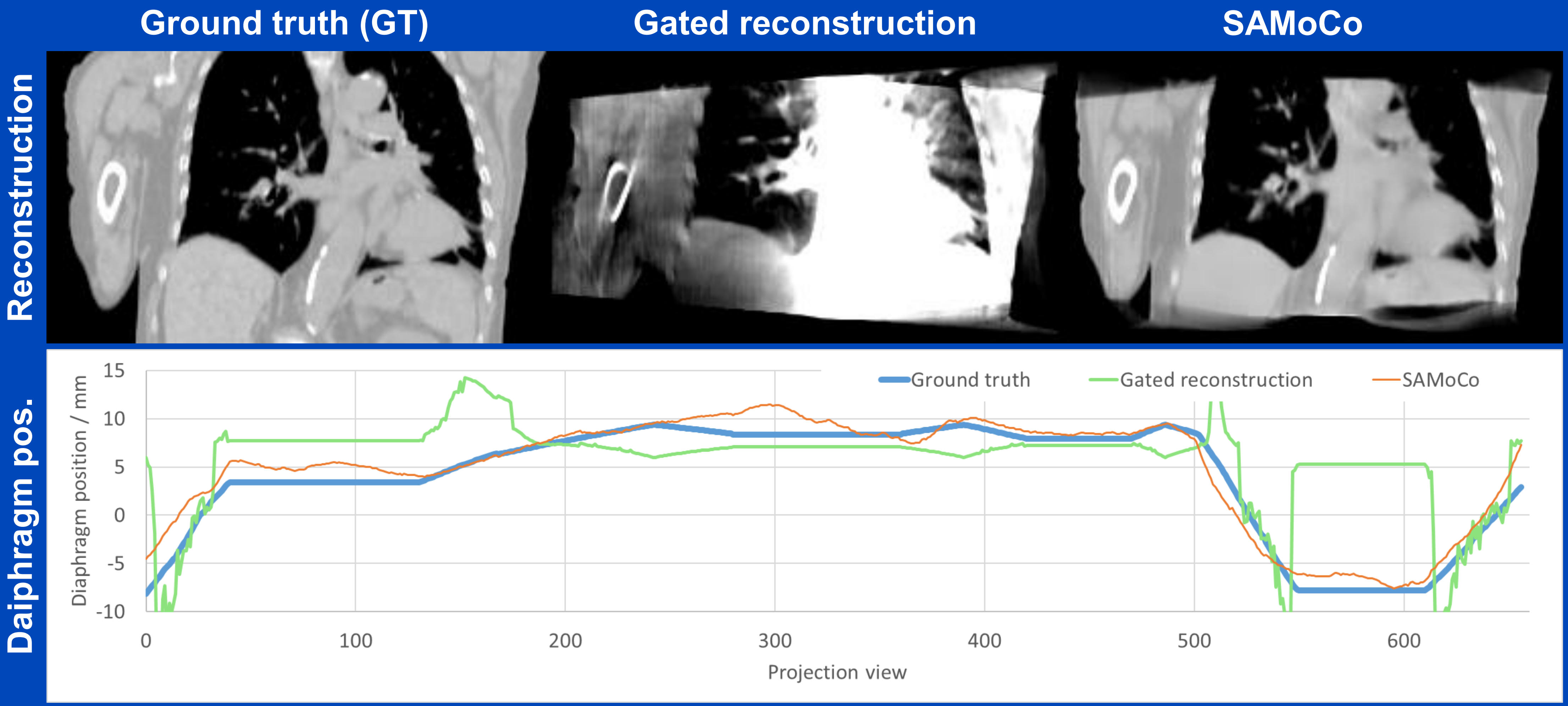
Top: C = -200 HU, W = 1000 HU, bottom: C = 0 HU, W = 600 HU

Results: Non-Periodic Simulation, Test Patient #2



Top: C = -200 HU, W = 1000 HU, bottom: C = 0 HU, W = 600 HU

Results: Non-Periodic Simulation, Test Patient #2



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Top: C = -200 HU, W = 1000 HU, bottom: C = 0 HU, W = 600 HU

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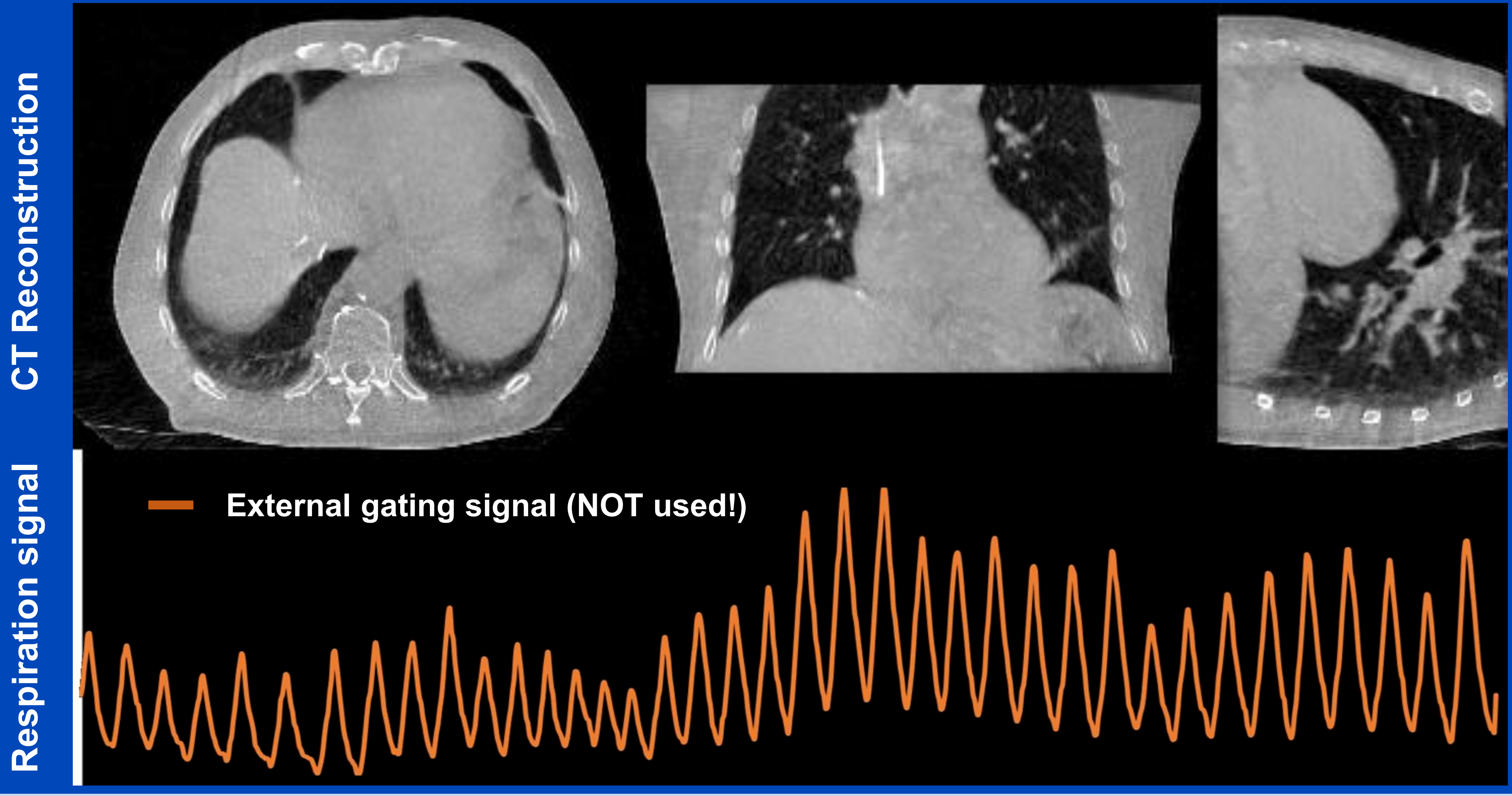
Results: Varian CBCT Measurement

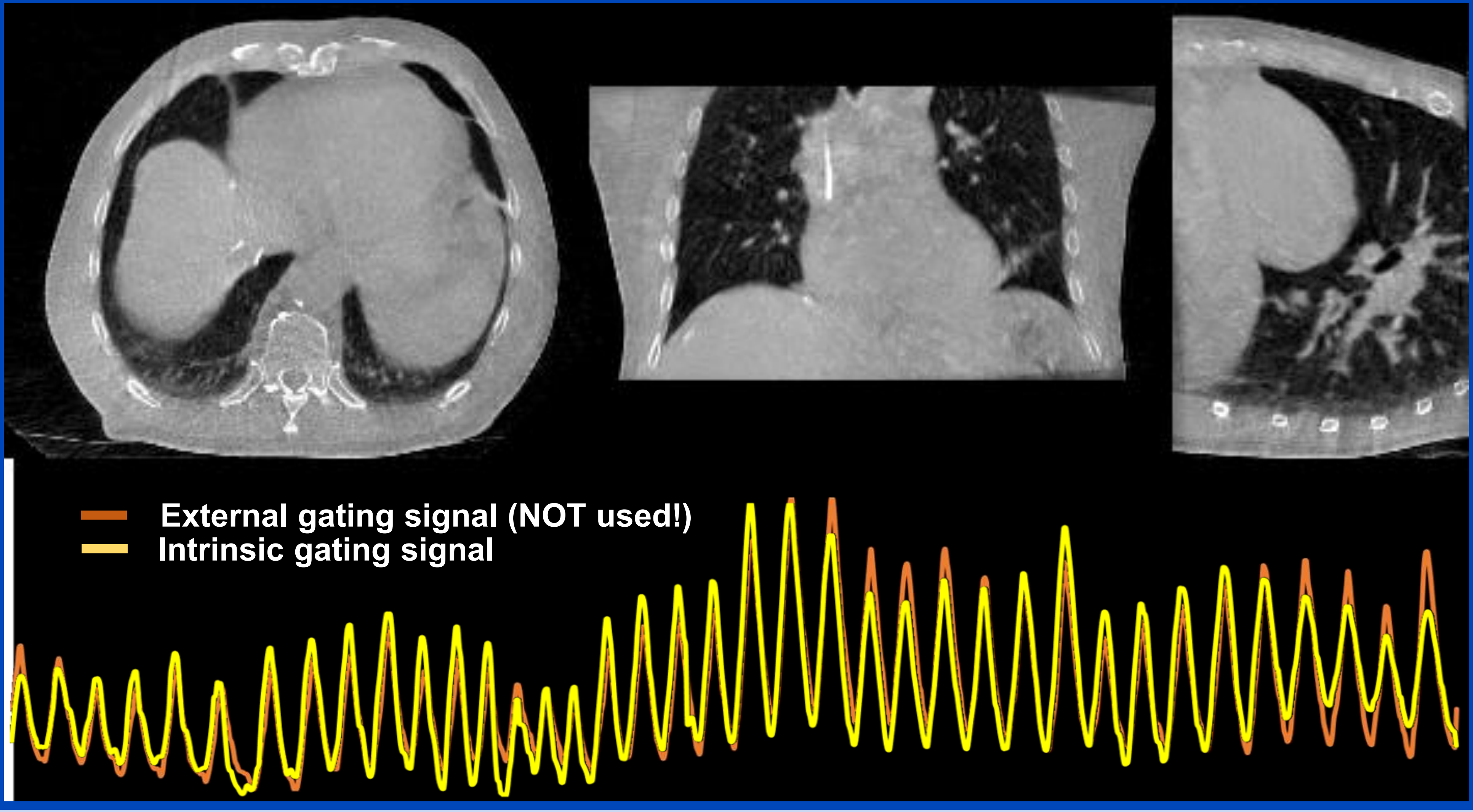


C = -200 HU, *W* = 1400 HU, video speed: 2 × real-time

Results: Varian CBCT Measurement

CT Reconstruction

Respiration signal



C = -200 HU, *W* = 1400 HU, video speed: 2 × real-time

Ensuring Raw Data Consistency: Deep rcSAMoCo

- **In general, optimal raw data fidelity can be achieved by:**

$$f_{\mathrm{opt},i} = \underset{\boldsymbol{u}}{\mathrm{argmin}}\ S(\mathsf{X} f_{\mathrm{ref}}(\boldsymbol{r}+\boldsymbol{u}), p_i)$$

- **To constrain the vector field to realistic deformations, we rather optimize:**

$$f_{\mathrm{opt},i} = \underset{\{c_n\}}{\mathrm{argmin}}\ S(\mathsf{X} f_{\mathrm{ref}}(\boldsymbol{r}+\sum_n c_n \boldsymbol{d}_n), p_i)$$

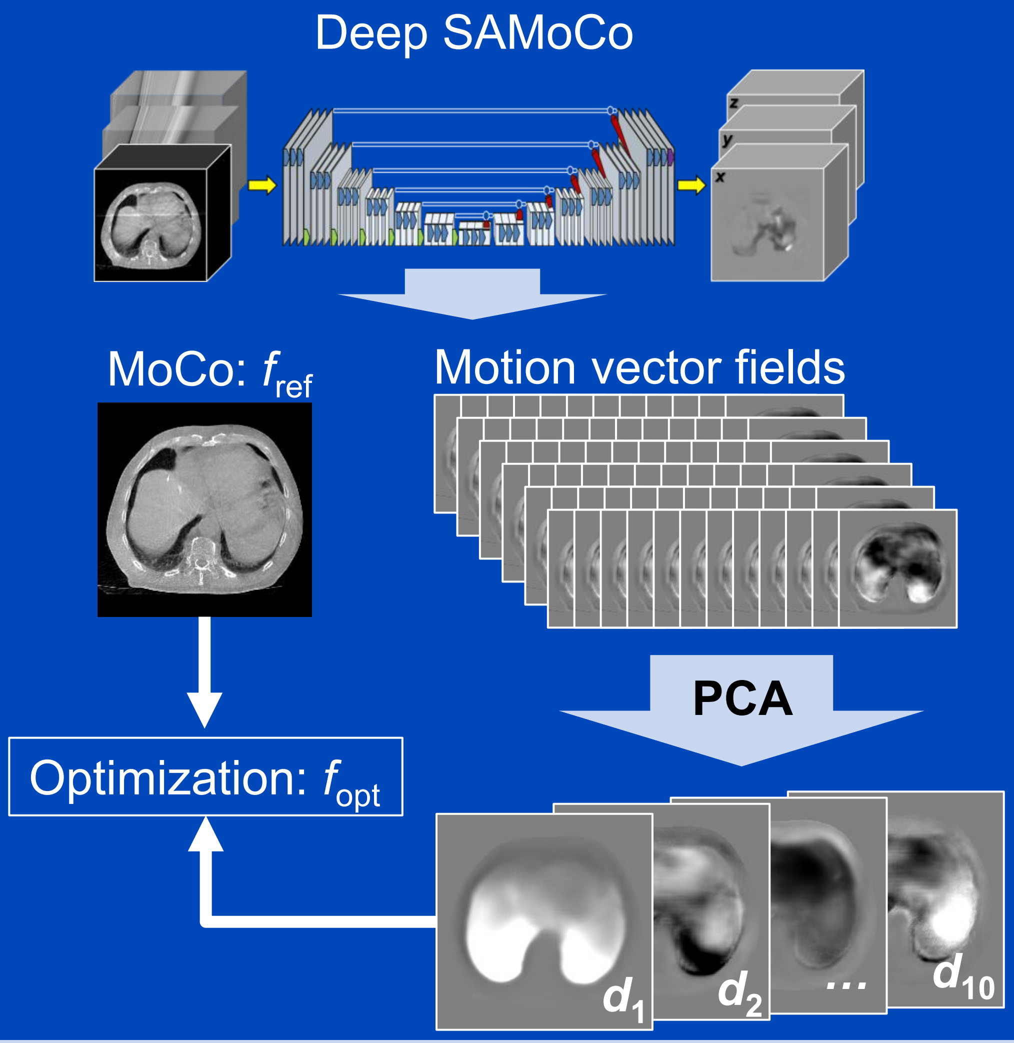
with :

$$S = \text{Similarity function}$$

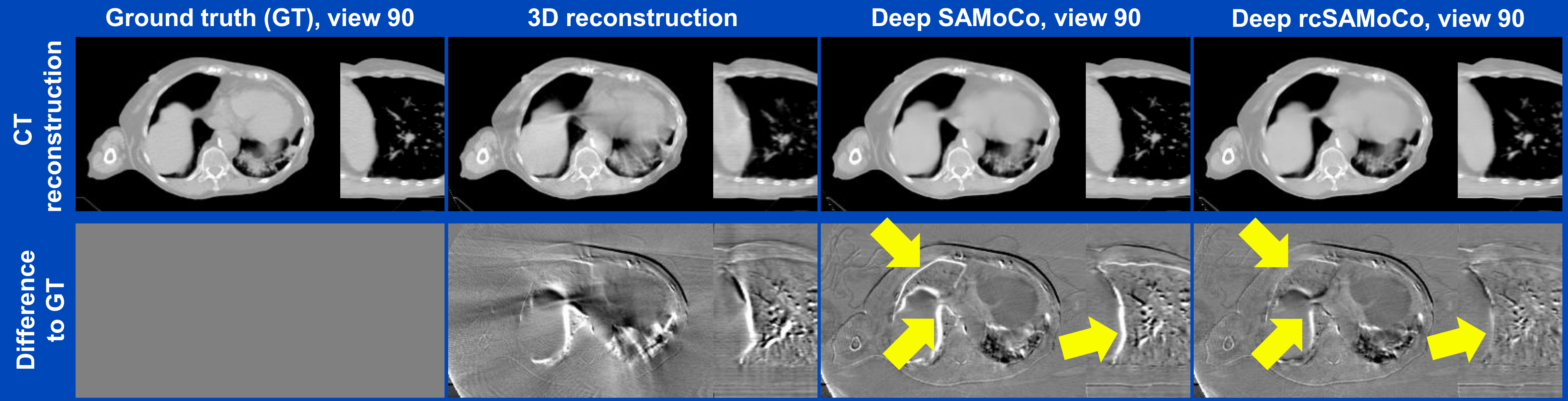
$$f_{\mathrm{ref}} = \text{Reference volume, i.e. initial MoCo}$$

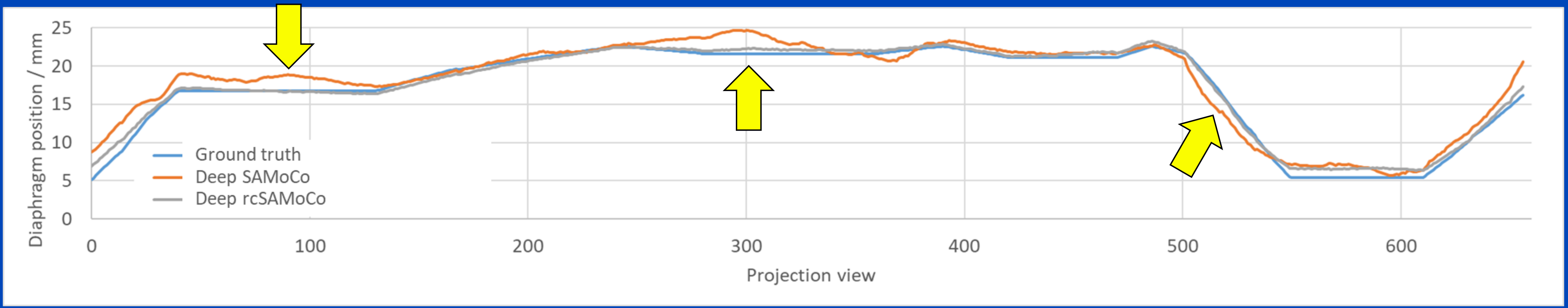
$$\{\boldsymbol{d}_n\} = \text{PCA basis from deep SAMoCo}$$

$$p_i = \text{Projection } i$$



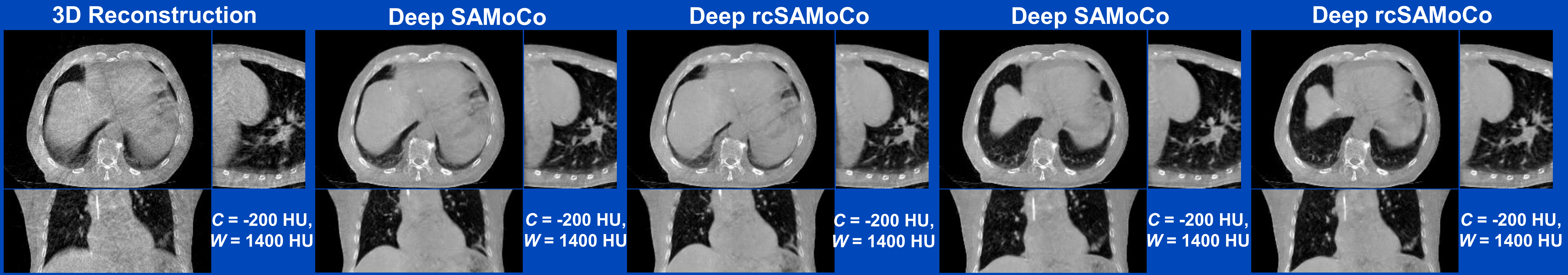
Results: Non-Periodic Simulation, Test Patient #2





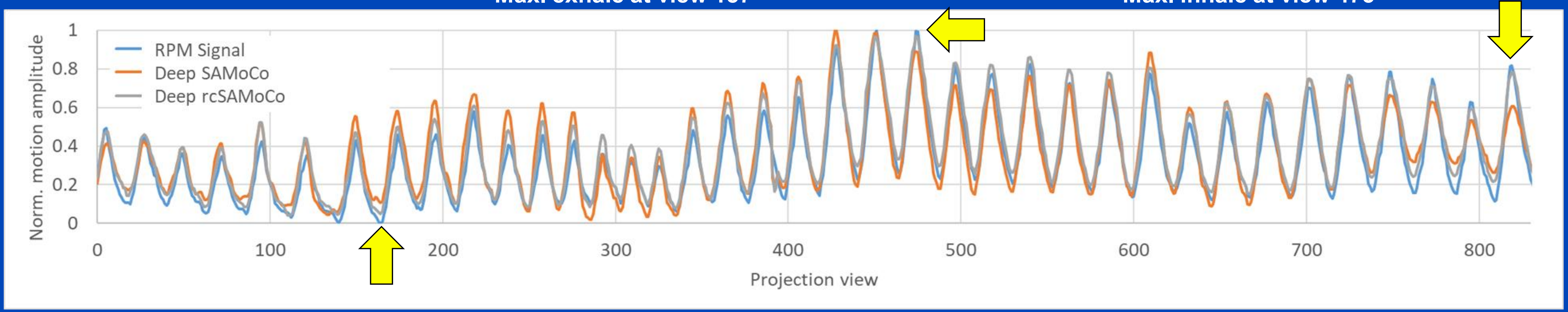
CT reconstructions: *C* = -200 HU, *W* = 1000 HU, difference images: *C* = 0 HU, *W* = 500 HU,

Results: Varian CBCT Measurement



Max. exhale at view 157

Max. inhale at view 475



Conclusions & Outlook

- Deep SAMoCo is able to resolve respiratory motion with single-view temporal resolution.
- High correlation between intrinsic respiration signal and Varian RPM marker block.
- Deep SAMoCo can potentially overcome limitations of gating-based motion compensation.
- Raw data consistency optimization can be easily implemented within the deep SAMoCo framework to further improve accuracy and reliability.
- Already, the deep SAMoCo is able to partially resolve cardiac motion. Further improvement is expected with cardiac-specific training data.

Thank You!

Job opportunities through DKFZ’s international PhD programs or through marc.kachelriess@dkfz.de.
Parts of the reconstruction software were provided by RayConStruct® GmbH, Nürnberg, Germany.

Toy Example

- Use the cylindrical voxel phantom shown on the right and scale it periodically to simulate motion-corrupted projection data:

  $$p_i = \mathsf{X}_i T_i \circ f_{\mathrm{D}},$$

  with f_{D} being the phantom and

  $$T_i : \boldsymbol{r} \to \begin{pmatrix} 1 + 0.1 \cdot \sin(0.15 \cdot i) & 0 & 0 \\ 0 & 1 + 0.1 \cdot \sin(0.15 \cdot i) & 0 \\ 0 & 0 & 1 \end{pmatrix} \cdot \boldsymbol{r}$$

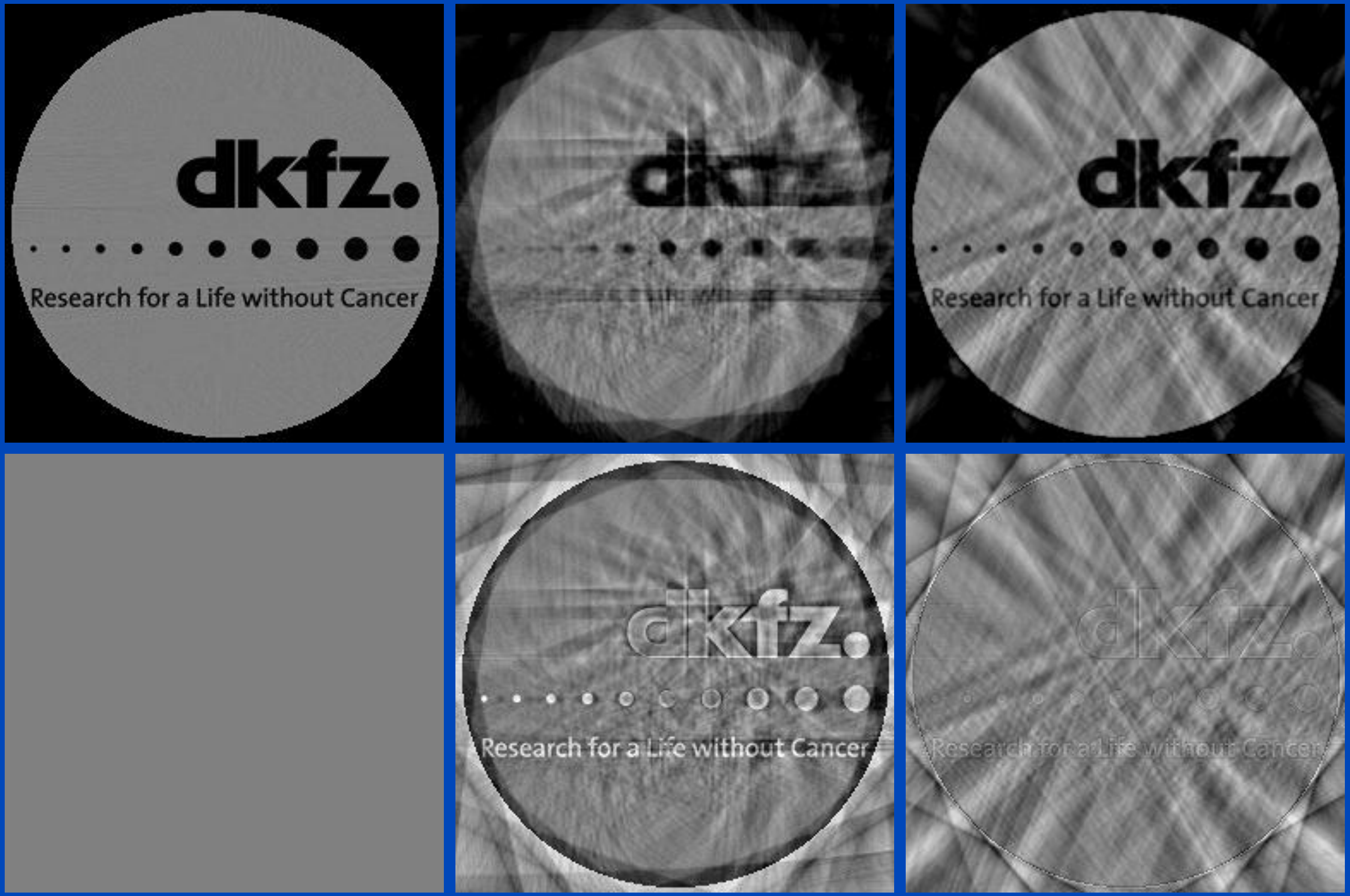
  representing the periodic scaling in the axial plane.
- For our purpose, the motion frequency was chosen to correspond to a typical number of respiratory cycles during a 60 s CBCT scan.
- Due to the simplicity of T_i, the SAMoCo can be performed using the exact inverse of T_i.

Results

Ground truth | 3D reconstruction | SAMoCo with known DVFs

CT reconstruction

Difference to ground truth

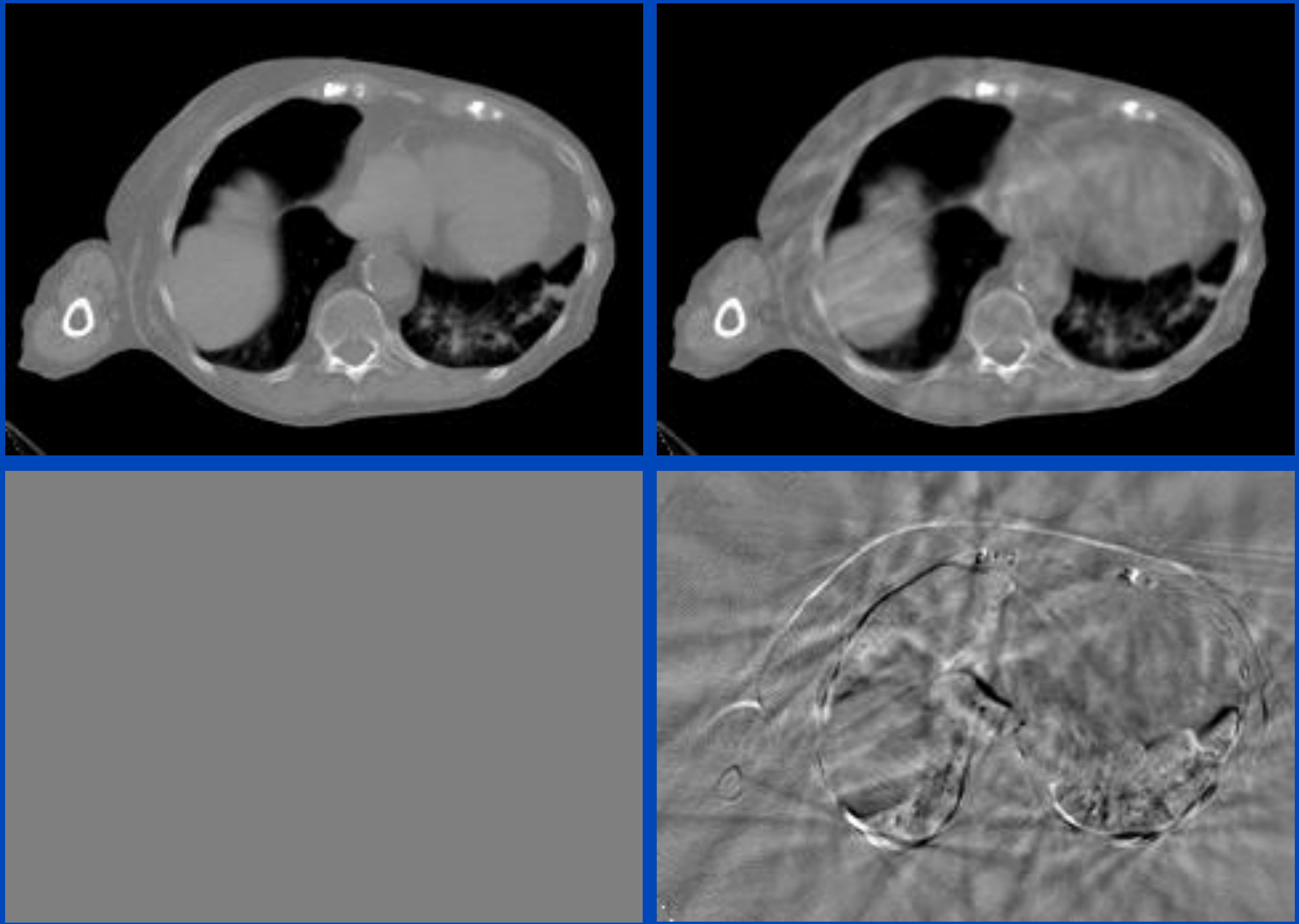


Results: Simulation Study

Ground Truth (GT) | SAMoCo

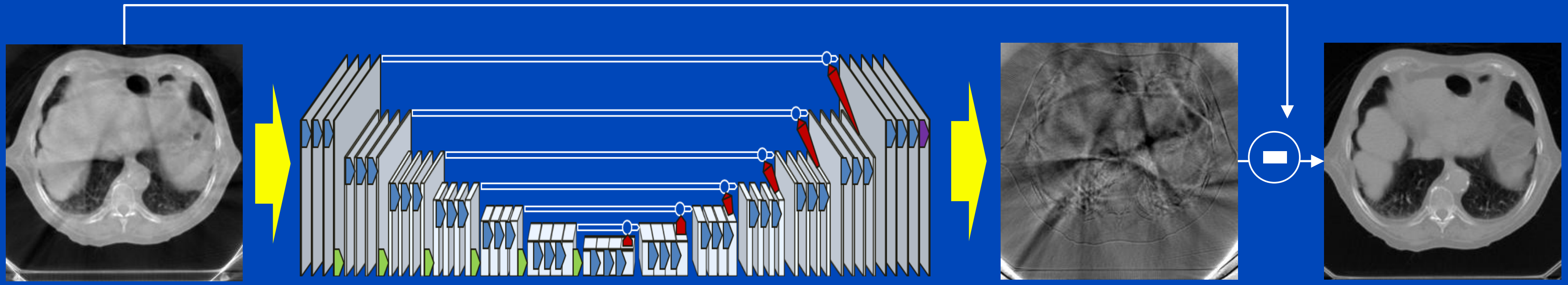
Reconstruction

Difference to GT



Top: C = 0 HU, W = 1500 HU, bottom: C = 0 HU, W = 750 HU

Improving Image Quality



Network (modified U-Net)

$$f_{\mathrm{in}} = \sum_{i}^{N} T_i^j \circ \mathrm{X}_i^{-1} \mathrm{X}_i f_i \qquad\qquad f_{\mathrm{lbl}} = \frac{1}{N} \sum_{i}^{N} T_i^j \circ f_i$$

- Use WashU dataset and take consecutive phases f_i=WashU[$c(i)$%10]. $c(i+1) = c(i)+1$ if rnd > 0.7, $c(i)$ else.
- Simulation of 20 random motion patterns per patient.
- Motion compensation of scan to random phase j.
- Forward- and backprojection in shifted detector geometry (Varian TrueBeam).
- Testing on real CBCT scans.