Dynamic MRI using Smoothness Regularization on Manifolds (SToRM)

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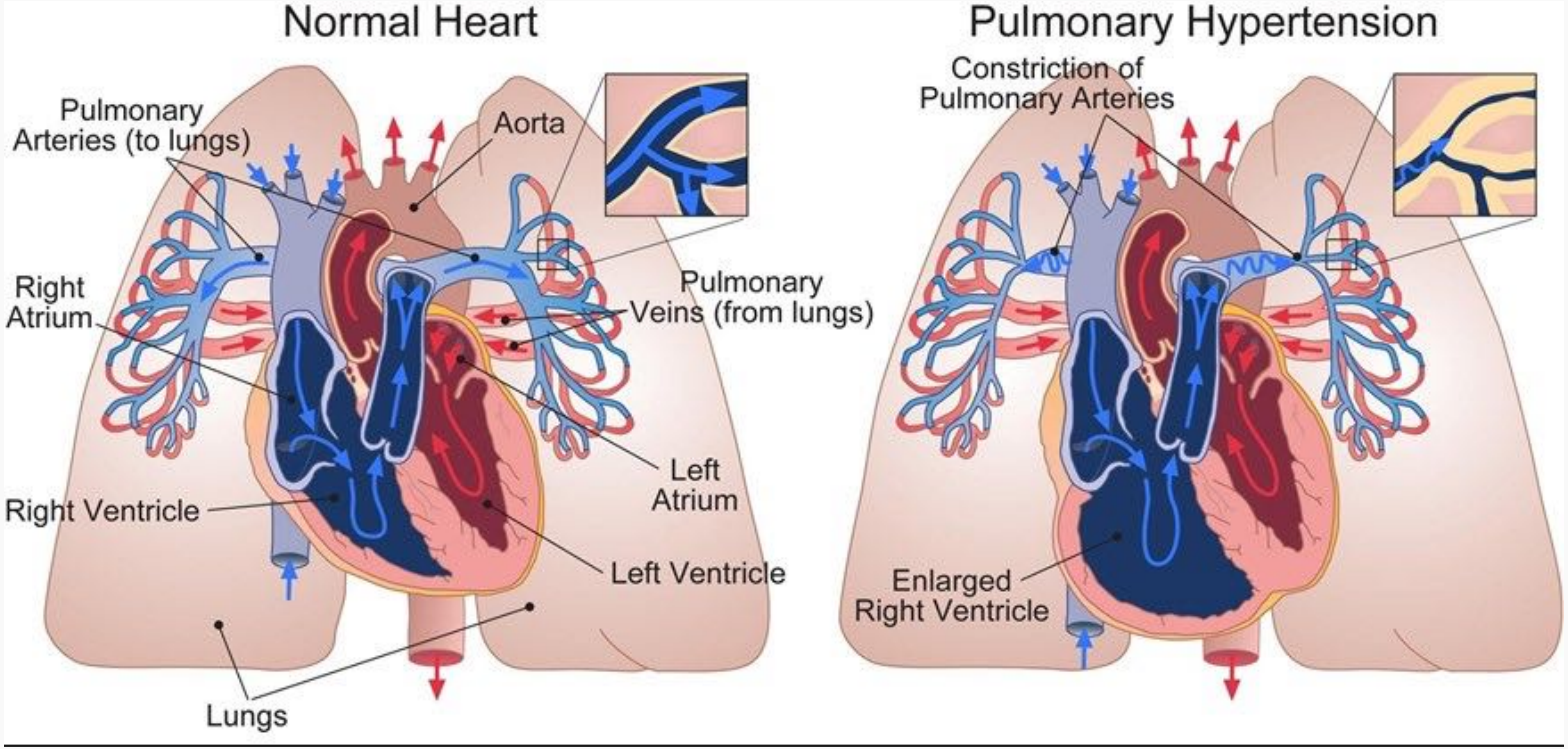
Main thrust: free breathing cardiopulmonary imaging



Free breathing and ungated cardiac/lung MRI

- Breath-held cardiac CINE MRI

  Long breath-hold durations: challenging for several patients

- Accelerated breath-held CINE

  Compressed sensing, Robust PCA, Deep Learning Methods

  Lustig et al, Sandino et al 2020, Schlemper et al, 2018

- Self gating FB and UG methods: motion resolved recovery

  XD-GRASP: Feng et al, MRM 2016, Multi-tasking: Christodolou, 2016, PROST: Bustin et al, 2020

  Bandlimited assumption to recover the gating signals

  Vulnerable to bulk motion

  Slice by slice recovery: difficult to merge the information

- Subspace methods

  Extreme MRI: Ong et al, MRM 2020, k-t SLR: Lingala et al, 2011

  Basis functions estimated from navigators or using nuclear norm minimization

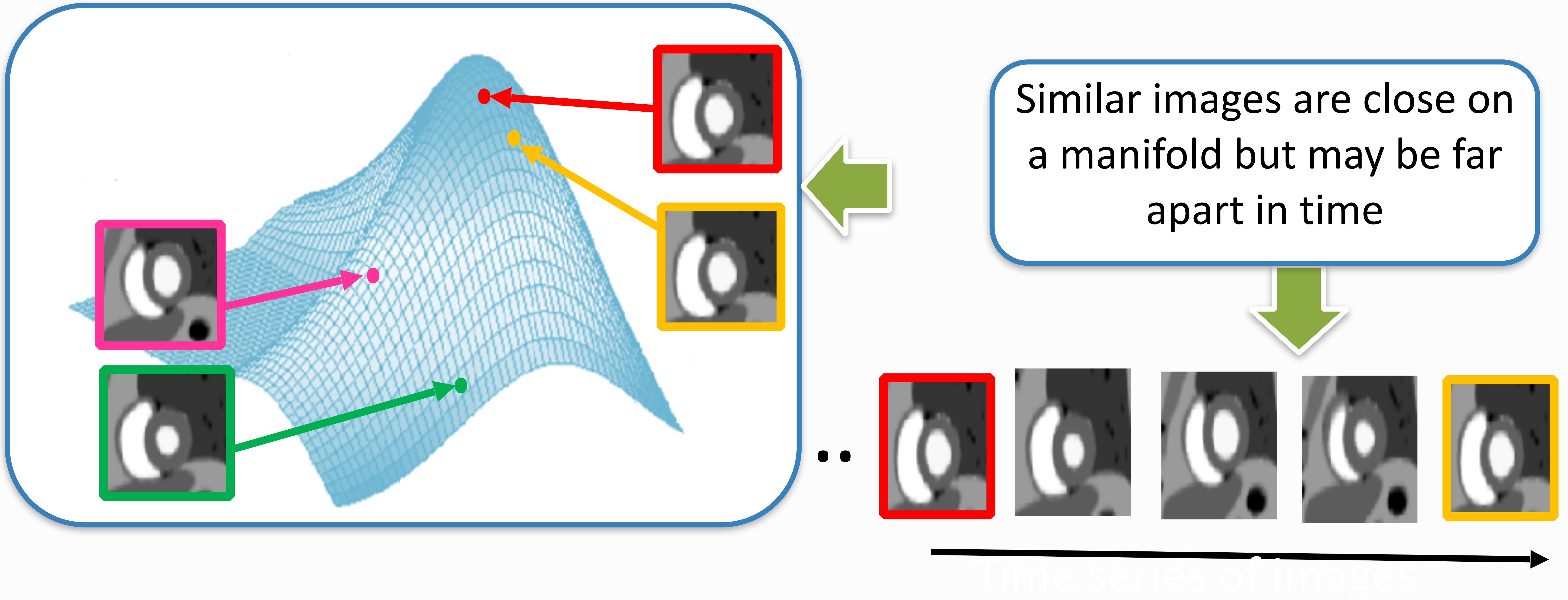
  Linear representation: tradeoff between number of basis functions and data

Manifold structure of FB & ungated cardiac MRI

FB & UG images

Images: points in high dimensional space

Smooth function of cardiac & respiratory phase

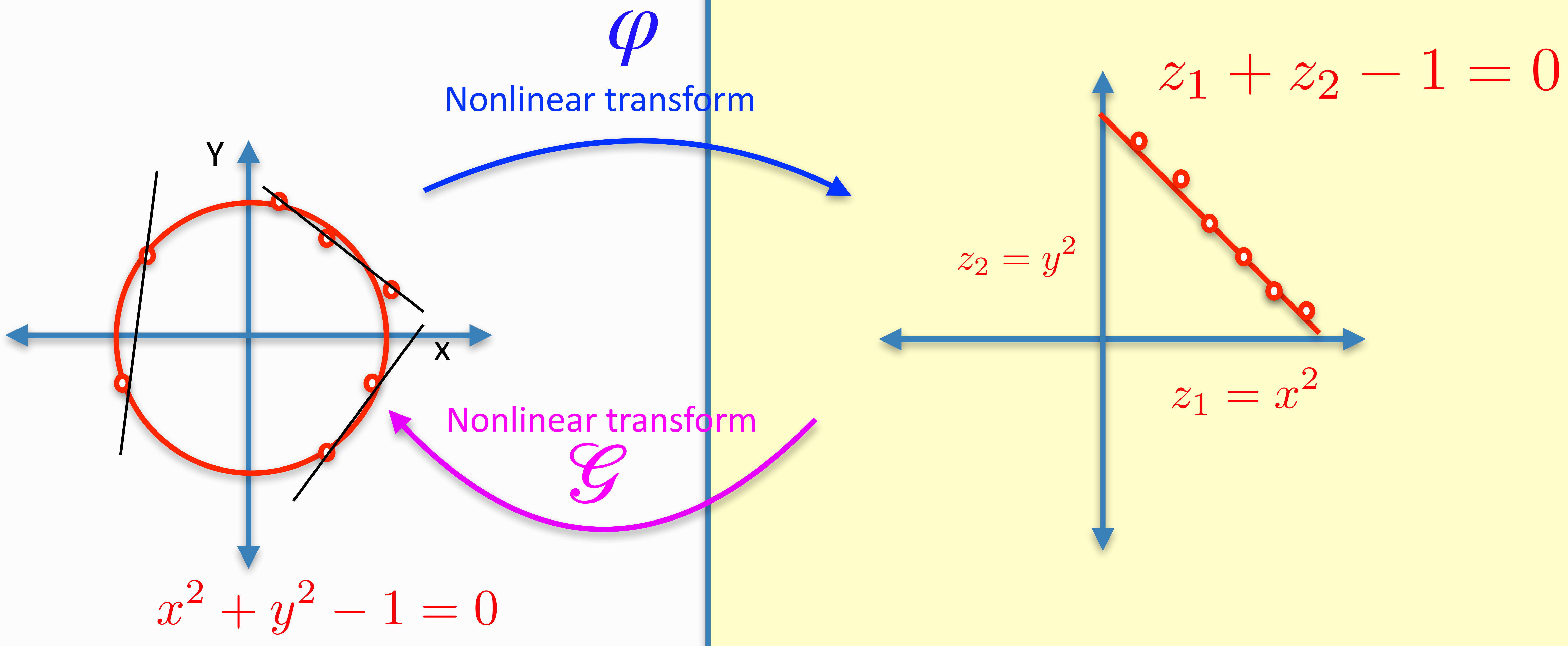


How do we use the manifold model to recover the images ?

Non-linear mapping: linear subspace

Points on a circle

Points on a line

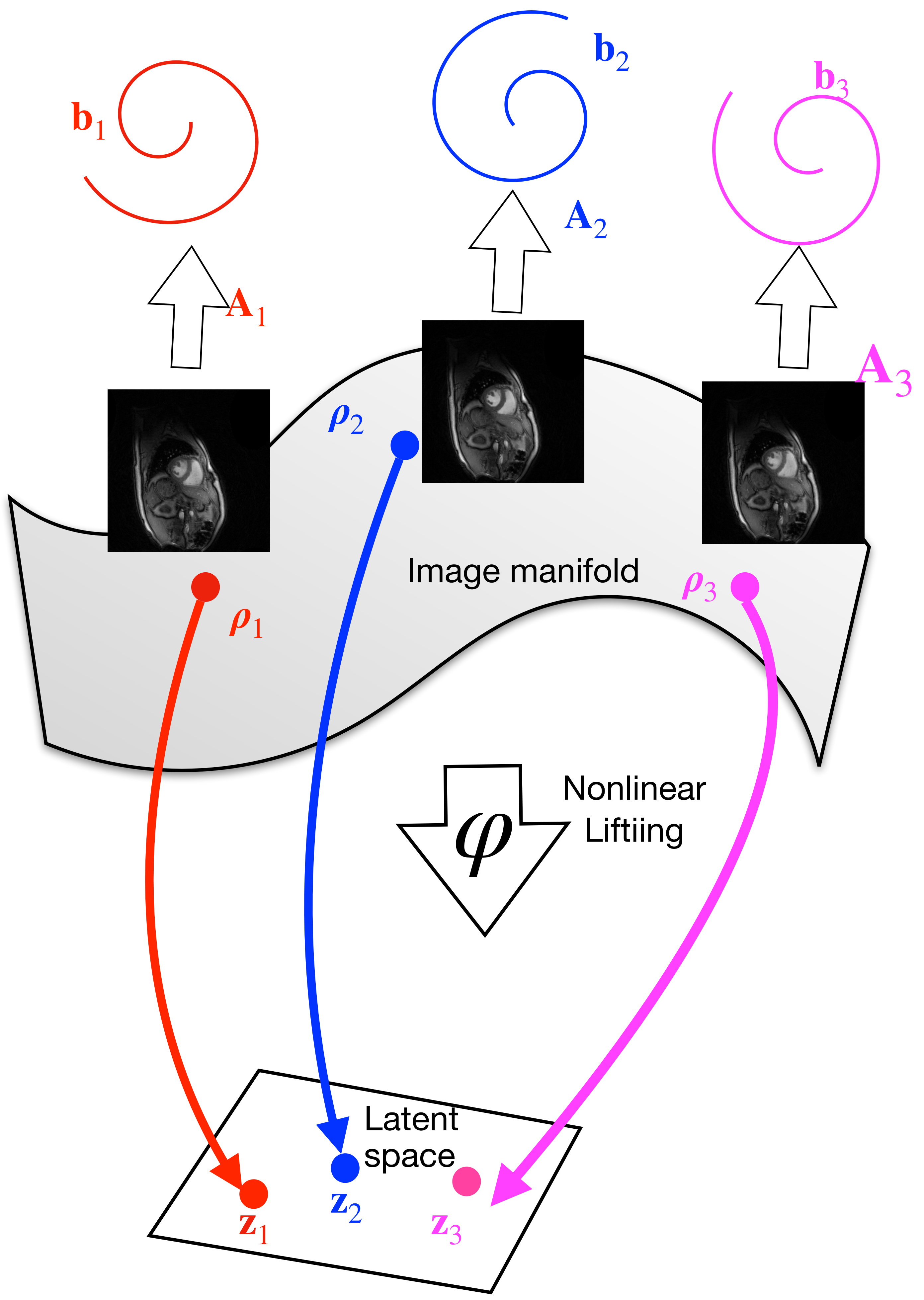


Modeling with subspaces inefficient

SmooThness Regularization on Manifold (SToRM)

[Poddar, Jacob, TMI 2016, TCI, 2019](#)

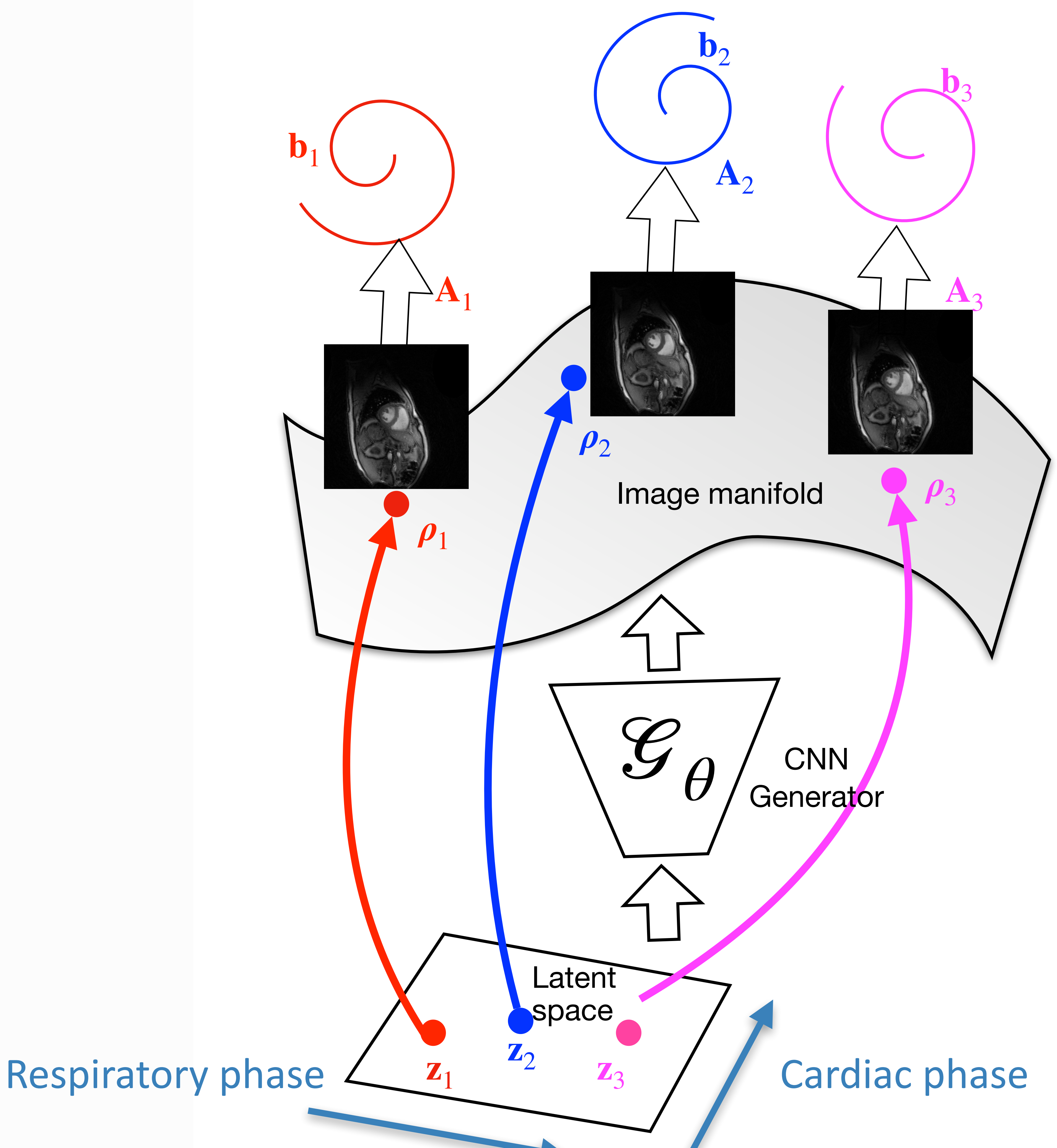
[Ahmed et al, TMI, 2020](#)



(a). Analysis STORM

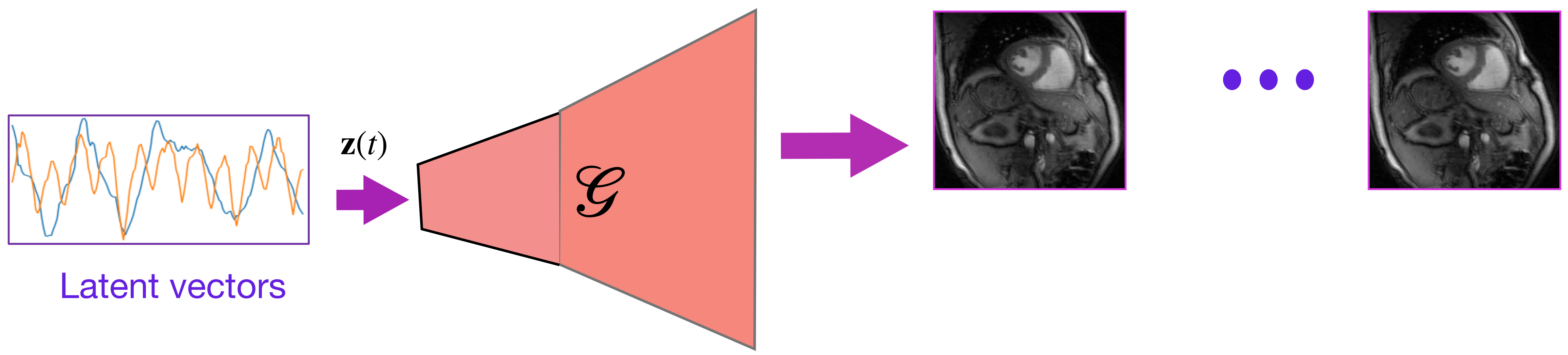
1. Need to store all the images in the time series!
2. Difficult to add spatial regularization!
3. Difficult to extend to high dimensions!

g-SToRM: dual approach of SToRM



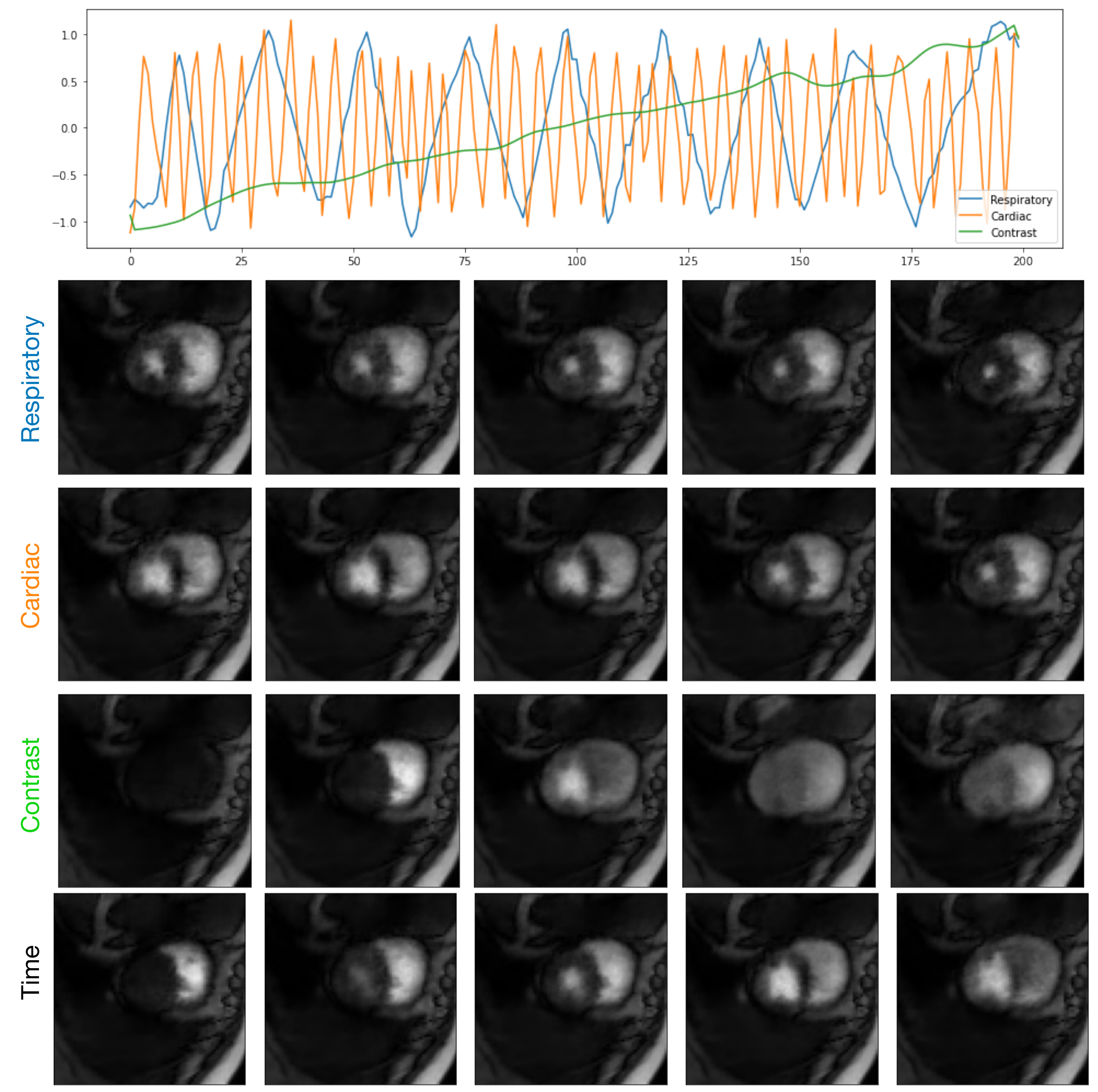
(b). Synthesis/Generative STORM

- Images: nonlinear mapping of latent vectors



- Learn generator and latent vectors from data

- Generate images on demand



Generative SToRM: learning a generative model from data

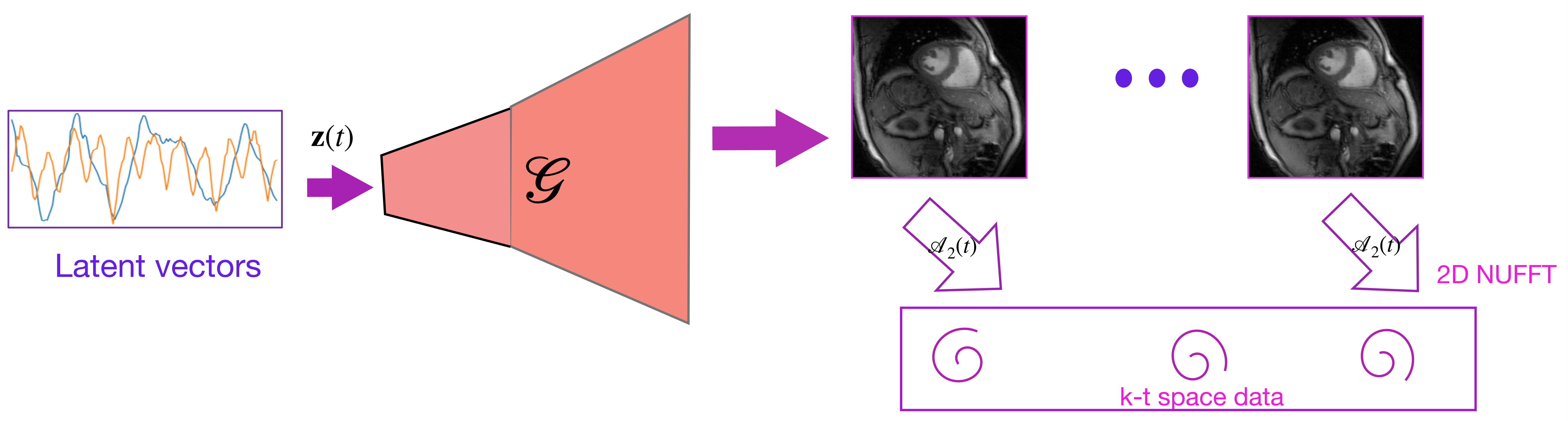
Compact model: image generated by $\mathcal{G}$

$$\rho_i = \mathcal{G}_{\theta}[z_i]; \quad i = 1,..,N$$

Learn unknown parameters from measured data

$$\{\mathbf{Z}, \theta\} = \arg\min_{\mathbf{Z},\theta} \sum_i \|\mathcal{A}_i \left(\mathcal{G}_{\theta}[z_i] - \mathbf{b}_i\right)\|^2$$

Generalization of DIP: multi-image/ensemble of measurement schemes

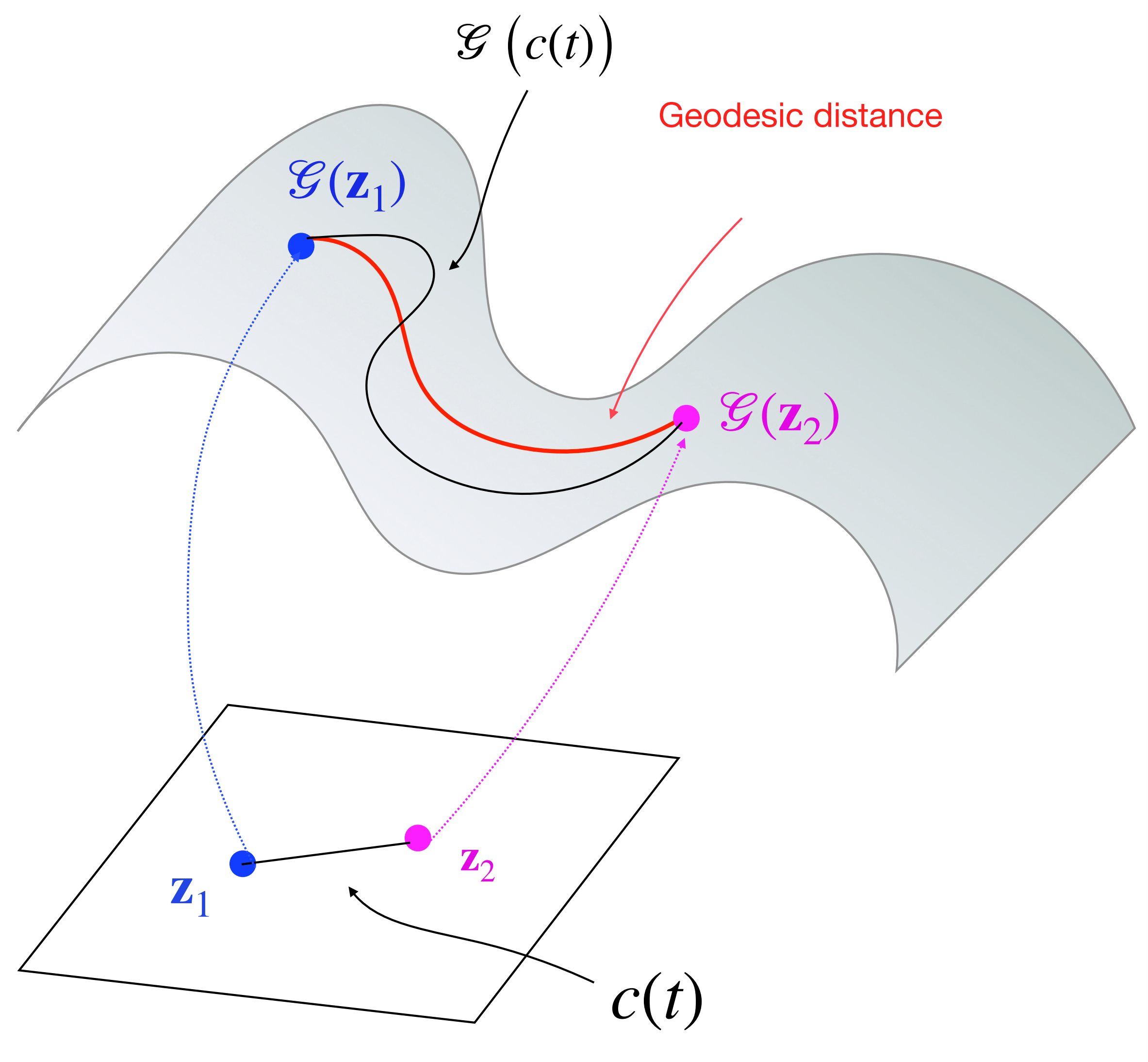


Zou et al, Generative STORM: TMI 21

Learn sensible mappings

Distance in latent space should match distance on manifold

$$\mathrm{dist}_{\mathscr{M}}\left(G[\mathbf{z}_1], G[\mathbf{z}_2]\right) \approx \|\mathbf{z}_1 - \mathbf{z}_2\|$$



Relation between distances

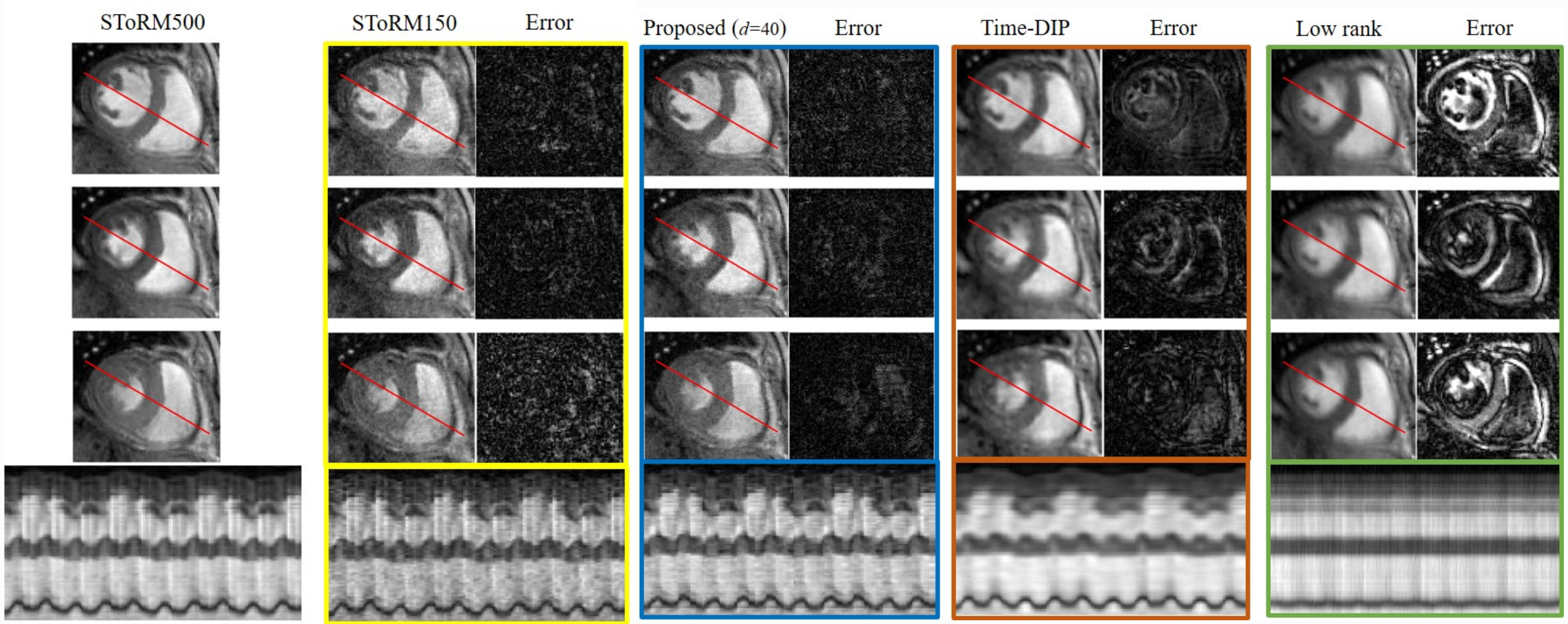
$$\mathrm{dist}_{\mathscr{M}}\left(G[\mathbf{z}_1], G[\mathbf{z}_2]\right) \leq \|\mathbf{z}_1 - \mathbf{z}_2\| \quad \|J_z(\mathscr{G})\|_F$$

High Jacobian $J_z(\mathscr{G})$: lack of correspondence between spaces

Add regularization term

$$\{\mathbf{Z}, \theta\} = \arg\min_{\mathbf{Z},\theta} \sum_i \|\mathscr{A}_i\left(\mathscr{G}_\theta[\mathbf{z}_i] - \mathbf{b}_i\right)\|^2 + \lambda_1 \underbrace{\|J_z(\mathscr{G}_\theta[\mathbf{z}])\|_F^2}_{\text{network reg.}} + \lambda_1 \underbrace{\|\nabla_t \mathbf{z}\|_F^2}_{\text{latent reg.}}$$

Comparison with competing methods



Scan time: 40 s/slice

Scan time: 12 s/slice

Scan time: 12 s/slice

Scan time: 12 s/slice

Scan time: 12 s/slice

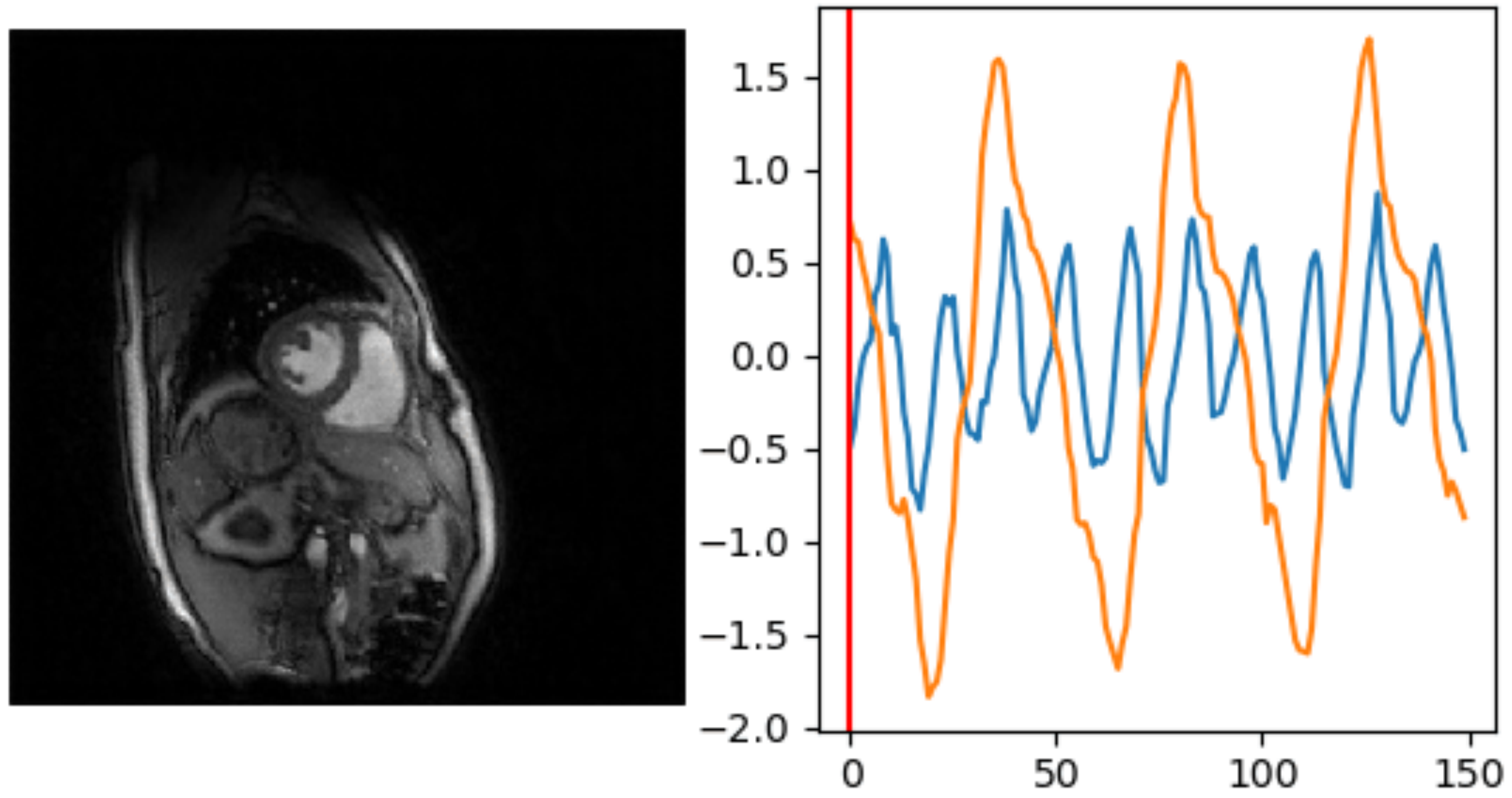
Methods	SToRM500	SToRM150	Propsed	Time-DIP
SER (dB)	NA	17.3	**18.2**	16.7
PSNR (dB)	NA	32.7	**33.5**	32.0
SSIM	NA	0.86	**0.89**	0.87
Brisque	**35.2**	40.2	37.1	42.9
Time (min)	47	13	17	57

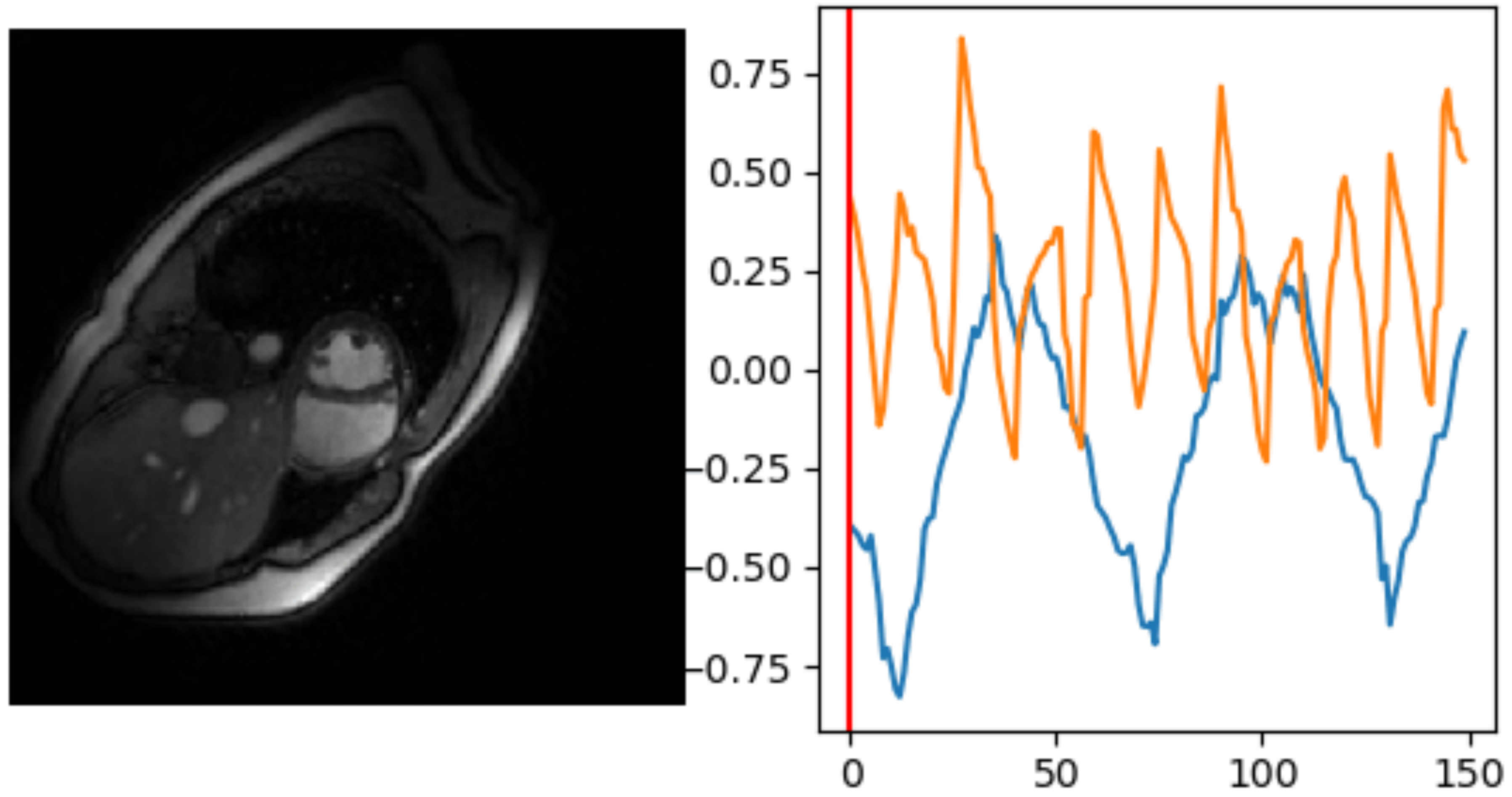
Zou et al, Generative STORM: TMI 21

Zou et al, Generative STORM: ISBI 21

Best paper award

Results





[Zou et al, Generative STORM: TMI 21]()

[Zou et al, Generative STORM: ISBI 21]()
[Best paper award]()

Dynamic MRI using SToRM

- Generative SToRM (g-SToRM) model
  - Brief review of SToRM
  - g-SToRM for single slice dynamic MRI
- Multi-slice dynamic MRI using g-SToRM
  - Background
  - Joint alignment and reconstruction of multi-slice dynamic MRI
- MoCo-SToRM
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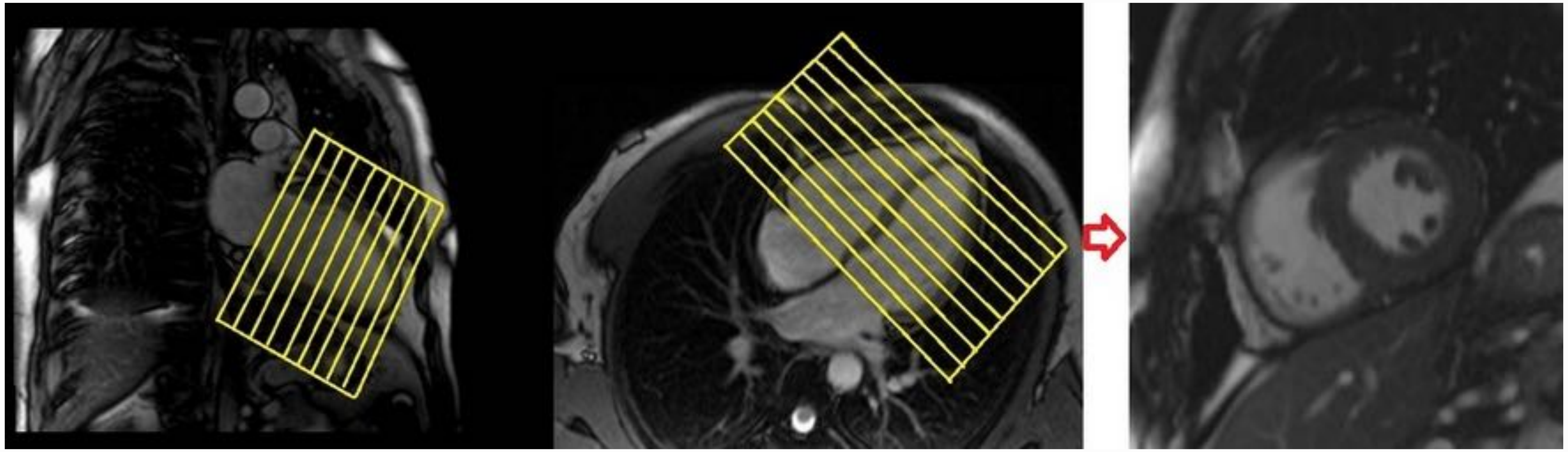
  - MoCo-SToRM

Multi-slice free-breathing acquisition



Multi-slice acquisition is preferred in cine MRI over 3D

- Good myocardium to blood-pool contrast because of in-flow effects
- Higher temporal resolution

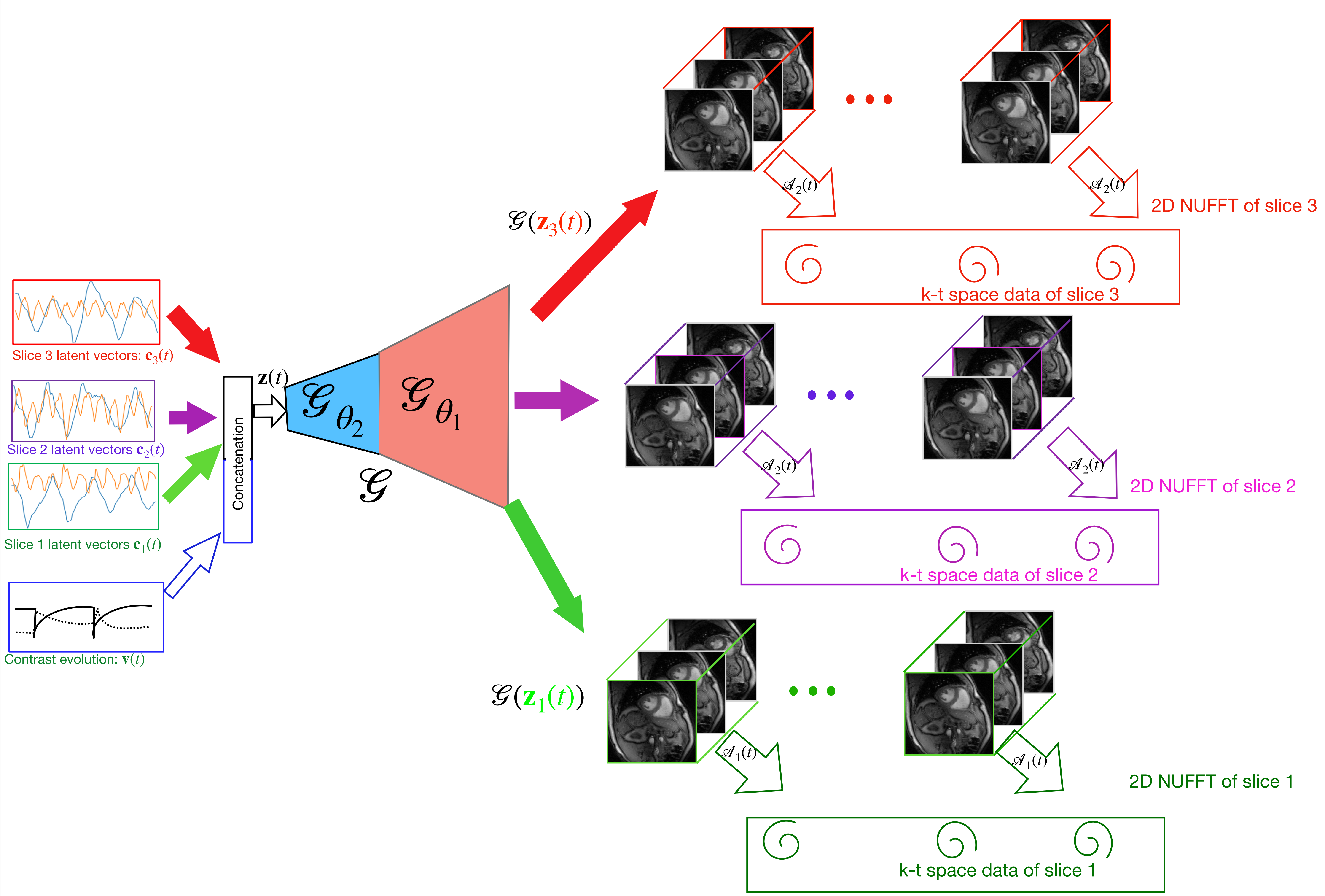
Current approaches: independent recovery of slices

- Different breathing patterns and heart-rate

Challenges

- Cannot exploit inter-slice redundancies
- Need to align the slices/phases post-reconstruction

Latent space alignment: multi-slice to 3D

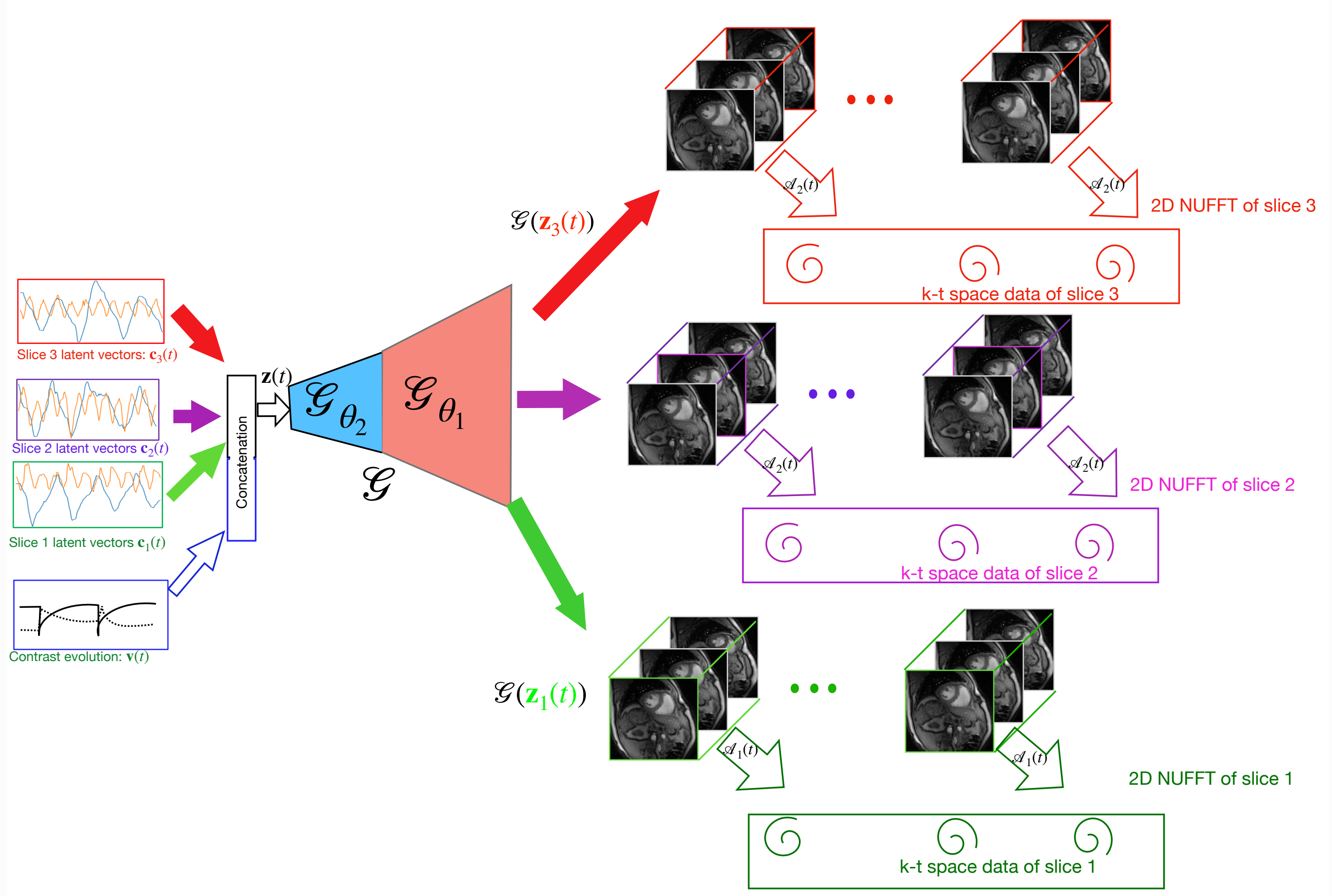


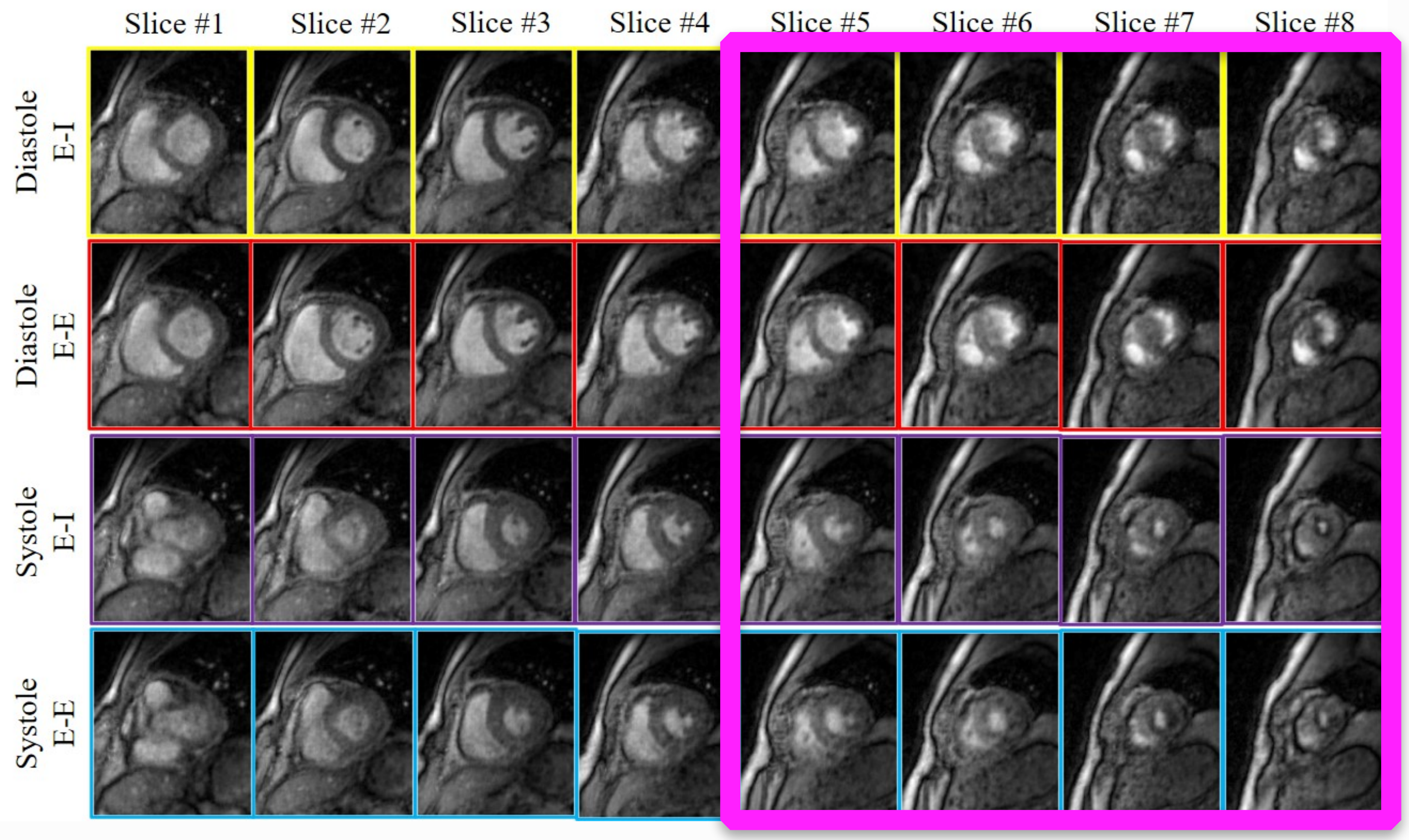
Idea: Jointly learn a 3D-generative model from multi-slice data

Each slice will have its own latent vectors that capture cardiac/respiratory motion

Post-recovery, excite with the latent vectors of any slice to create aligned volume time series

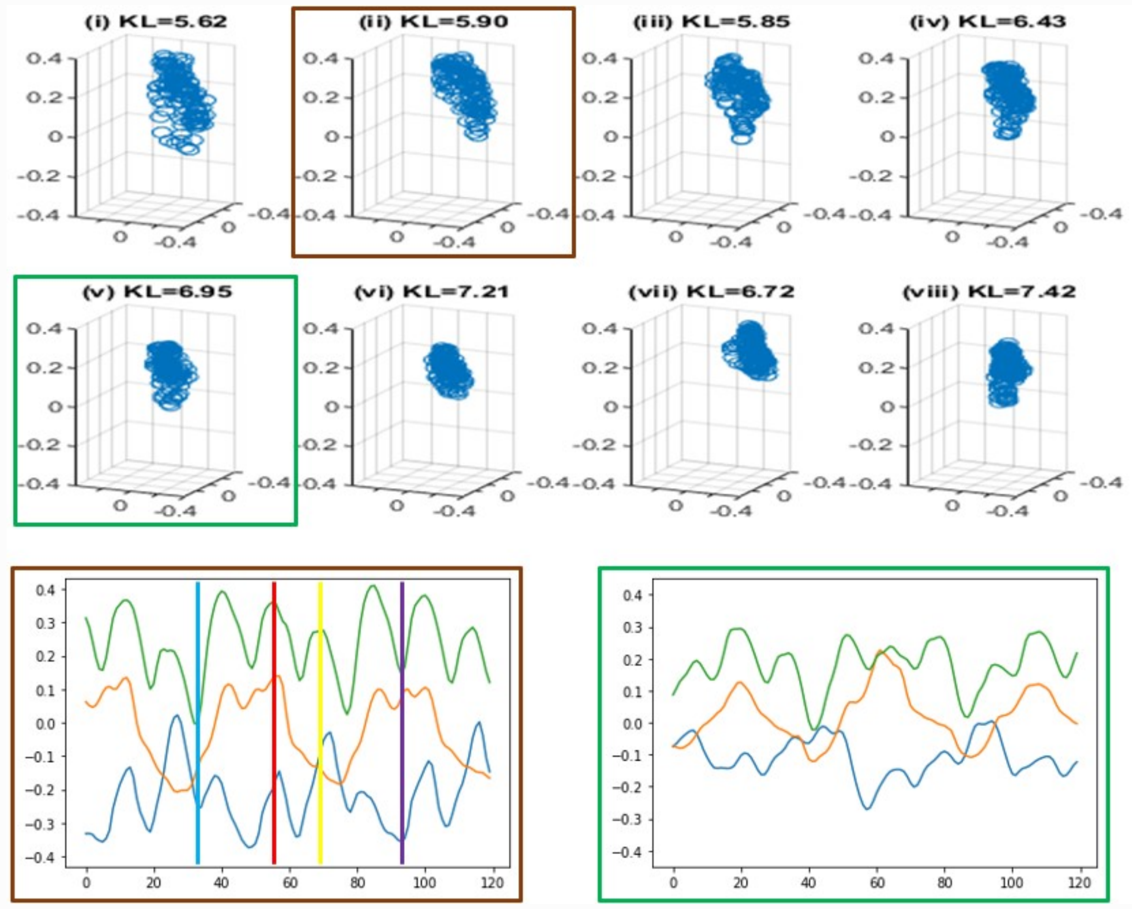
Challenge





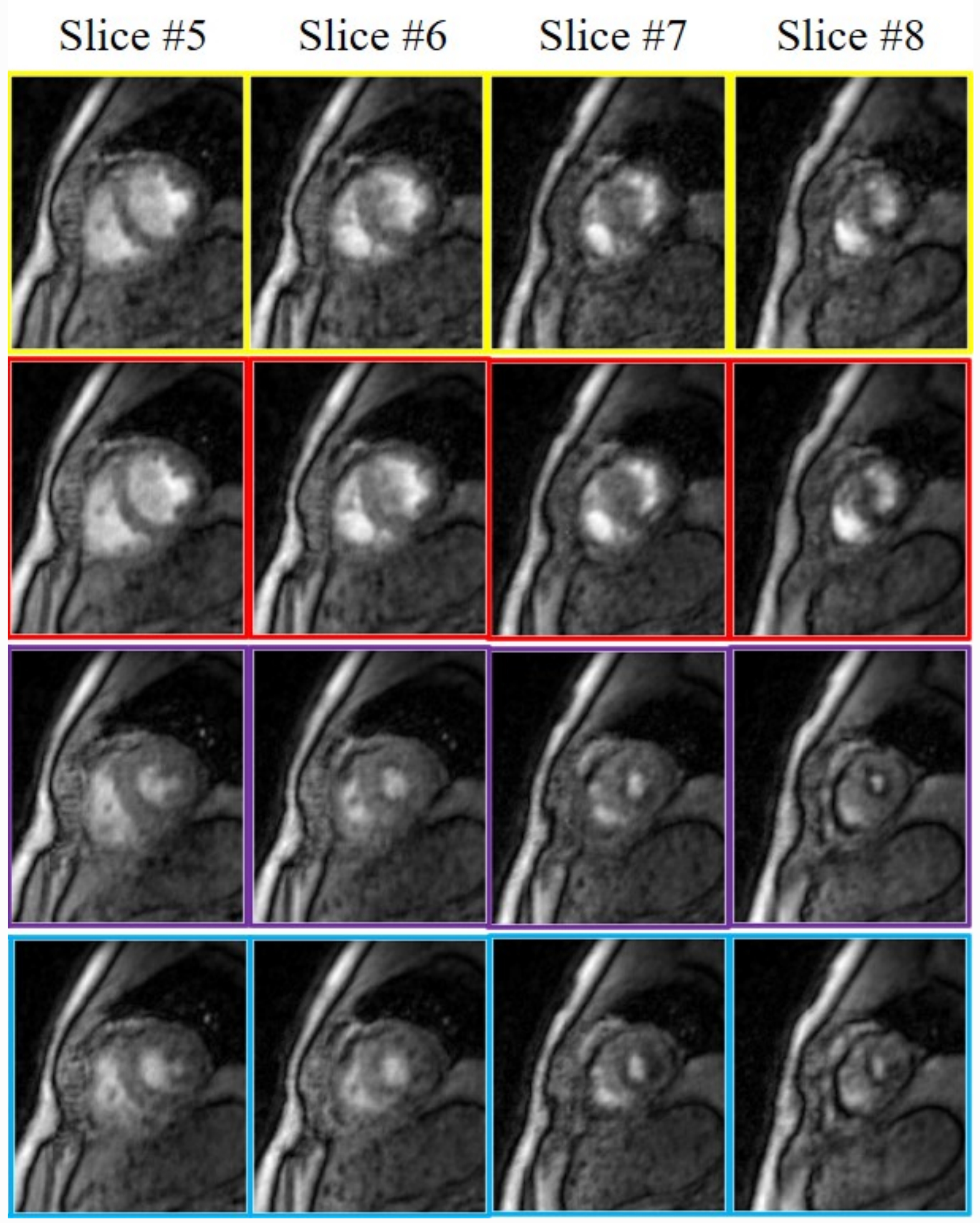
(b) Alignment and recovery of eight slices using G-SToRM

Different slices may have different latent distributions

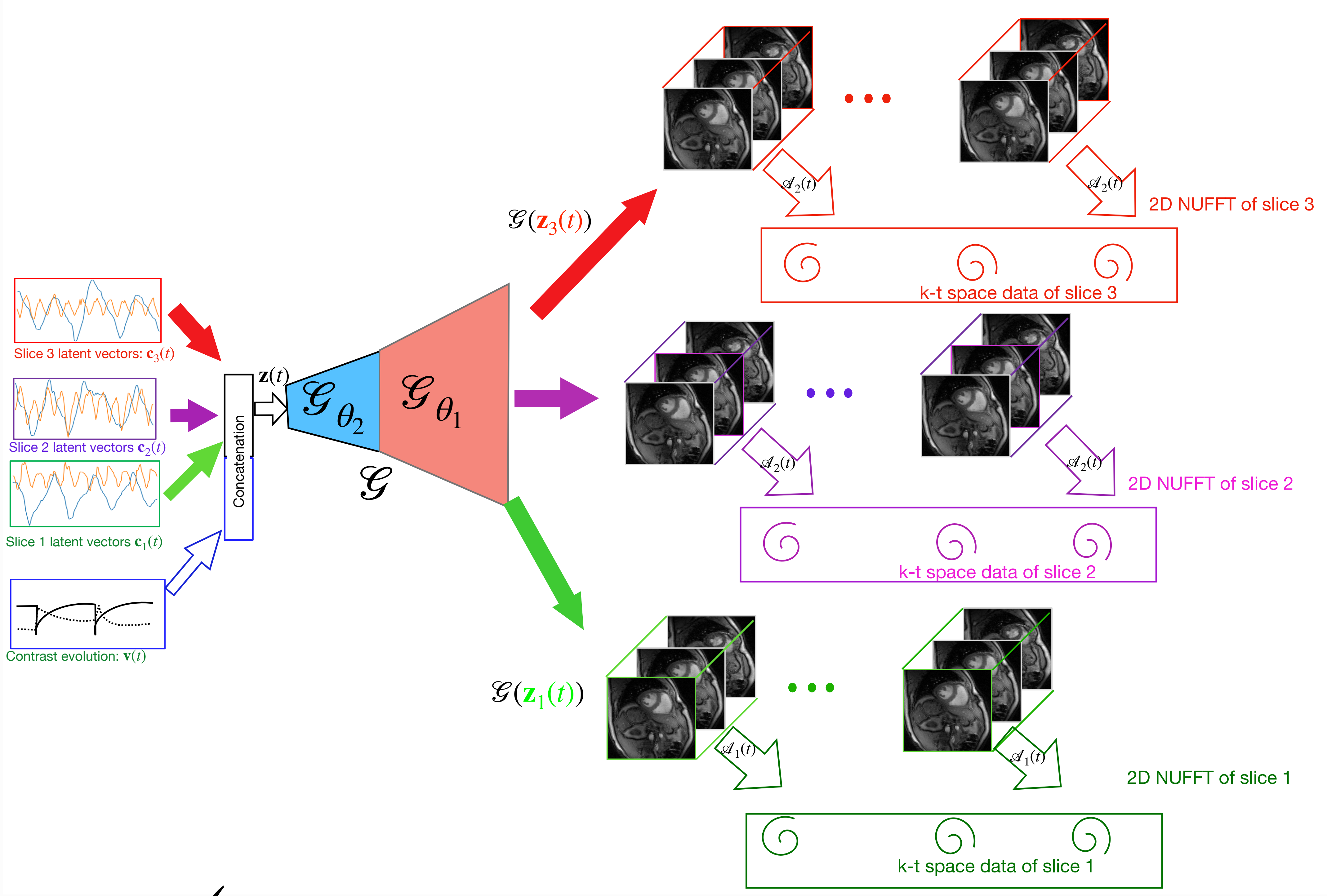


(d) Latent vectors obtained by G-SToRM:MS

Poor reconstructions !!

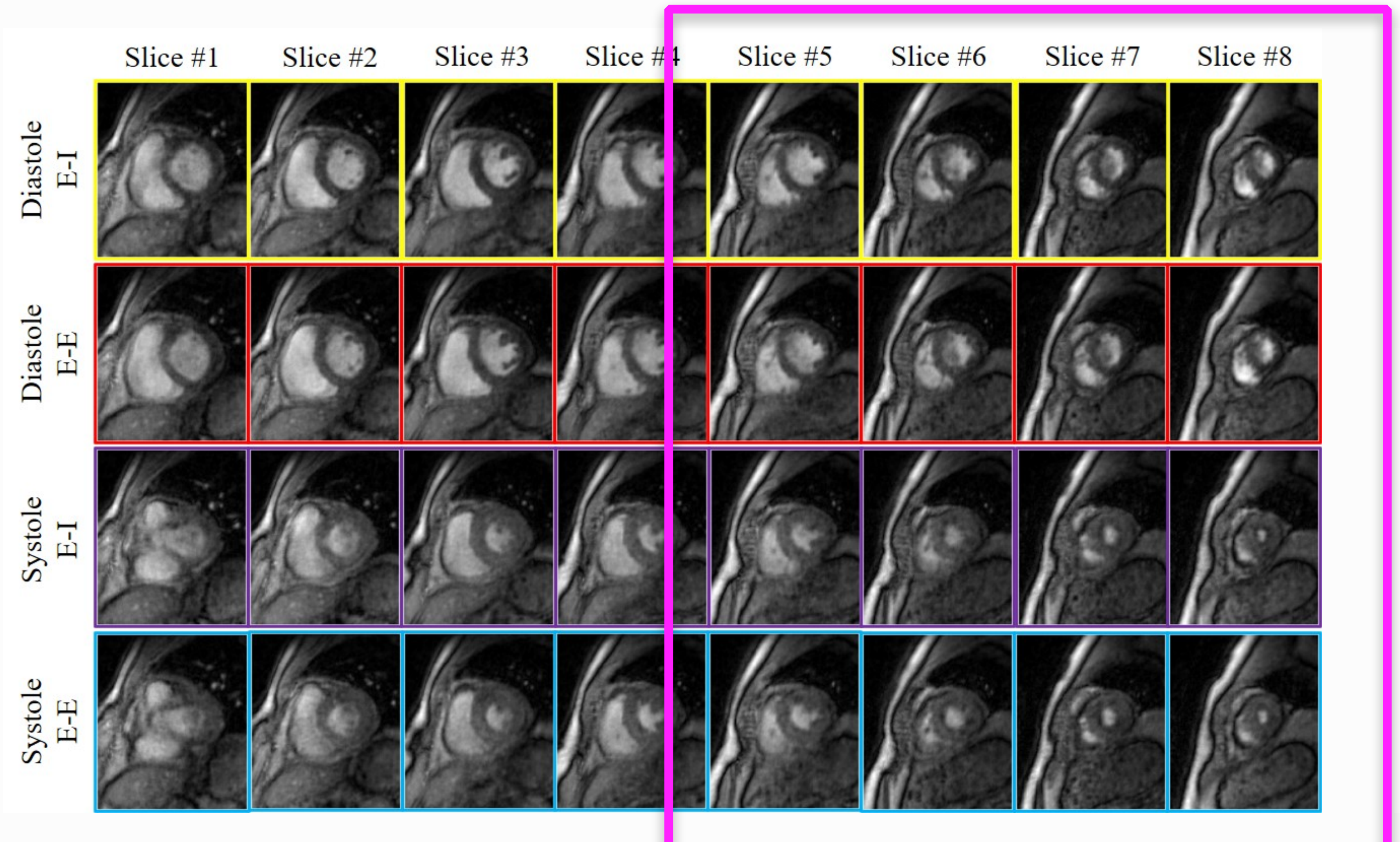


Variational formulation: motivated by VAE

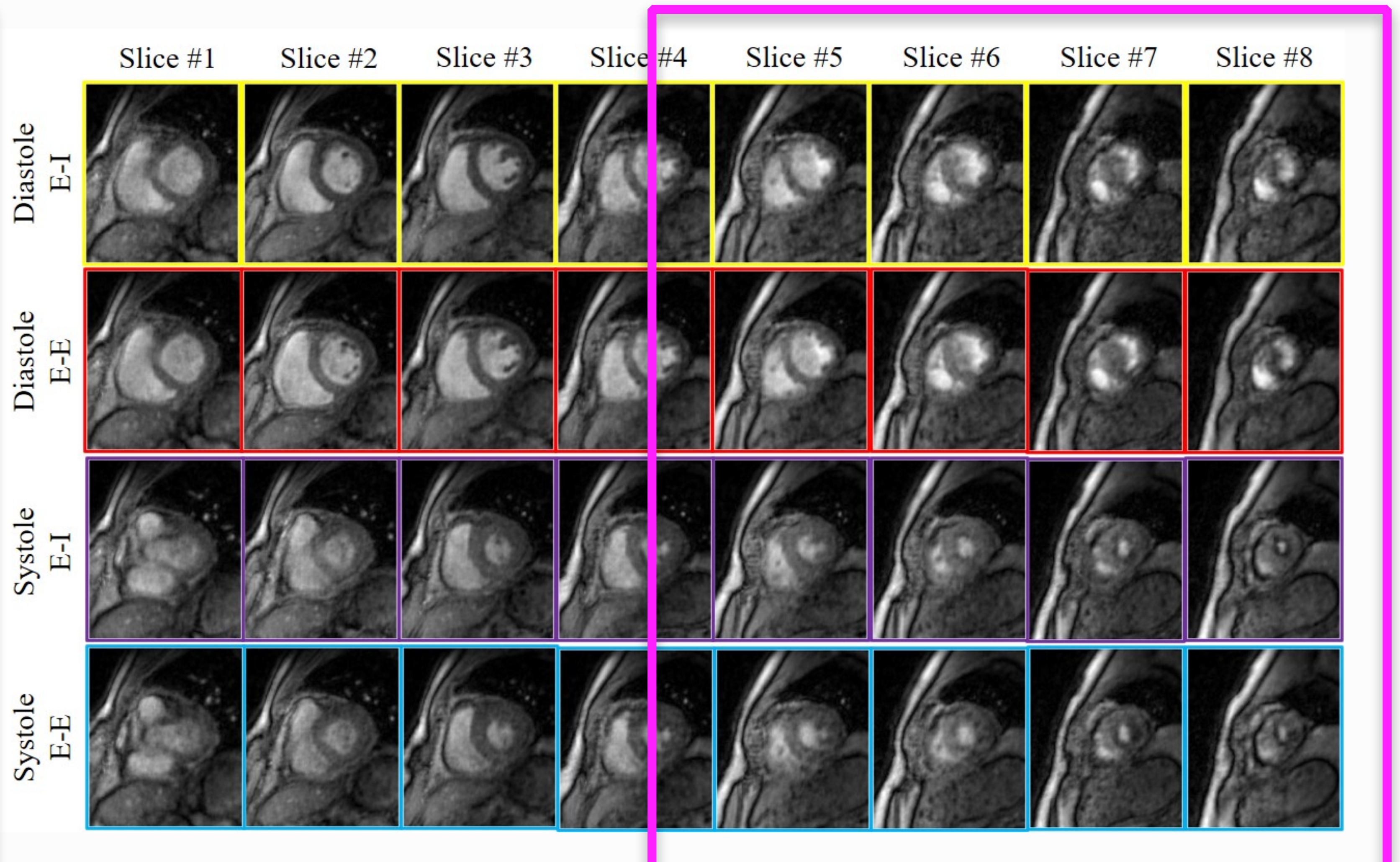


$$\{\mathbf{Z},\theta\} = \arg\min_{\mathbf{Z},\theta} \left(\sum_{i,j} \|\mathcal{A}_{i,j}\left(\mathcal{G}_{\theta}[z_{i,j}] - \mathbf{b}_i\right)\|^2 + \underbrace{KL(q(z_{i,j})\,|\,p(z)))}_{\text{Gaussian prior}} \right)$$

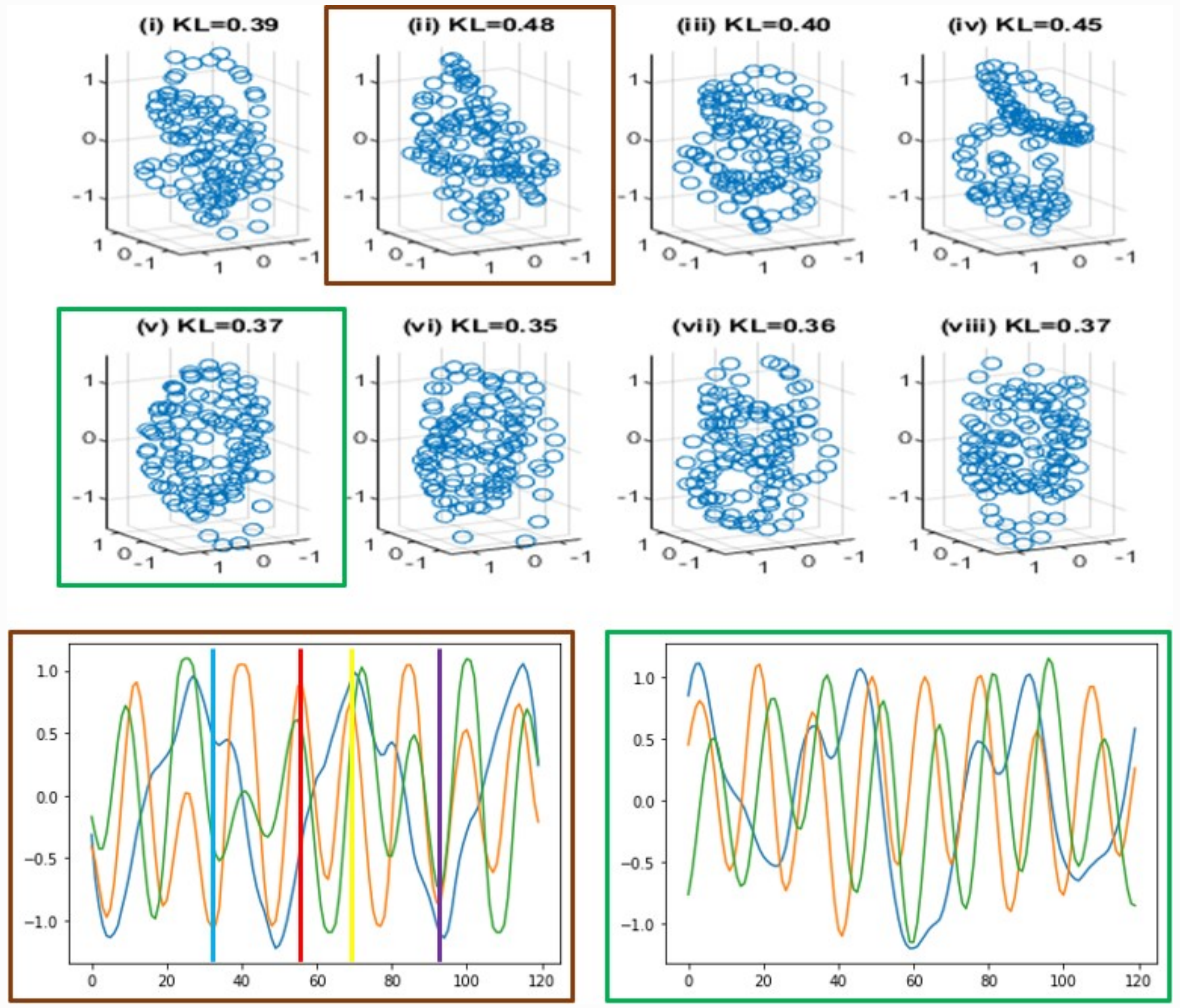
Alignment of latent spaces: KL divergence penalty



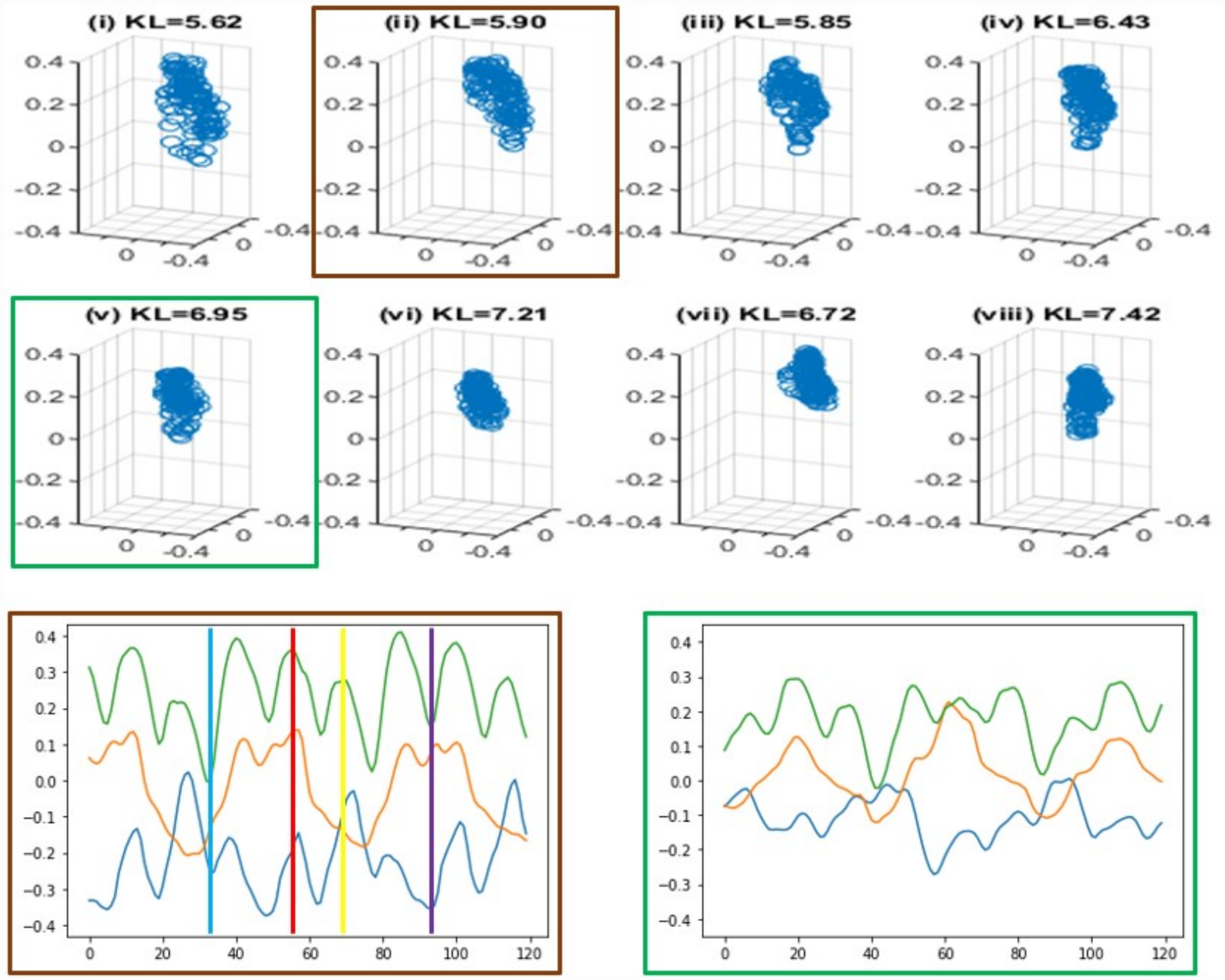
(a) Alignment and recovery of eight slices using V-SToRM



(b) Alignment and recovery of eight slices using G-SToRM



(c) Latent vectors obtained by V-SToRM:MS



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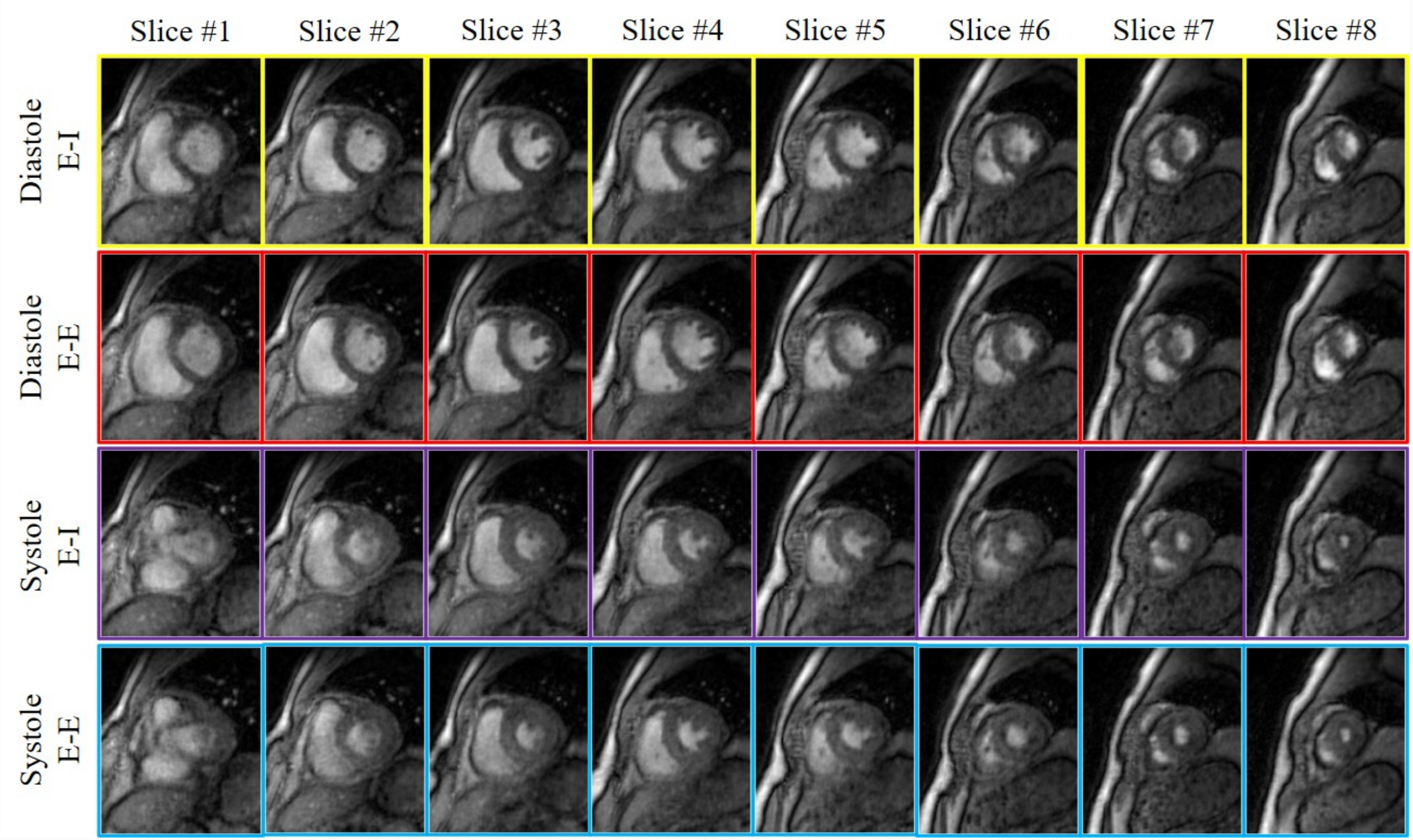
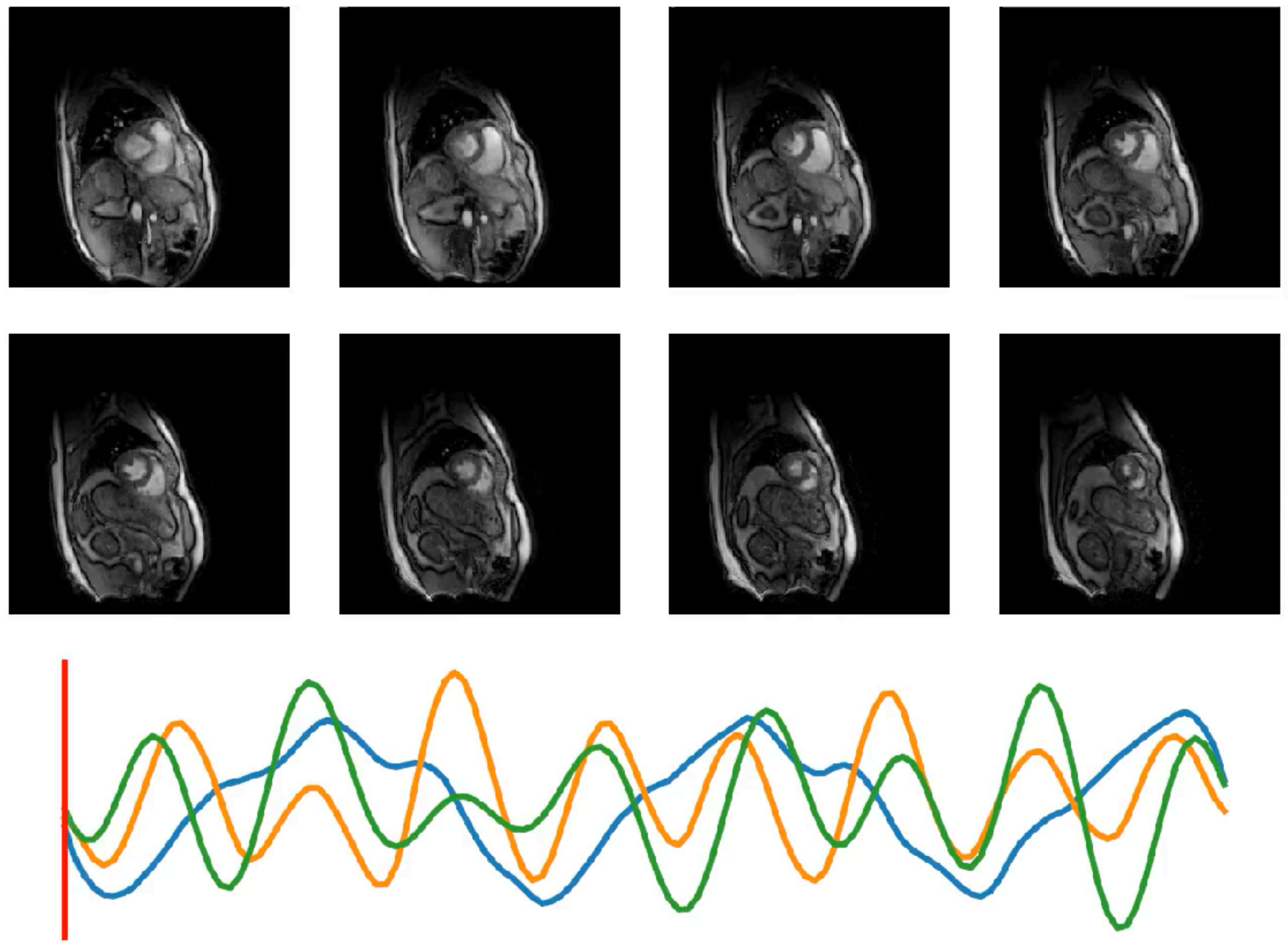
Alignment of latent spaces: KL divergence penalty



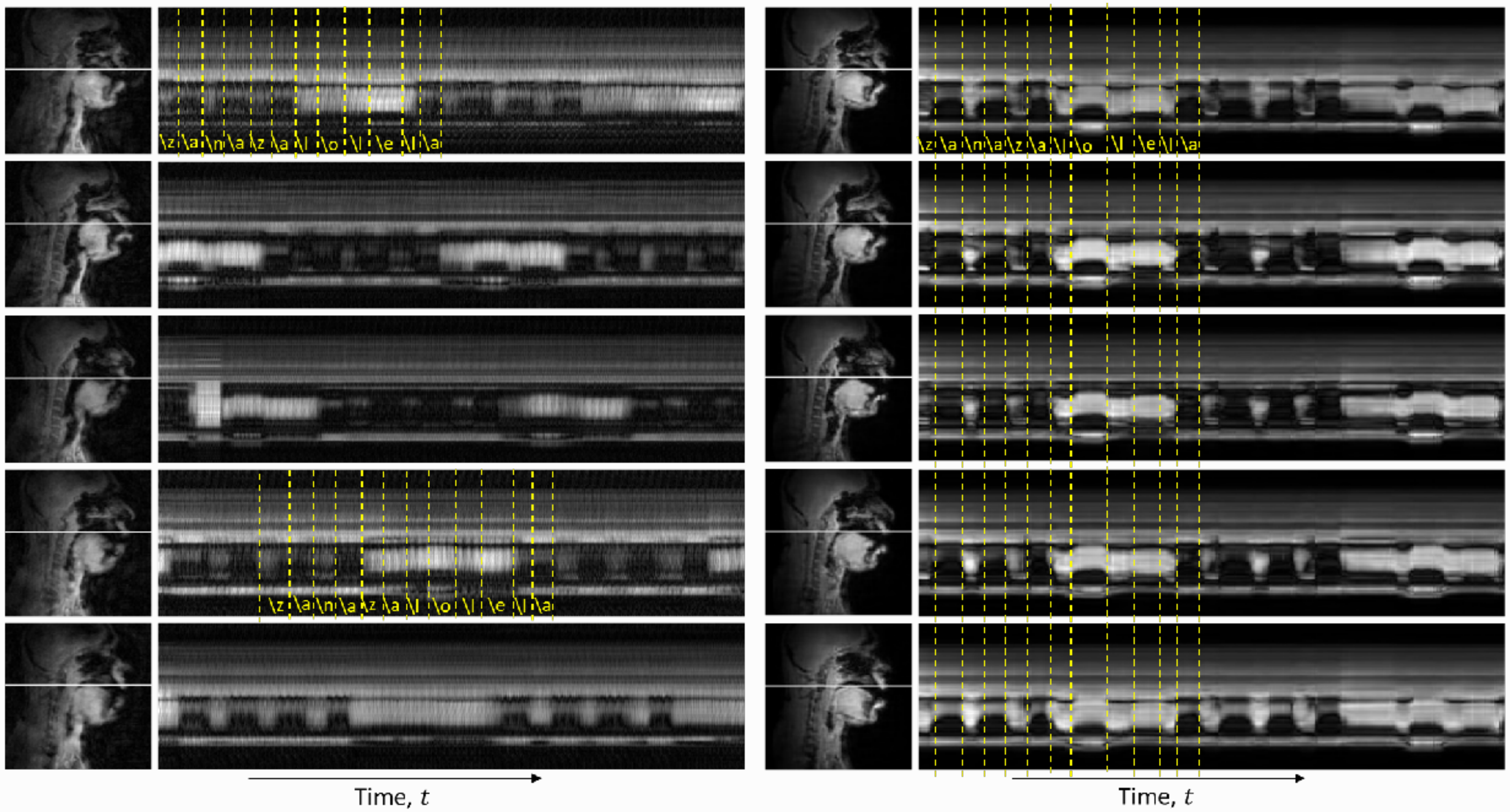
(a) Alignment and recovery of eight slices using V-SToRM

Joint alignment and recovery: 1minute/8 slices



Zou et al., https://arxiv.org/abs/2101.08196

Application to multi-slice speech MRI

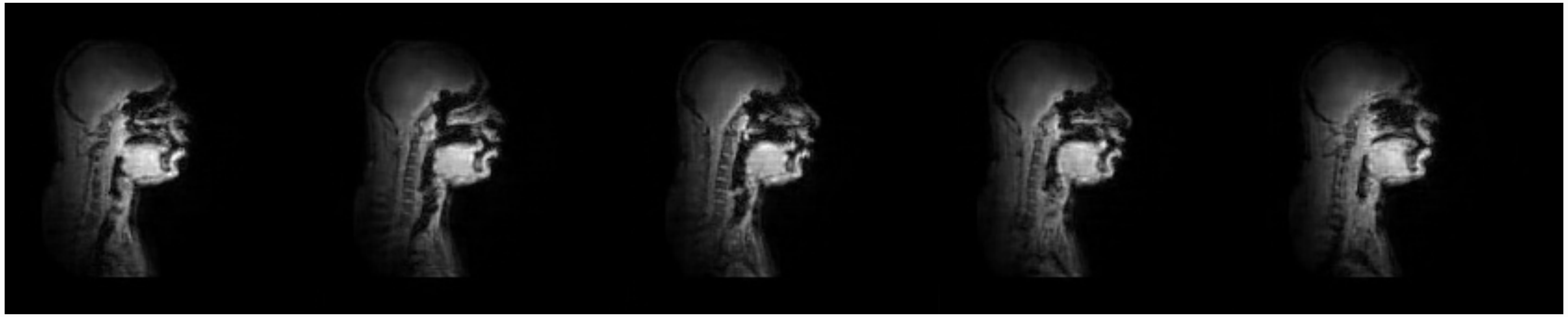


(a) l2 SToRM
(b) Deep generative SToRM

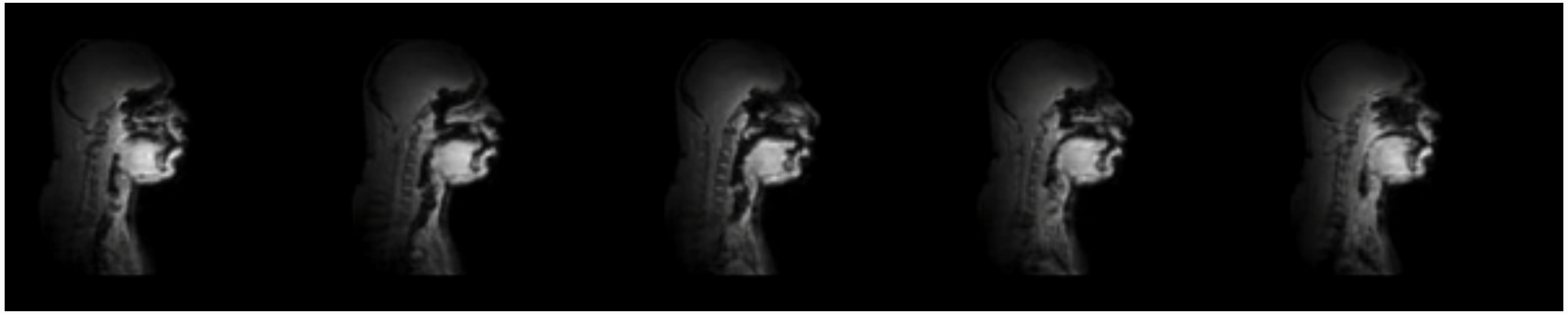
Need high temporal resolution: 2D multi-slice acquisition preferred over 3D

R. Rushdi, Q. Zou, M. Jacob, S. Lingala, ISMRM 2022

Application to multi-slice speech MRI



za-na-za-loo-lee-la



one-two-three-four-five

R. Rushdi, Q. Zou, M. Jacob, S. Lingala, ISMRM 2022

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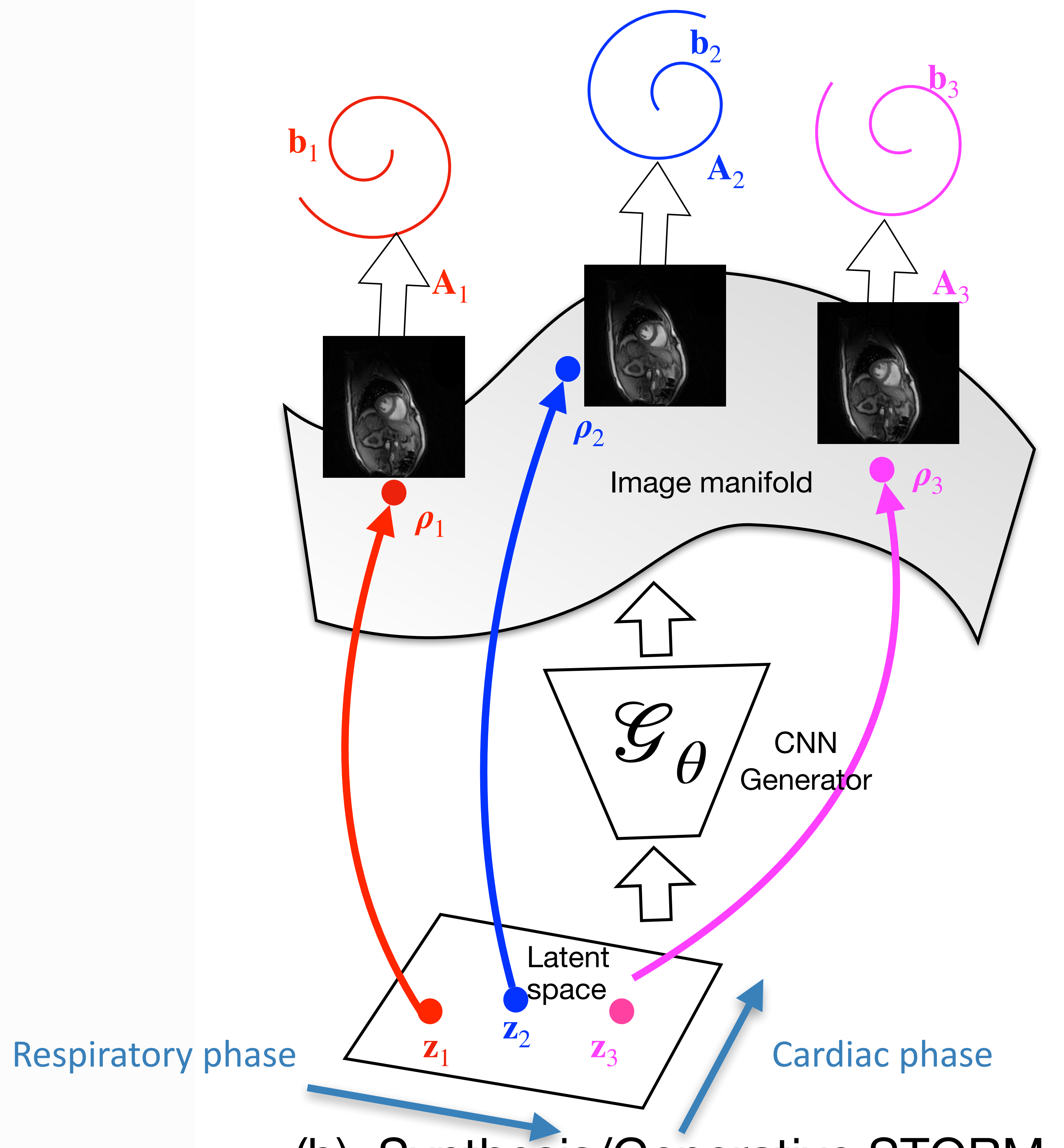
Extension to motion-compensated image recovery

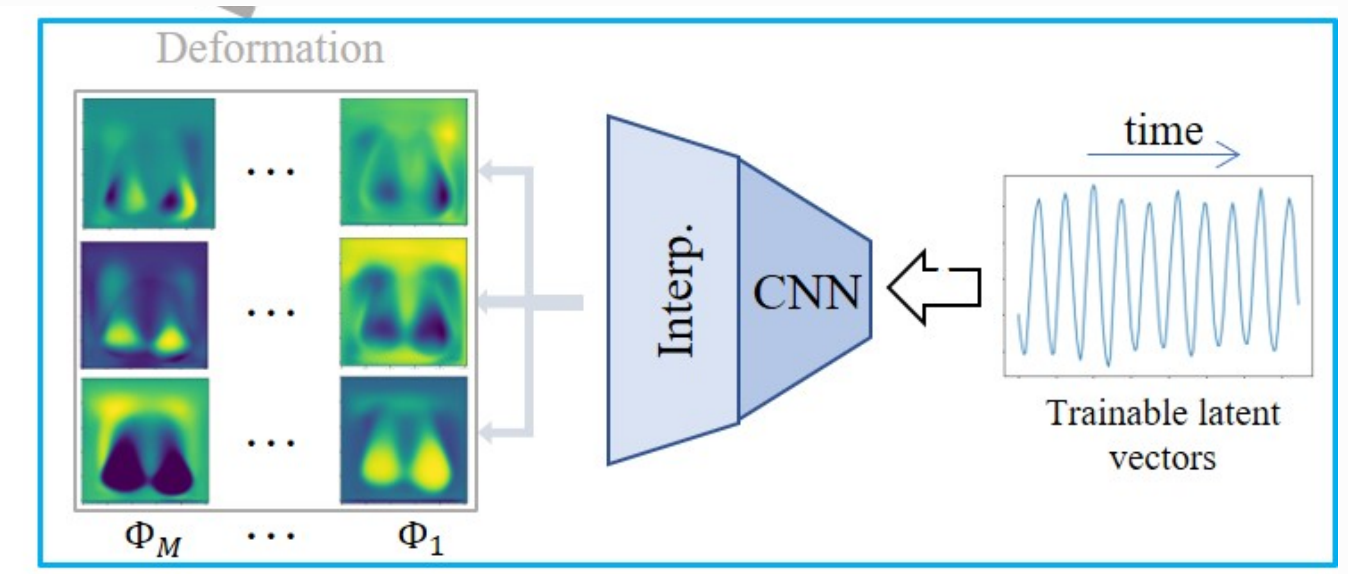


(b). Synthesis/Generative STORM

Motion-compensated recovery: combine information from different motion states

More data efficient

Motion compensated manifold recovery (MoCO-STORM)



Time varying motion fields

$$\Phi_t(\mathbf{r}) = \mathcal{G}_\theta[z(t)]$$

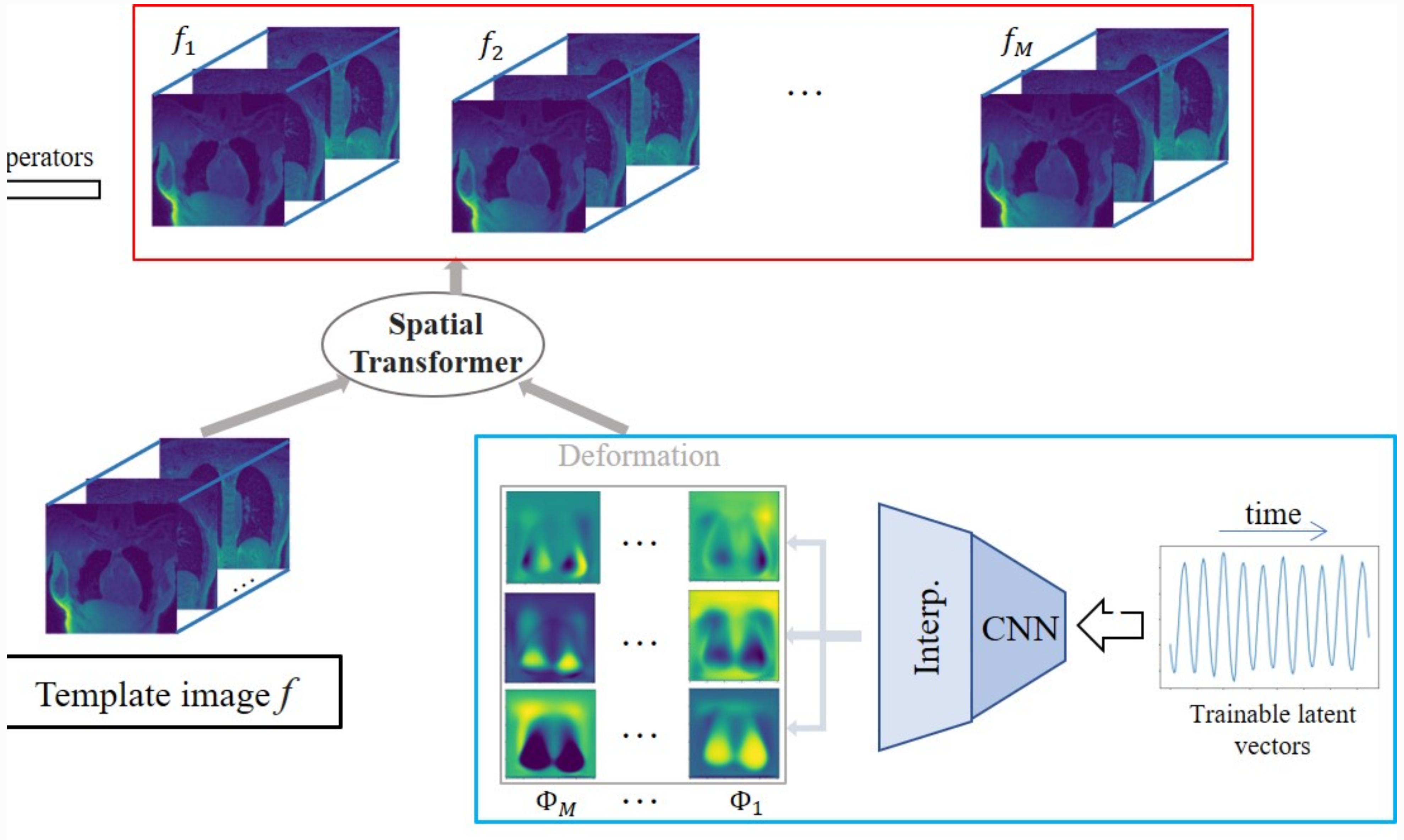
Learned latent vectors

$$z(t)$$

Deformations: generated by a CNN, when driven by time varying latent vectors

Motion compensated manifold recovery (MoCO-STORM)

Image at each time instant: Deformed version of a template f



Static Image

$f(\mathbf{r})$

Time varying motion fields

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Motion compensated manifold recovery (MoCO-STORM)

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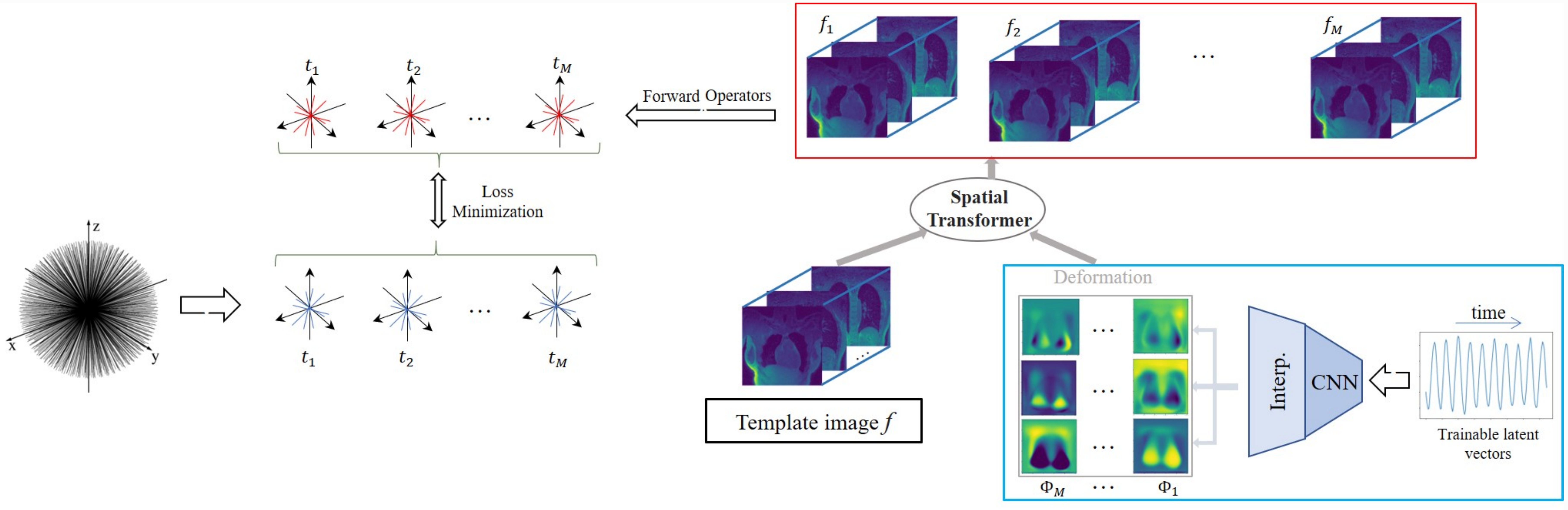


Static Image

Time varying motion fields

Learned latent vectors

$f(\mathbf{r})$

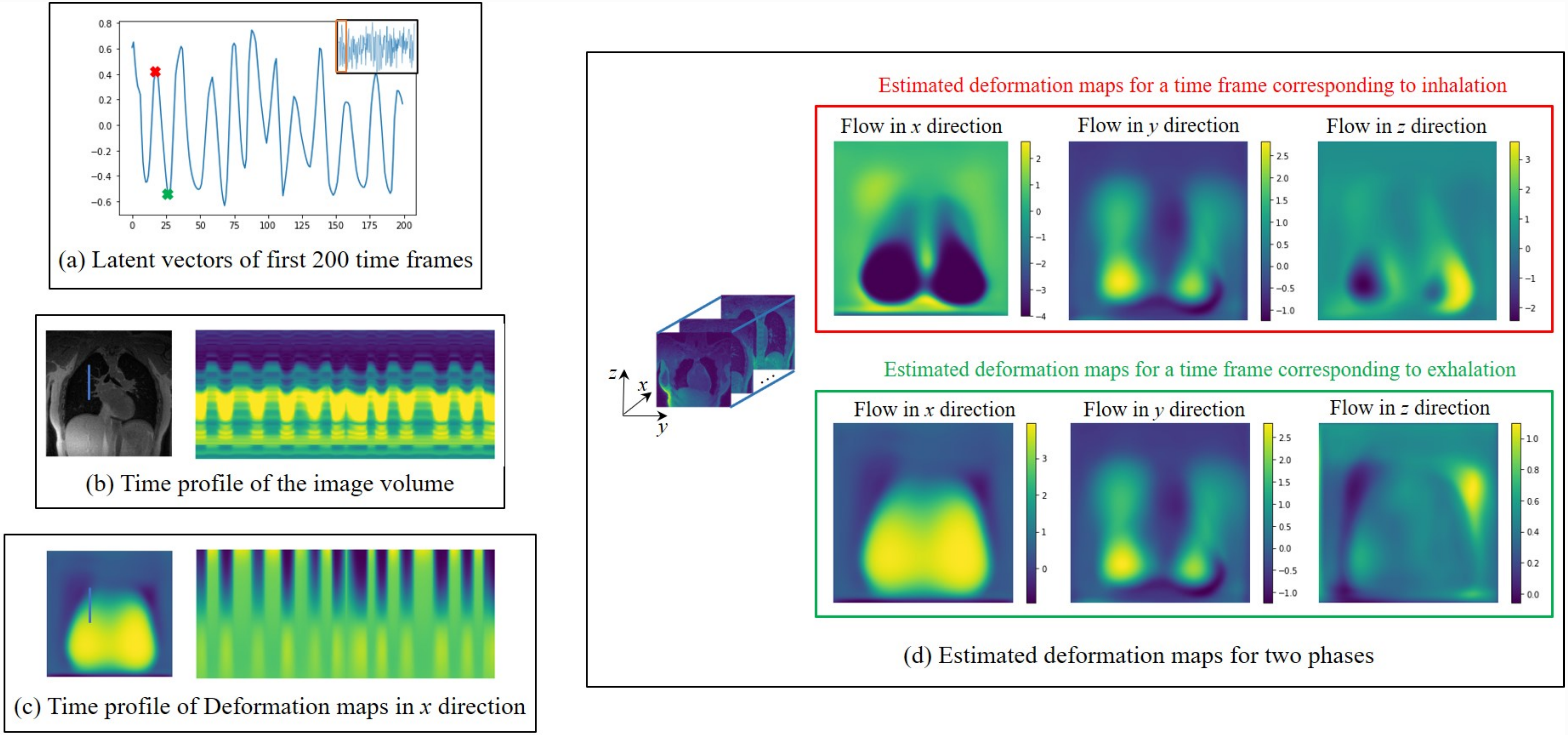
$\Phi_t(\mathbf{r}) = \mathcal{G}_\theta[z(t)]$

$z(t)$

Deformations: generated by a CNN, when driven by time varying latent vectors

Reconstruction: joint recovery of $f(r)$, θ, and $z(t)$

Motion compensated manifold recovery (MoCO-STORM)



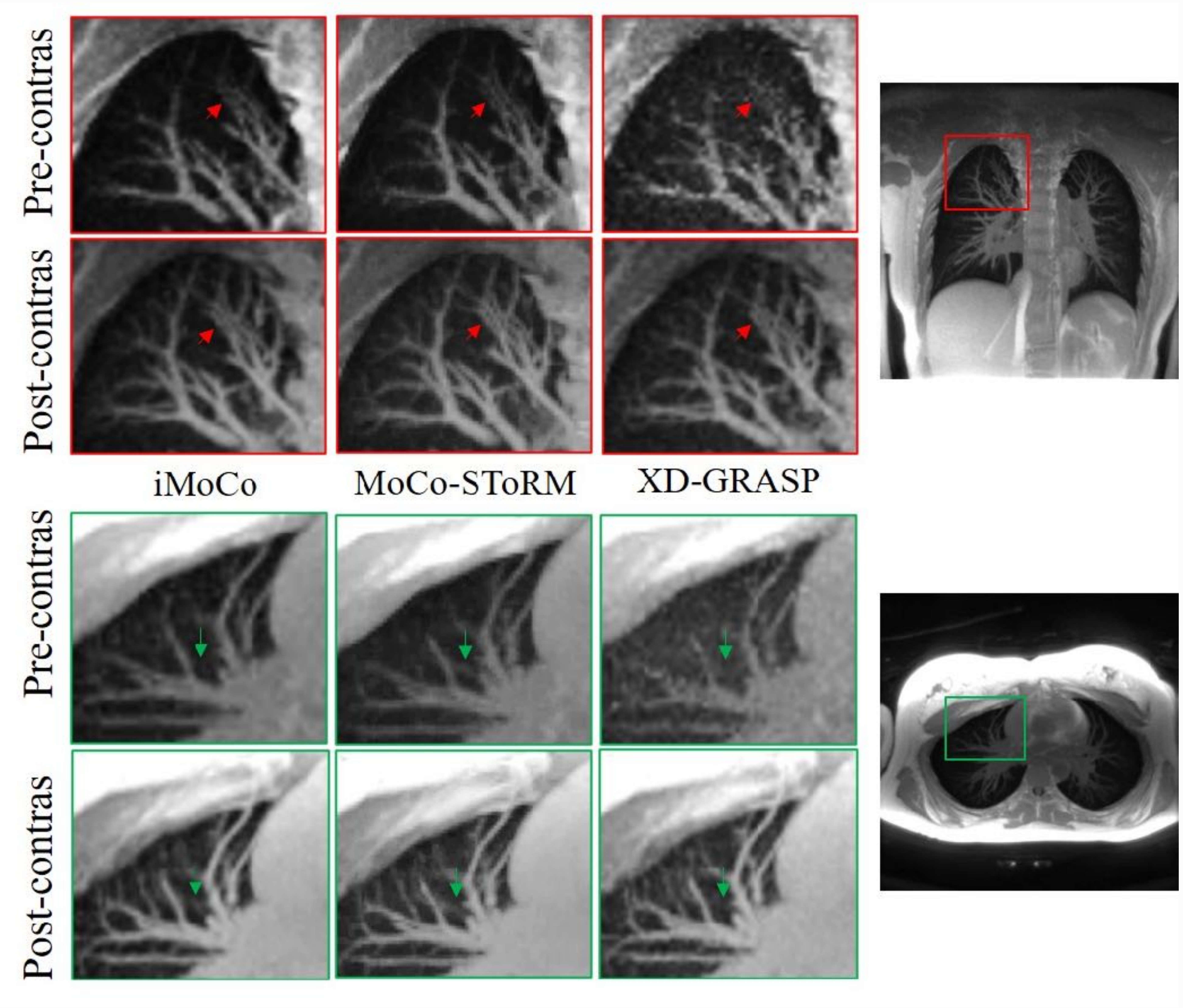
(a) Latent vectors of first 200 time frames

(b) Time profile of the image volume

(c) Time profile of Deformation maps in x direction

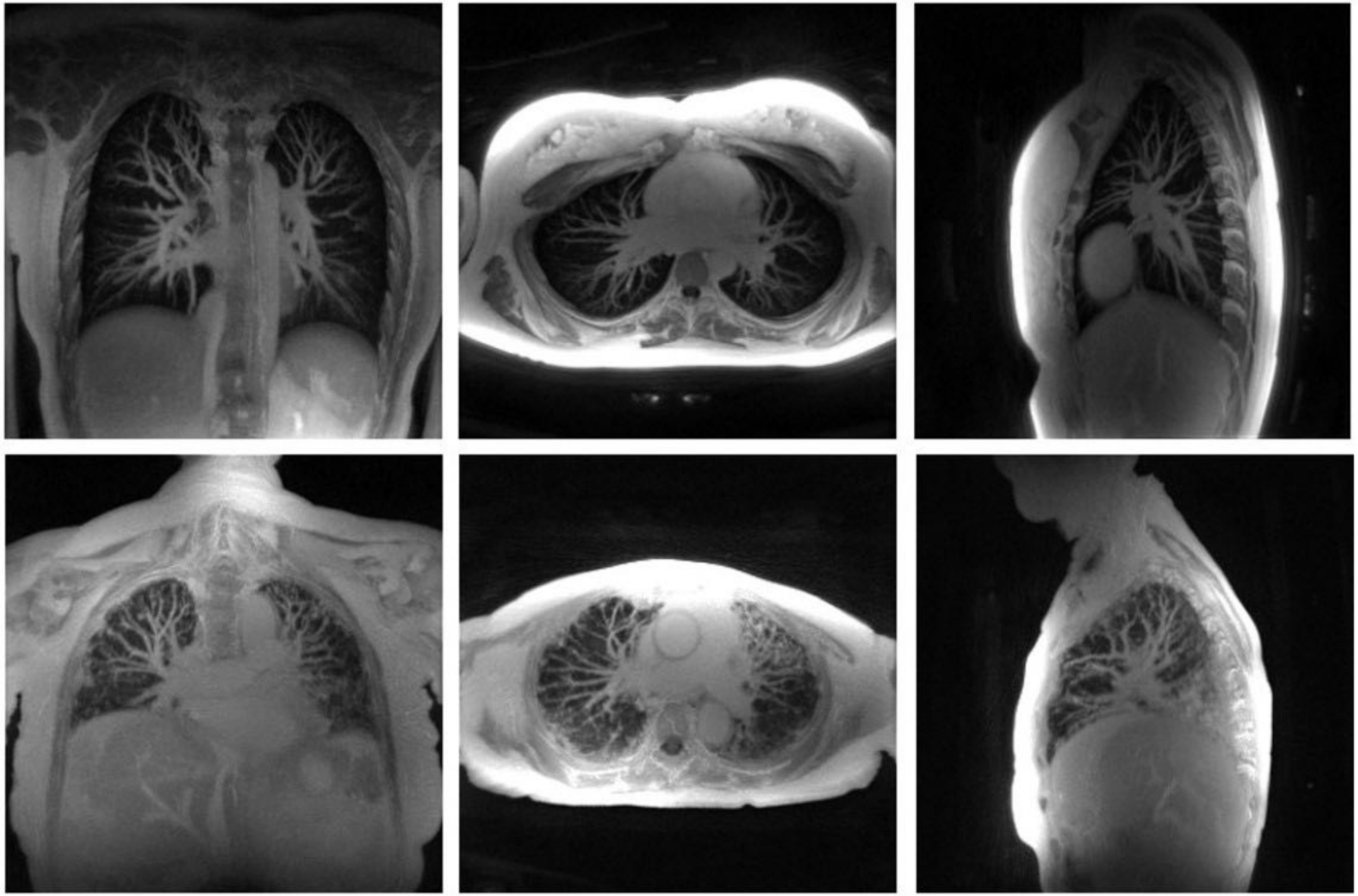
(d) Estimated deformation maps for two phases

MoCO-STORM vs XD-GRASP vs iMoCO: normal subject

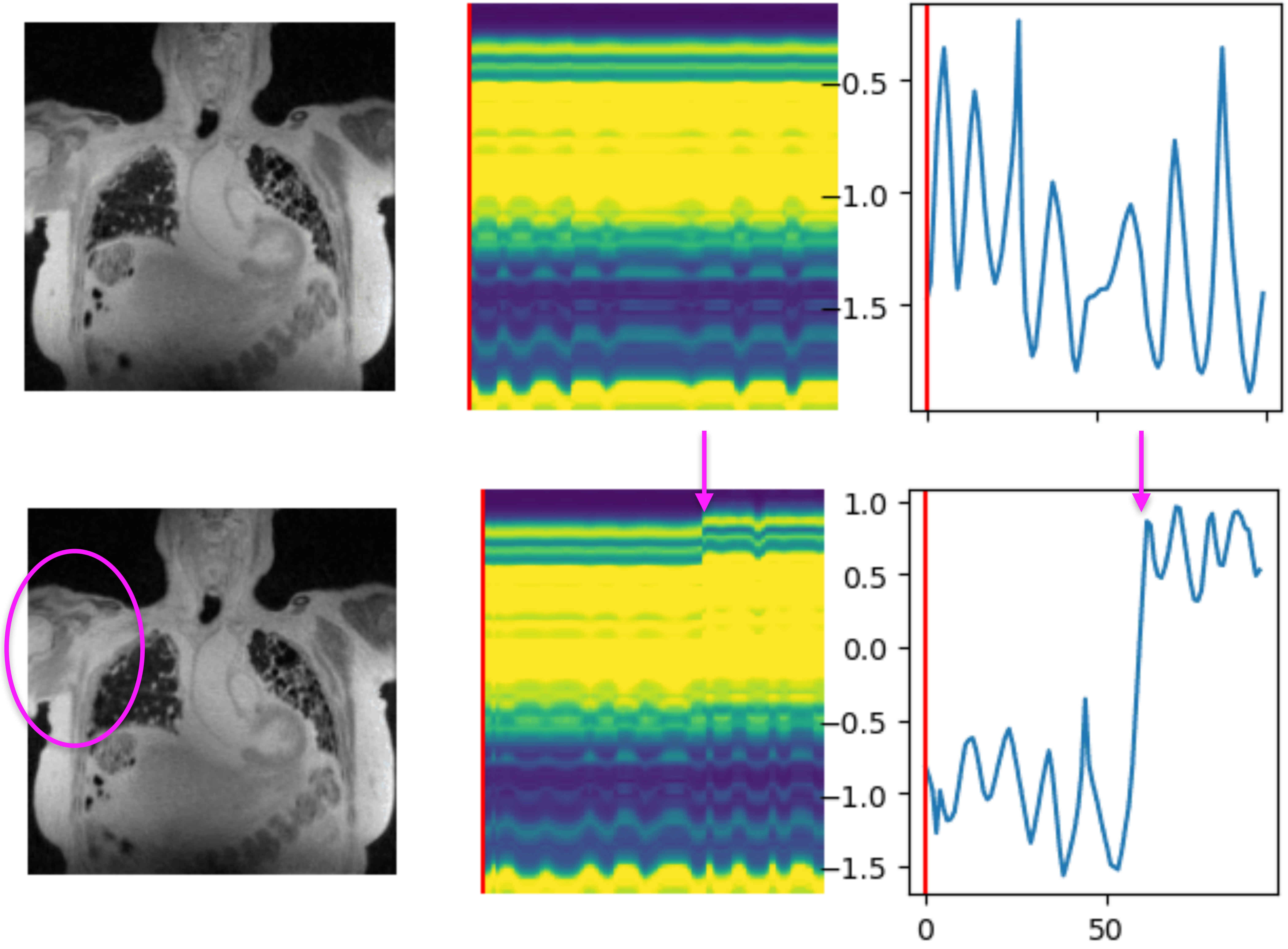


Zou et al, MoCo-SToRM: http://arxiv.org/abs/2111.10887

MoCO-STORM: Maximum intensity projections



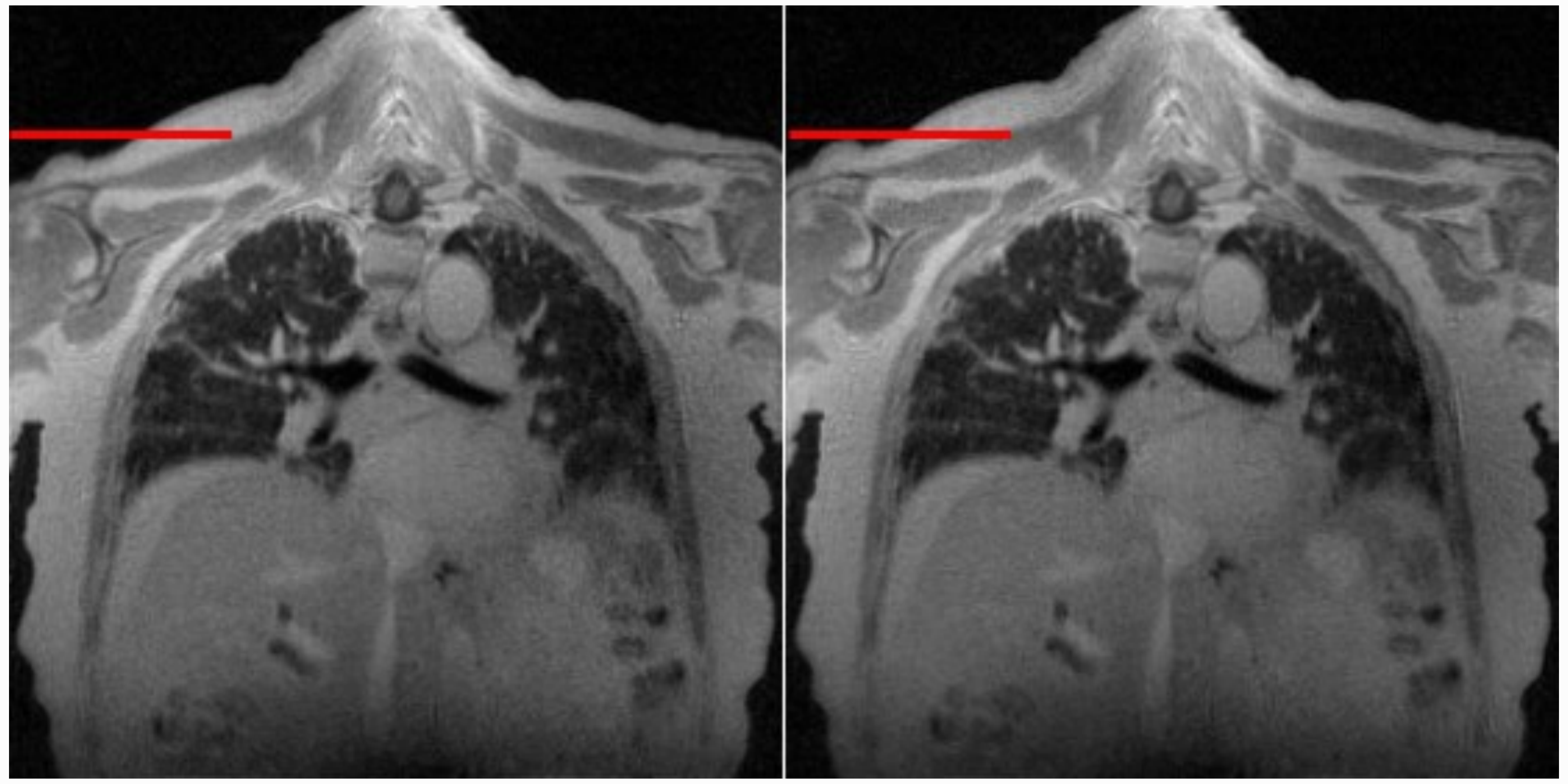
Robustness to bulk motion artifacts

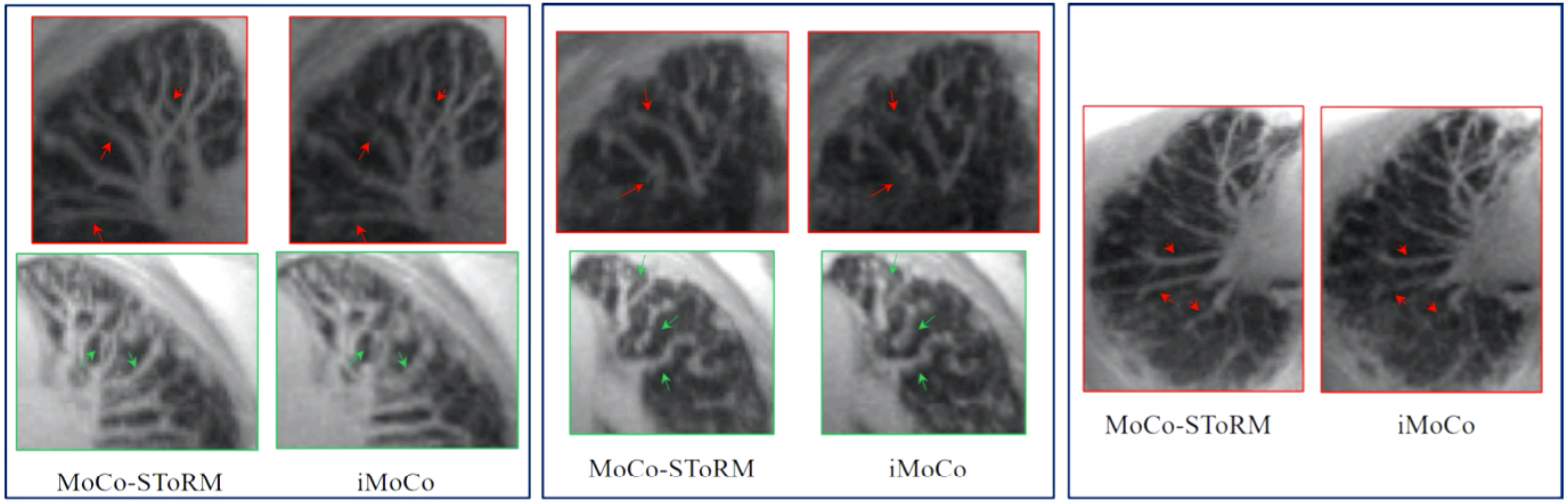


Joint recovery of 256x256x256x1000 volumes

Zou et al, MoCo-SToRM: http://arxiv.org/abs/2111.10887

Benefit of bulk motion compensation





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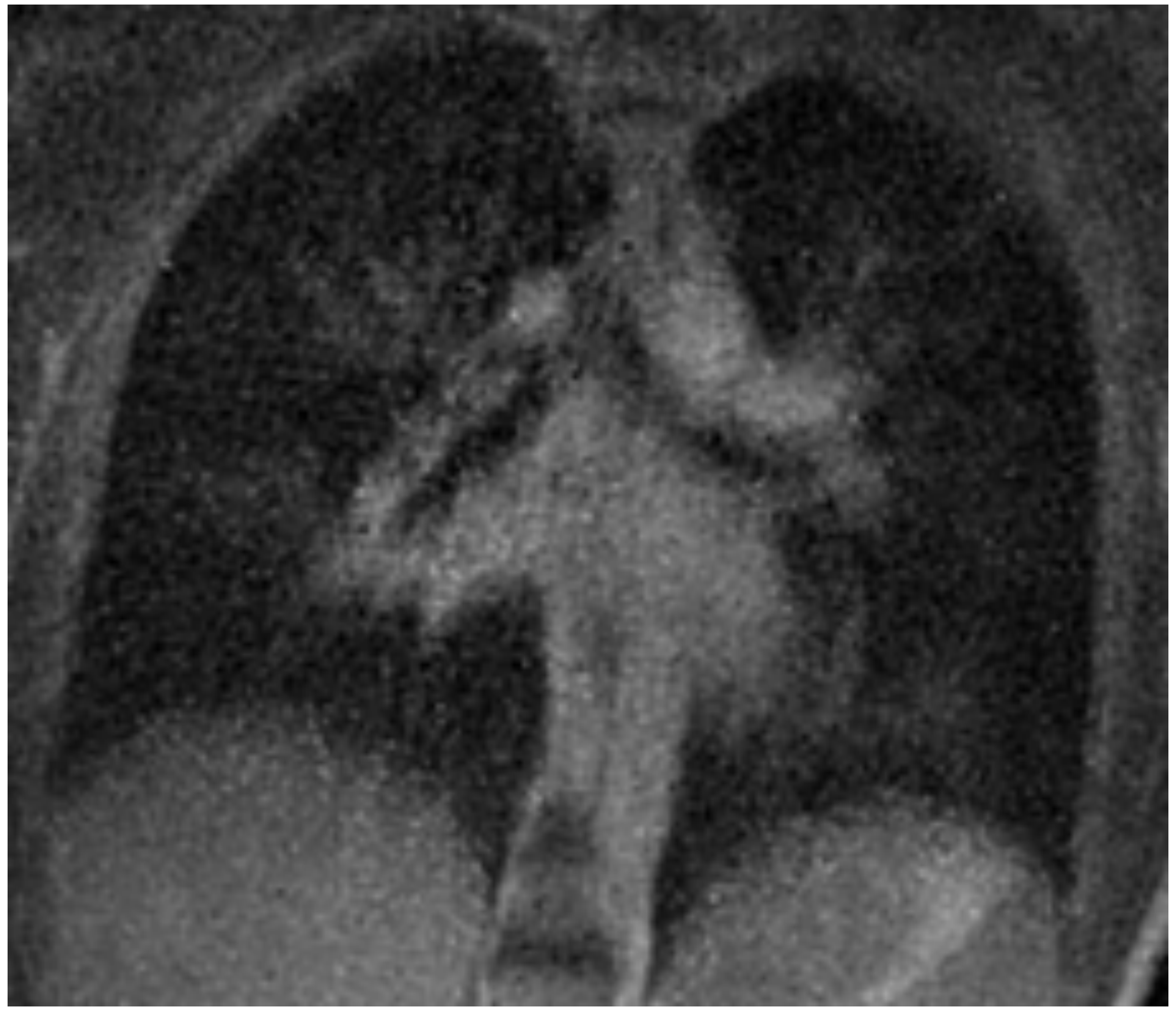
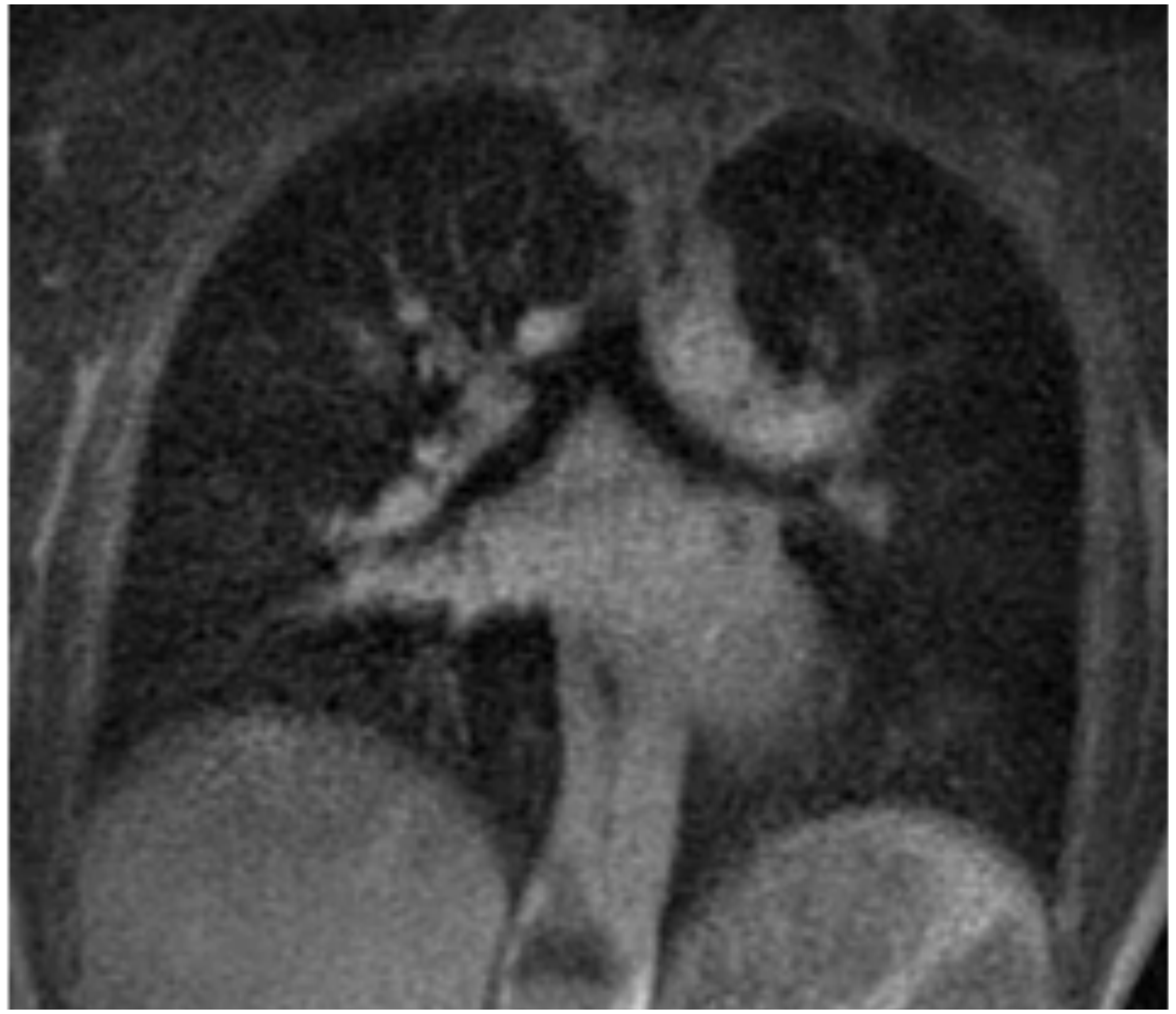


Motion resolved recon.

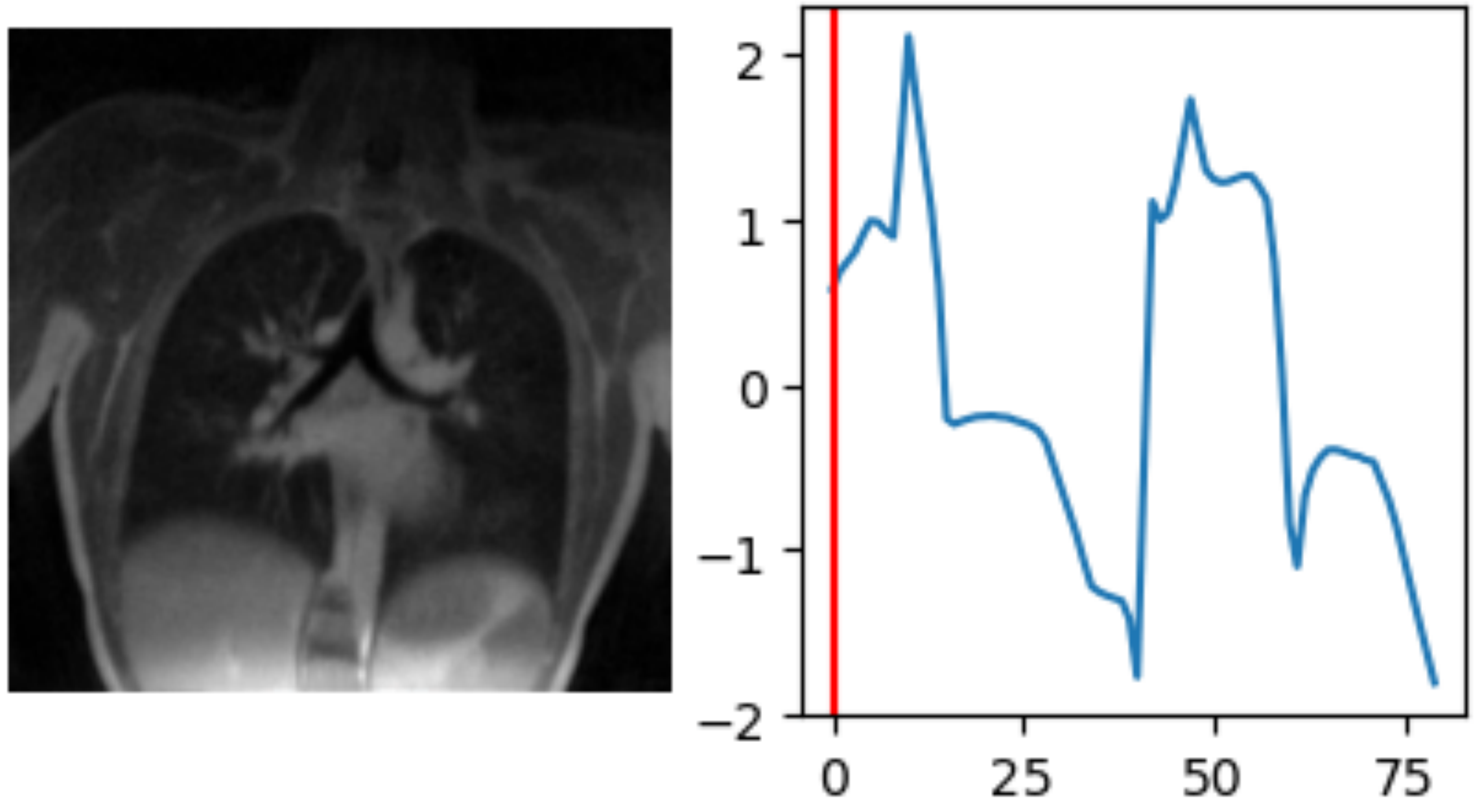


Extreme MRI

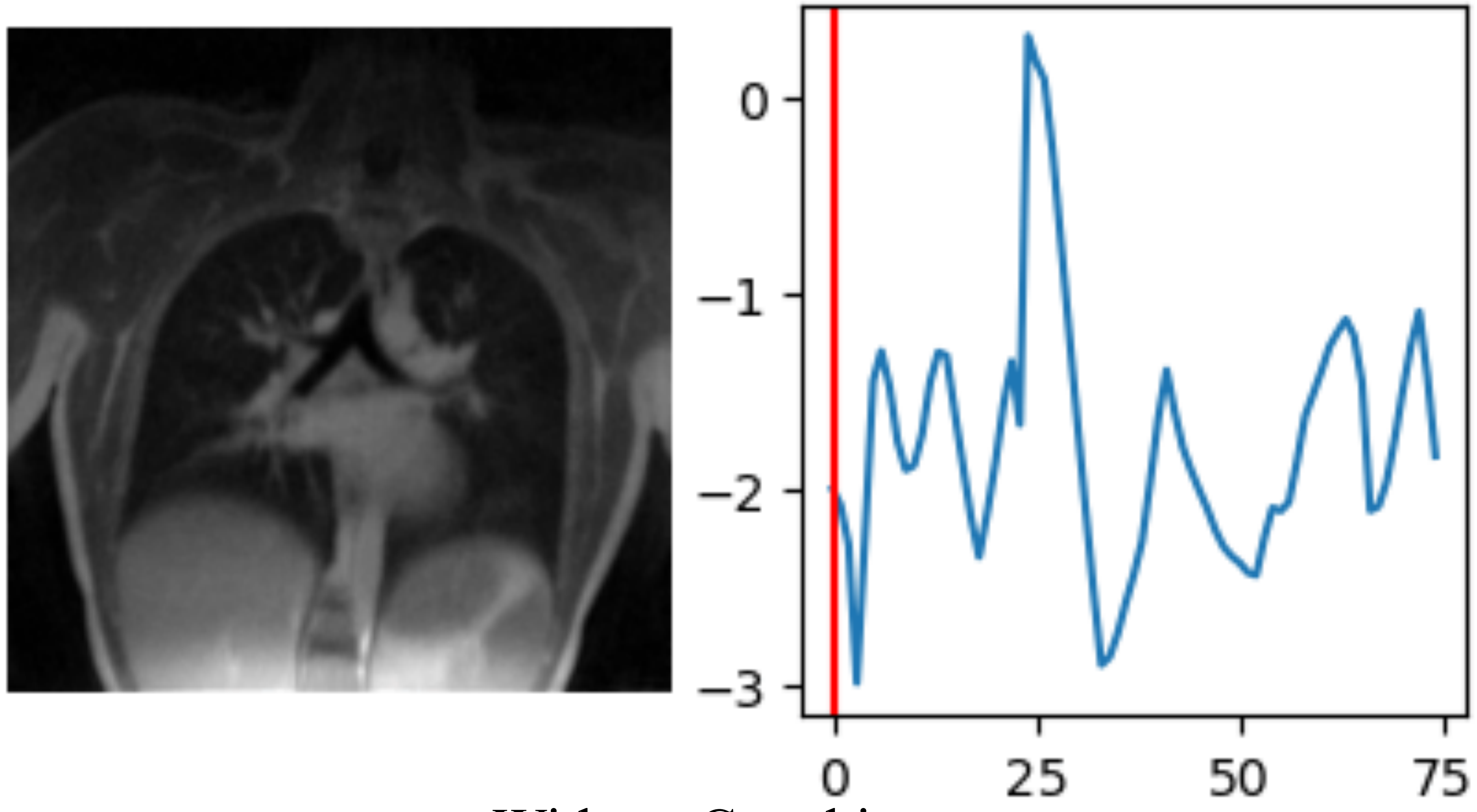
MoCo-SToRM
Matrix size:256x256x256
Temporal resolution: 260 ms

Spatial resolution:1.25x1.25x1.25
Matrix size: 408x183x379
Temporal resolution: 515 ms

Copied from the "Extreme MRI" paper.



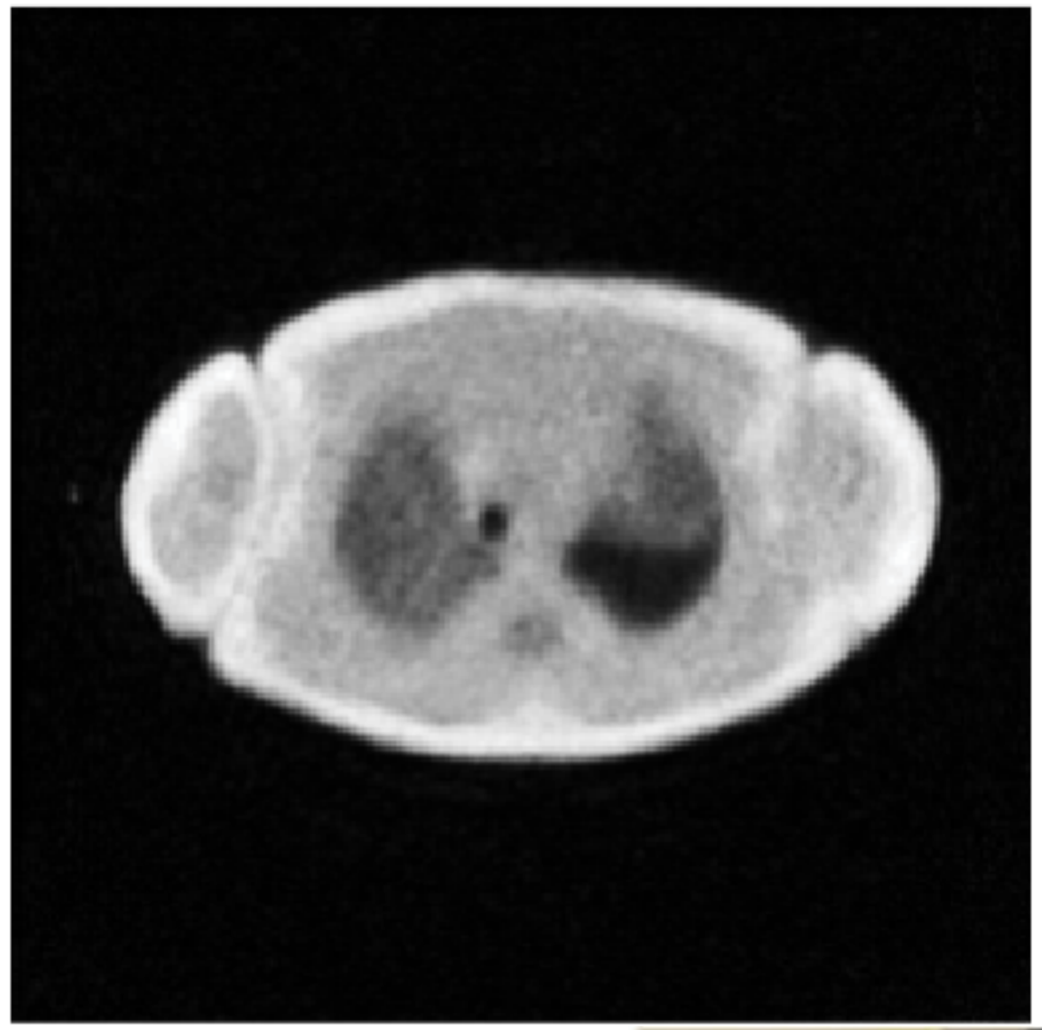
Coughing

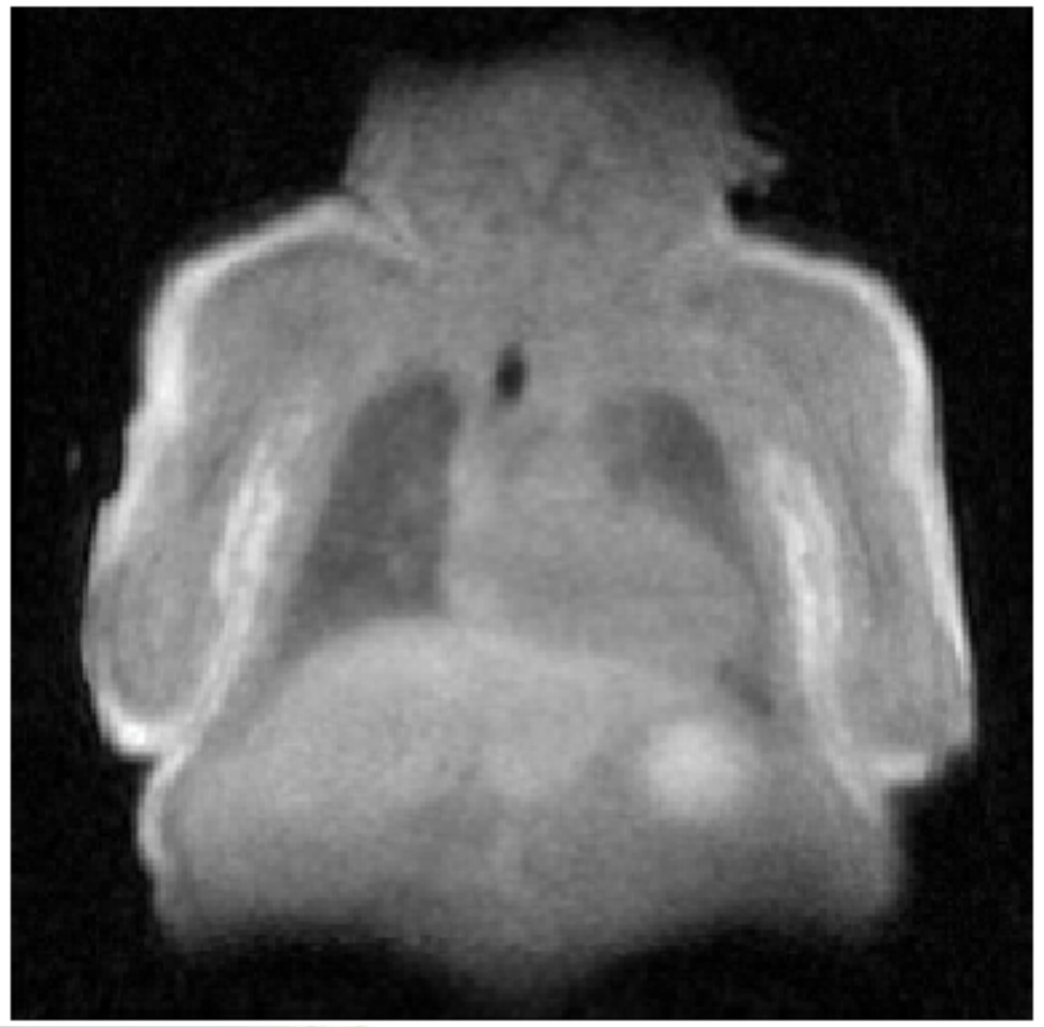


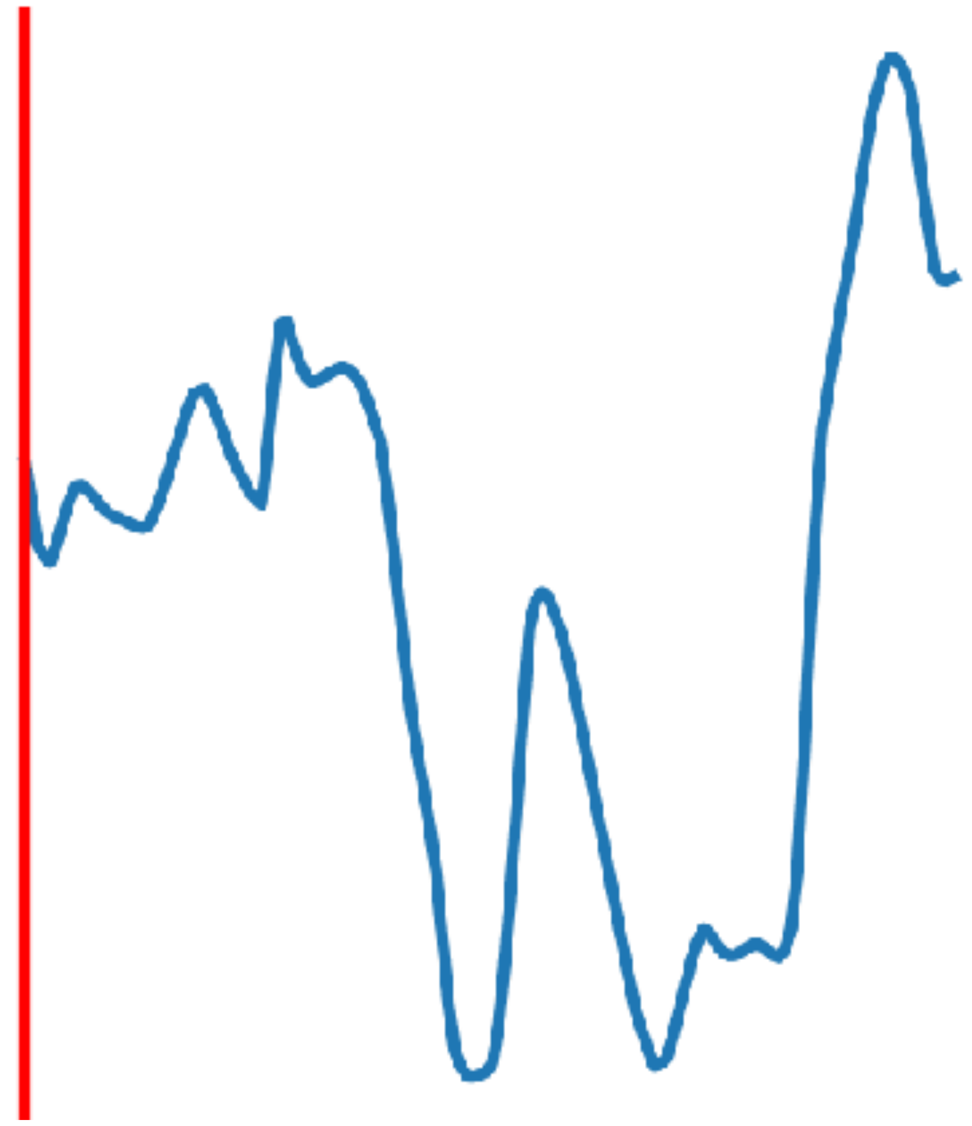
Without Coughing

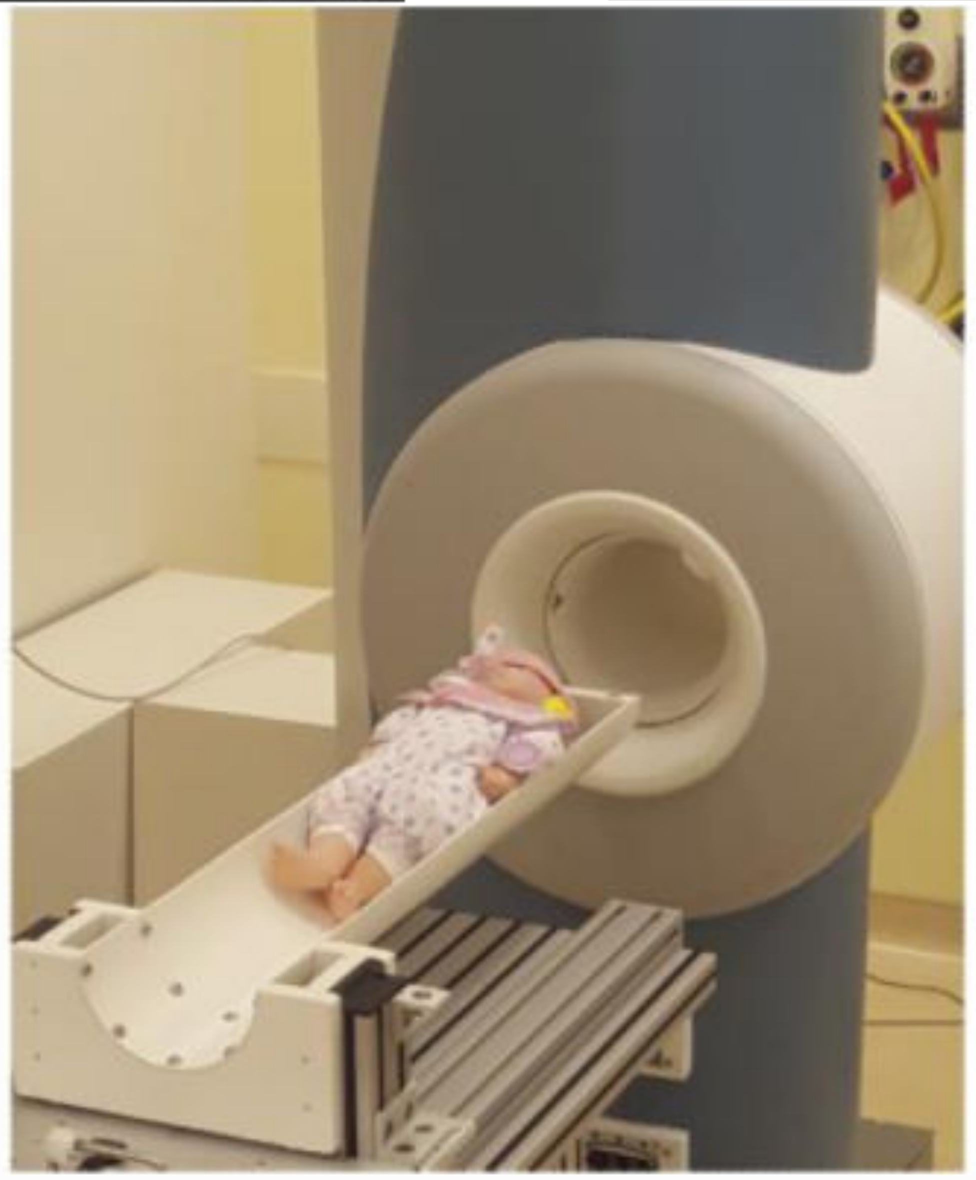
Preliminary study: pediatric imaging (NICU subject)

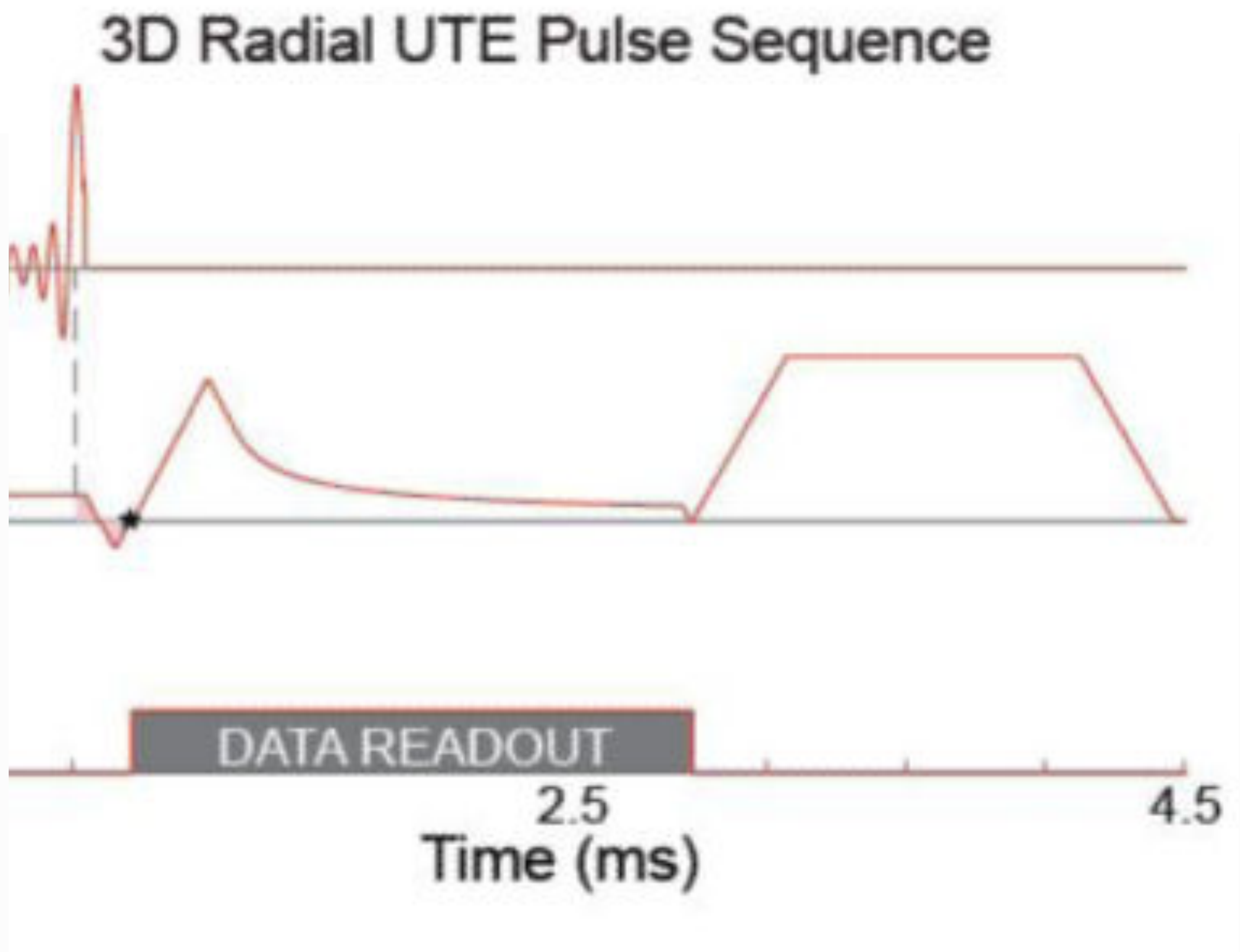
Joint recovery of 256 x 256 x 256 x 10,000 volumes







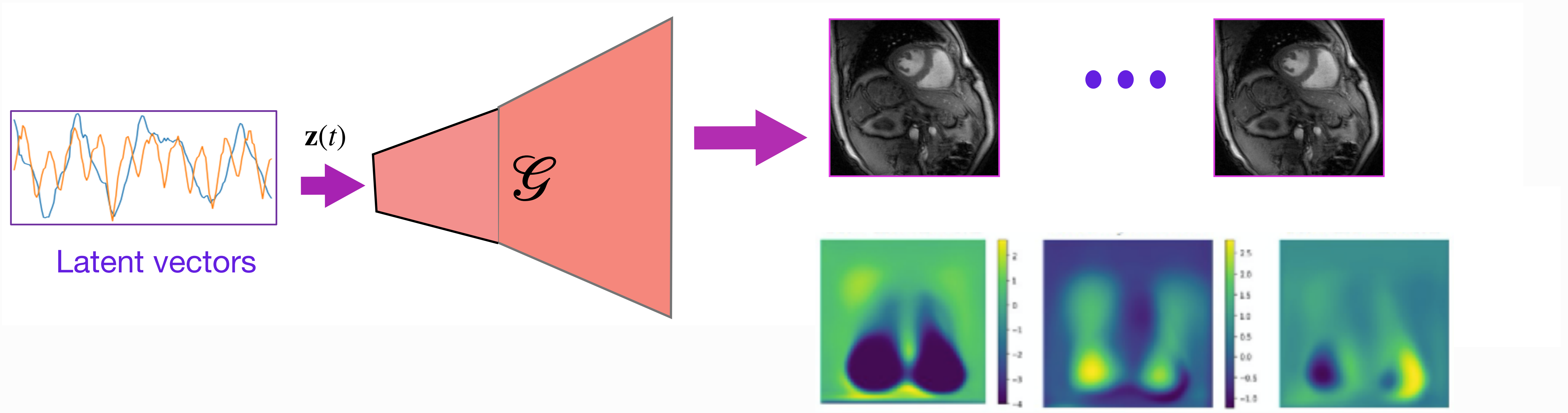




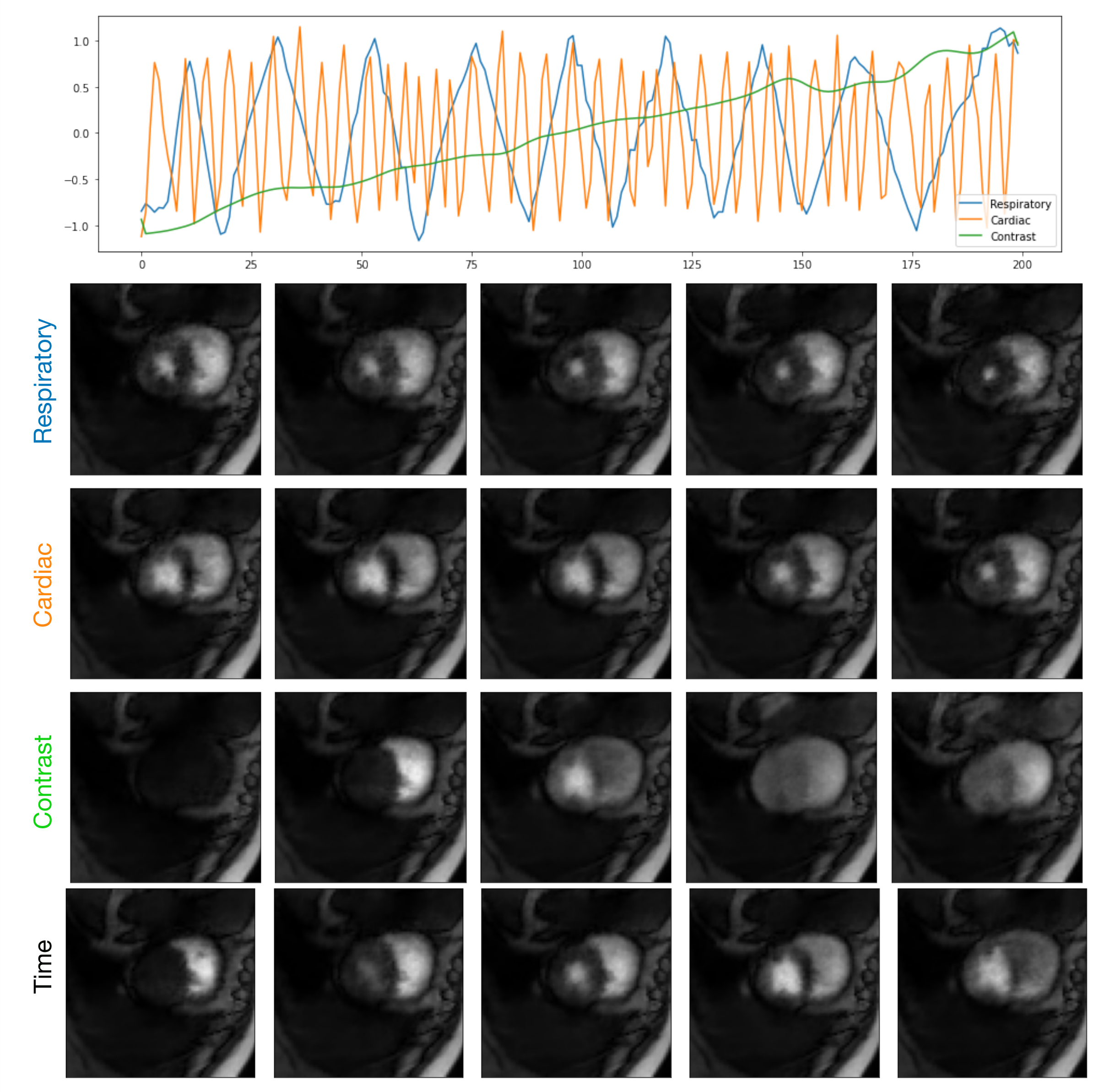
In collaboration with N. Higano, A. Bates, L. Torres, S. Fain,

Summary of g-SToRM

- Images or motion fields: nonlinear mapping of latent vectors



- Learn generator and latent vectors from data



- Generate images on demand