

Dynamic MRI: Current Status & Emerging Applications

Imaging Across Dimensions

ISMRM Workshop on Data Sampling and Image Reconstruction

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Assistant Professor, Electrical and Computer Engineering

University of Texas at Austin

www.jtsense.com

January 14, 2026

Sedona, AZ



A scenic view of a red rock canyon in Sedona, Arizona, with snow-dusted peaks and a circular inset showing a different view of the canyon.

**Sedona, AZ, USA - ISMRM Workshop on Data Sampling
and Image Reconstruction**

Declaration of Financial Interests or Relationships

Speaker Name: Jon Tamir

Company Name: Aspect Imaging

Type of Relationship: Research Support

High-dimensional

~~Dynamic~~ MRI: Current Status & Emerging Applications

Imaging Across Dimensions

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Sedona, AZ



What is dynamic MRI?

- Using BART's definition*

```
11  ✓ enum mri_dims {  
12      READ_DIM,  
13      PHS1_DIM,  
14      PHS2_DIM,  
15      COIL_DIM,  
16      MAPS_DIM,
```

} Spatial dimensions
}
} Coil dimensions

Sedona '13

[Software Toolbox & Programming Library for Compressed Sensing & Parallel Imaging](#)

*<https://github.com/mrirecon/bart/blob/master/src/misc/mri.h>

What is dynamic MRI?

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11  enum mri_dims {  
12      READ_DIM,  
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14      PHS2_DIM,  
15      COIL_DIM,  
16      MAPS_DIM,  
17      TE_DIM,  
18      COEFF_DIM,  
19      COEFF2_DIM,  
20      ITER_DIM,  
21      CSHIFT_DIM,  
22      TIME_DIM,  
23      TIME2_DIM,  
24      LEVEL_DIM,  
25      SLICE_DIM,  
26      AVG_DIM,  
27      BATCH_DIM,  
28  };
```

} Spatial dimensions

} Coil dimensions

} Everything else

Sedona '13

Software Toolbox & Programming Library for Compressed Sensing & Parallel Imaging

Sedona '16



Generalized Magnetic Resonance Image Reconstruction using The Berkeley Advanced Reconstruction Toolbox

*<https://github.com/mrirecon/bart/blob/master/src/misc/mri.h>

What is dynamic MRI?

- Using BART's definition*

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11  enum mri_dims {  
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23      TIME2_DIM,  
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25      SLICE_DIM,  
26      AVG_DIM,  
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28  };
```

} Spatial dimensions

} Coil dimensions

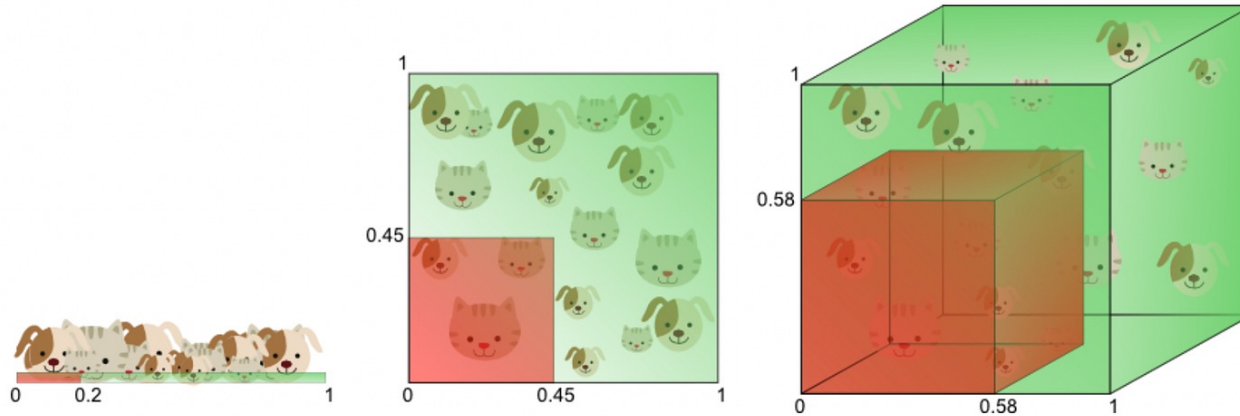
} Everything else

- Physiological dynamics: cardiac motion, breathing, blood flow, bulk motion, ...
- Signal dynamics: relaxation, dynamic contrast enhancement, ...

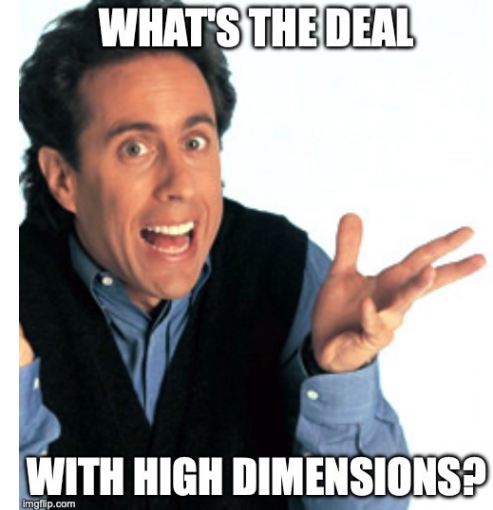
*<https://github.com/mrirecon/bart/blob/master/src/misc/mri.h>

Curse and blessing of dimensionality

Curse: exponential growth

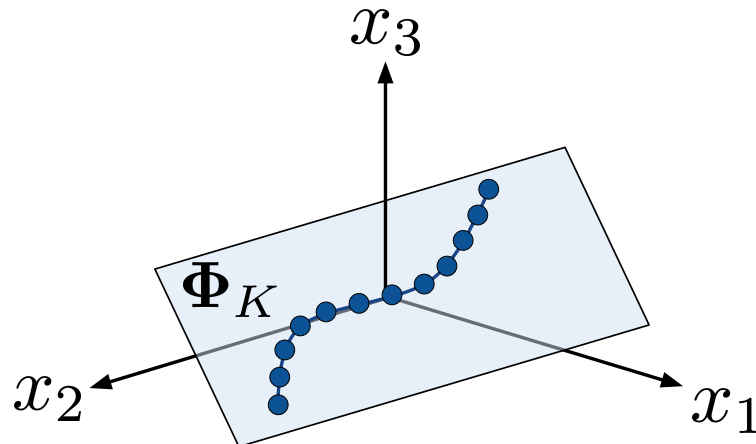


<https://medium.com/@gokcenazakyol/what-is-curse-of-dimensionality-machine-learning-2-739131962faf>



$$\text{MRF dictionary} \propto N^D$$

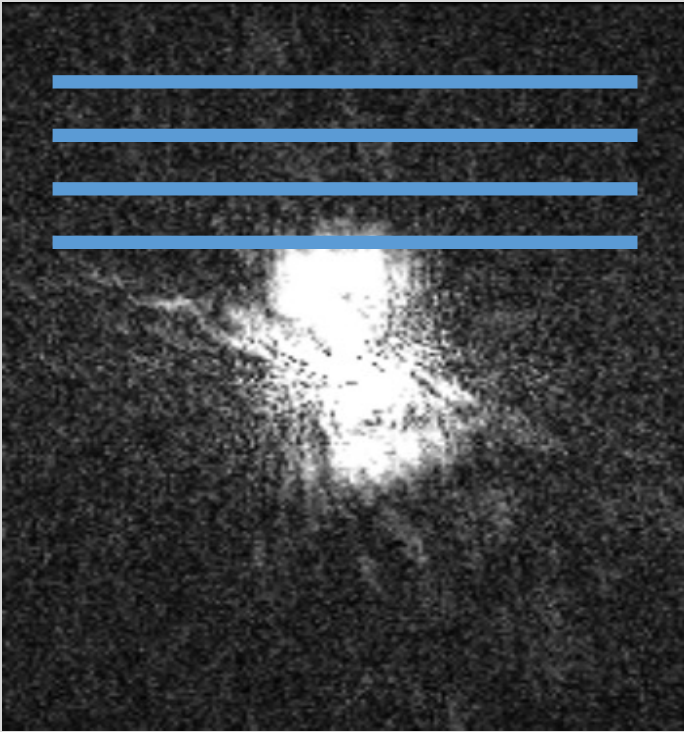
Blessing: low-dimensional structure



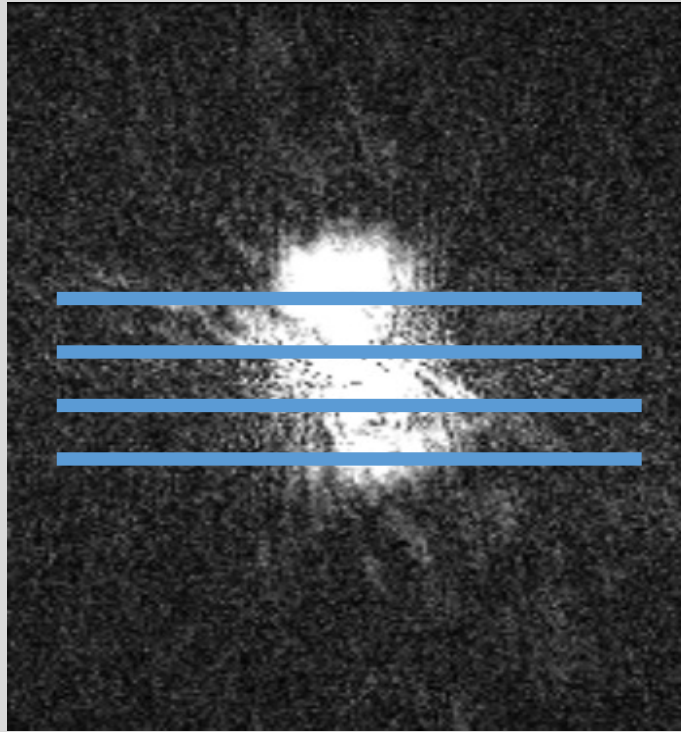
What we need

- ✓ Efficient sampling
- ✓ Compact signal modeling

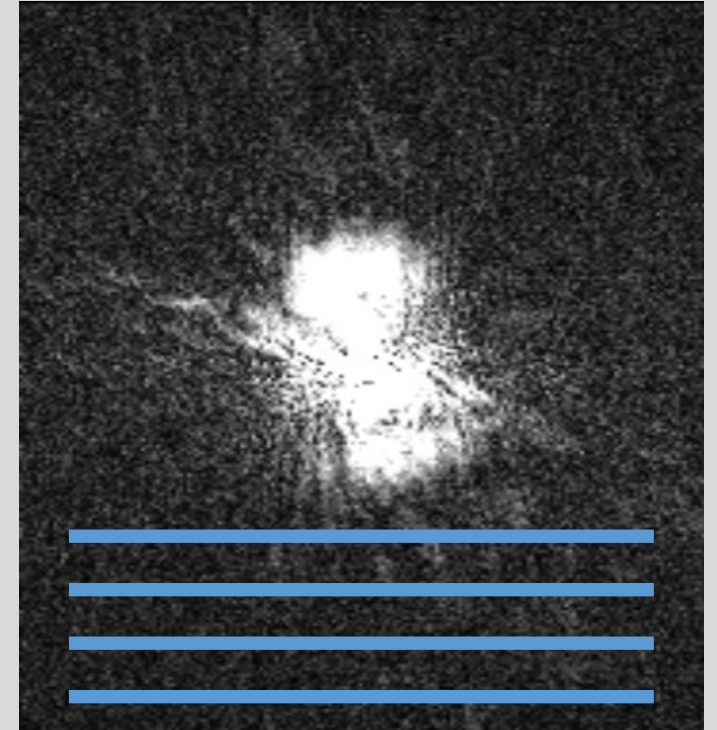
Dynamic MRI Acquisition



Frame 1



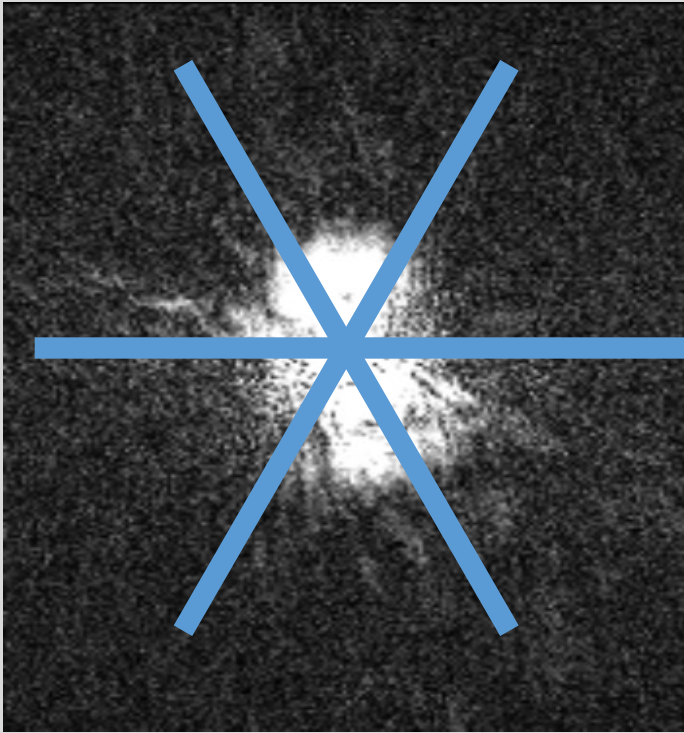
Frame 2



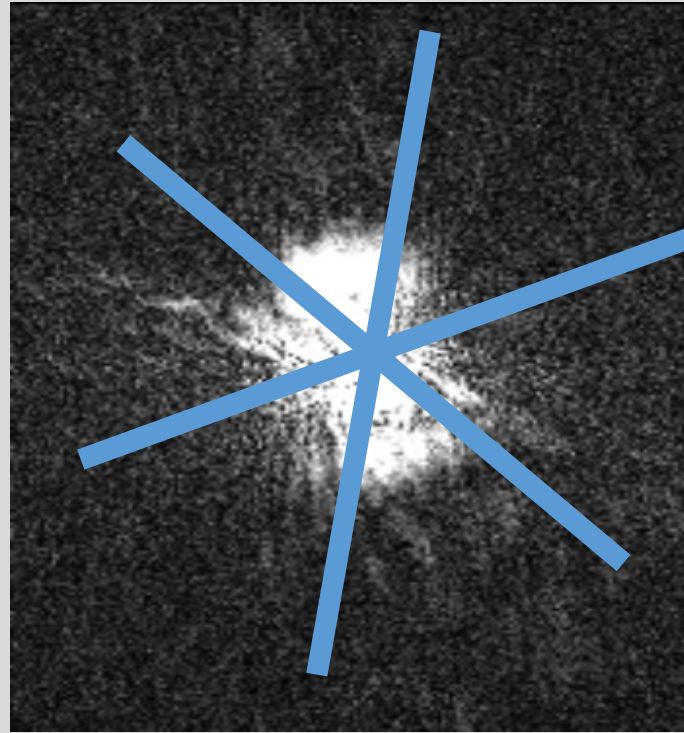
Frame 3

For desired $<1s$ temporal resolution
Can acquire only partial k-space in each frame

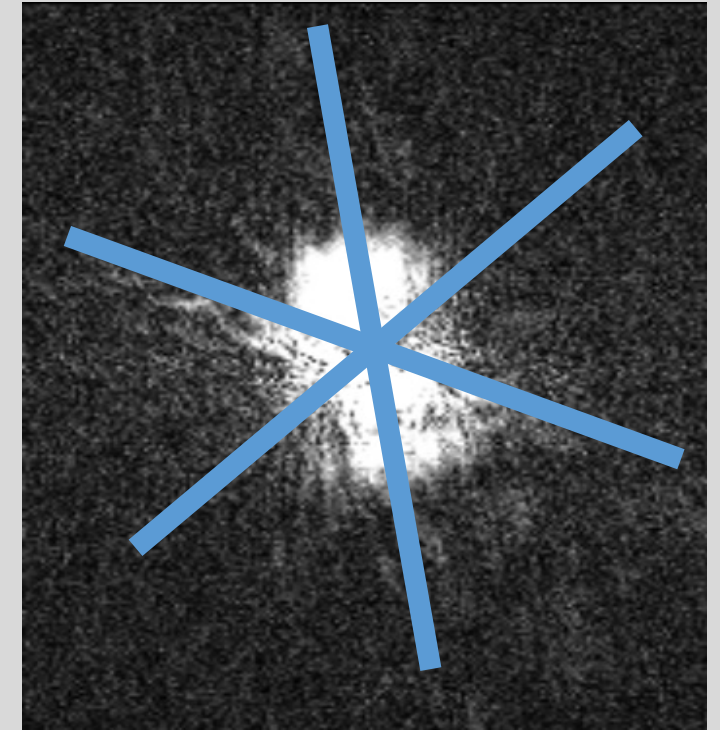
Dynamic MRI Acquisition



Frame 1



Frame 2

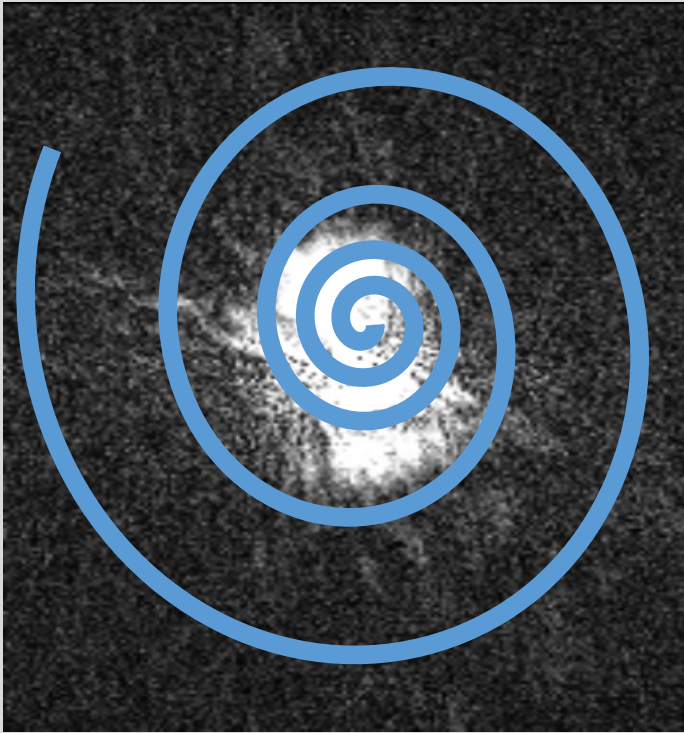


Frame 3

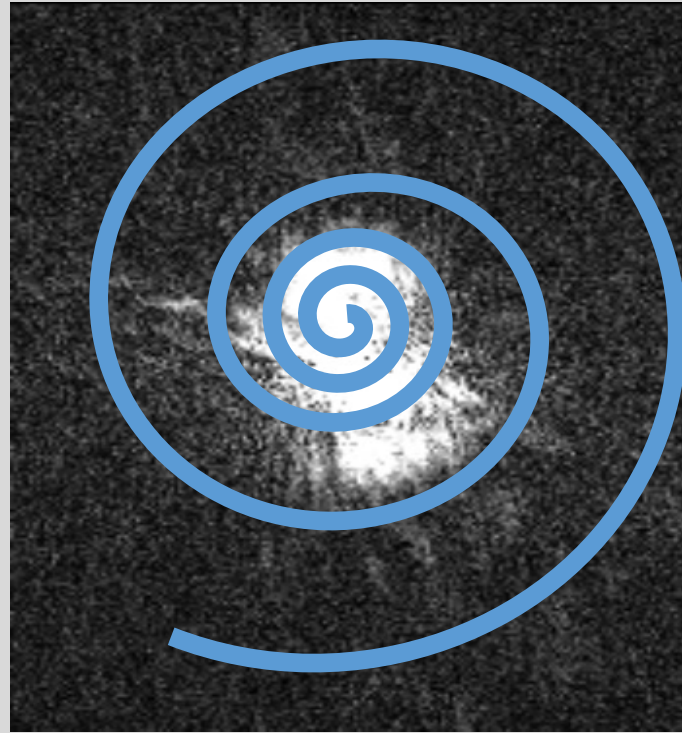
For desired $<1s$ temporal resolution
Can acquire only partial k-space in each frame

Courtesy Frank Ong

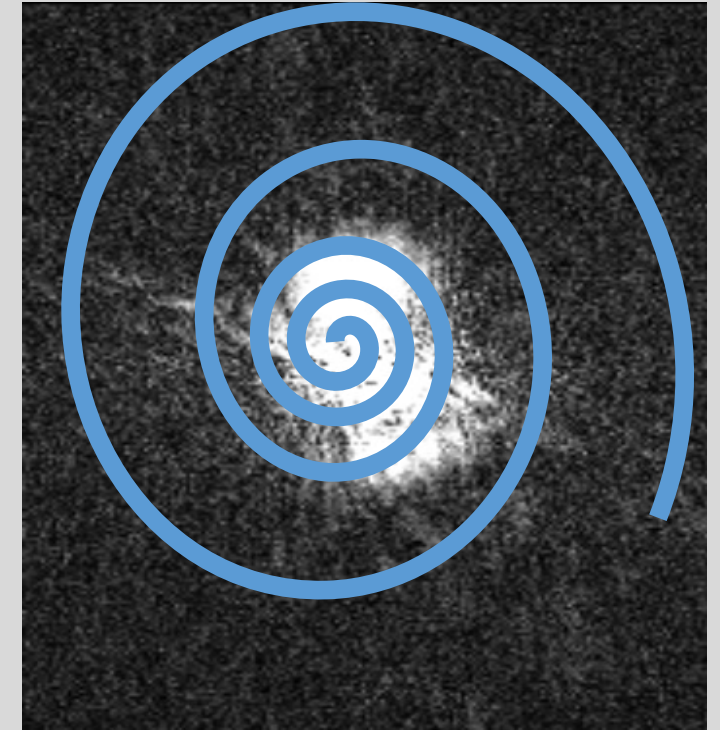
Dynamic MRI Acquisition



Frame 1



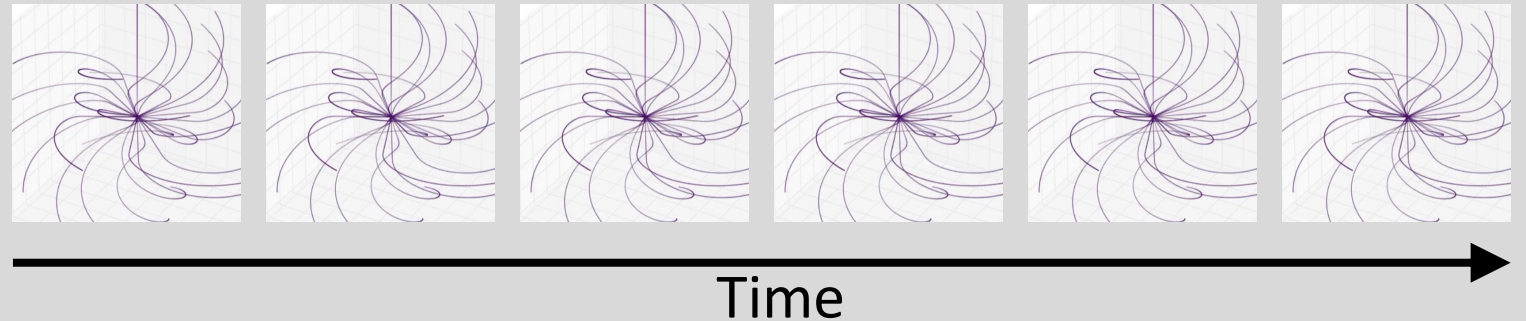
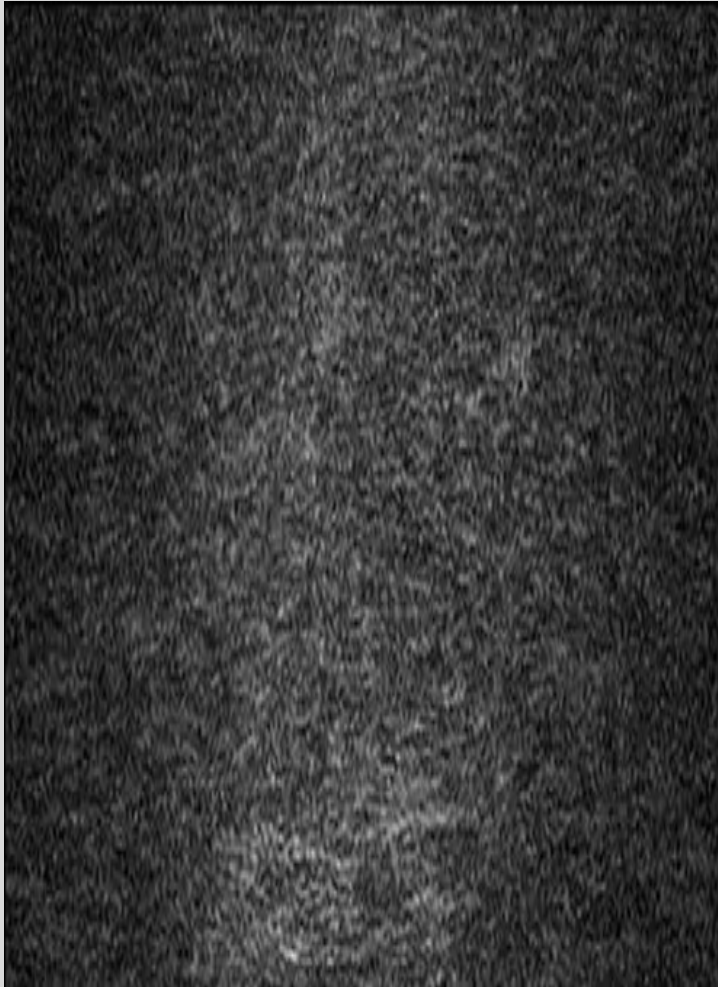
Frame 2



Frame 3

For desired $<1s$ temporal resolution
Can acquire only partial k-space in each frame

High-res 3D dynamic MRI reconstruction



Vastly underdetermined

- Want ~100GB image from ~2GB k-space

Computation/memory demanding

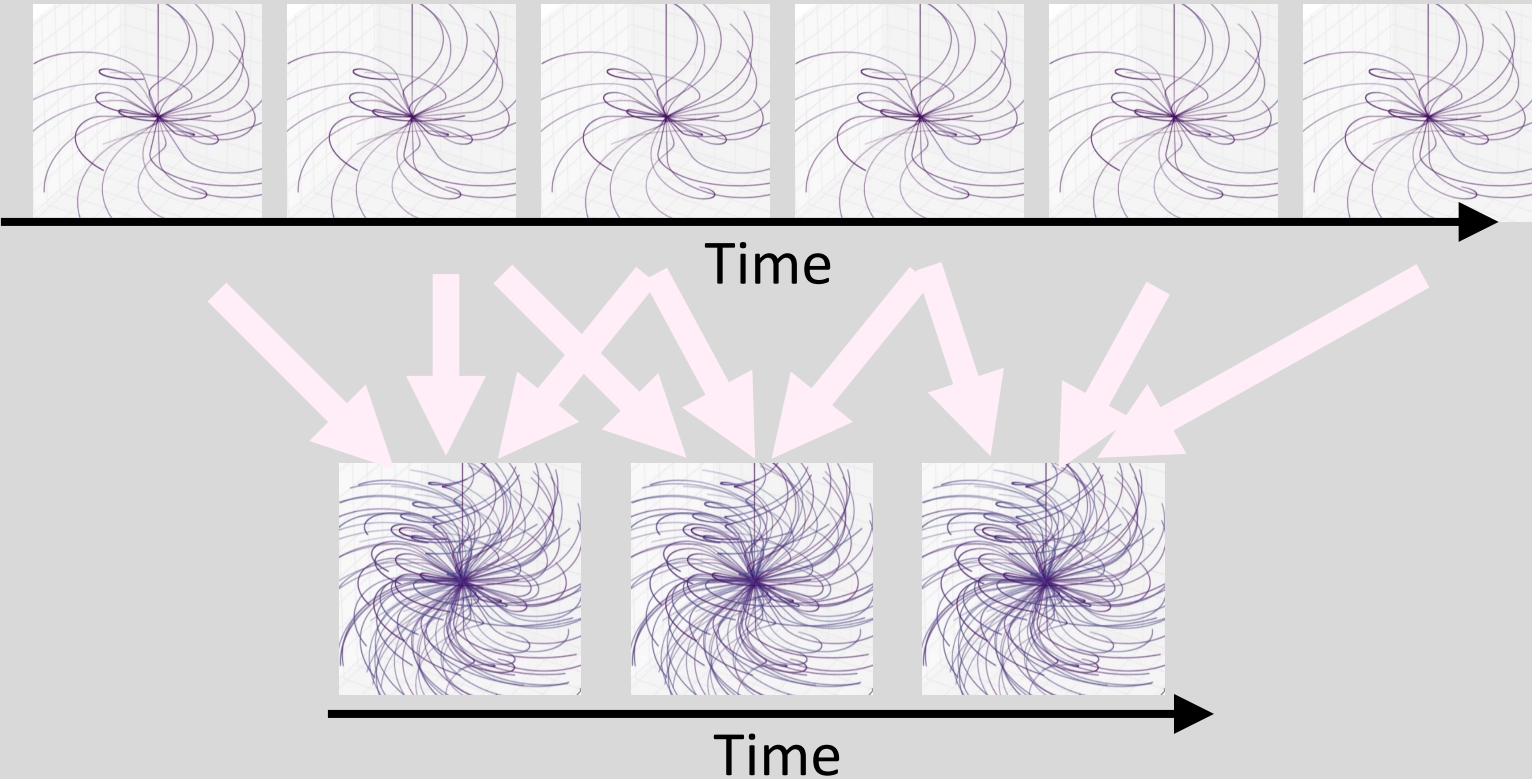
Direct inverse recon. of a 5-minute scan
with high frame-rate

Courtesy Frank Ong

Sliding window reconstruction

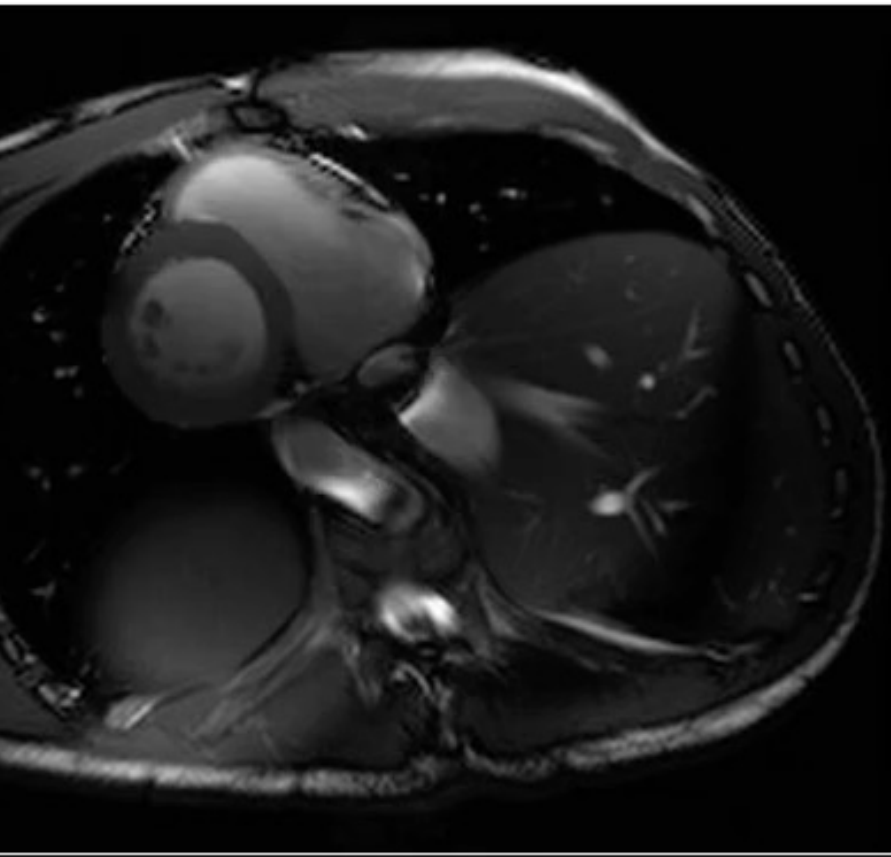


Direct inverse recon. of a 5-minute scan
with low frame-rate



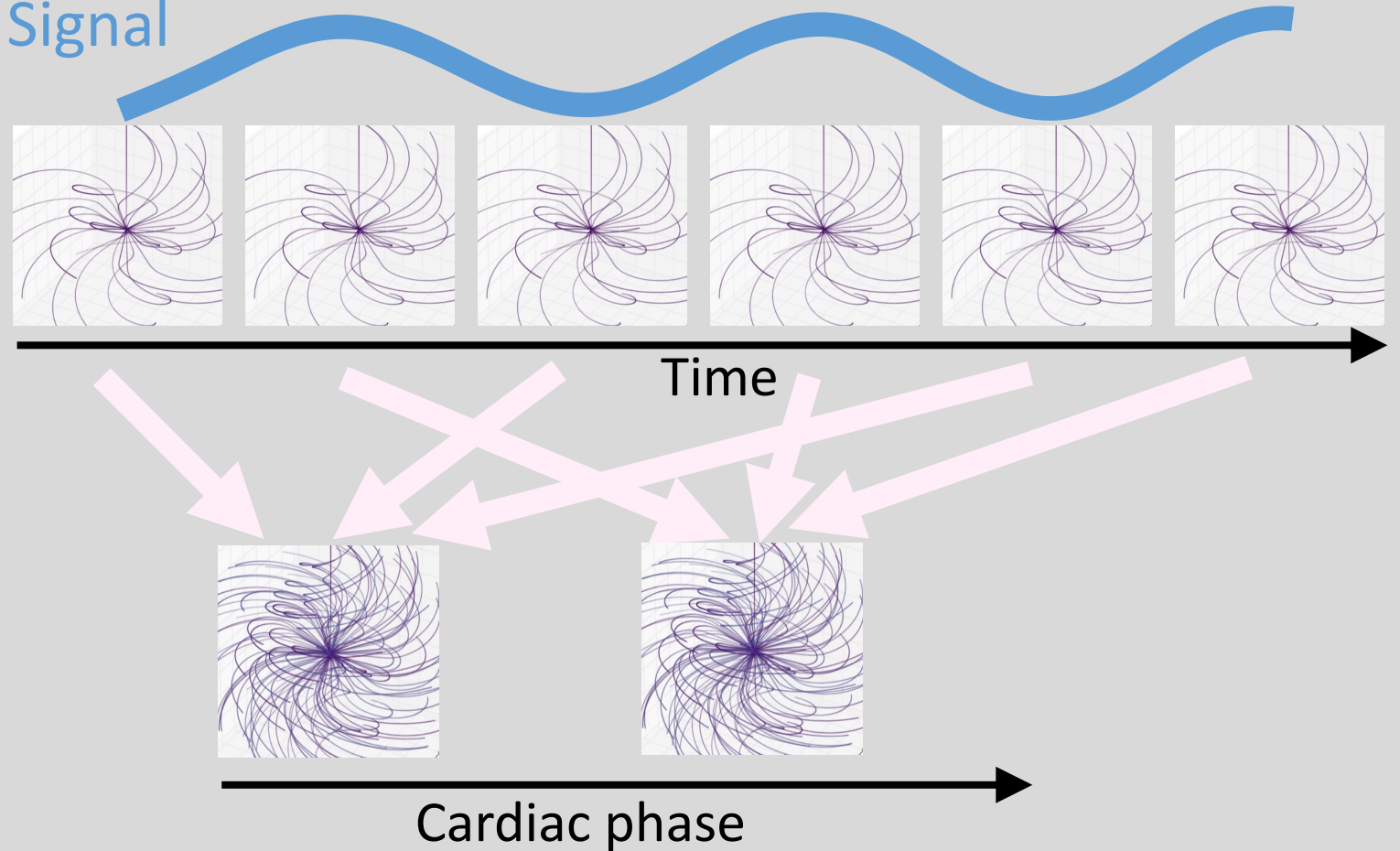
Less underdetermined
Low temporal resolution

Binning reconstruction



Cardiac Gated Reconstruction

Cardiac Signal



Can be made fully-sampled

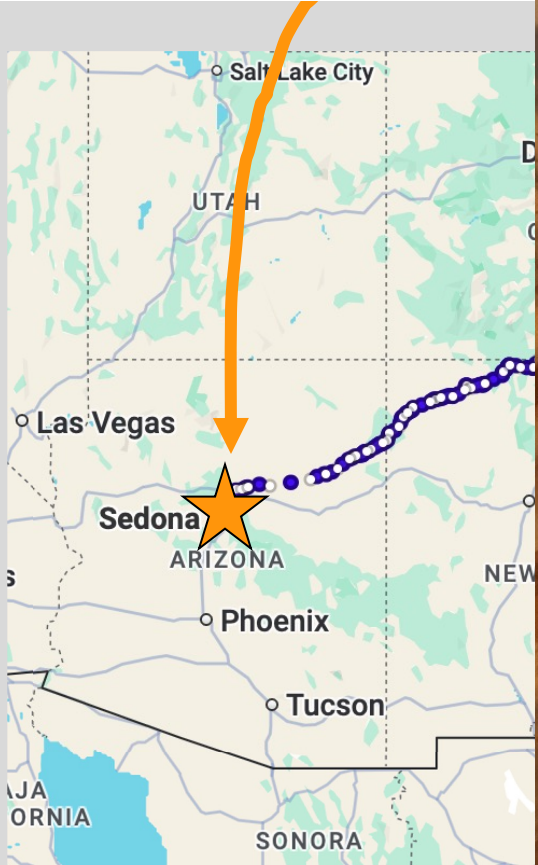
Only works for periodic dynamics

Compact signal models

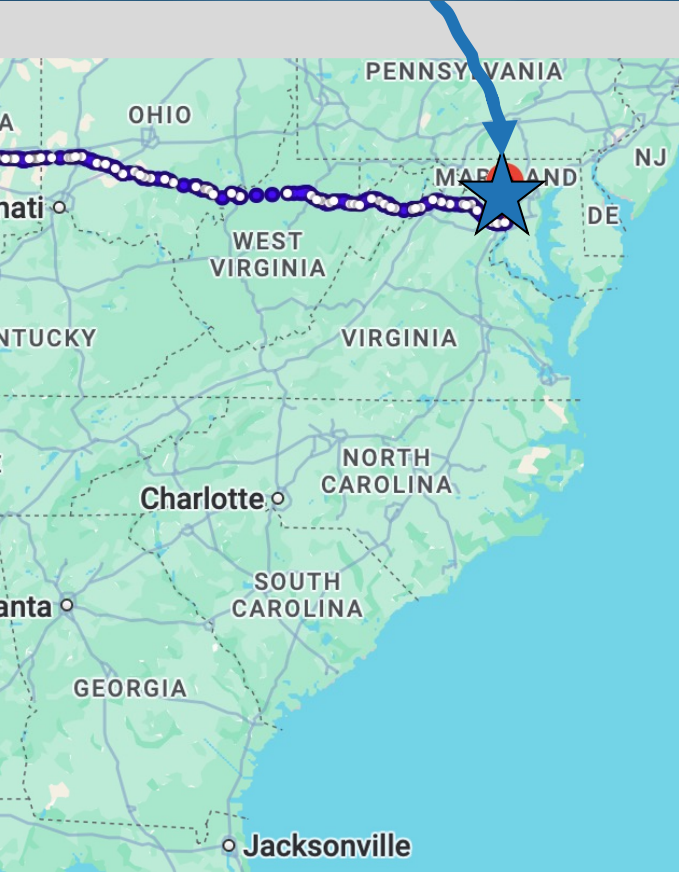
- Model redundancy in the signal $\rightarrow$ reduced dimensionality

Compact signal

International Society for Magic
Workshop on Non-
25-28 February 2007 ~ Enchantment



International Symposium
on Optical Imaging:
from Micro to Macro
Crystal Gateway Marriott • Metro Washington, D.C., U.S.A.



Compact signal models

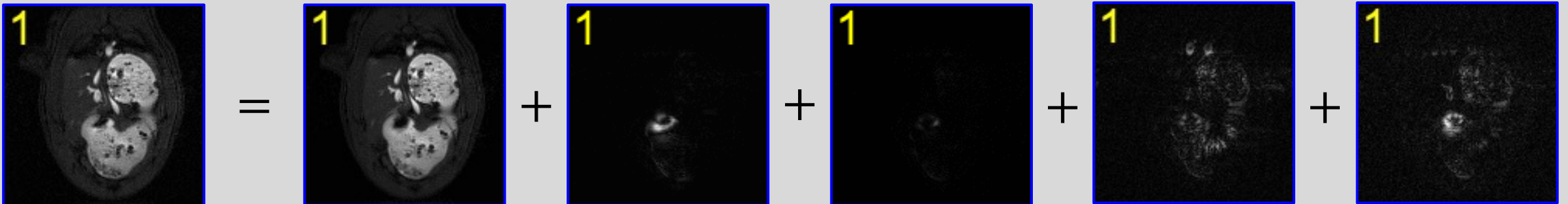
- Model redundancy in the signal $\rightarrow$ reduced dimensionality

SPATIOTEMPORAL IMAGING WITH PARTIALLY SEPARABLE FUNCTIONS

Zhi-Pei Liang

$$\rho(\mathbf{r}, t) = \sum_{\ell=1}^L \tilde{c}_{\ell}(\mathbf{r}) \varphi_{\ell}(t)$$

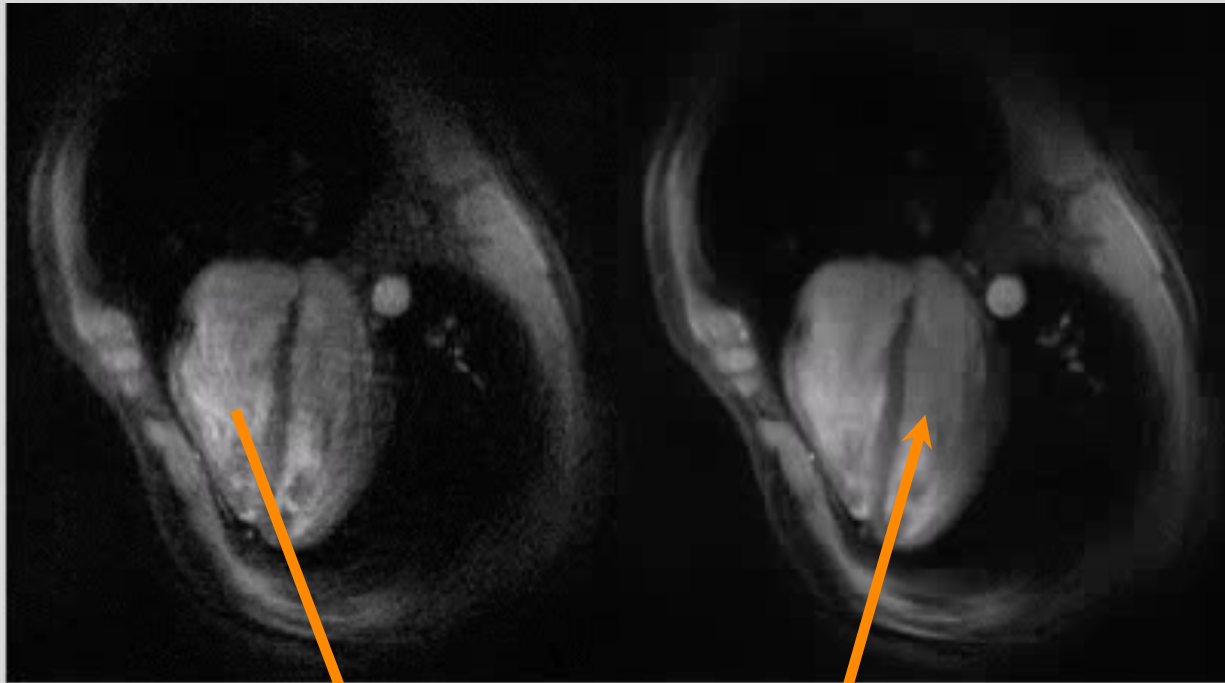
IEEE ISBI 2007



Low-Rank Models

noisy

low-rank denoised



Zhi-Pei Liang, UIUC

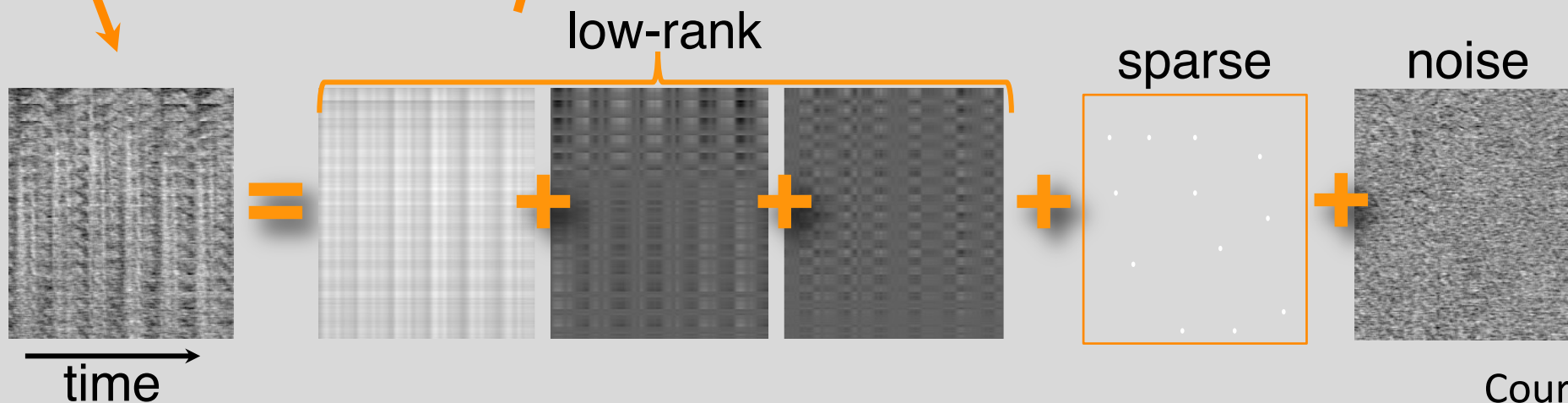
J. Haldar, USC

R. Otazo, Candes MSKCC/Stanford

J. Trzasko, Mayo Clinic

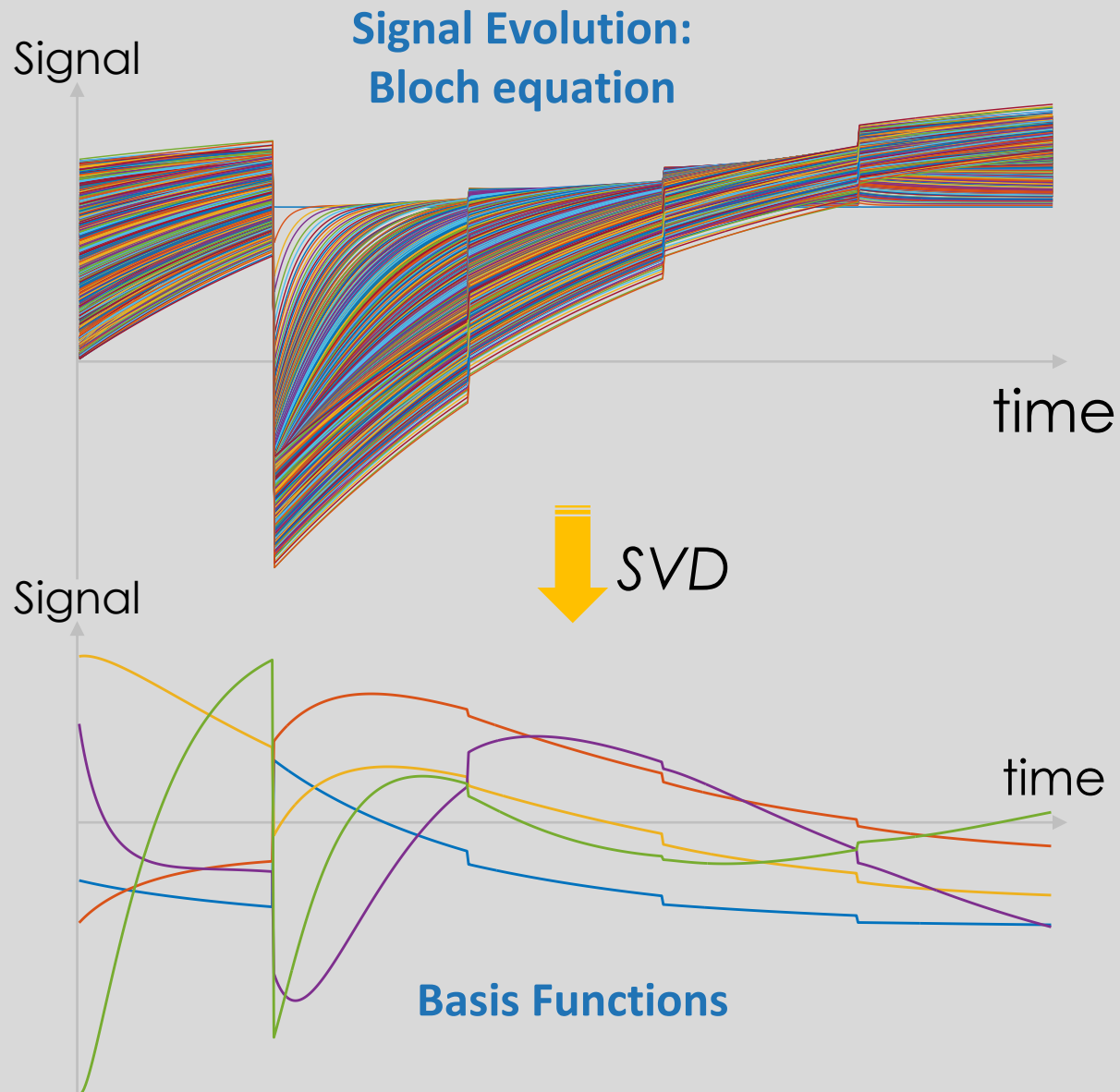
M Lustig, UC Berkeley

T. Zhang, Stanford



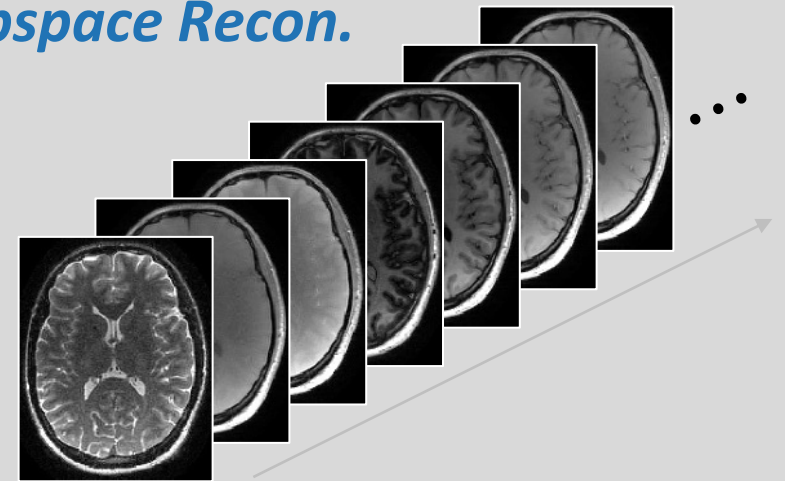
Courtesy Miki Lustig

Subspace constraints for dynamic imaging



Huang et al., MRM 2012
Zhao et al., IEEE TMI 2012
Zhao et al., MRM 2016
Tamir et al., MRM 2017
Asslander et al., MRM 2018
Zhao et al., MRM 2018
Dong et al., MRM 2020

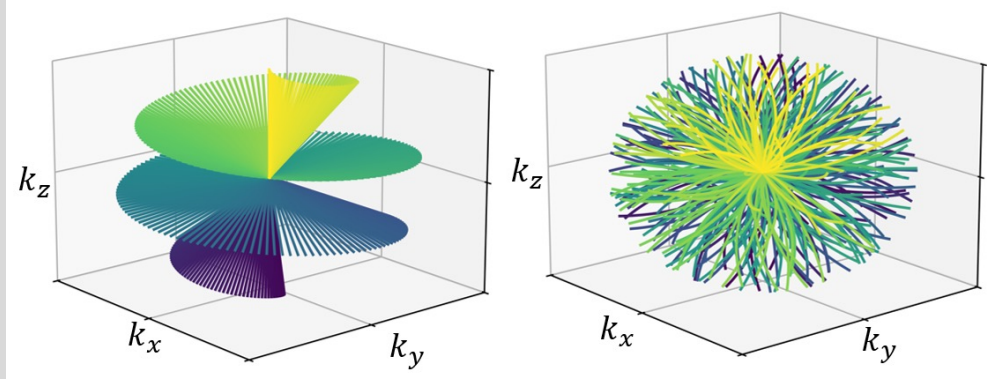
Subspace Recon.



Courtesy Berkin Bilgic

Subspace constraints for dynamic imaging

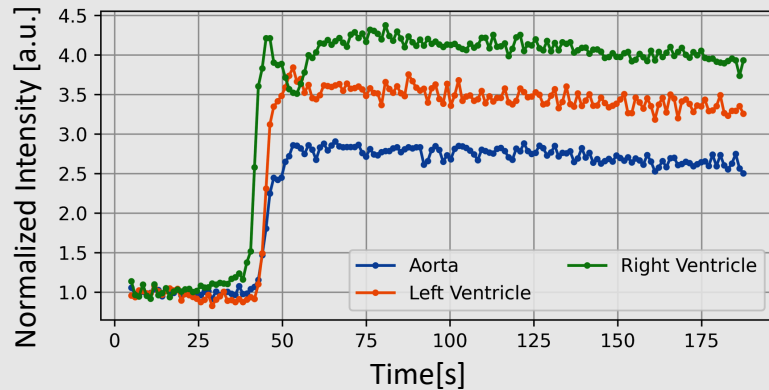
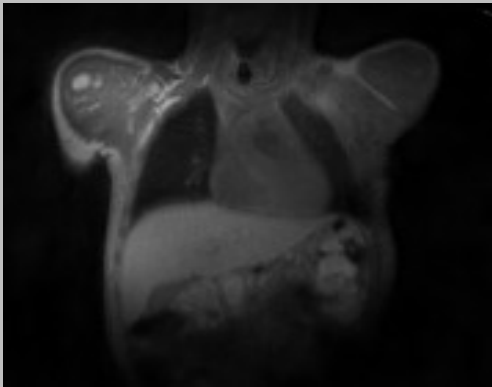
Near-silent dynamic T1w MRI using Zero-TE



~30dB quieter than conventional sequences

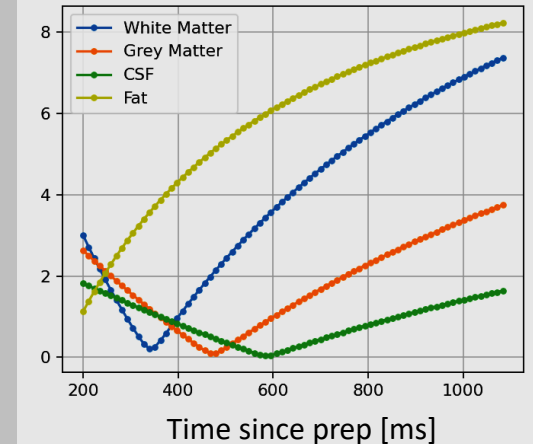
- + temporal subspace
- + locally low rank regularization
- + polynomial preconditioning

Resolving contrast uptake dynamics (1.1s/frame)



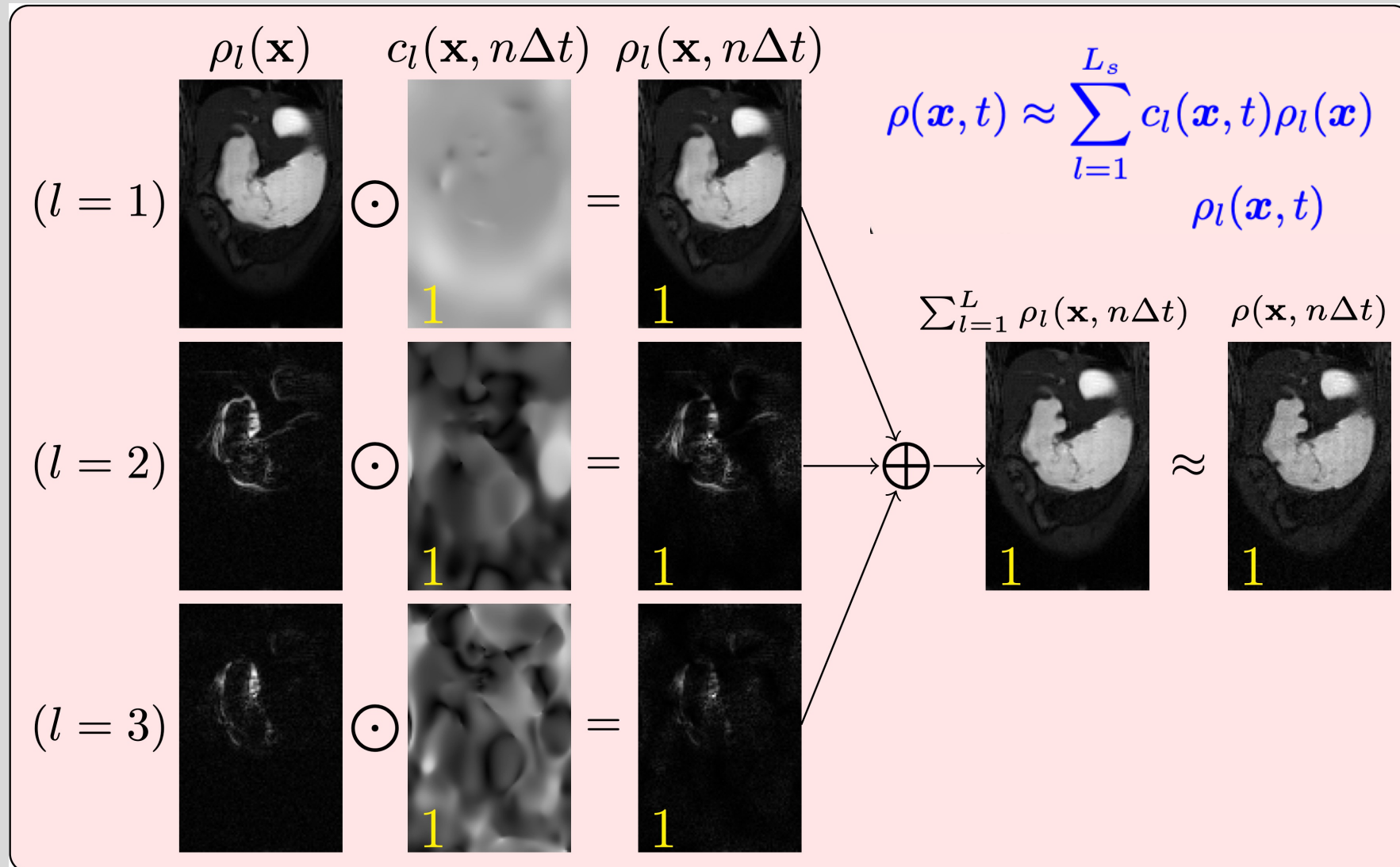
2.9ms TR, ± 31.25 kHz BW, 3° FA, 1.4mm res, 1.1s/frame, Recon. Rank 16

Resolving T1 recovery dynamics

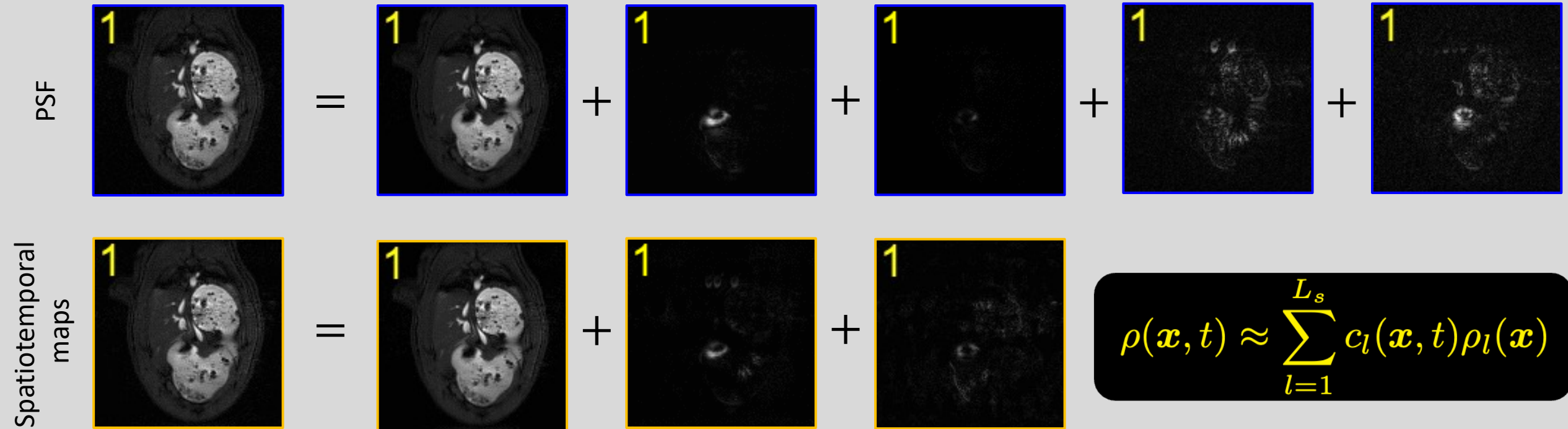


2.4ms TR, ± 31.25 kHz BW, 3° FA, 0.9mm res, Recon. Rank 3

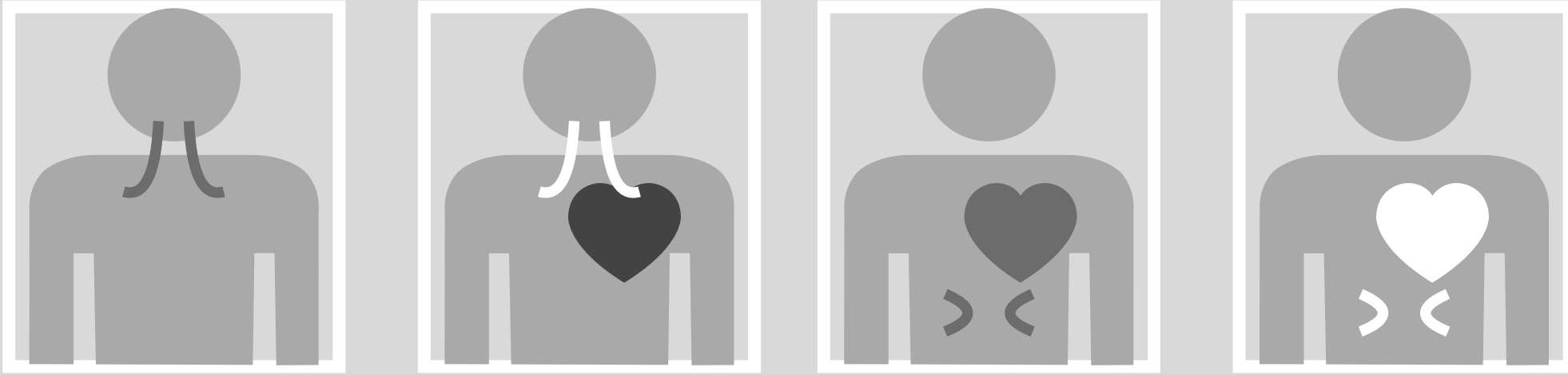
Extending partial separability: spatiotemporal decomposition



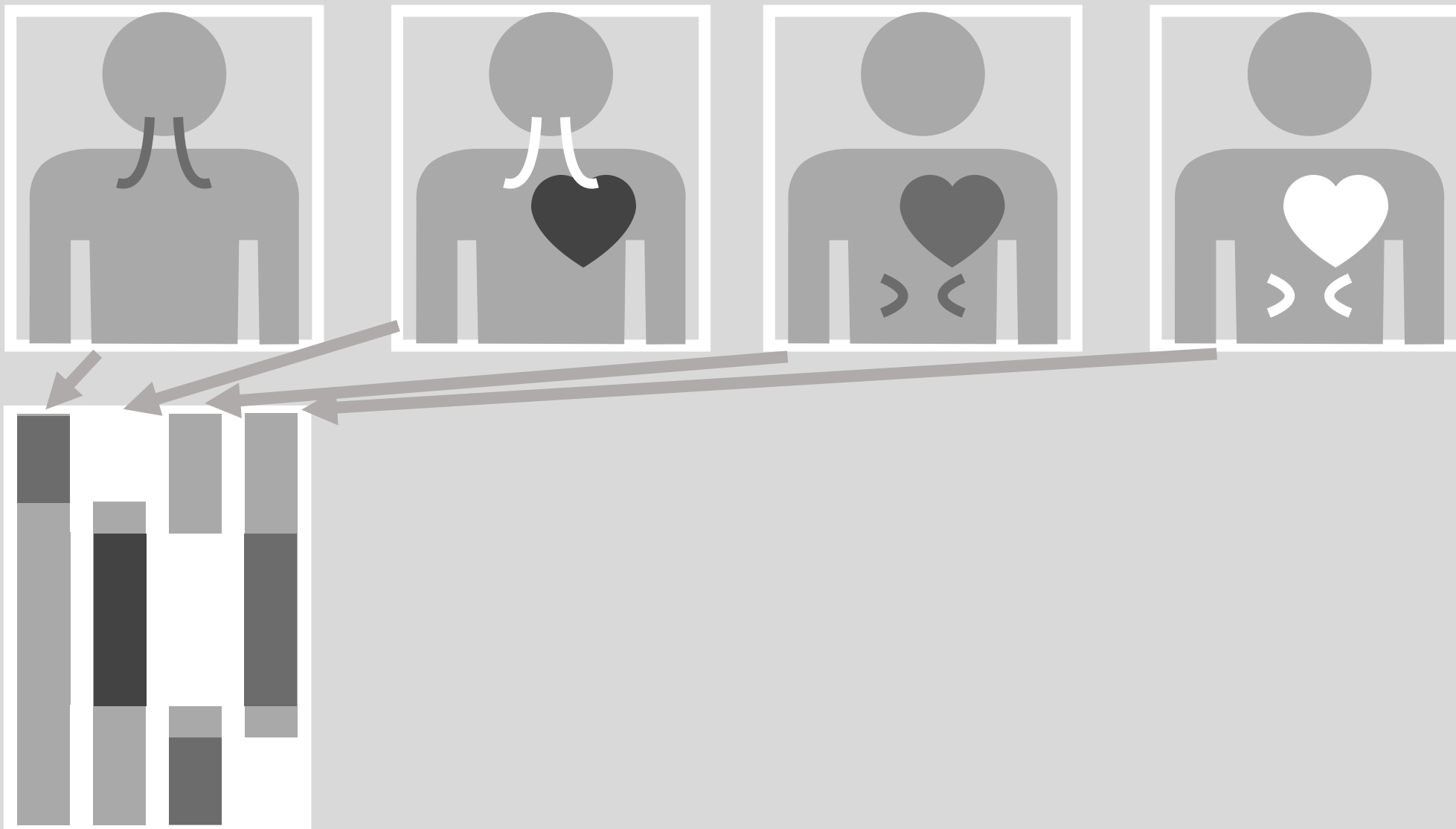
Extending partial separability: spatiotemporal decomposition



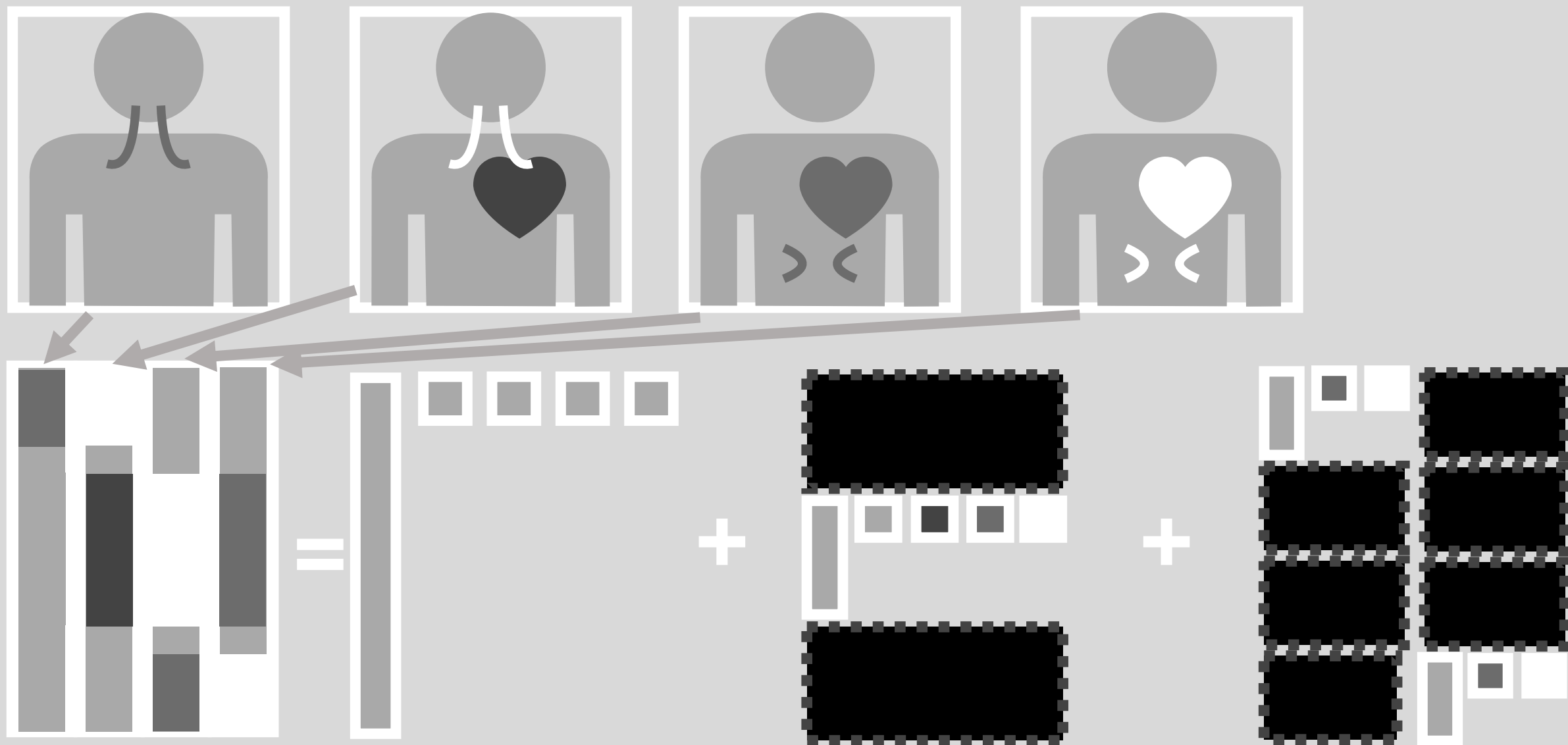
Extending local low rank: multi-scale low rank



Extending local low rank: multi-scale low rank



Extending local low rank: multi-scale low rank

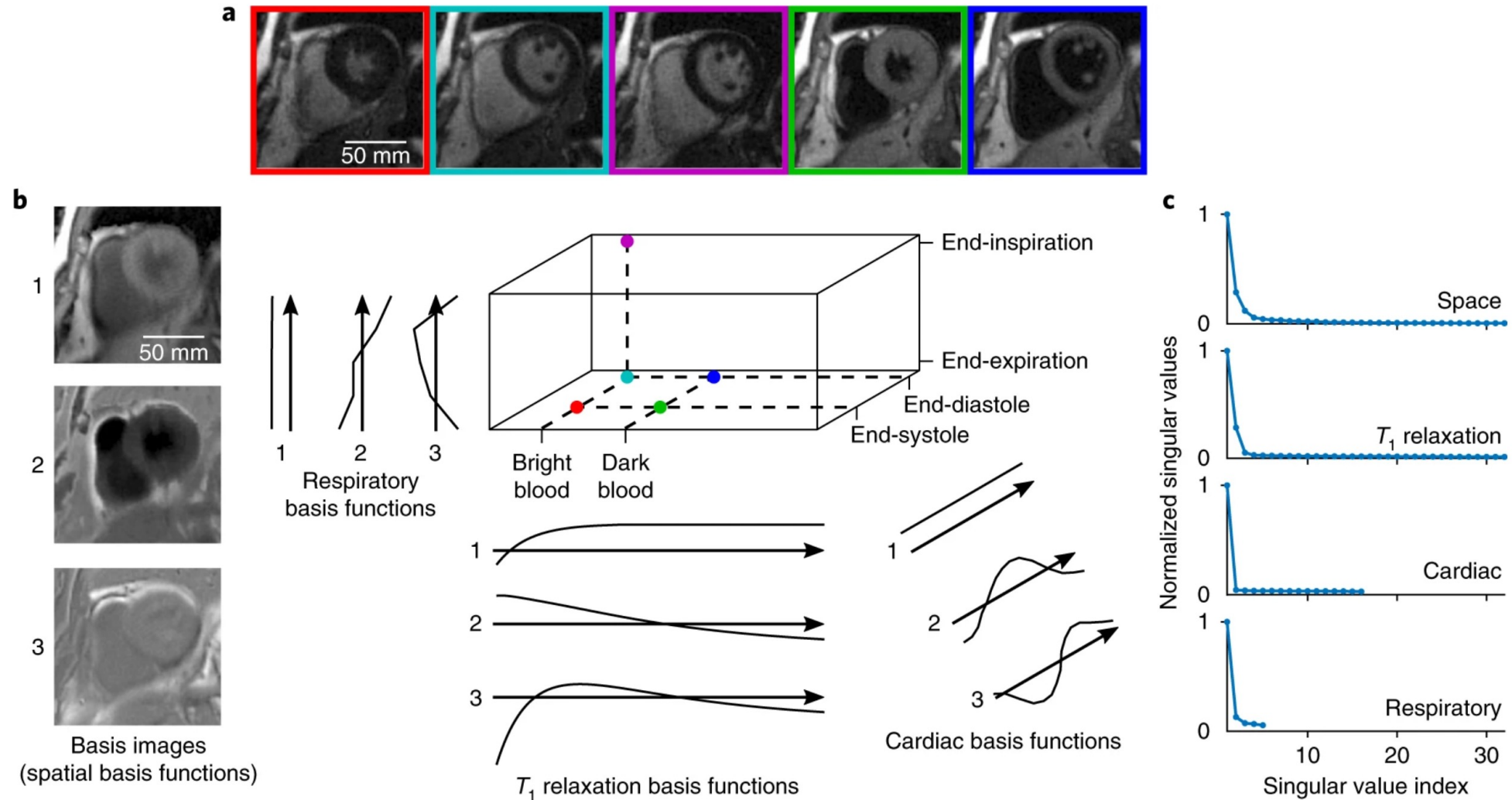


Extending local low rank: multi-scale low rank



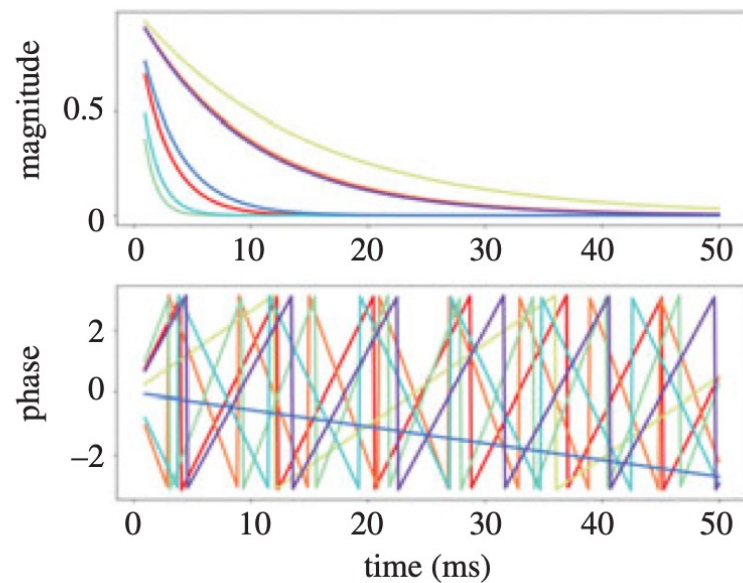
Scan time:	4m 40s
Temporal Res	580 ms
Matrix Size	392 x 318 x 165
Spatial Res	

Extending low rank: MR Multitasking

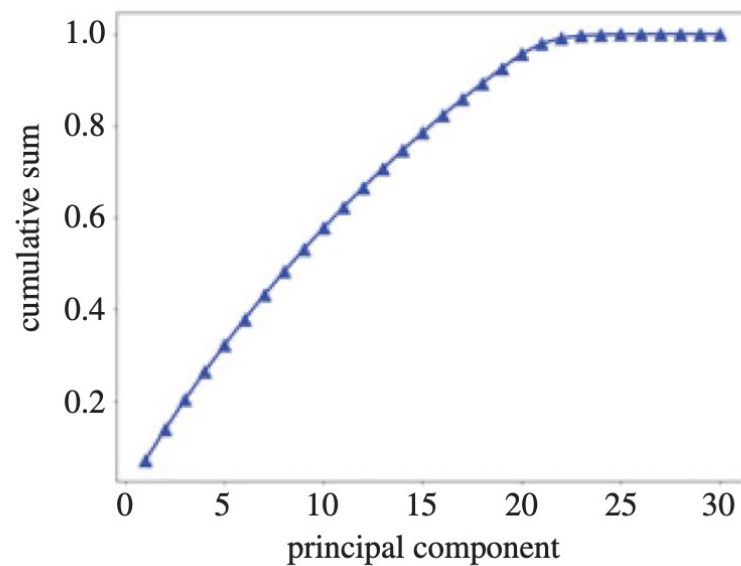


Explicit signal (or motion) modeling

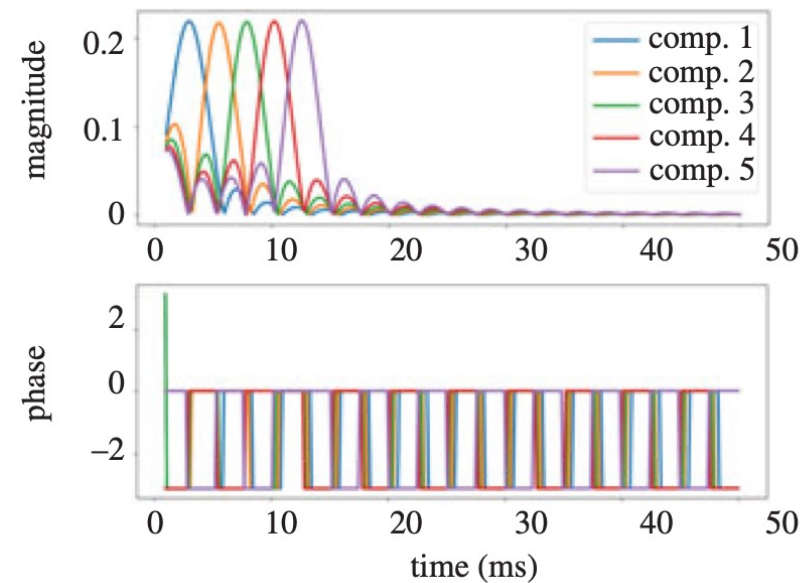
simulated dictionary (subset)



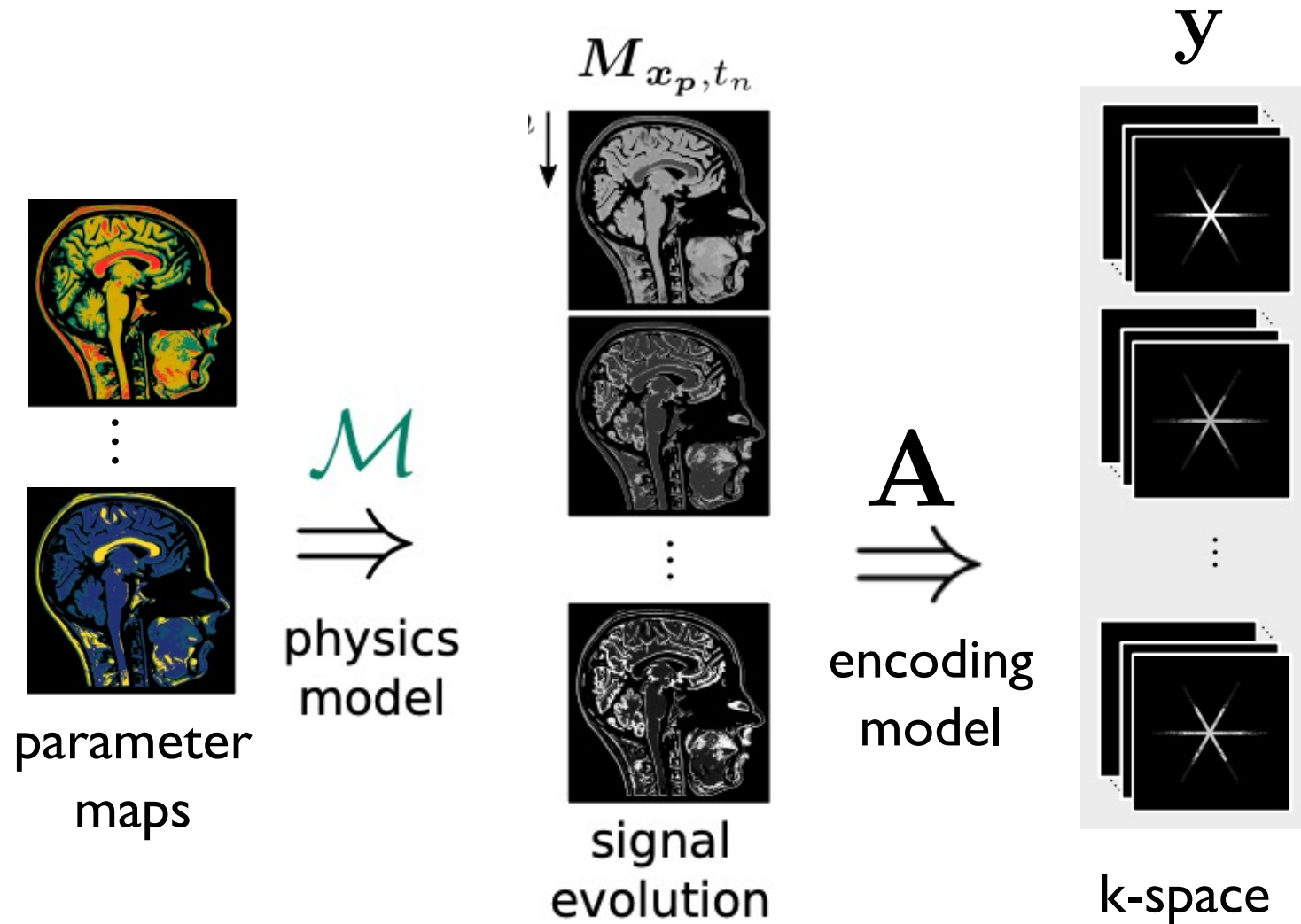
accumulated PCA coefficients



temporal subspace curves

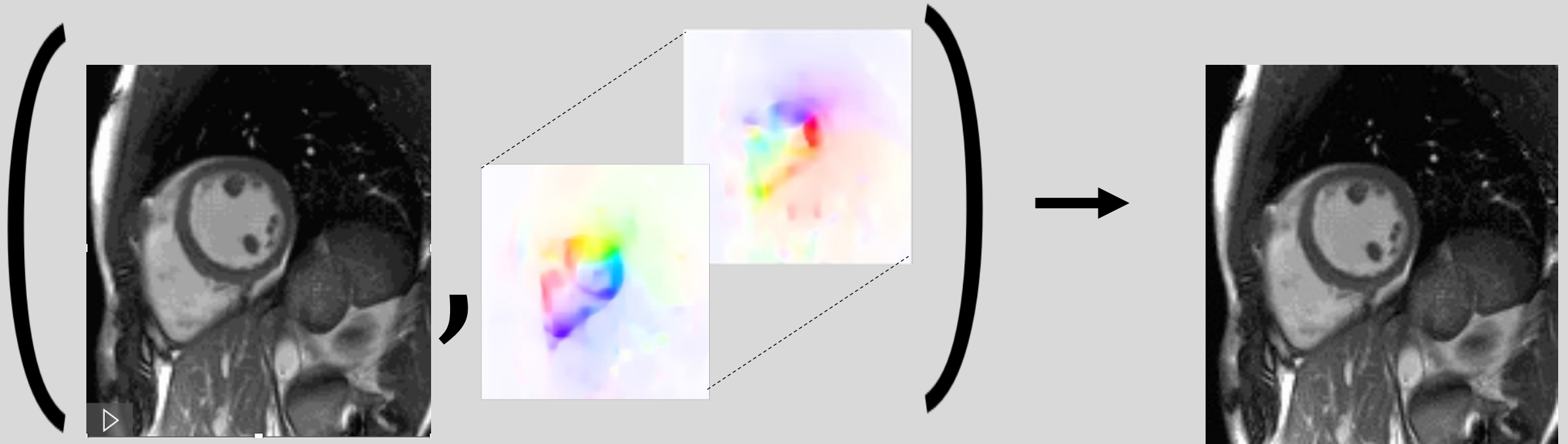


Explicit signal (or motion) modeling



Explicit signal (or motion) modeling

$$x(r, t) = \text{Warp}(\rho(r), u(t))$$

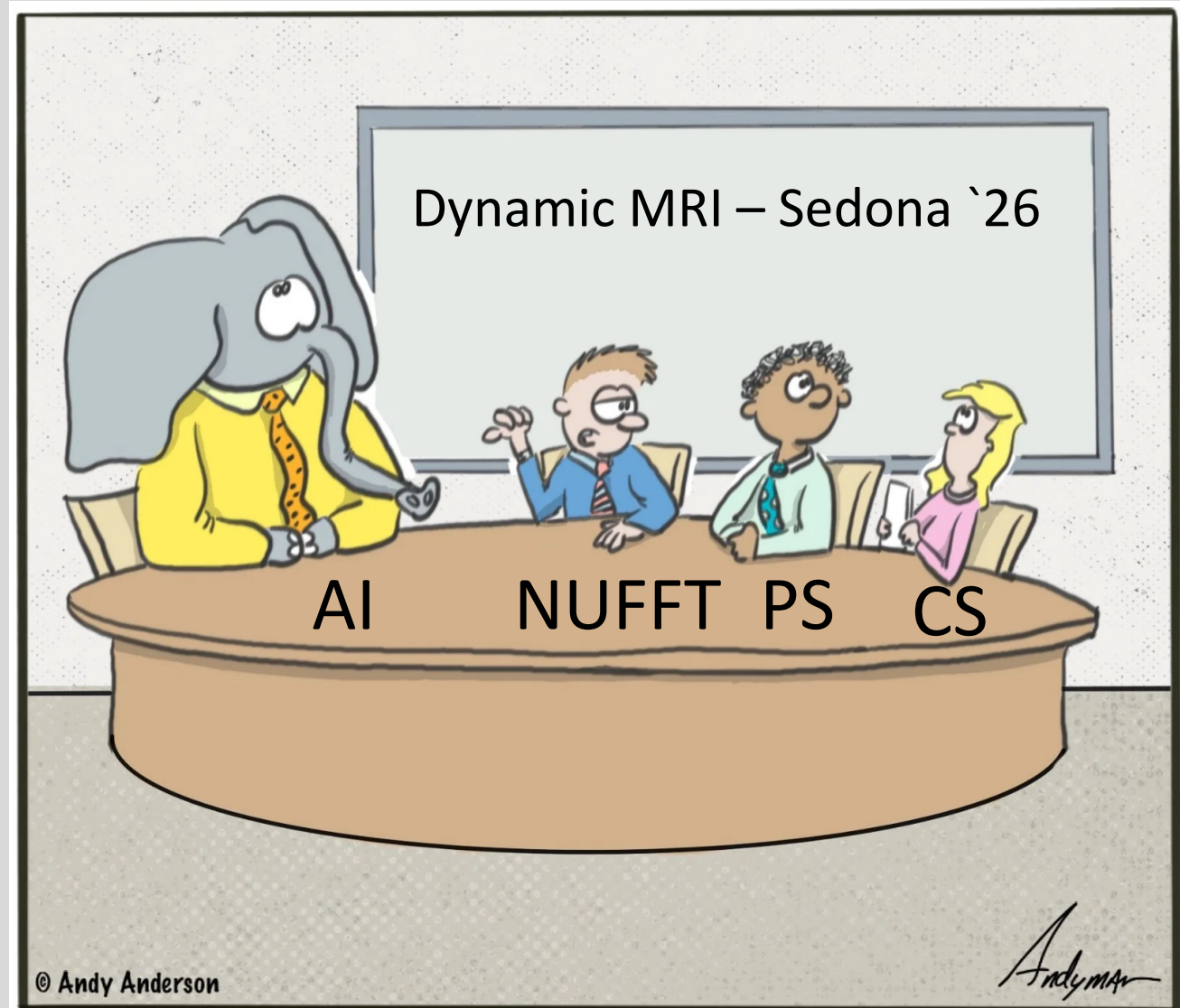


Rueckert et al., MICCAI 2006
Lingala et al., IEEE TMI 2014
Huttinga et al., PBM 2020

Courtesy Thomas Küstner

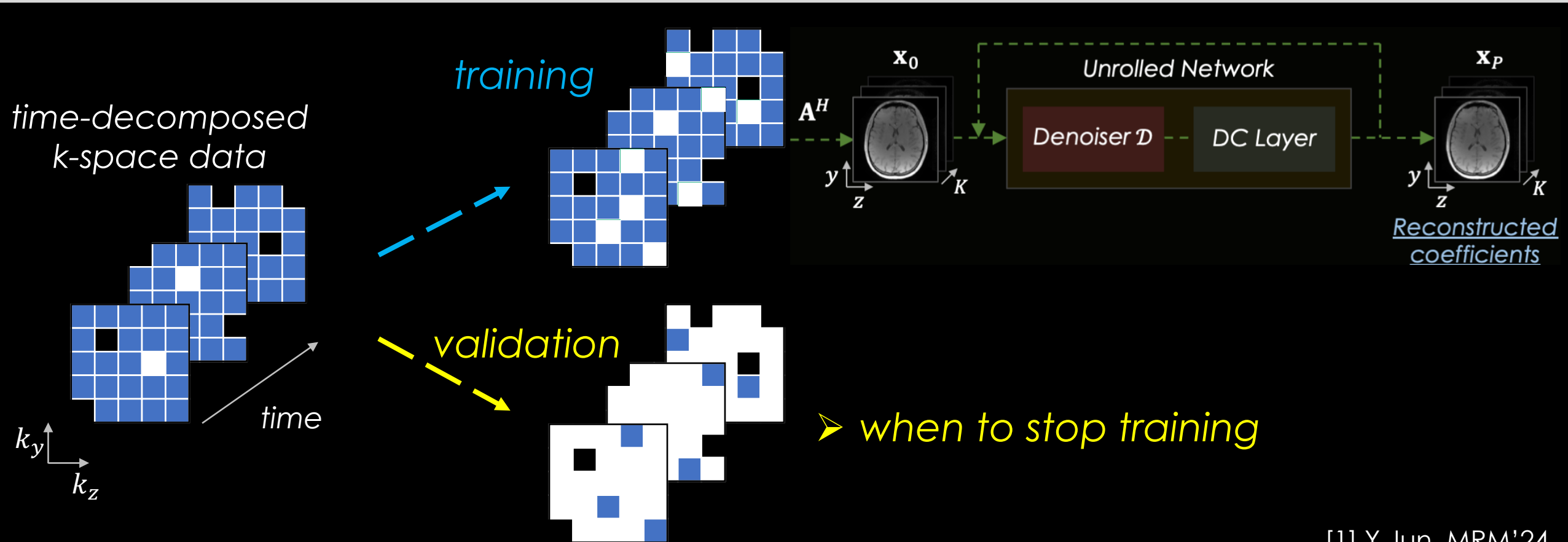
Dynamic MRI with deep learning

- Use neural networks as either explicit or implicit priors
 - + subspace constraints
 - + explicit signal/motion model



SO WE'RE NOT GOING TO DISCUSS IT?

Deep learning + subspace constraint



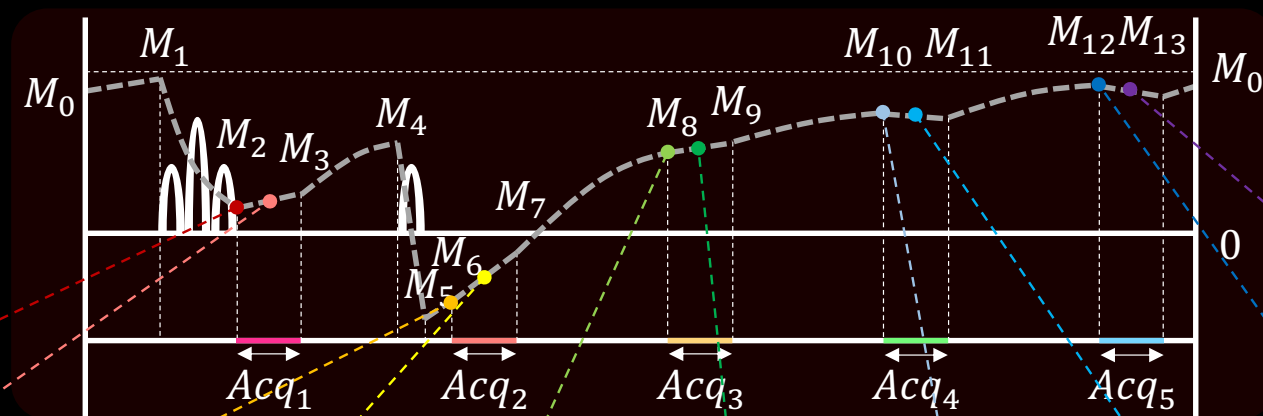
- [1] Y Jun, MRM'24
- [2] B Yaman, ICLR'22



Self-supervised AI recon

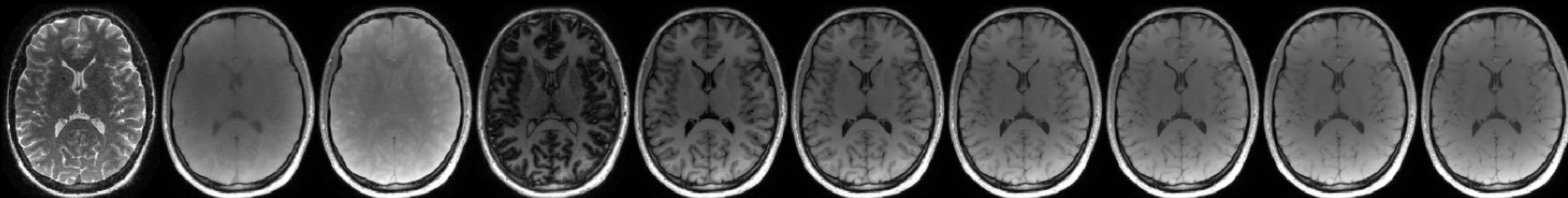
R=10 @ 1.15 mm iso in 1:40 min
time-resolved QALAS

resolve 600+ echoes



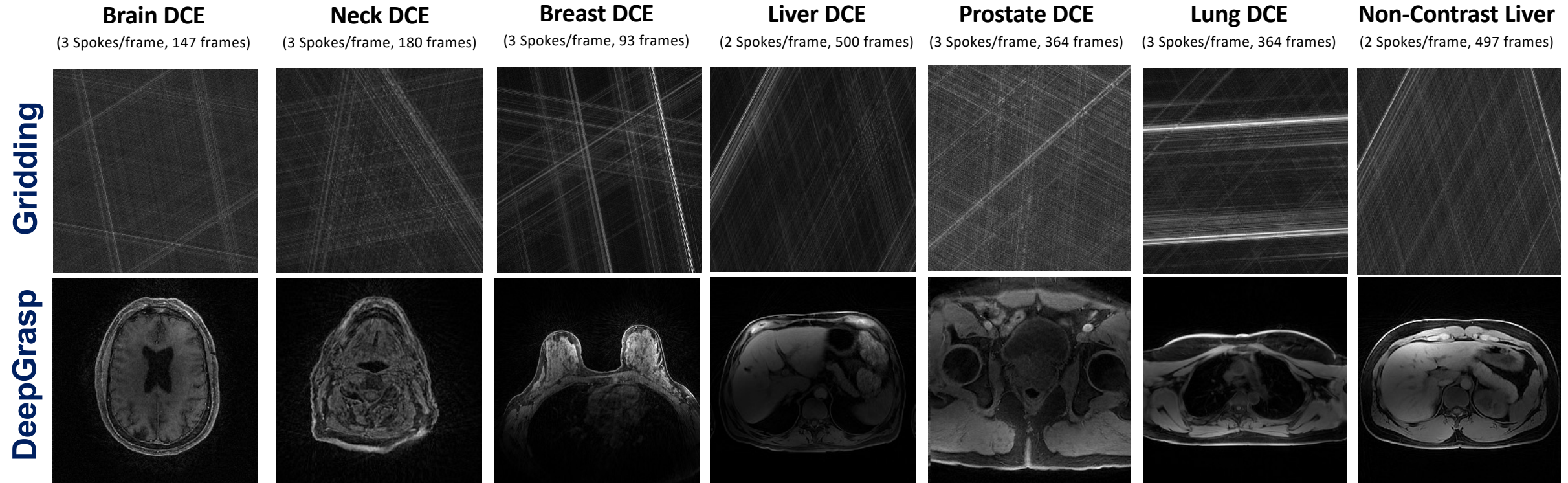
Time (ms)

168.5 531.4 1068.5 1431.4 1968.5 2331.4 2868.5 3231.4 3768.5 4131.4



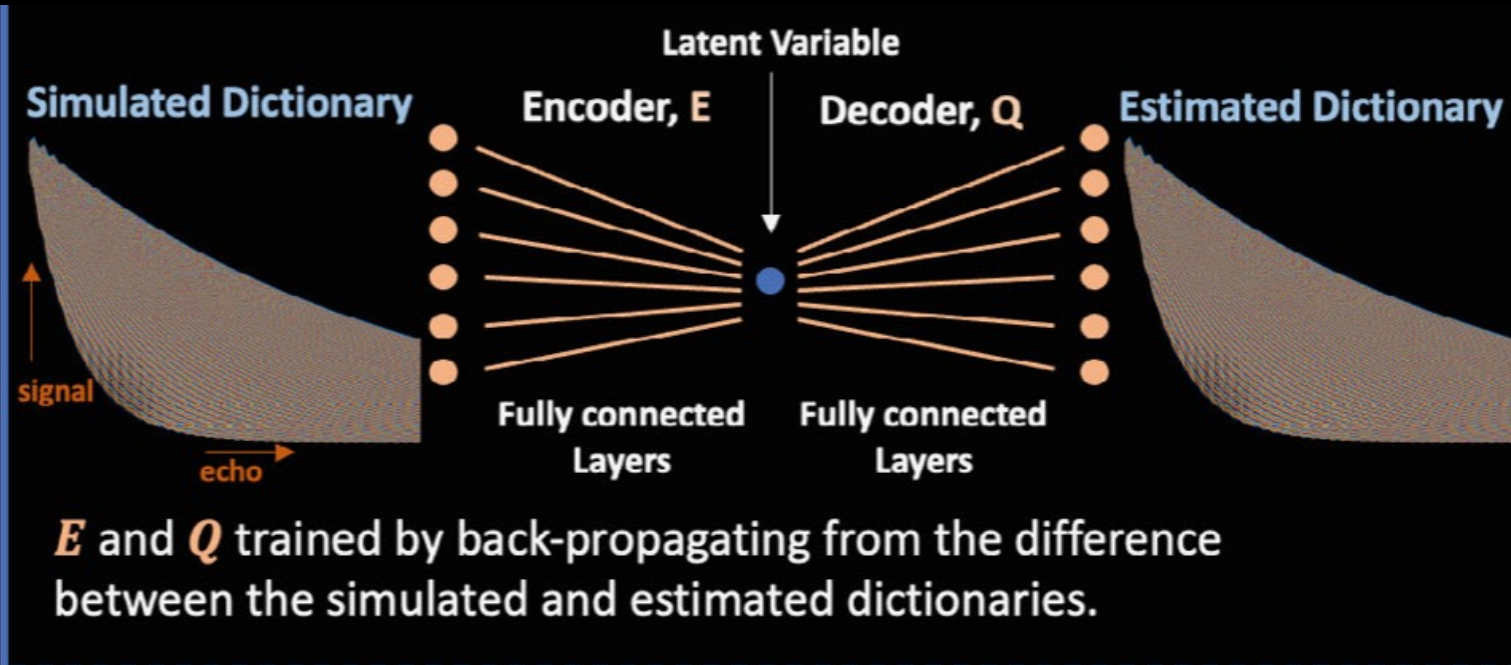
Courtesy Berkin Bilgic

DeepGrasp: A unified All-in-One model for generalized 4D radial MRI

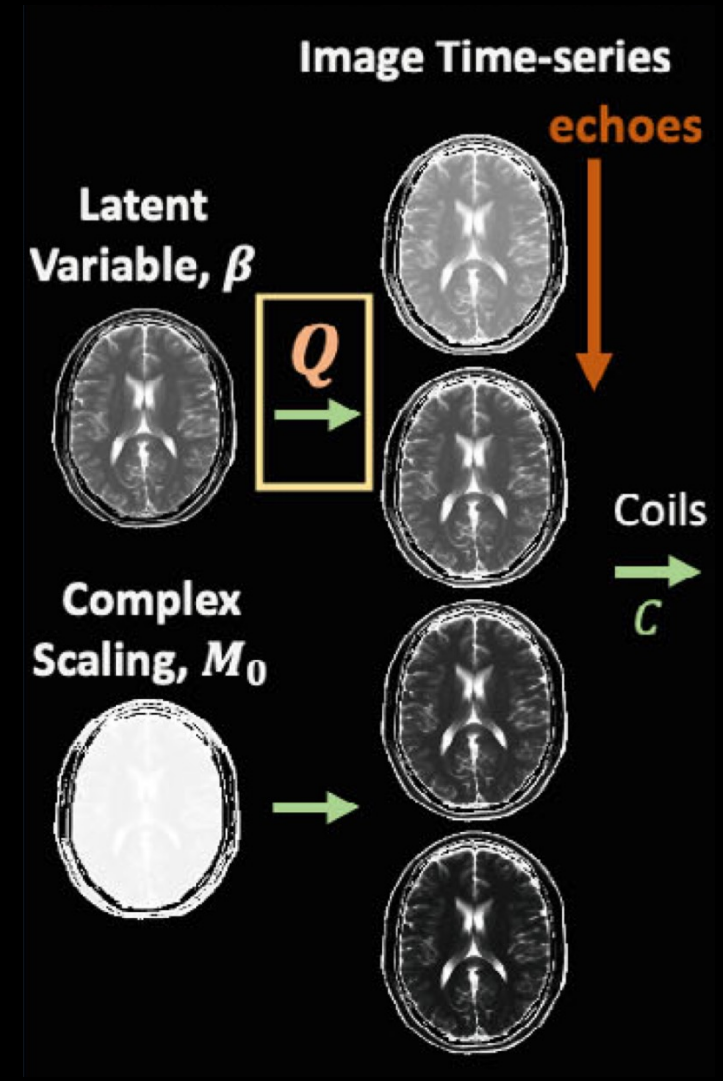


- A single unified model based on self-supervised learning
- 2 or 3 spokes per image frame (sub-second temporal resolution)
- Network training using 15,372 dynamic image slices

Latent signal model

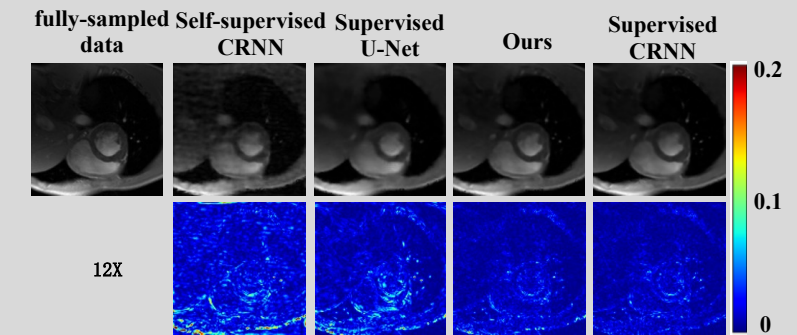
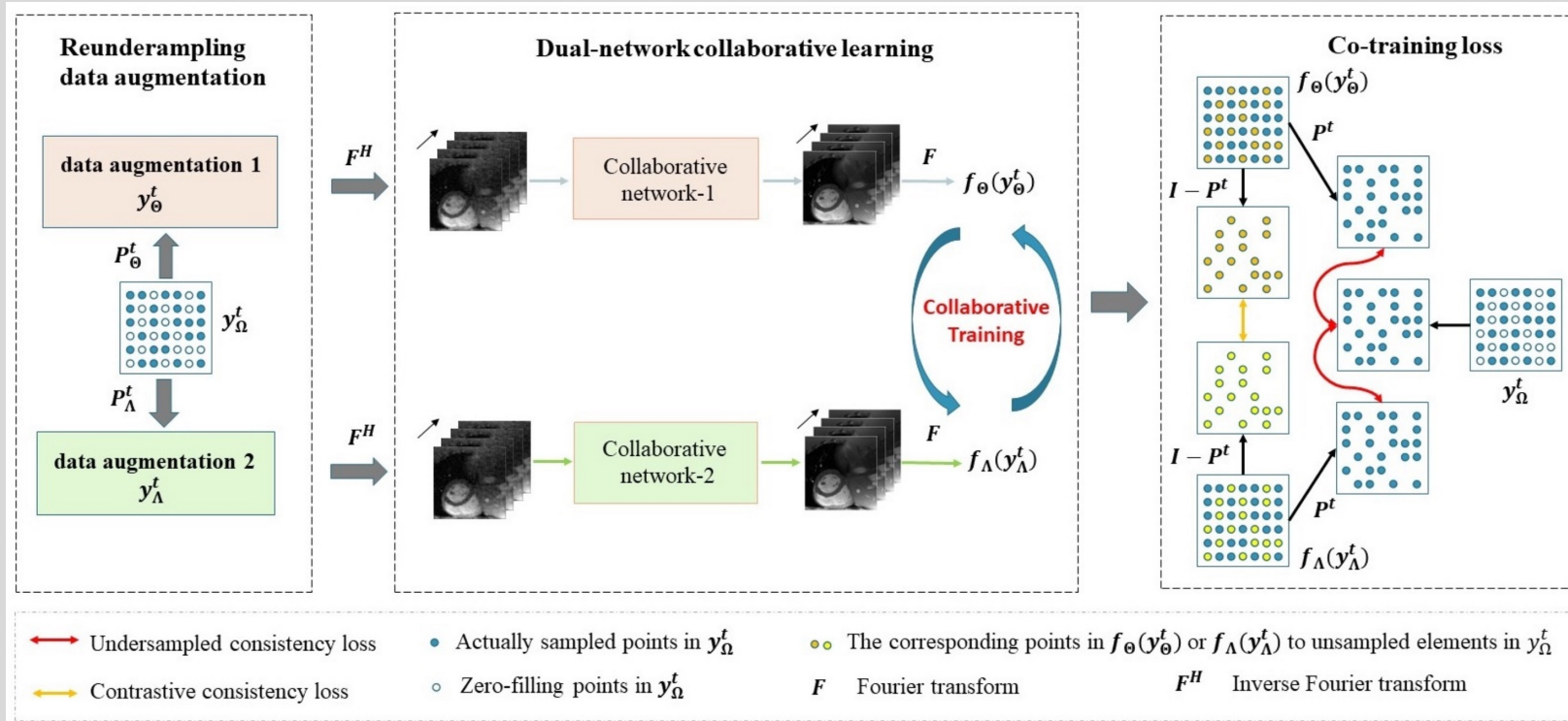


+



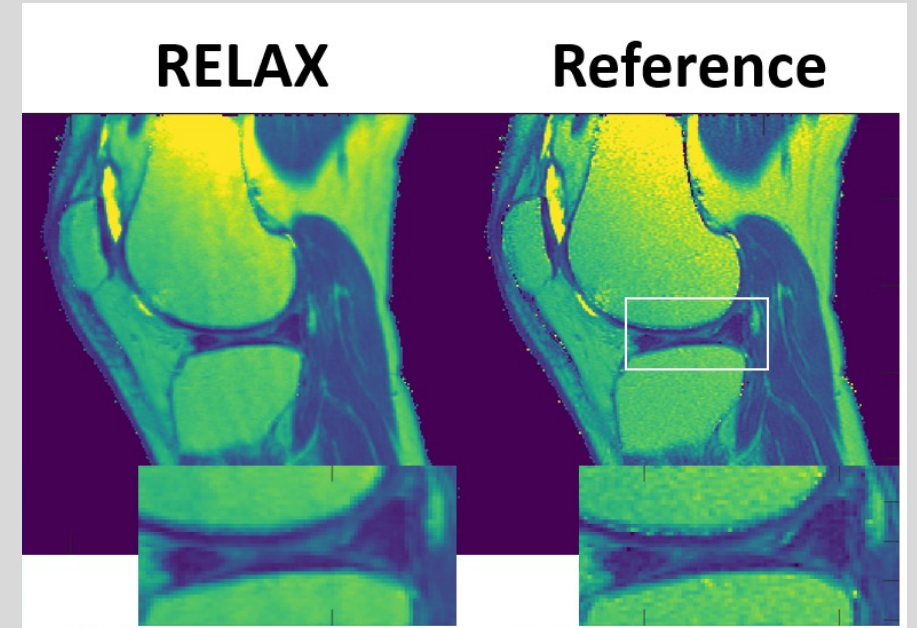
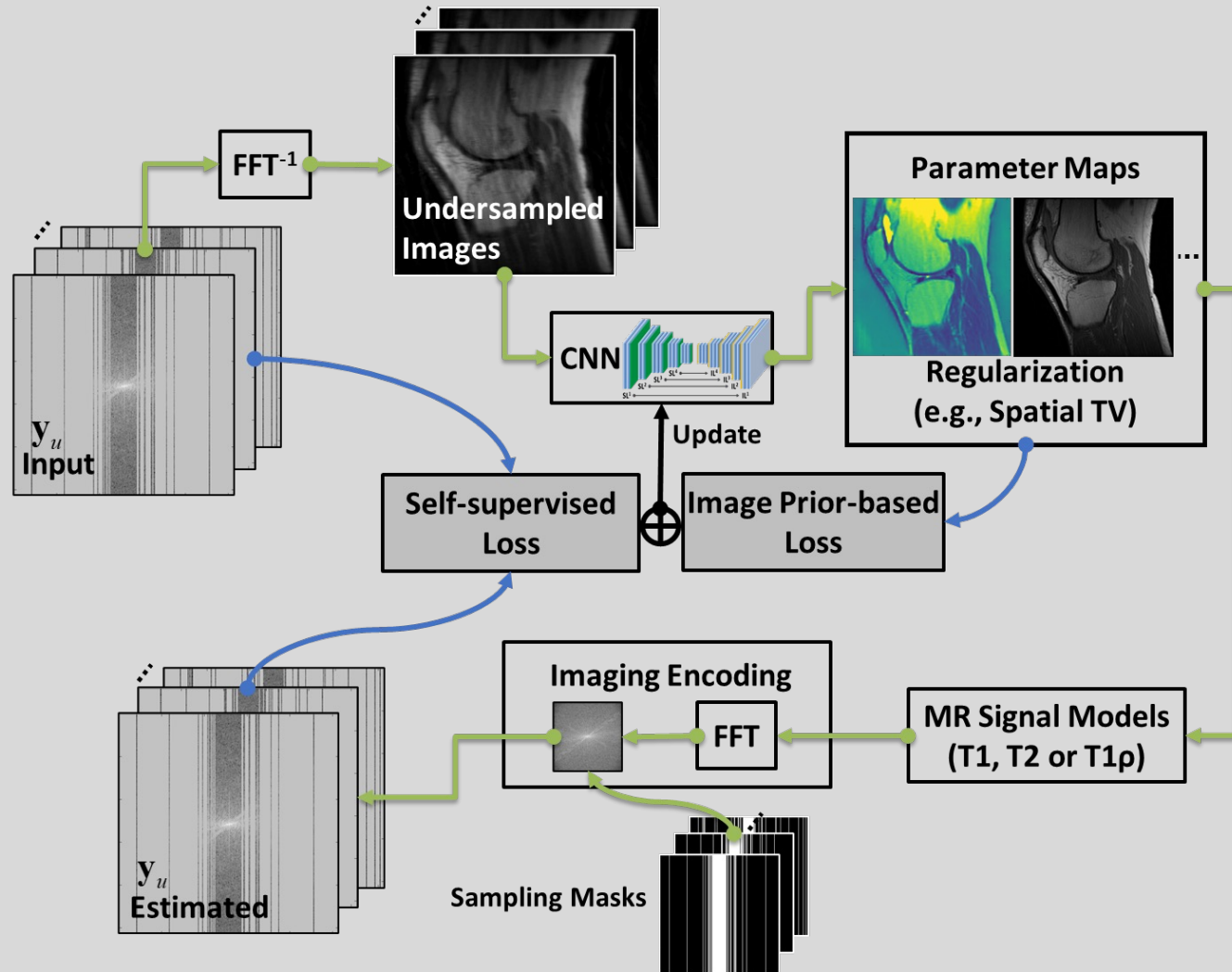
Dynamic MRI with Self-supervised learning

- Due to physiological motion and imaging speed limitations, fully sampled dynamic MRI data are generally unavailable.
- The spatiotemporal correlation in dynamic MRI can be leveraged for self-supervised learning.

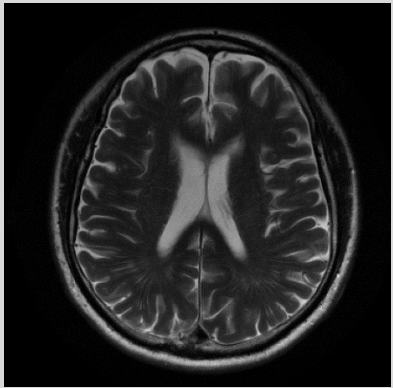


Proposed self-supervised collaborative learning framework enables high-quality and fast dynamic MR imaging

Quantitative MRI with self-supervised learning



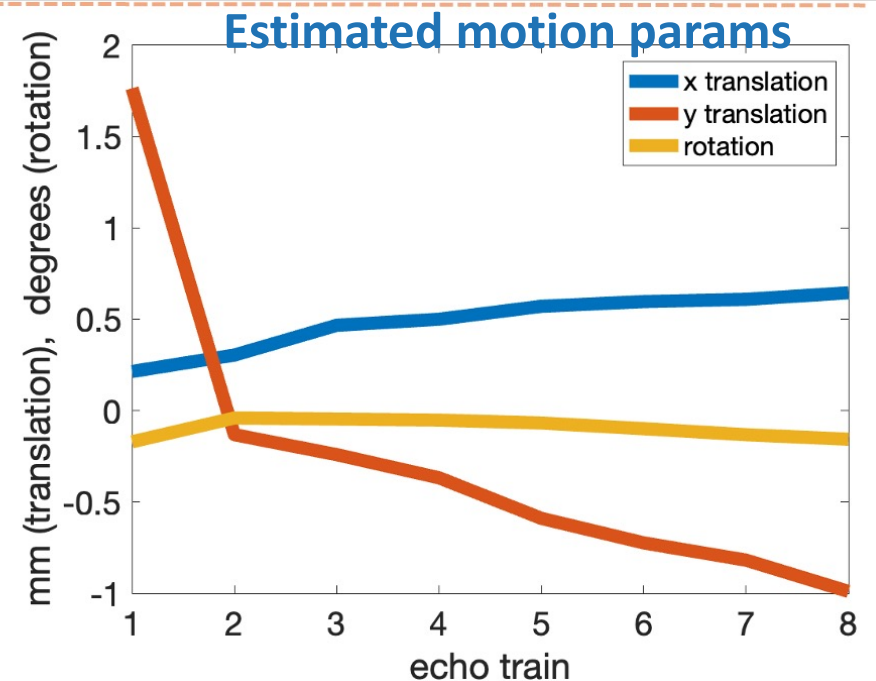
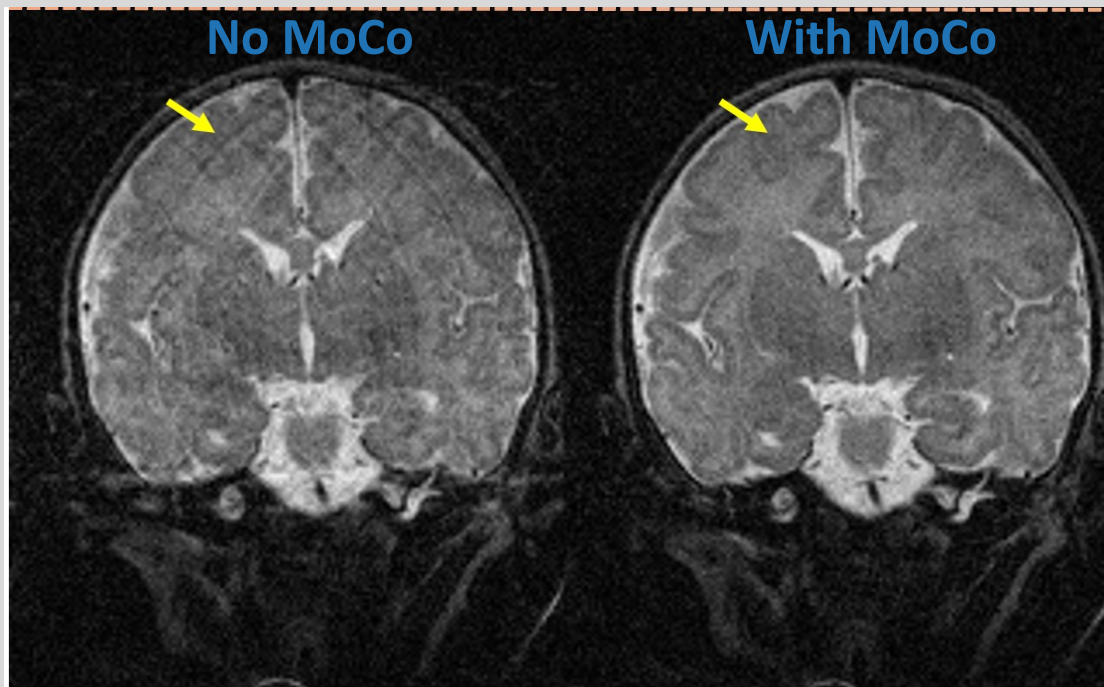
Generative model + explicit motion model



$$\mathbf{y} = \mathbf{A}_{\kappa} \mathbf{x} + \mathbf{v}$$

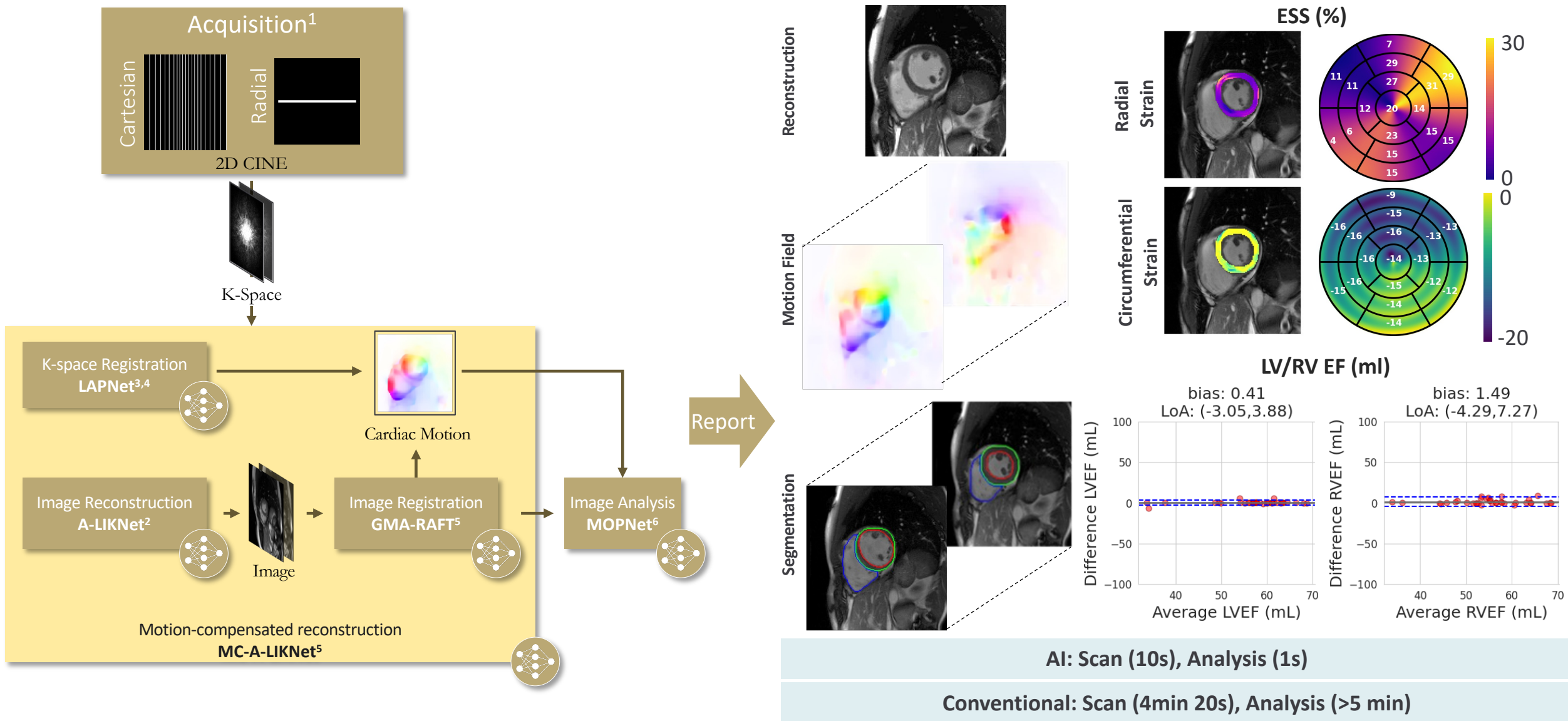
Motion parameters

$$(\mathbf{x}, \kappa) \sim p(\mathbf{x}, \kappa | \mathbf{y})$$



Cardiac Imaging

AI accelerated cardiac functional assessment



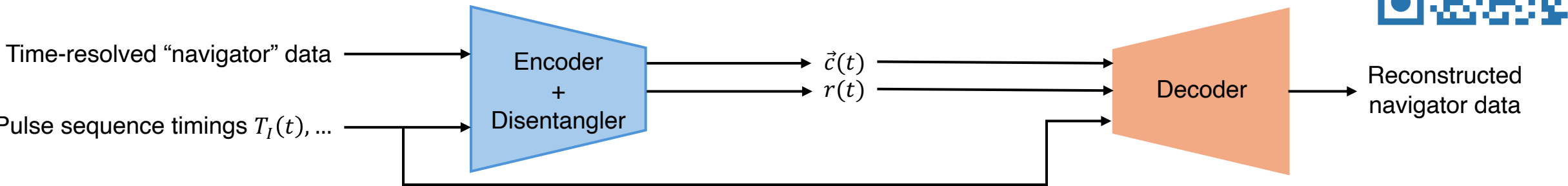
Generative MR Multitasking for high-dimensional imaging

For imaging with multiple “time dimensions”, e.g., $I(\vec{x}, c, r, T_1, \dots)$ (cardiac, respiratory, inversion time, ...)

Conditional variational autoencoder (CVAE) structure

Uses known pulse sequence timings $T_I(t), \dots$ as conditional inputs

Latent space represents unknown motion timings $c(t), r(t)$

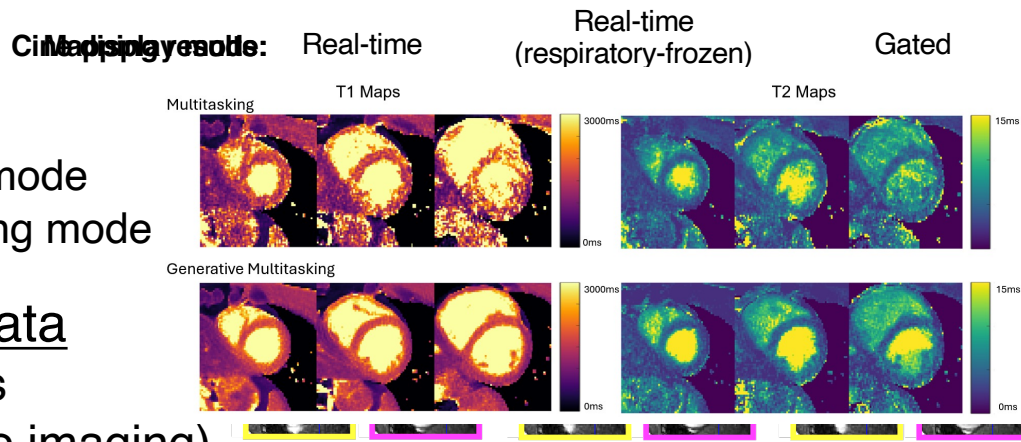


Encoder learns motion timings

“Disentangler” module (filter bank + harmonic analysis) learns both:
cardiac phase (timing), for gated imaging mode
cardiac “amplitude” (beat-to-beat functional variation), for real-time imaging mode

Decoder learns an implicit neural representation of navigator data

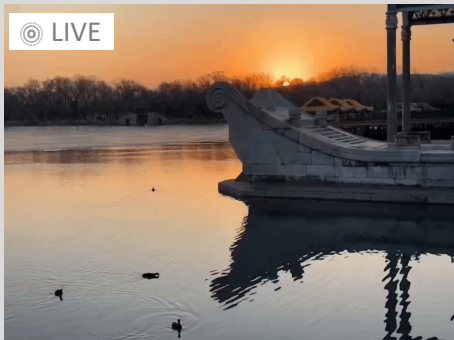
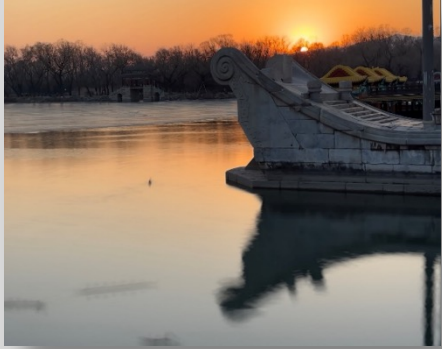
Can be queried to generate data at arbitrary combinations of timings
(e.g., for multicontrast/quantitative imaging)



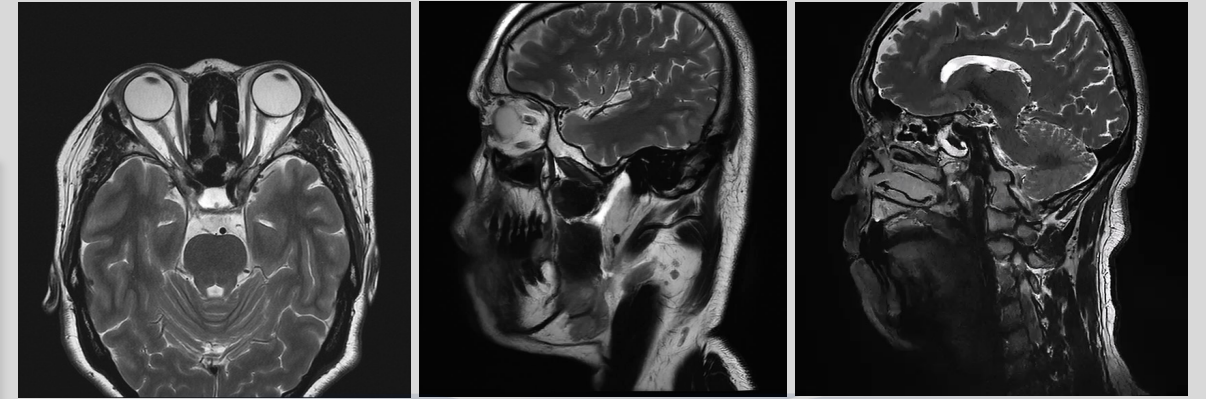
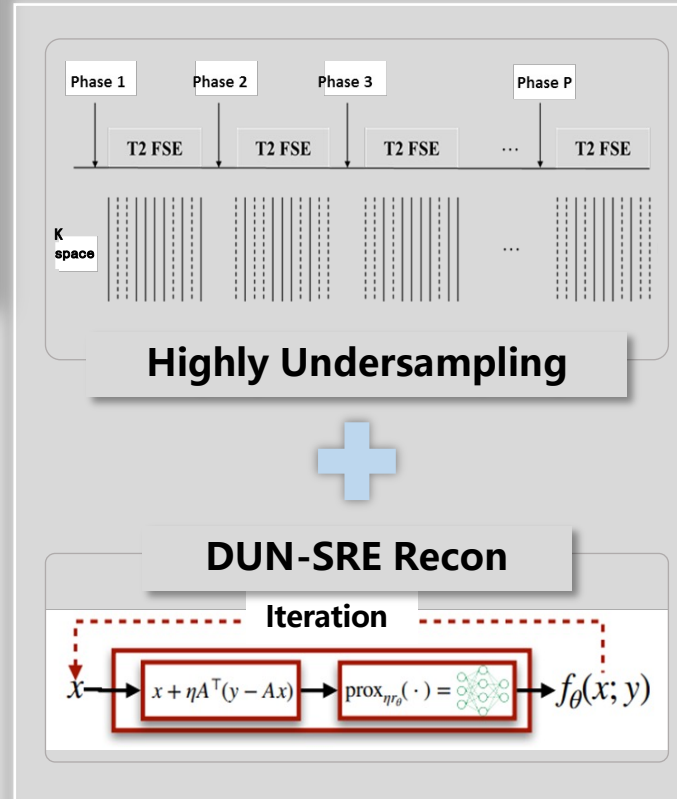
What really is “static imaging” ?

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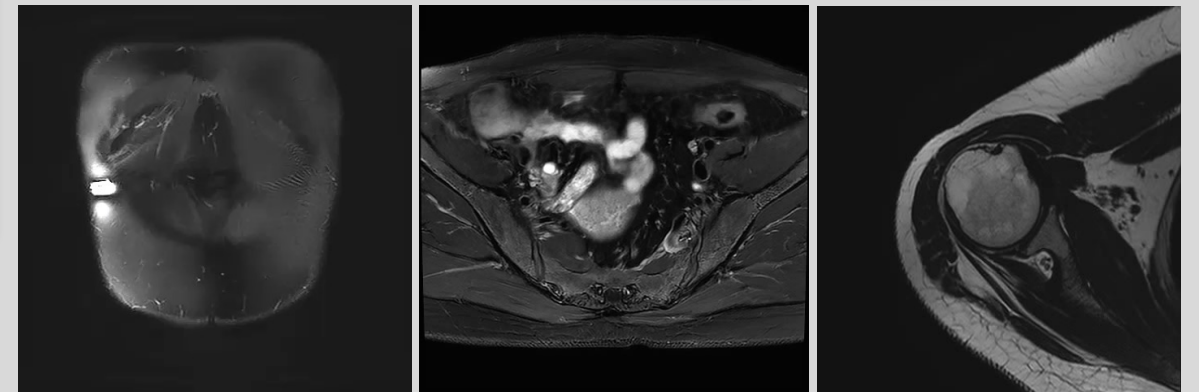
MR LIVE Imaging



Record the real moments



Whole-body LIVE imaging



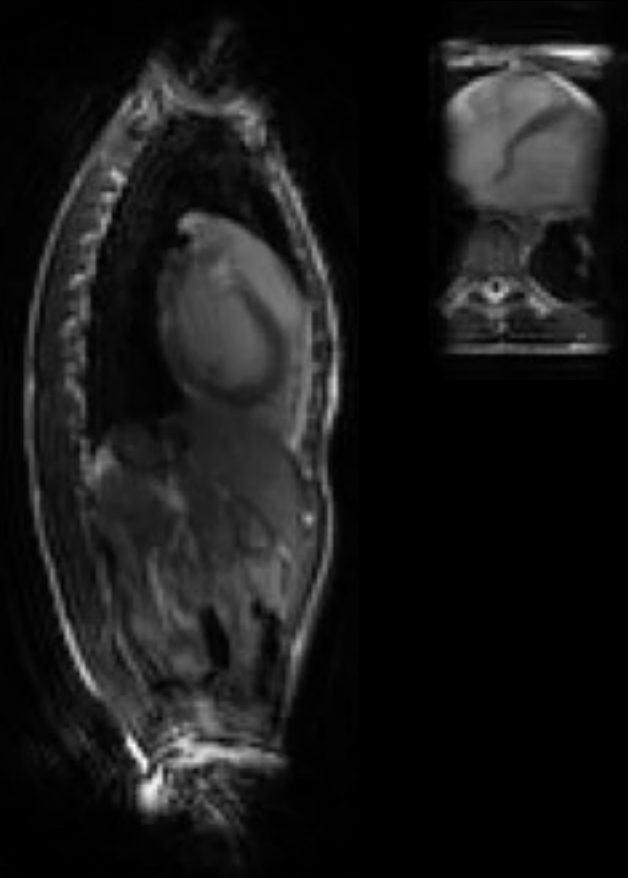
Courtesy Dong Liang

Real-time imaging + Real-time
reconstruction

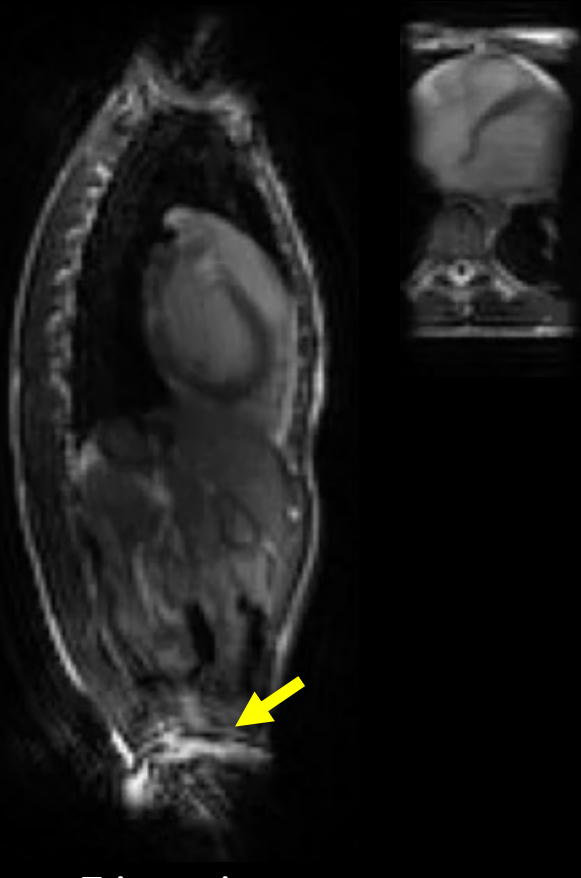
Real-time Reconstruction

3.0mm³ Isotropic, 513.4 ms/frame, 40 slices

Gridding
Reconstruction

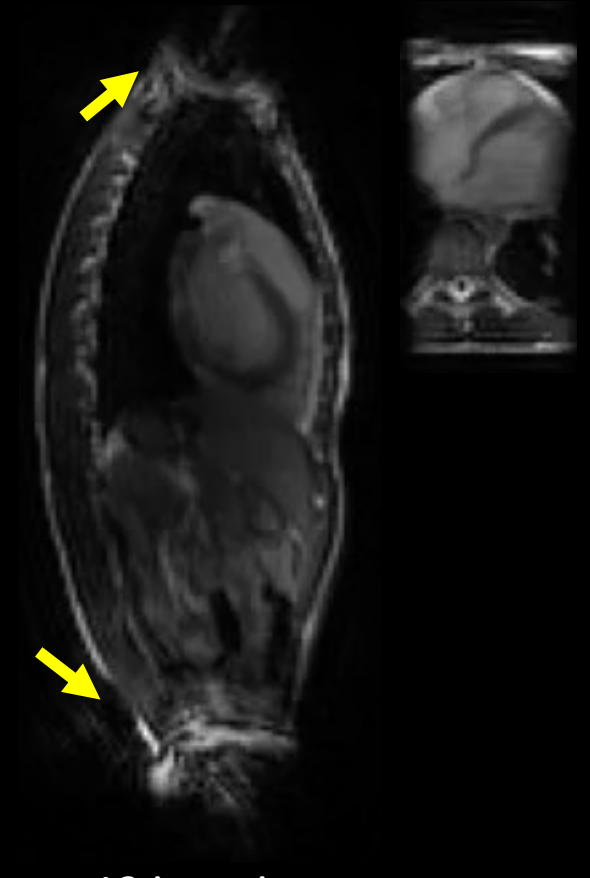


Iterative
Reconstruction



7 iterations
55ms/iter

Iterative +
Automatic ROVir



12 iterations
30ms/iter



National Heart, Lung,
and Blood Institute

MR SIGNature MAtching (MRSIGMA)

- Real-time 3D MRI for the MR-Linac

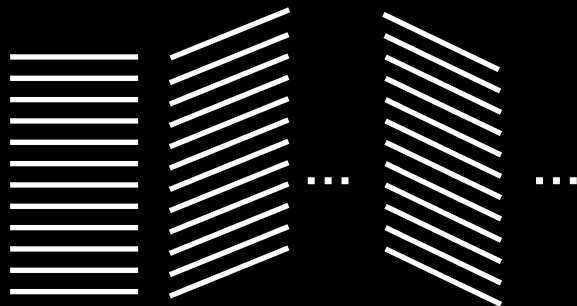
- Motion learning

- Movienet
- Non-real-time

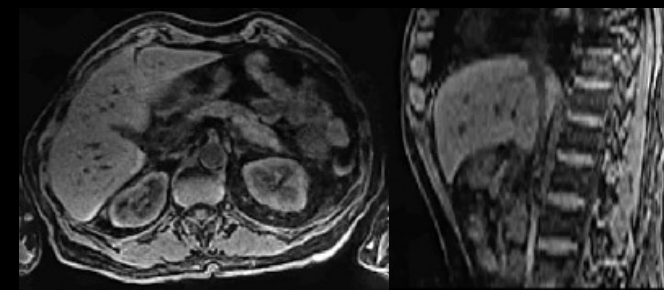
- Signature matching

- Real-time

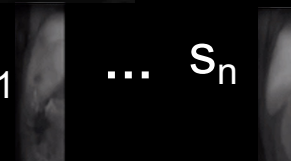
3D stack-of-stars (~5 min)



motion dictionary



signatures: s_1 ... s_n



matching instead of reconstruction

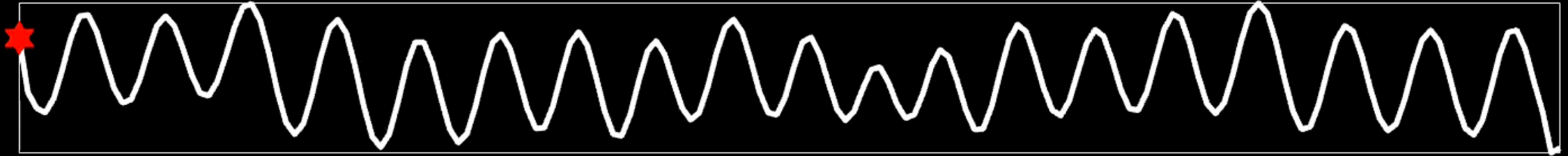
acquisition: ~250ms

matching: ~25ms

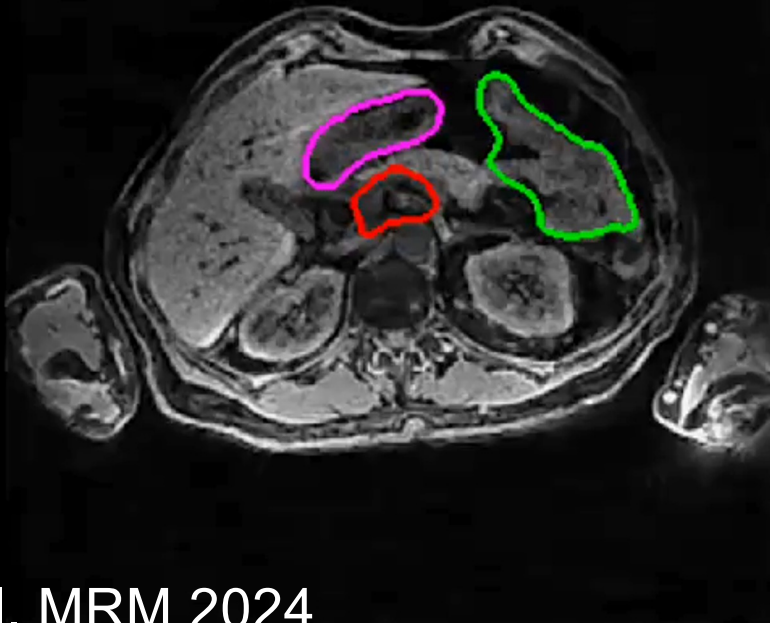
latency: ~275ms

MRSIGMA – tumor in the pancreatic head

- Elekta Unity 1.5T MR-linac, ~275ms/volume



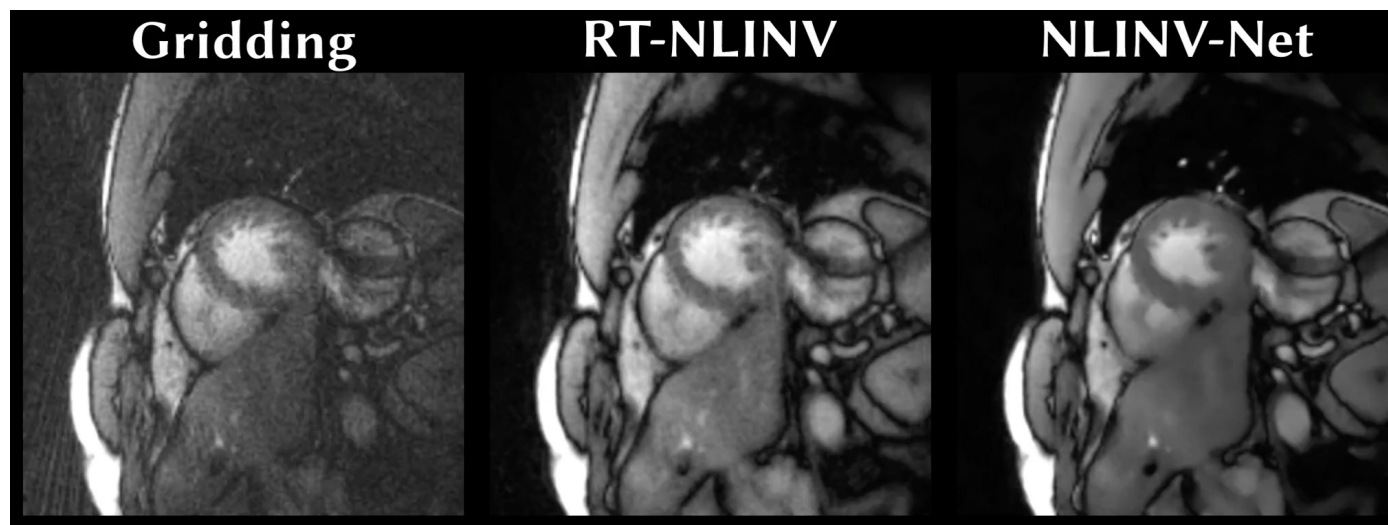
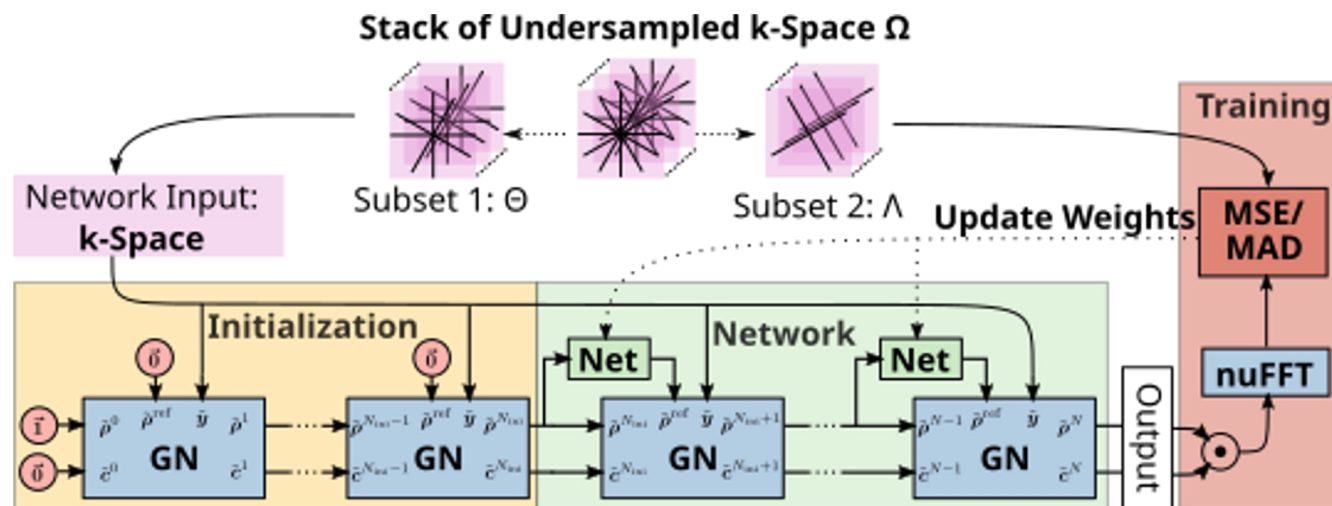
— tumor — duodenum-stomach — small bowel



Self-Supervised Learning for Cardiac Real-Time MRI with NLINV-Net¹

No ground truth exists for real-time MRI

- SSDU² training based on k-space data consistency
- Focus training loss on ROI around heart by ROViR³-CC
- Unrolled network based on RT-NLINV⁴⁵
- end-2-end as coils are estimated jointly



(1) Blumenthal et al. MRM 2024 (2) Yaman et al. MRM 2020
 (3) Kim et al. MRM 2021 (4) Uecker et al. MRM 2008 (5) Uecker et al. MRM Biomed 2010

New BART¹ Features Enable Interactive RT-MRI Reconstruction Pipelines

BART Looping: BART options to activate slice-wise processing

BART Streaming: Immediate data processing across pipelines

Result: Combine BAP and neural reconstruction pipelines for interactive RT-MRI²

```
rtreco.sh -n -f -
```

Conventional:

```
for i in 0 1 2; do
    bart slice 13 $i ksp tmp
    bart pics tmp coils img_$i
done
bart join 13 img_0 img_1 img_2
```

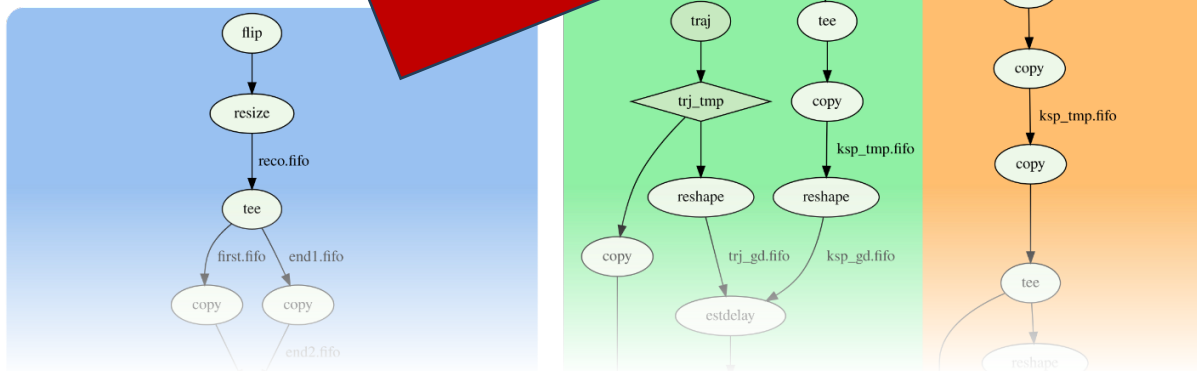
NEW - BART Looping:

```
bart -l8192 -o2 s ksp coils img
```

Conventional:

```
bart fft -i 3 ksp - | bart rss 8 - img
```

RELEASE THE FILES!



1: Uecker et al., ISMRM Workshop Sedona 2013

2: Schaten et al., submitted to MRM: arxiv.org/abs/2512.02748

Courtesy Martin Uecker

Conclusion

- The field of dynamic imaging is.... Dynamic 🤪
- Heavy focus on compact signal modeling (w/wo AI)
- Not discussed but equally important: efficient sampling/acquisition
- Please release code and data!

Computational Sensing and Imaging Lab

www.jtsense.com



Slides: Miki Lustig, Shreya Ramachandran, Berkin Bilgic, Yamin Arefeen, Dong Liang, Anthony Christodoulou, Shanshan Wang, Prakash Kumar, Thomas Kuestner, Ricardo Otazo, Li Feng, Fang Liu, Rodrigo Lobos, Frank Ong

