Motion compensated reconstruction

Educational course: Image acquisition and Reconstruction
25th Annual meeting of the ISMRM, Honolulu, 2017

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Declaration of Financial Interests or Relationships

Speaker Name: Sajan Goud Lingala

I have the following financial interest or relationship to disclose with regard to the subject matter of this presentation:

Company Name: Siemens Healthineers
Type of Relationship: Employee

Outline

- Introduction

- Explicit motion constrained recovery schemes
  - Generalized reconstruction of inverted coupled systems (GRICS)
  - Motion compensated Compressed Sensing
    -- Sparsity, low rank based
  - Applications
  - Challenges

- Heuristic based implicit motion constrained recovery schemes
  - Data sorting
  - XD GRASP
  - Next talk: Manifold approaches

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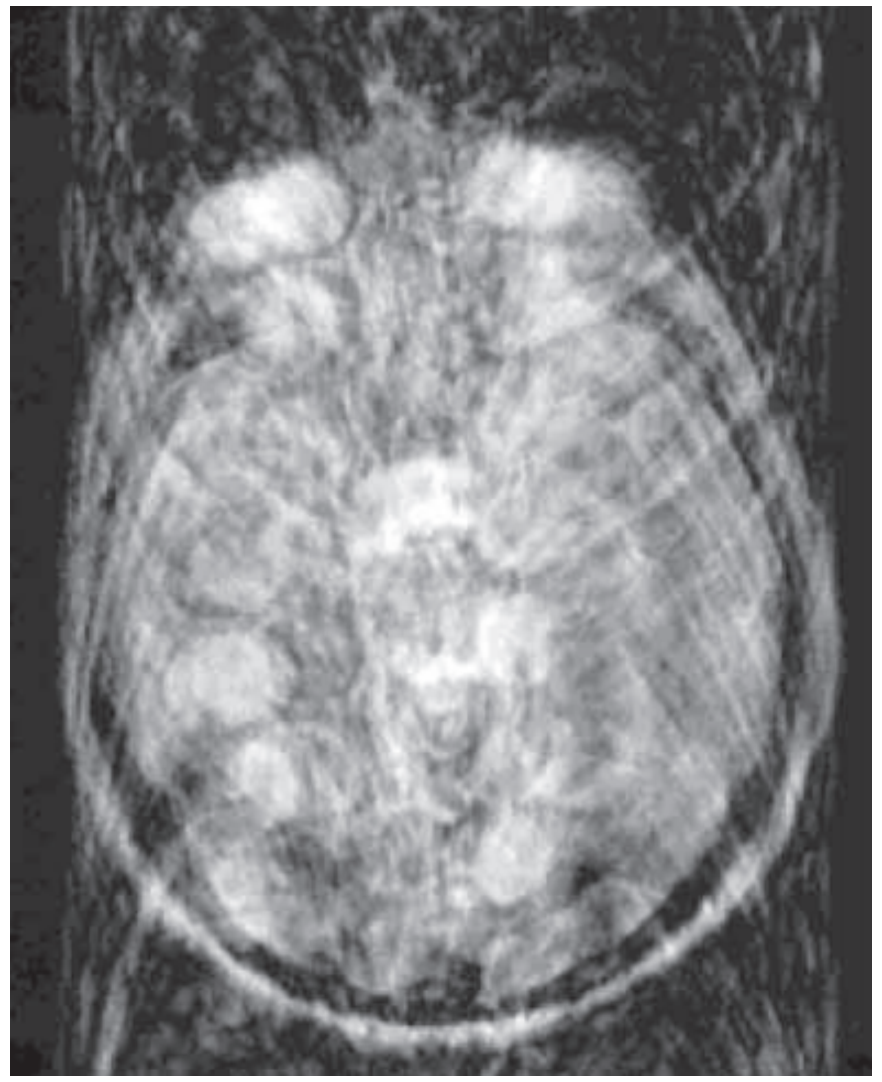
- Heuristic based implicit motion constrained recovery schemes
  - Data sorting
  - XD GRASP
  - Manifold based implicit methods: next talk

Introduction

- Occurrence of motion is common in several MRI exams

Head motion



J. Pipe et al, 99

Introduction

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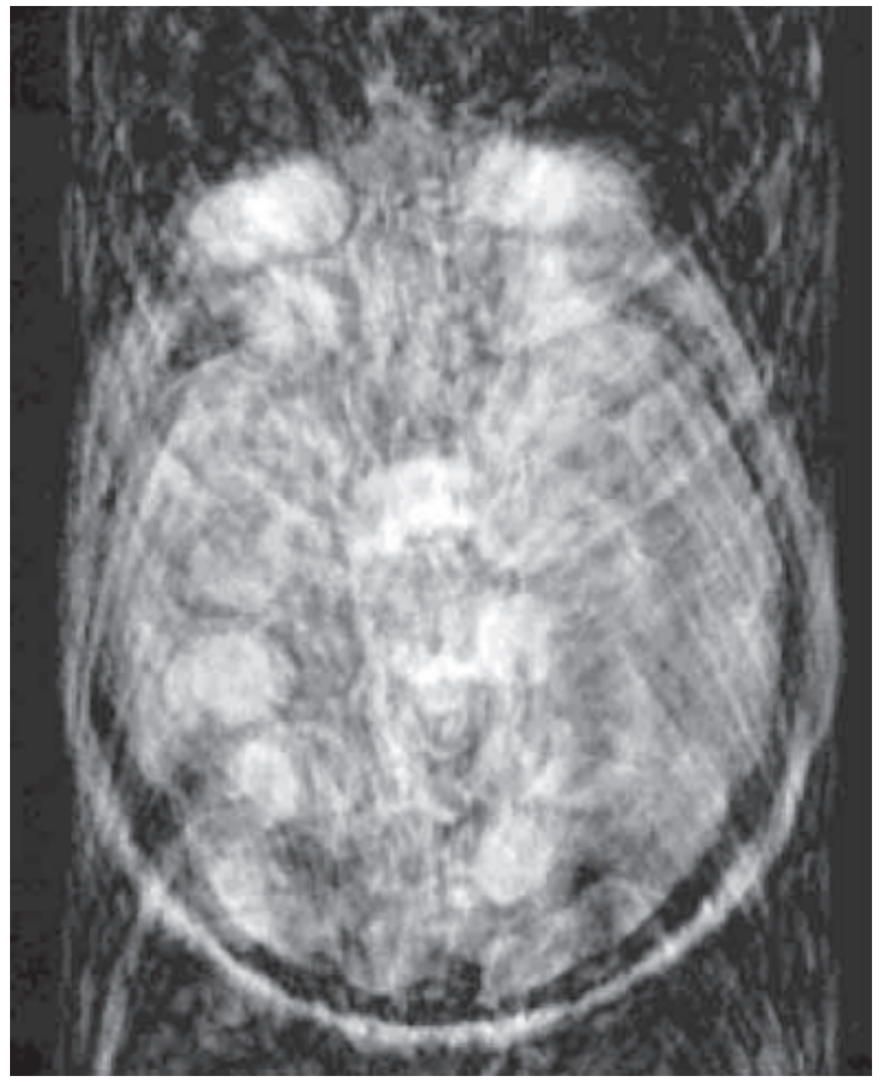
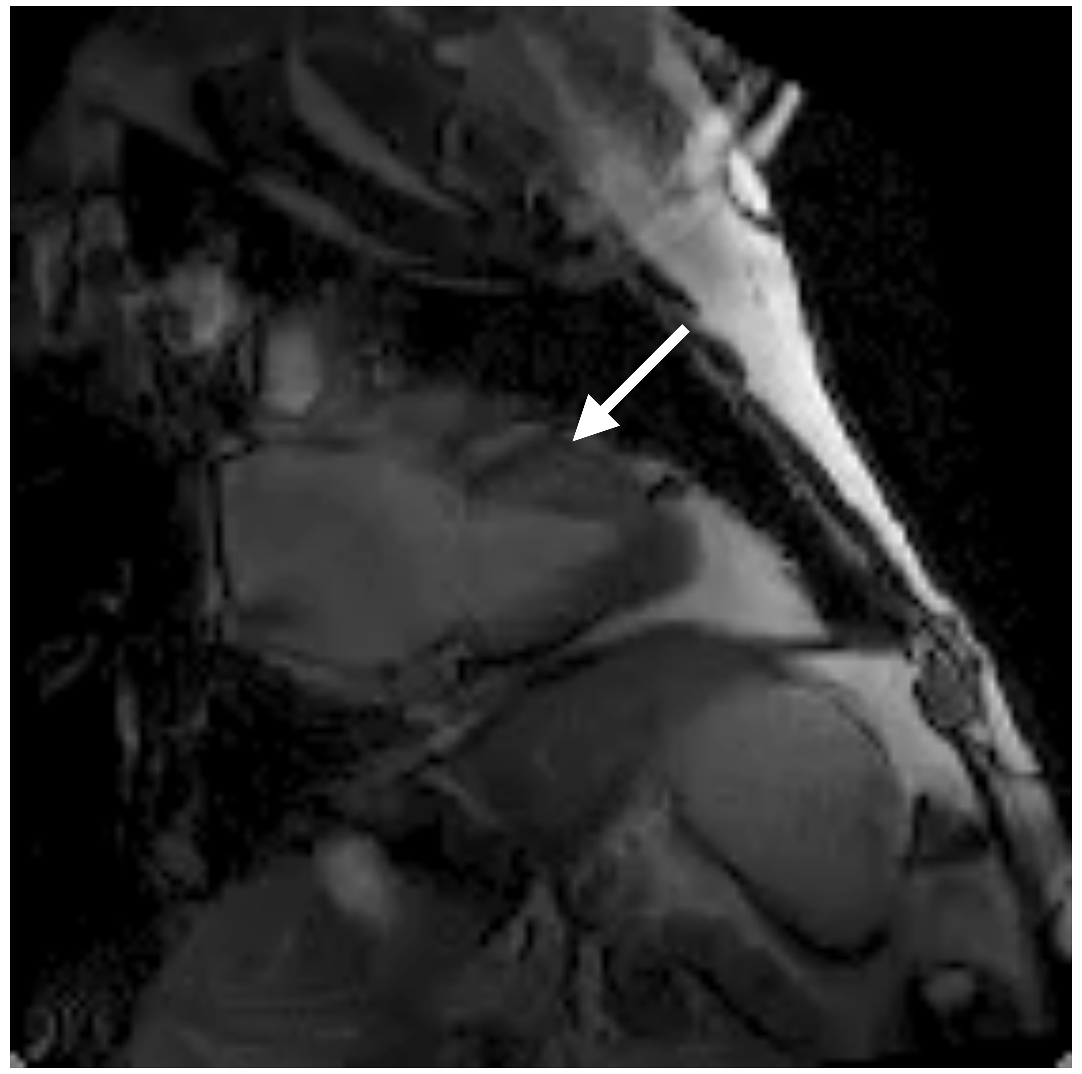


J. Pipe et al, 99

Cardiac arrhythmias



Courtesy: Andrew Yoon, USC

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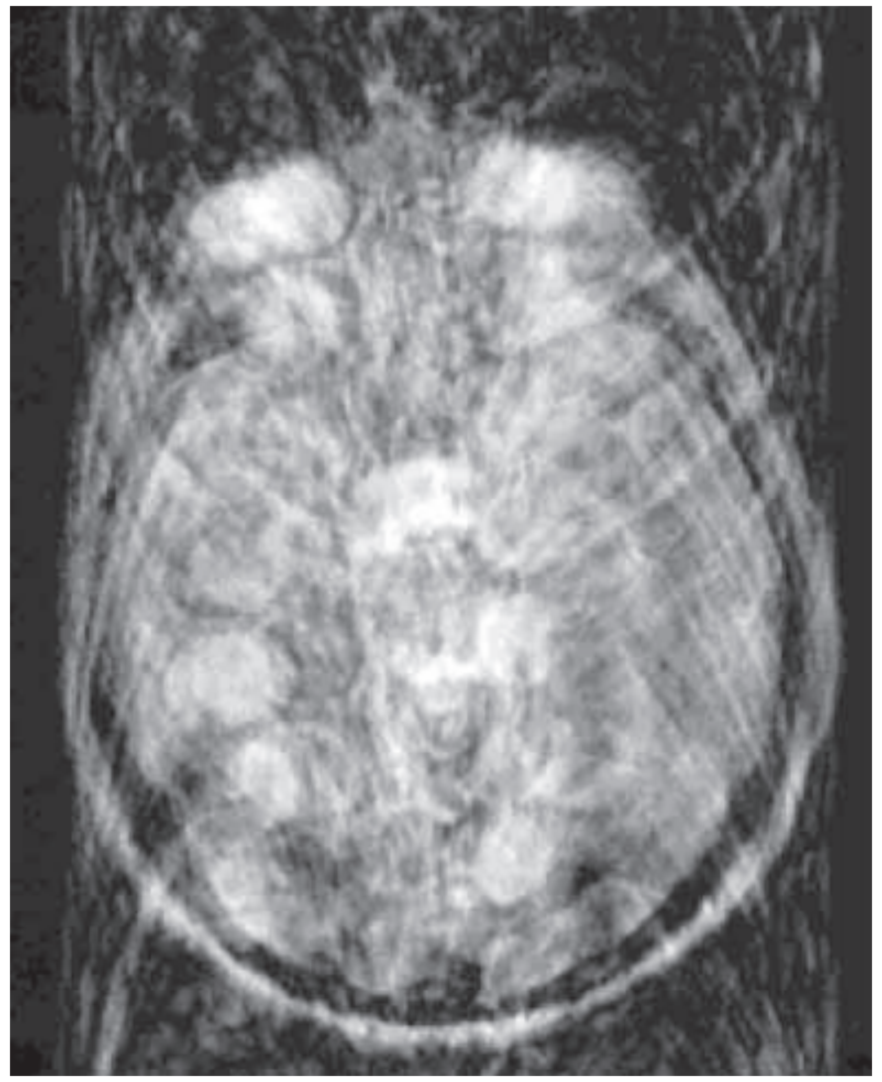

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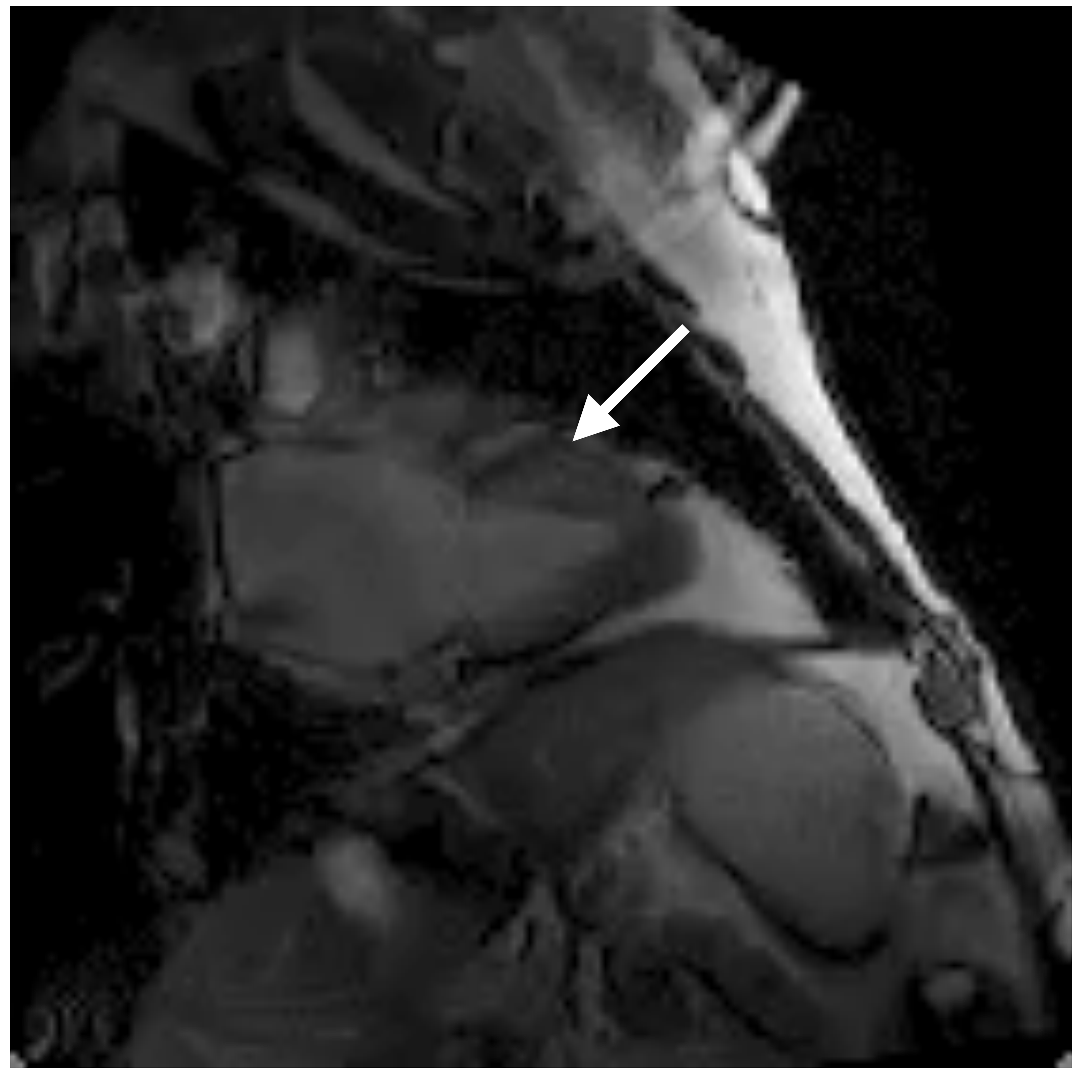


Courtesy: Andrew Yoon, USC

Breathing motion

Courtesy: Li Feng, NYU

……

Motion and k-space

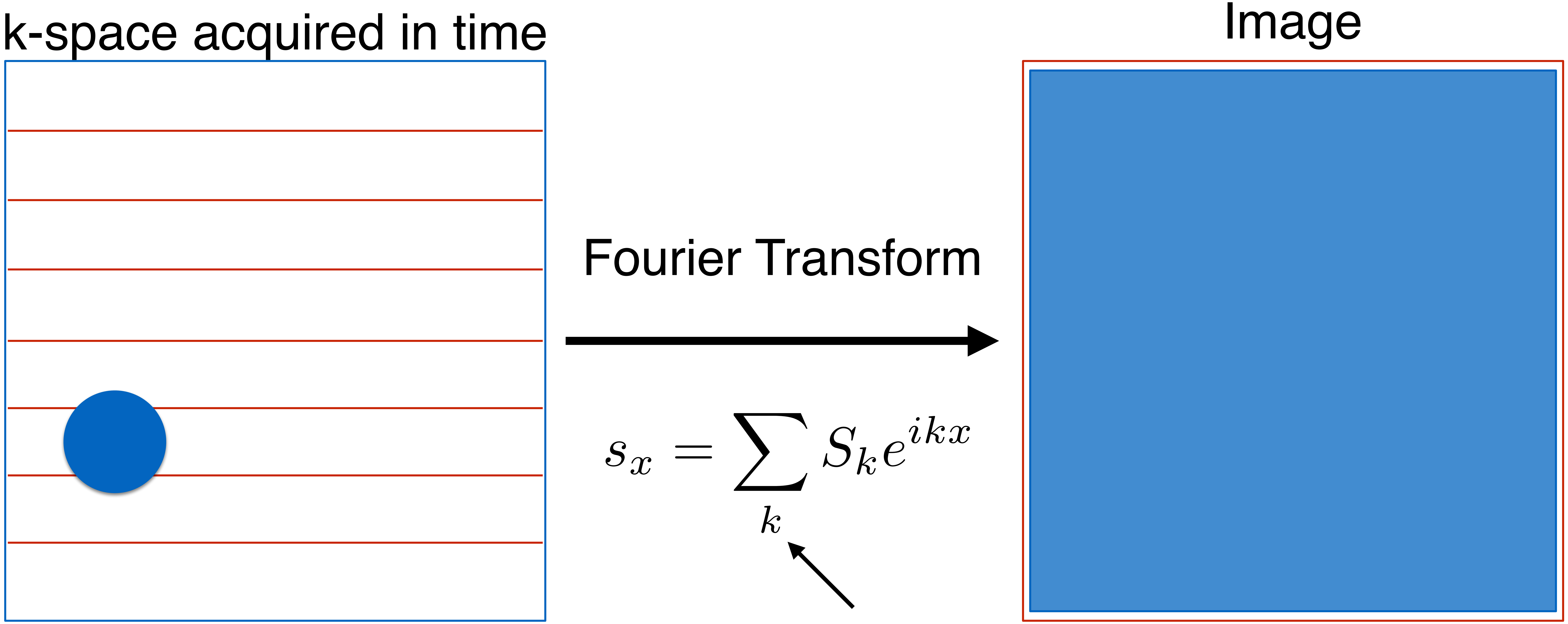
k-space acquired in time

Image

Fourier Transform

$$s_x = \sum_k S_k e^{ikx}$$

Motion and k-space



$$s_x = \sum_k S_k e^{ikx}$$

The sum in the Fourier Transform implies that motion at any time can affect every pixel

k-space corrections for affine motion

Image motion		**k-space effect**
Translation (rigid shift)	→	Phase ramp

k-space corrections for affine motion

<u>**Image motion**</u>		<u>**k-space effect**</u>
Translation (rigid shift)	→	Phase ramp
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k-space corrections for affine motion

Image motion		**k-space effect**
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Expansion	→	Contraction

k-space corrections for affine motion

Image motion		**k-space effect**
Translation (rigid shift)	$\longrightarrow$	Phase ramp
Rotation	$\longrightarrow$	Rotation (same angle)
Expansion	$\longrightarrow$	Contraction
General affine	$\longrightarrow$	Affine transform

$$\mathcal{A}(\mathrm{x}) = \mathbf{A} \cdot \mathrm{x} + \mathrm{t}$$

$$\mathcal{V} \xrightarrow{\mathcal{A}} \mathcal{V}'$$

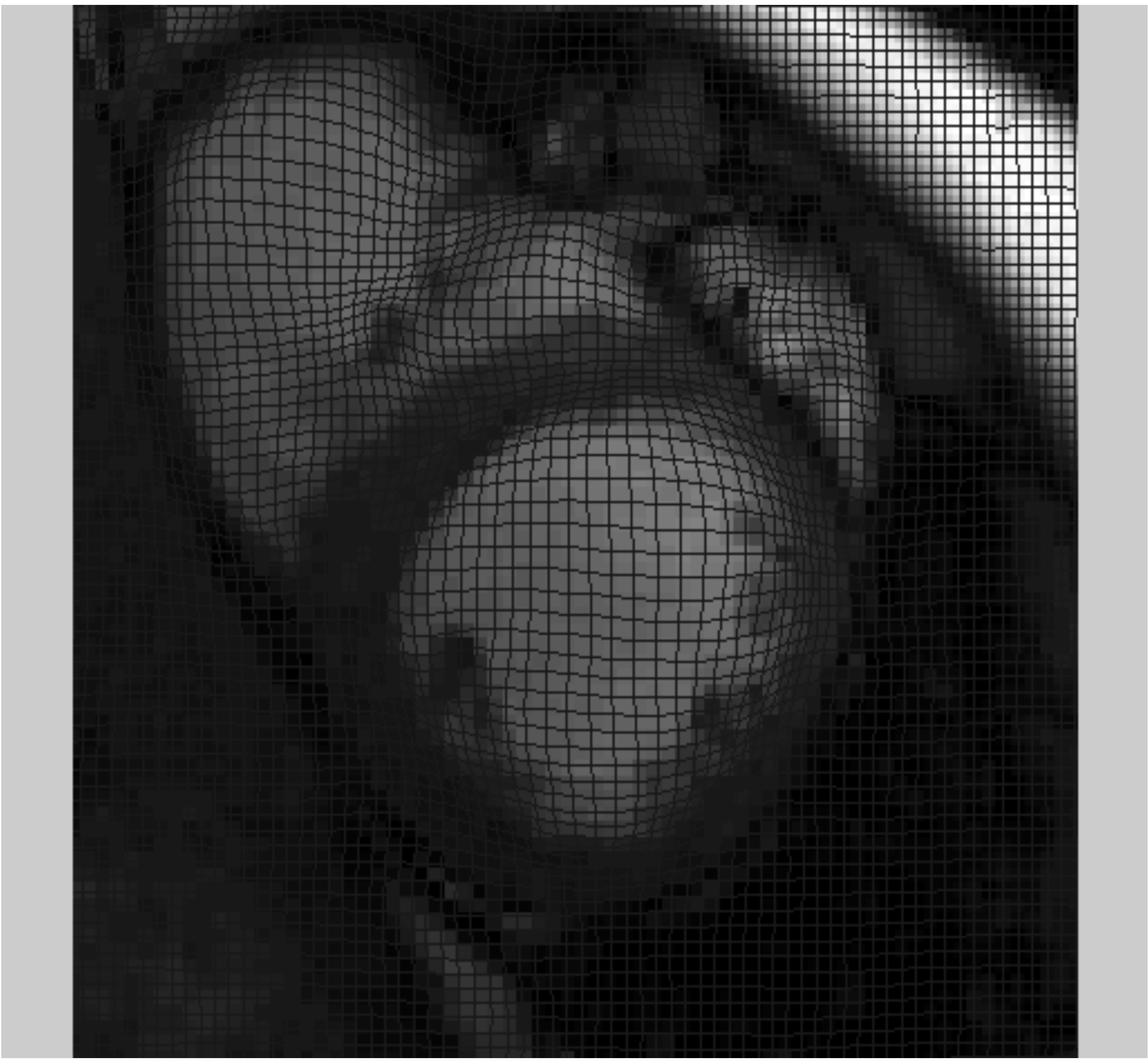
$$\mathbf{k}' = \mathcal{A}^{-T}\mathbf{k}$$

$$\mathcal{F}(\mathbf{k}) = \frac{e^{i2\pi(\mathbf{k}'\cdot t)}}{|det(\mathbf{A})|}\mathcal{F}'(\mathbf{k}')$$

D. Atkinson, ISMRM 2010

Non-rigid motion

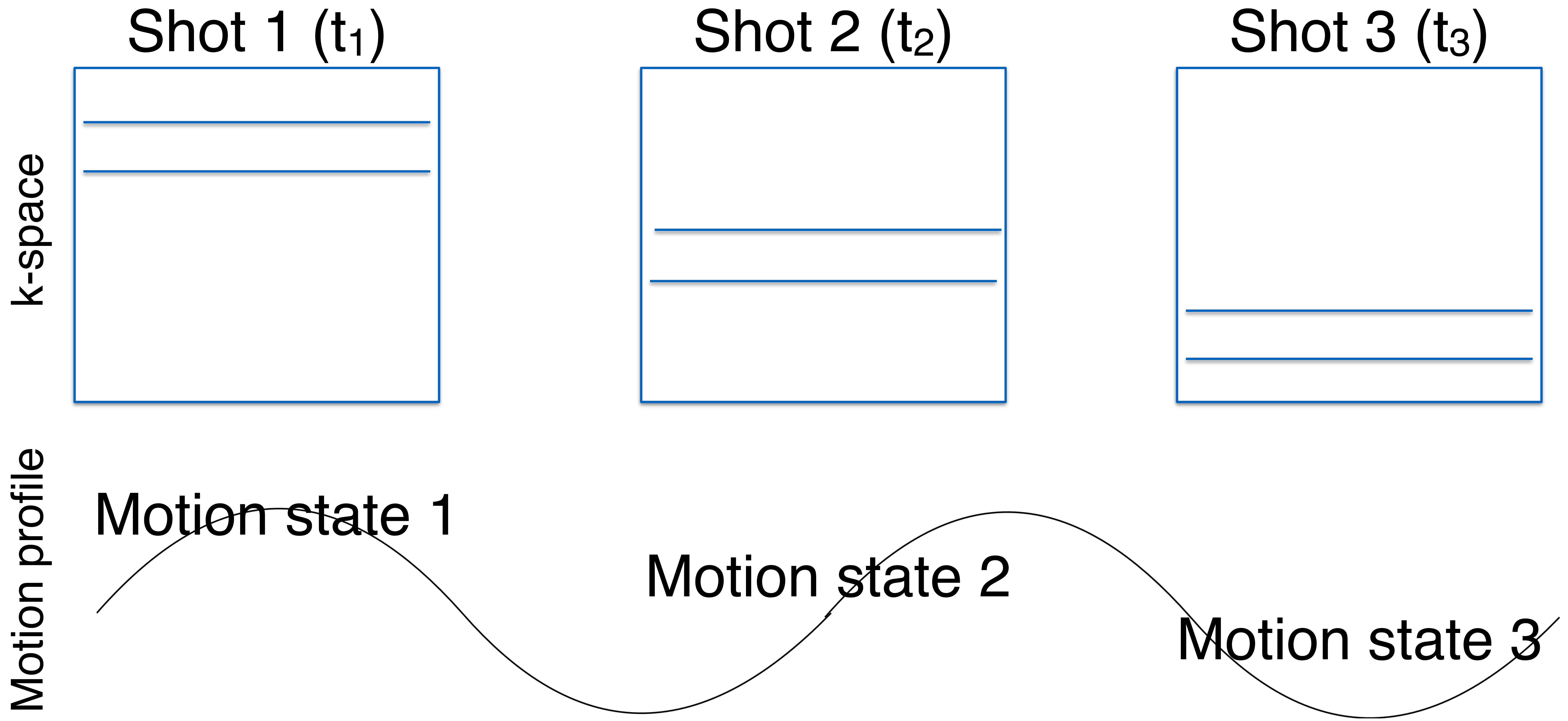
- Most physiological motion is non-rigid
- Not straightforward to directly correct in the k-space



Royuela et al., MRM 2015

Motion corrected reconstruction: early approaches

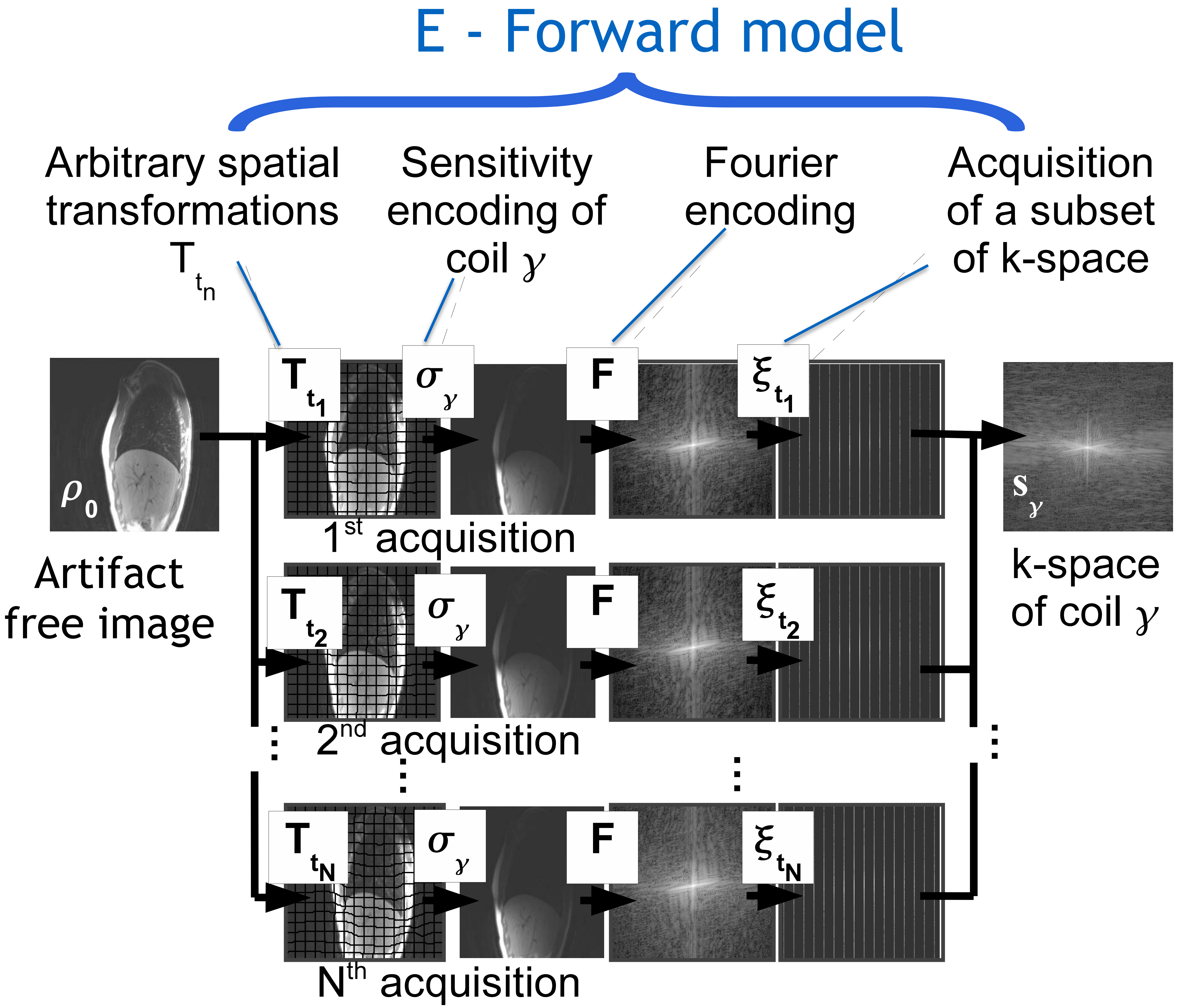
- Problem of combining k-space shots that are at different motion states



PG. Batchelor et al., MRM 2005; F. Odille et al., MRM 2008

Motion corrected reconstruction: early approaches

- Knowledge of forward model



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Motion corrected reconstruction: early approaches

- Knowledge of forward model

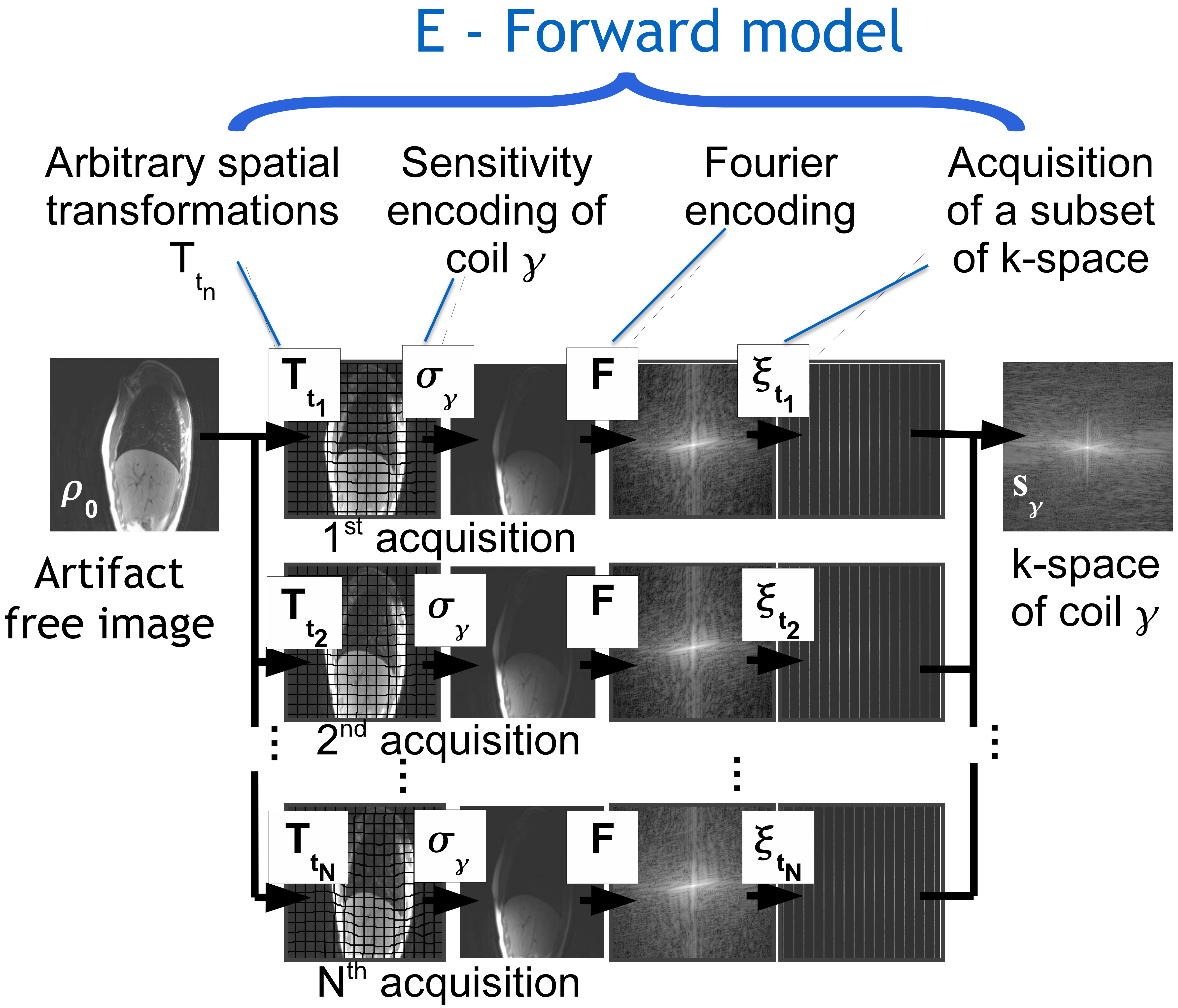
Artifact free image

Measured data

$$min_\rho ||\mathbf{E}(\rho) - \mathbf{b}||_2^2$$

Forward model: Motion, Coil sensitivities, etc.

Least squares problem



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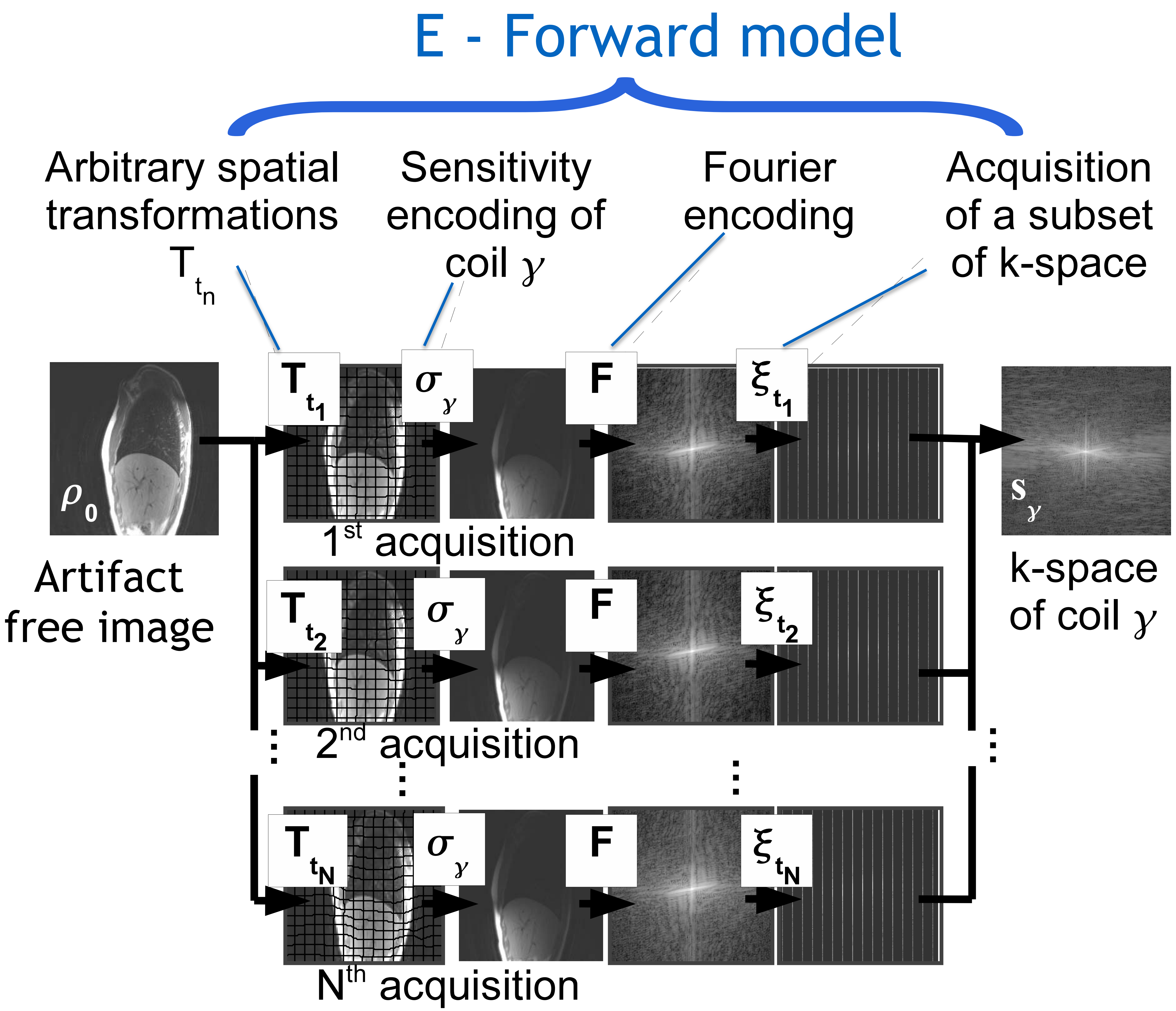
Least squares problem
Solved by Conjugate Gradients



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Motion estimation

- External measures
  - respiratory bellows, optical tracking, etc.

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  - pencil beam navigator, FID navigators, central k-space lines, etc.

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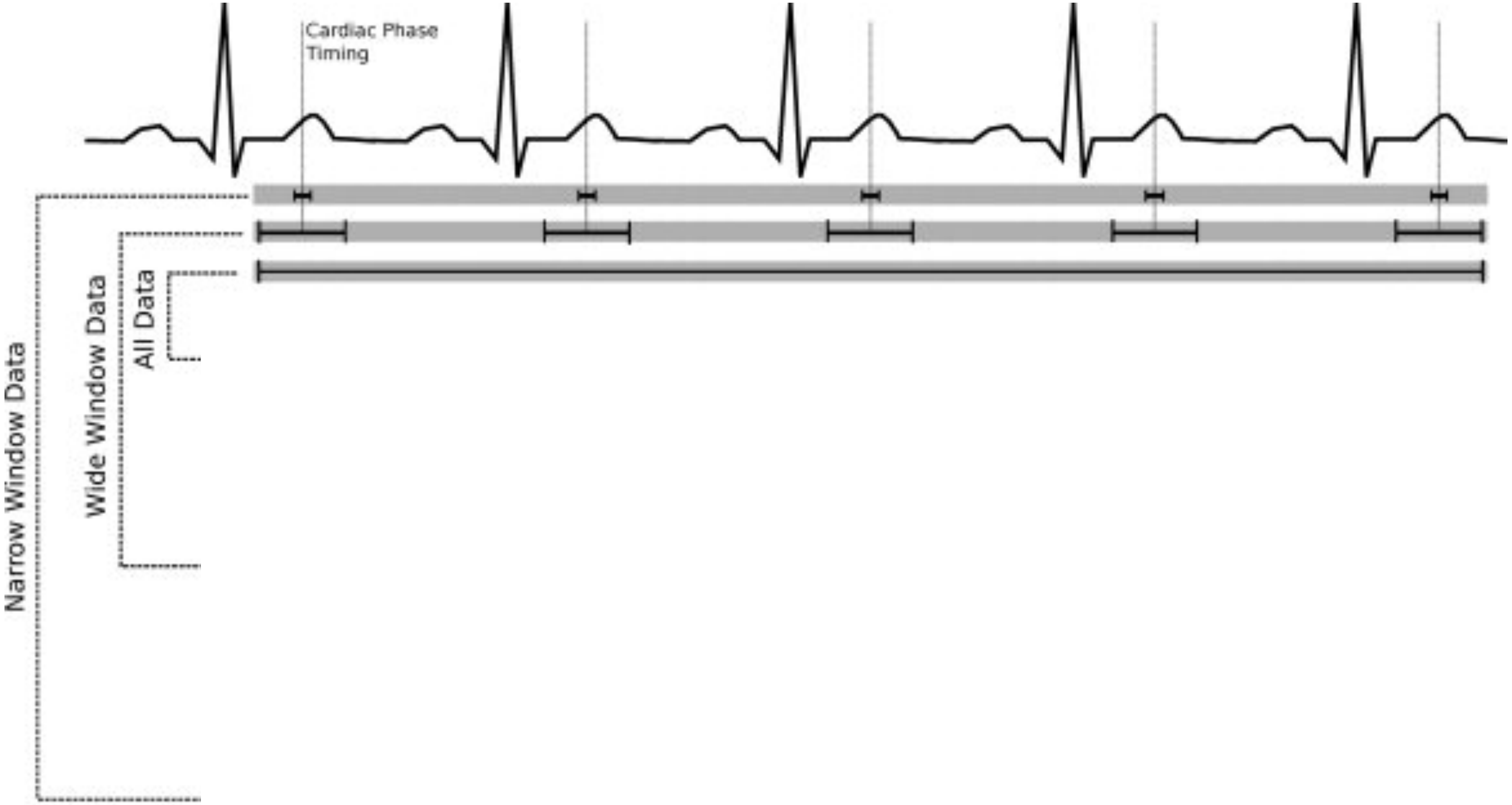
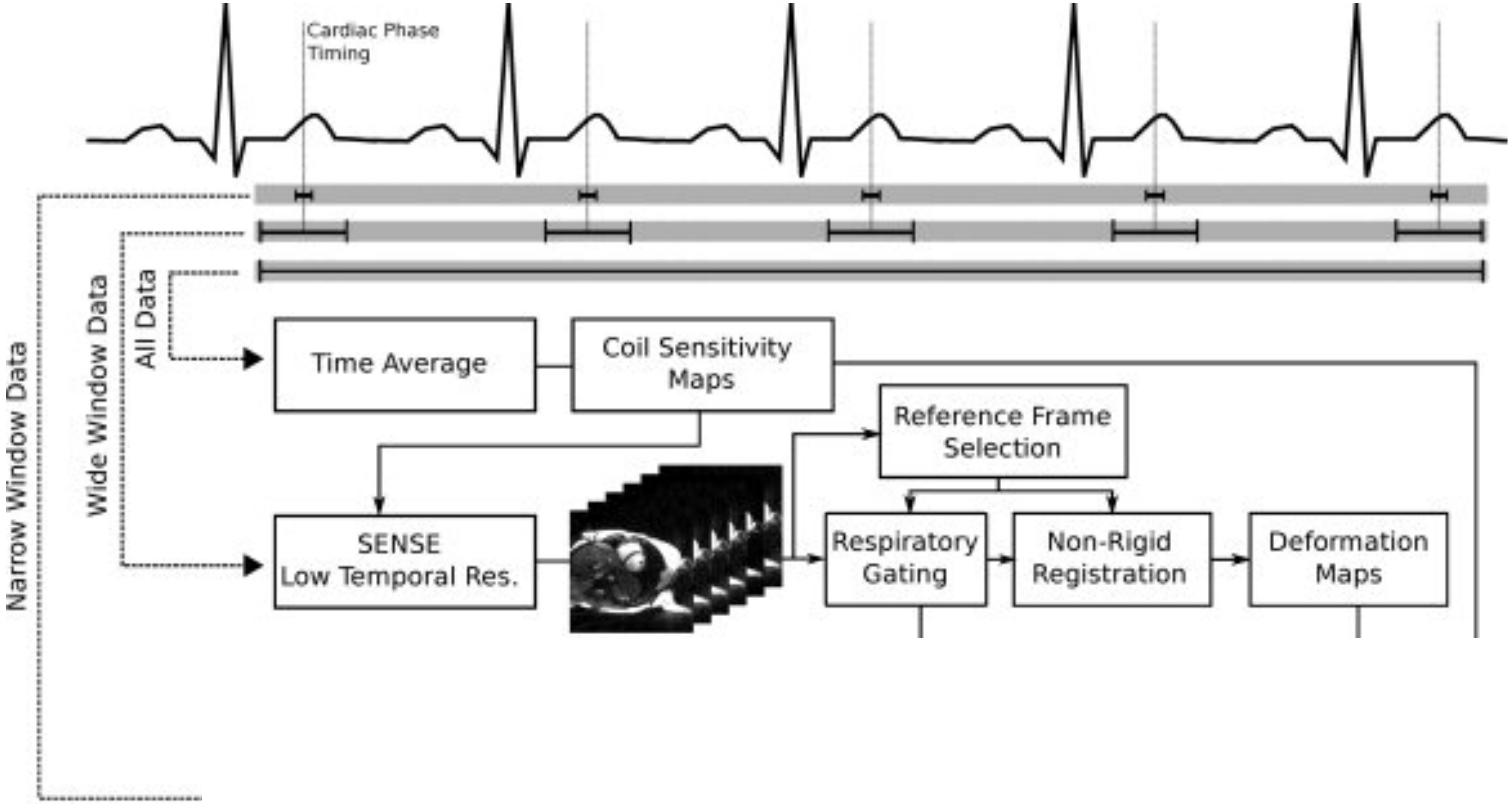
- Self-navigated approaches
  - PROPELLER, radial, spiral trajectories, etc.
- Motion models
  - Joint estimation of motion and reconstruction parameters

Retrospective reconstruction of cine images using iterative motion correction



M. Hansen et al., MRM 2011

Retrospective reconstruction of cine images using iterative motion correction



Deformation due to respiration estimated from low temporal resolution data

M. Hansen et al., MRM 2011

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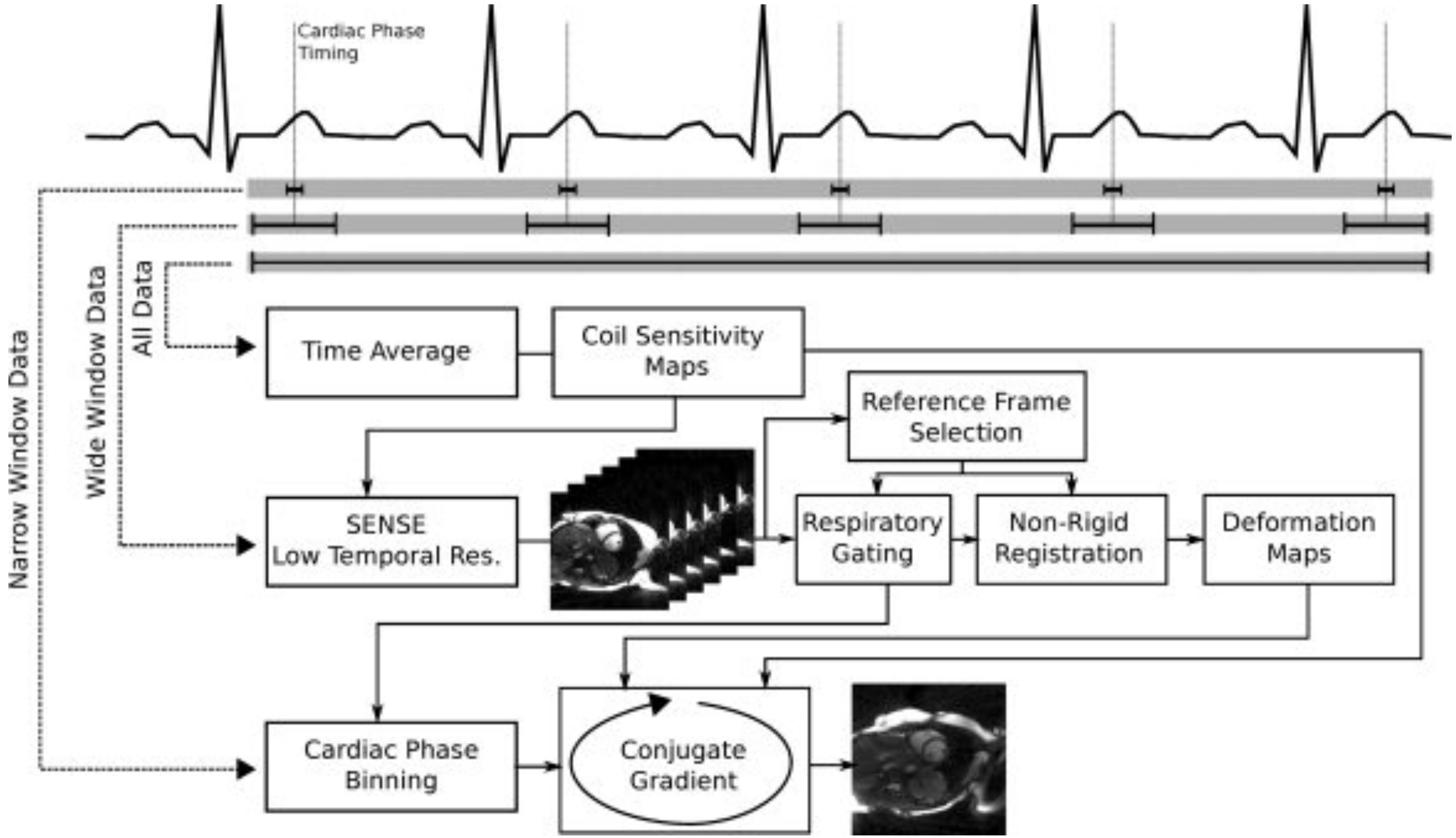

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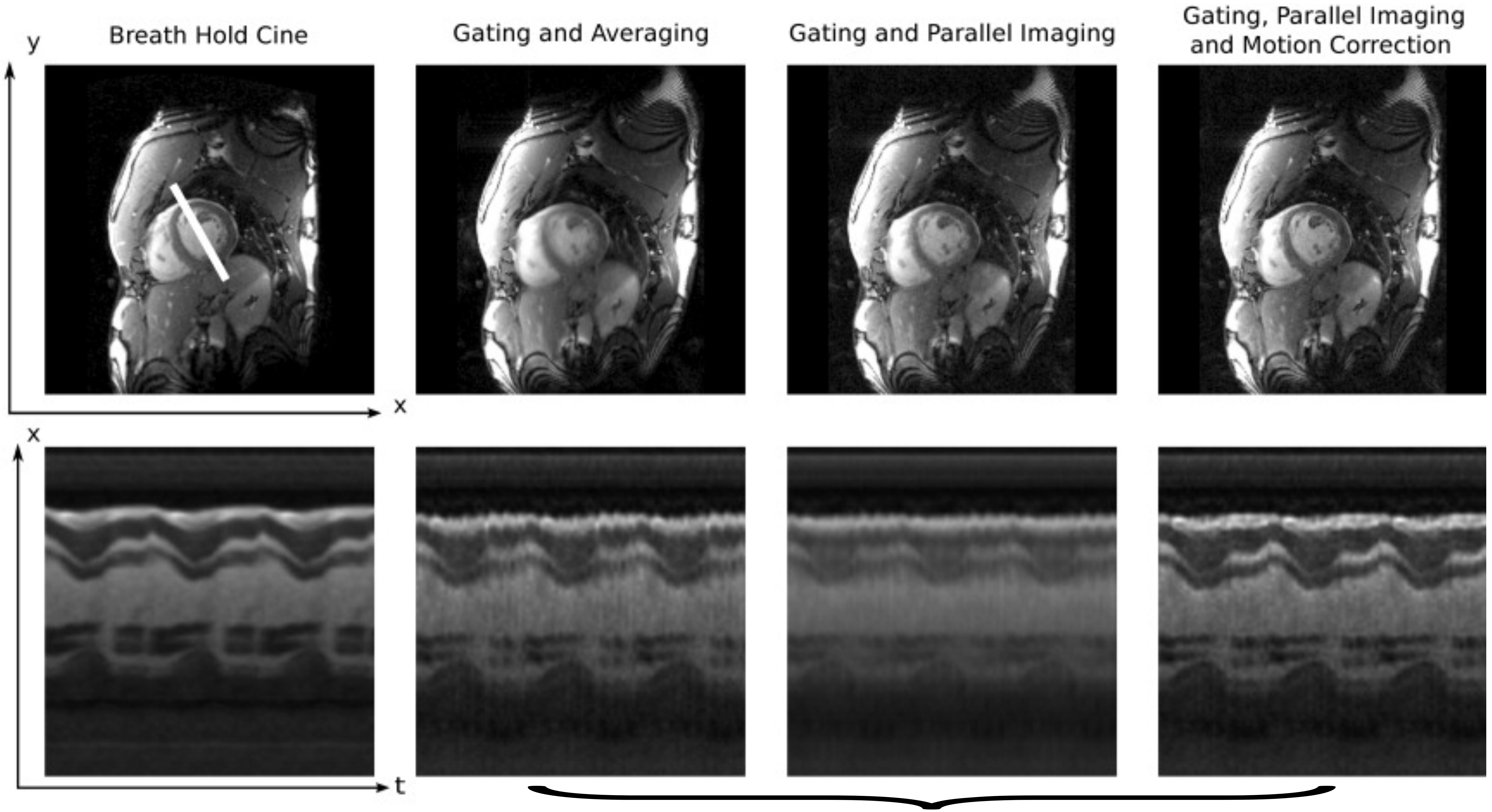


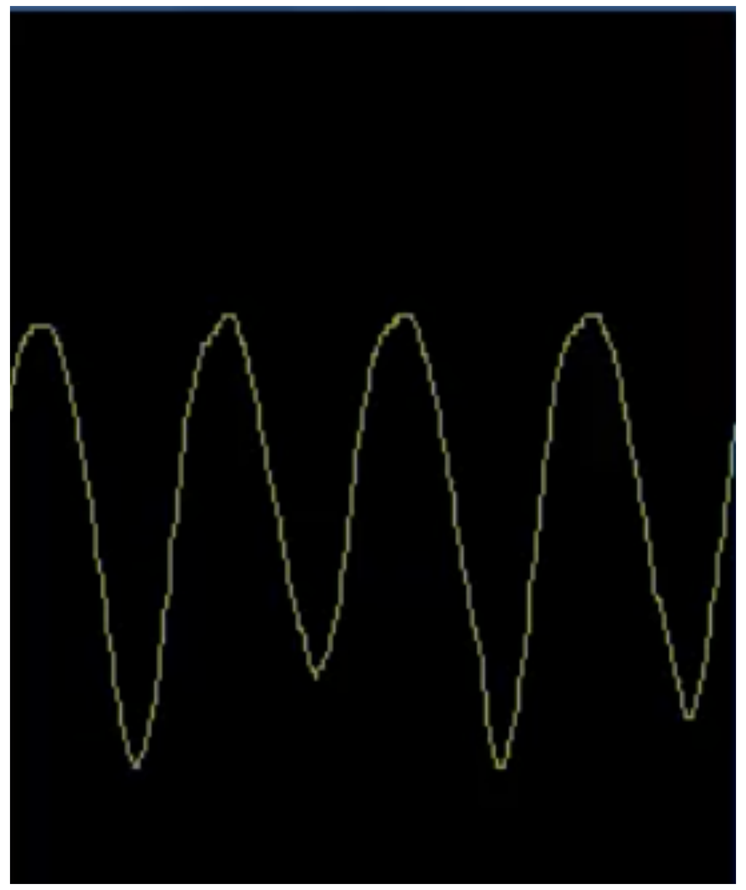
Free breathing

M. Hansen et al., MRM 2011

Joint estimation of motion and reconstruction

- Parameterizing motion based on motion sensor signals (eg. bellows)

$$\underbrace{u(\mathbf{r},t)}_{\text{displacement fields}} = \sum_{i=1}^{M} \underbrace{\alpha_m(\mathbf{r})}_{\text{motion parameters}} \underbrace{S_m(t)}_{\text{motion sensors}}$$



F. Odille et al., MRM 2008

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$$\underbrace{u(\mathbf{r},t)}_{\text{displacement fields}} = \sum_{i=1}^{M} \underbrace{\alpha_m(\mathbf{r})}_{\text{motion parameters}} \underbrace{S_m(t)}_{\text{motion sensors}}$$

- Generalized reconstruction of inversion coupled systems (GRICS):

$$min_{\rho,\alpha} \underbrace{||E(\alpha)\rho - b||}_{\text{data consistency}}{}_2^2 + \underbrace{\mu_1 R(\alpha)}_{\text{regularization on motion parameters}} + \underbrace{\mu_2 R(\rho)}_{\text{regularization on image}}$$

F. Odille et al., MRM 2008

Joint estimation of motion and reconstruction

- $$min_{\rho,\alpha} \underbrace{\|E(\alpha)\rho - b\|_2^2 + \mu_1 R(\alpha) + \mu_2 R(\rho)}_{\mathcal{C}(\alpha,\rho)}$$

Motion estimation

$$min_{\alpha} C(\alpha, \rho_n)$$

Reconstruction

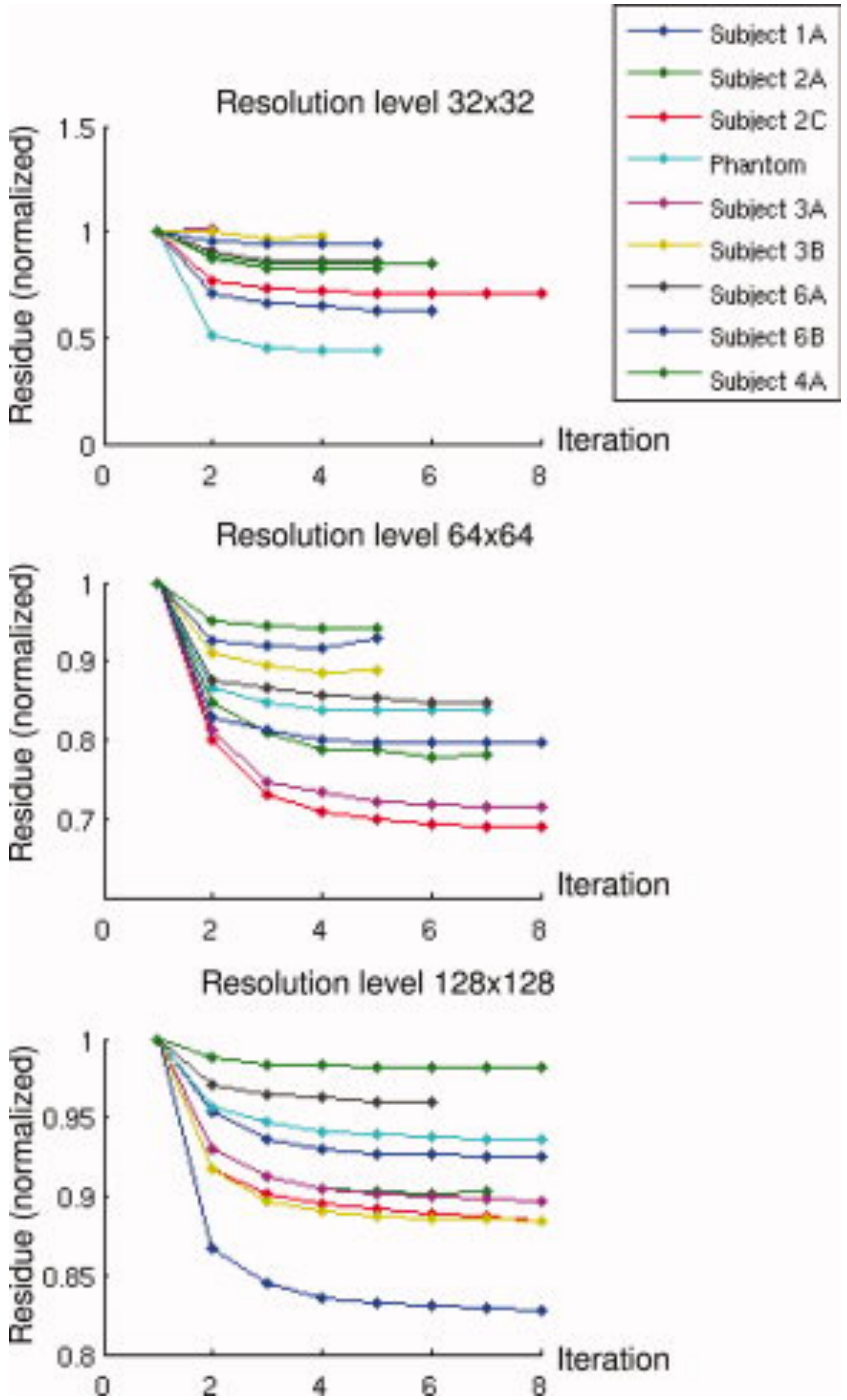
$$min_{\rho} C(\alpha_n, \rho)$$

F. Odille et al., MRM 2008

Joint estimation of motion and reconstruction

- $$min_{\rho,\alpha} \underbrace{\|E(\alpha)\rho - b\|_2^2 + \mu_1 R(\alpha) + \mu_2 R(\rho)}_{\mathcal{C}(\alpha,\rho)}$$

Motion estimation		Reconstruction
$min_\alpha C(\alpha, \rho_n)$	$\rightleftarrows$	$min_\rho C(\alpha_n, \rho)$



- Coarse to fine resolution strategies are commonly used to avoid local minima

- Convergence: only empirical

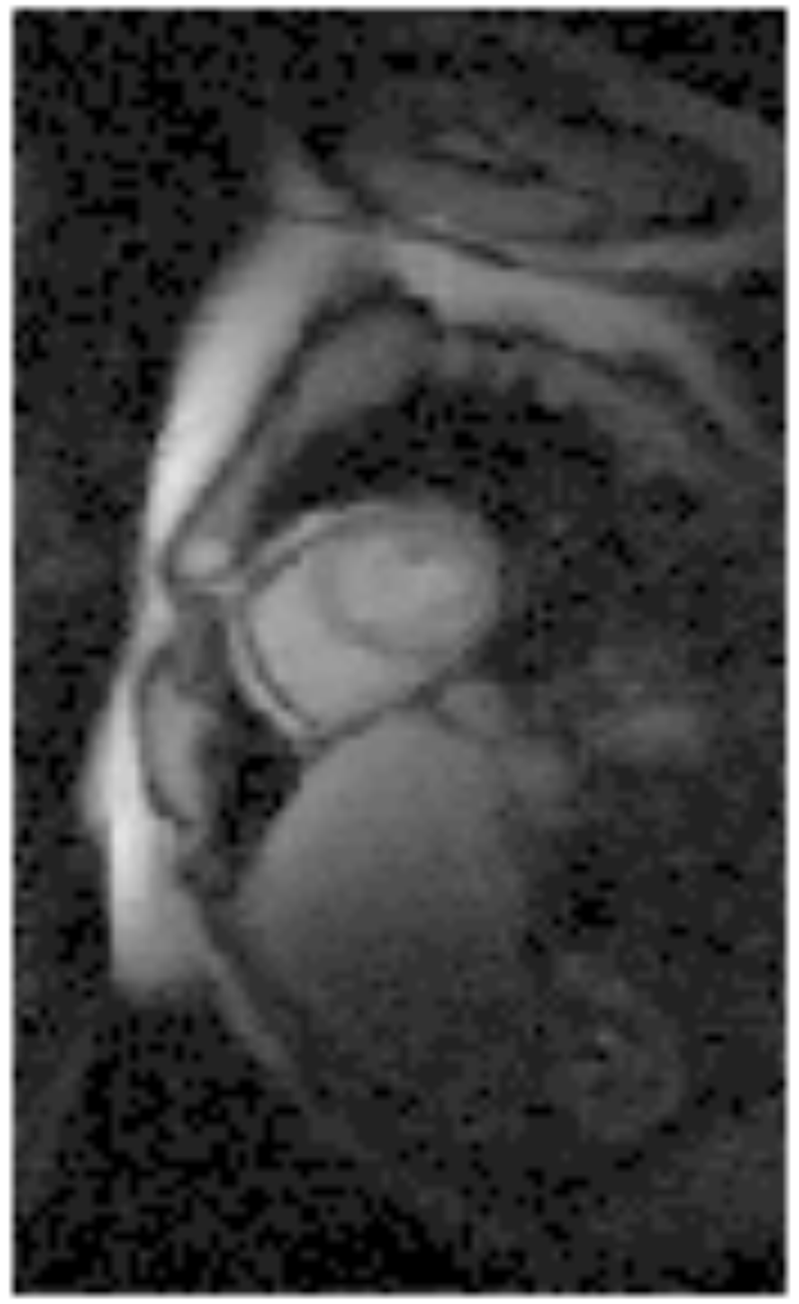
F. Odille et al., MRM 2008

Improving constrained reconstruction with motion correction

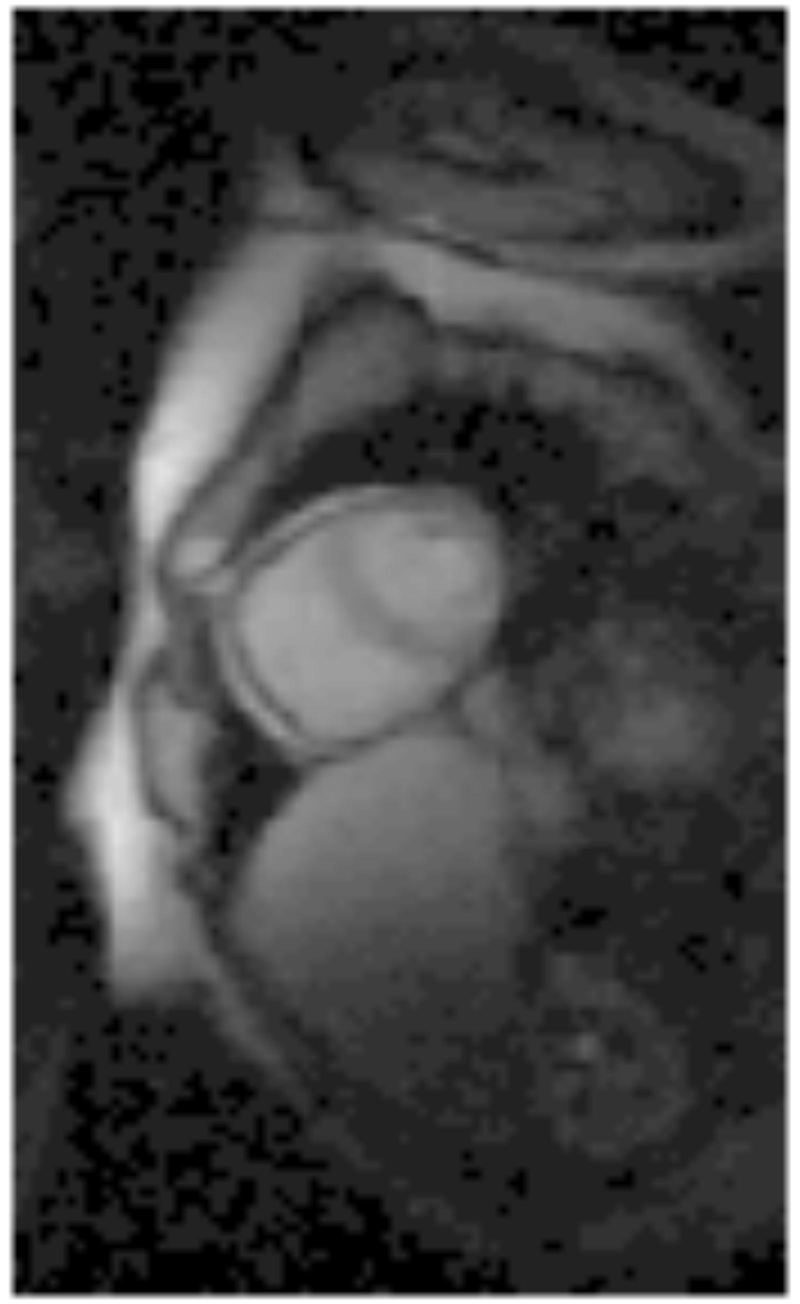
Improving constrained reconstruction with motion correction

- Example of myocardial perfusion data with motion

Original



Deformation corrected



S.G.Lingala, IEEE-TMI, 2015

*Data acquired in accordance with IRB approval, University of Utah

Improving constrained reconstruction with motion correction

- Example of myocardial perfusion data with motion

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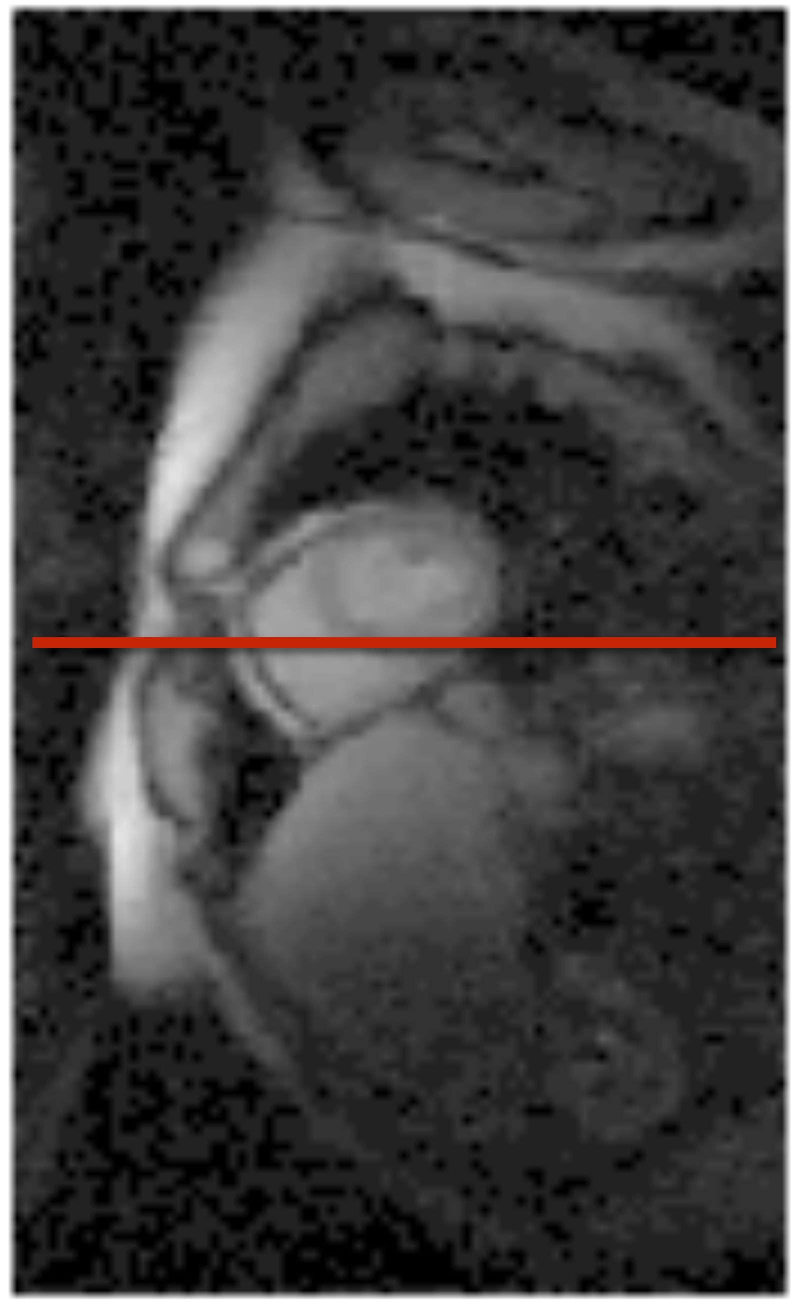
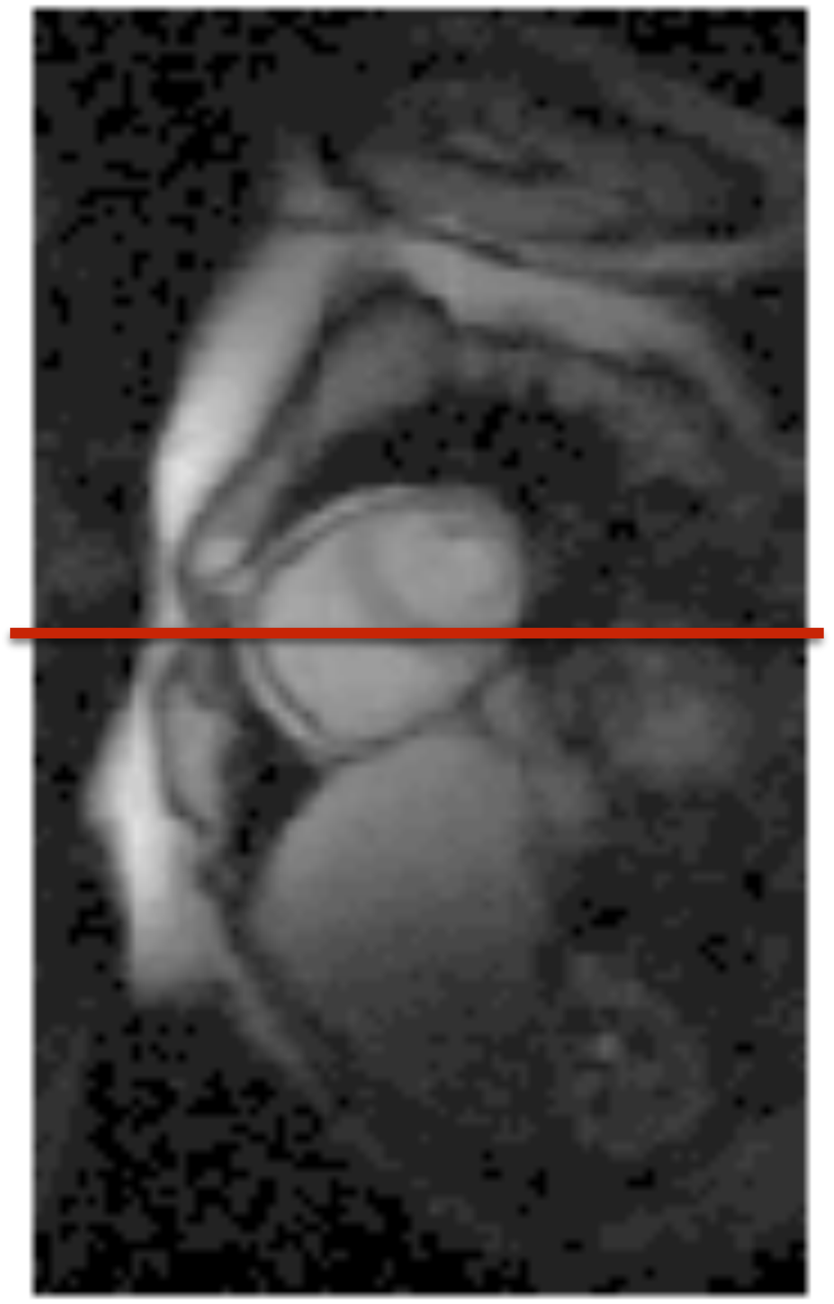


Deformation corrected



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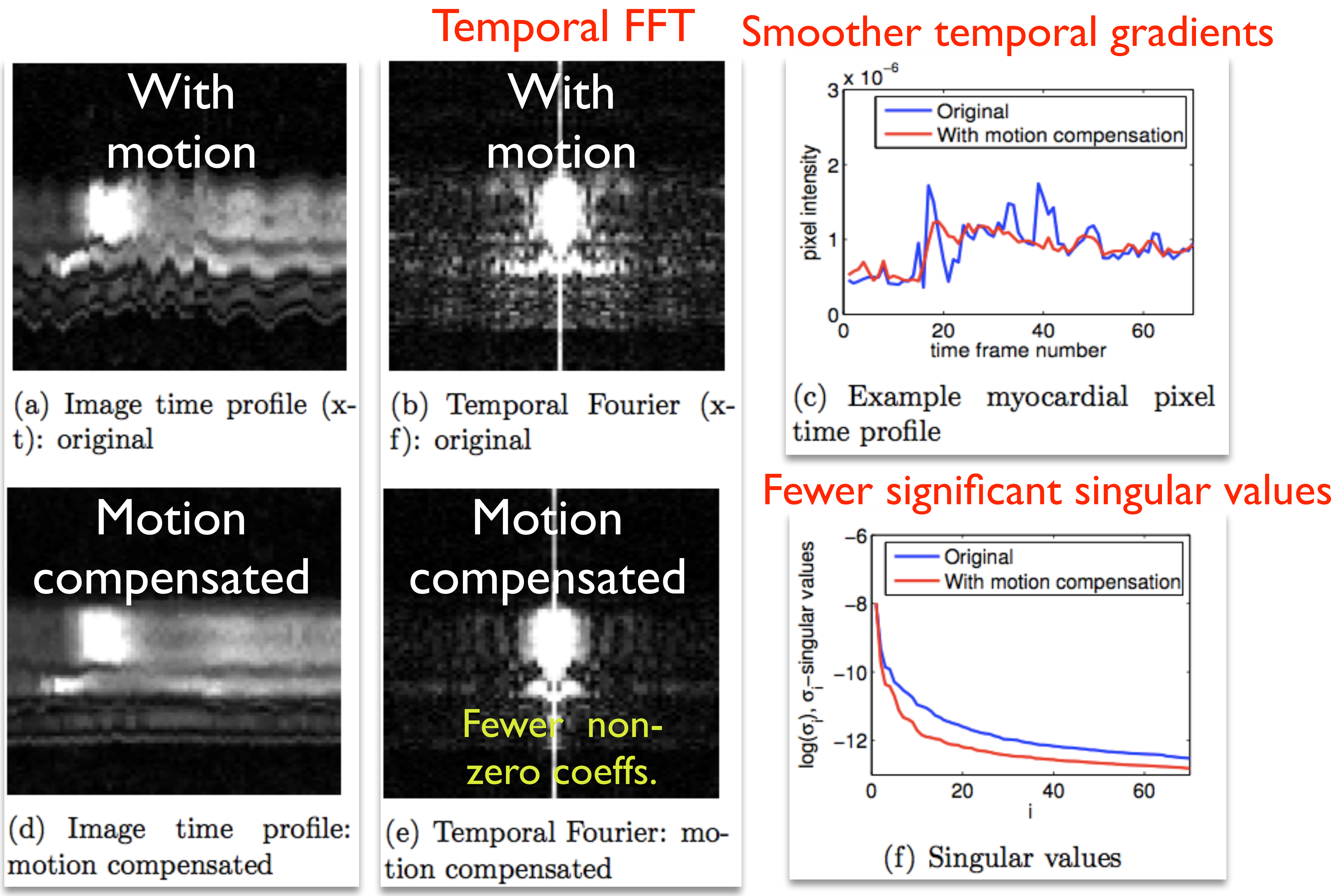
Improving constrained reconstruction with motion correction

- Deformation corrected data is more sparse/compact in transform domains

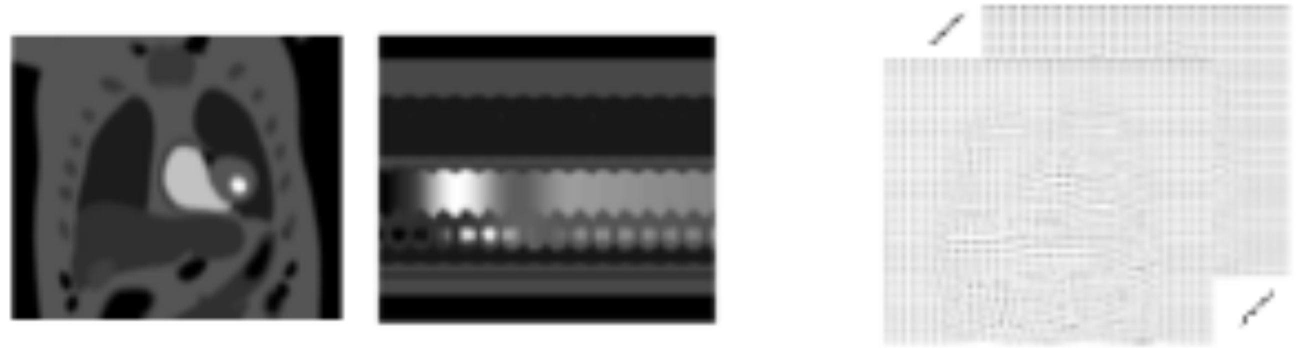


Formulation

$$\{f,\theta\}^* = \min_{f,\theta} \underbrace{\|\mathcal{A}(f)-\mathbf{b}\|_2^2}_{\text{data consistency}} + \underbrace{\lambda\|\varphi(\mathcal{T}_\theta\cdot f)\|_1}_{\text{temporal regularization}} \qquad (1)$$

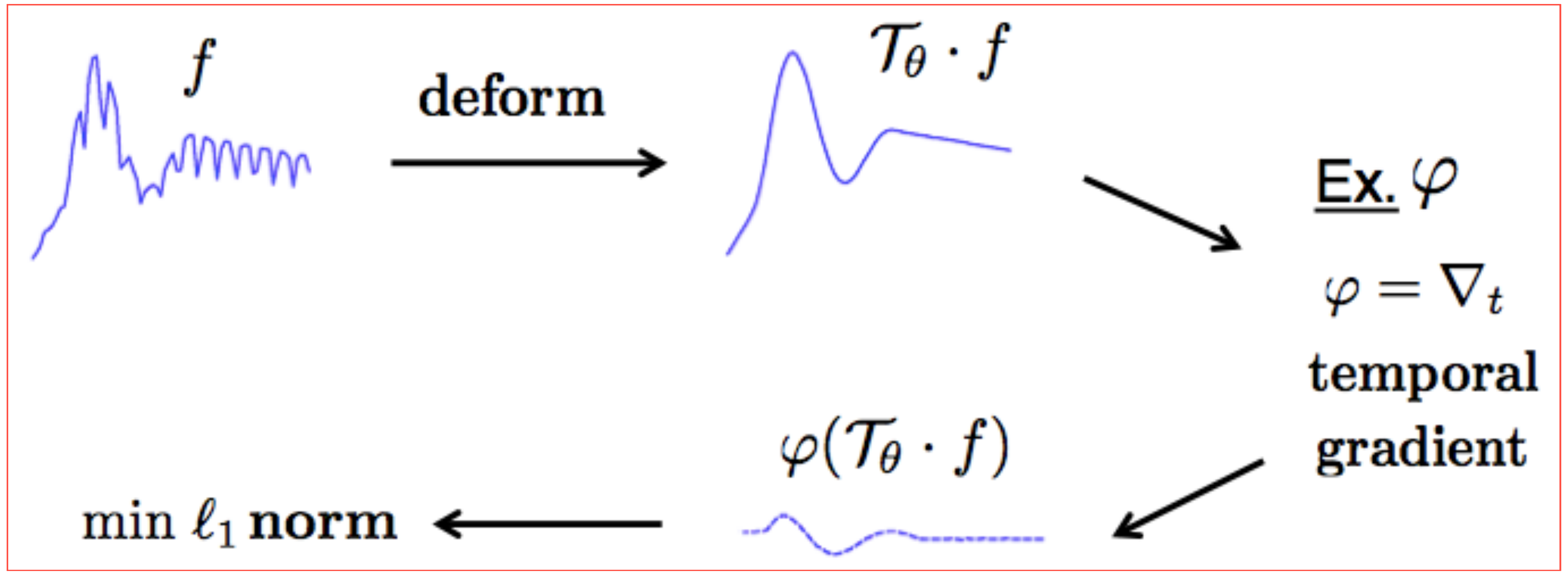
$f(\mathbf{x},t)$ Dynamic scene

$\mathcal{T}_\theta(\mathbf{x},t)$ Deformation maps



φ - Transform domain operator

Ex:
- Temporal gradient
- Temporal Fourier Transform (x-f)
- Low rank



S.G.Lingala, IEEE-TMI, 2015

Variable splitting and continuation strategies

- Original problem

$$\{f^*, \theta^*\} = \min_{f,\theta} \|\underbrace{\mathcal{A}(f) - \mathbf{b}}_{\text{data consistency}}\|_2^2 + \lambda \|\underbrace{\Phi\left(\mathcal{T}_\theta \cdot f\right)}_{\text{temporal regularization}}\|_{\ell_1};$$

- Splitting allows to decouple deformation estimation from reconstruction

$$\min_{f,\theta,g} \|\mathcal{A}(f) - \mathbf{b}\|_2^2 + \lambda \|\Phi\left(g\right)\|_{\ell_1};$$

$$s.t., \mathcal{T}_\theta \cdot f = g;$$

Variable splitting and continuation strategies

- Modified cost function

$$\min_{f,\theta,g} \|\mathcal{A}(f) - \mathbf{b}\|_2^2 + \lambda\|\Phi\left(g\right)\|_{\ell_1};$$

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Variable splitting and continuation strategies

- Modified cost function

$$\min_{f,\theta,g} \|\mathcal{A}(f) - \mathbf{b}\|_2^2 + \lambda \|\Phi(g)\|_{\ell_1};$$

$$s.t., \mathcal{T}_\theta \cdot f = g;$$

- Penalize the quadratic violation by introducing a parameter β

$$\min_{f,\theta,g} \|\mathcal{A}(f) - \mathbf{b}\|_2^2 + \lambda \left[\|\Phi(g)\|_{\ell_1} + \frac{\beta}{2} \|\mathcal{T}_\theta \cdot f - g\|_2^2 \right]$$

- Is equivalent to the original cost when β tends to ∞

Alternate between well defined subproblems

- Continuation: Iterate while gradually increasing β

$$\min_g \mathcal{D}_\beta$$

$$\min_g \; \|\Phi\left(g\right)\|_{\ell_1} + \frac{\beta}{2}\|\underbrace{\mathcal{T}_\theta \cdot f}_{\hat{f}} - g\|_2^2$$

Denoising/dealiasing step

$$\min_f \mathcal{D}_\beta$$

$$\min_f \|\mathcal{A}(f) - \mathbf{b}\|_2^2 + \frac{\lambda\beta}{2}\|\mathcal{T}_\theta \cdot f - g\|_2^2$$

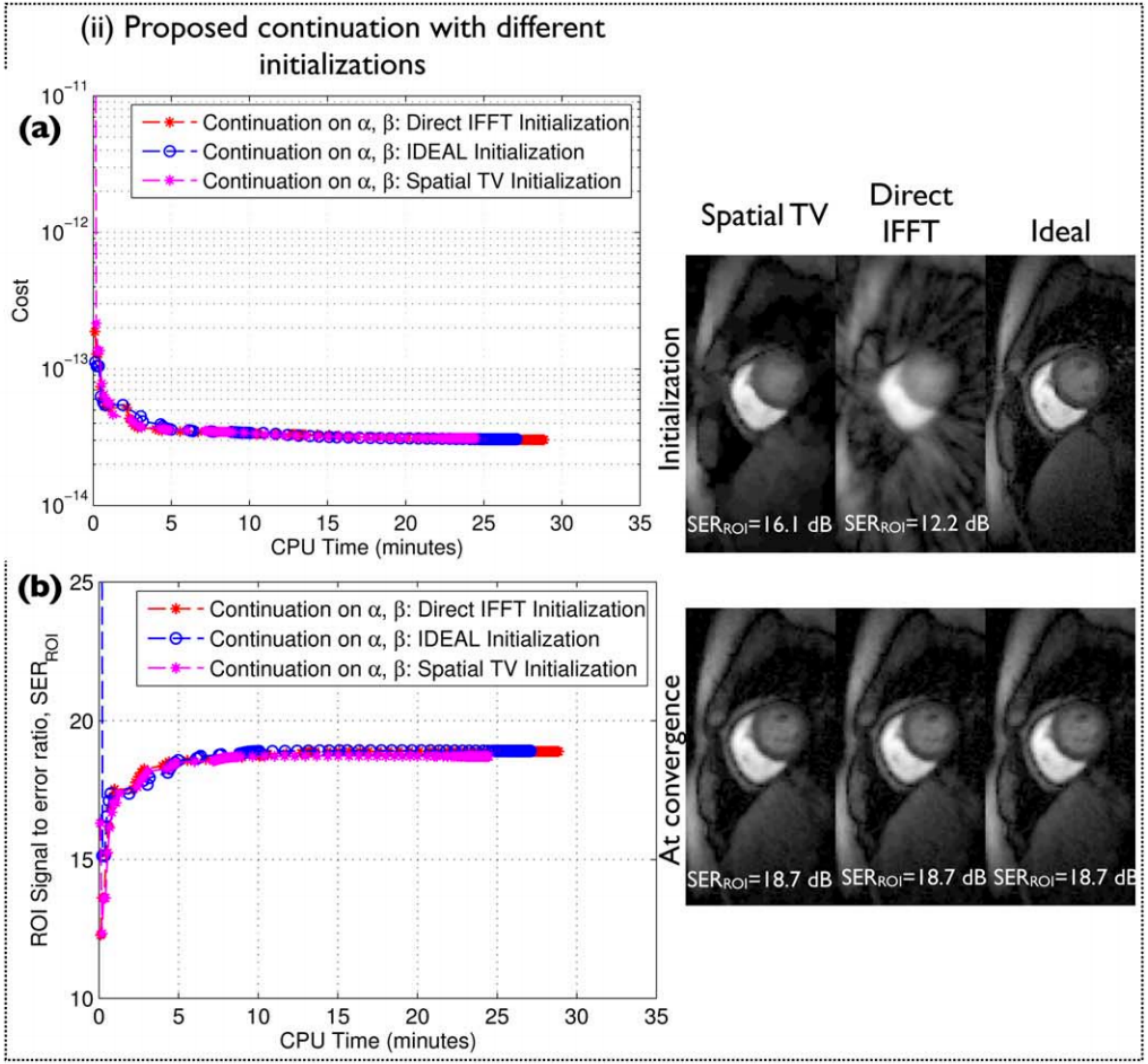
Reconstruction update

$$\min_\theta \mathcal{D}_\beta$$

$$\min_\theta \|\mathcal{T}_\theta \cdot f - g\|_2^2$$

Image registration

- Demonstration of robustness to initialization with continuation strategies



S.G.Lingala, IEEE-TMI, 2015

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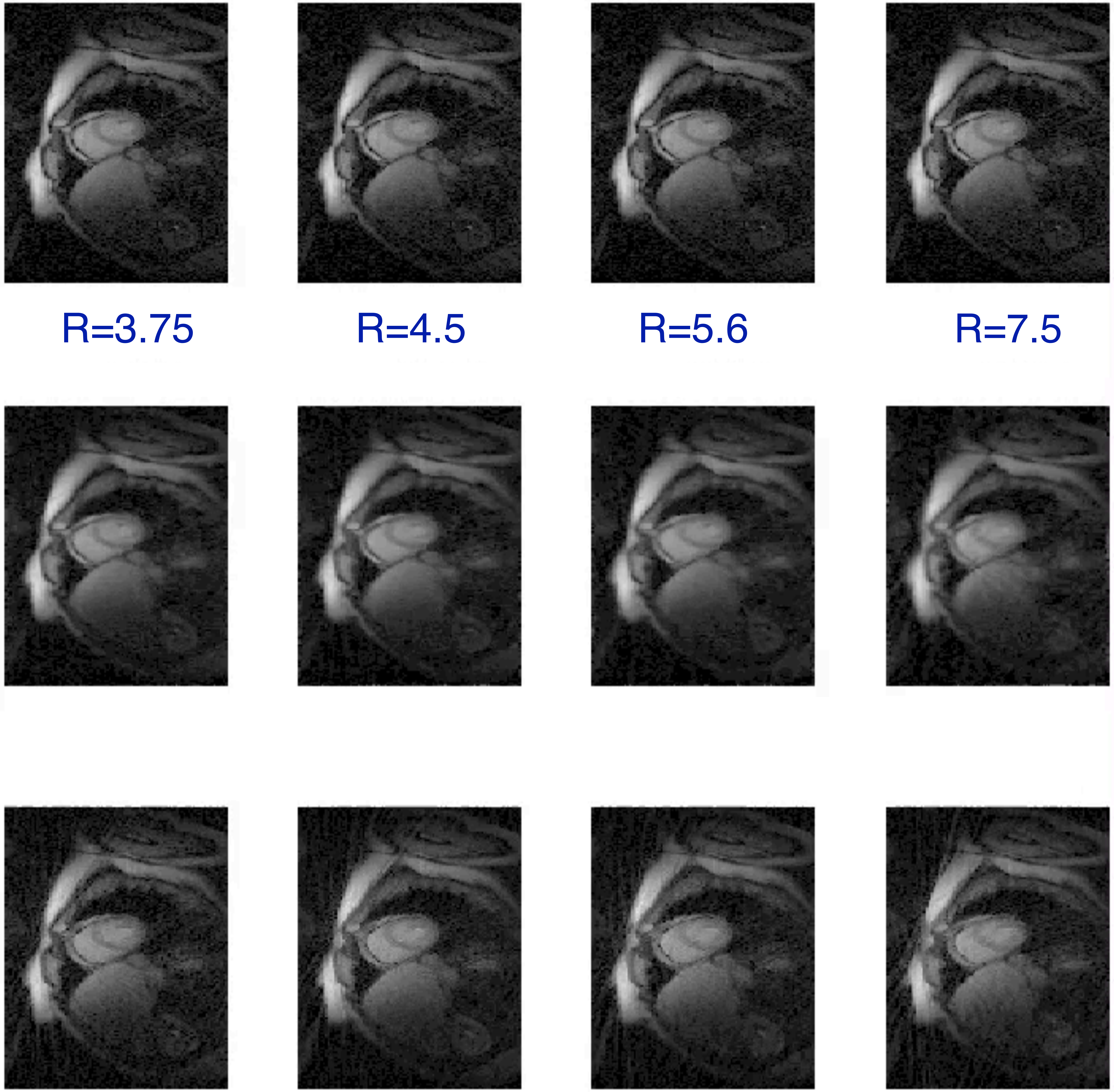
Fully sampled

Deformation corrected temporal finite difference

Temporal Finite Difference



S.G.Lingala, IEEE-TMI, 2015

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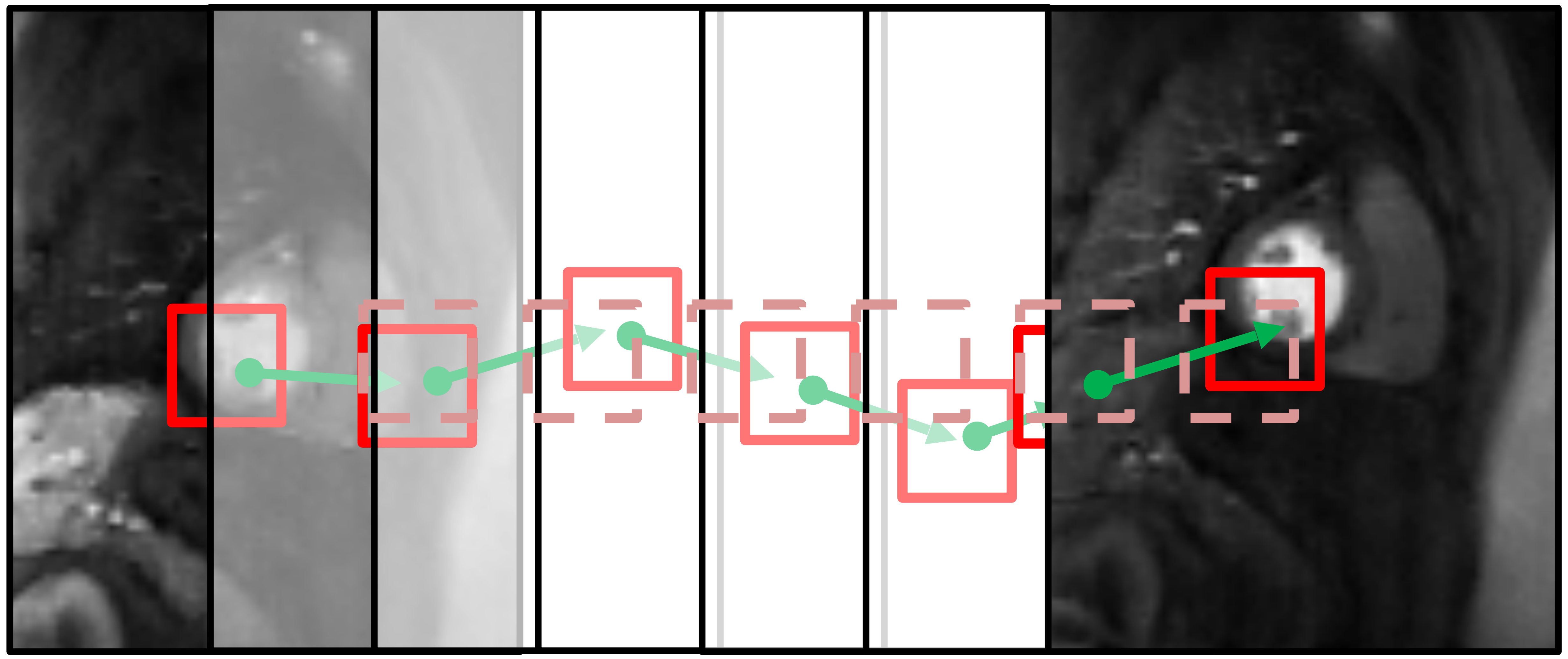
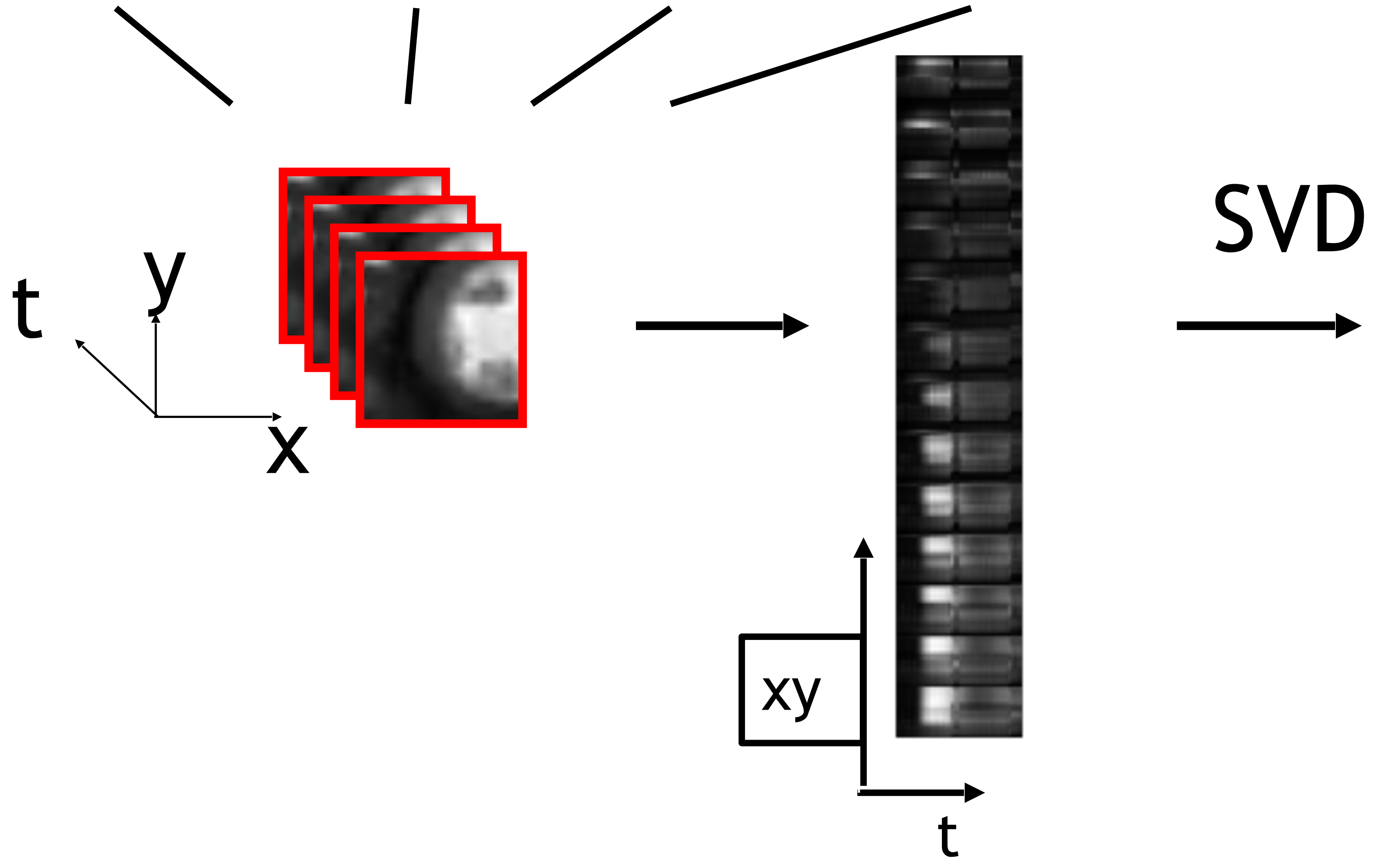
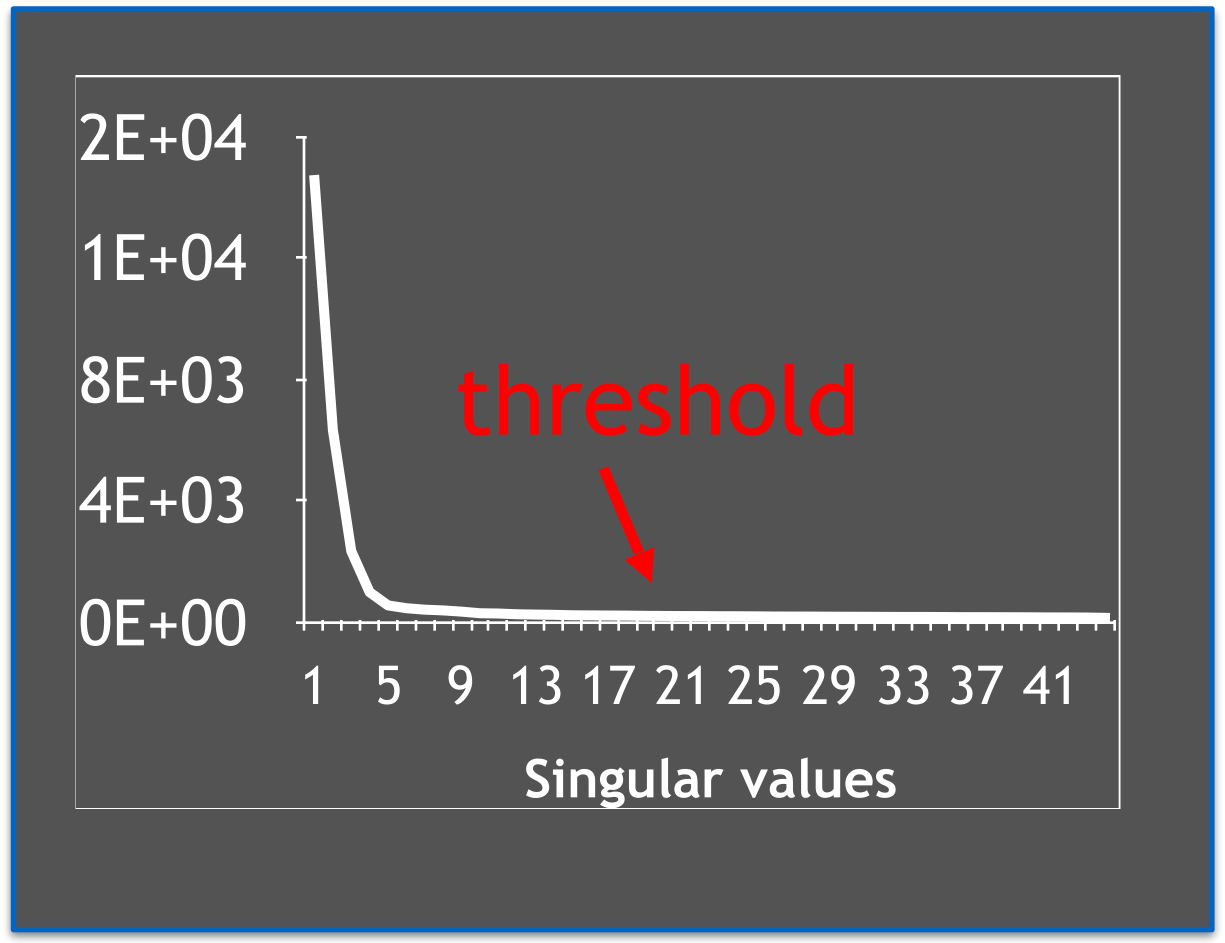
Block low rank sparsity with motion guidance (BLOSM)



ANTS non-rigid registration
Coarse to fine resolution correction
Block low rank constraint





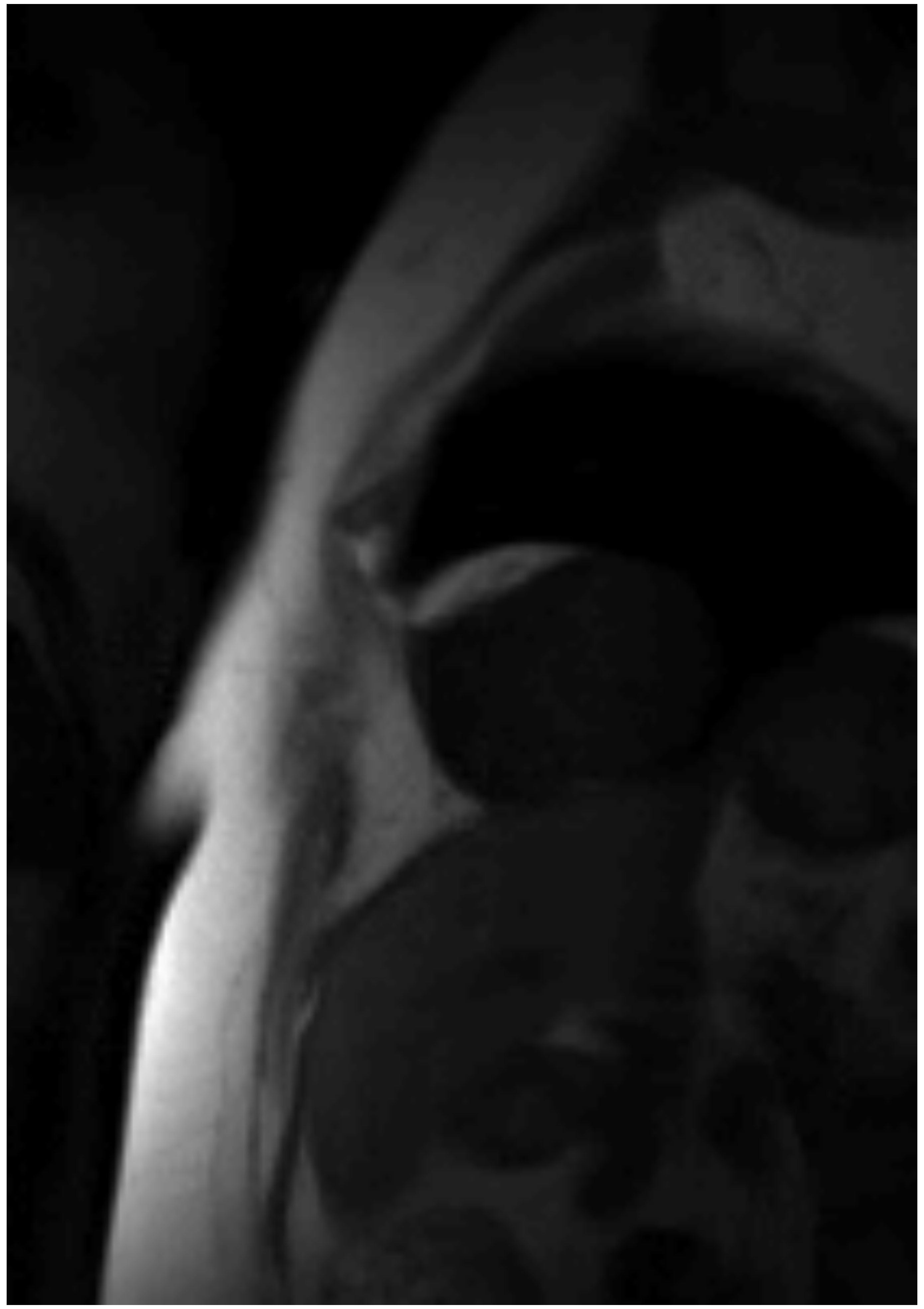
X Chen et al. MRM 2014;72(4):1028-38

Block low rank sparsity with motion guidance (BLOSM)

Free breathing myocardial perfusion MRI

Moderate respiratory motion

Severe respiratory motion

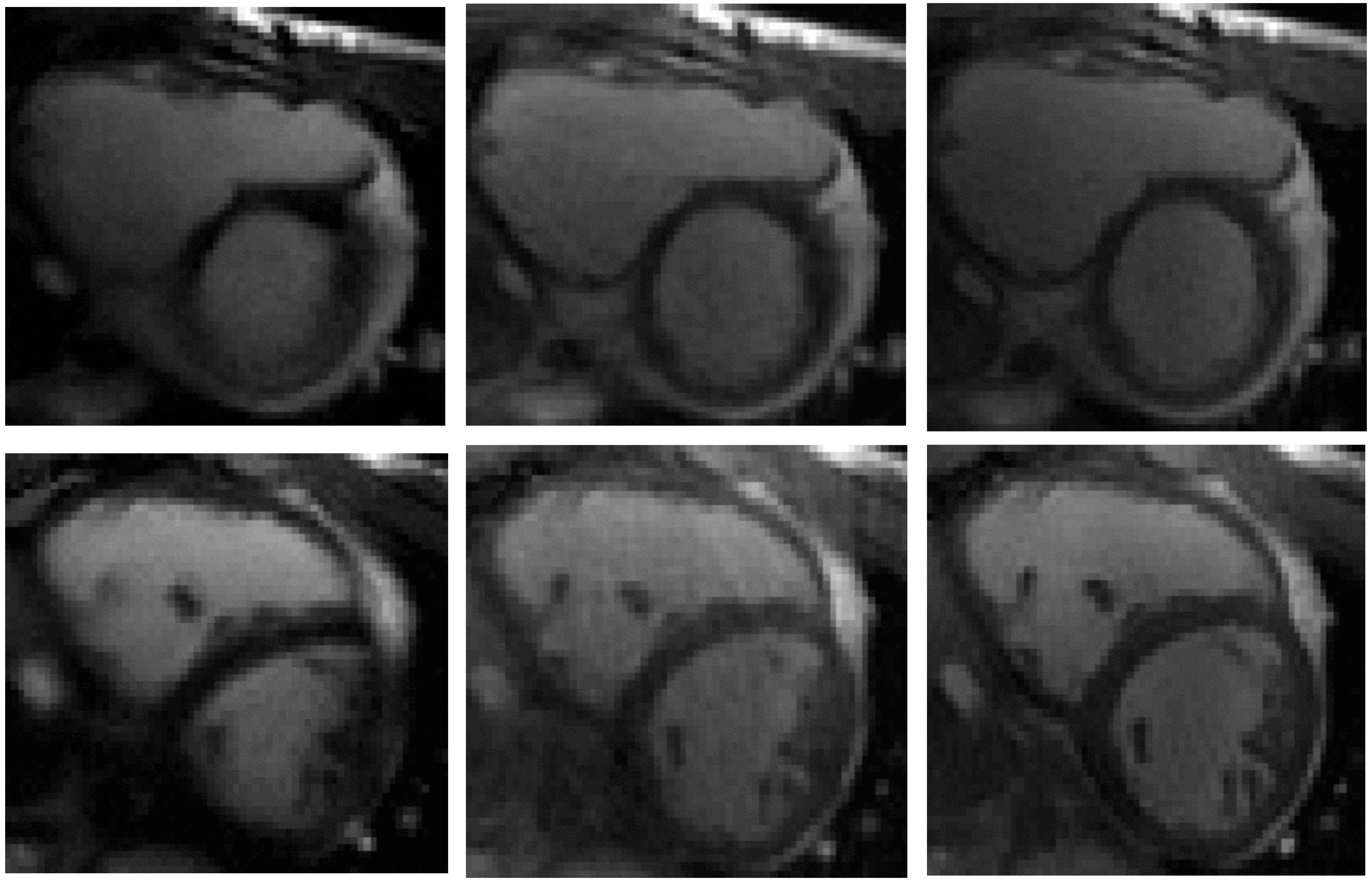


X Chen et al. MRM 2014;72(4):1028-38

*IRB approved study at University of Virginia

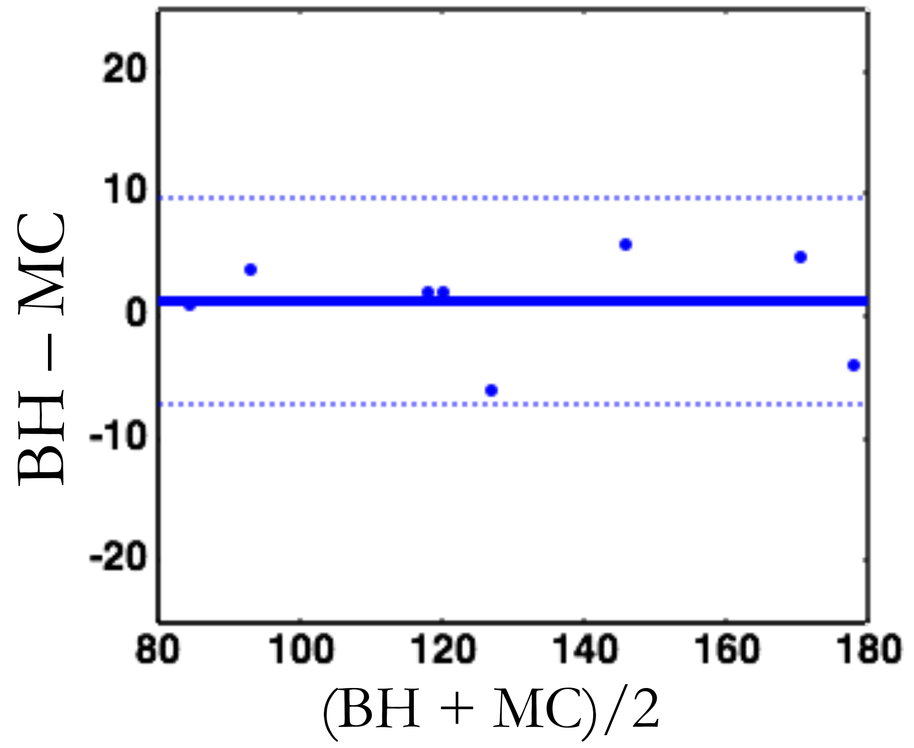
Motion corrected CS: free breathing cardiac cine

Free breathing No Motion Correction	Free breathing Proposed Method	Breath-hold (BH) Reference

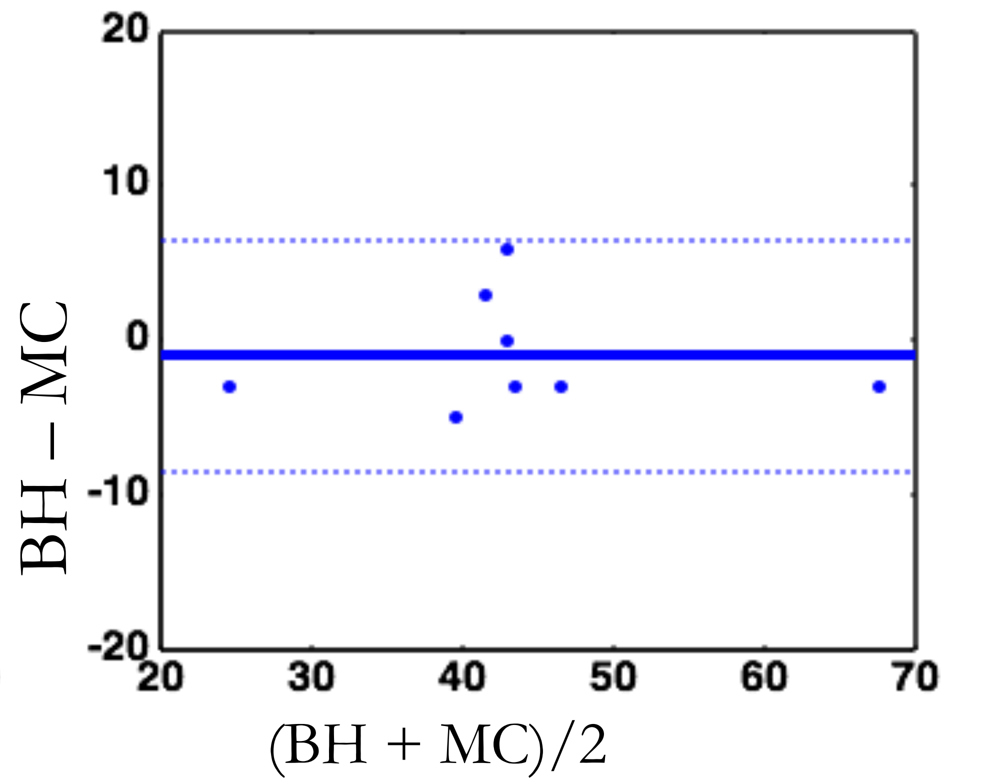


2 min acquisition	2 min acquisition	10 min acq. (including BHs recovery)

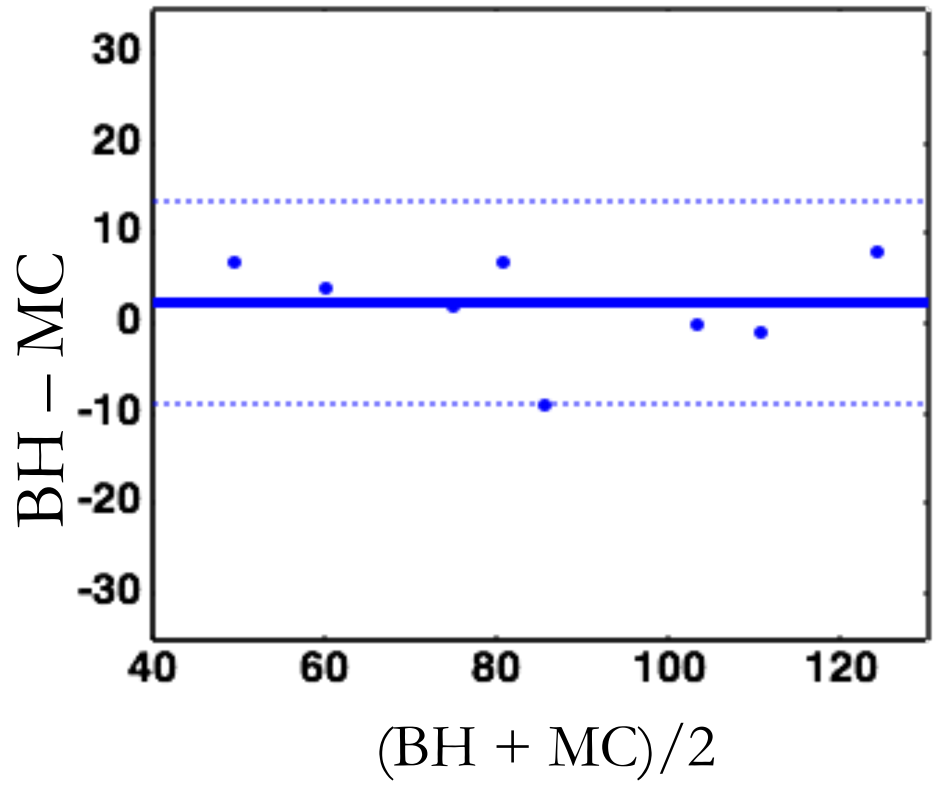
End-diastolic volume (ml)
Proposed vs. reference



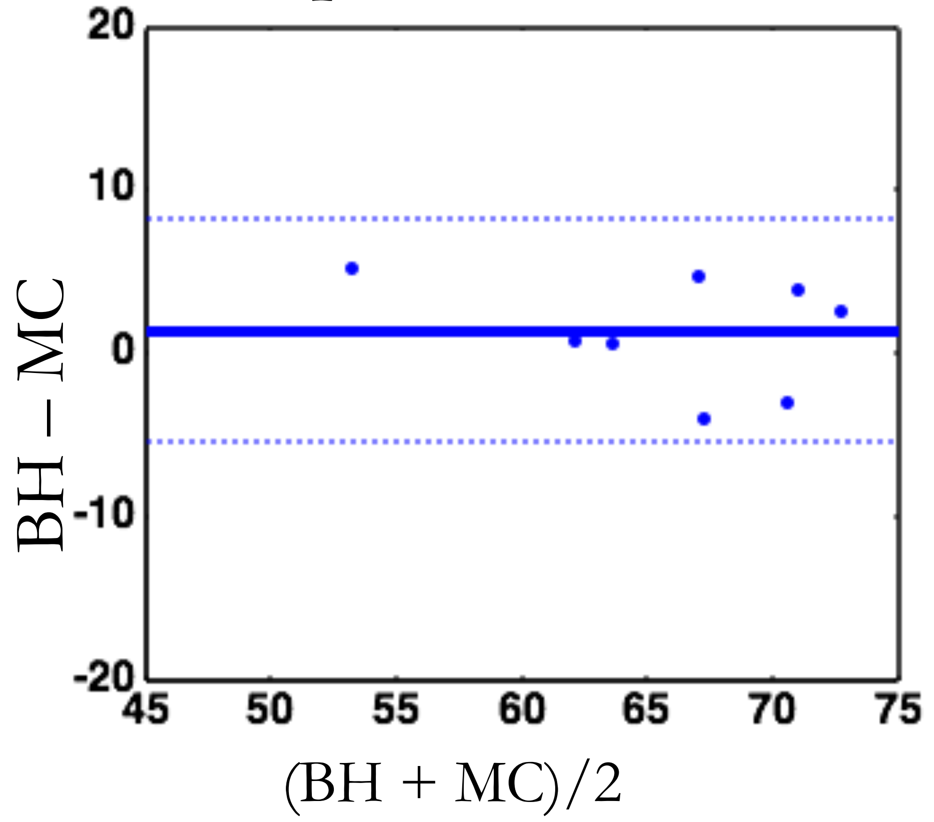
End-systolic volume (ml)
Proposed vs. reference



Stroke Volume (ml)
Proposed vs. reference



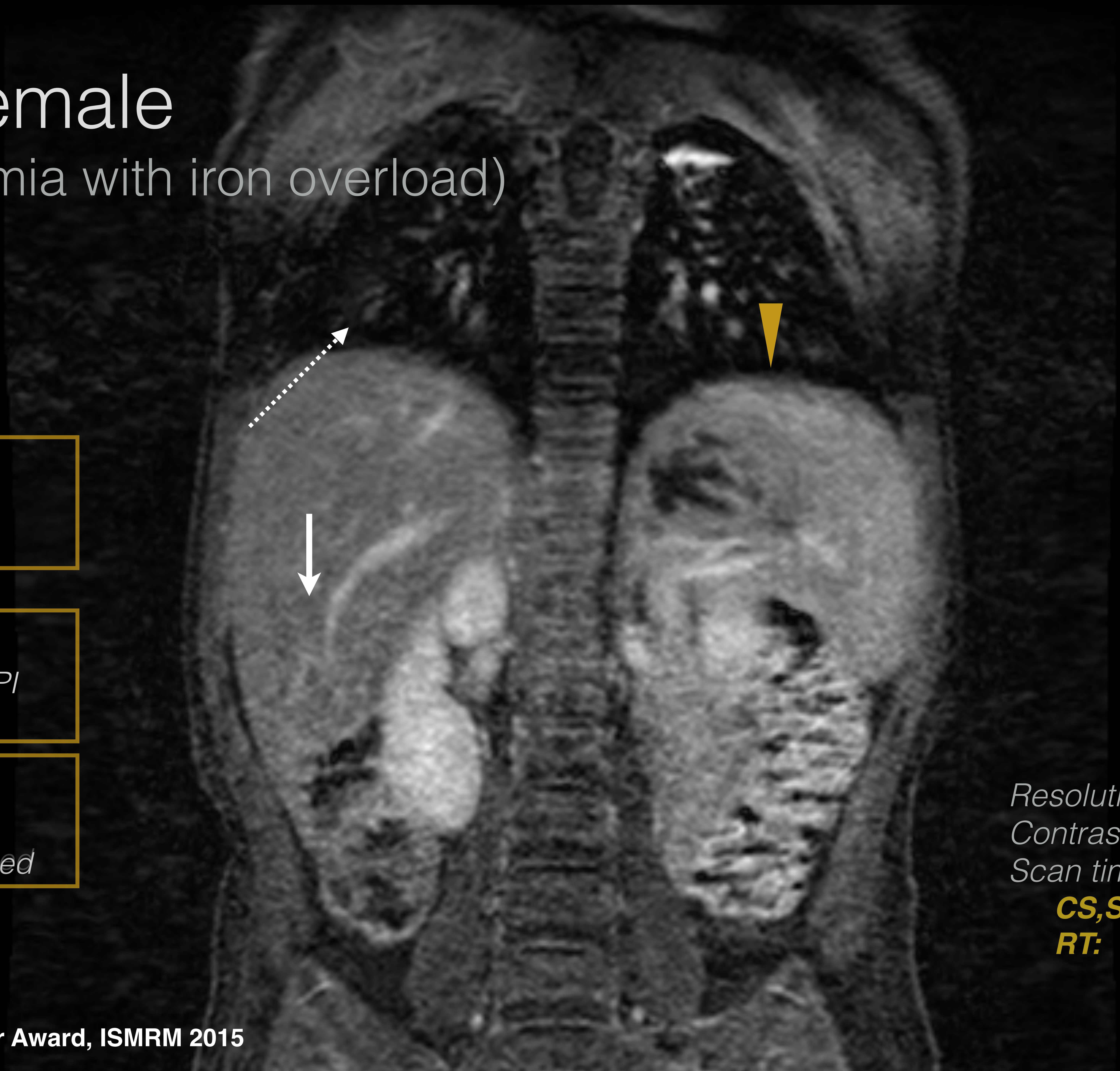
Ejection fraction (%)
Proposed vs. reference



M.Usman et.al, MRM 2011

1.6 year female

(beta thalassemia with iron overload)



CS
Conventional
CS & PI

wAF
Soft-gated CS & PI
w/ autofocusing

RT
Prospective
respiratory trig/gated

Resolution: 0.9x1.3x1.6 mm^3
Contrast: Gadavist
Scan times:
***CS,SG,wAF:* 29.6 sec**
***RT:* 102.6 sec**

JY Cheng et al, Young Investigator Award, ISMRM 2015

Challenges:
Explicit motion estimation and corrected reconstruction

- Involves non-convex optimization
    - No convergence guarantees
    - Continuation strategies are crucial to monitor convergence
    - Coarse to fine, variable splitting, etc.

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  - Prior guess of motion estimates, coarse-fine correction, GPUs, parallel computing, etc.

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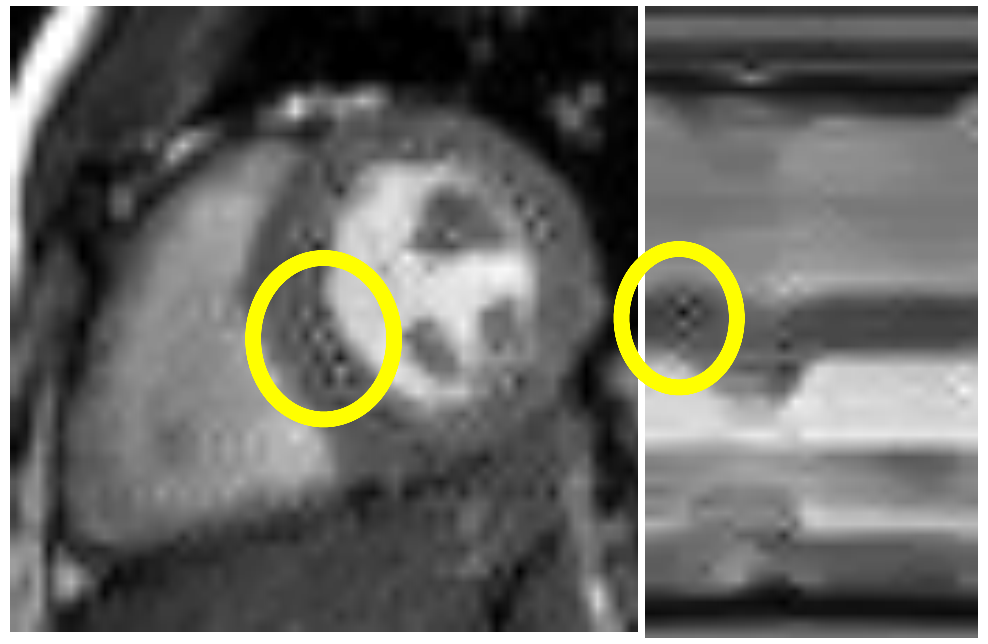

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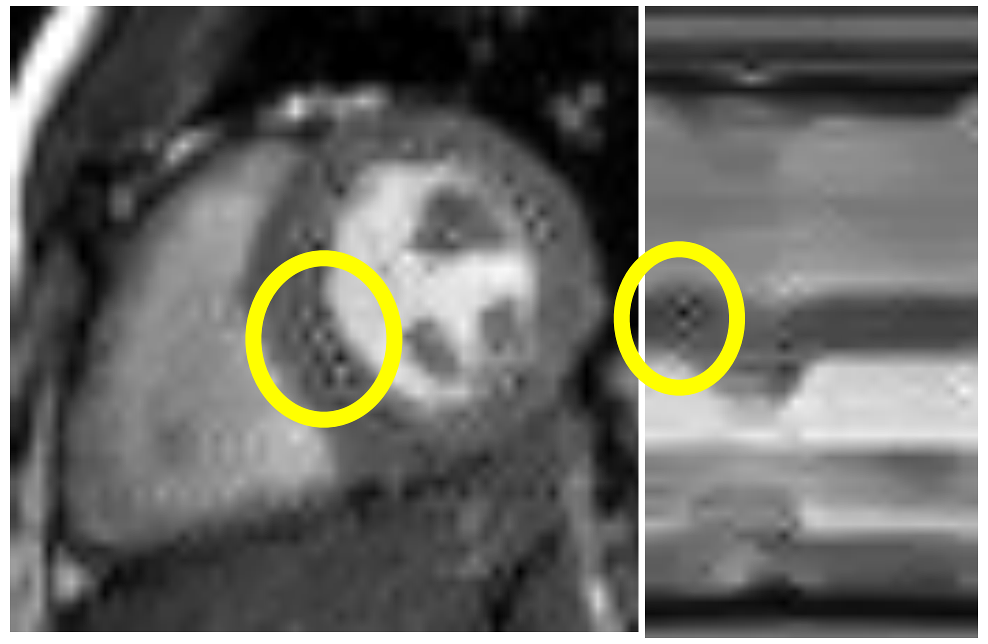
- Interpolation errors while correcting for large deformation errors
  - Modified Jacobian weighting in regularization (Royuela, 2016)



“Implicit” motion corrected reconstruction: Reordering prior based

- Reorder intensities of signal estimate based on prior reconstruction (eg. CS based)

G.Adluru et al., Int Journal Biomedical Imaging, 2008
G.Adluru et al., Med Physics 2016

"Implicit" motion corrected reconstruction: Reordering prior based

- Reorder intensities of signal estimate based on prior reconstruction (eg. CS based)

- Sparsity/Low rank constraint applied on the "reordered" data set

Reordering prior (known)

$$min_f \|A(f) - b\|_2^2 + \lambda \|\Phi(\mathcal{R} \cdot f)\|_1;$$

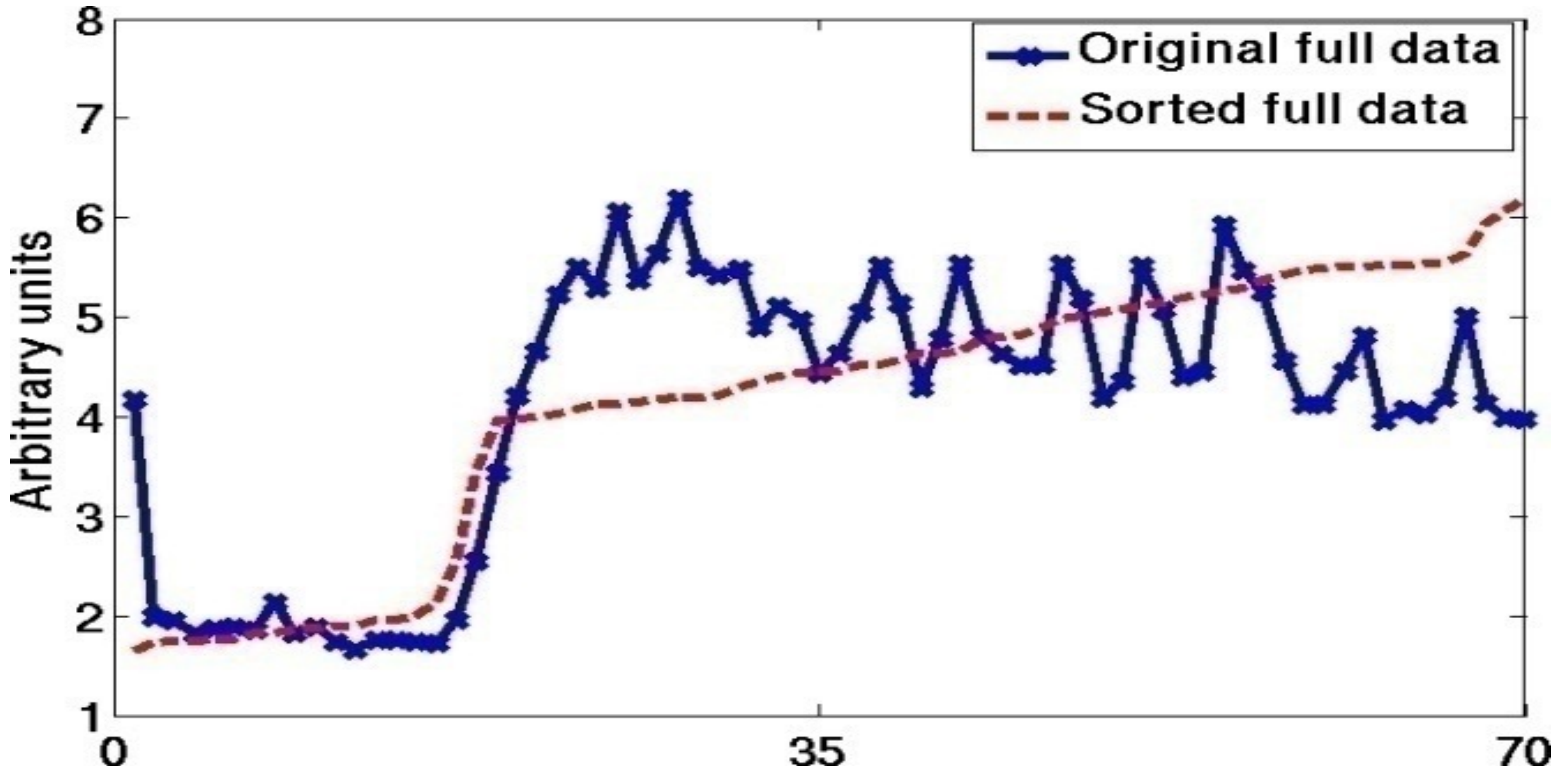
Sparsifying operator

- Temporal Fourier Transform
- Temporal finite difference
- Spectral operators for PCA

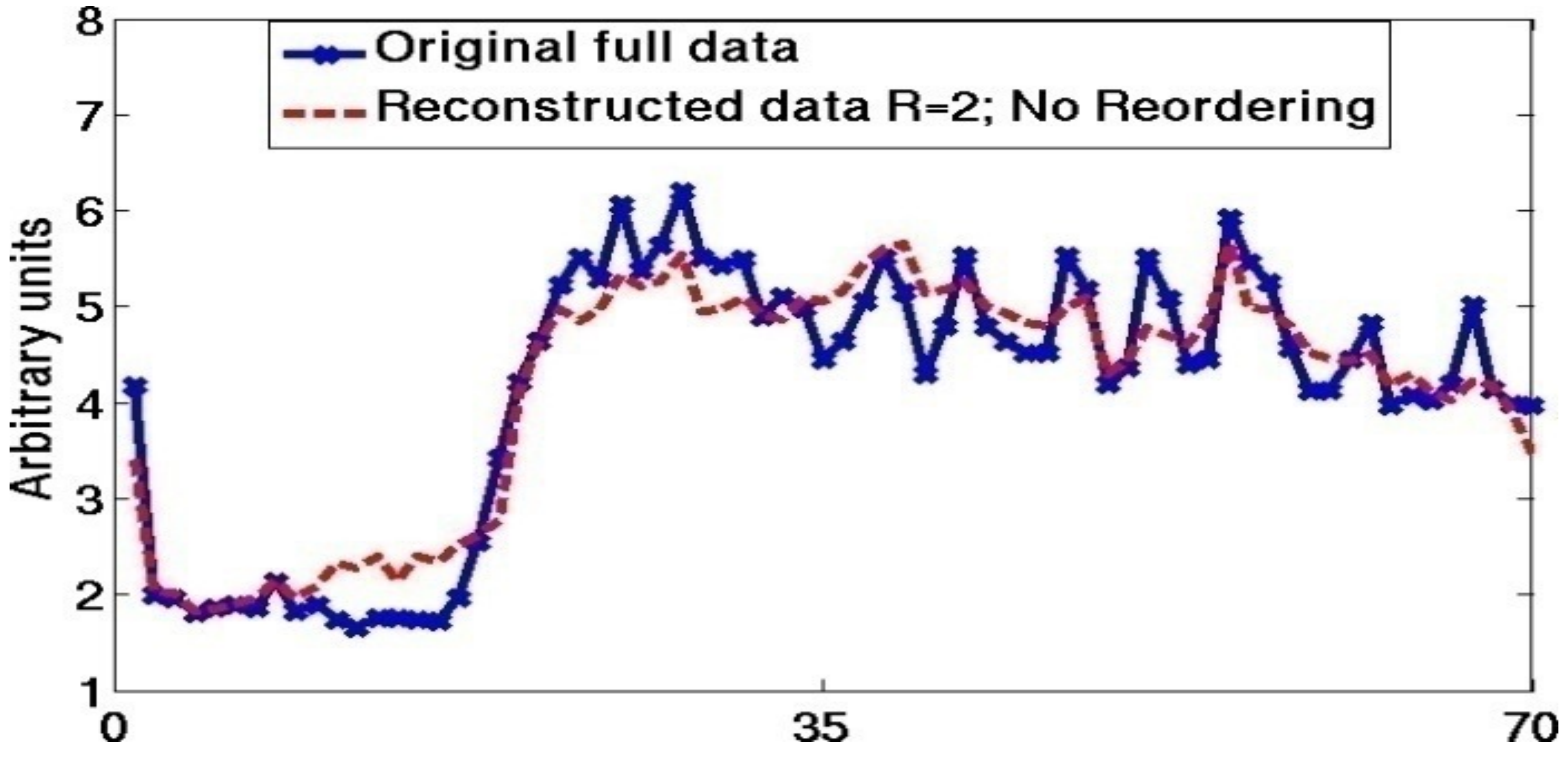
G.Adluru et al., Int Journal Biomedical Imaging, 2008
G.Adluru et al., Med Physics 2016

Reordering based prior: 1D example

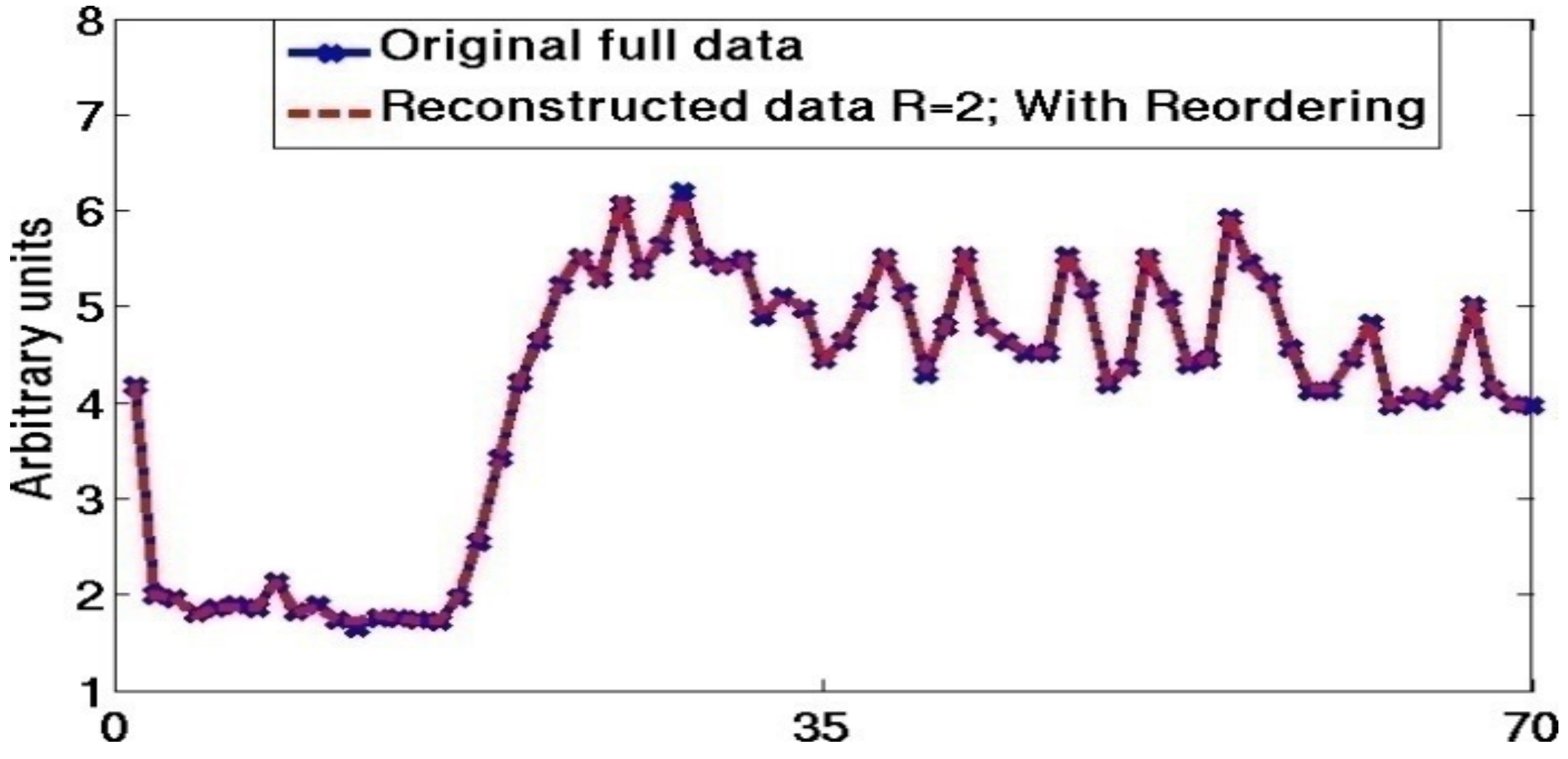
A rapidly varying fully sampled signal and its sorted version



Reconstruction without reordering (R=2)

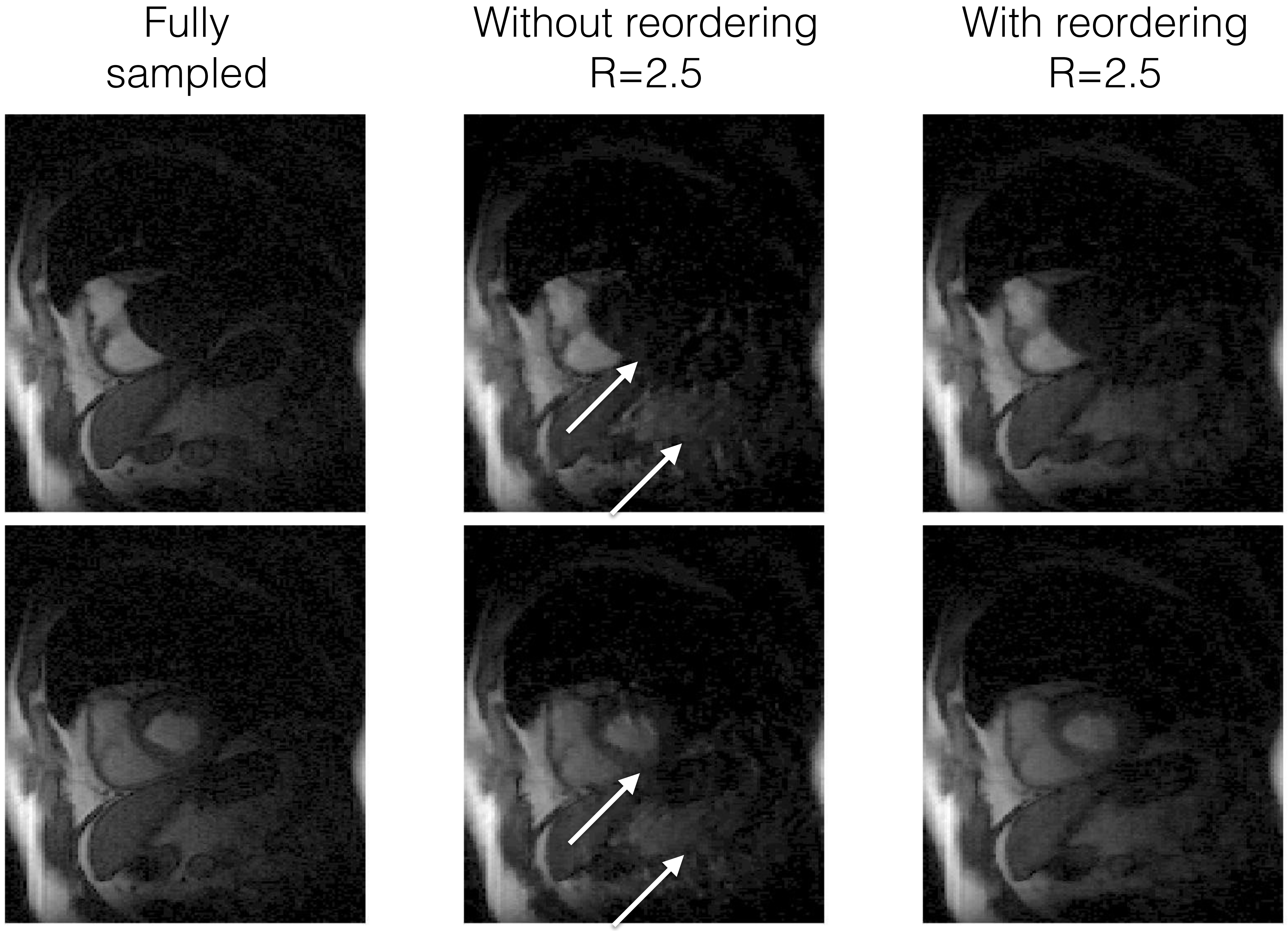


Reconstruction with reordering (R=2)



G.Adluru et al., Int Journal Biomedical Imaging, 2008
G.Adluru et al., Med Physics 2016

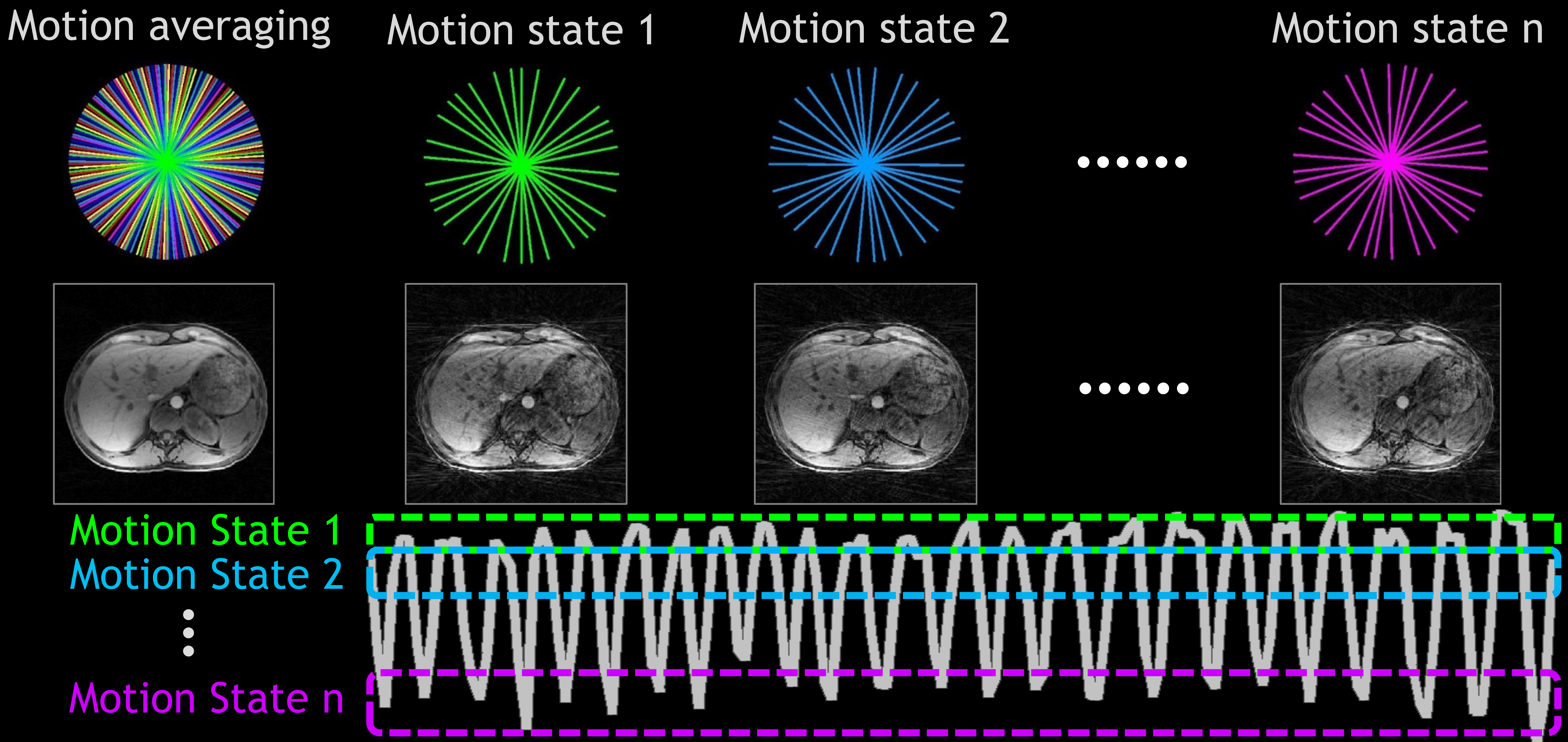
Sparsity based re-ordering prior
Example of myocardial perfusion MRI



G.Adluru et al., Int Journal Biomedical Imaging, 2008
G.Adluru et al., Med Physics 2016

*IRB approved study at University of Utah

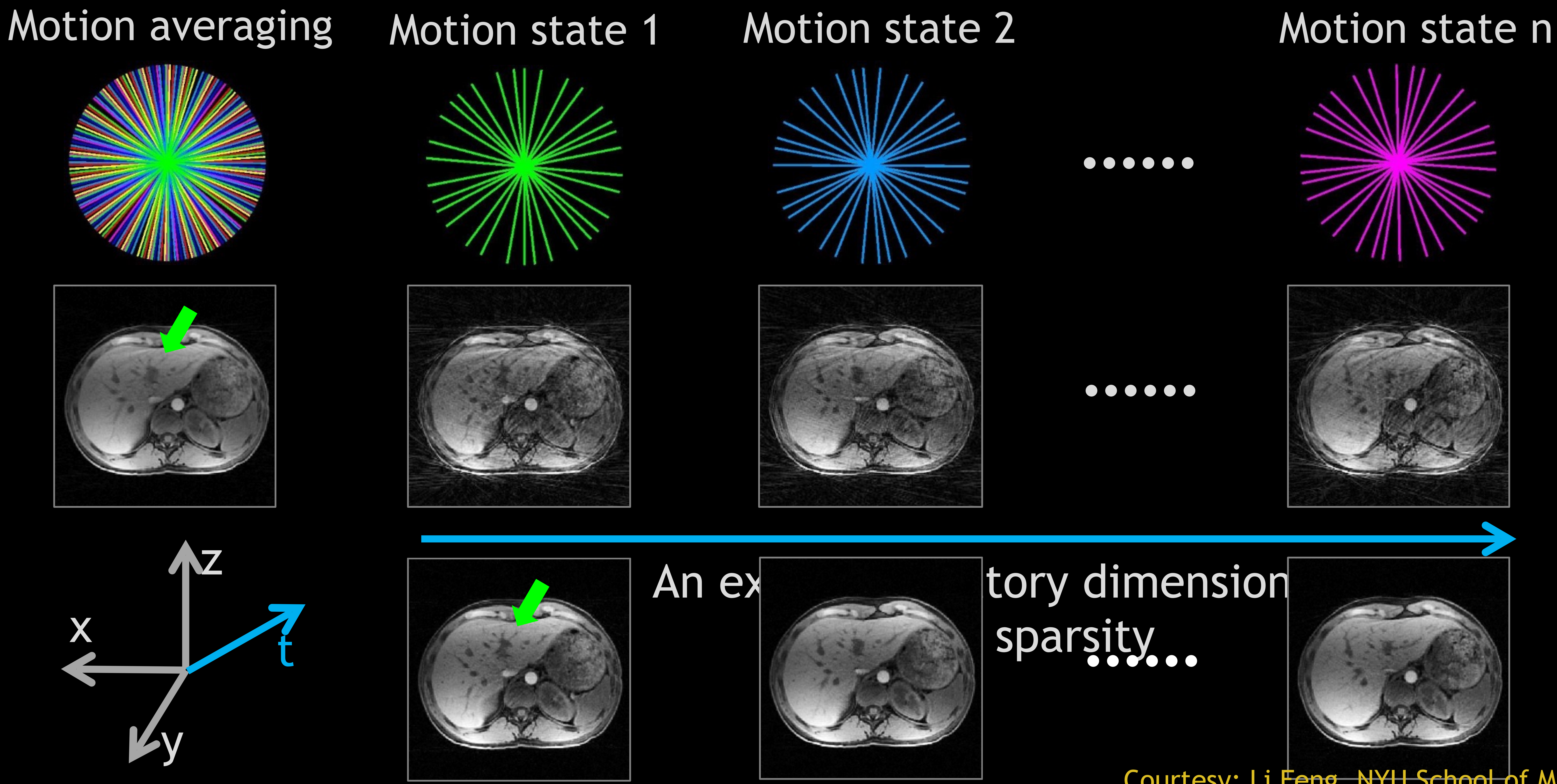
XD-GRASP: A Simple Example



Feng L et al. ISMRM 2015 p568

Courtesy: Li Feng, NYU School of Medicine

XD-GRASP: A Simple Example



Feng L et al. ISMRM 2015 p568

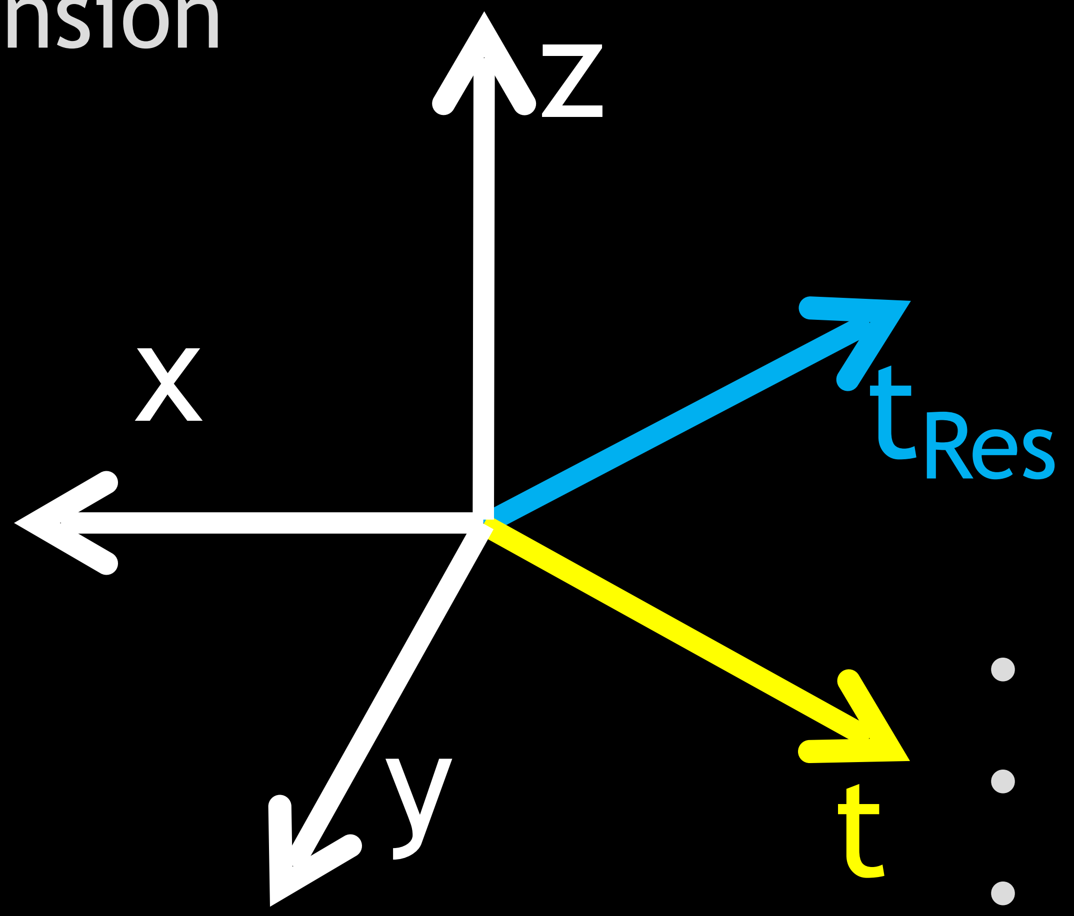
Courtesy: Li Feng, NYU School of Medicine

XD-GRASP Reconstruction

$$x = \arg\min_{x} \|E \cdot x - y\|_2^2 + \lambda_1 \|S_1 \cdot x\|_1 + \lambda_2 \|S_2 \cdot x\|_1 \cdots\cdots$$

x : Multidimensional images to be reconstructed
S_1 : Sparsifying transform along the 1st temporal dimension
S_2 : Sparsifying transform along the 2nd temporal dimension

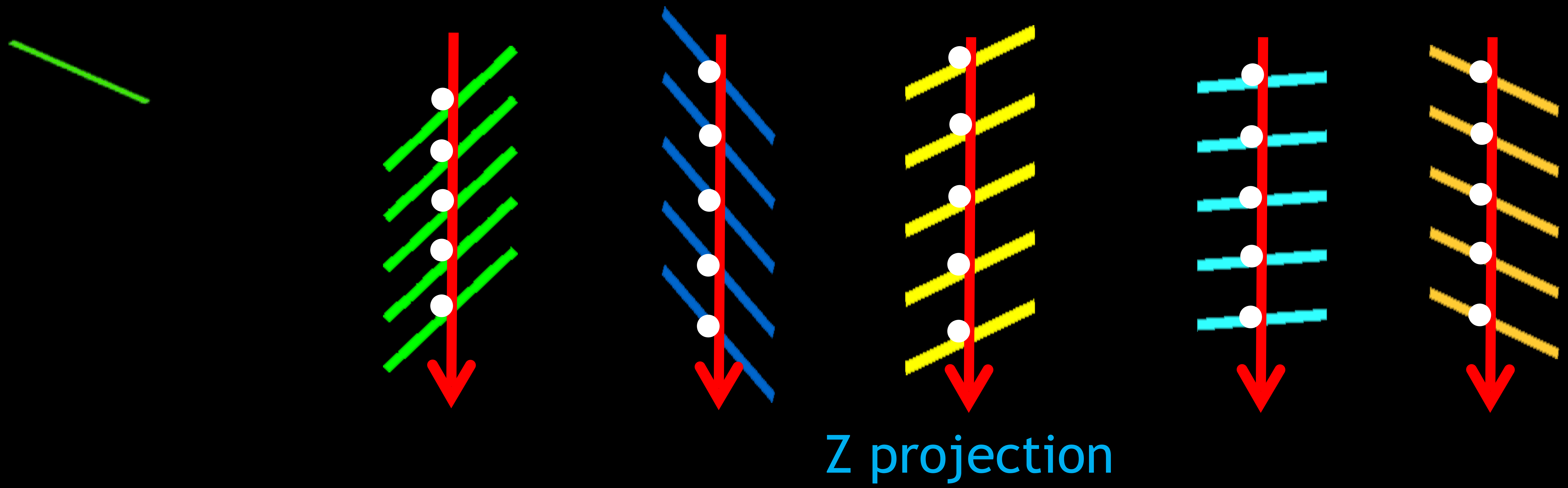
y: Sorted k-space
E: Encoding function (multicoil)
λ: Regularization parameters

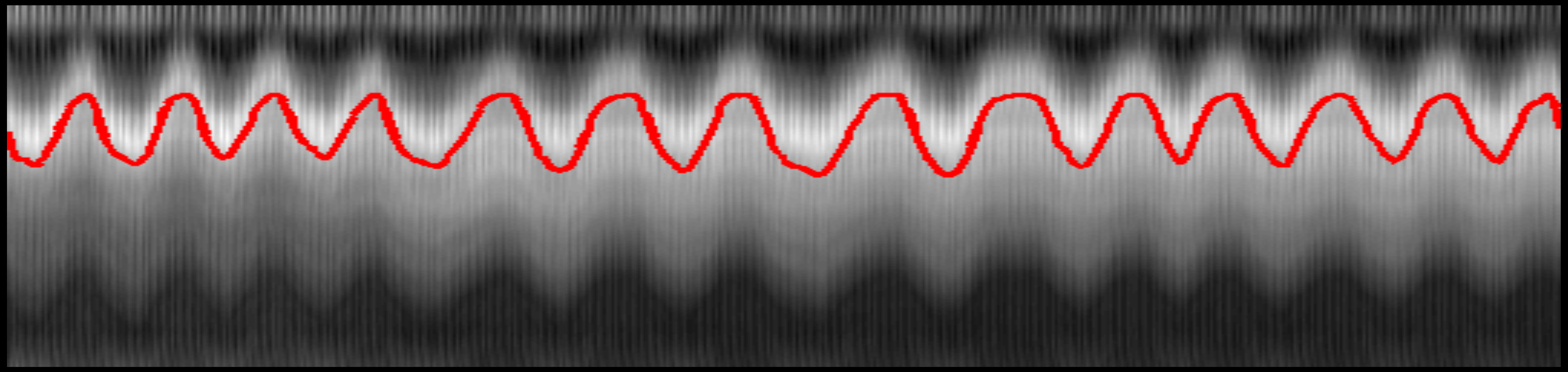


- Contrast enhancement
- Cardiac motion
- Multiple echoes
- Flow encoding

Courtesy: Li Feng, NYU School of Medicine

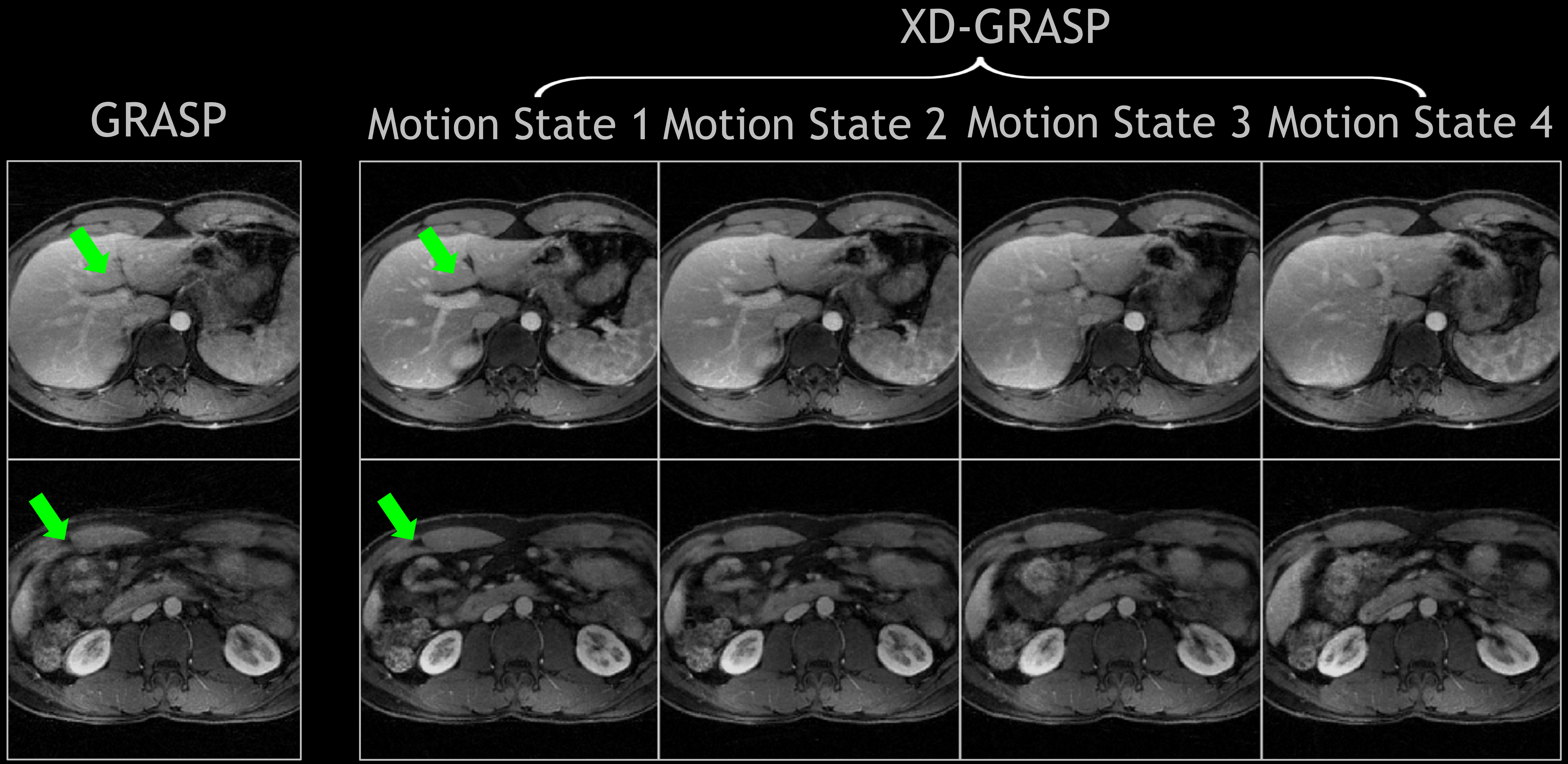
XD-GRASP for DCE-MRI of the Liver





Liu J et al. MRM 2010 63(5): 1230-1237
Spincemaille P et al 2011 29(6): 861-868.
Pang J et al. MRM 2014 72(5):1208-1217

Respiratory Motion-Resolved DCE-MRI



Conclusions

- Explicit Motion estimation and compensation methods can address the motion sensitivity of current sparsity/low rank based models
- Continuation strategies are used for well behaved convergence
- Increased computation times and nontrivial interpolation artifacts remain a challenge
- Implicit motion constrained recovery methods show promise to address the challenges with explicit methods

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