Joint reconstruction of image and motion in MRI

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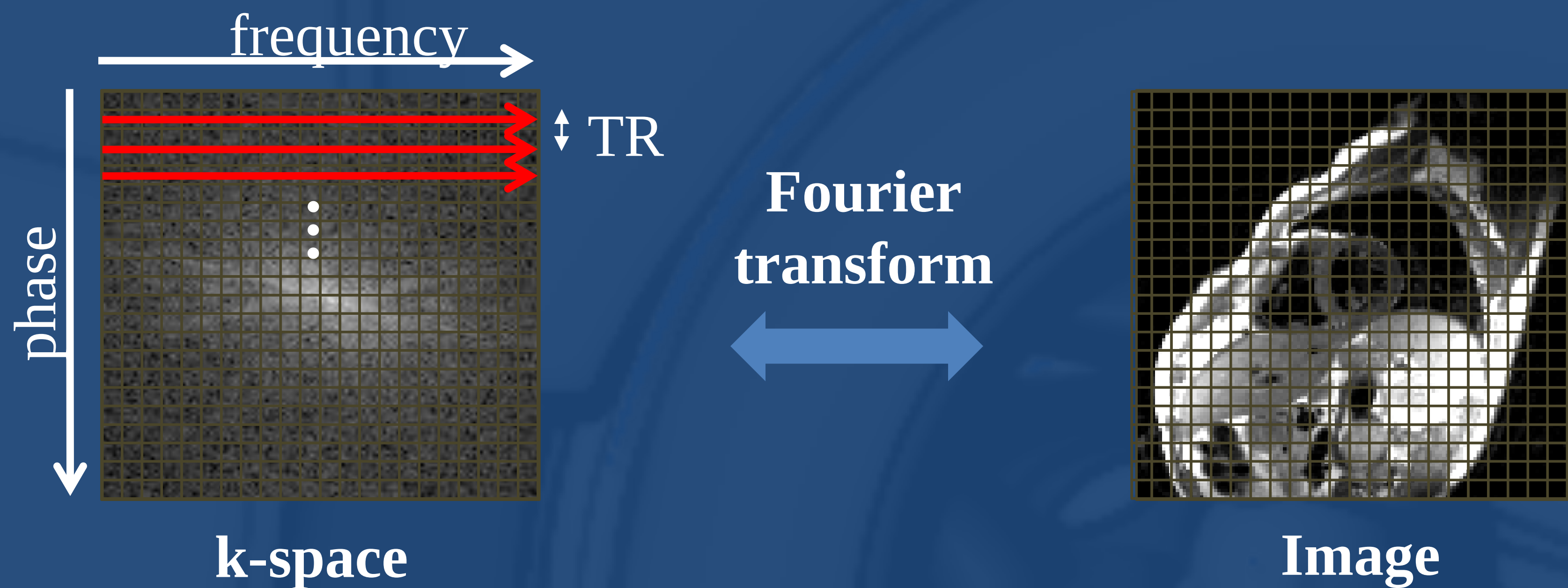
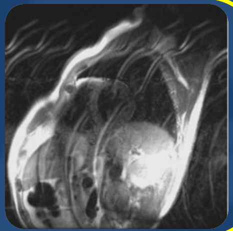
Motion during MRI



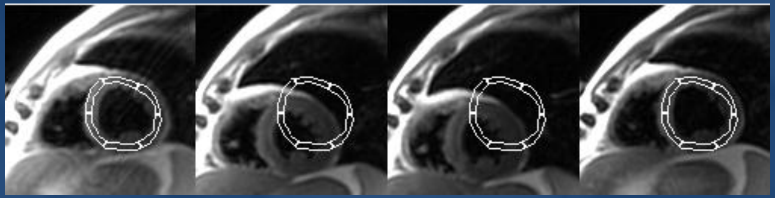
Motion during MRI – Temporal characteristics

- Cardiovascular/body imaging:
  - Respiration
  - Cardiac motion
  - Peristaltic motion

- Characteristic period of motion T_{motion} :
  - T_{motion} < TR => MR signal loss (intra-view motion)
  - TR< T_{motion} < $T_{total\ acq}$ => Spatial encoding errors (inter-view motion)



  - $T_{total\ acq}$ < T_{motion} => No artefact (real-time/repeated breath-holds) (image registration)



Motion during MRI – Spatial characteristics

Rigid (or affine)

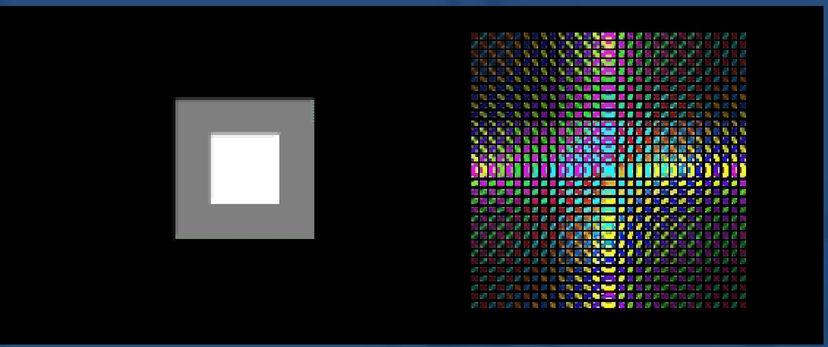
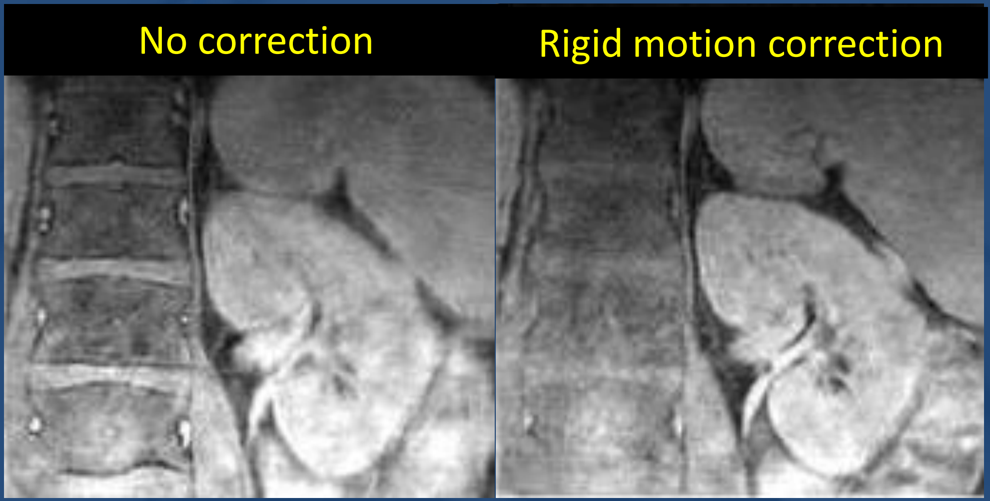


Image k-space



Nehrke et al., 2005, *MRM*, 54: 1130-1138

Nonrigid (or non-affine)

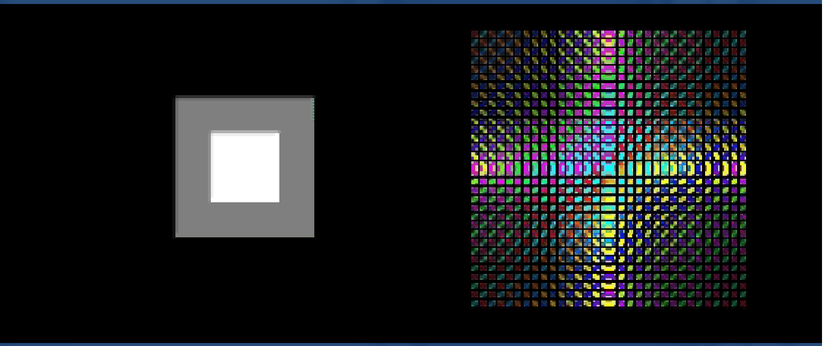


Image k-space

Magnetic Resonance in Medicine 54:1273–1280 (2005)

Matrix Description of General Motion Correction Applied to Multishot Images

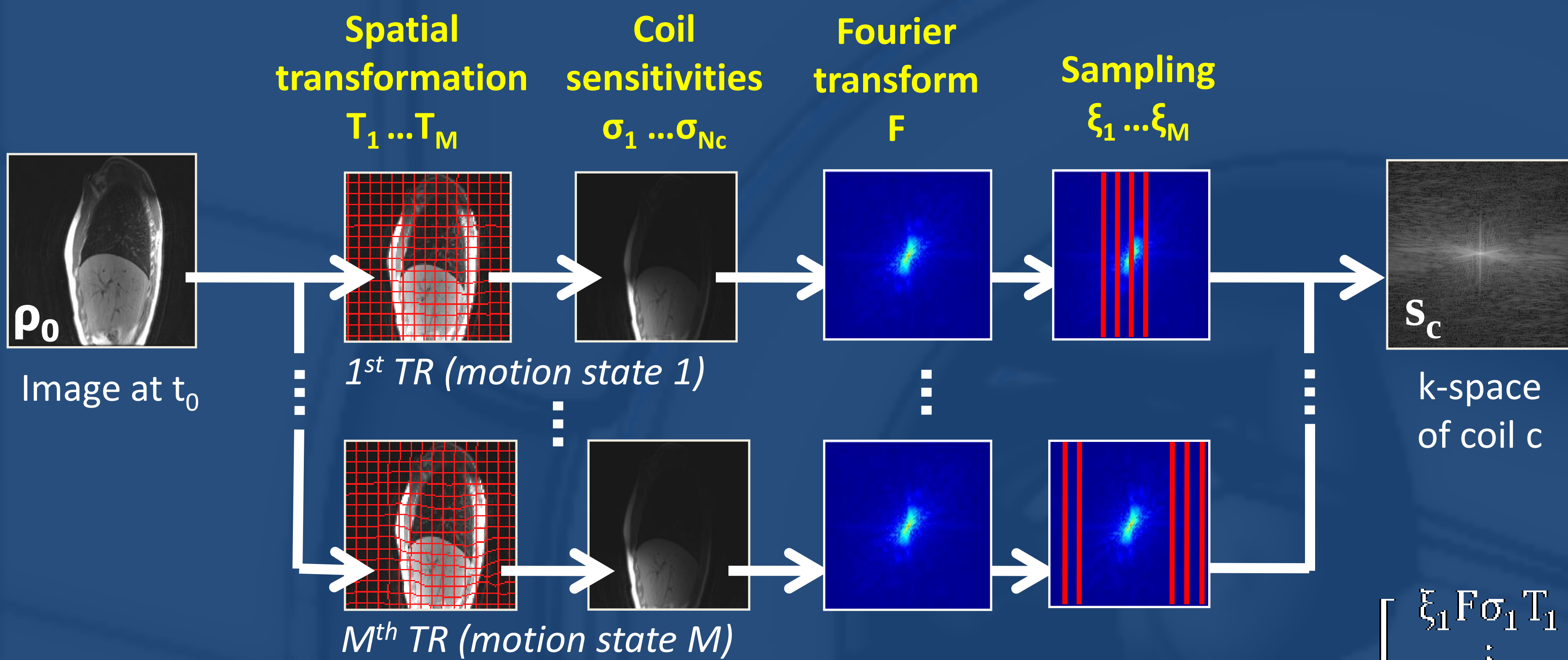
P. G. Batchelor,[1*] D. Atkinson,[1] P. Irarrazaval,[2] D. L. G. Hill,[1] J. Hajnal,[3] and D. Larkman[3]

Motion of an object degrades MR images, as the acquisition is time-dependent, and thus *k*-space is inconsistently sampled. This causes ghosts. Current motion correction methods make restrictive assumptions on the type of motions, for example, that it is a translation or rotation, and use special properties of *k*-space for these transformations. Such methods, however, cannot be generalized easily to nonrigid types of motions, and

rection method could be used to spatially transform the ghosted image by the transformation corresponding to a shot, pick the *k*-space lines corresponding to that shot, and repeat this operation for all shots (this is a version of the method used in (1)). We could then rebuild an image by inverse Fourier transform. This method is in

Forward acquisition model in presence of motion

Odille et al., MRM 2008, 59:1401-1411



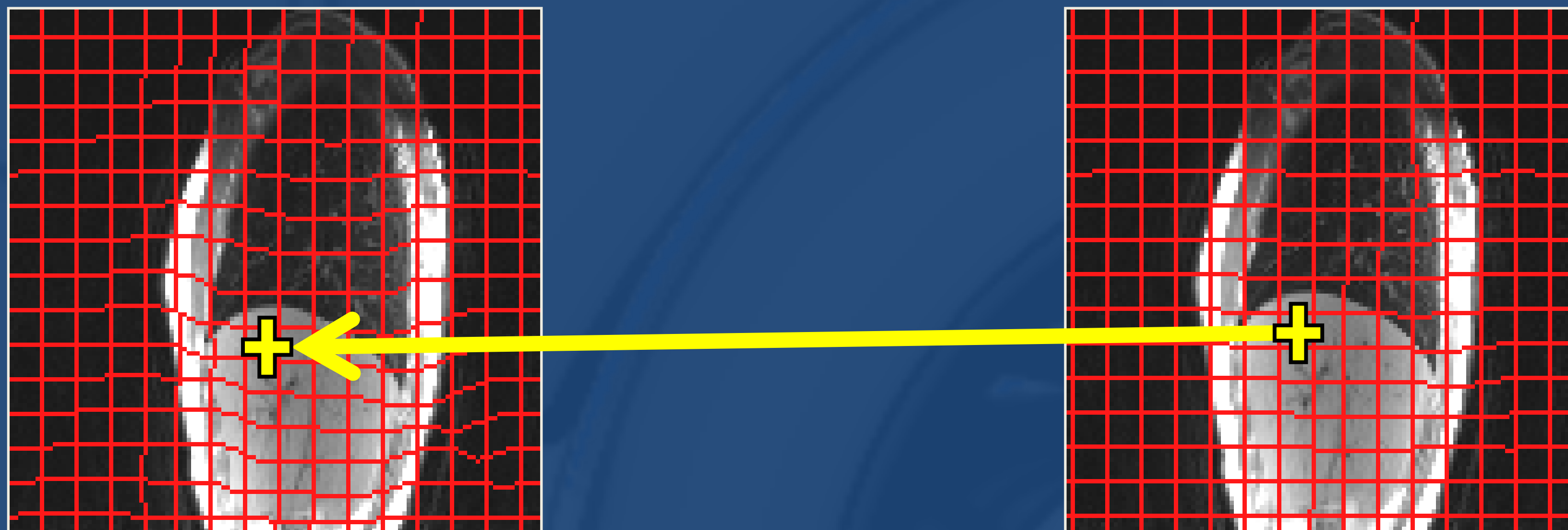
$$s = E\,\rho_0$$ with $$E = \begin{bmatrix} \xi_1 F \sigma_1 T_1 \\ \vdots \\ \xi_M F \sigma_1 T_M \\ \hline \vdots \\ \hline \xi_1 F \sigma_{N_c} T_1 \\ \vdots \\ \xi_M F \sigma_{N_c} T_M \end{bmatrix}$$

k-space data

unknown image

The spatial transformation matrices T_m

Input image ρ_0 $\xrightarrow{T_m}$ Output image ρ_m



$$\begin{pmatrix} x_i \\ y_i \end{pmatrix} = \begin{pmatrix} x + u_x(x,y) \\ y + u_y(x,y) \end{pmatrix}$$

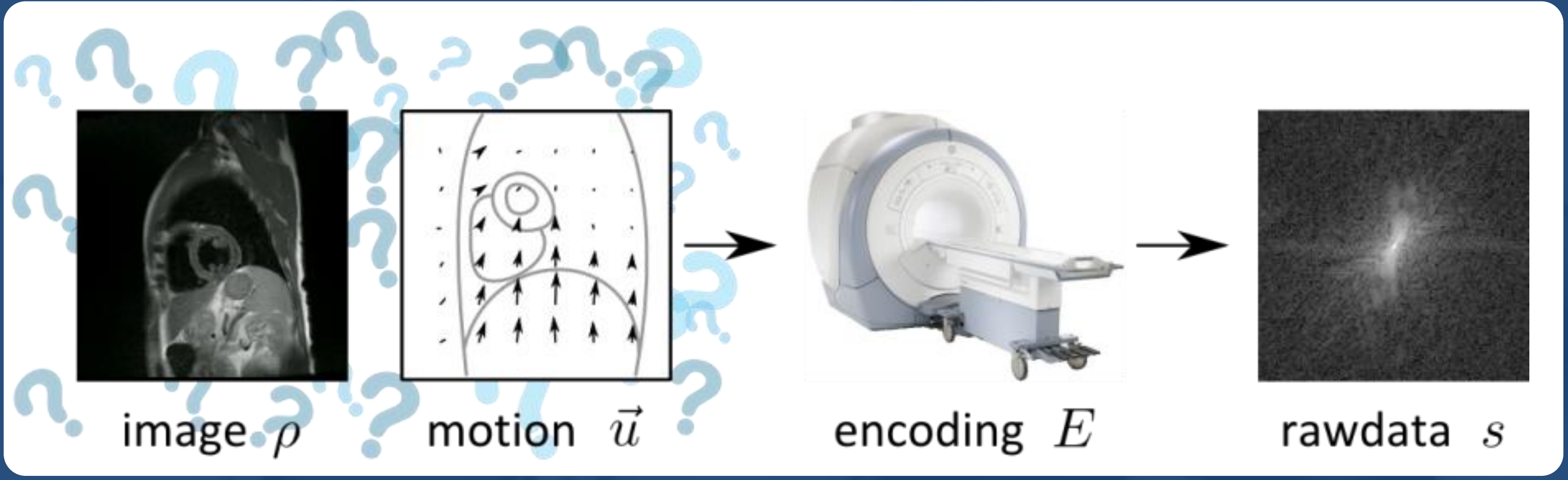
$$\begin{pmatrix} x \\ y \end{pmatrix}$$

- Use the displacement field of the inverse transformation to form T_m:

  For each pixel in the output image, find the corresponding coordinate in the input image and interpolate the intensity value from the surrounding pixels (using an interpolation kernel)

- T_m = sparse matrix (e.g. for a bi-linear interpolation : 4 nonzero elements per row)

Joint optimization of image and motion

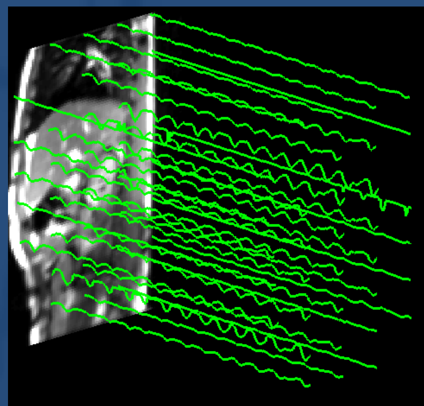


- General formulation: $$\min_{(\rho_0,u)} \|E(u)\rho_0 - s\|^2 + \mu R(u)$$

Joint optimization of image and motion

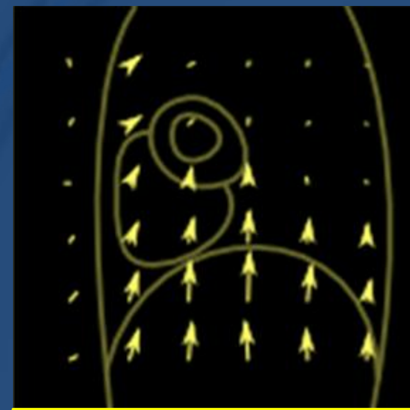
- Parametrizing motion

$$u(x,y,z,t) = \sum_{k=1}^{K} \underline{\alpha_k(x,y,z)}\,\underline{S_k(t)}$$



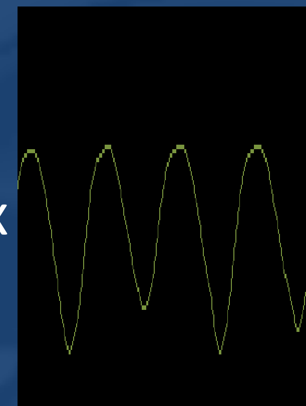
Displacement fields for each motion state

=



Motion model parameters α

x



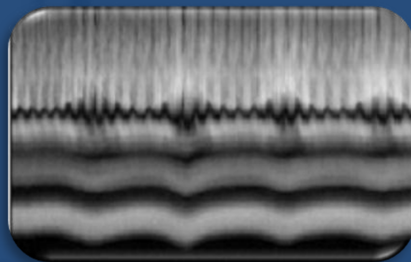
Motion sensor signals *S(t)*

- Reformulation as: $$\min_{(\rho_0,\alpha)} \|E(\alpha)\rho_0 - s\|^2 + \mu R(\alpha)$$

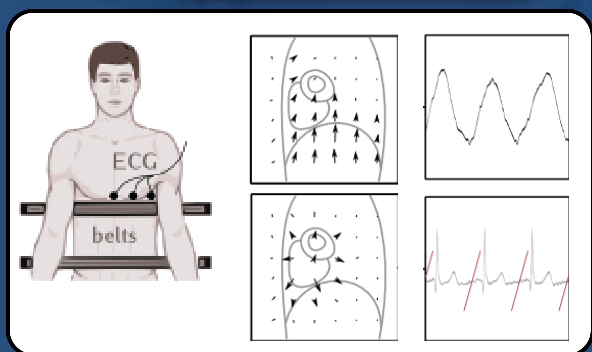
Separable motion model

Physiological signals

Partial MR data (navigators)

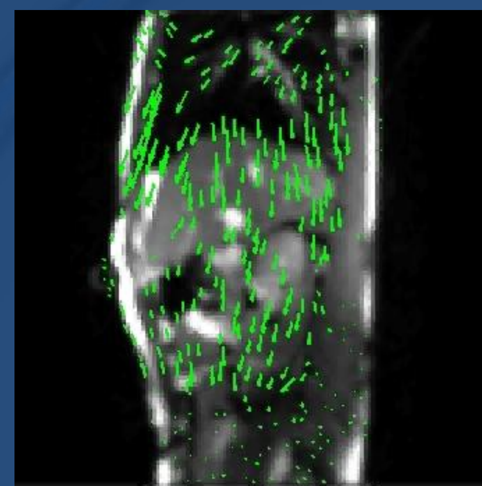


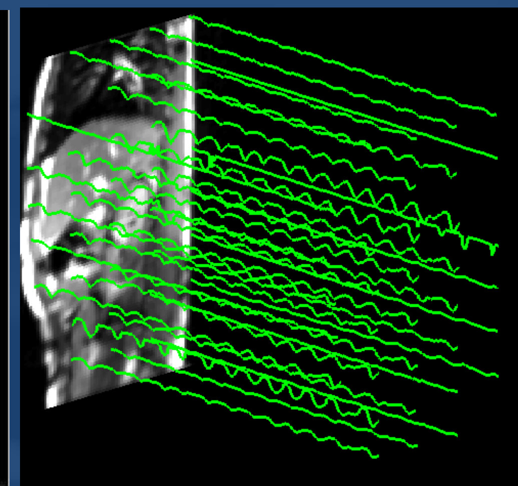
External sensors



Tissue/organs' motion

Displacement fields





$S_k(t)$

Linear model

$$u(r,t) = \sum_{k=1}^{K} \alpha_k(r) S_k(t)$$

Inputs

Outputs

- Respiratory motion models: a review

McClelland *et al.*, Med Image Anal, 2013, 17:19–42

$$\min_{(\rho_0,\alpha)} \|E(\alpha)\rho_0 - s\|^2 + \mu R(\alpha)$$

- Multi-resolution, alternating least-squares optimization

Initialize motion model: $\alpha = 0$

For resolution=low to high (e.g. 32x32, 64x64, …, 256x256)

For iter=1:maxit (e.g. maxit=4)

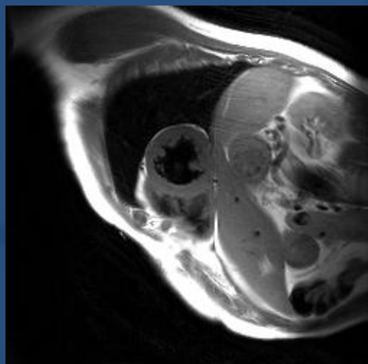
- *Reconstruct motion-corrected image:* *minimize w.r.t. ρ_0*
- *Calculate residual reconstruction error:* $\varepsilon = E\,\rho_0 - s$
- *Optimize motion model:* *minimize w.r.t. α ($\delta\alpha$)*
- *Update motion model:* $\alpha = \alpha + \delta\alpha$

end

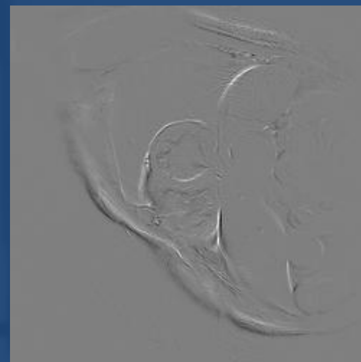
end

The optic flow equation

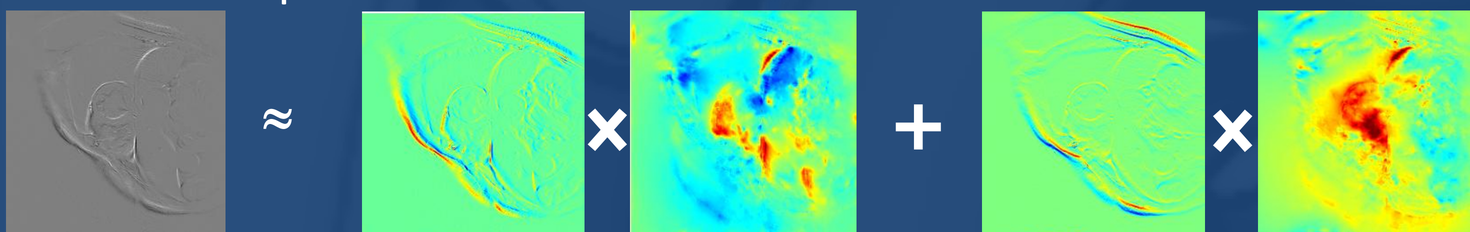
ρ



$\delta\rho$

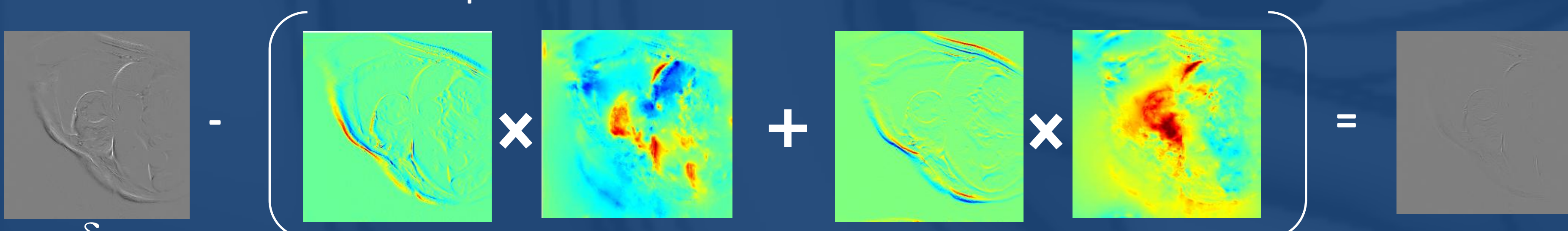


For small displacements



$\delta\rho \quad \partial\rho/\partial x \quad \delta u_x \quad \partial\rho/\partial y \quad \delta u_y$

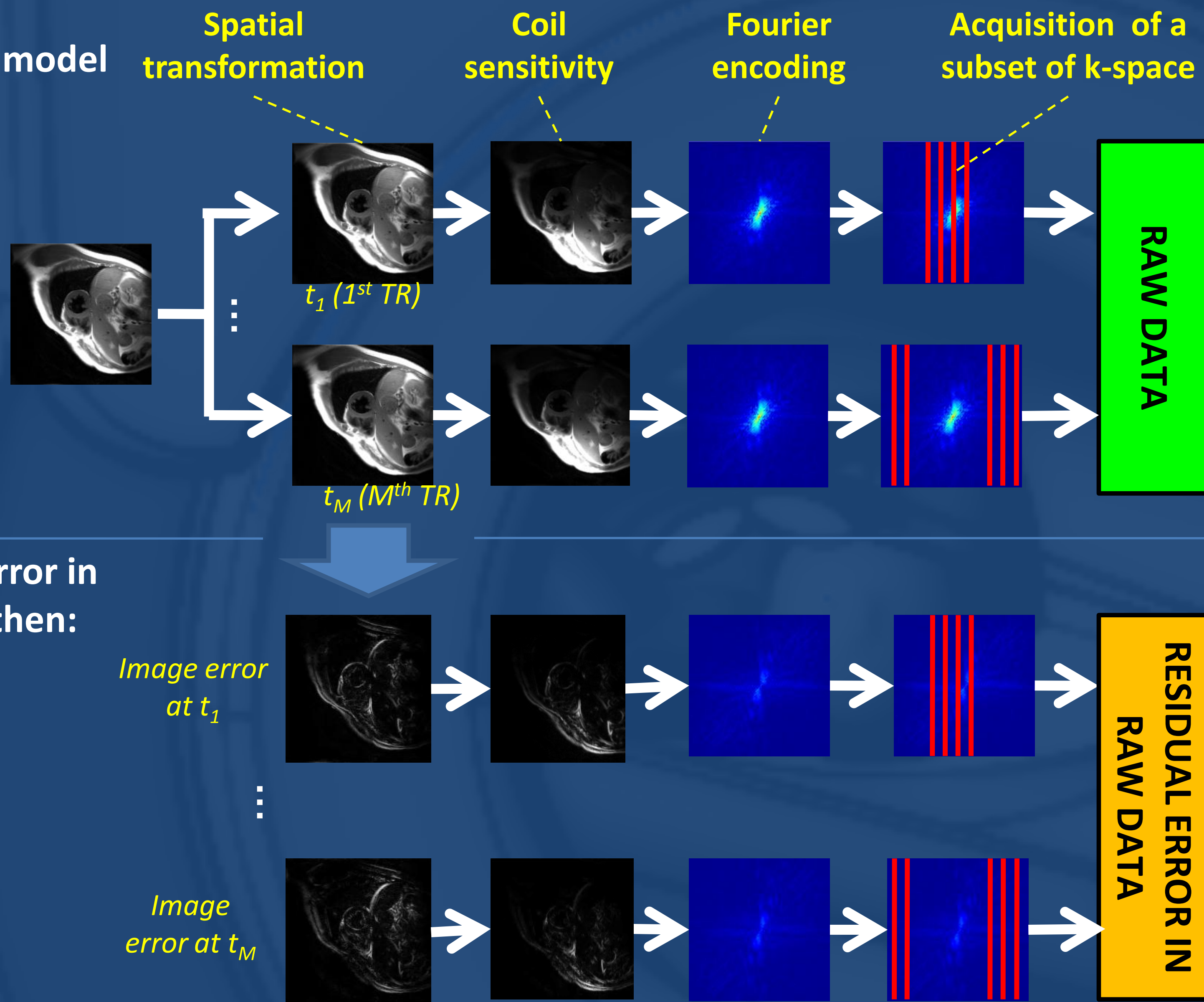
Verification on this example



$\delta\rho \quad \partial\rho/\partial x \quad \delta u_x \quad \partial\rho/\partial y \quad \delta u_y$

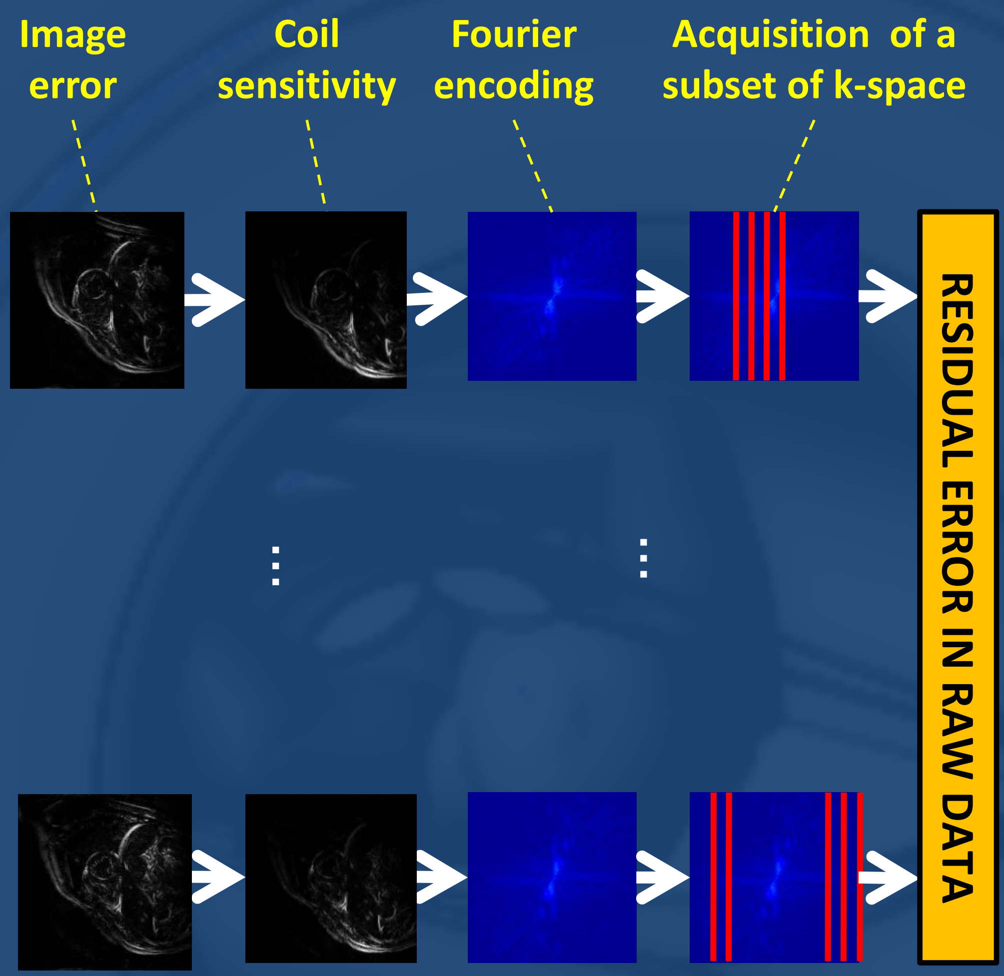
Propagation of a small error on motion

Forward acquisition model

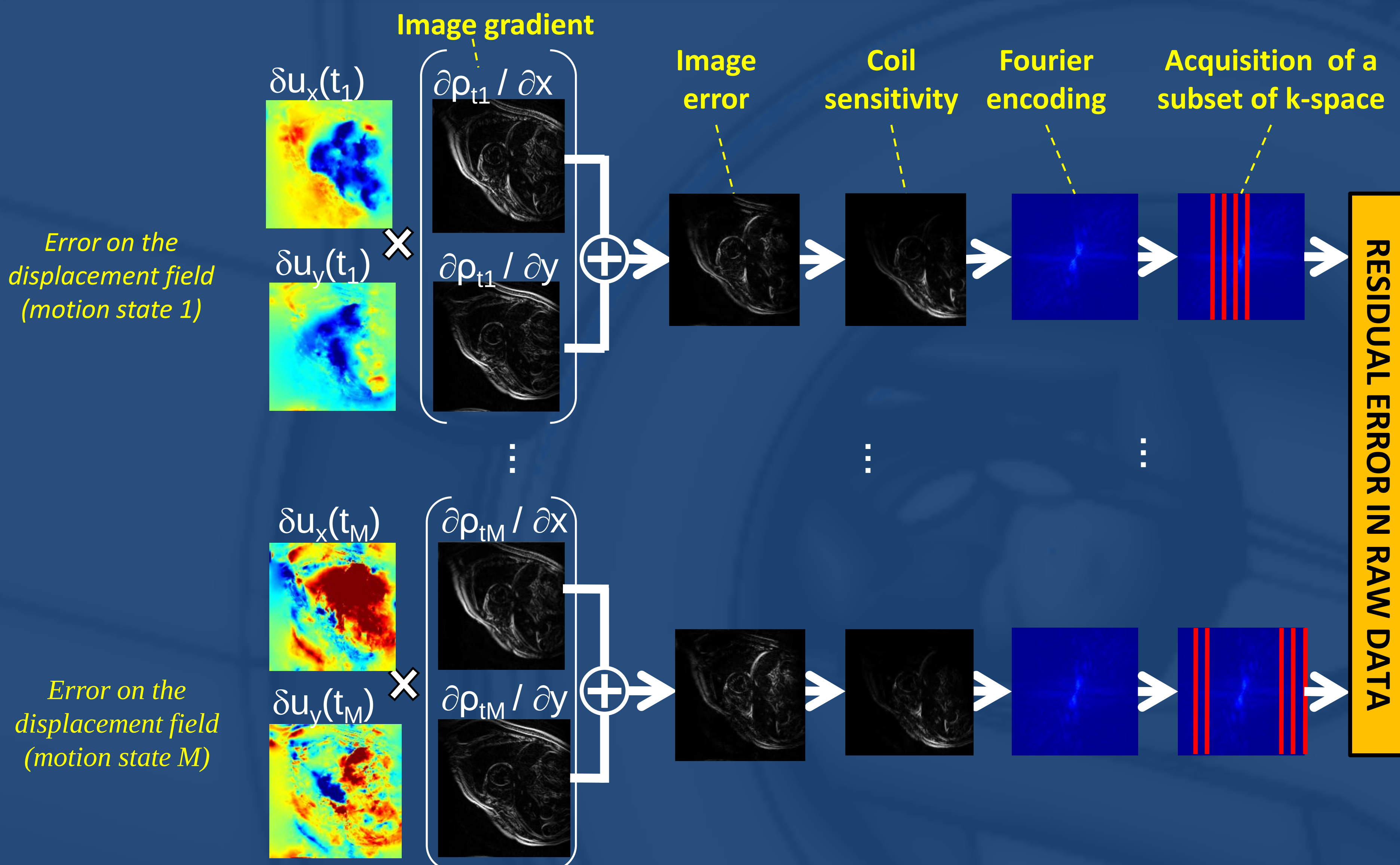


If we have a small error in motion estimates then:

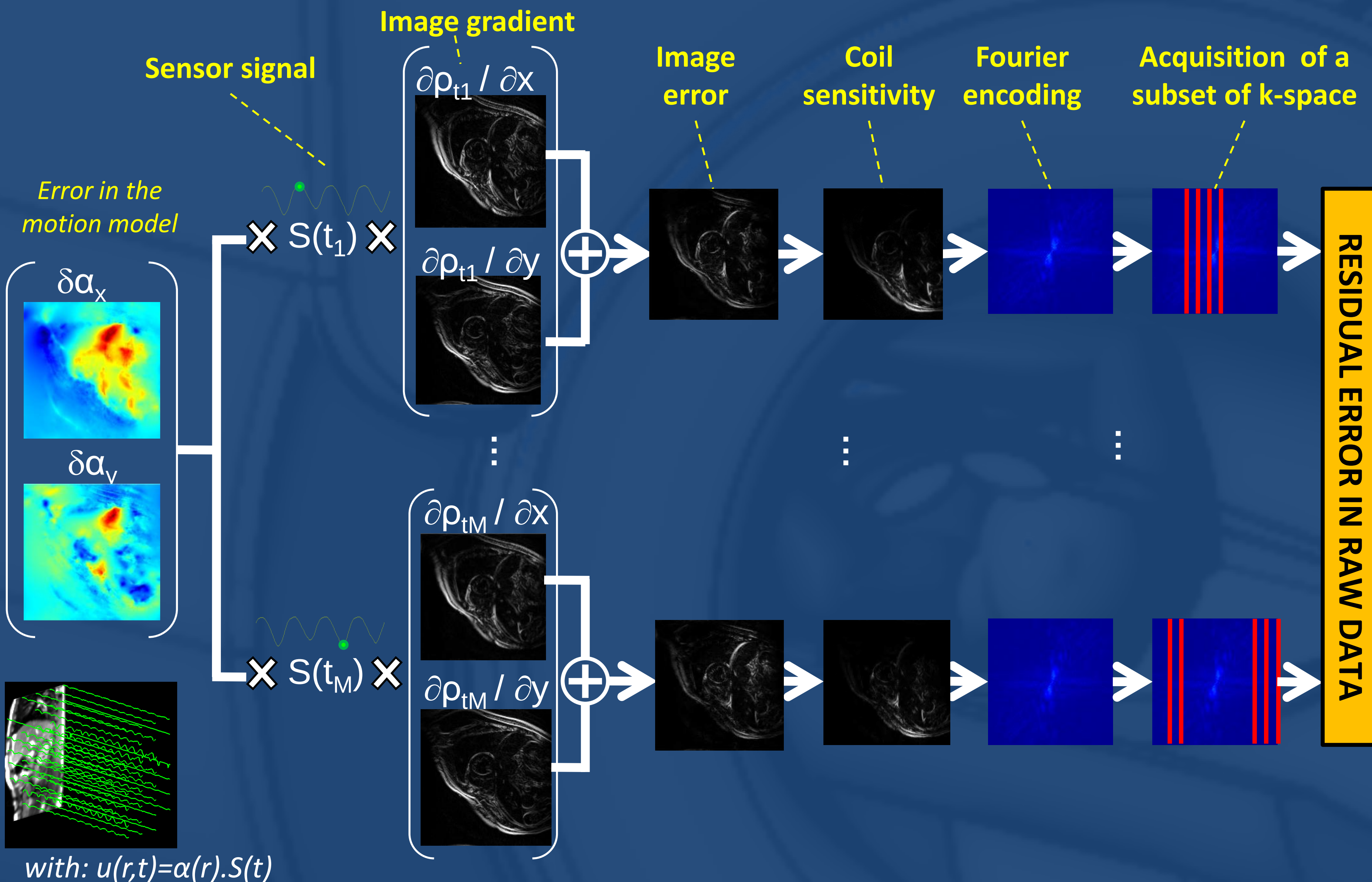
Propagation of a small error on motion



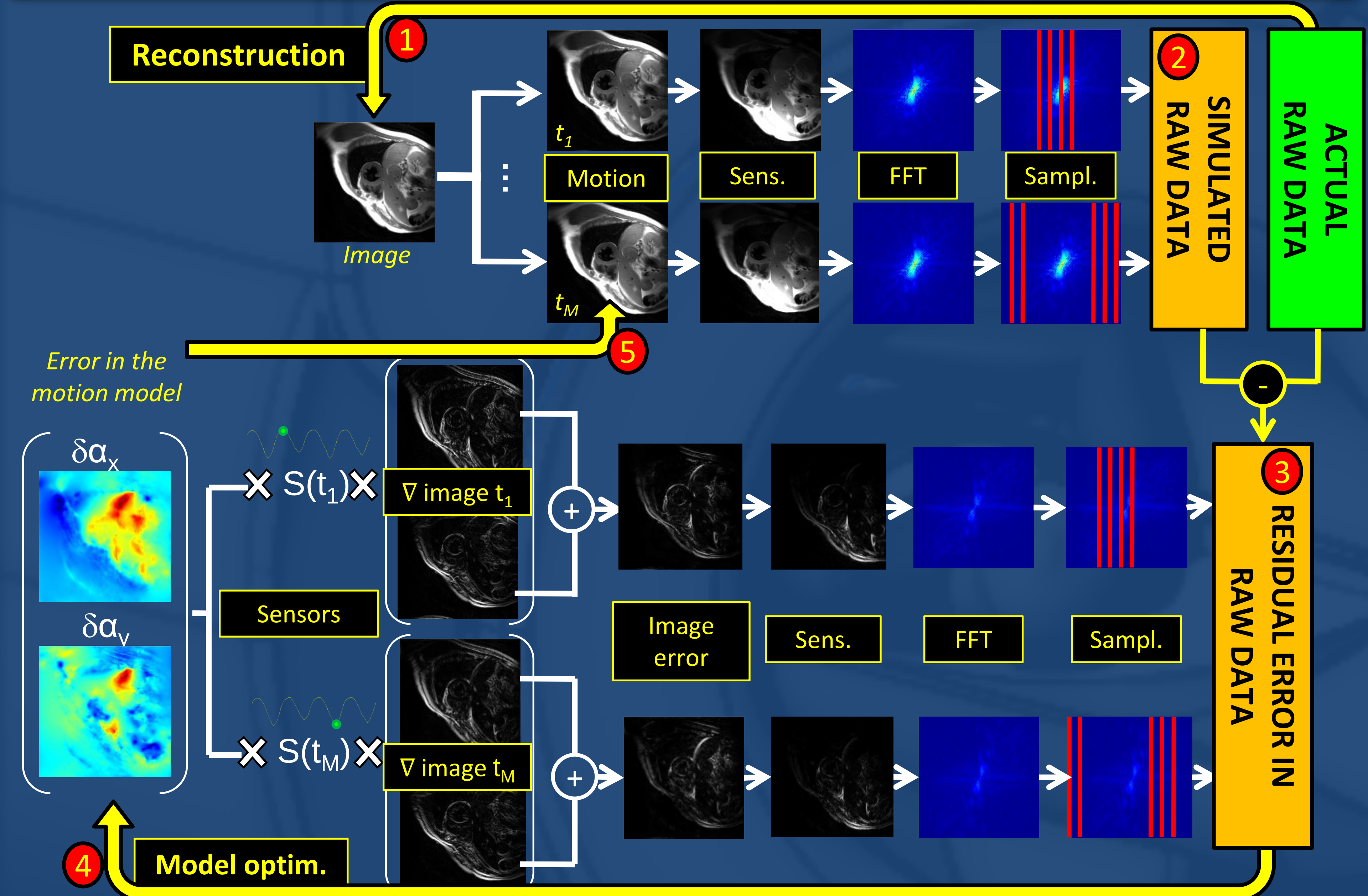
Propagation of a small error on motion



Propagation of a small error on motion



GRICS (generalized reconstruction by inversion of coupled systems)



GRICS (generalized reconstruction by inversion of coupled systems)

$$\min_{(\rho_0,\alpha)} \|E(\alpha)\rho_0 - s\|^2 + \mu R(\alpha)$$

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end

end

- Similarities with Gauss-Newton and augmented Lagrangian schemes

Numerical implementation

- **Reconstruction step**
  - Solve the Hermitian symmetric system $E^H E \rho_0 = E^H s$
    (use the actual transpose of the sparse matrices T_m)
  - Matrix-free solver (conjugate gradient…)

- **Motion model optimization step**
  - Regularization
    (smooth motion fields)

Spatial gradient
(finite differences)

$$\min_{\delta\alpha} \|R\delta\alpha - \varepsilon\|^2 + \mu \|G(\alpha + \delta\alpha)\|^2$$

Reconstruction
residue

  - Solve: $$(R^H R + \mu G^H G)\delta\alpha = R^H \varepsilon - \mu G^H G \alpha$$

Reconstruction step
Sources of ill-conditionning

- **Errors in the motion transformations**

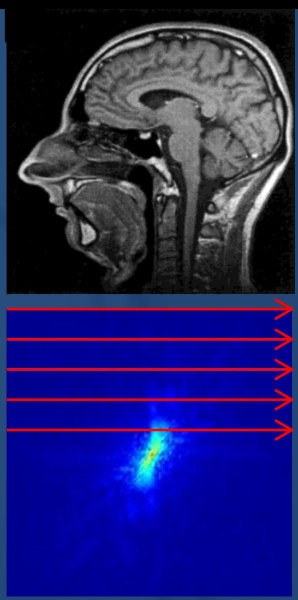
  (motion estimation + interpolation kernel)

- **(Errors in the sensitivity maps)**

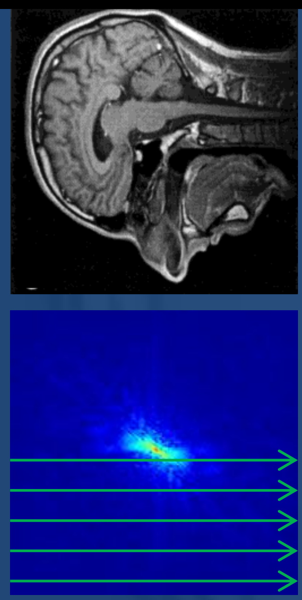
- **Loss of information due to motion effects on sampling**

Atkinson *et al.*, MRM 2003, 49:183-187

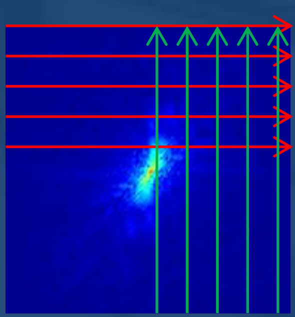
Motion state 1



Motion state 2



Resulting k-space coverage



Reconstruction step

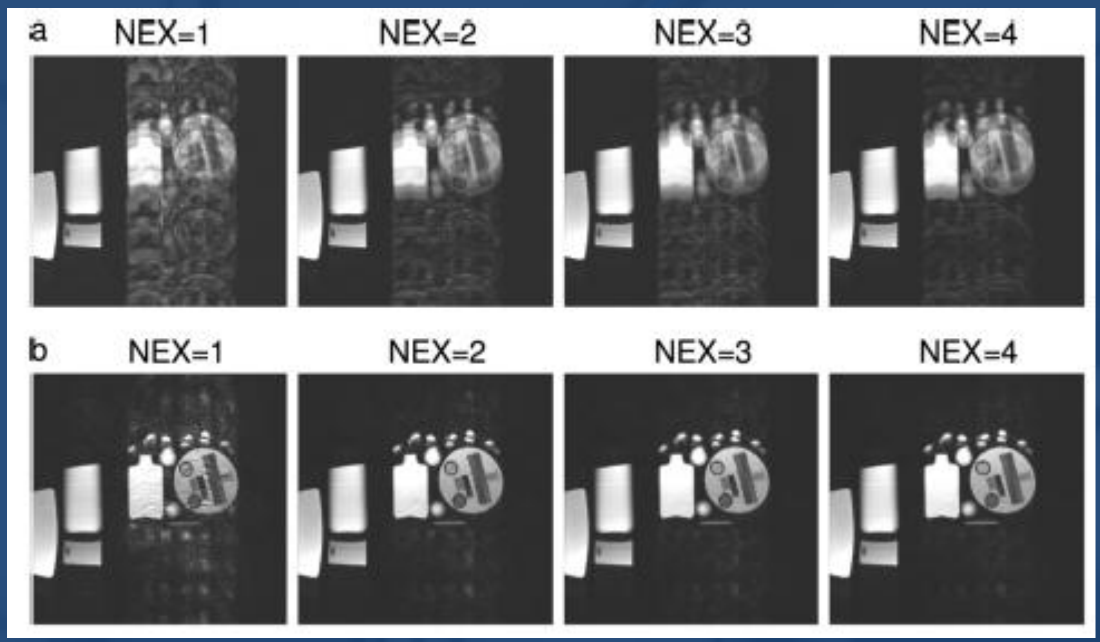
How to improve the condition number ?

Odille *et al., MRM 2008*, 59:1401-1411

- **Use Nex>1**, i.e. sample k-space several times in different motion states
  => adds new linearly independent data to the system

Uncorrected

Corrected



Static phantom

- **Regularization** (e.g. Tikhonov)

$$\min \|E\rho - s\|^2 + \lambda \|R\rho\|^2$$

The solution becomes:

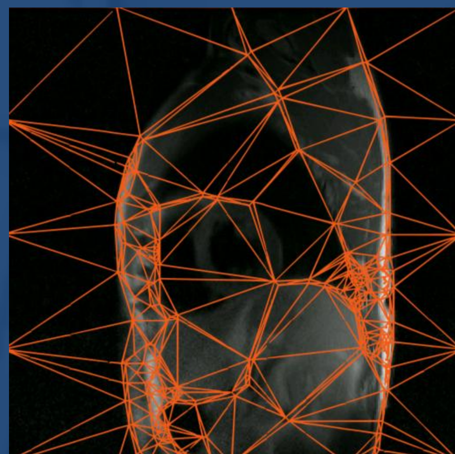
$$\rho = \left(E^H E + \underline{\lambda R^H R}\right)^{-1} E^H s$$

Motion model optimization step

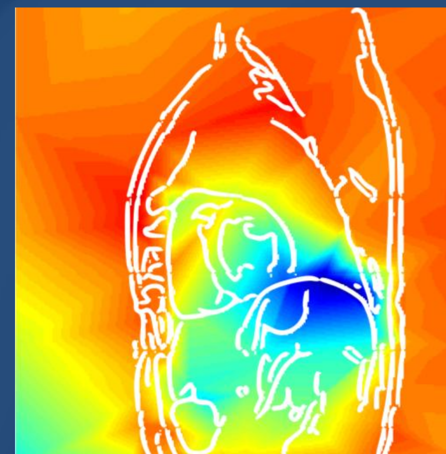
Implicit regularization of motion using an adaptive mesh

Menini et al, MICCAI 2012, 15(Pt 1):264-71

$$\min_{(\rho_0,\alpha)} \|E(\alpha)\rho_0 - s\|^2 + \cancel{\mu R(\alpha)}$$



Adaptive mesh
(node density depending on
image and motion gradients)



α map

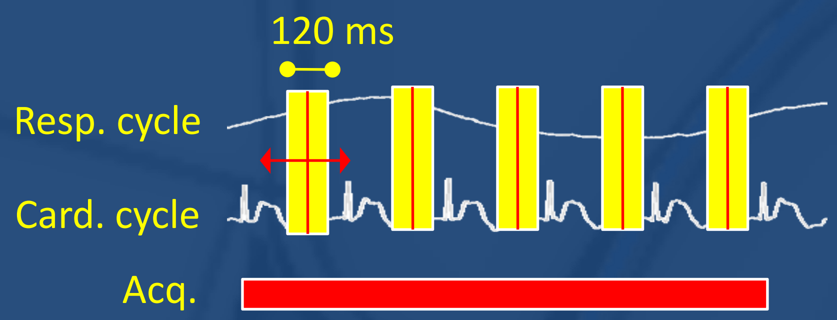
- Reduces number of unknows
- Improves convergence speed
- Minimal loss of precision in image and motion

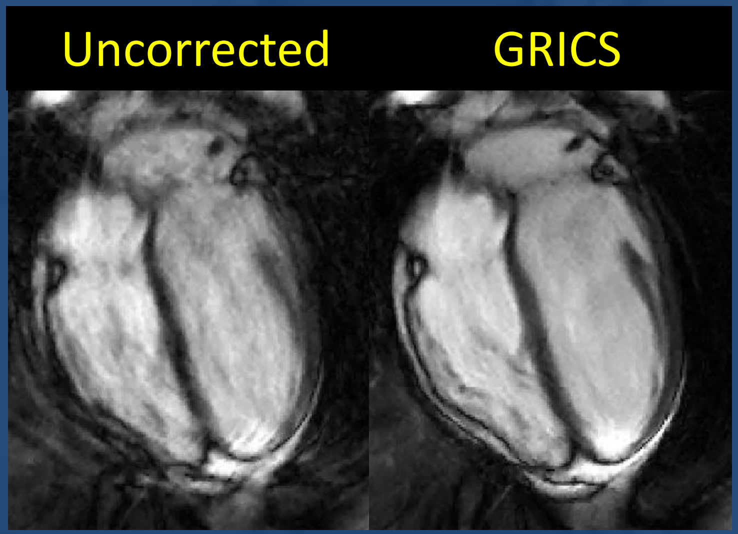
Example reconstructions in cardiac MRI

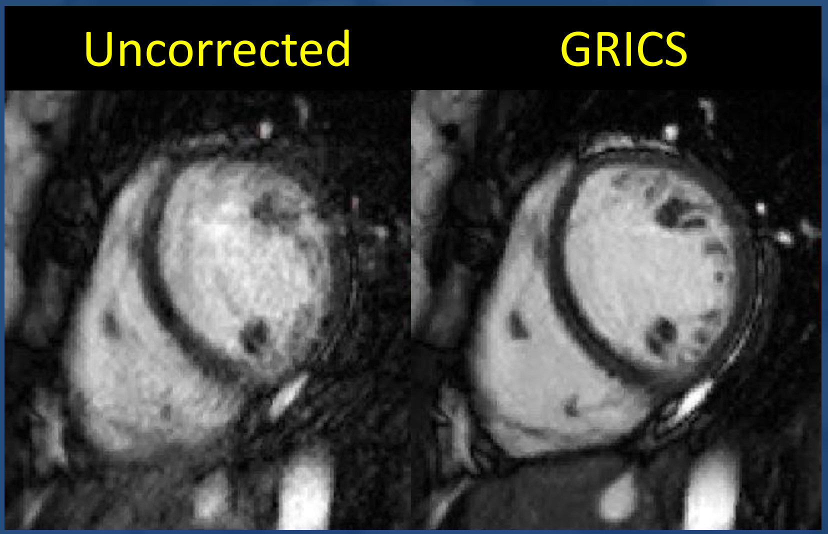
- Cine-GRICS = motion-compensated sliding window

Odille *et al.*, MRM 2010, 63:1247–1257

Vuissoz *et al.*, JMRI 2012, 35:340–351







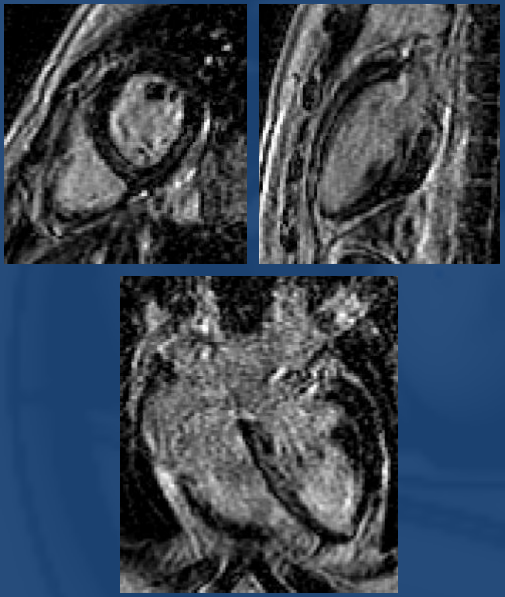
Example reconstructions in cardiac MRI

- Entire cardiac examination during free-breathing
  (Duchenne muscular dystrophy patients)

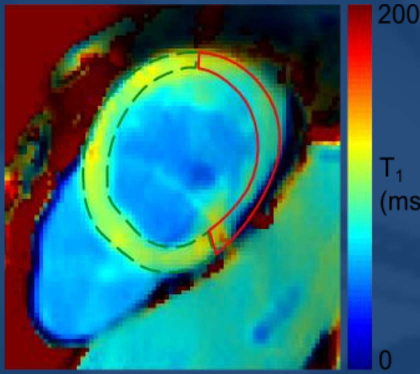
2D multi-slice cine
(fast LV coverage)

Post-injection
2D cine

3D MDE



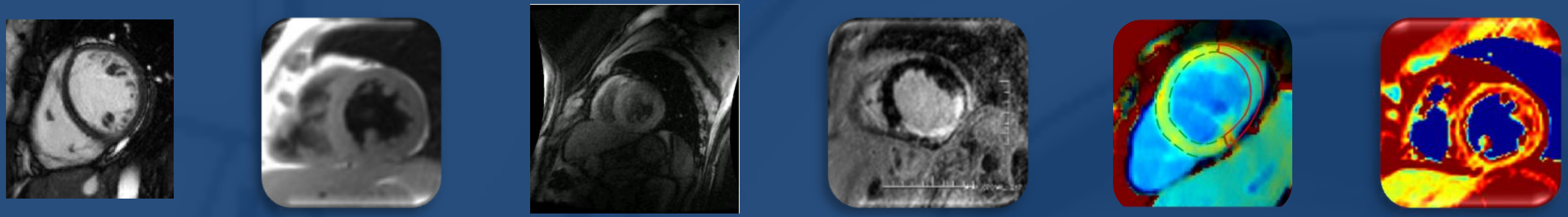
T1 quantification
(Smart$_1$map)



Joint reconstruction of N images and motion (multi-contrast acquisition)

- An MRI examination consists of several acquisitions

  (N sequences with different contrast mechanisms)



- A lot of redundancies
  - Temporal redundancies (pseudo-periodic motion)
  - Spatial redundancies (preserved anatomy)

- Data analysis/interpretation is performed as a whole

- Can we also regard the data acquisition/reconstruction as a whole?

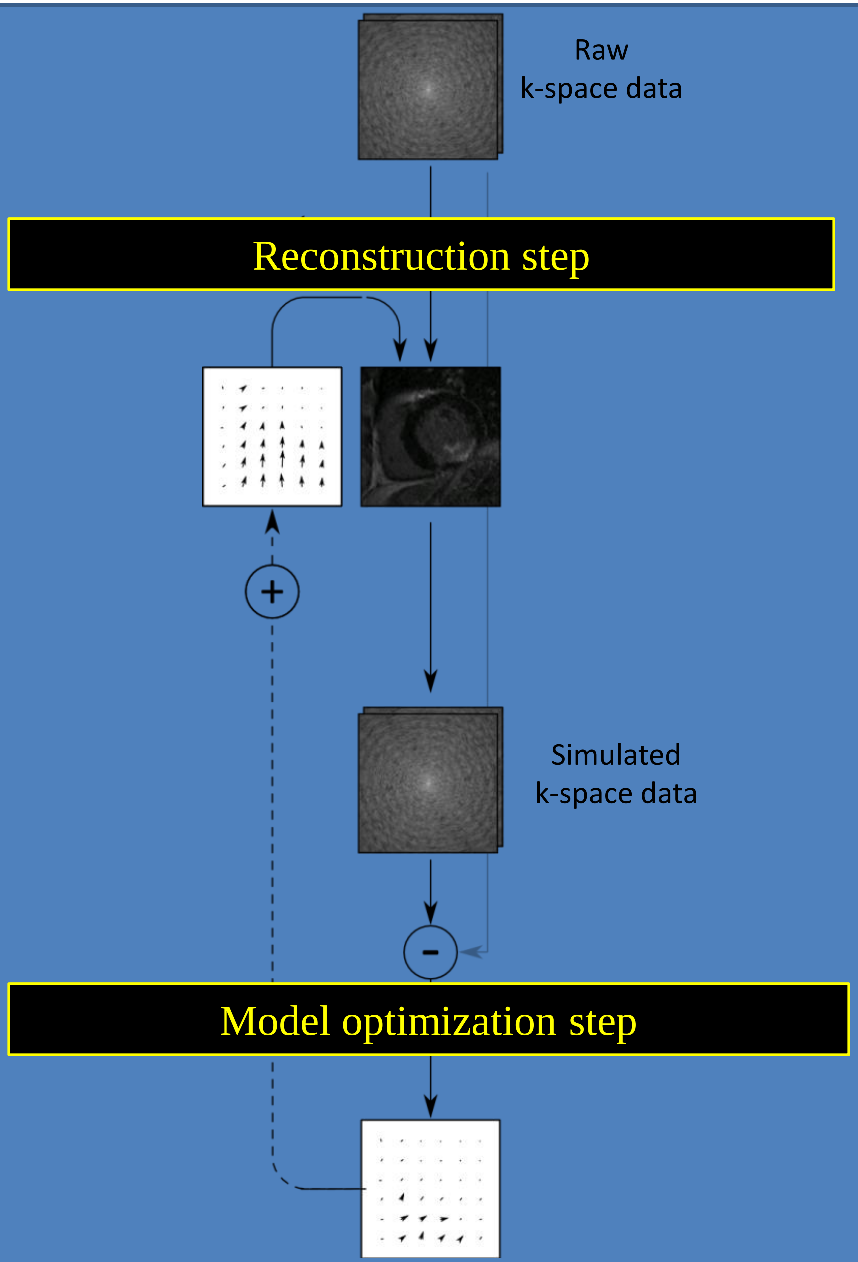
Multi-contrast GRICS

Menini et al, MAGMA 2014, in press

1 image ρ

1 motion model α

$$\min_{(\rho,\alpha)} \|E(\alpha)\rho - s\|^2$$



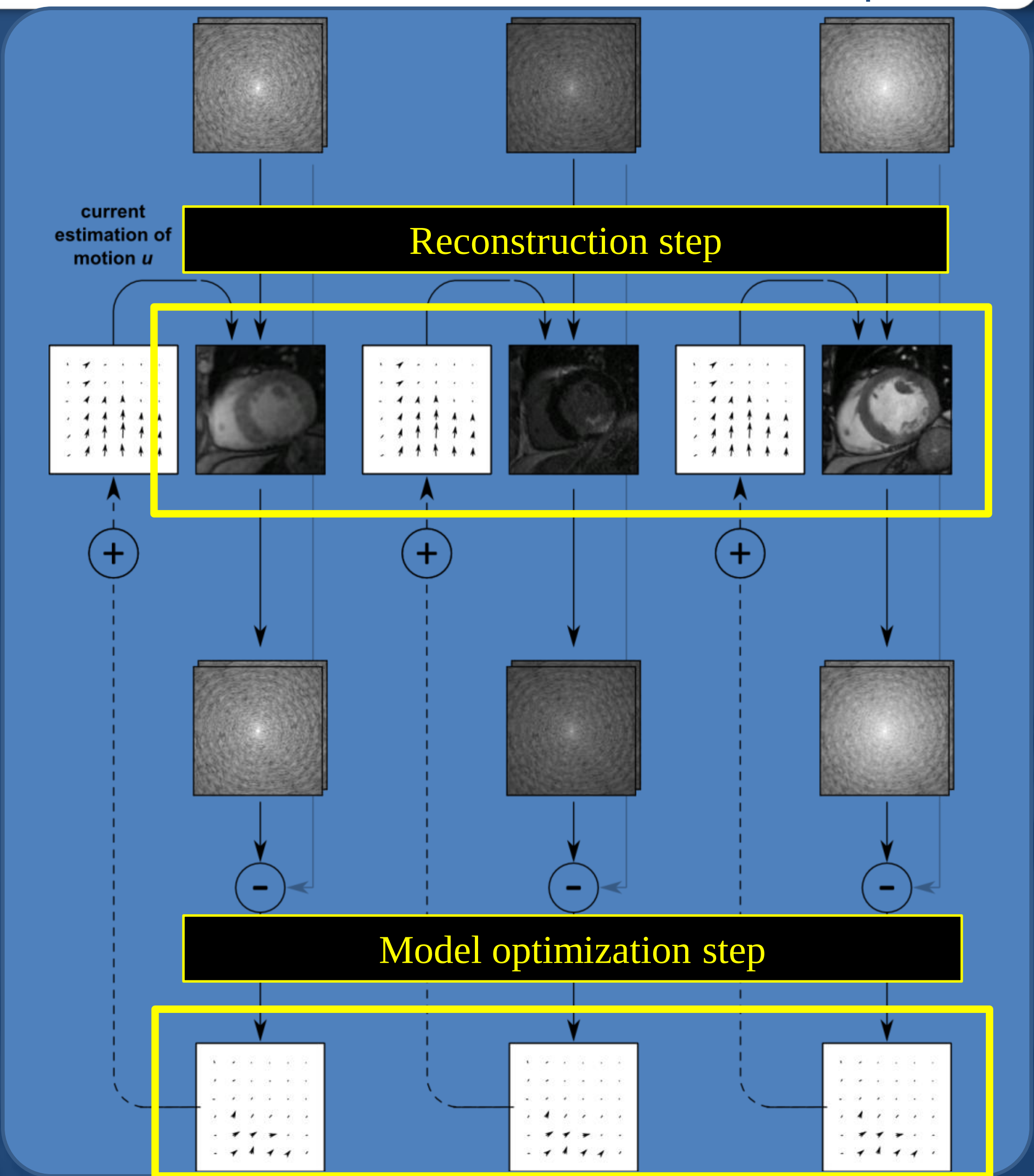
Multi-contrast GRICS

Menini et al, MAGMA 2014, in press

N images $\rho_1, \ldots, \rho_N$

N motion models $\alpha_1, \ldots, \alpha_N$

$$\min_{(\rho_1,\ldots,\rho_N,\alpha_1,\ldots,\alpha_N)} \sum_{i=1}^{N} \left\| E^{(i)}(\alpha_i)\rho_i - s \right\|^2$$



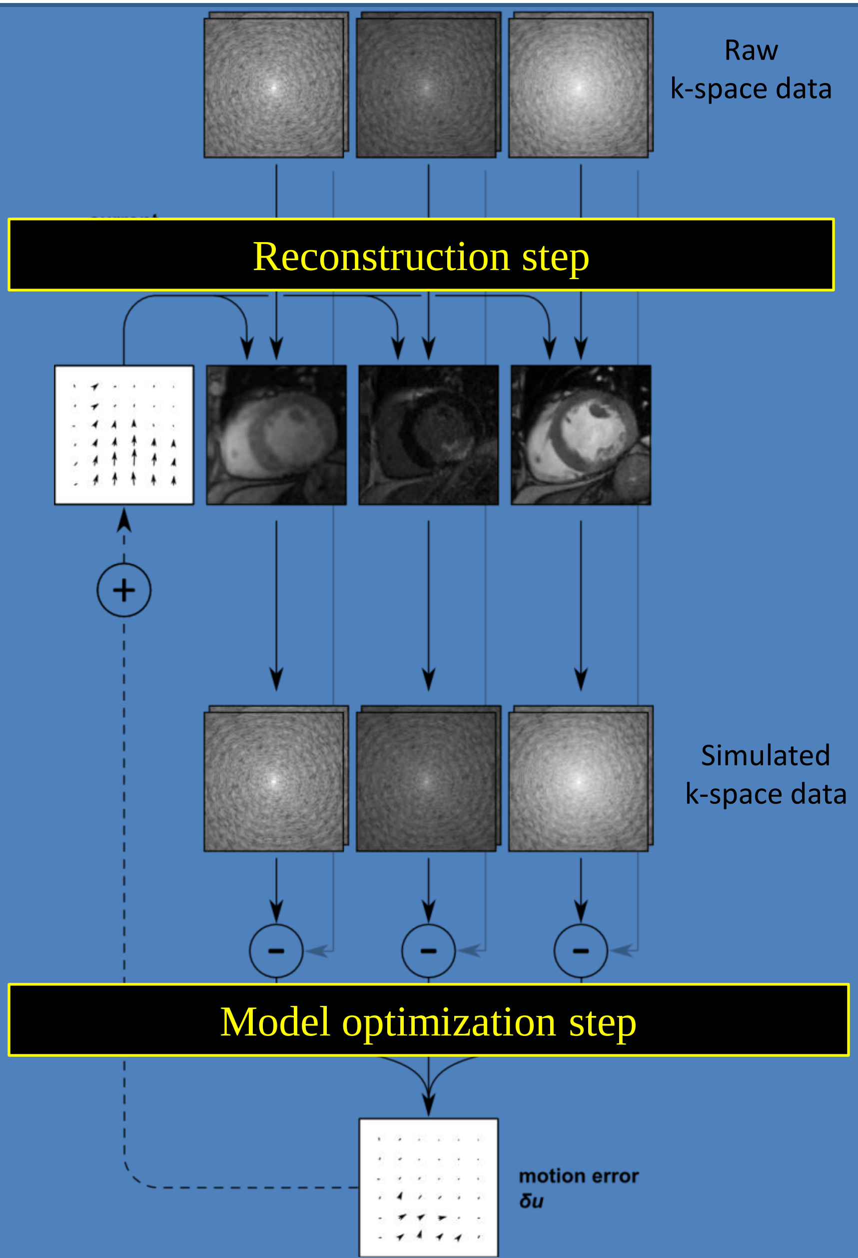
Multi-contrast GRICS

Menini et al, MAGMA 2014, in press

N images $\rho_1, \ldots, \rho_N$

1 motion model α

$$\min_{(\rho_1,\ldots,\rho_N,\alpha)} \sum_{i=1}^{N} \left\| E^{(i)}(\alpha)\rho_i - s \right\|^2$$



Multi-contrast GRICS

Menini et al, MAGMA 2014, in press

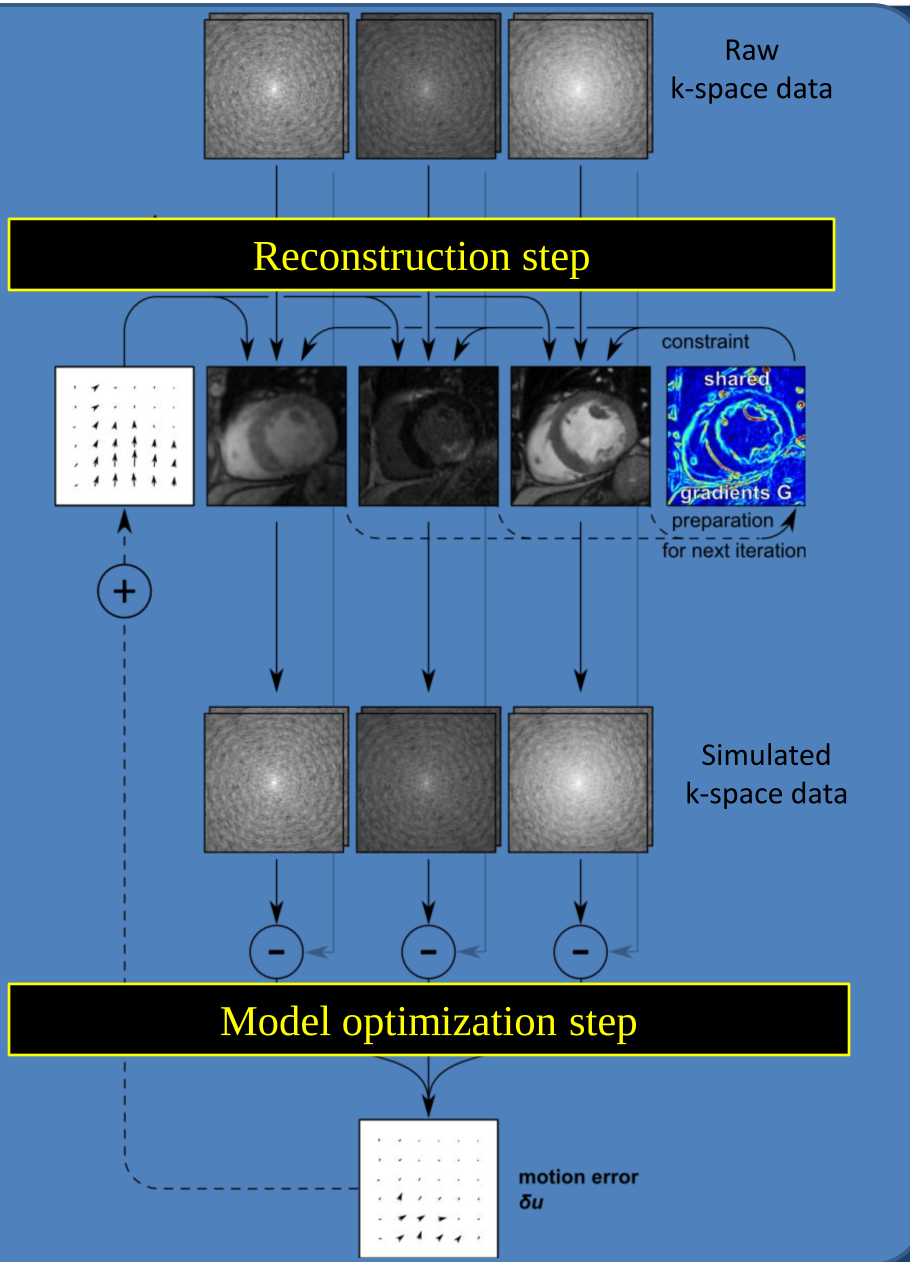
N images $\rho_1, \ldots, \rho_N$

1 motion model α

Multi-contrast constraint Q

(e.g. gradient cooccurrence)

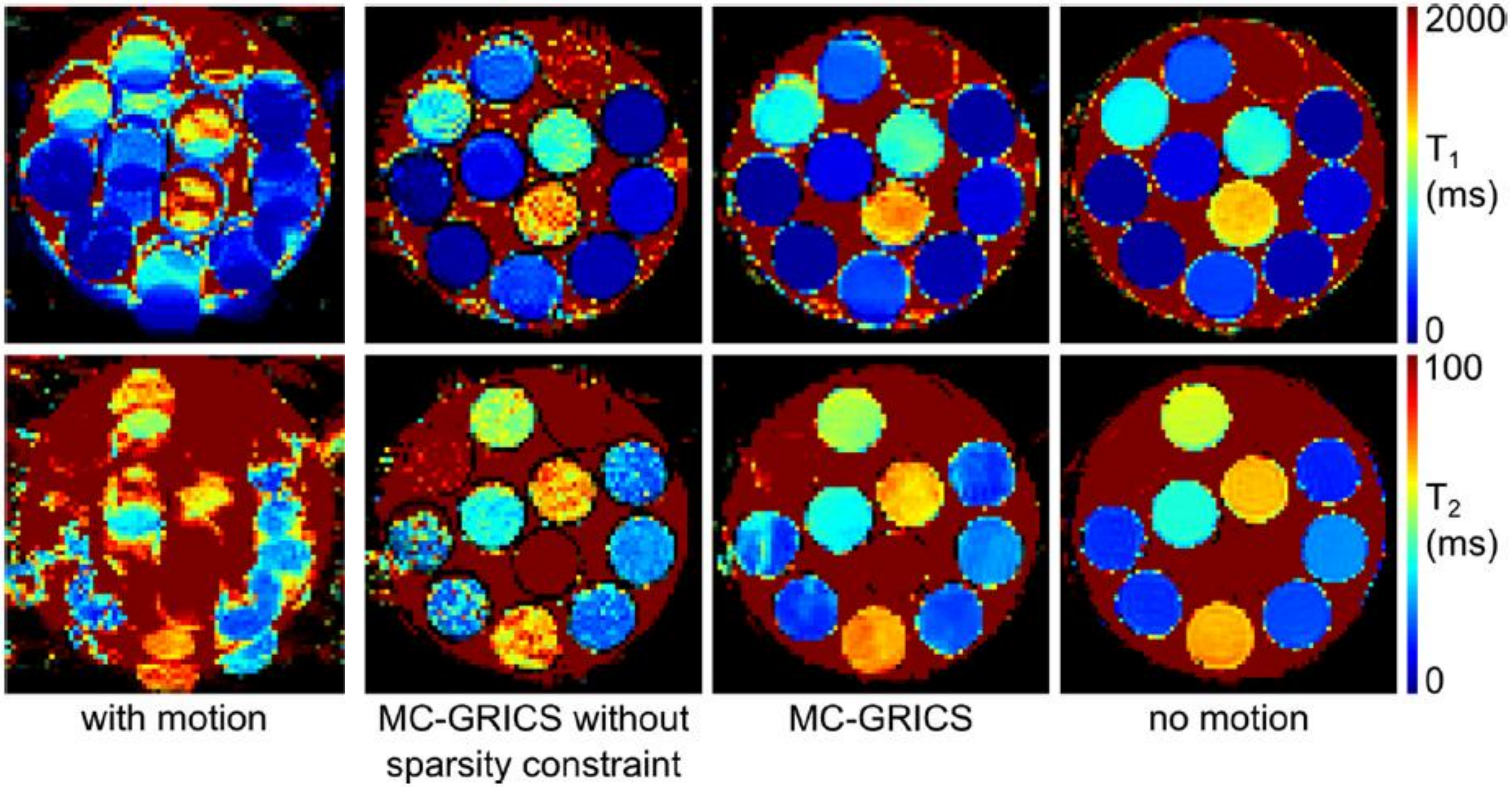
$$\min_{(\rho_1,\ldots,\rho_N,\alpha)} \sum_{i=1}^{N} \left\| E^{(i)}(\alpha)\rho_i - s \right\|^2 + \lambda\, Q(\rho_1,\ldots,\rho_N)$$



Example MC-GRICS reconstructions

Phantom results

- Joint reconstruction of T_1 and T_2 data
  - SmarT_1Map (saturation-recovery, 5 saturation times)
  - Multi-echo FSE (8 echo times)

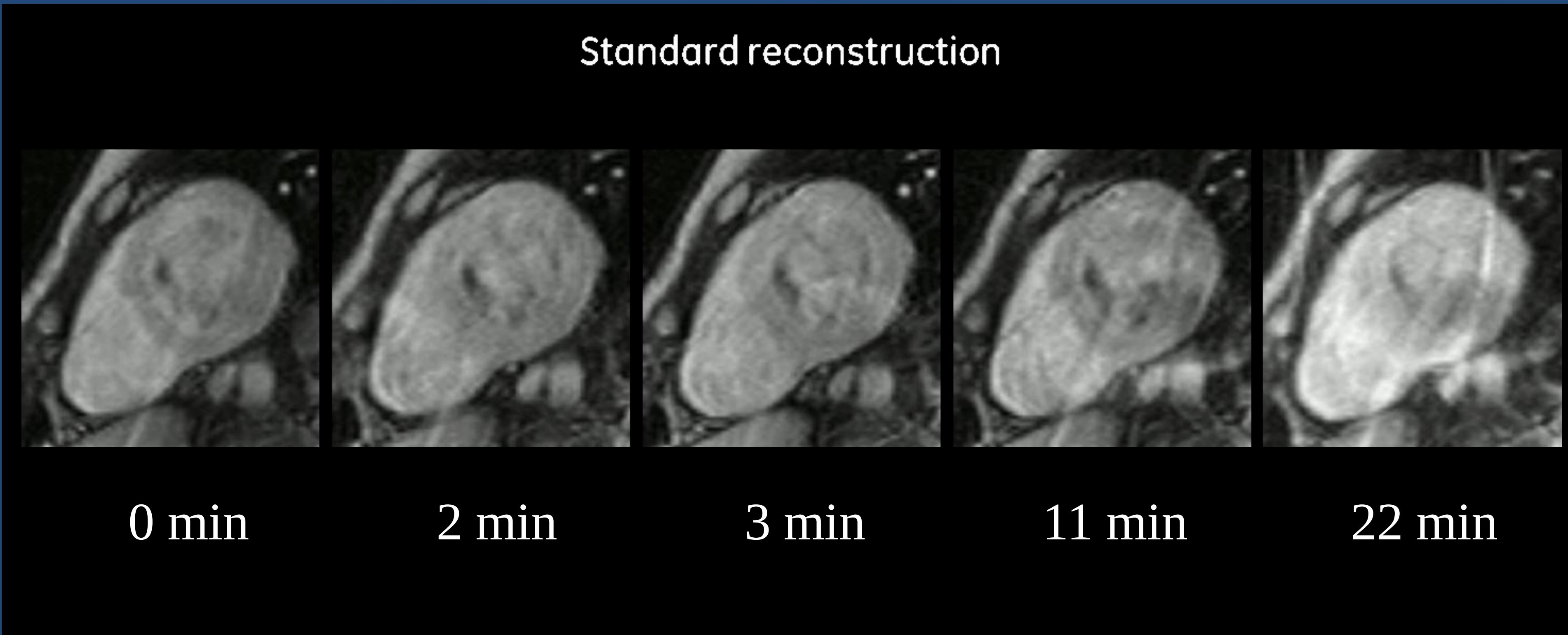


Example MC-GRICS reconstructions

Preliminary results in patients

Menini et al, ISMRM 2014

- Cardiac T_1 mapping at different time points after injection
- Desired for evaluating diffuse fibrosis



Conclusion

- **Joint reconstruction of image and motion** can be implemented
  - Motion models (prior knowledge from sensors or navigators)
  - Complex (nonrigid) motion to be corrected

- **Always need to be aware of the physics**

  (spin history, through-plane motion, B_0, B_1 fields…)

- **Main applications**
  - Lengthy acquisitions (breath-holding not possible): 3D, 4D, high resolution
  - Multi-parametric imaging

- **Open questions**
  - Faster implementation?
  - Optimal regularization parameters?

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