Imperial College London

Learning clinically useful information from medical images

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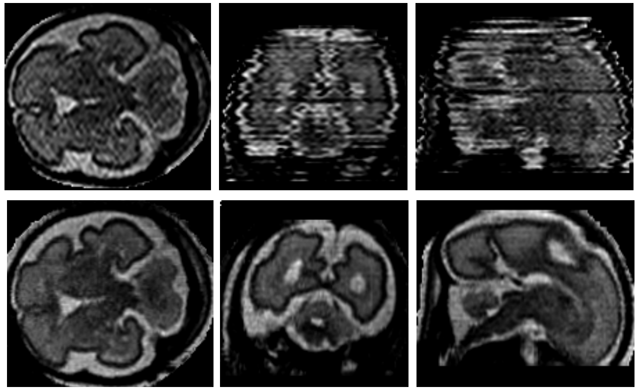
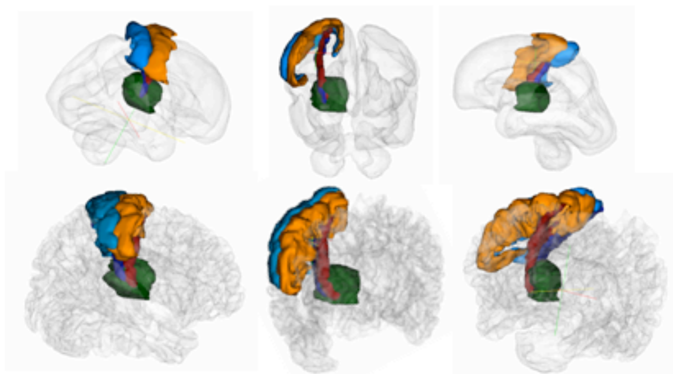
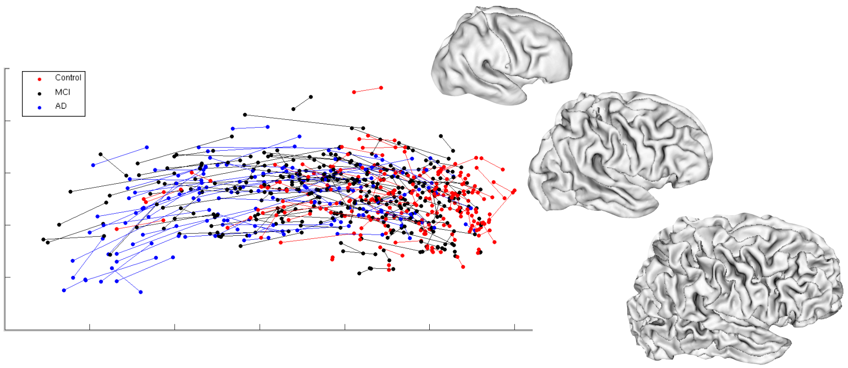
Overview



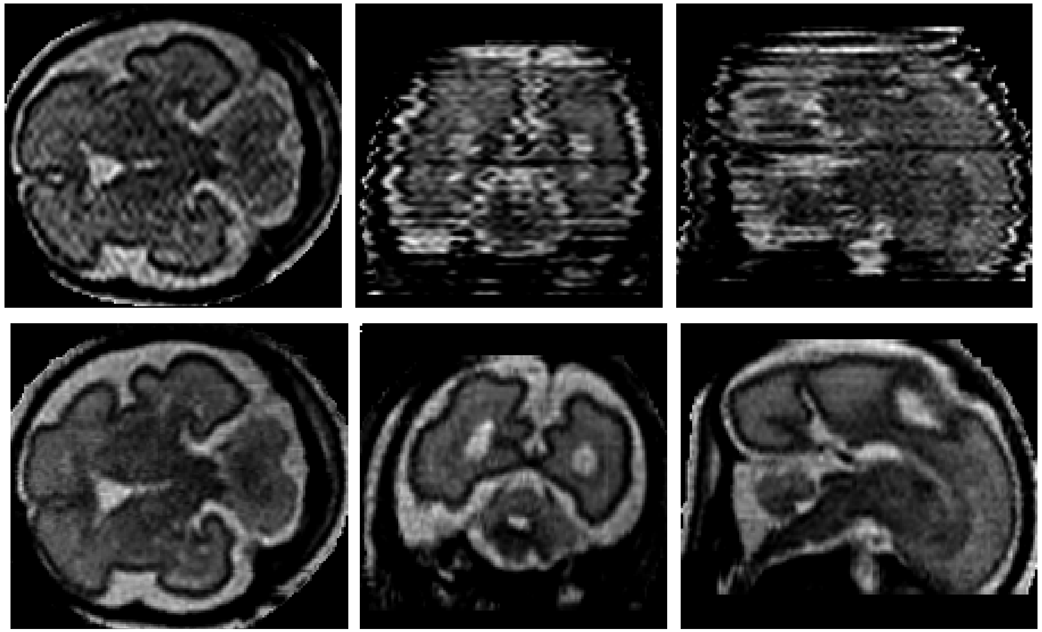
Intelligent imaging



Segmentation



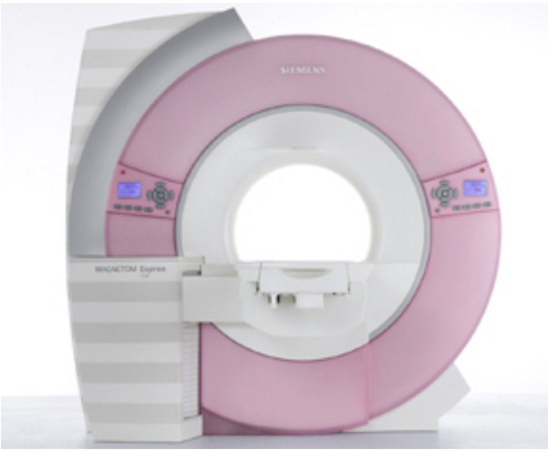
Biomarker discovery



Intelligent imaging

MR image acquisition

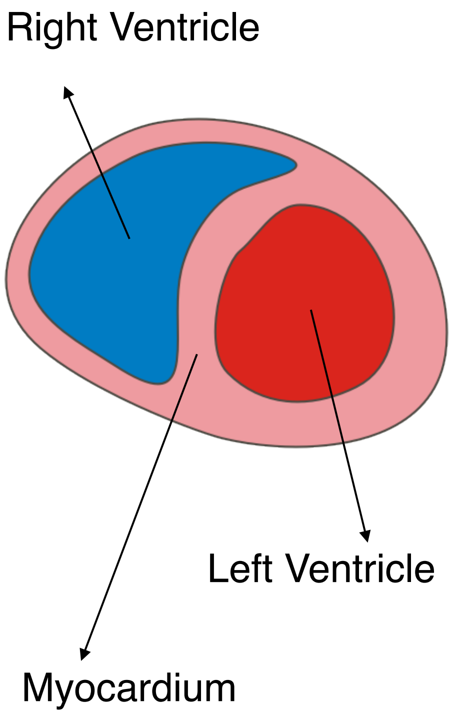


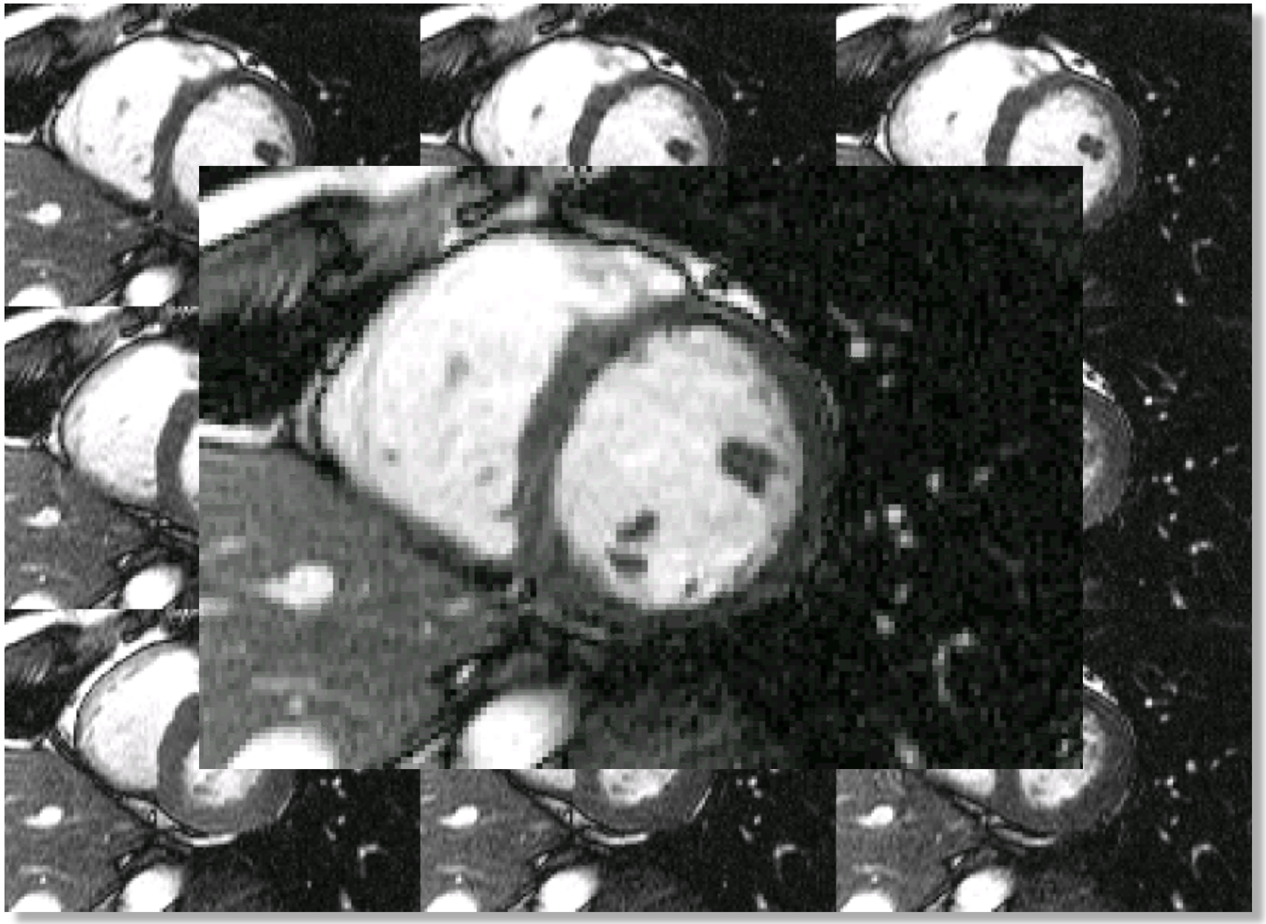



MR image acquisition: Challenges

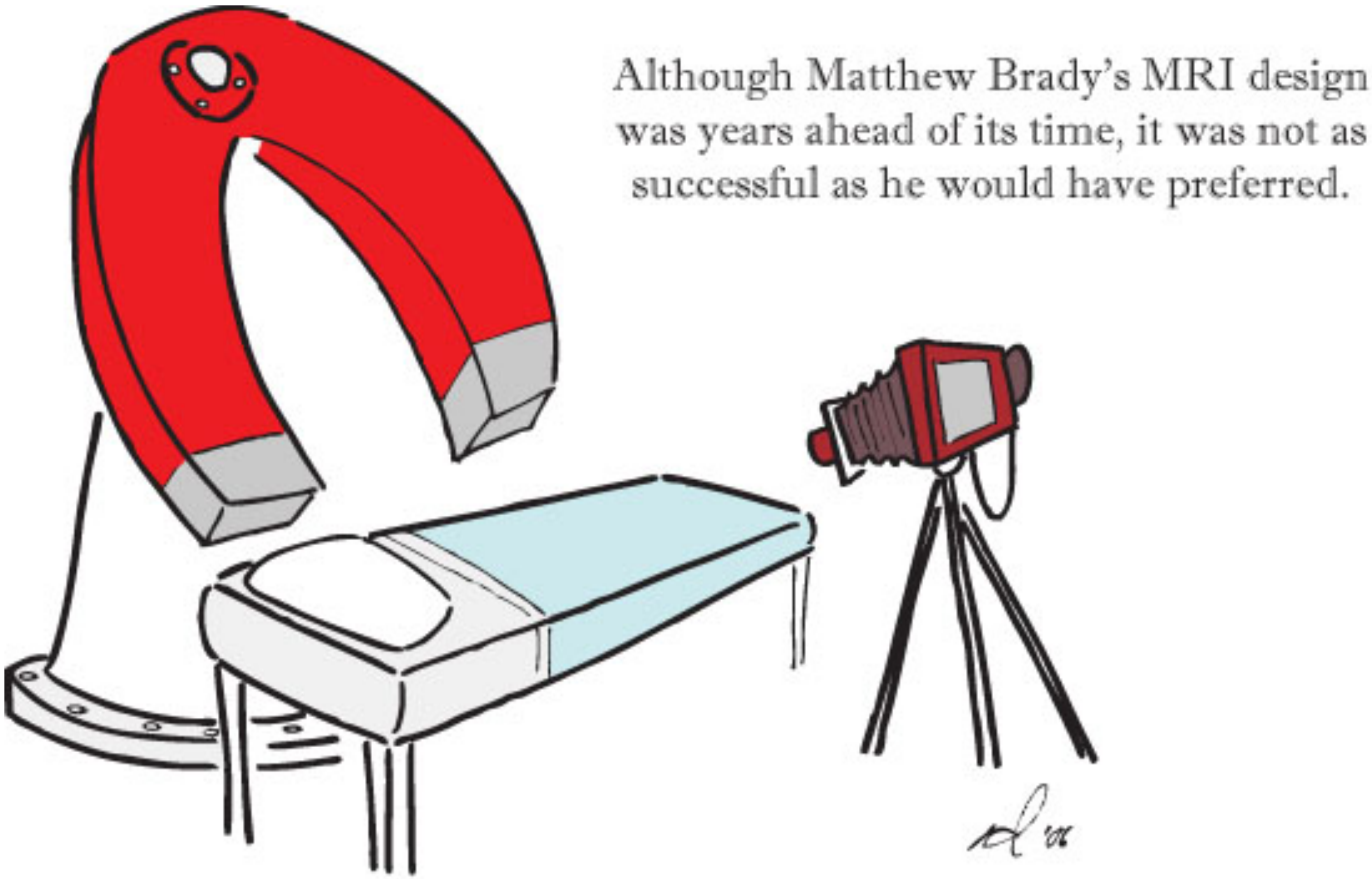
- Magnetic Resonance Imaging (MRI)
  – MRI acquisition is inherently a slow process
  – Slow acquisition is
    - ok for static objects (e.g. brain, bones, etc)
    - problematic for moving objects (e.g. heart, liver, fetus)
  – Options for MRI acquisition:
    - real-time MRI: fast, but 2D and relatively poor image quality
    - gated MRI: fine for period motion, e.g. respiration or cardiac motion but requires gating (ECG or navigators) leading to long acquisition times (30-90 min).

MR image acquisition: Cardiac MR





MR image acquisition

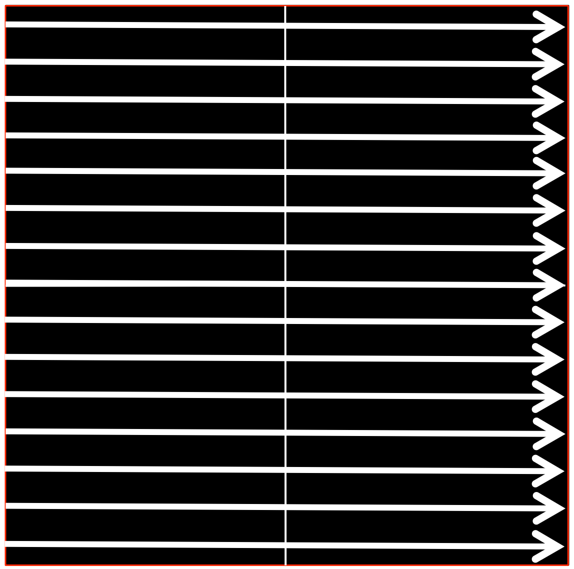


MR full acquisition

- MRI acquisition is performed in k-space by sequentially traversing sampling trajectories.

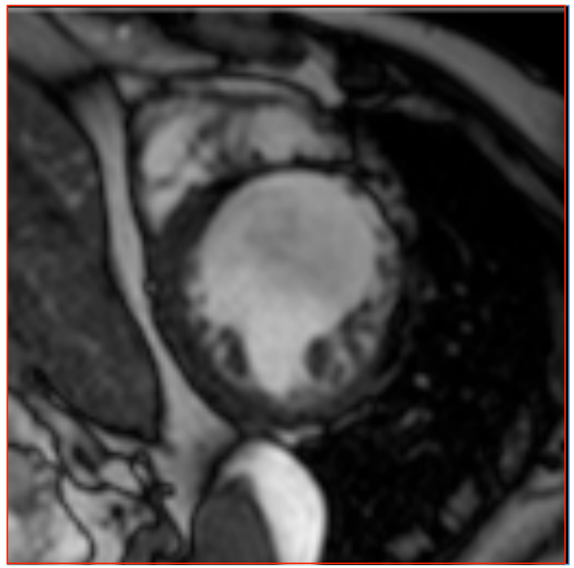
K-space

t = 0



$\mathcal{F}^{-1}\{.\}$

Signal space



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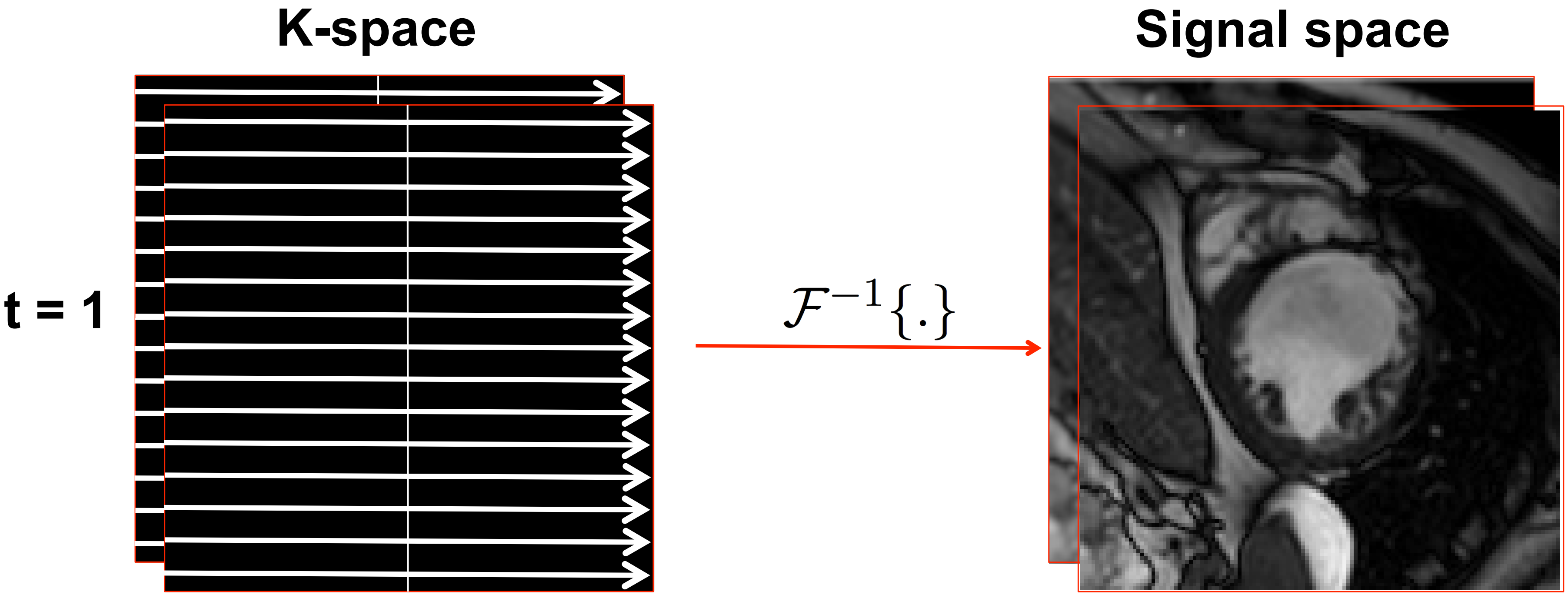

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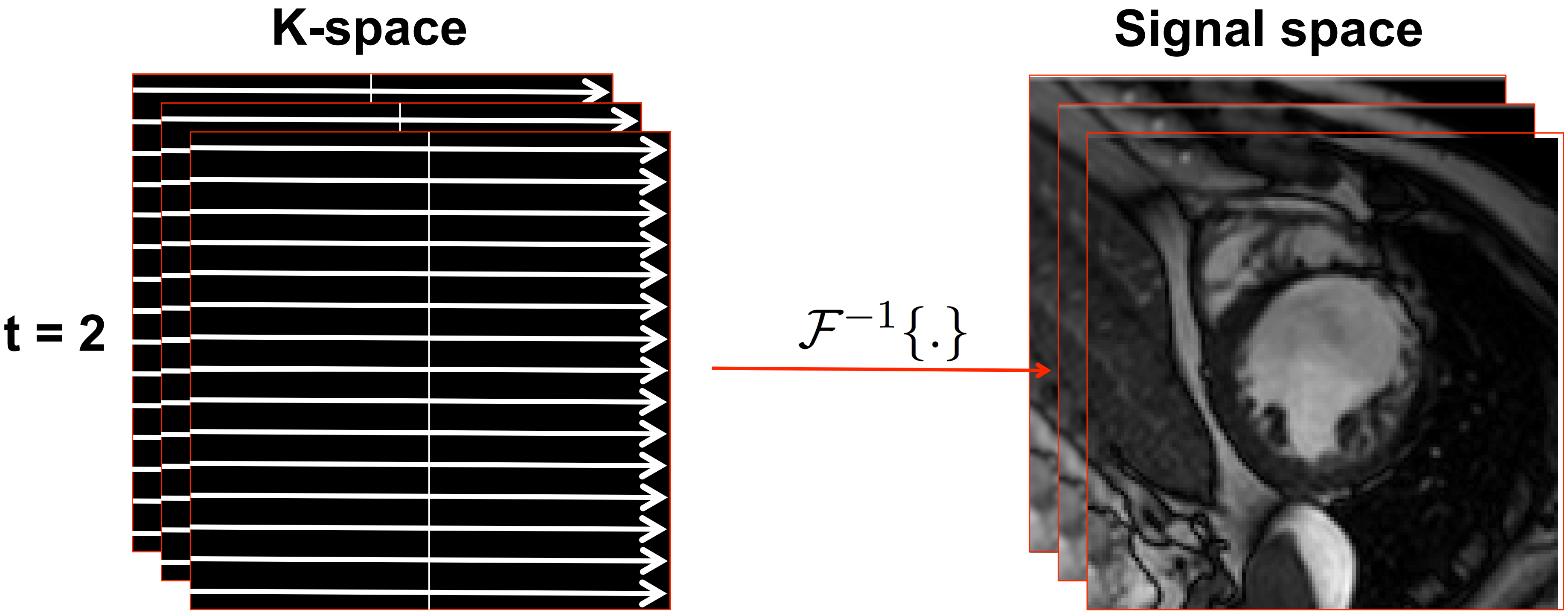

MR full acquisition

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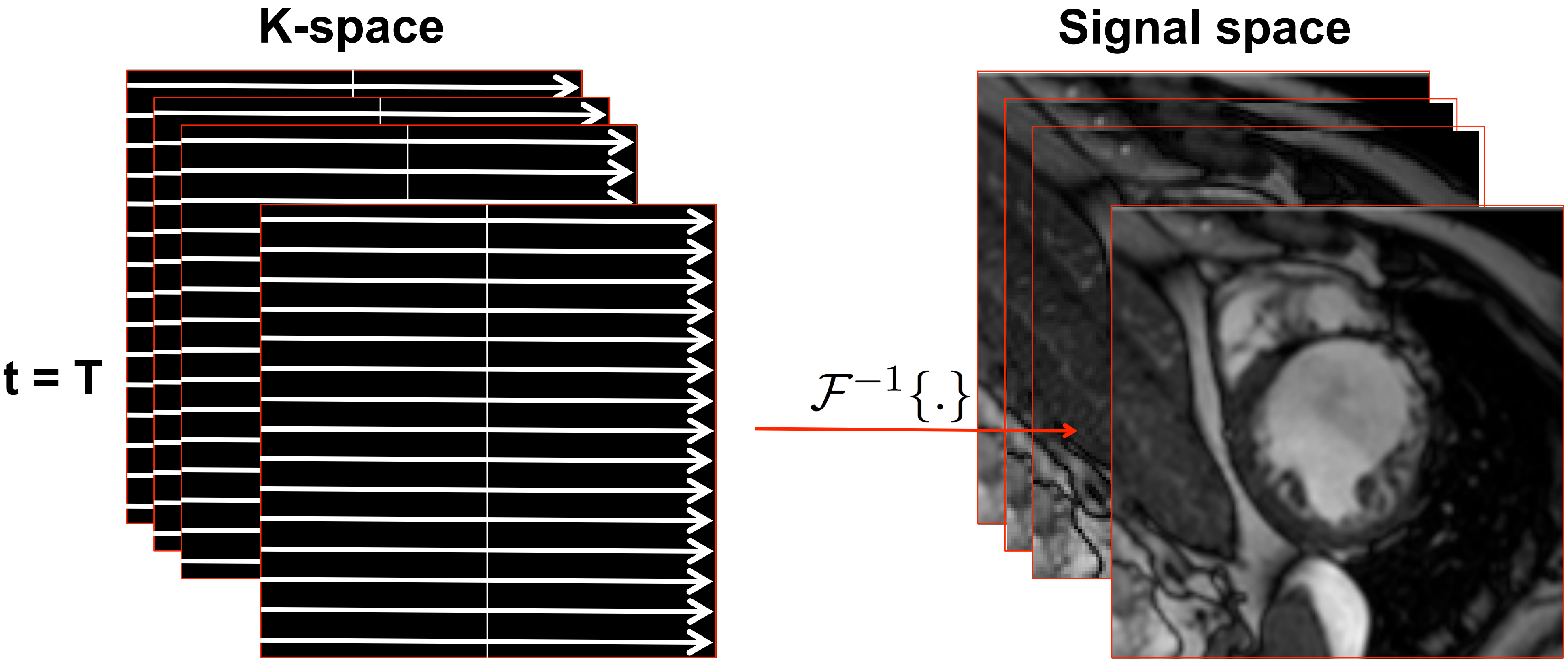

K-space undersampling

- Acquiring a fraction of k-space **accelerates** the process but introduces **aliasing** in signal space.

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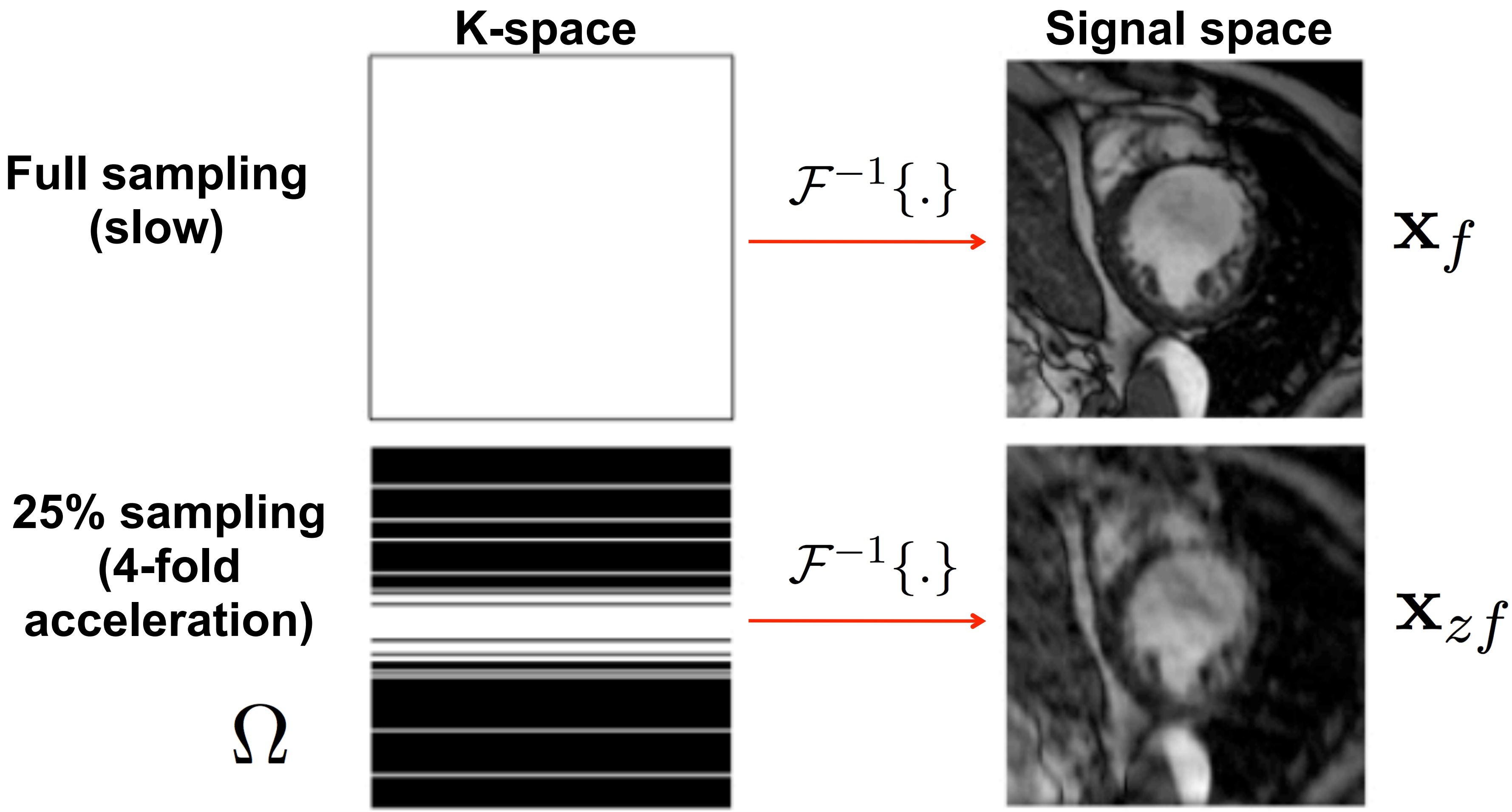
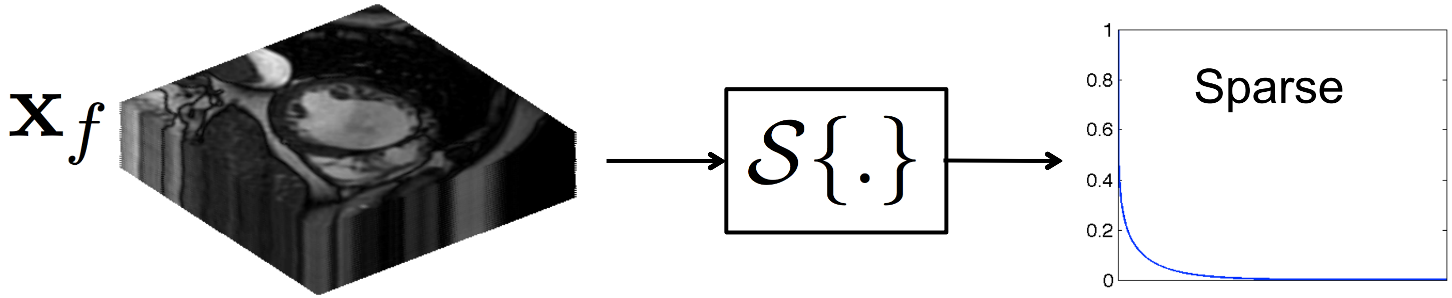
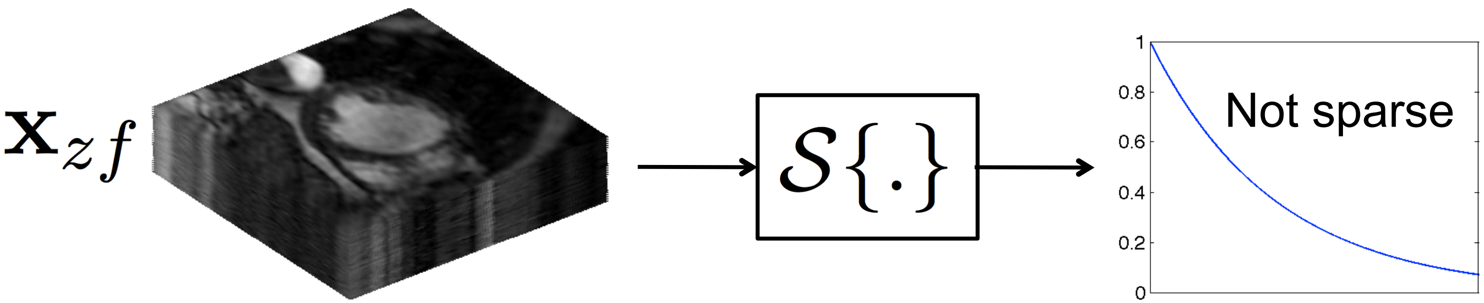


Sparsity

- Most natural signals are compressible under some domain.



- Aliasing makes this assumption break down, so it can be imposed on the reconstruction of a signal.



Compressed sensing

- Assume $\hat{\mathbf{x}}_u$ is the undersampled observation in k-space and $\mathcal{F}_u$ is the undersampled Fourier operator.
- We look for solution $\mathbf{x}$ such that:

Compressed sensing

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  - It is consistent with k-space observation.

$$\boxed{\|\mathcal{F}_u\{\mathbf{x}\} - \hat{\mathbf{x}}_u\|_2^2 < \epsilon}$$

Compressed sensing

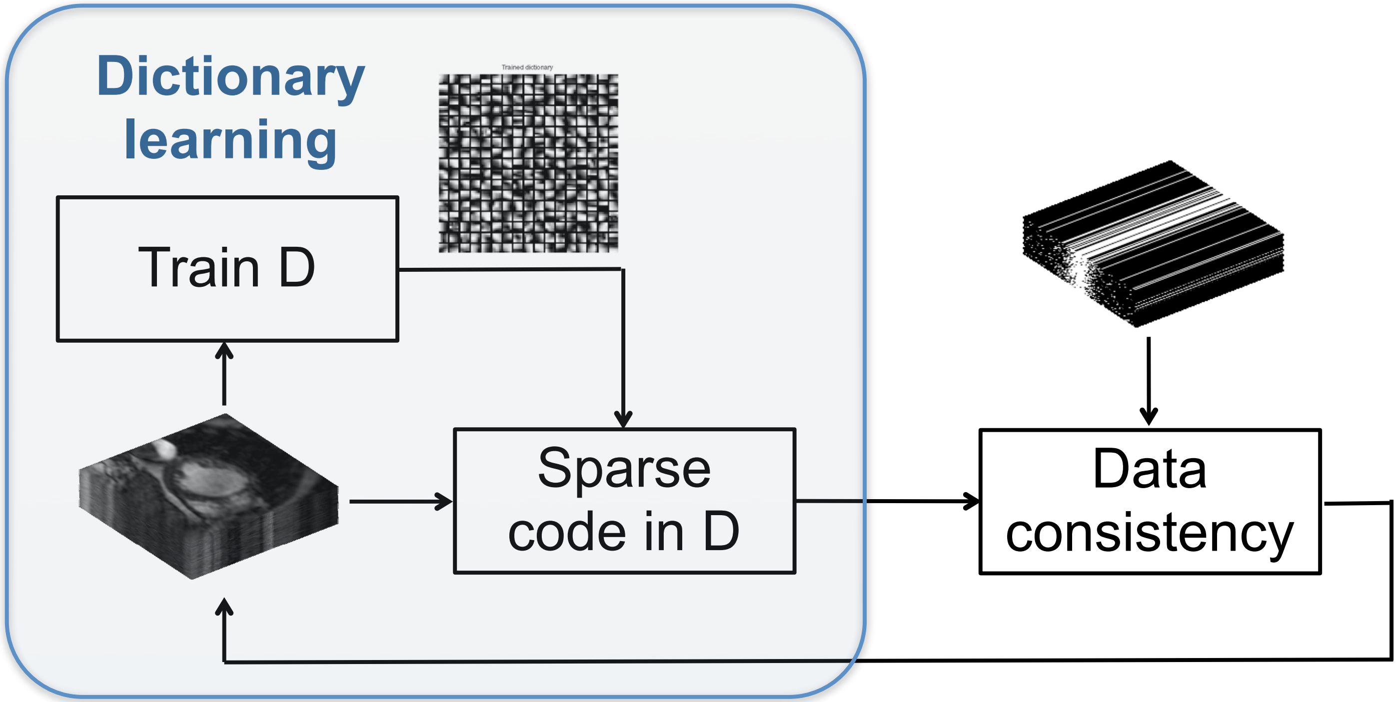
- Assume $\hat{\mathbf{x}}_u$ is the undersampled observation in k-space and $\mathcal{F}_u$ is the undersampled Fourier operator.
- We look for solution $\mathbf{x}$ such that:
  - It is consistent with k-space observation.
  - It has the sparsest representation under $\mathcal{S}\{\mathbf{x}\}$.

$$\boxed{\min_{\mathbf{x}} \|\mathcal{S}\{\mathbf{x}\}\|_0}$$

$$\boxed{\|\mathcal{F}_u\{\mathbf{x}\} - \hat{\mathbf{x}}_u\|_2^2 < \epsilon}$$

Dictionary learning for MR reconstruction

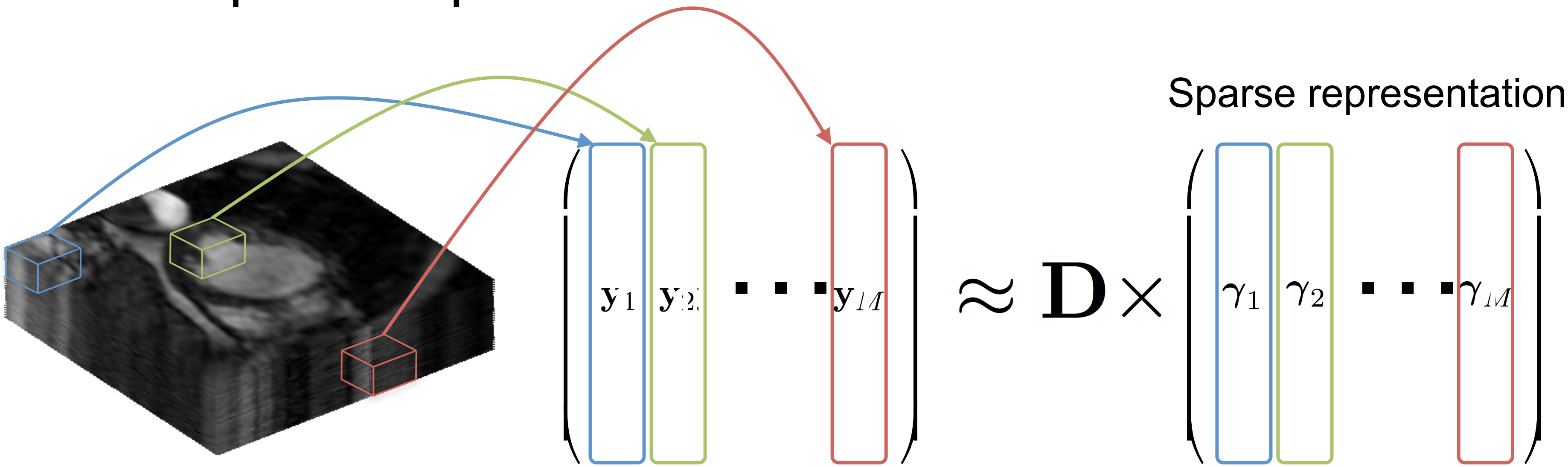
- Objective: Out of all solutions consistent with the acquired k-space, we look for the one that is sparsest under the learned dictionary.



Caballero et al., IEEE TMI 2014

Step 1: Dictionary learning

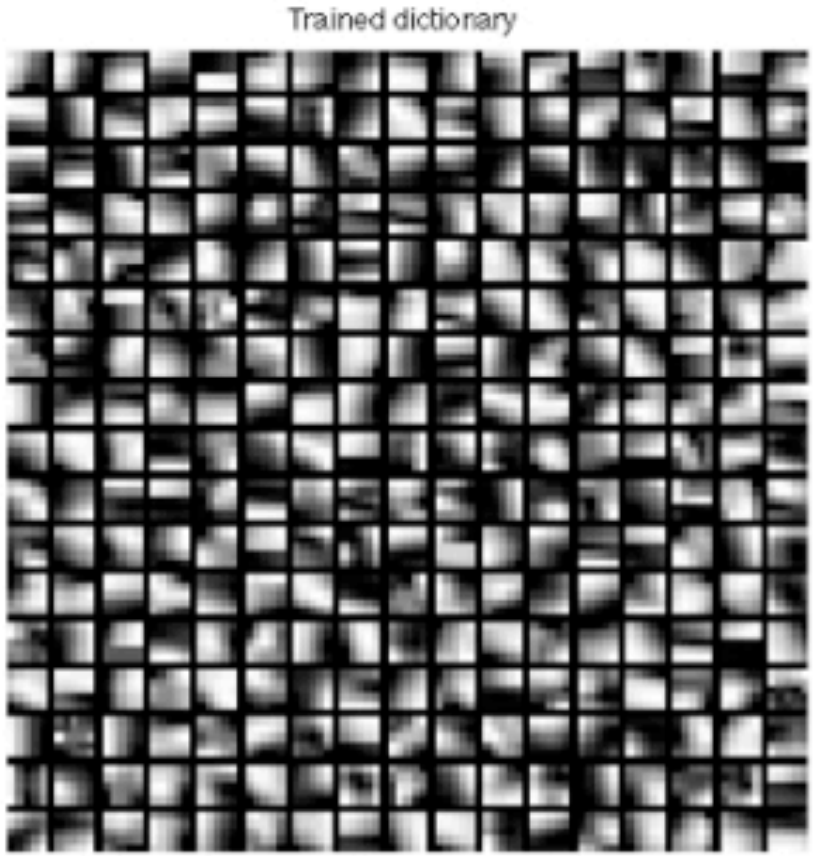
- **Training:** Learn a dictionary that will sparsely represent 3D patches randomly extracted from the corrupted sequence.



$$\min_{\mathbf{\Gamma},\mathbf{D}} \|\boldsymbol{\gamma}_i\|_0 \qquad s.t. \qquad \|\mathbf{y}_i - \mathbf{D}\boldsymbol{\gamma}_i\|_2^2 < \epsilon, \forall i$$

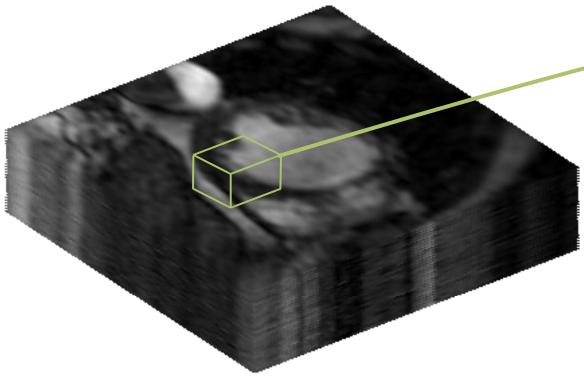
Dictionary learning – Example

- The dictionary is adapted to features in the data and by construction provides a sparse representation of it.



Step 2: Sparse coding

- **<u>Coding:</u>** The entire sequence is sparsely coded using $\mathbf{D}$.

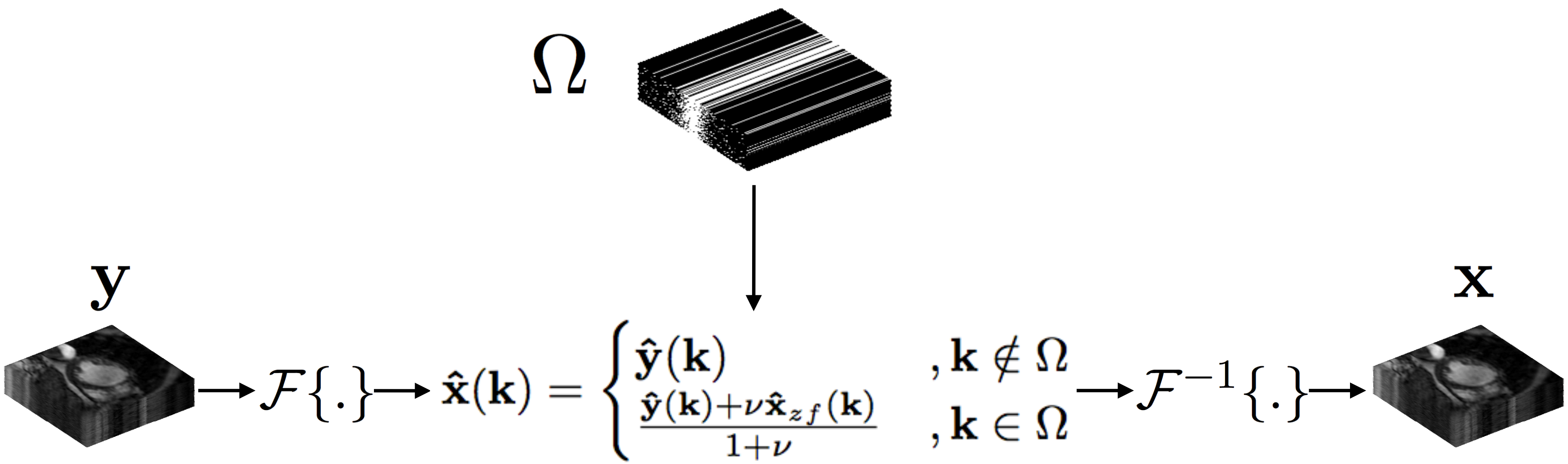


$$\min_{\boldsymbol{\Gamma}} \sum_{j=1}^{P} \|\boldsymbol{\gamma}_j\|_0 \qquad s.t. \qquad \sum_{j=1}^{P} \|\mathbf{R}_j\mathbf{y} - \mathbf{D}\boldsymbol{\gamma}_j\|_2^2 < \epsilon_1$$

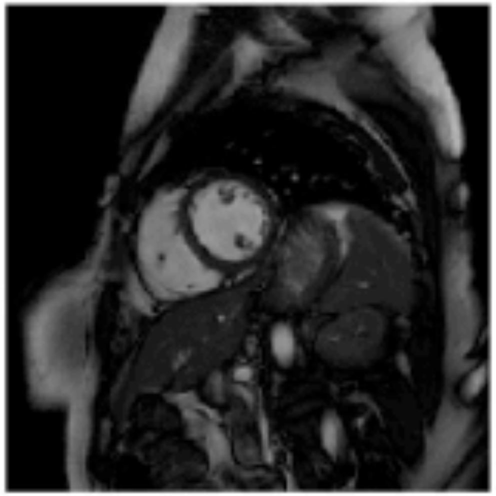
- The sparse coding $\boldsymbol{\Gamma}$ provides an approximation of the sequence $\mathbf{D}\boldsymbol{\Gamma}$ excluding part of the aliasing.

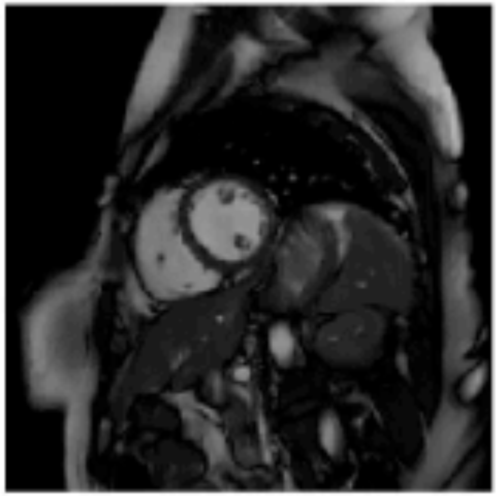
Step 3: Data consistency

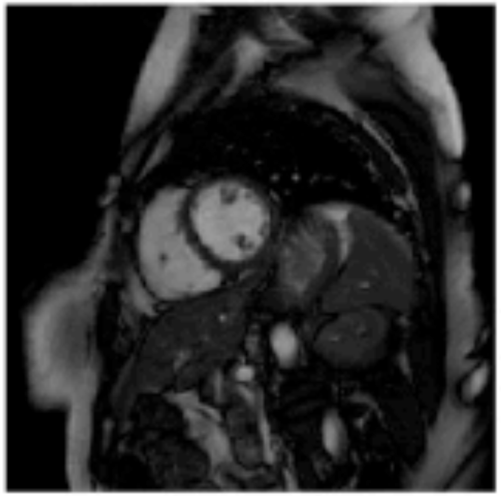
- Processing in signal space will make the k-space of solution $\mathbf{x}$ different from the initial observations.
- Data consistency in k-space must be enforced.

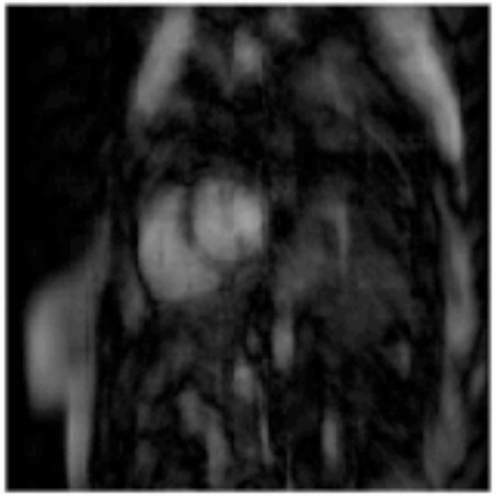


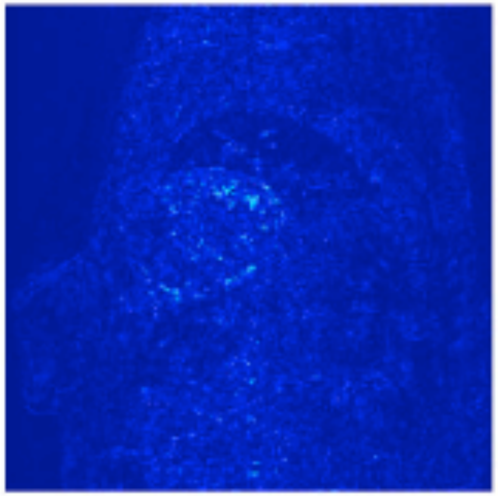
Magnitude reconstruction (8-fold)

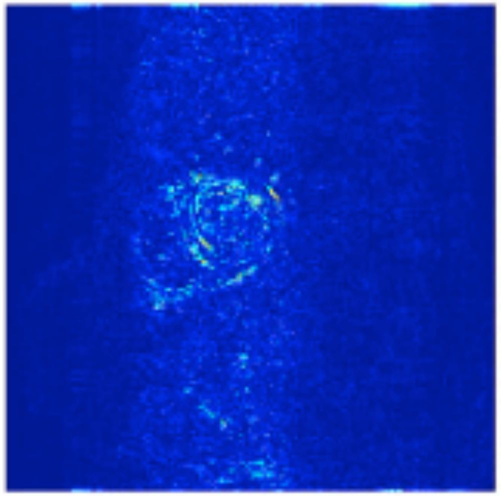

Original


DLTG (36.7 dB)

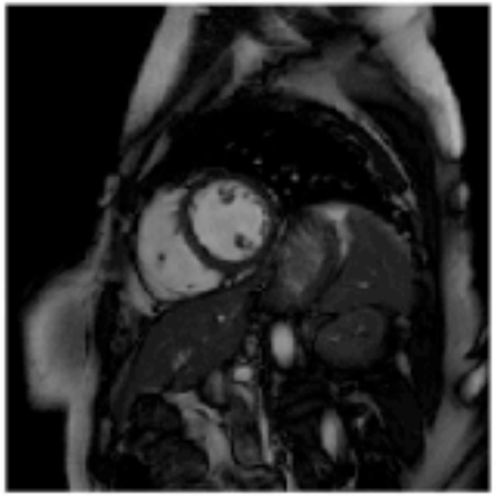

k-t FOCUSS (34.3 dB)


Zero-filled (22.7 dB)

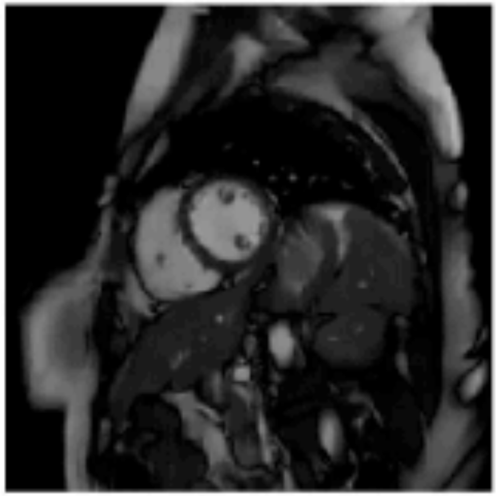

DLTG error x5


k-t FOCUSS error x5

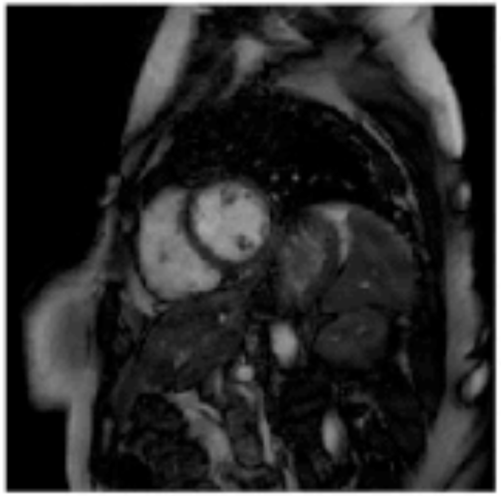
Magnitude reconstruction (12-fold)



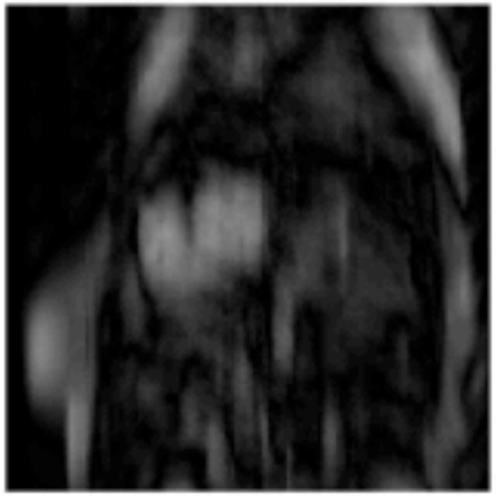
Original



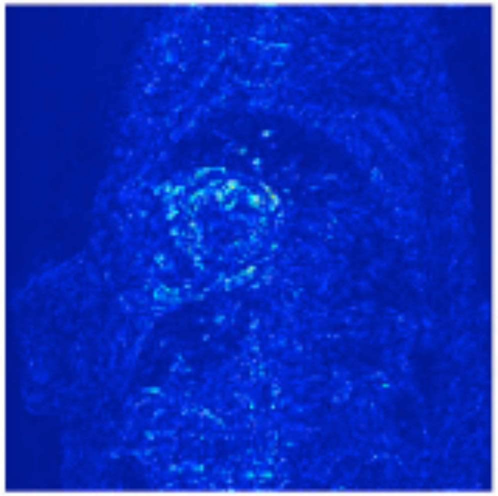
DLTG (34.0 dB)



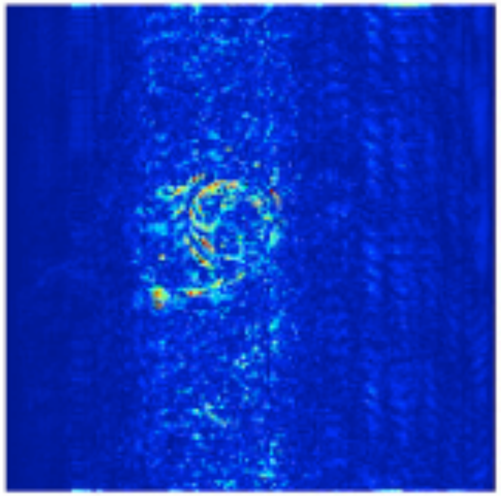
k-t FOCUSS (31.4 dB)



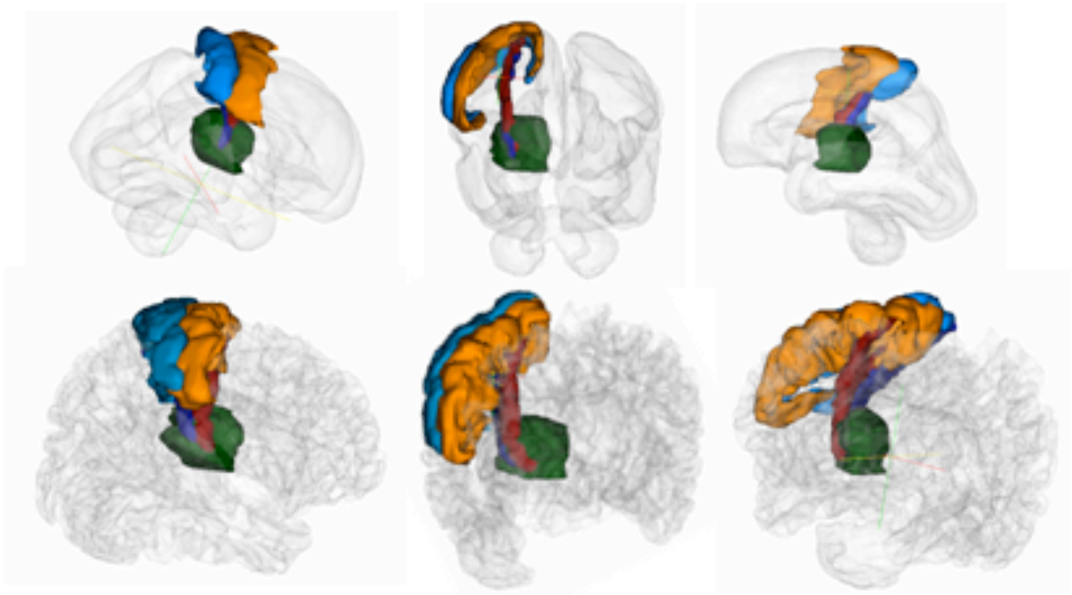
Zero-filled (21.9 dB)



DLTG error x5



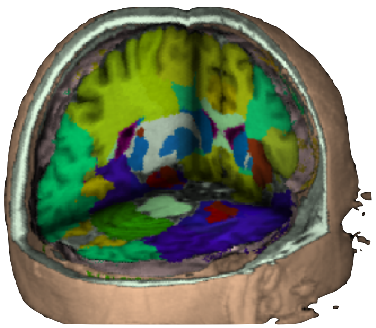
k-t FOCUSS error x5



Segmentation

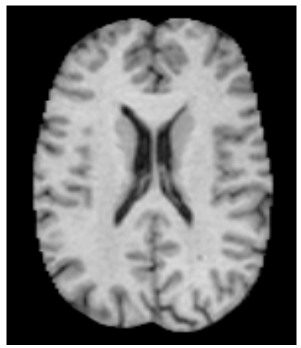
Segmentation using registration

Atlas/Model



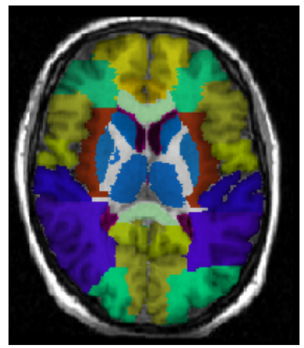
Registration or matching

New image

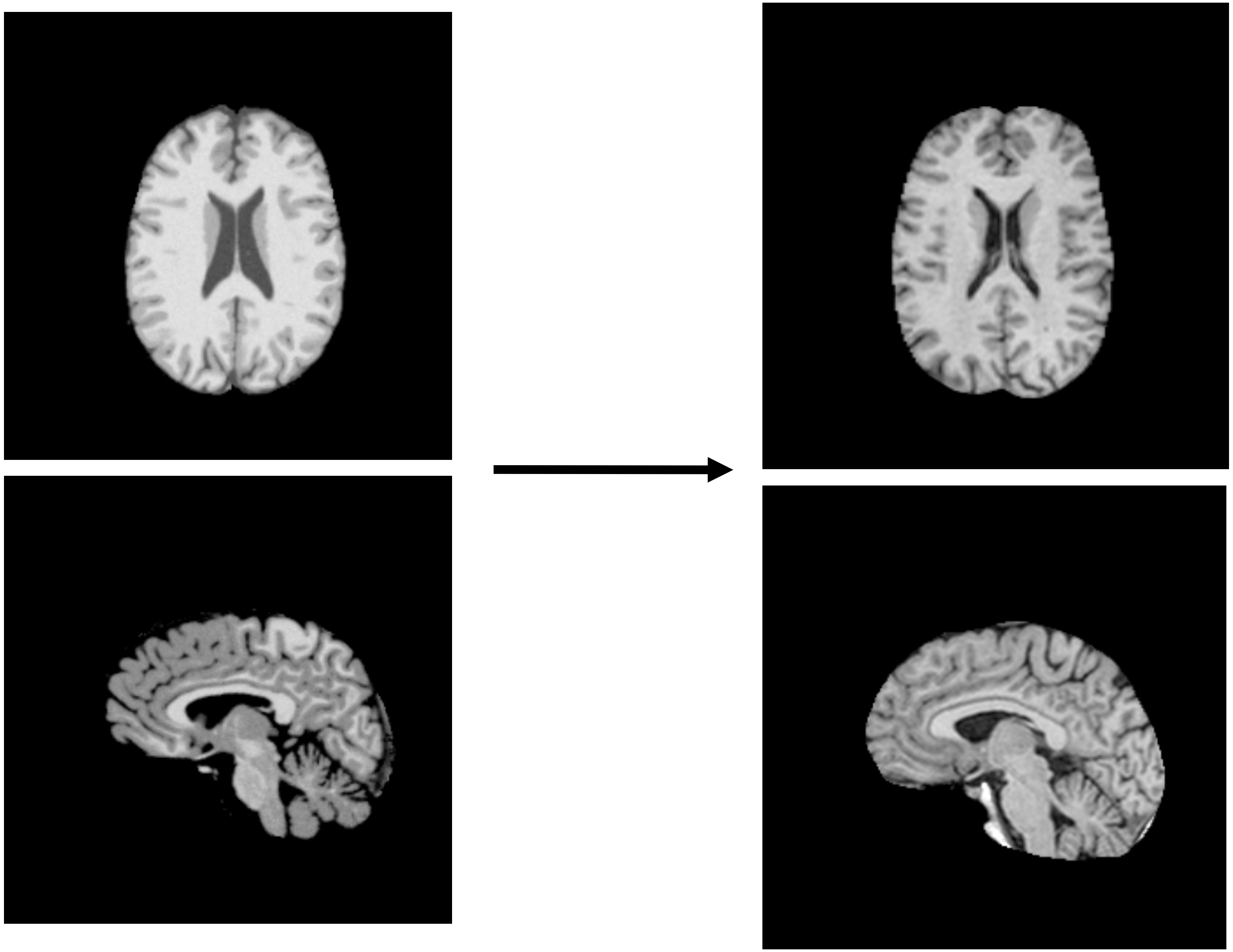


Propagation of segmentation

Segmentation

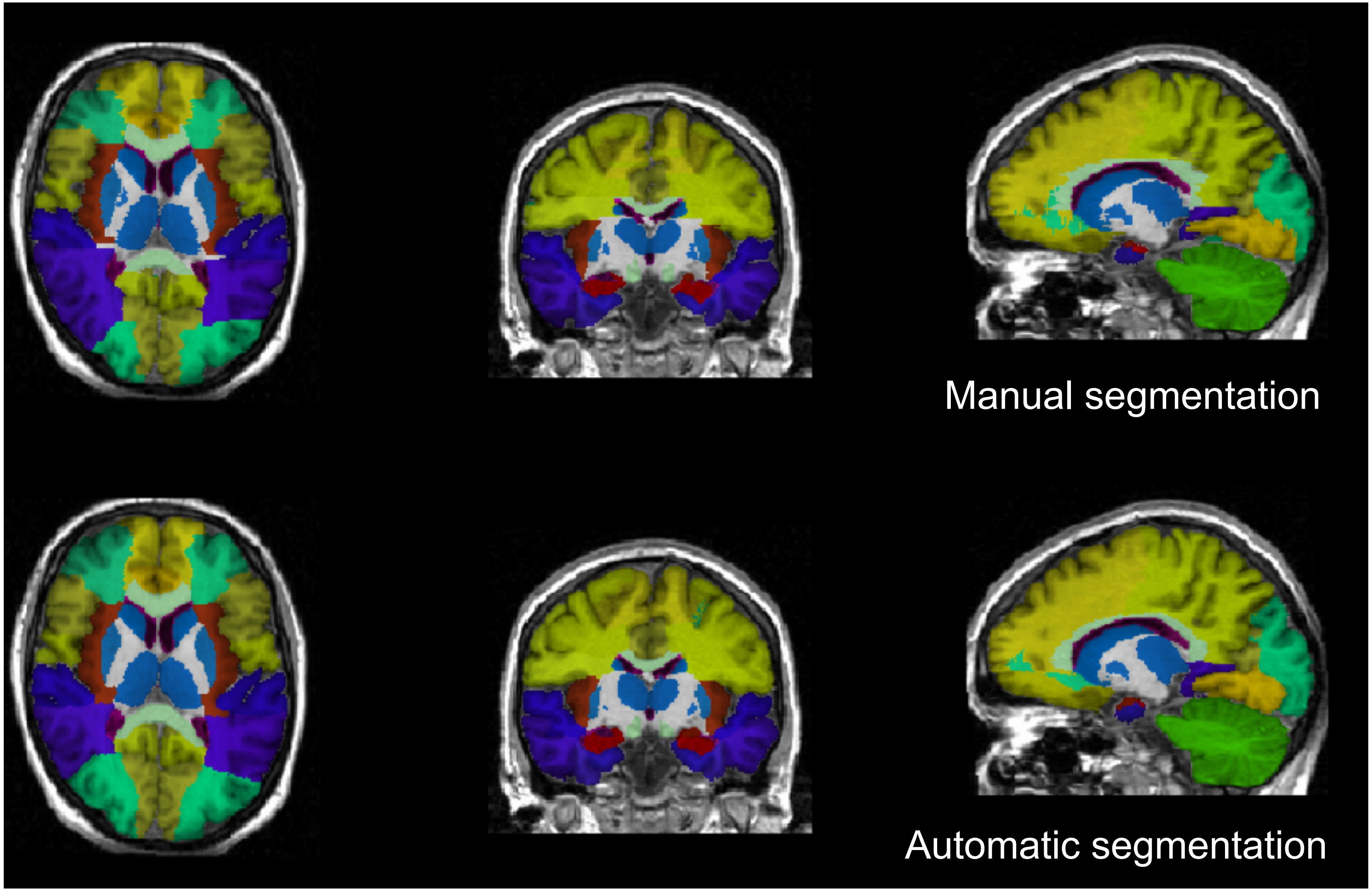


Segmentation using registration

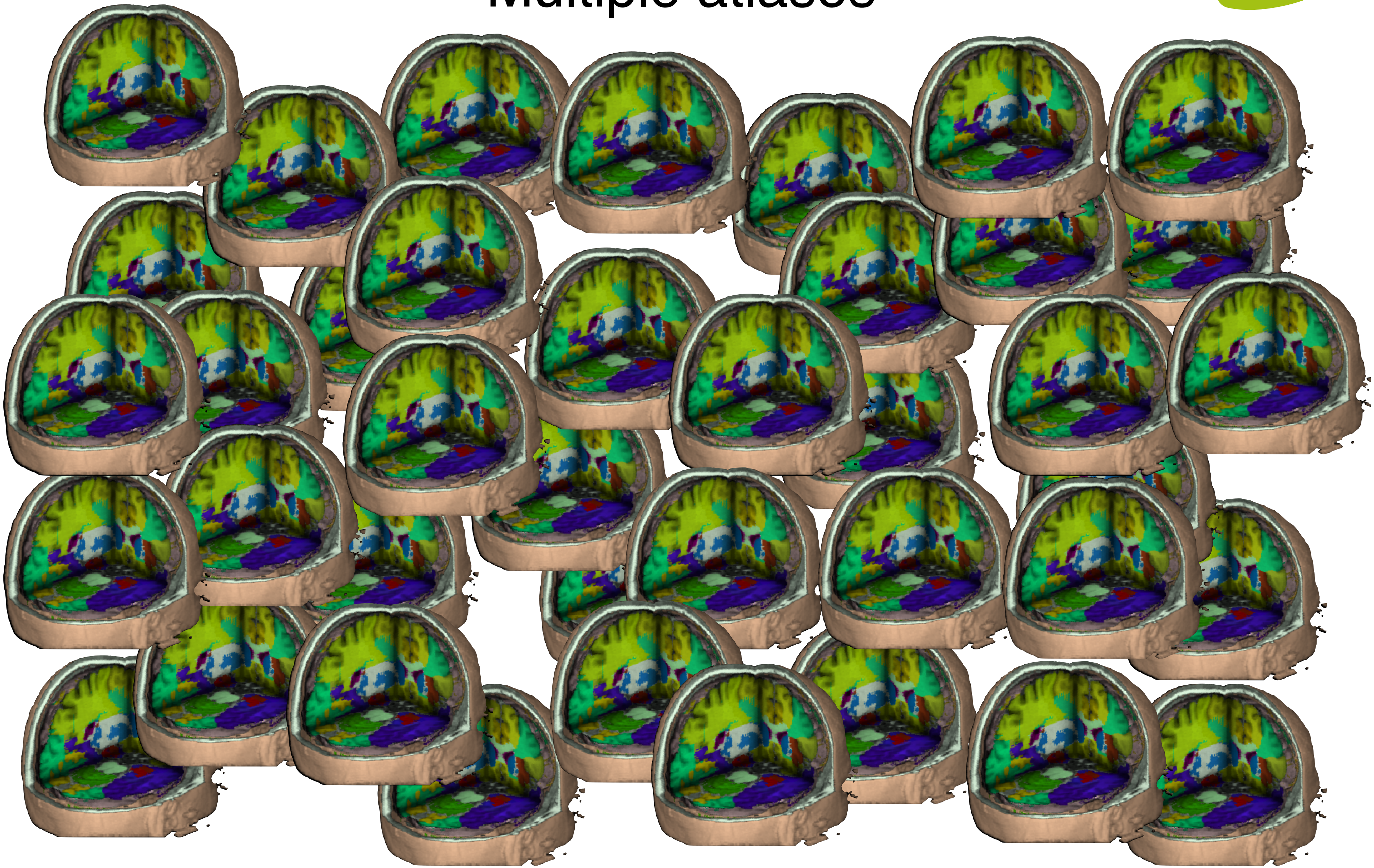


Rueckert et al. IEEE TMI 1999

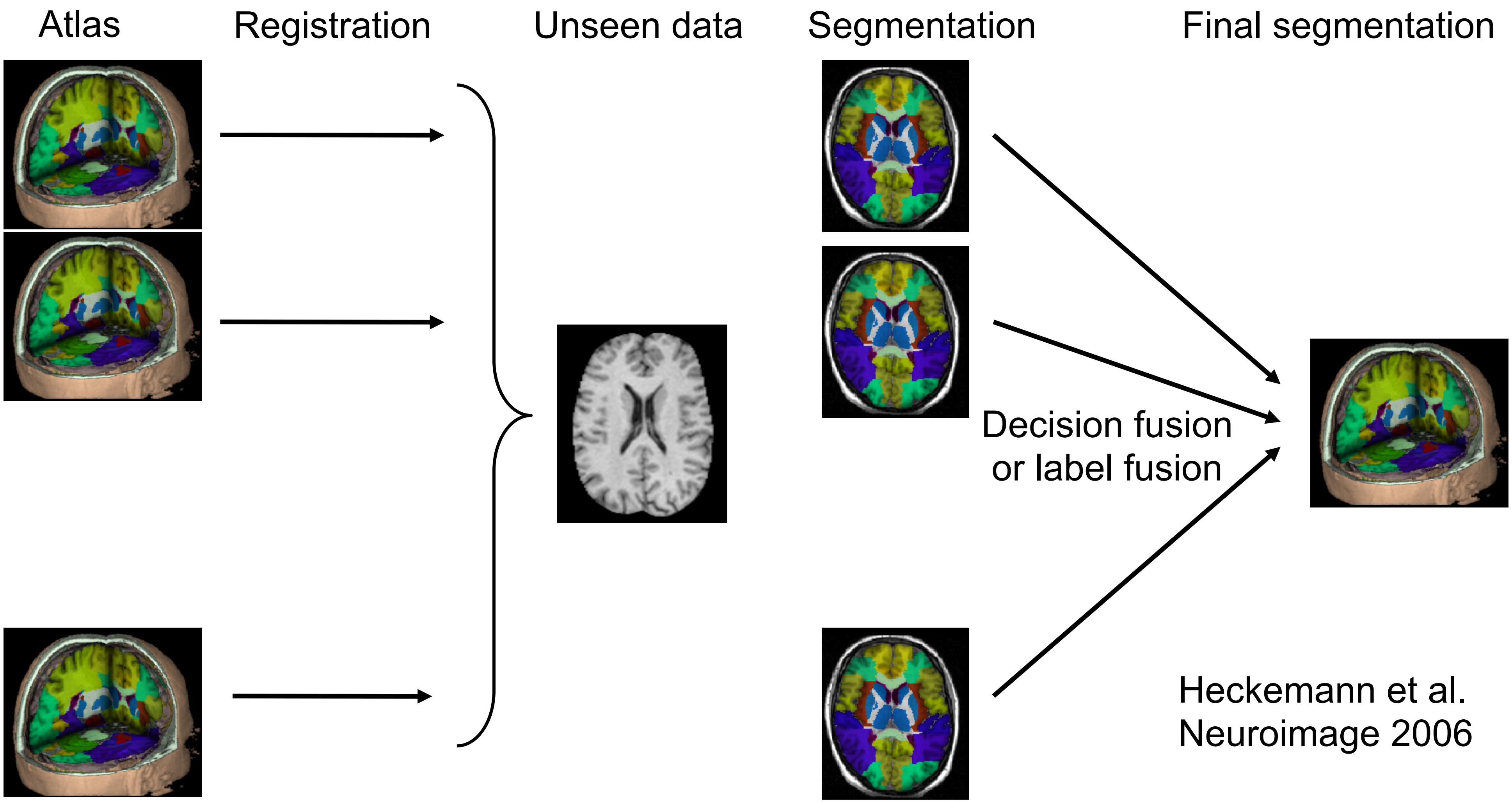
Segmentation using registration



Multiple atlases



Multi-atlas segmentation using classifier fusion



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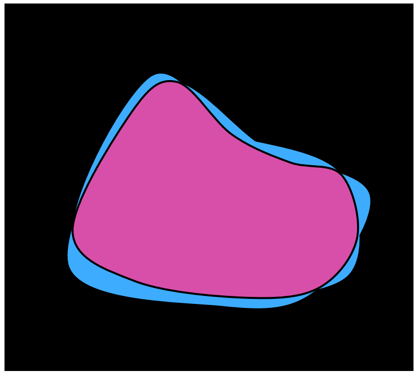
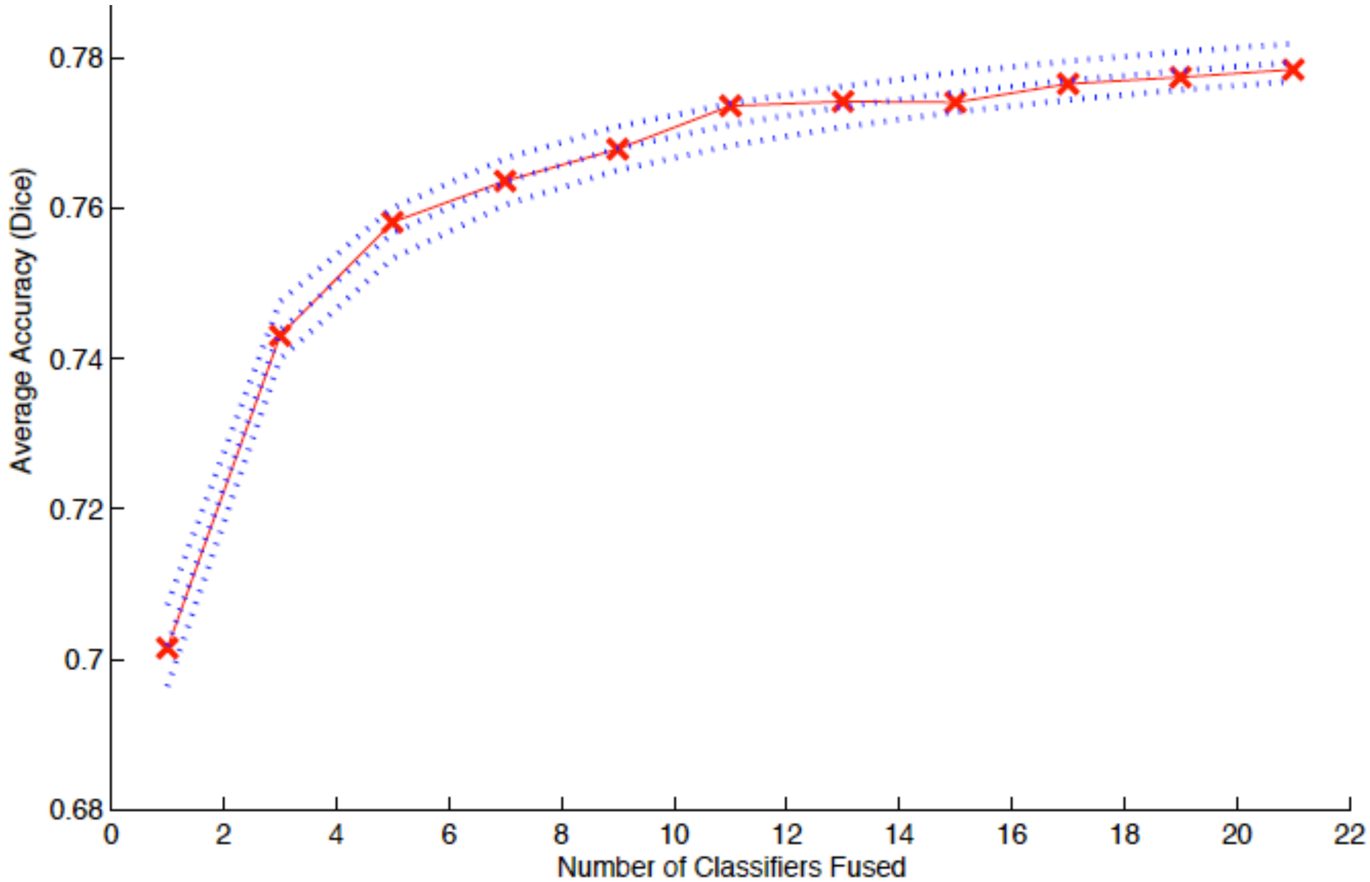


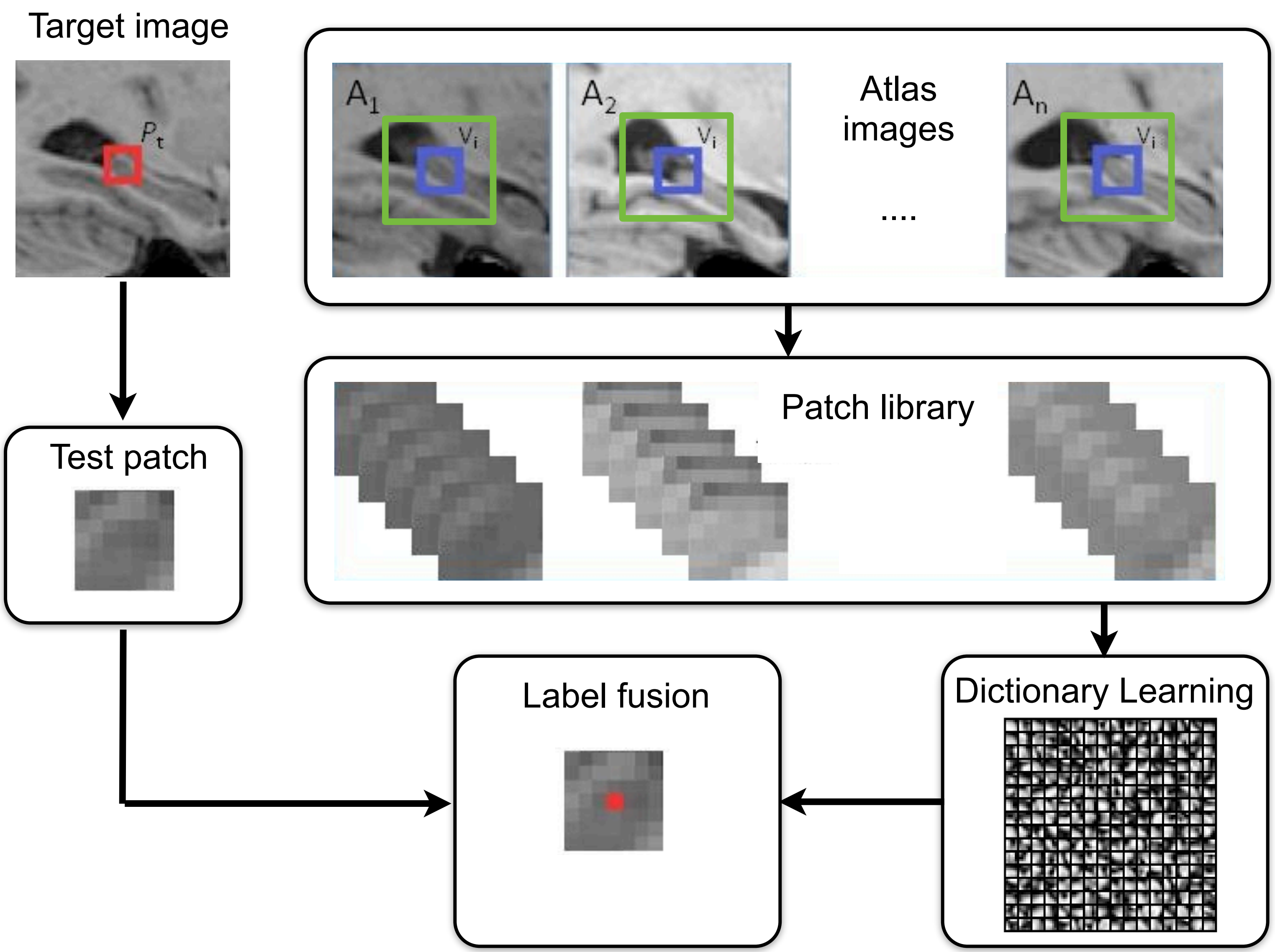


Heckemann et al.
Neuroimage 2006

Multi-atlas segmentation using classifier fusion

- Works very well ***but:***
  - Requires large number of atlases that should be customized to the target subject in question
  - Requires accurate registration
- Problems:
  - Number of atlases is typically limited by time, manpower
  - Computing many non-rigid registrations is expensive
- Solution:
  - Use ***dictionary learning*** to relax requirement for accurate registration and large number of atlases

Dictionary learning for patch-based segmentation

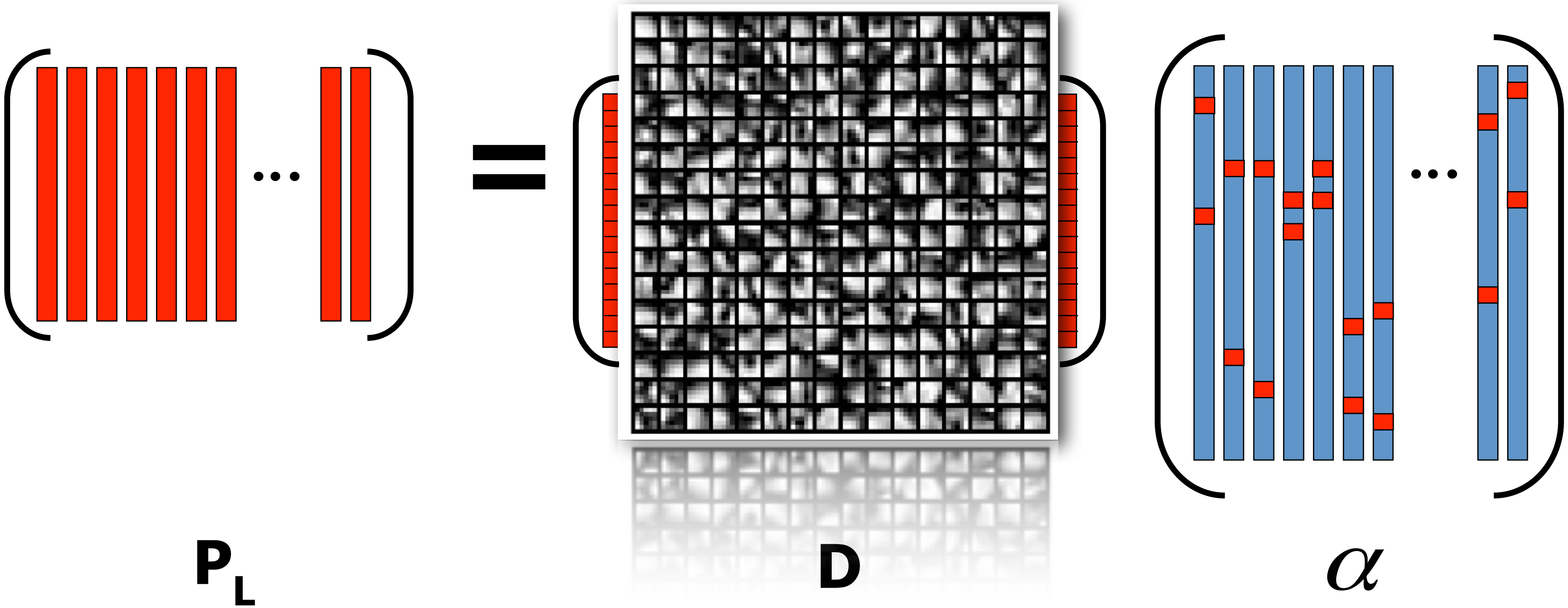


Tong et al, NeuroImage, 2013

Dictionary learning: Interpreting medical images

- Learning a dictionary D from image patches P_L

$$\langle D, \alpha \rangle = \underset{D,\alpha}{\arg\min} \|\mathrm{P_L} - D\alpha\|_2^2 \quad \text{subject to} \quad \|\alpha\|_0 \leq T$$

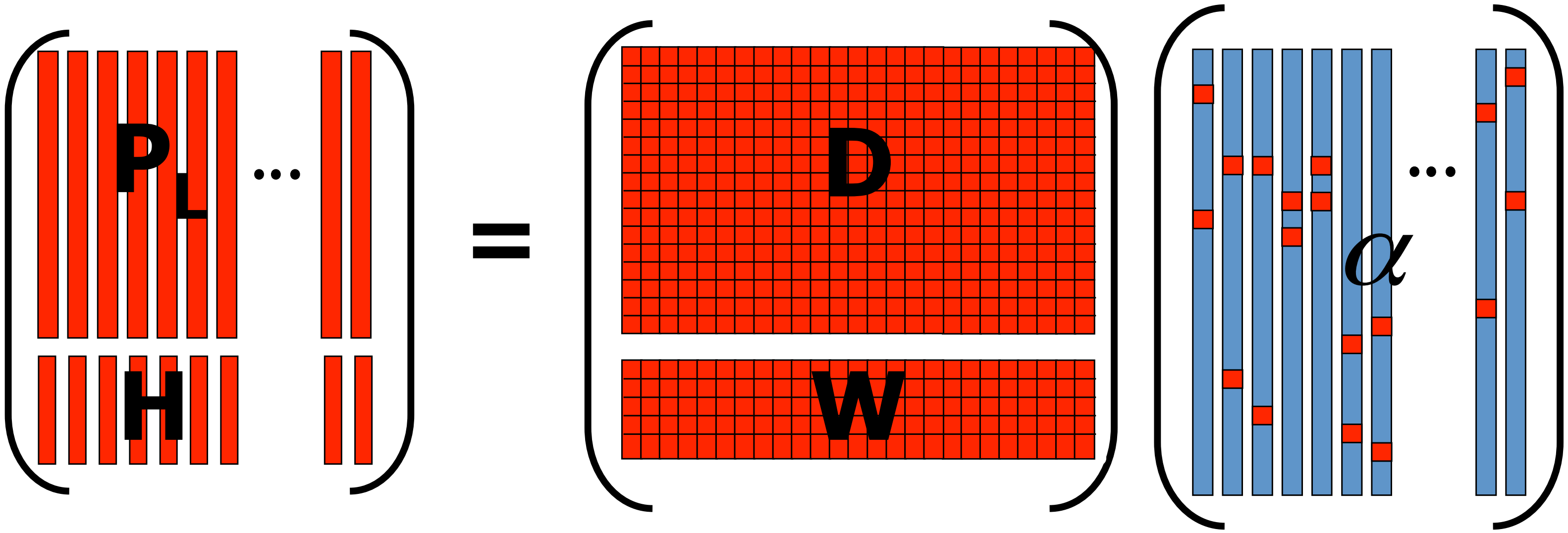


Tong et al, NeuroImage, 2013

Discriminative Dictionary Learning

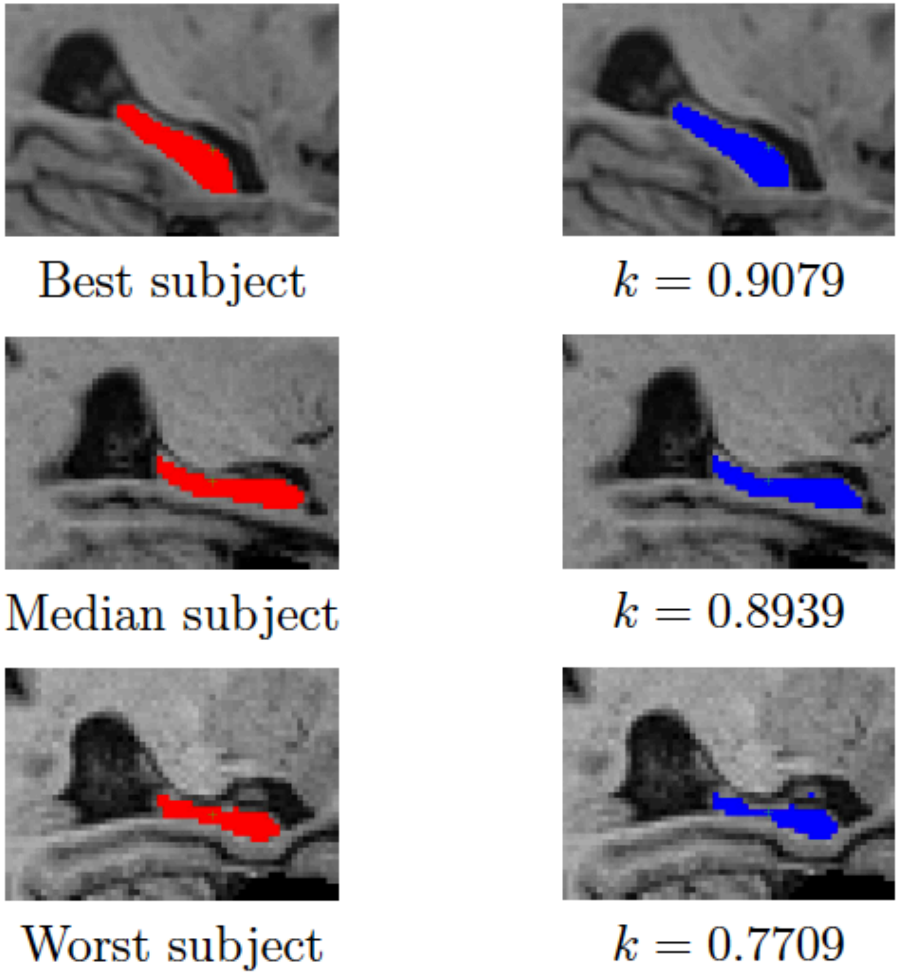
- Add a classification error term $\|H - W\alpha\|_2^2$:

$$\langle D, W, \alpha \rangle = \underset{D,W,\alpha}{\arg\min} \|\mathrm{P_L} - D\alpha\|_2^2 + \beta_1 \|H - W\alpha\|_2^2$$
$$\text{subject to} \quad \|\alpha\|_0 \leq T$$



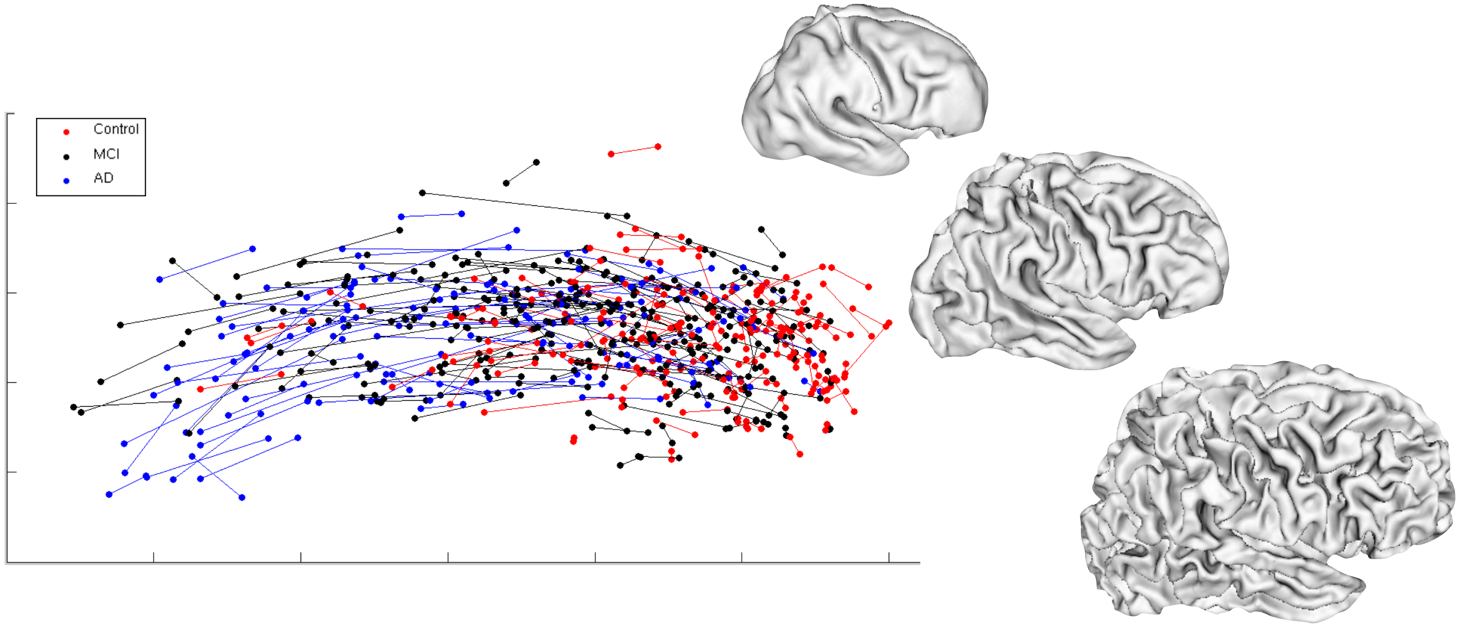
Tong et al, NeuroImage, 2013

Discriminative Dictionary Learning for Segmentation (DDLS)



Manual segmentation   Dictionary Learning

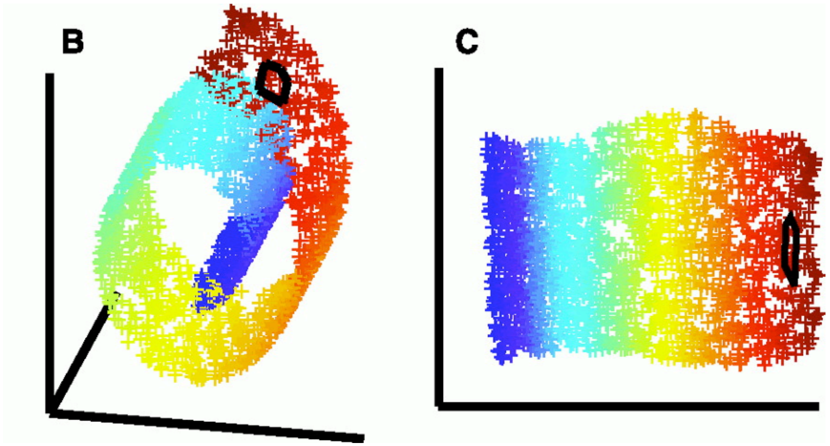
Tong et al, NeuroImage, 2013



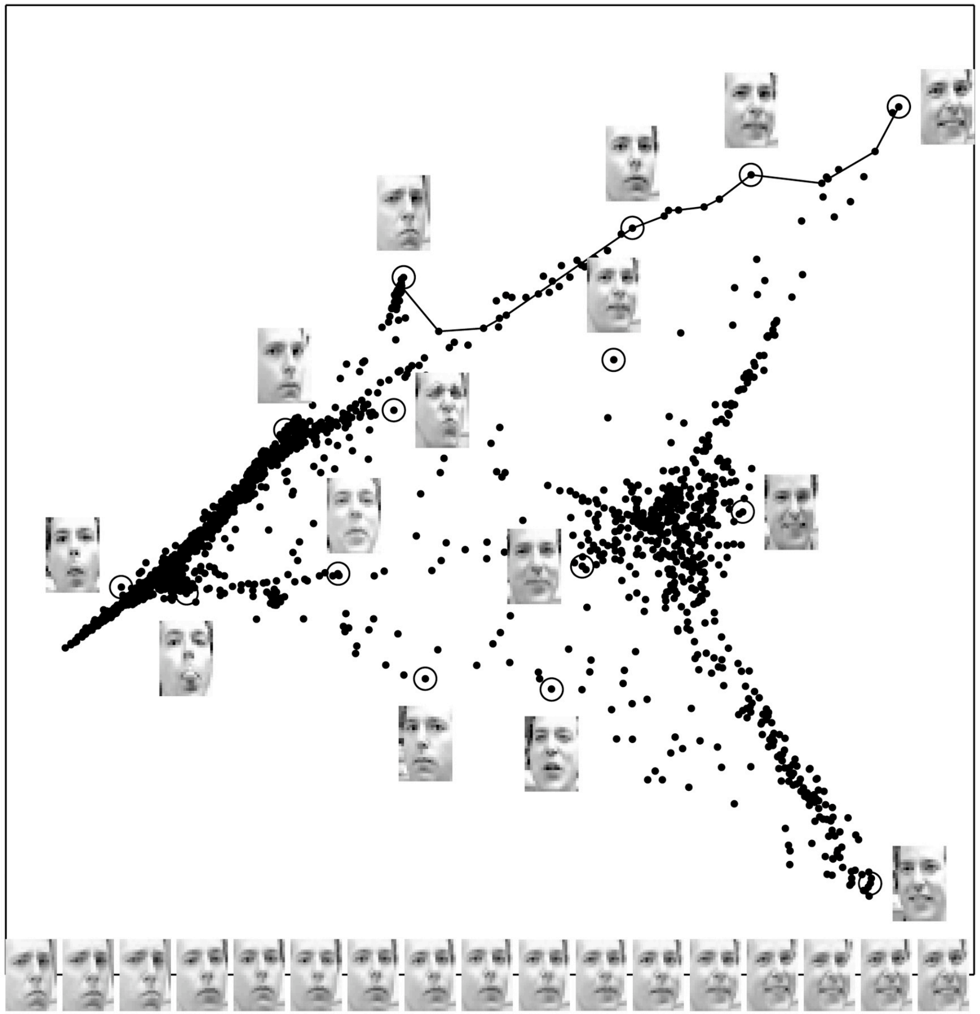
Biomarker discovery

Manifold learning

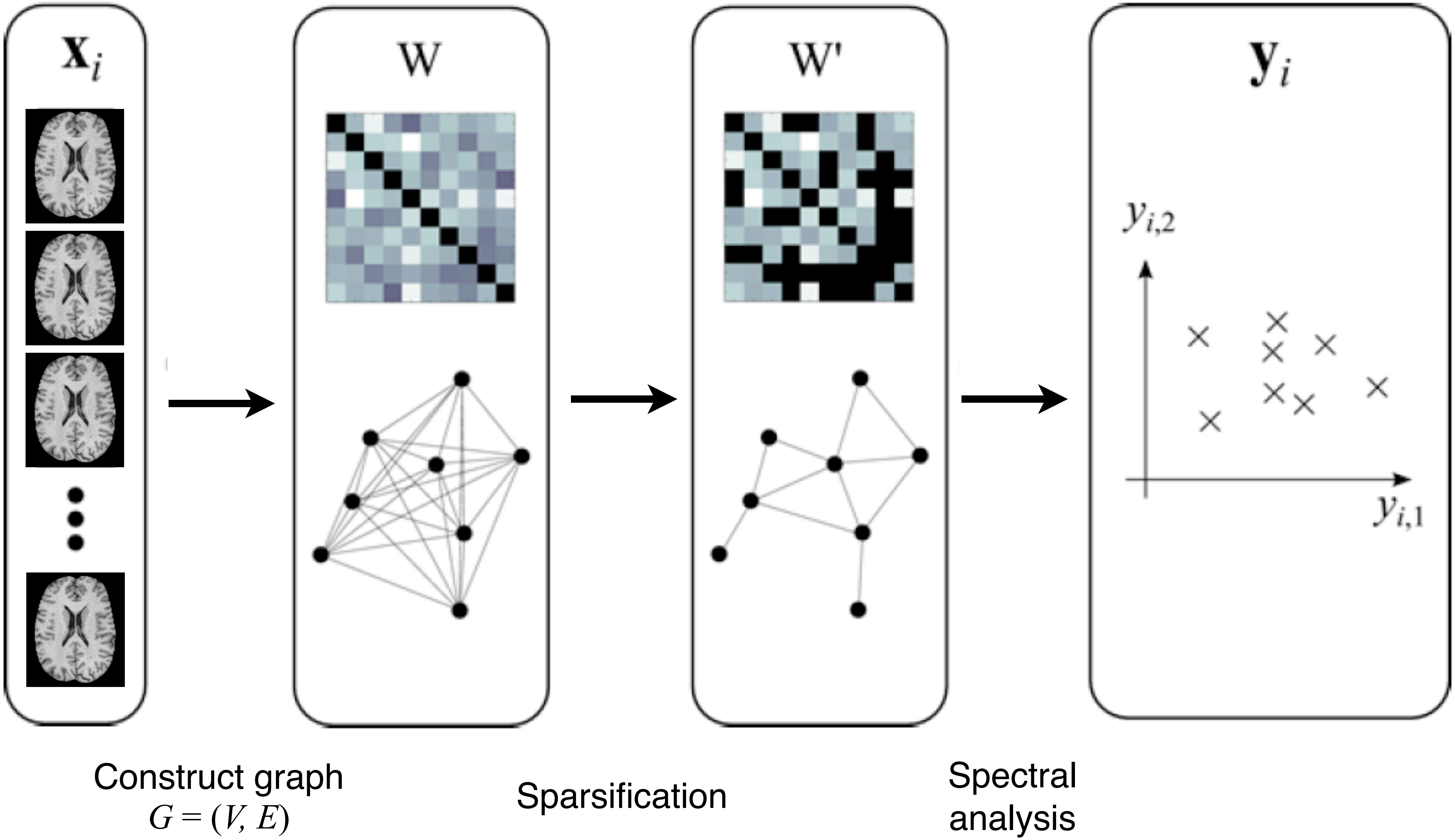
Manifold learning aims to model the
space of images through
a low-dimensional manifold



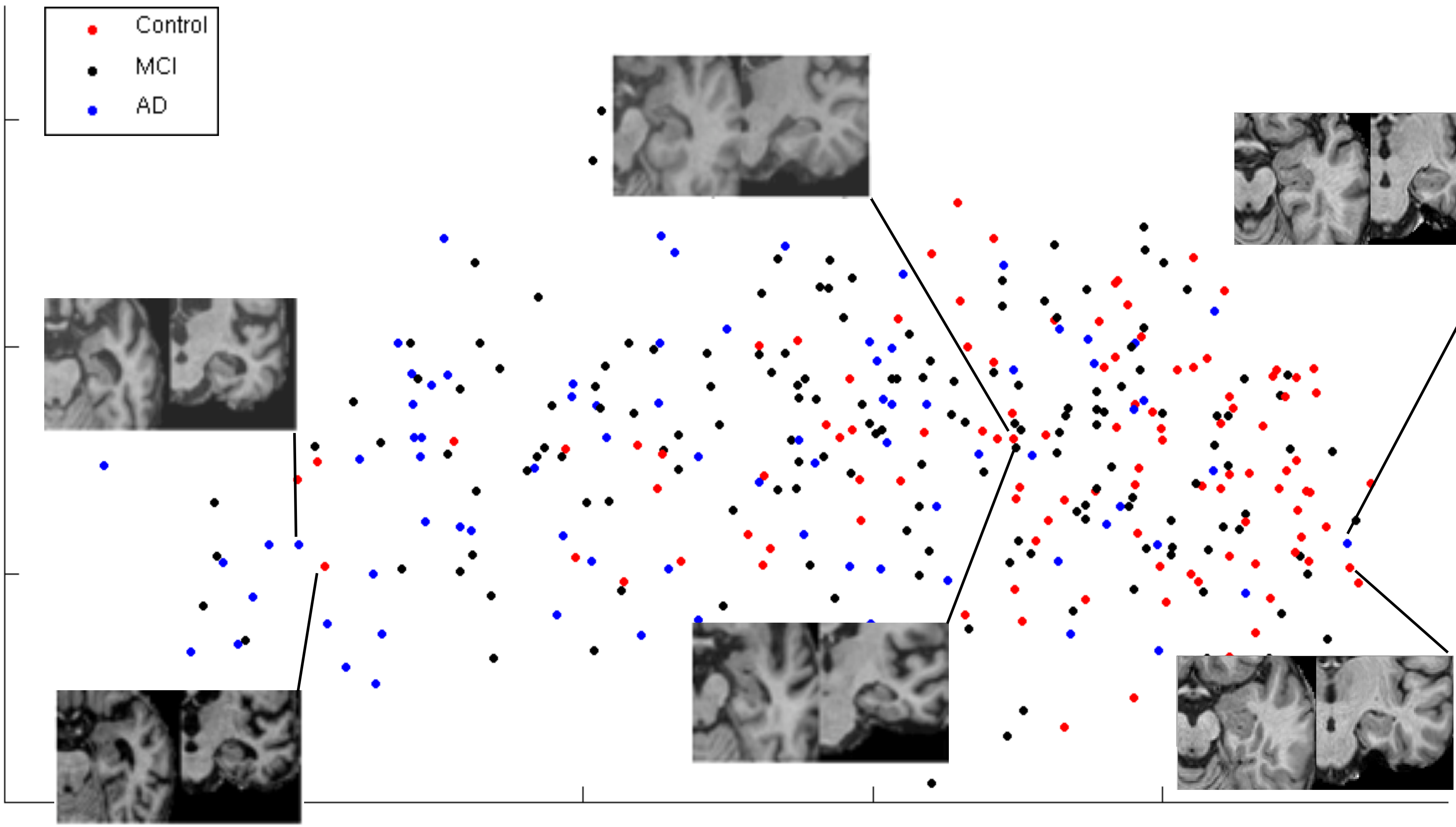
Local linear embedding,
Roweis, Science 2000
Other approaches: MDS,
Isomap, Laplacian eigenmaps



Manifold learning

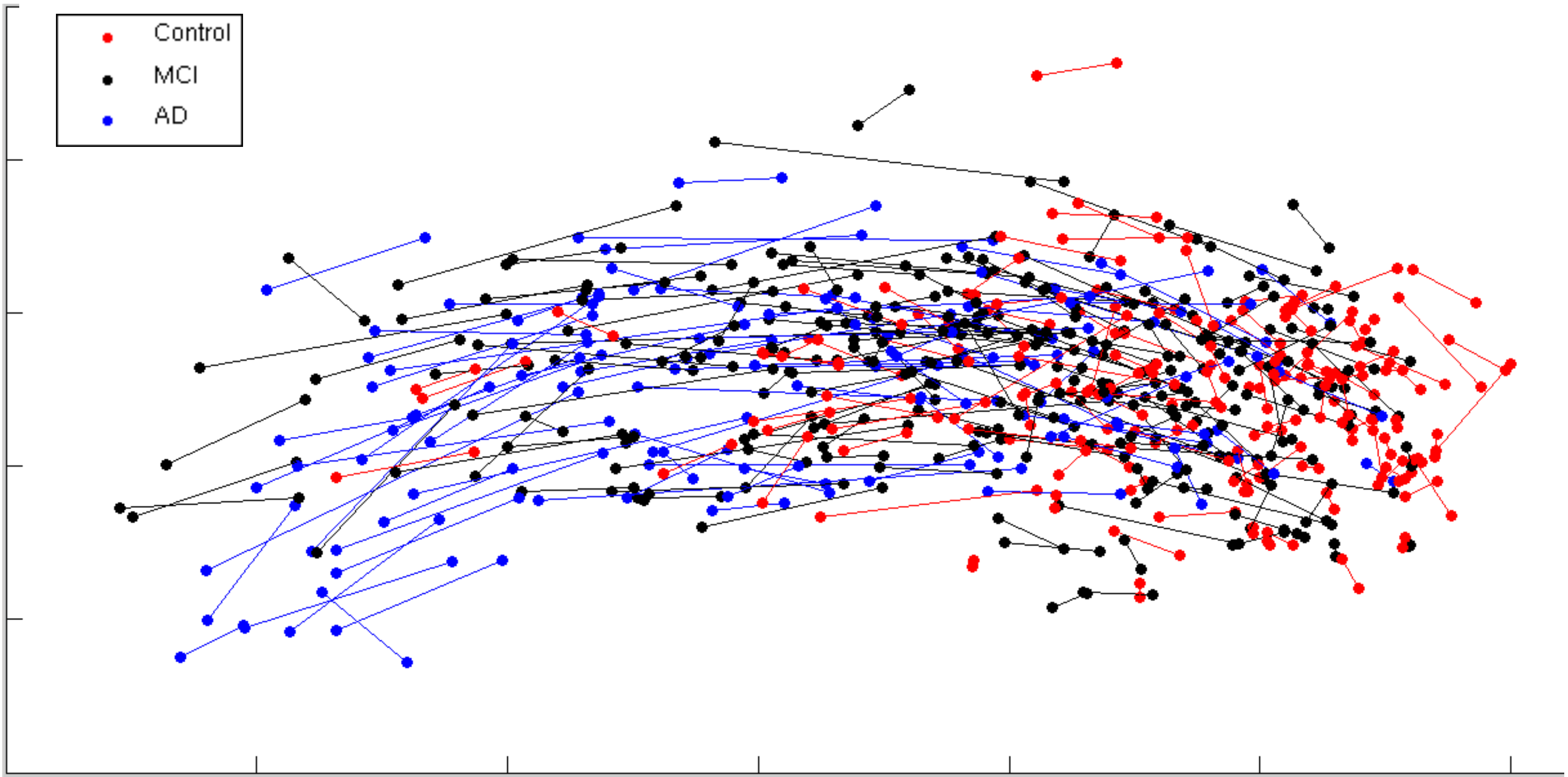


Manifold learning for biomarker discovery



Wolz et al., MICCAI MLMI, 2010

Manifold learning for biomarker discovery: Using longitudinal information



Wolz et al., MICCAI MLMI, 2010

Manifold learning for biomarker discovery: Using longitudinal information

- T1-weighted 1.5T MR images from
  - 362 subjects from the ADNI study consisting of patients with mild AD (N=83), MCI (N=165) and healthy control subjects (N=114).
  - baseline, 12 month and 24 month scans.

	AD vs CN	P-MCI vs CN	P-MCI vs S-MCI
Class. rate:	88%	82%	67%
Sensitivity	85%	76%	64%
Specificity	90%	86%	70%

Understanding brain development:
Motivation

Better detection of fetal abnormalities

Understanding of the cause of pre-term birth

Improved intensive neonatal care

Early diagnosis of long-term problems

Understanding brain development: Motivation and challenges

Better detection of fetal abnormalities

Understanding of the cause of pre-term birth

Improved intensive neonatal care

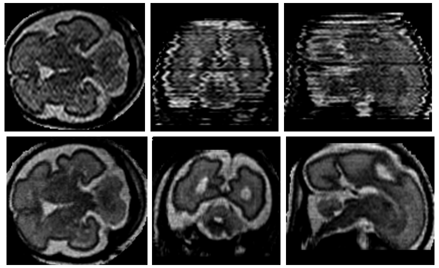
Early diagnosis of long-term problems

Motion makes image acquisition challenging

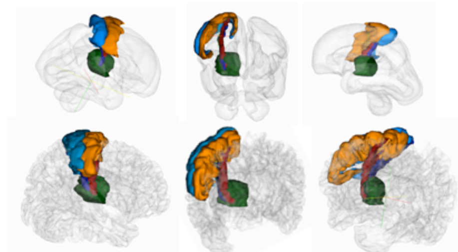
Pre-term infants are vulnerable and more difficult to image

The fetal and neonatal brain is small compared to adults

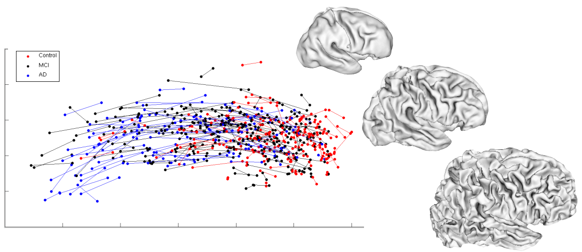
Understanding brain development: Bringing it together



Intelligent imaging



Segmentation

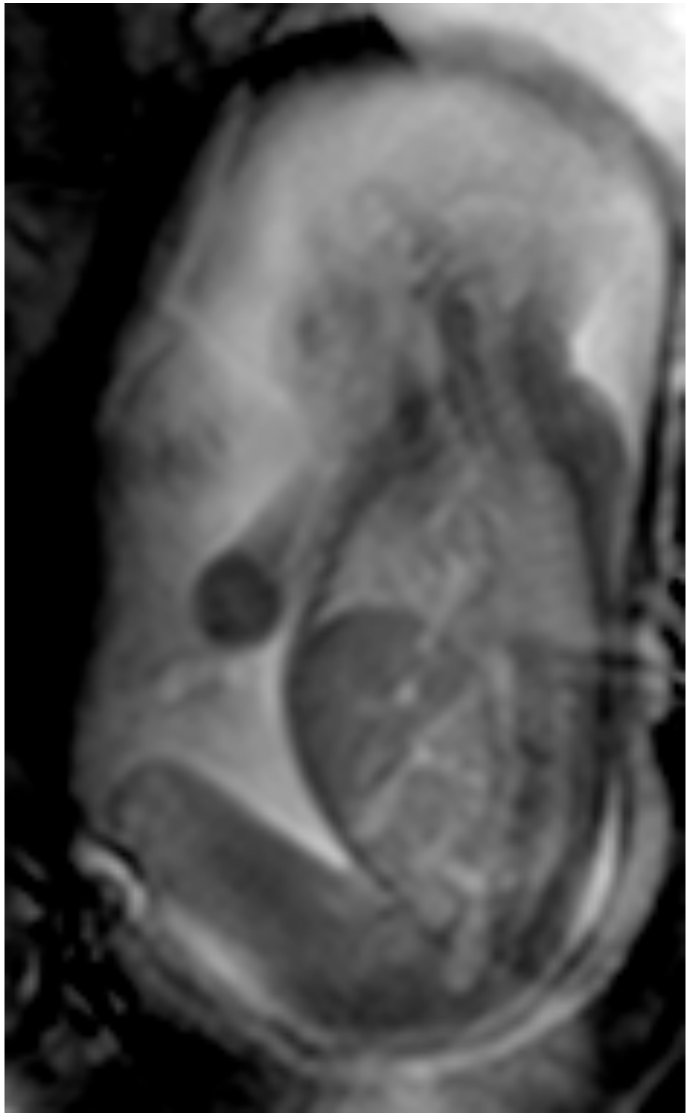


Biomarker discovery

Example: Fetal MR imaging

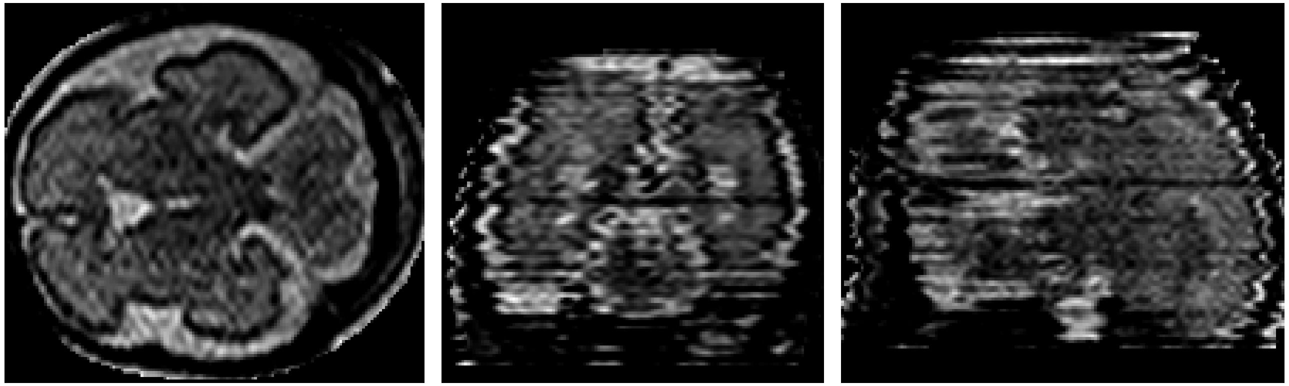
Challenges:

1. Long acquisition times
2. Fetal motion and maternal breathing



fast single-shot techniques are 2D acquisitions that freeze the motion in time **but ...**

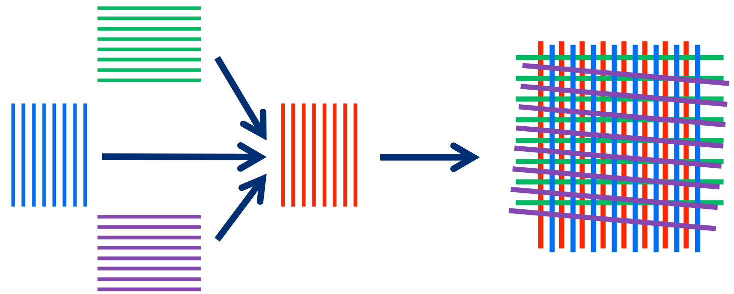
Motion compensated fetal MRI



Motion compensated fetal MRI

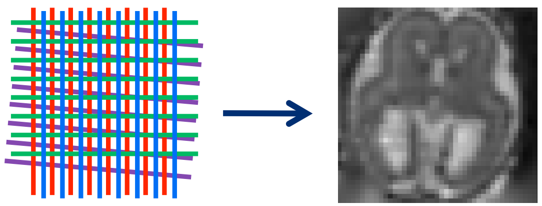
Acquisition:
several loops of single-shot slices

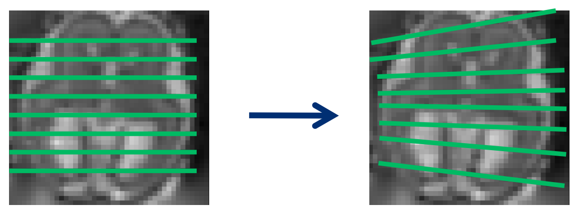
Volumetric registration:
aligning stacks (1 loop) to a stack



3D reconstruction:
interpolation of the slices to reconstruct 3D volume

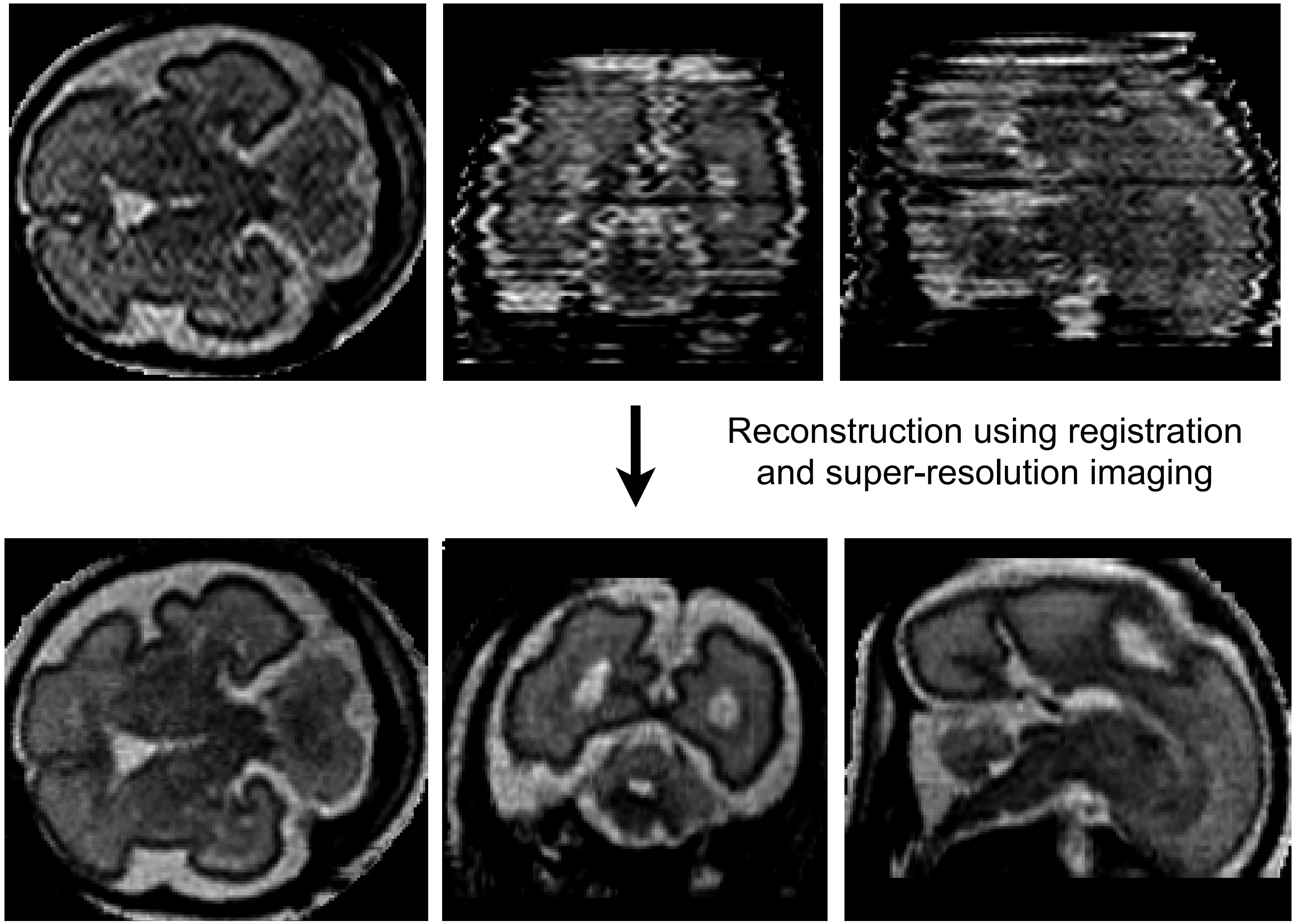
Slice-to-volume registration:
align each slice with latest reconstructed 3D volume





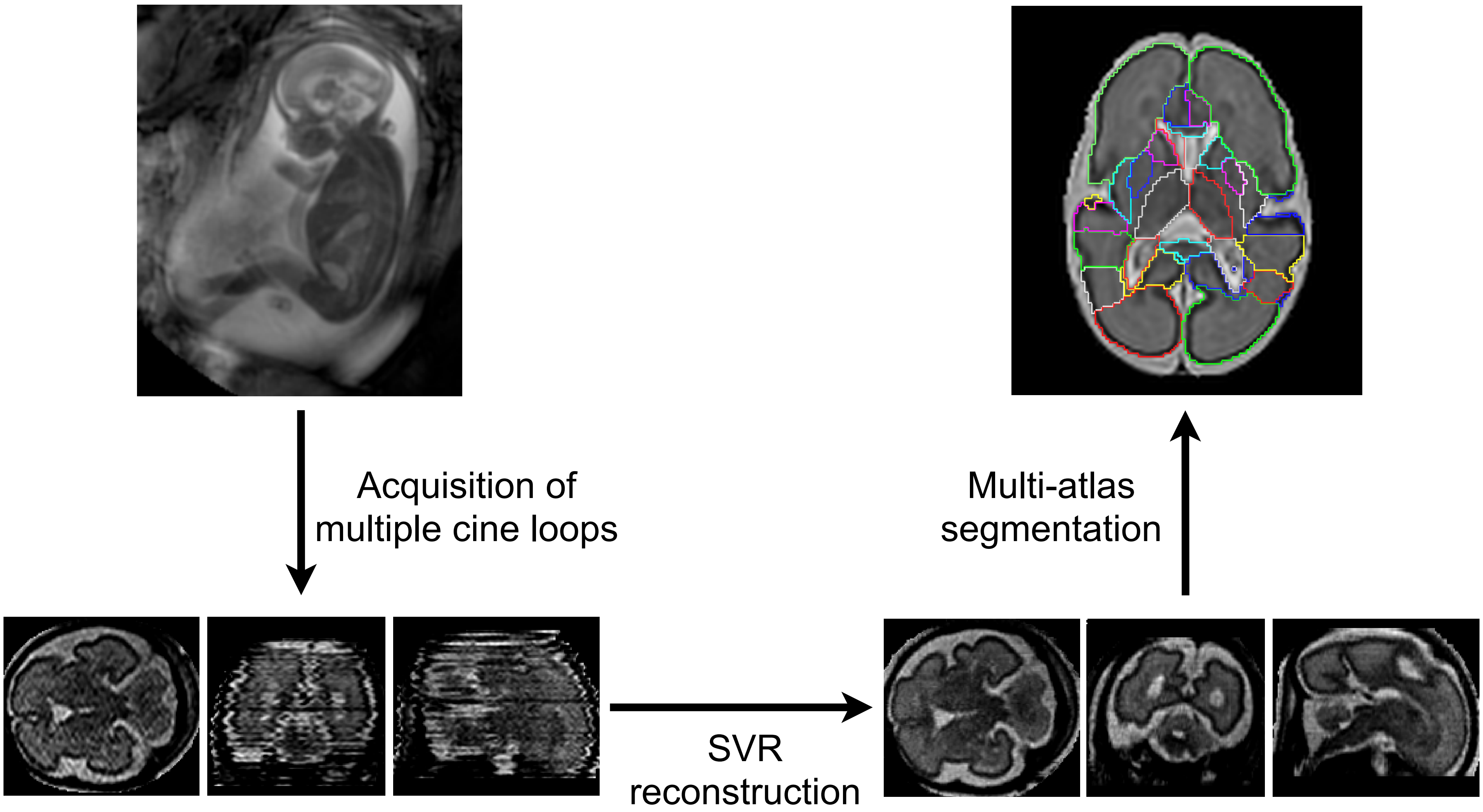
Rousseau, Academic Radiology 2006; Jiang, IEEE TMI 2007

Motion compensated fetal MRI

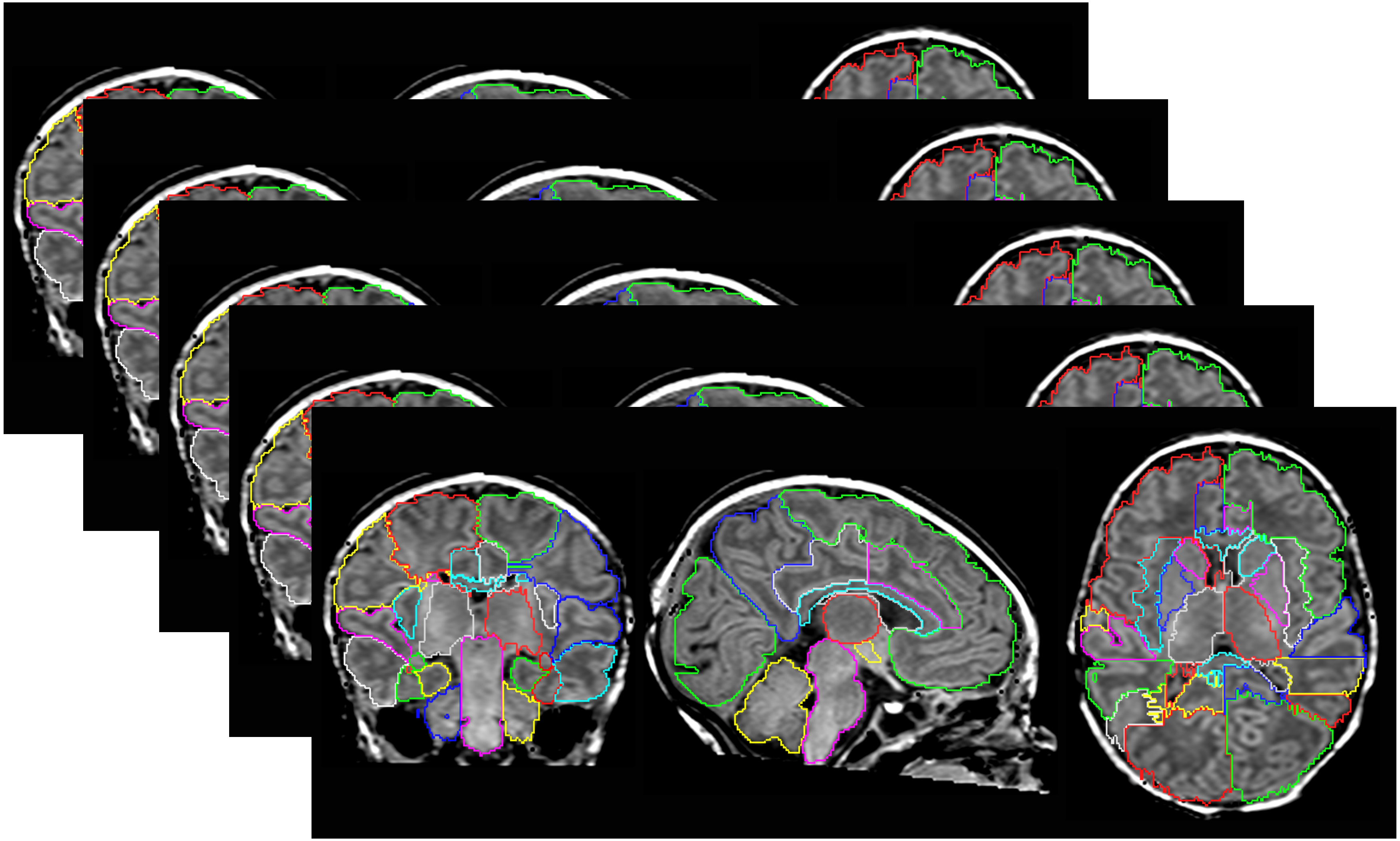


S. Jiang et al. MRI of moving subjects using multi-slice snapshot images with Volume Reconstruction. IEEE TMI, 2007.
Can also be done with DTI data (S. Jiang et al, MRM 2009)

Multi-atlas segmentation: Application to fetal MRI



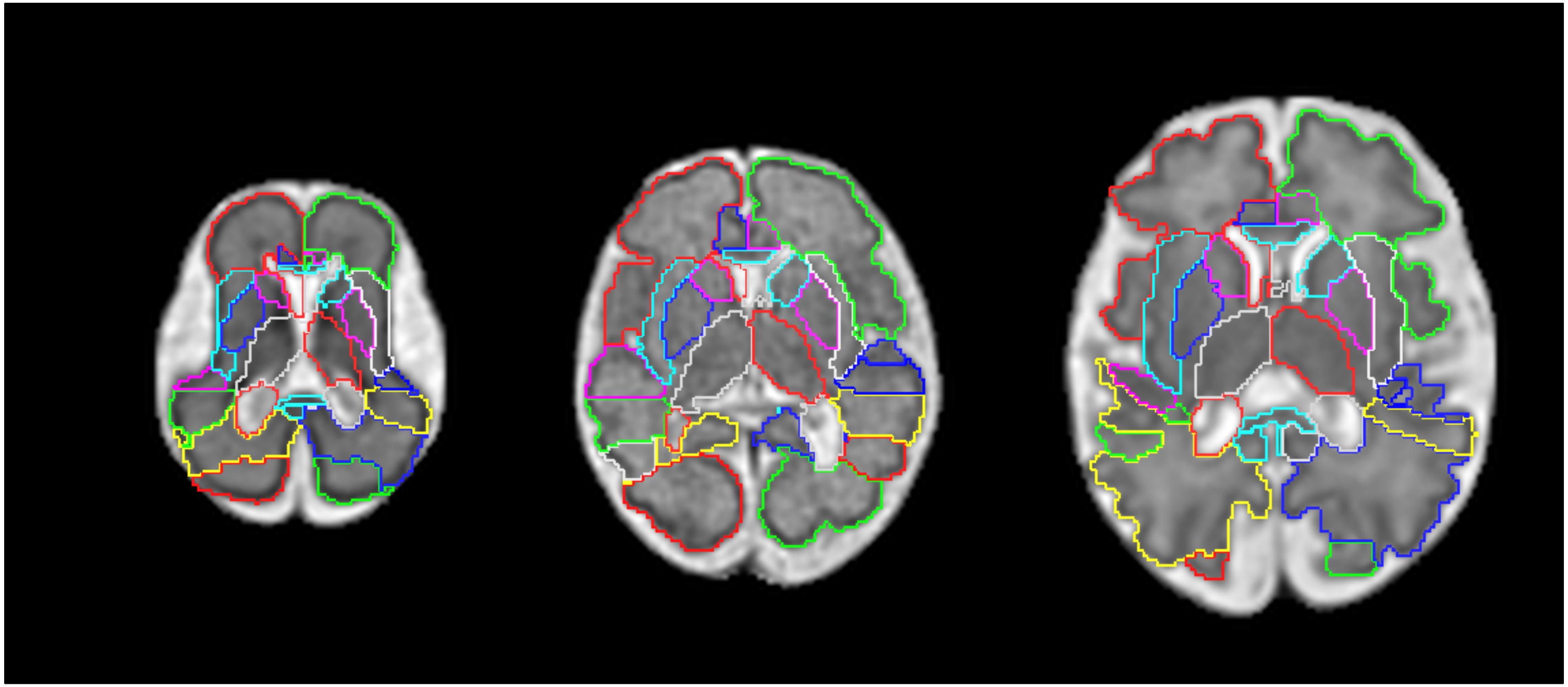
Multi-atlas segmentation: Application to neonatal and fetal MRI



20 manually labelled brain atlases dividing the brain into 50 regions

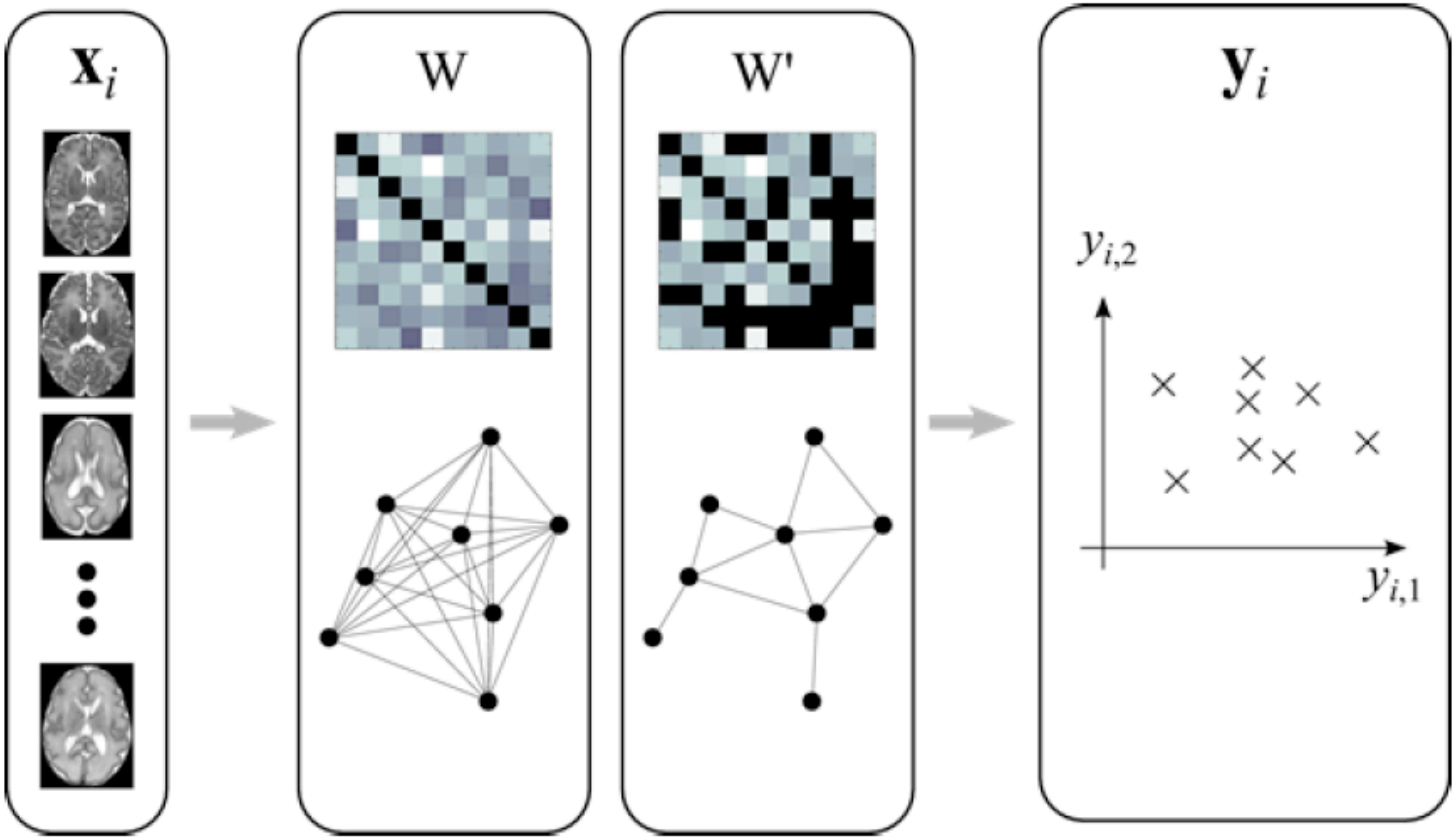
I. Gousias et al., Neuroimage, 2012

Multi-atlas segmentation: Application to fetal MRI



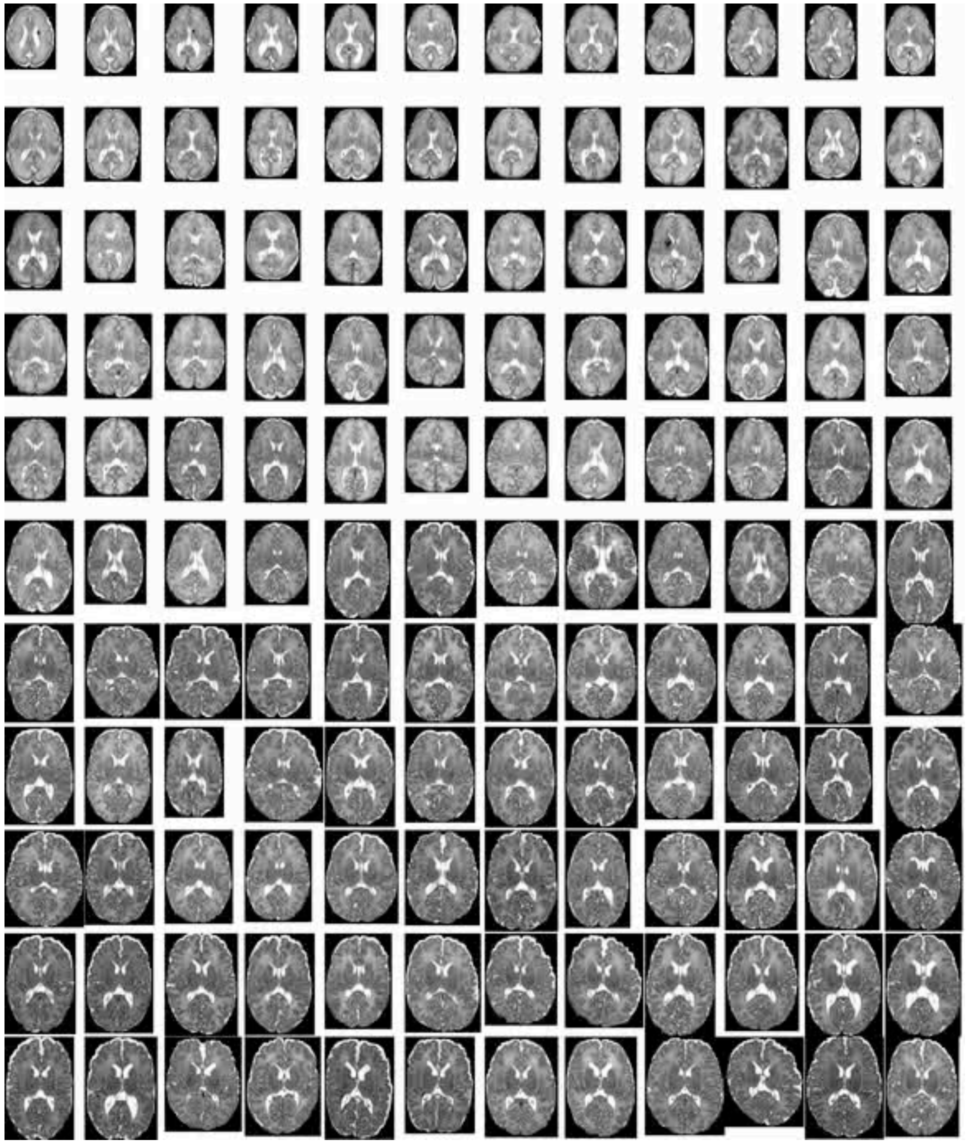
Multi-atlas segmentation: Application to fetal MRI

Manifold learning for longitudinal image analysis: Measurement of growth



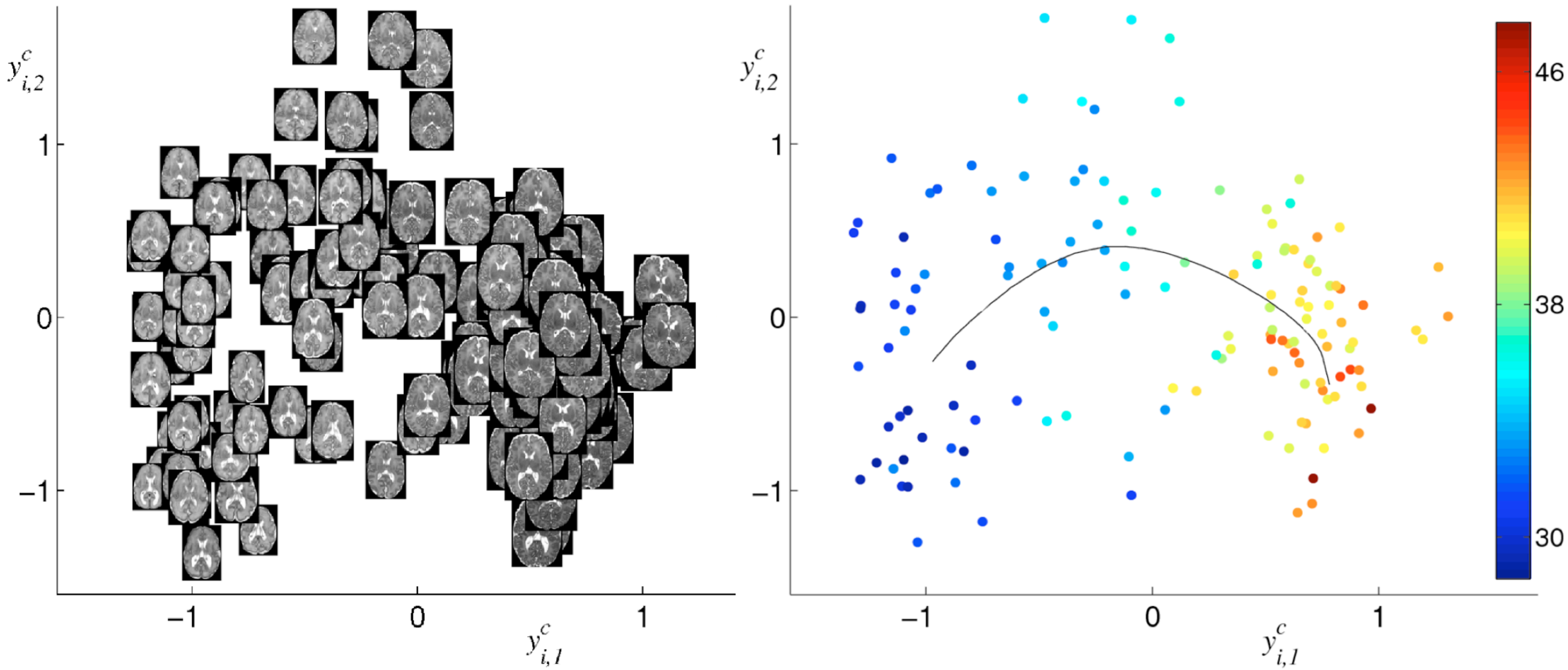
Aljabar et al., TMI, 2011

Manifold learning for longitudinal image analysis: Measurement of growth



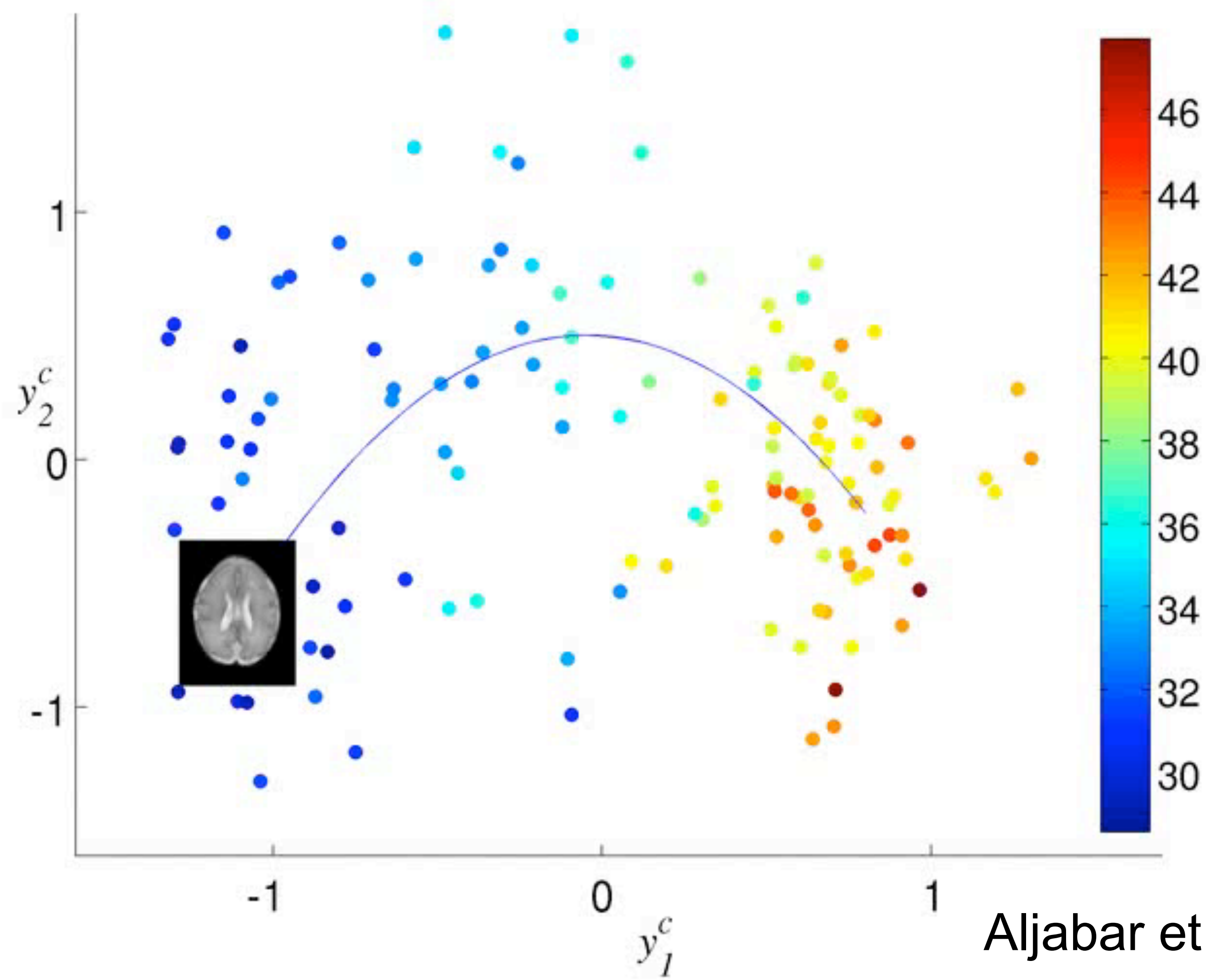
Aljabar et al., TMI, 2011

Manifold learning for longitudinal image analysis: Measurement of growth



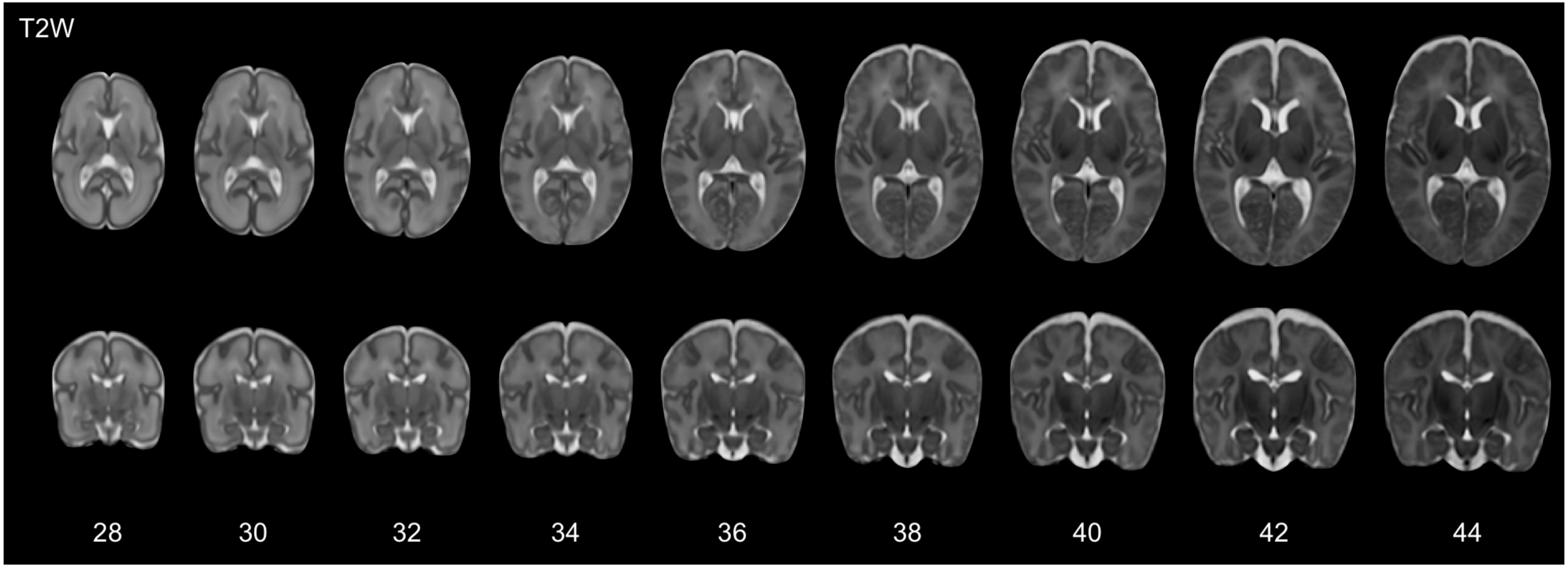
Aljabar et al., TMI, 2011

Manifold learning for longitudinal image analysis: Measurement of growth



Aljabar et al., TMI, 2011

Spatio-temporal atlas of brain development



A. Serag et al., Neuroimage, 2012

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