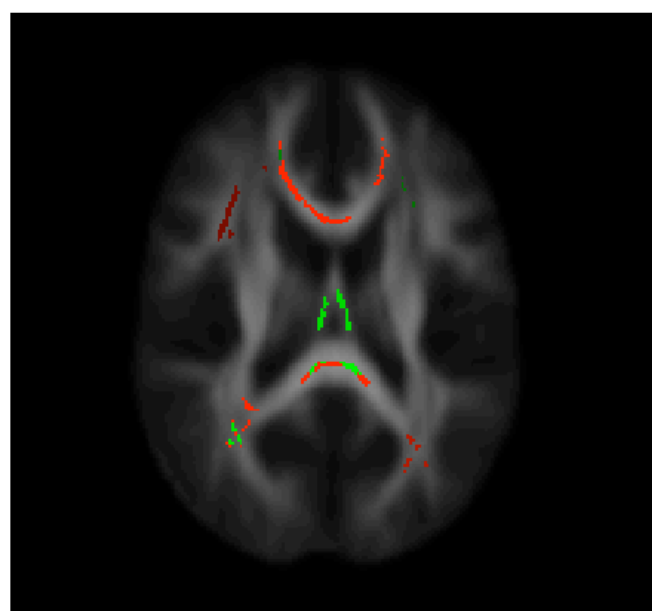
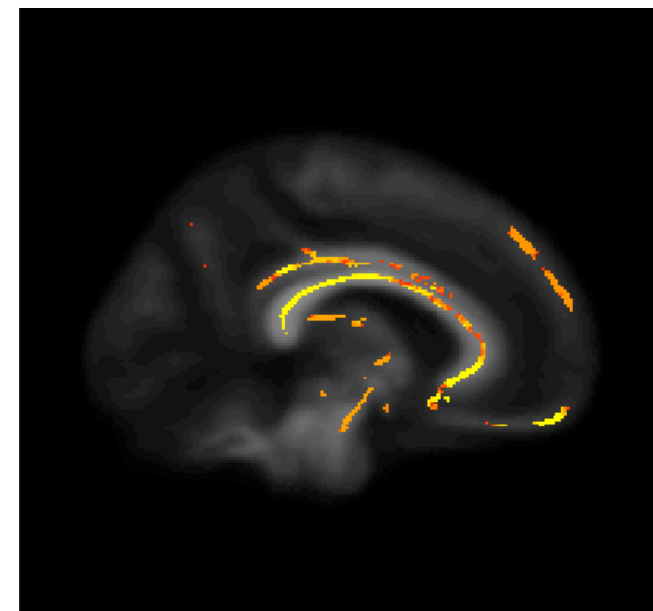
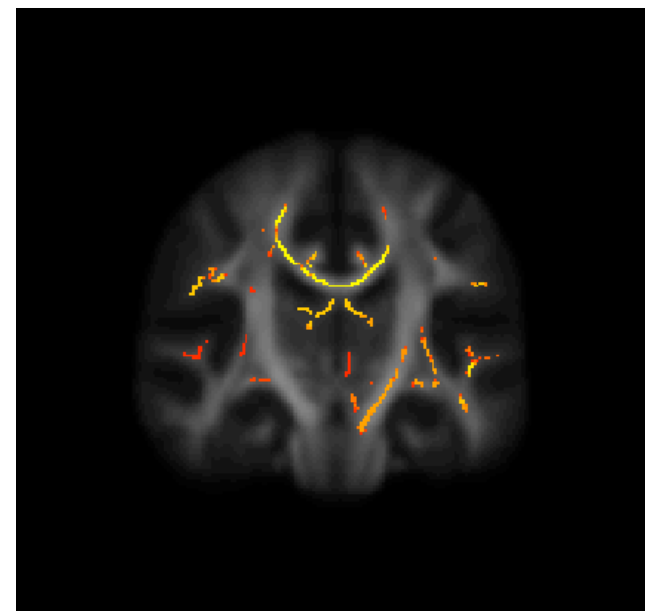
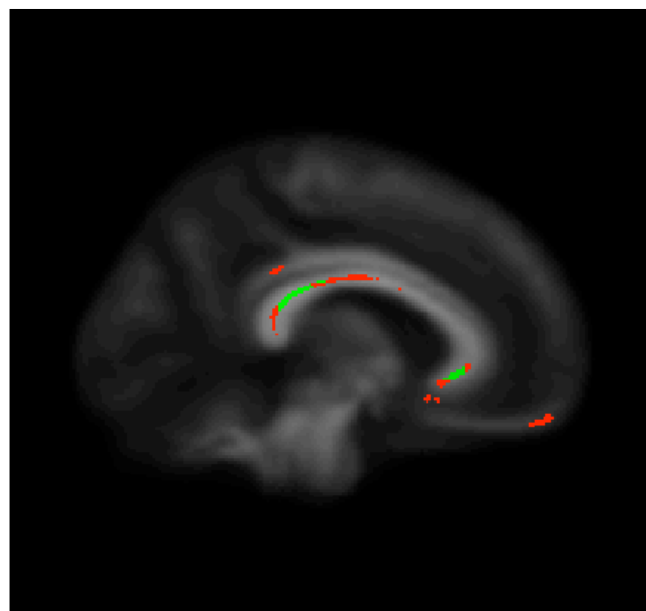
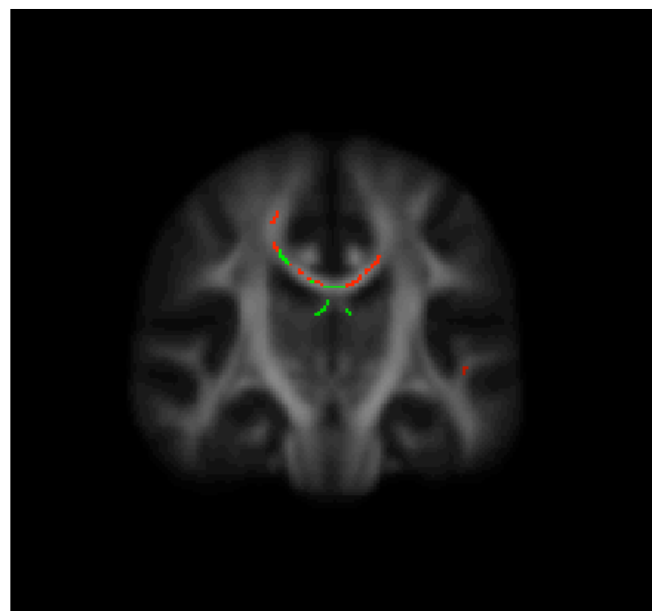




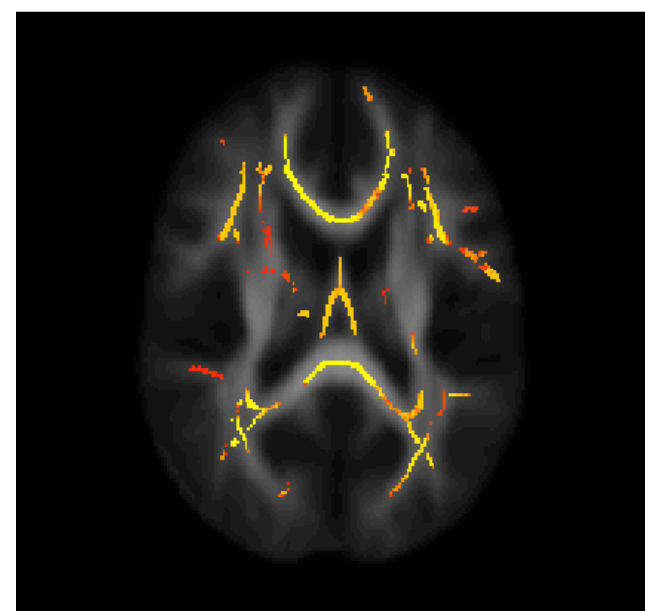
# TFCE for TBSS

controls > schizophrenics

$p < 0.05$  corrected for multiple comparisons across space,  
using randomise



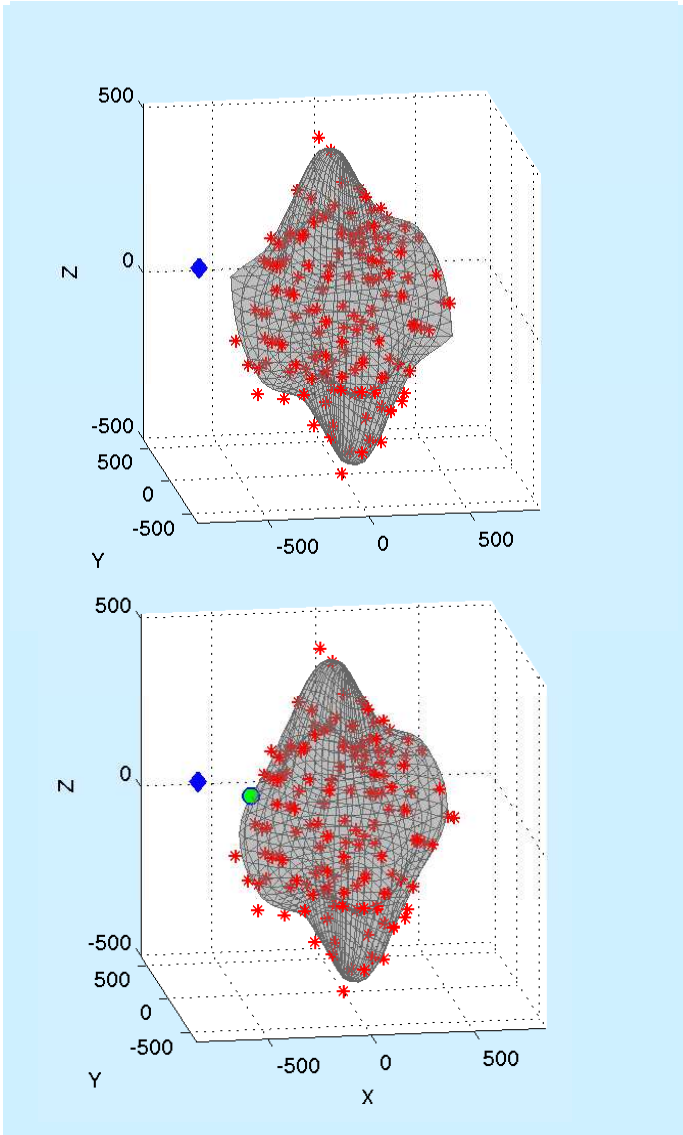
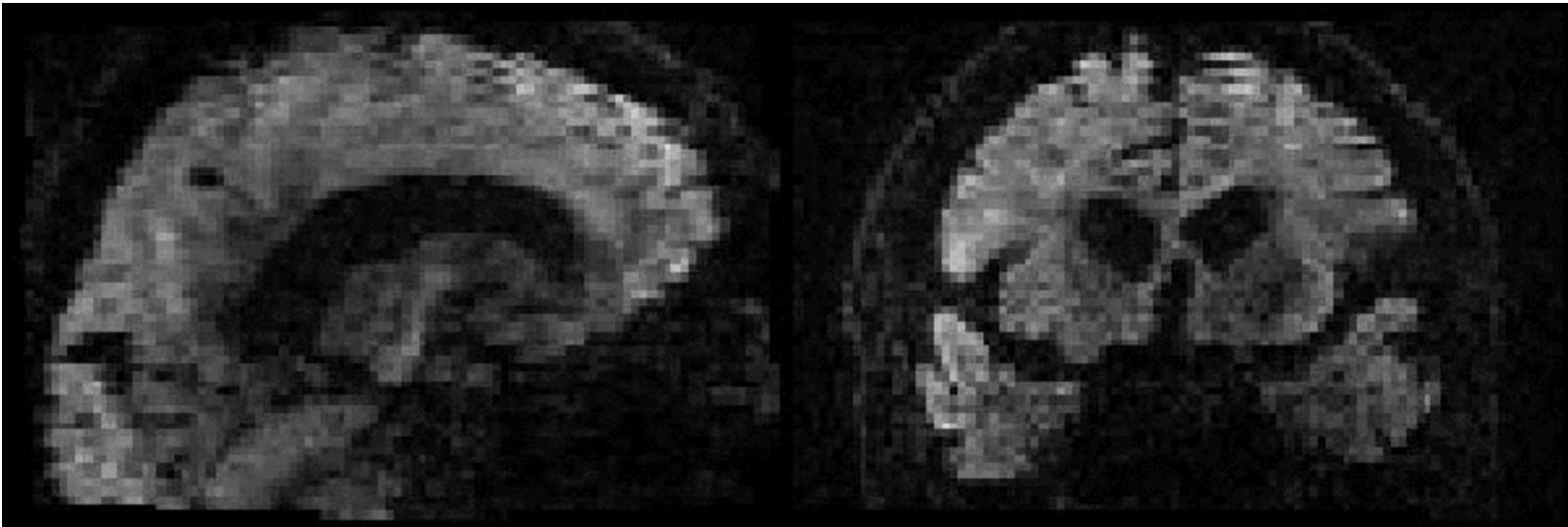
cluster-based:  
cluster-forming  
threshold =  
**2** or **3**



TFCE

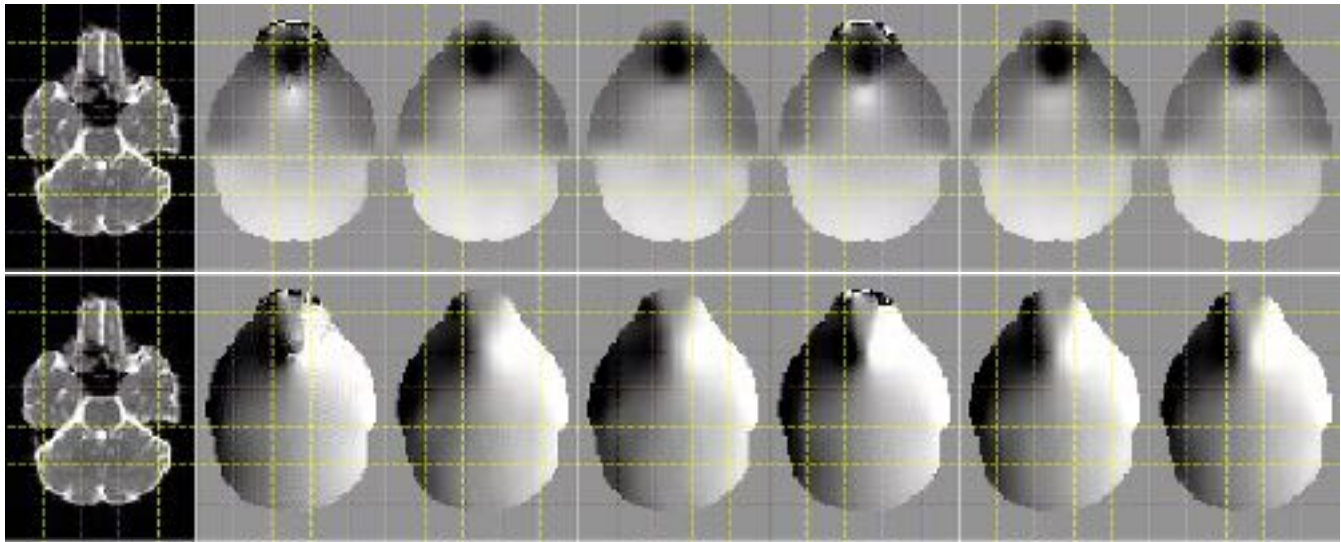


# eddy - Advanced features



$$\frac{\partial \omega}{\partial \theta}$$

$$\frac{\partial \omega}{\partial \phi}$$





# Outline of the talk

- “Advanced” eddy features
  - Movement-induced dropout
  - Intra-volume motion
  - Susceptibility-by-movement



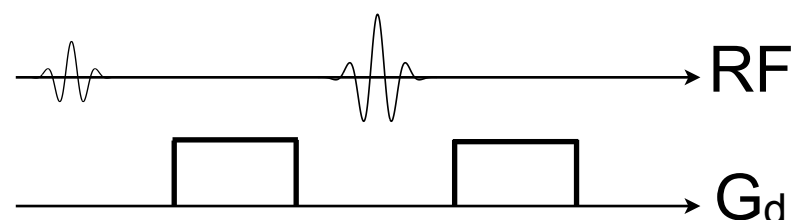
# Outline of the talk

- “Advanced” eddy features
  - Movement-induced dropout
  - Intra-volume motion
  - Susceptibility-by-movement

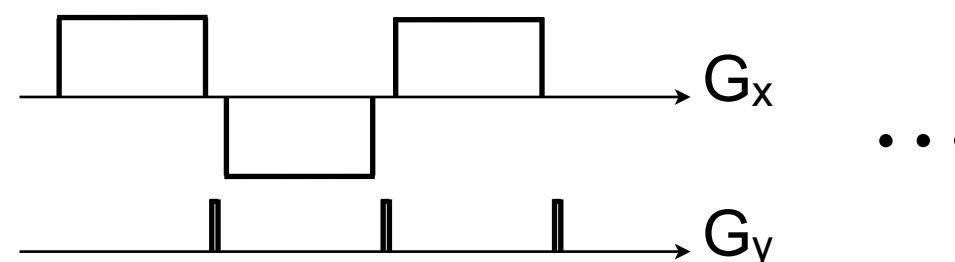


# Movement induced dropout

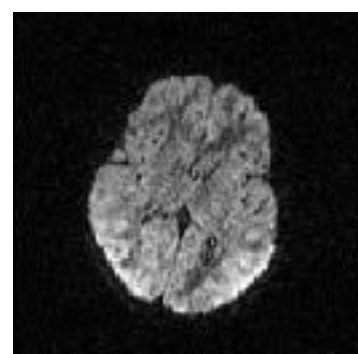
## Diffusion encoding



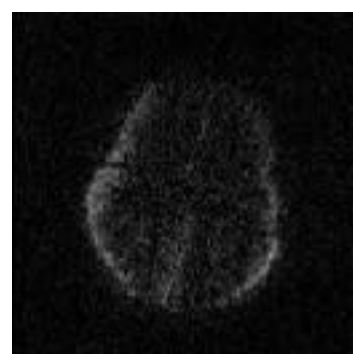
## Image encoding



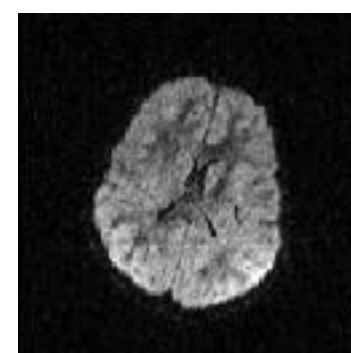
If there is movement during this part...



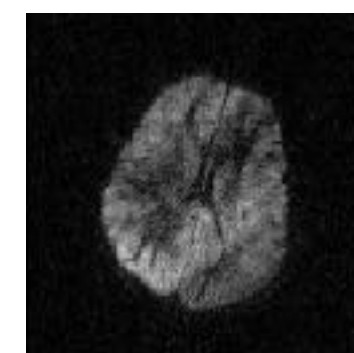
this



can turn  
to this



or this



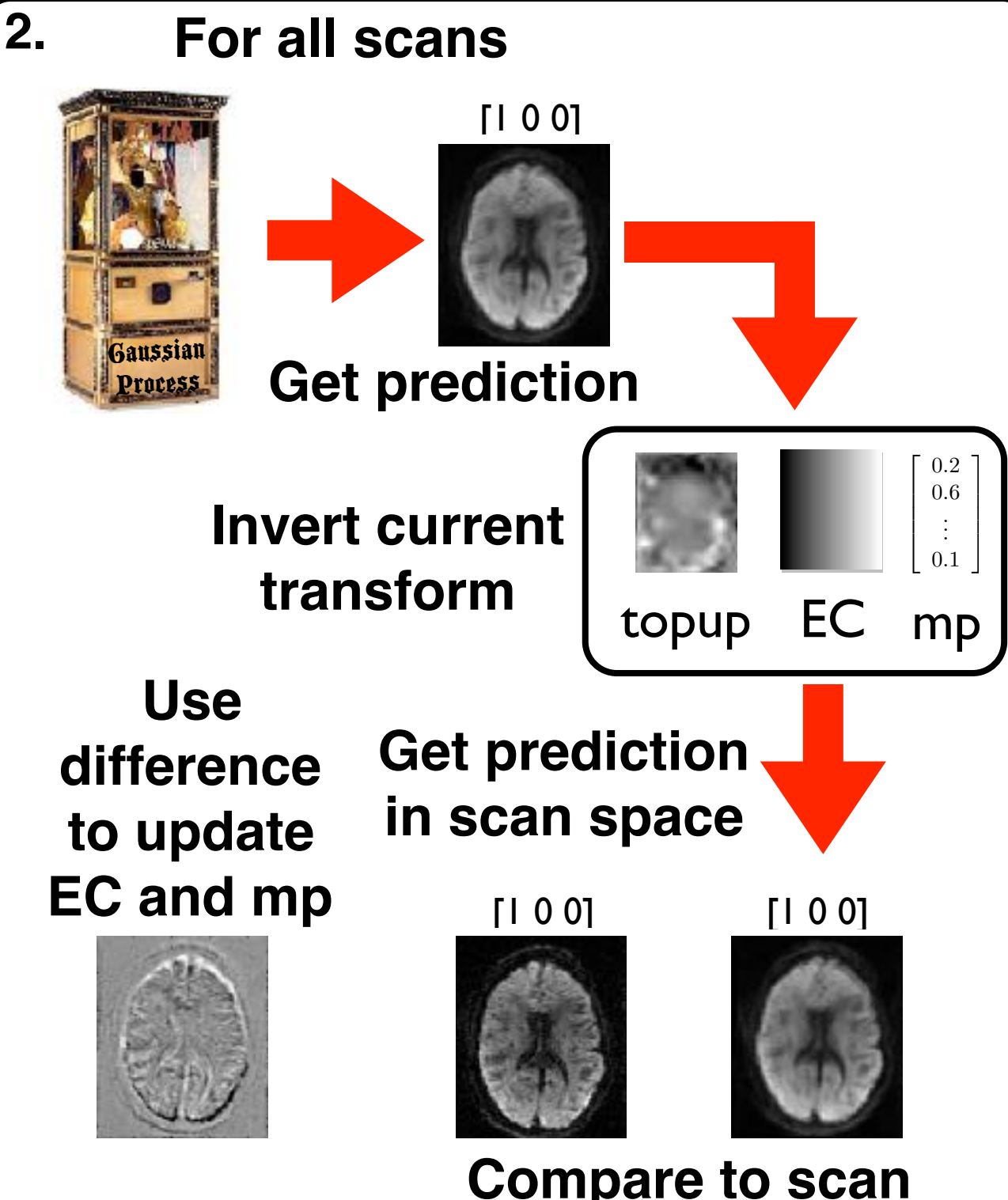
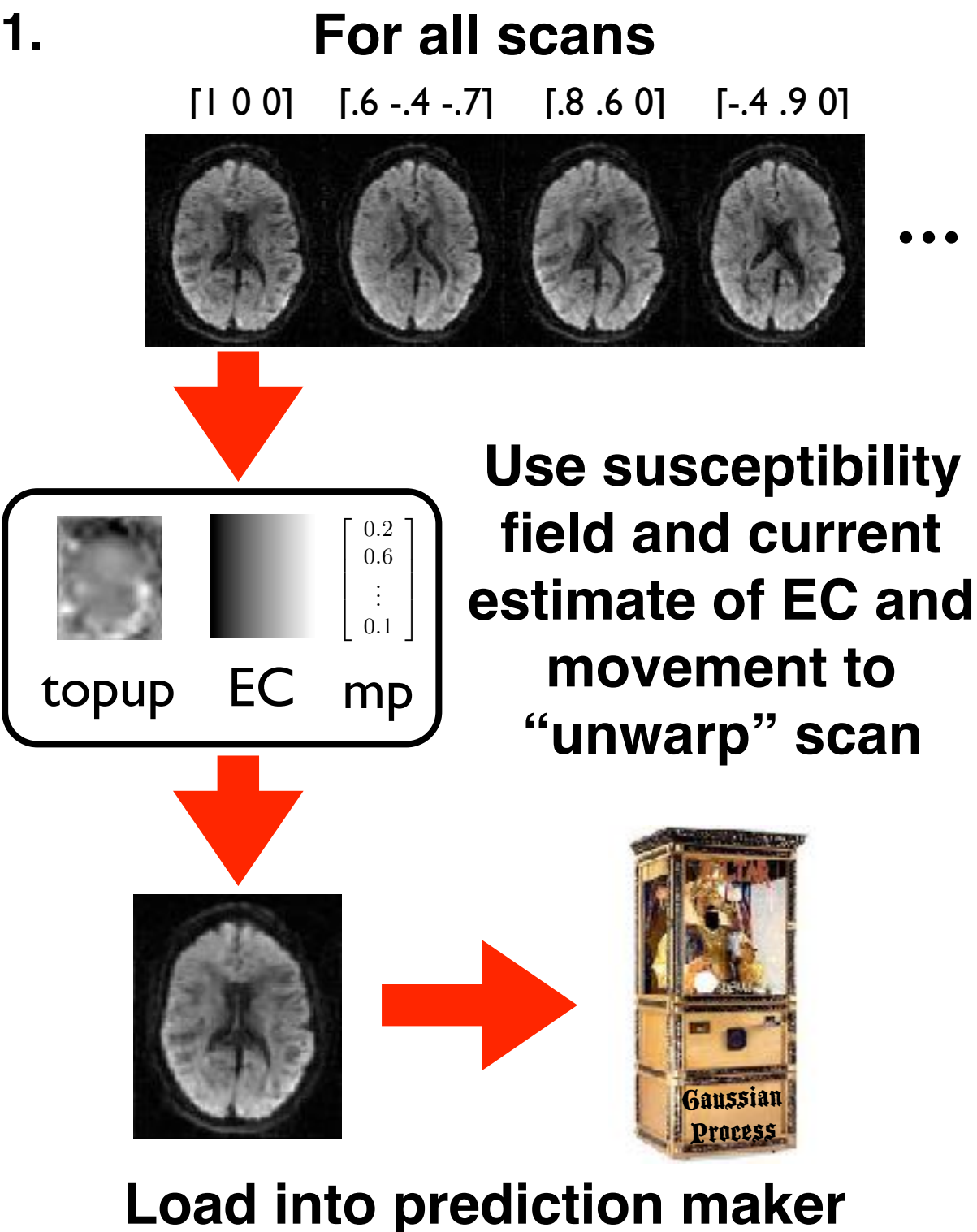
to this





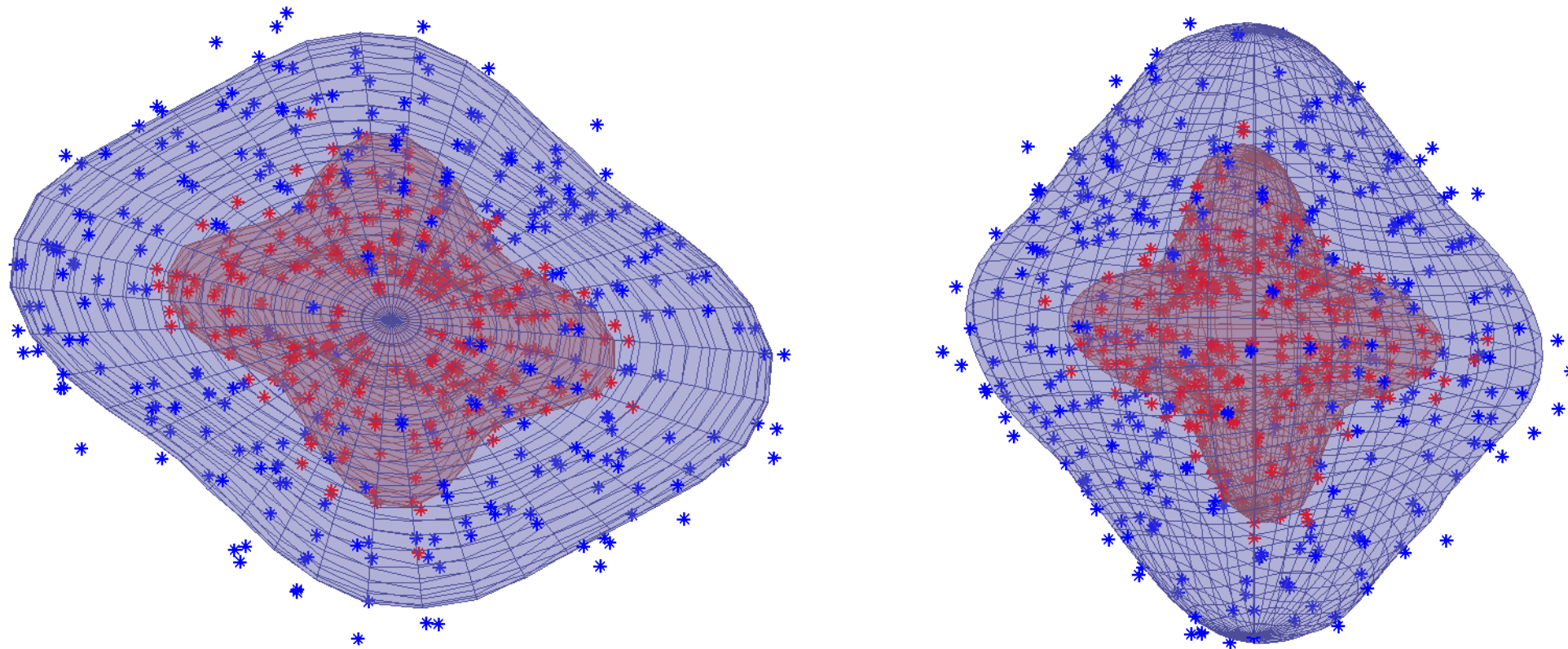
# What can eddy do about it?

## But first a little recap of eddy





# How are the predictions made?



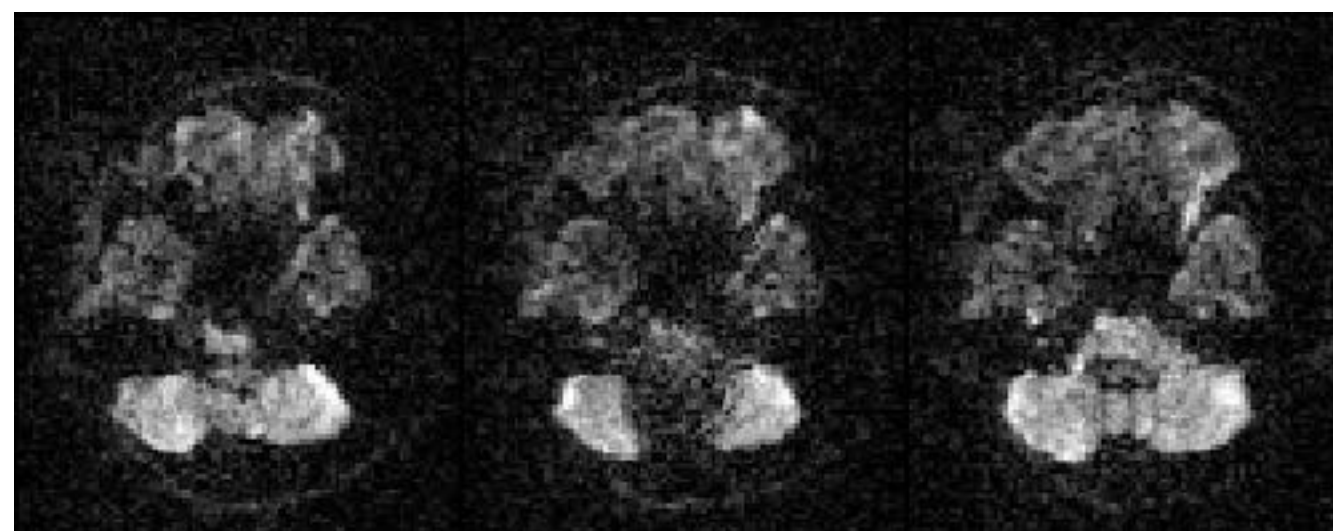
A Gaussian process that simply assumes that the signal varies smoothly as we move in Q-space  
Very few assumptions. Hyperparameters calculated by leave-one-out.

$$\hat{y}_{\mathbf{g}} = K(\mathbf{g}, \mathbf{G}) [K(\mathbf{G}, \mathbf{G}) + \sigma^2 \mathbf{I}]^{-1} \mathbf{y}$$

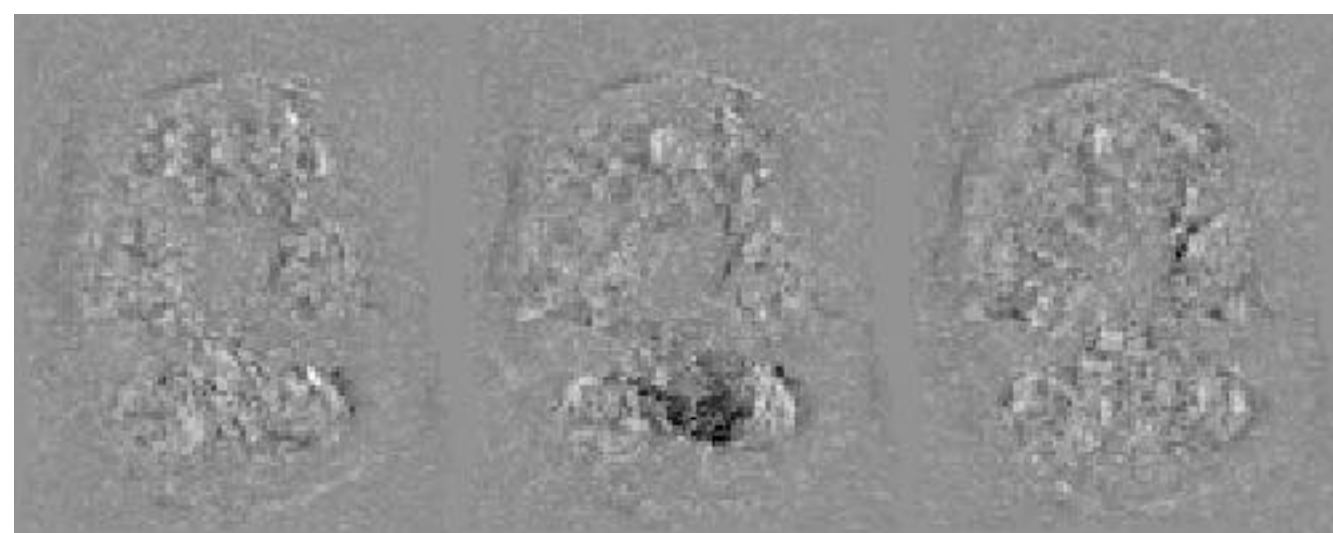


# Outlier detection

Observed data



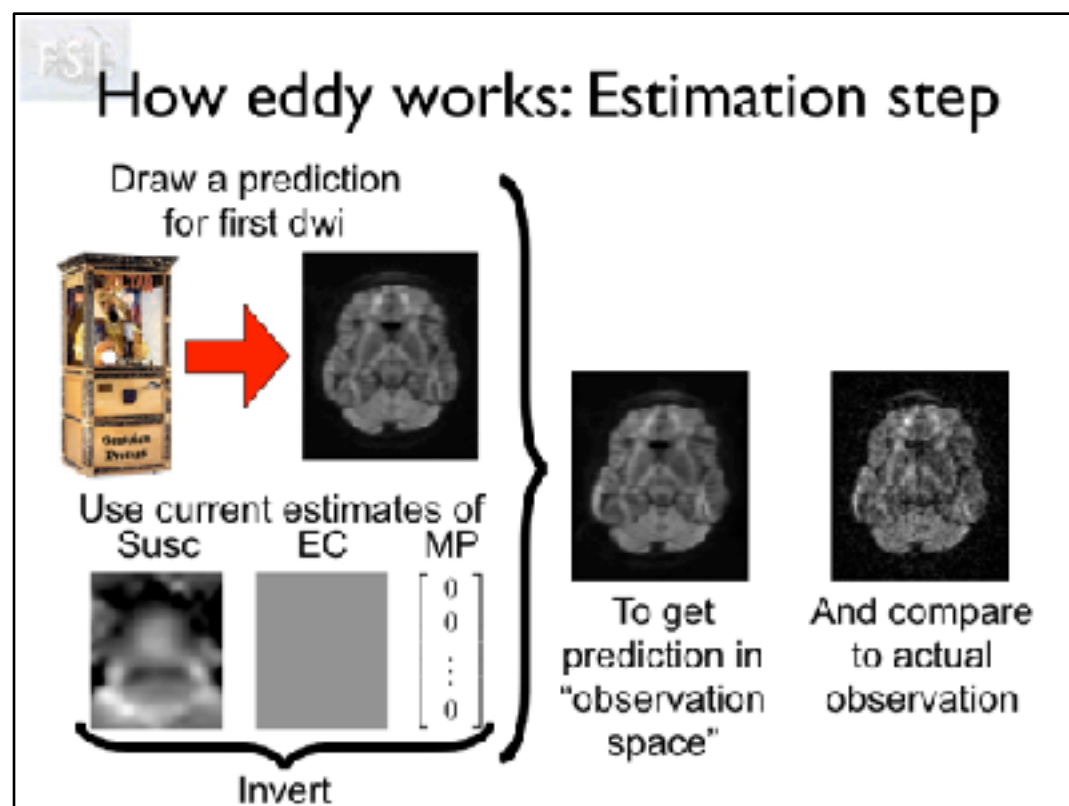
Observed - predicted



$$\bar{x} = 0.084 \quad \bar{x} = -0.791 \quad \bar{x} = -0.125$$

Remember that we do all comparisons in observation space.

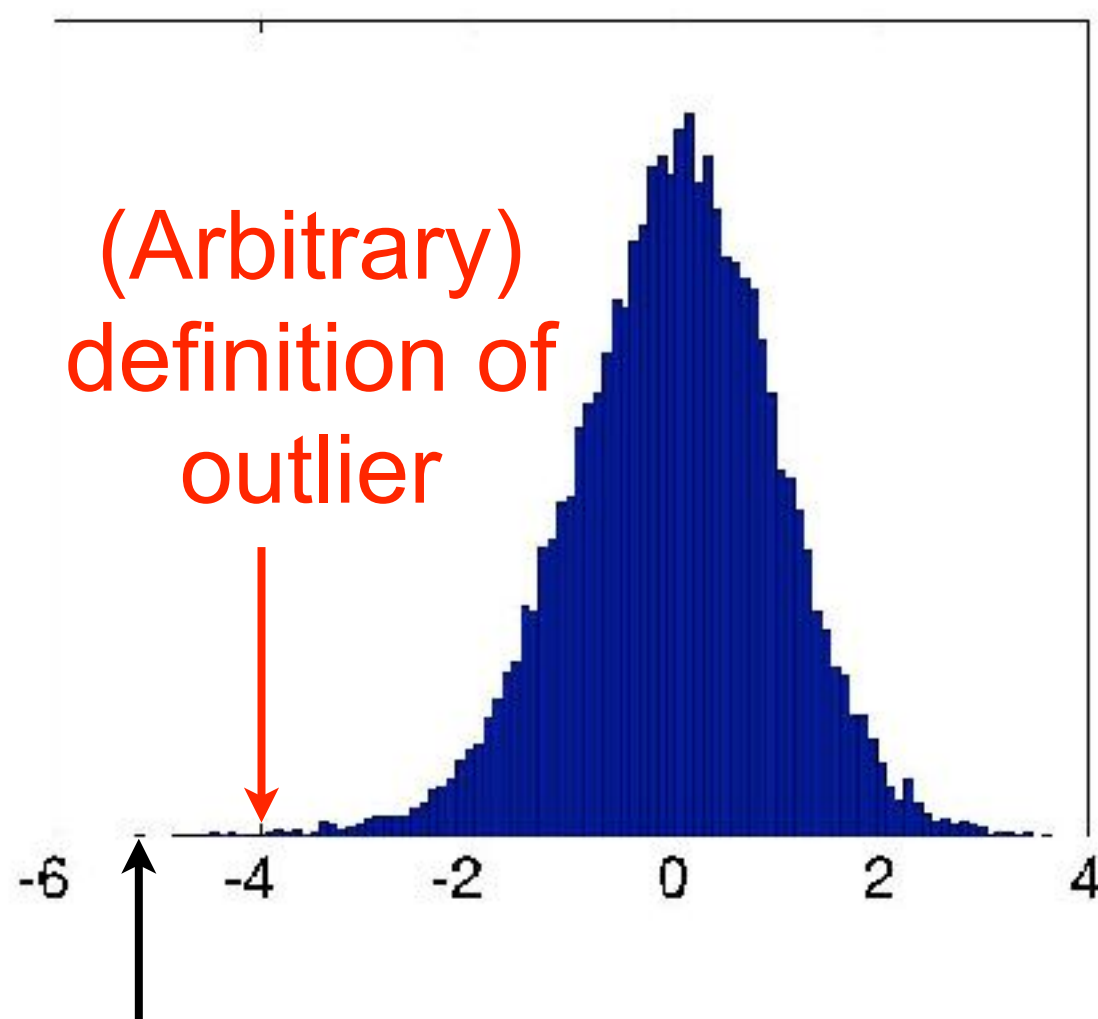
This allows us to calculate the per-slice mean difference between observation and prediction



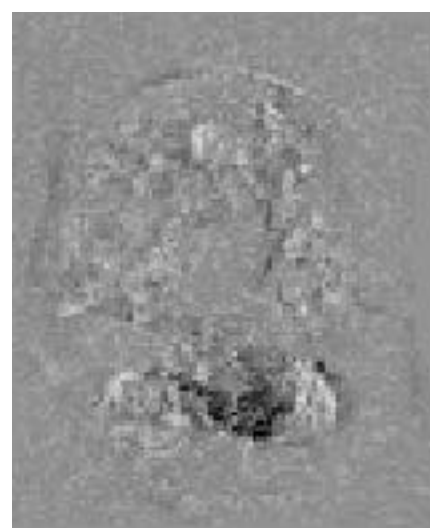




# Outlier detection



We can calculate the mean difference for every slice in every volume and get an empirical distribution that we can convert to z-scores



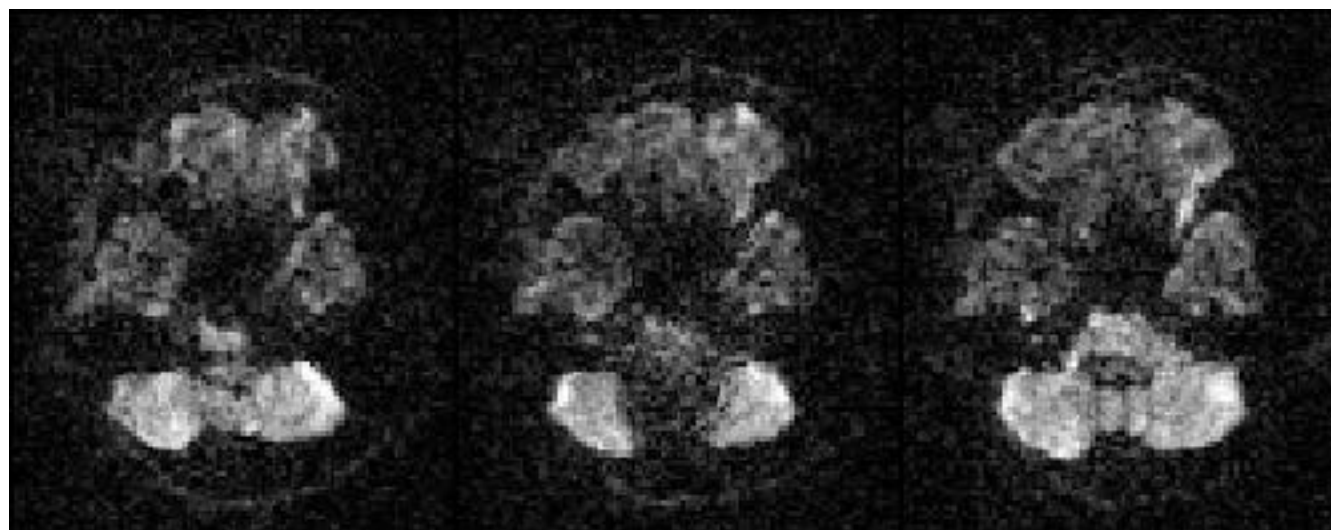
We can define an outlier slice as one with a z-score above an (arbitrary) threshold. We then have a choice of reporting outliers and/or replacing them with their predictions.

Worst slice

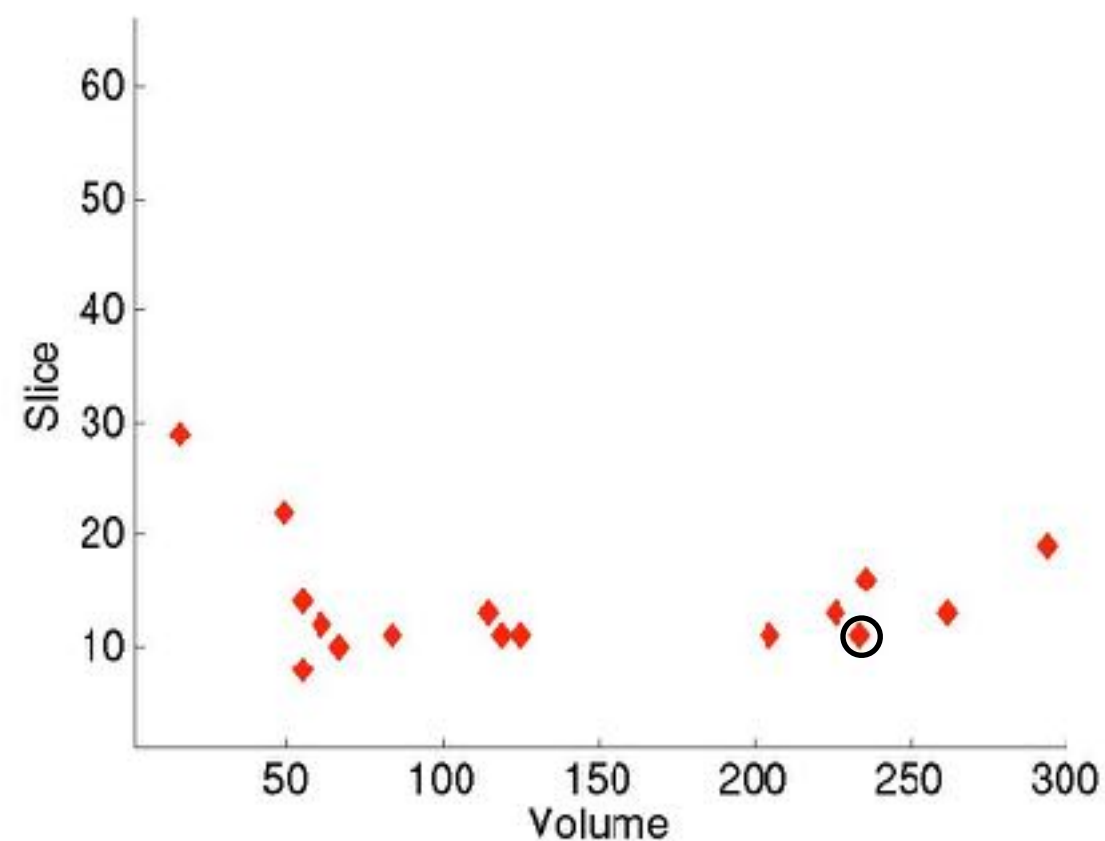
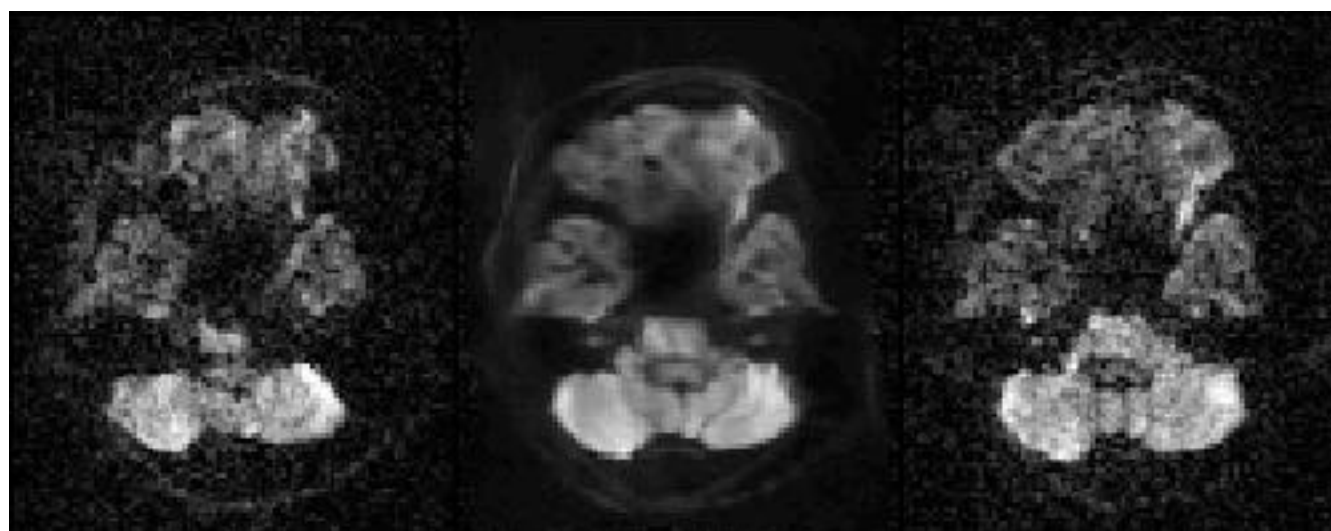


# Outlier detection

Original data



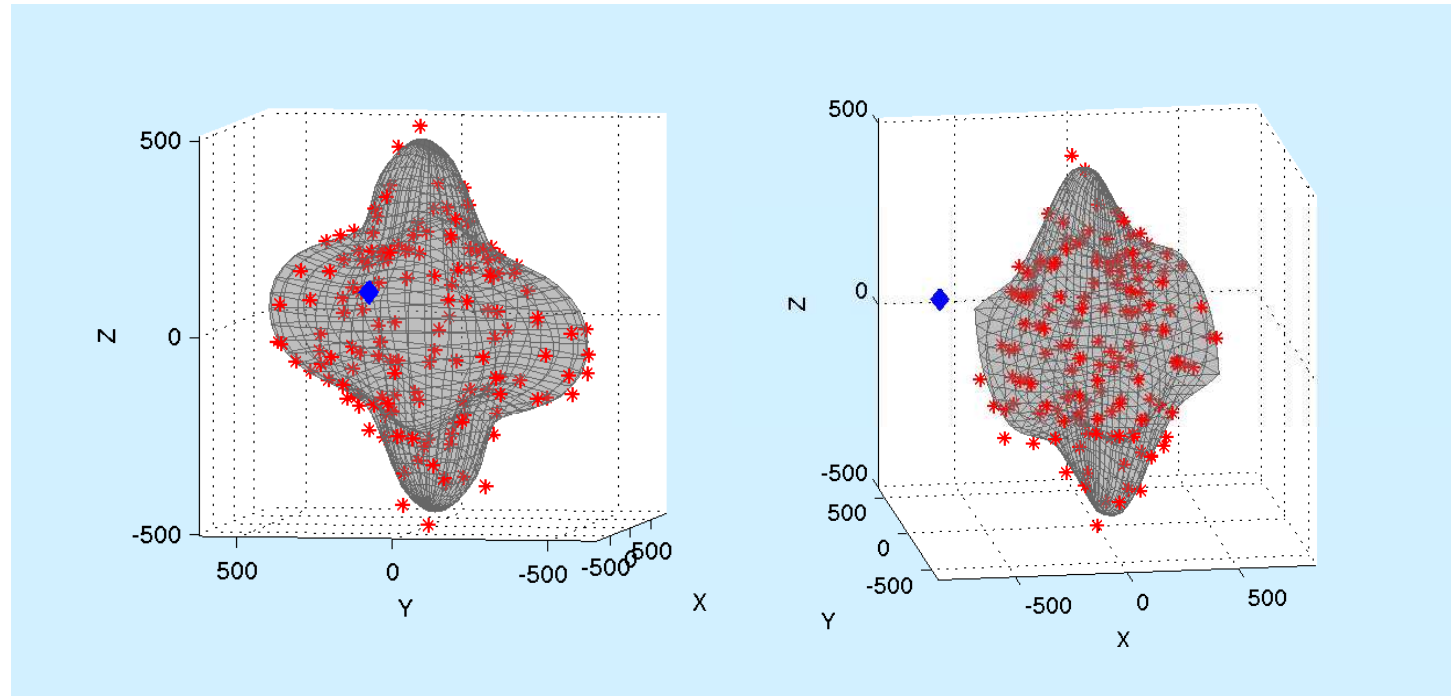
Data after replacement



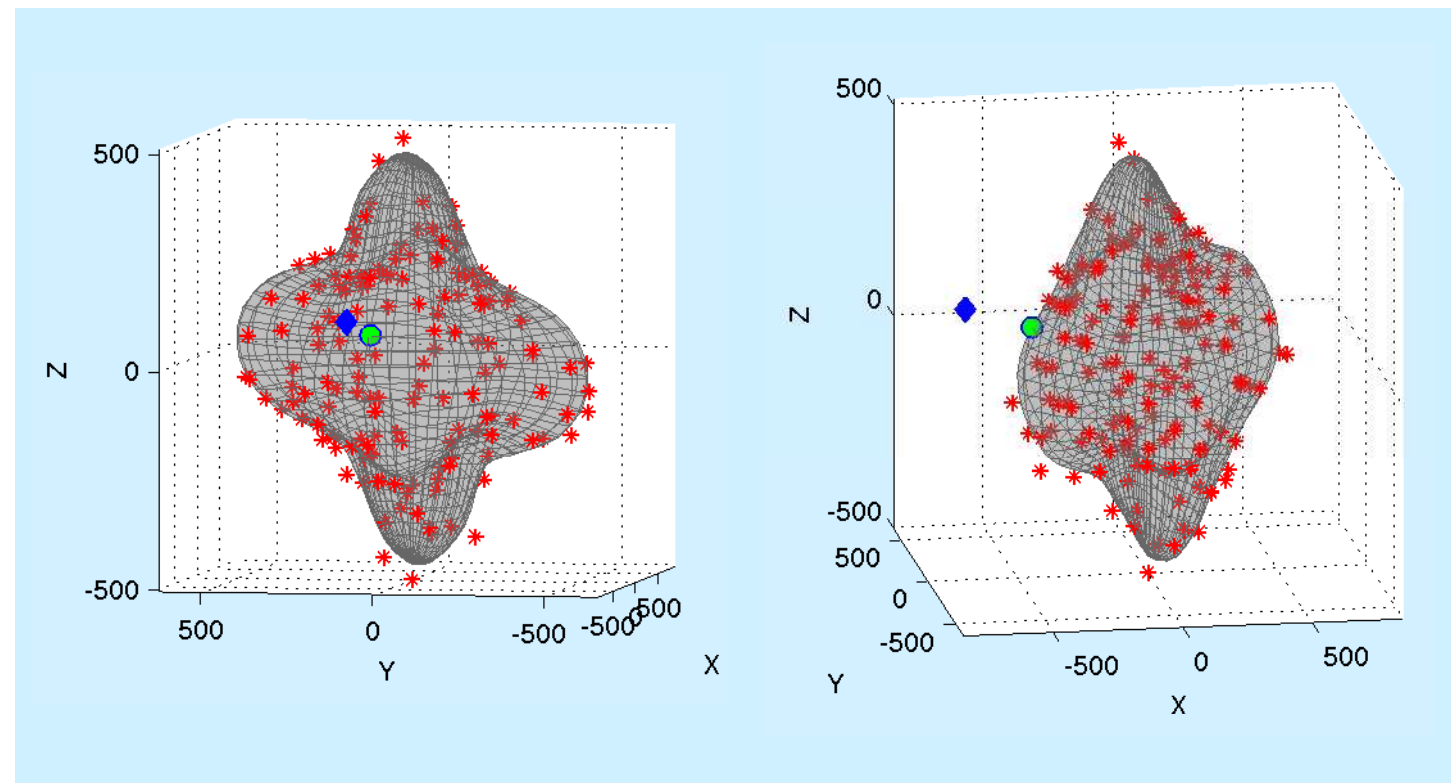
Outliers for a very still volunteer. Outliers mainly in basal slices.



# How to make the “right” prediction



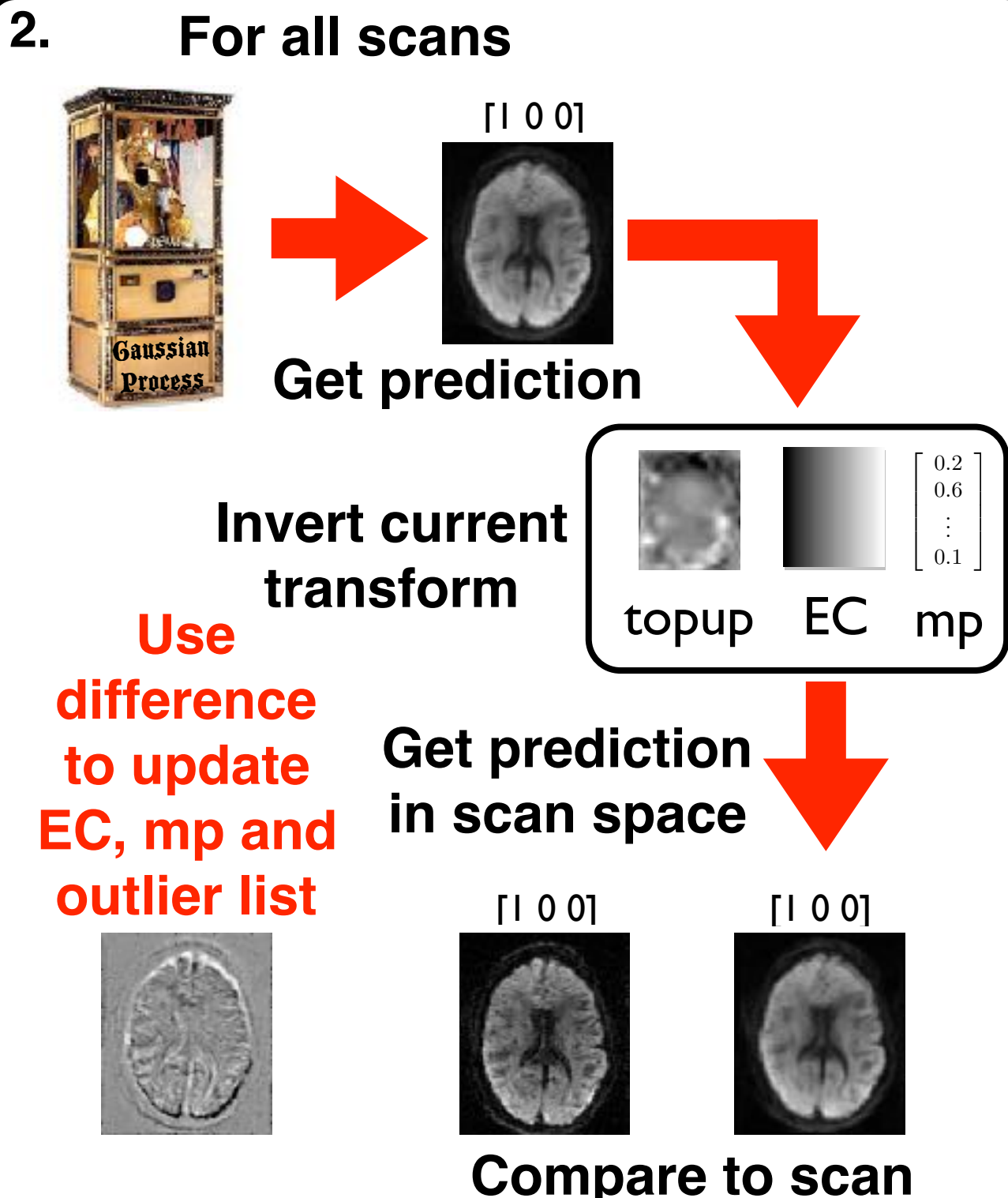
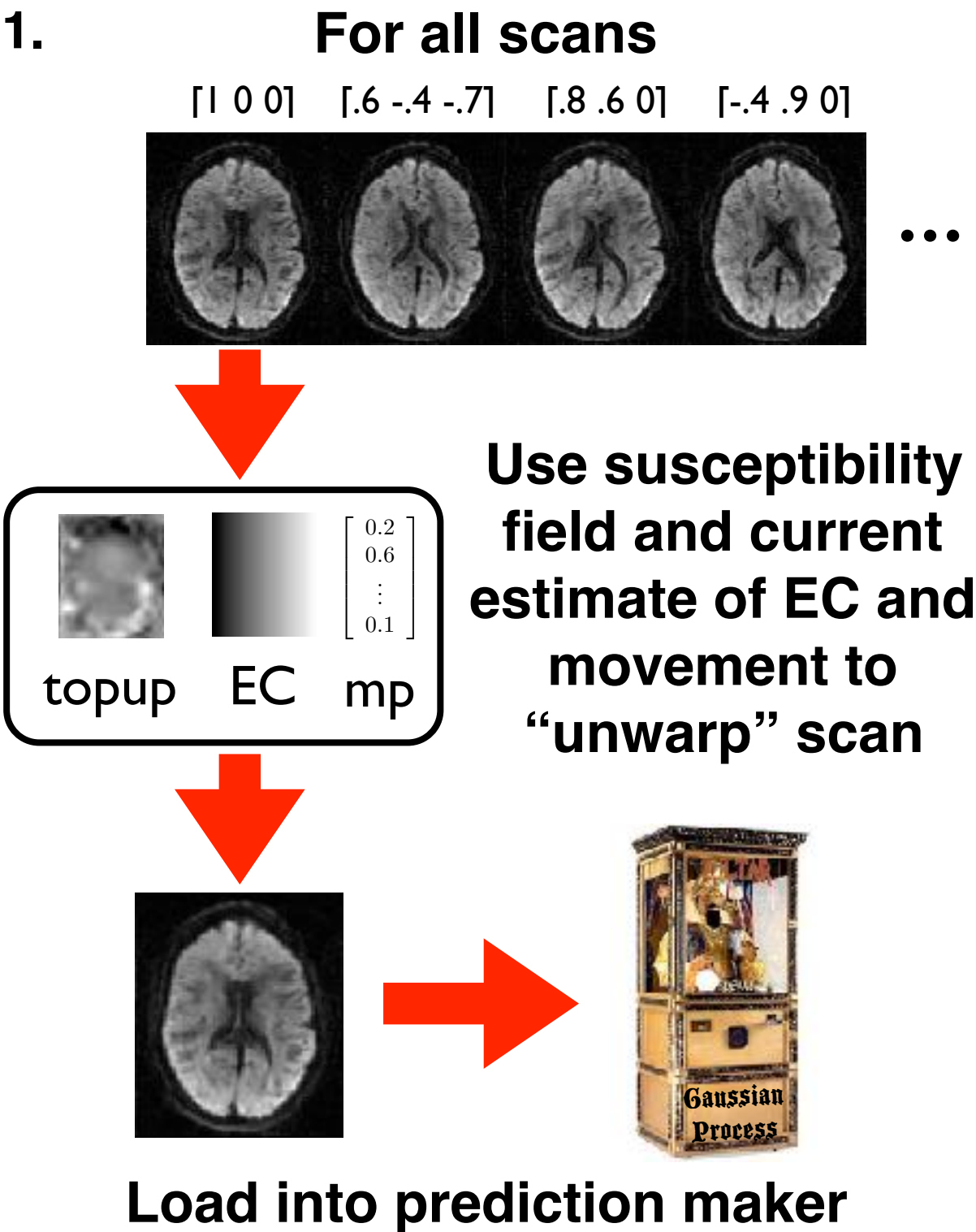
The outlier skews the predictions, but is still recognisable as an outlier



Remove the outlier and recalculate the “model”. The prediction is taken from this new “model”.



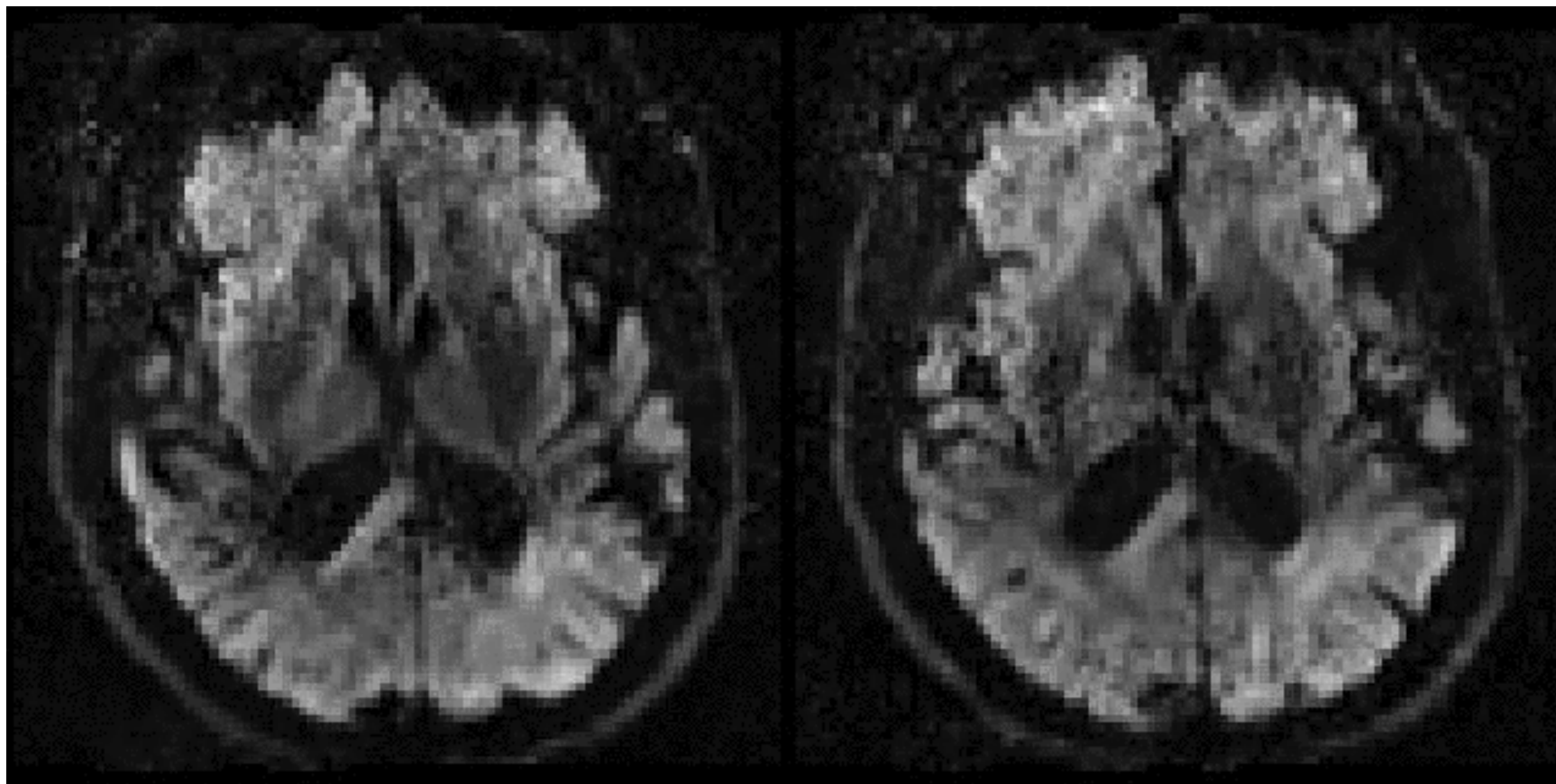
# eddy revisited







# Outlier detection



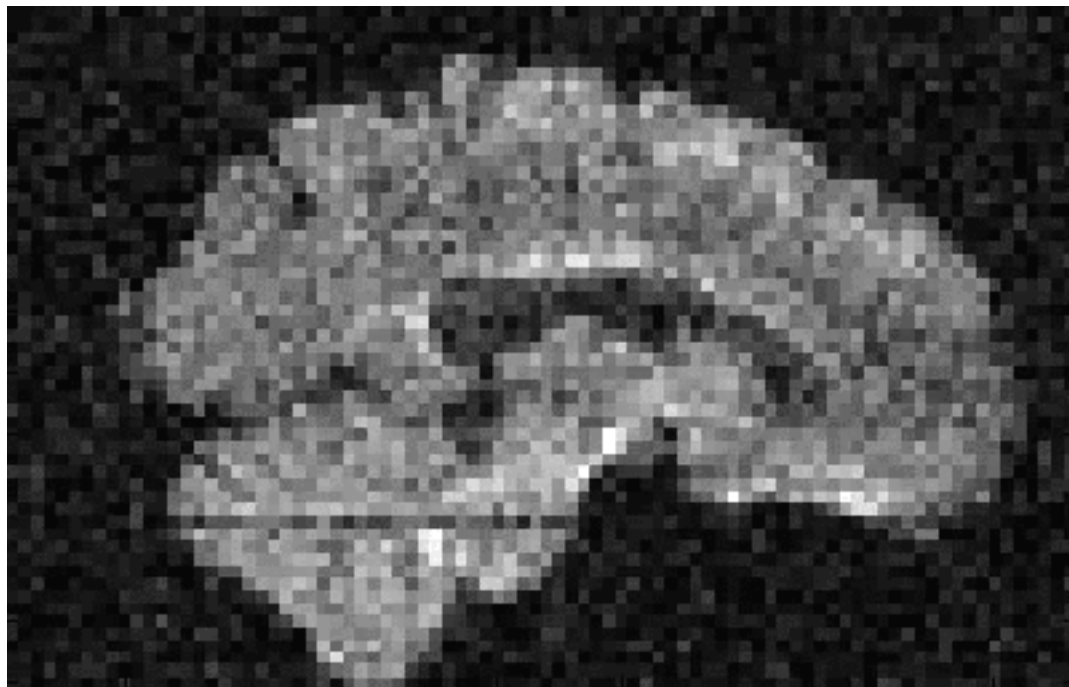
If movement correction is performed with outliers in place they will be rotated into “diagonal bands” in the corrected images.



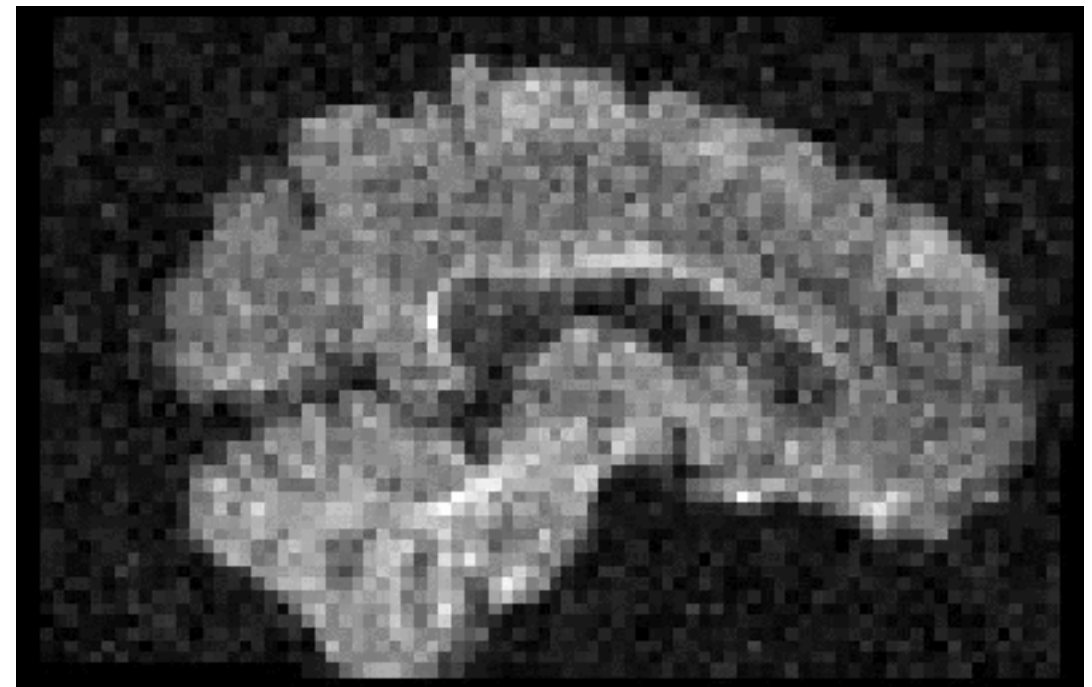
# How accurate are the predictions?

## Simulated data

Simulations courtesy of Mark Graham, UCL.



Before

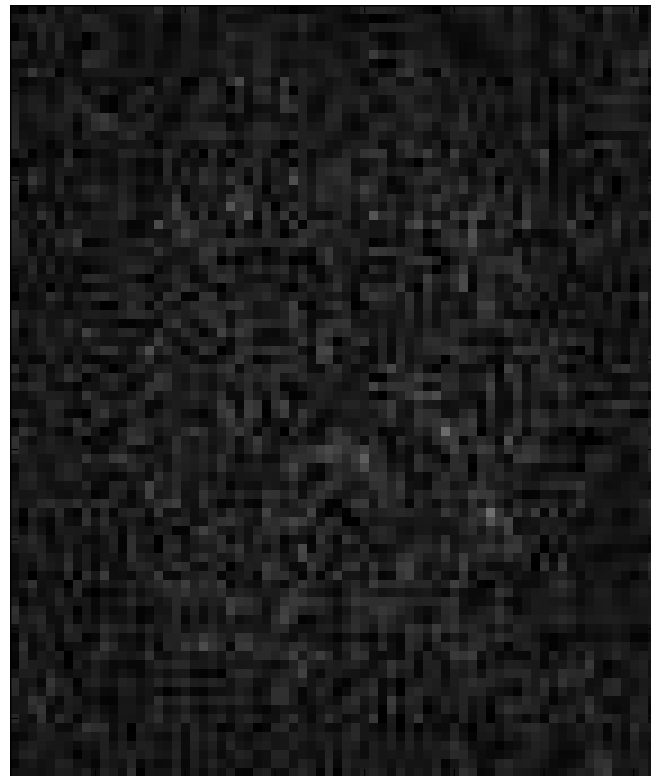


After

Looks good. But is it the “truth”?



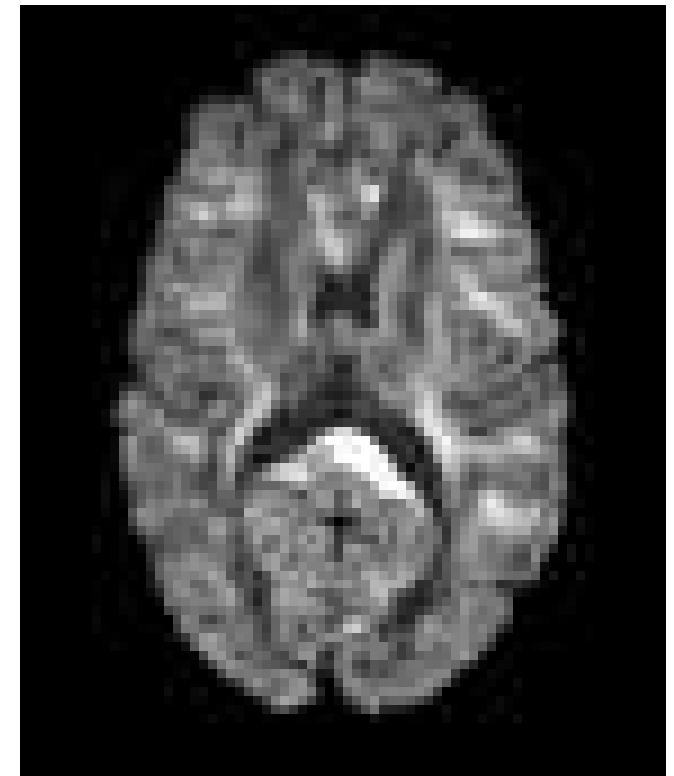
# How accurate are the predictions?



Outlier



eddy's  
guesstimate

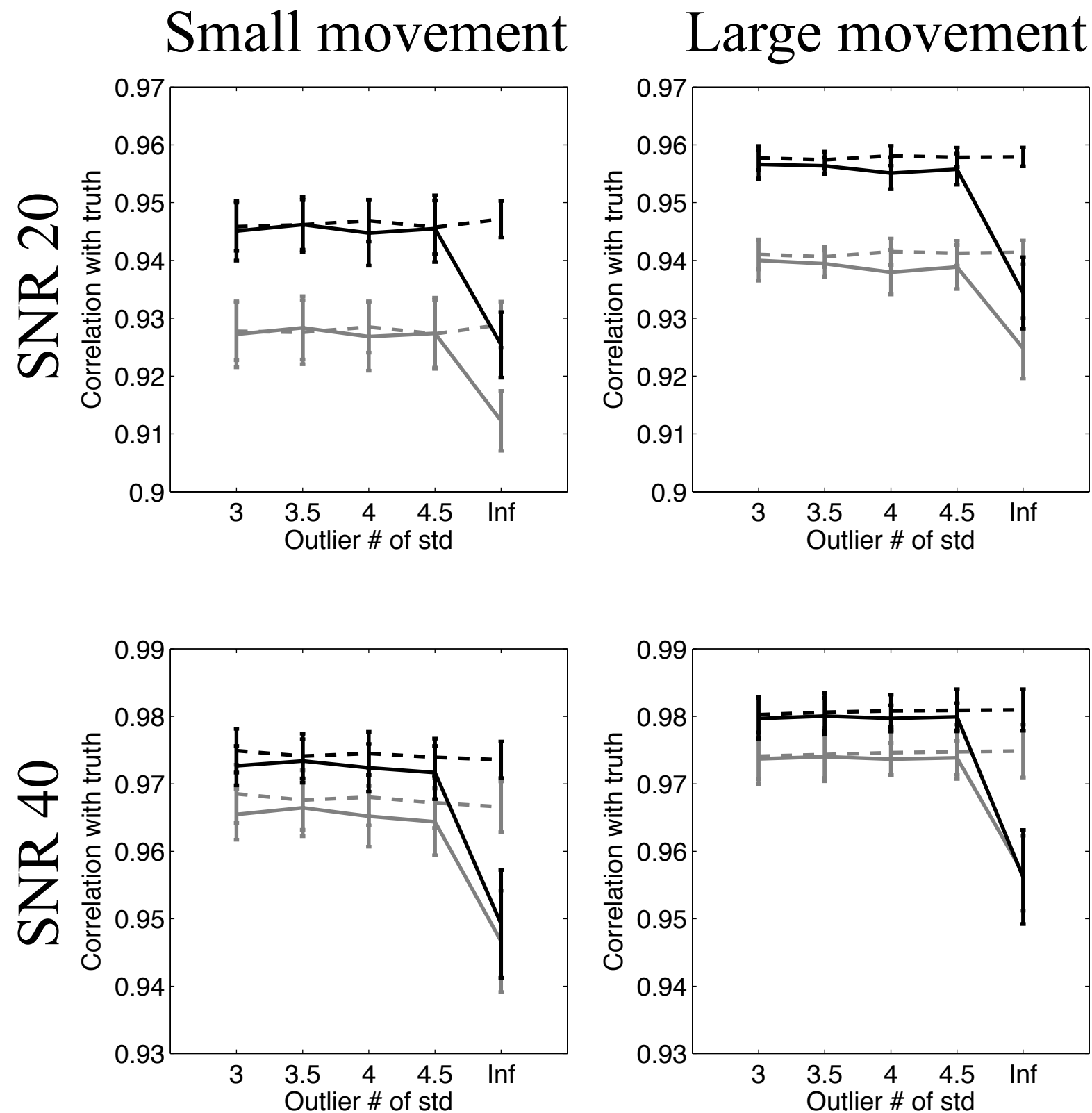


Ground  
truth

With the simulations we know the  
“ground truth”



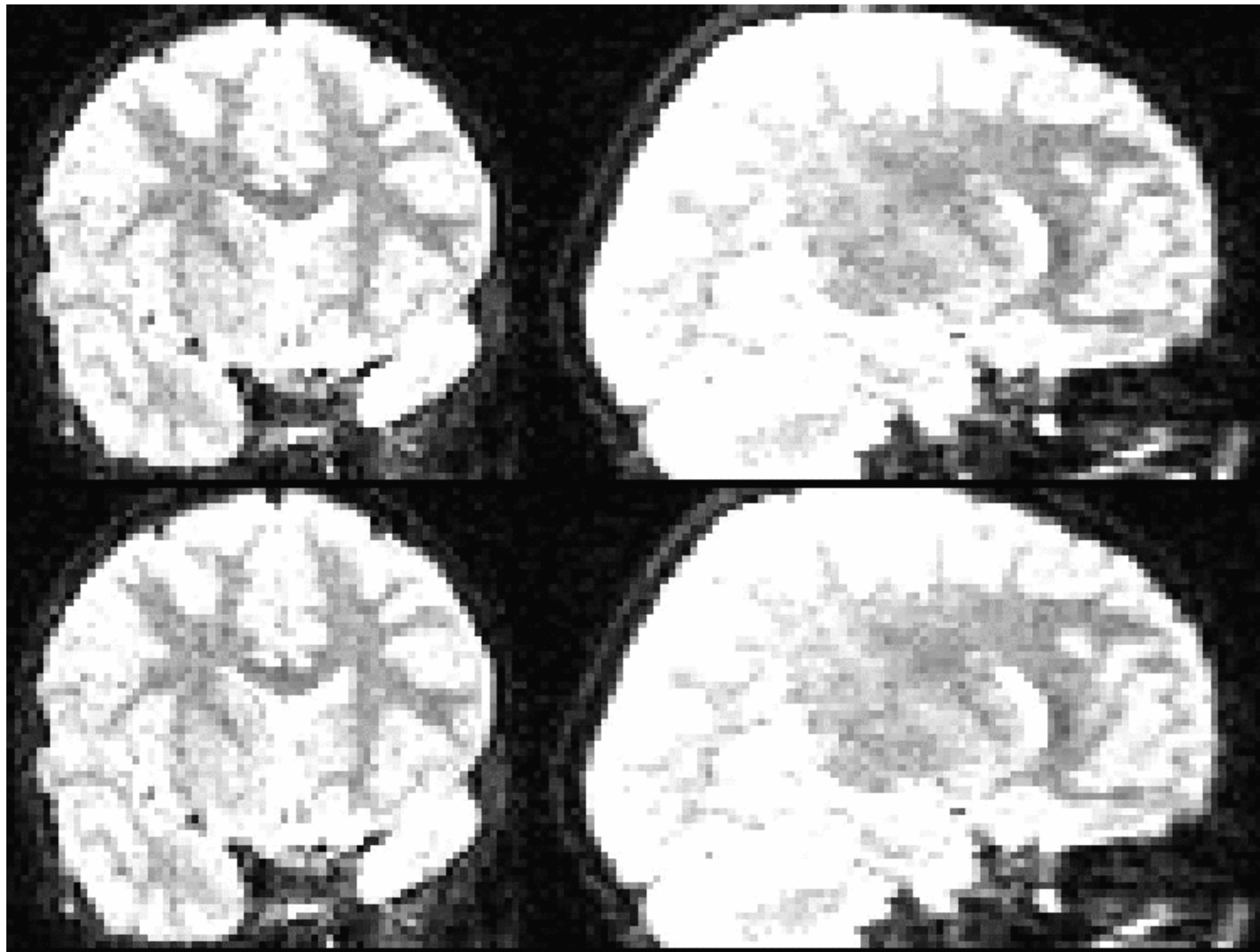
# How accurate are the predictions?







# Norwegian data. 32 directions. Hundreds of children.



Eight year  
old who gets  
tired towards  
the end of  
scanning

After outlier  
detection  
and  
replacement  
by eddy



And all you need to do is to add  
**--repol** to your command line

```
eddy --imain=LR_RL --acqp=acqparams.txt  
--index=indx.txt --bvecs=bvecs  
--bvals=bvals --mask=brain_mask  
--topup=my_topup --out=my_eddy --repol
```



# Outline of the talk

- “Advanced” eddy features
  - Movement-induced dropout
  - Intra-volume motion
  - Susceptibility-by-movement



# Outline of the talk

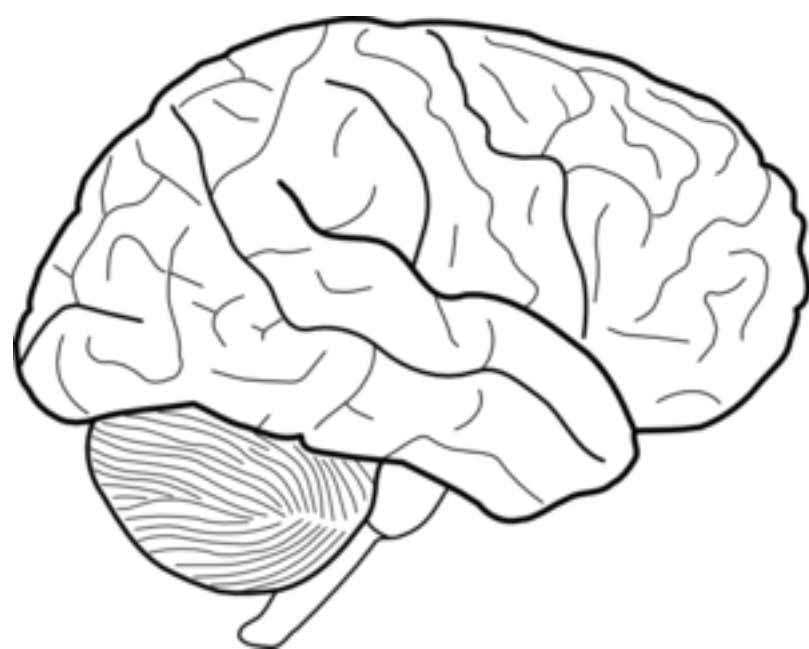
- What is the problem with diffusion data?
- Off-resonance field
- Registering diffusion data
- Practicalities
- Some results
- “New” eddy features
  - Movement-induced dropout
  - Intra-volume motion
  - Susceptibility-by-movement





# Intra-volume movement

One of the (possibly naive) assumptions of most movement correction is that any movement is instantaneous and occurs between the acquisition of consecutive volumes.

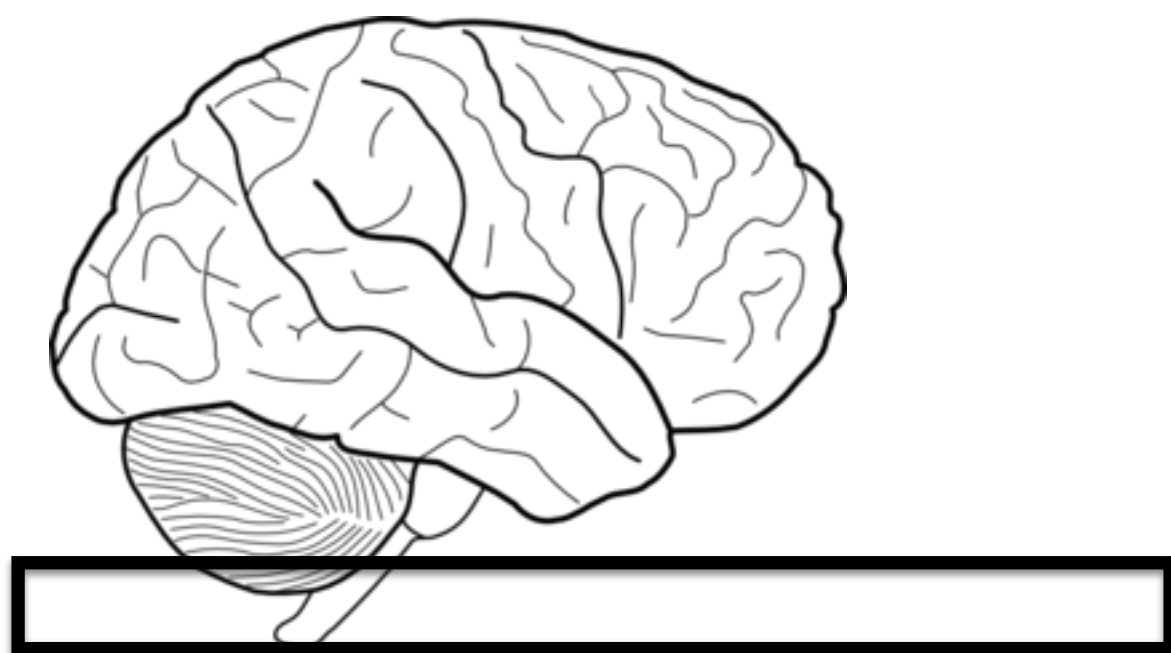


This is the brain  
we set out to  
image



# Intra-volume movement

One of the (possibly naive) assumptions of most movement correction is that any movement is instantaneous and occurs between the acquisition of consecutive volumes.



This is the brain  
we set out to  
image



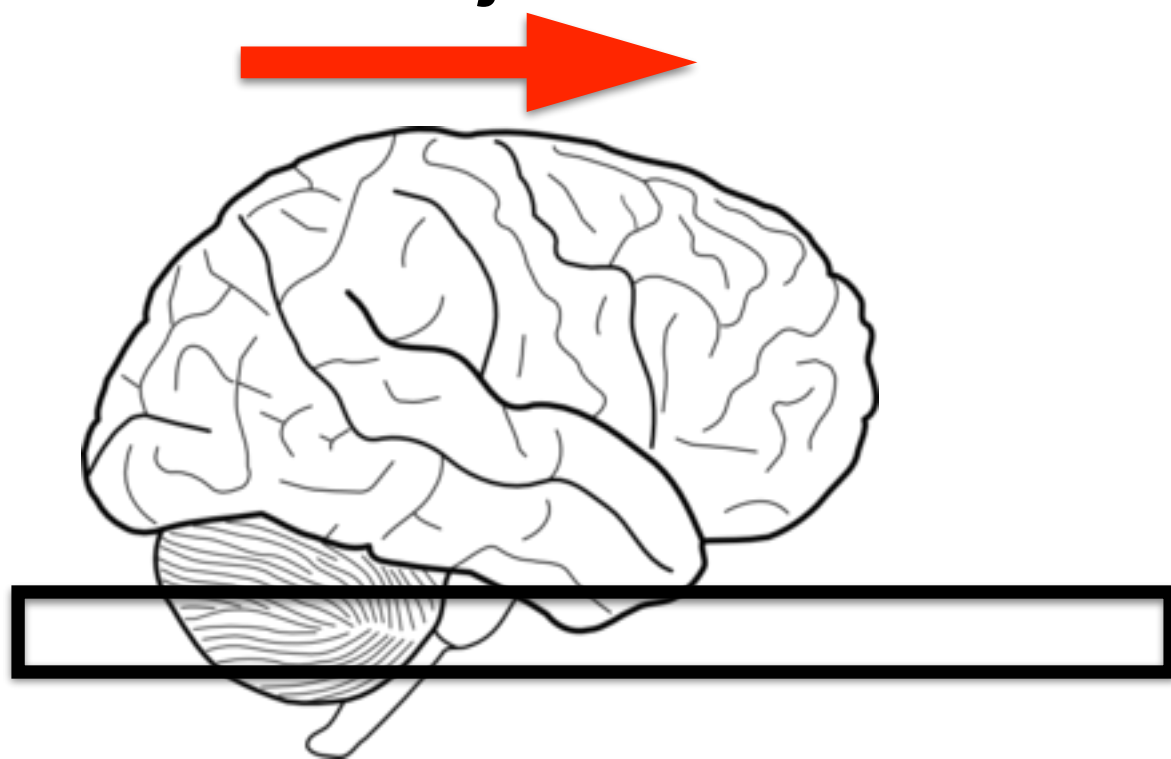
And here we have  
acquired the first  
slice



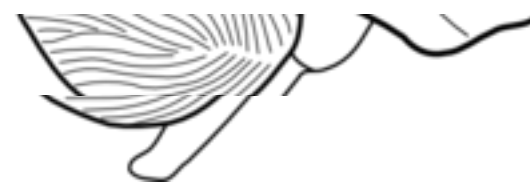
# Intra-volume movement

One of the (possibly naive) assumptions of most movement correction is that any movement is instantaneous and occurs between the acquisition of consecutive volumes.

But the subject moves



This is the brain  
we set out to  
image



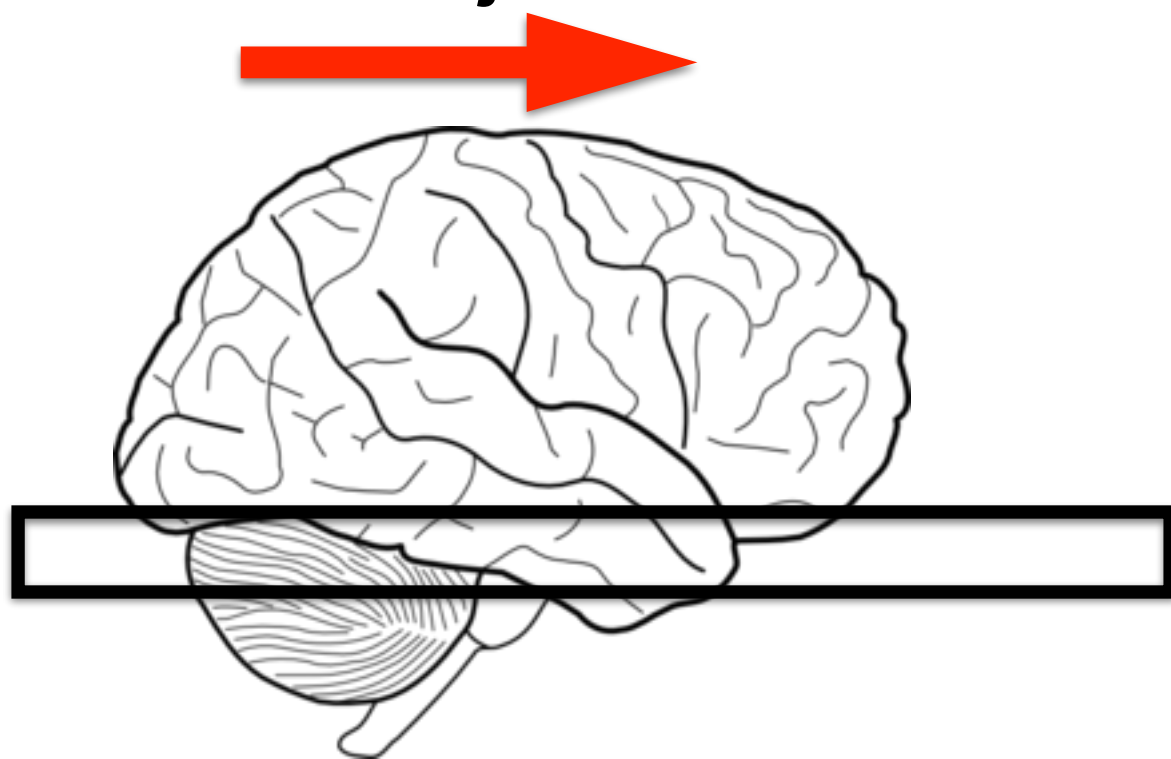
So the brain is  
offset in the  
second slice



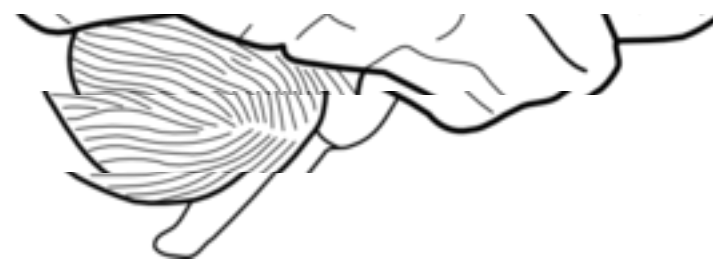
# Intra-volume movement

One of the (possibly naive) assumptions of most movement correction is that any movement is instantaneous and occurs between the acquisition of consecutive volumes.

But the subject moves



This is the brain  
we set out to  
image



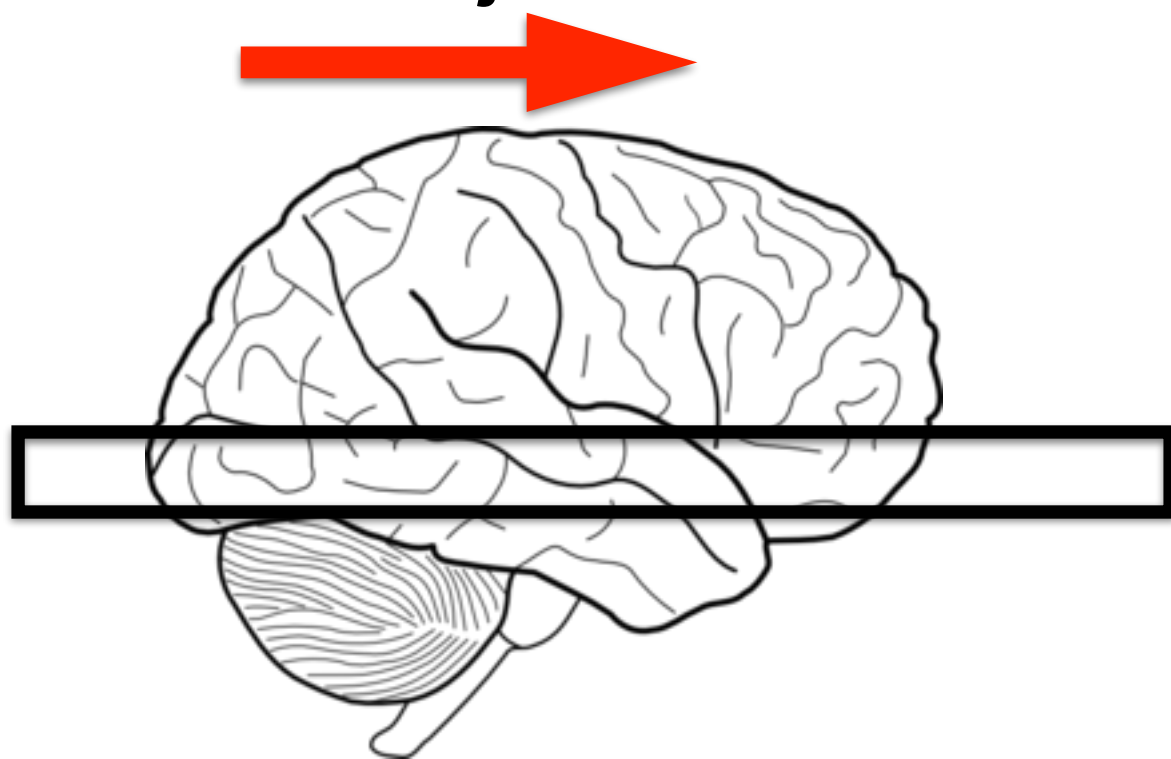
And even more so  
in the third slice



# Intra-volume movement

One of the (possibly naive) assumptions of most movement correction is that any movement is instantaneous and occurs between the acquisition of consecutive volumes.

But the subject moves



This is the brain  
we set out to  
image



And more ...

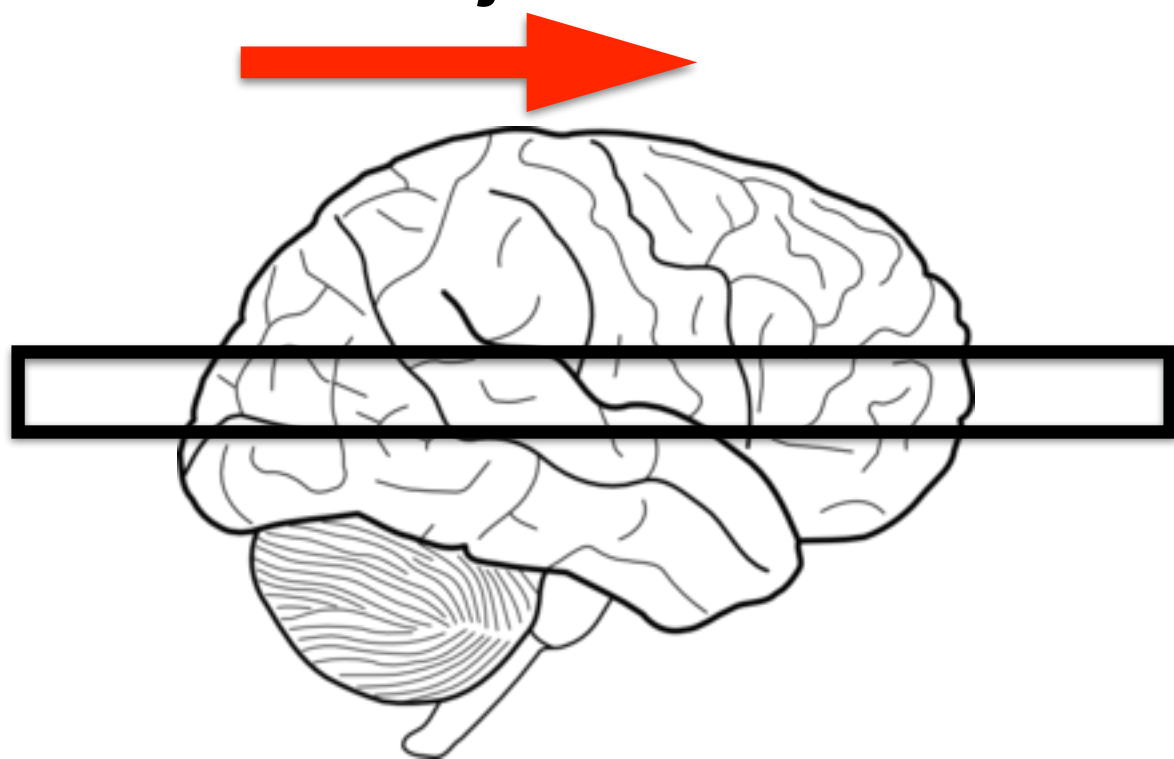




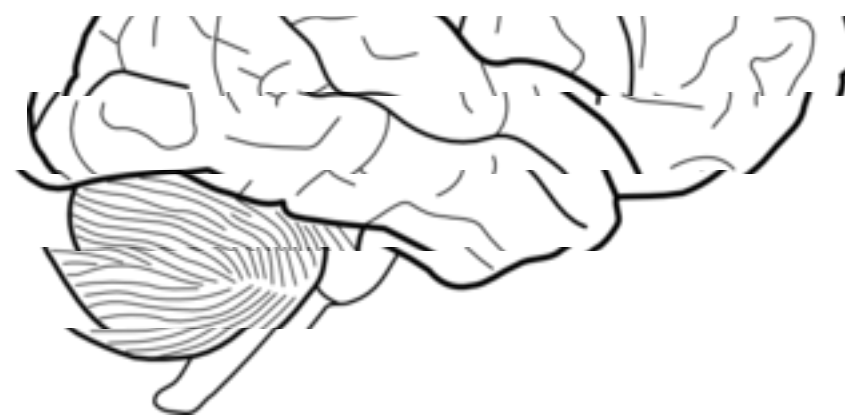
# Intra-volume movement

One of the (possibly naive) assumptions of most movement correction is that any movement is instantaneous and occurs between the acquisition of consecutive volumes.

But the subject moves



This is the brain  
we set out to  
image

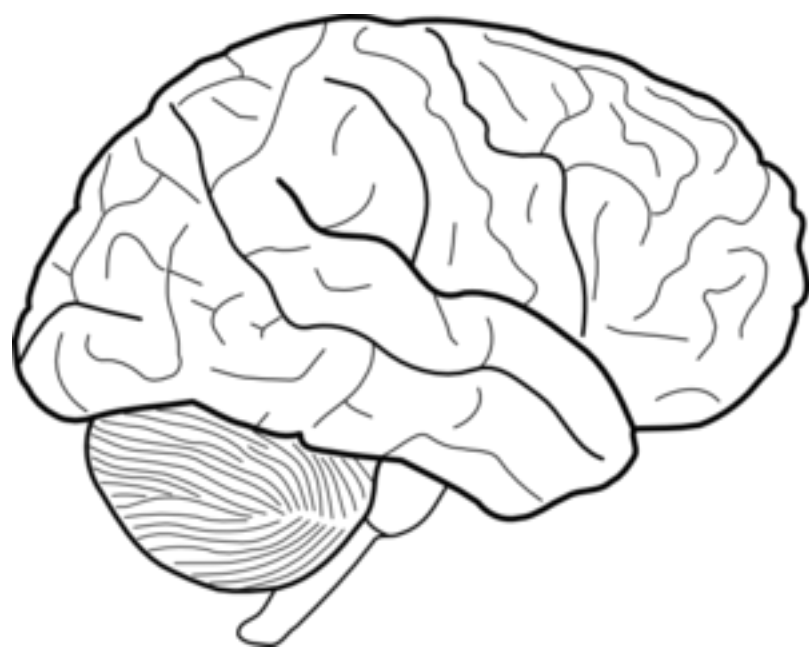


... and more ...

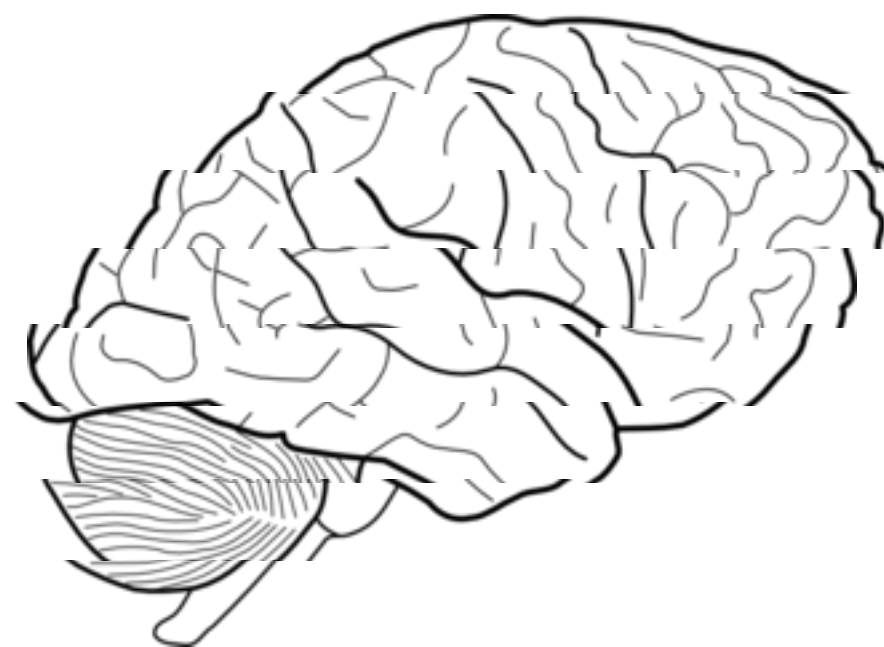


# Intra-volume movement

One of the (possibly naive) assumptions of most movement correction is that any movement is instantaneous and occurs between the acquisition of consecutive volumes.



This is the brain  
we set out to  
image

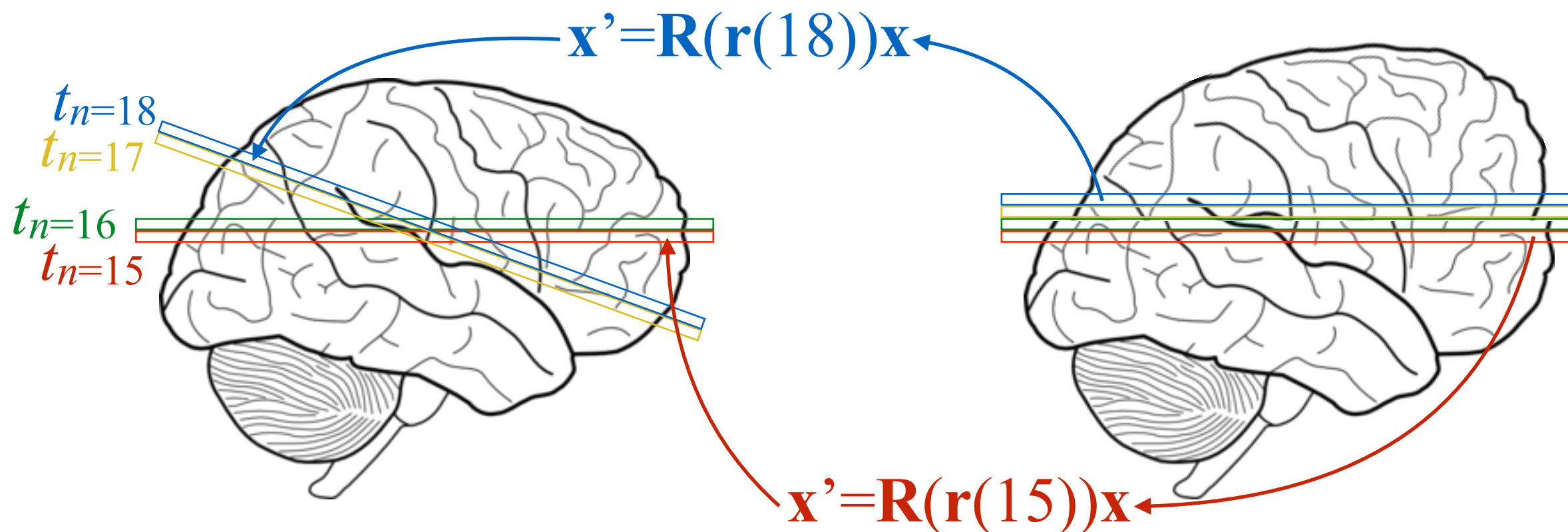


*etc.*



# Intra-volume movement

- This is known as the “slice-to-vol” problem or the “intra-volume movement” problem.
- The new version of eddy addresses this problem.
- It estimates the slice wise movement through the same Gaussian Process based forward model.

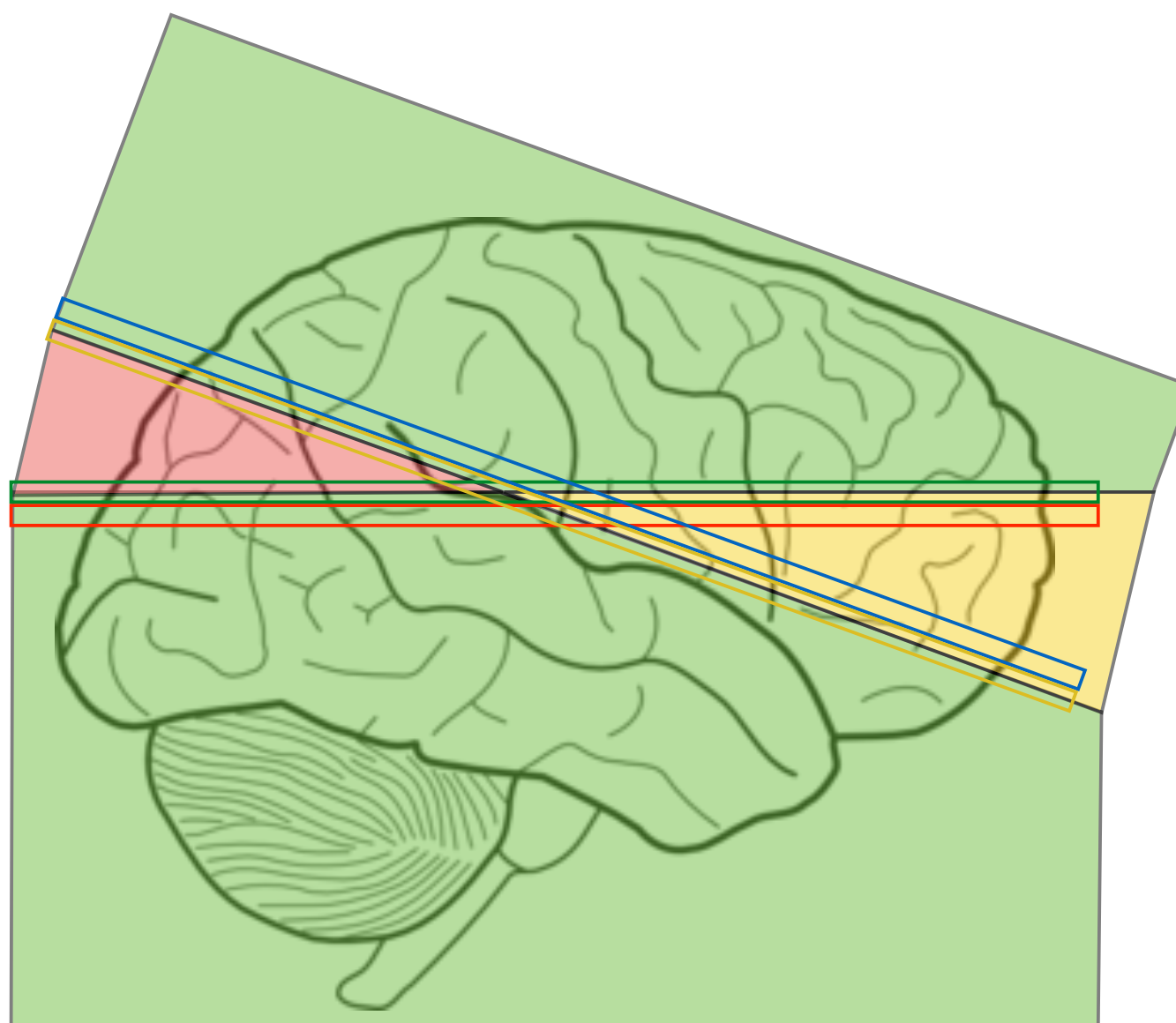




# Intra-volume movement

- But it is considerably harder to go the other way, *i.e.* to tell what the image should have looked like had the subject not moved.
- In particular there is a problem with data that was never acquired.

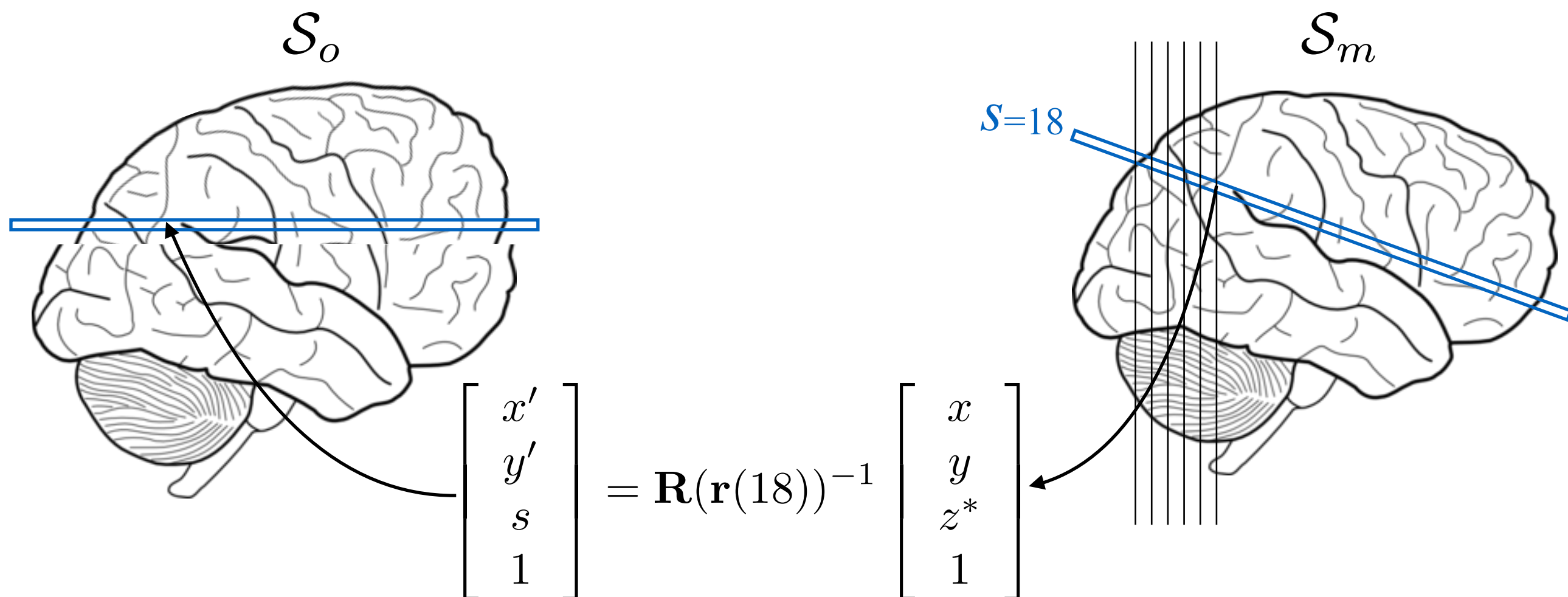
Subject “looks up”  
half way through  
acquisition.





# Intra-volume movement

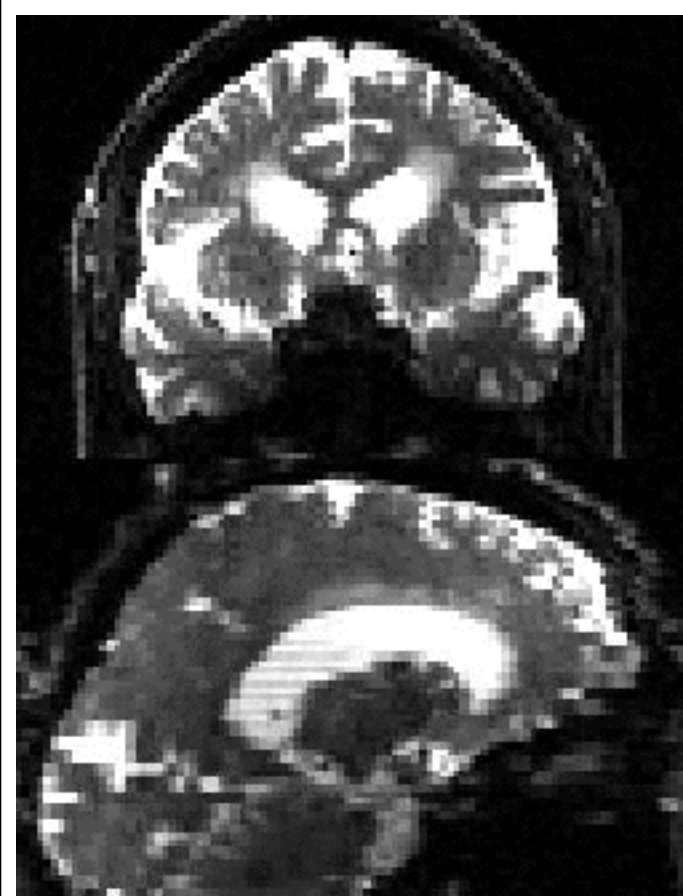
- We have solved this through a hybrid resampling, which consists of regular in-plane interpolations followed by 1D irregular spline resampling.
- This is combined with supplementing the data with predictions.







# Intra-volume movement

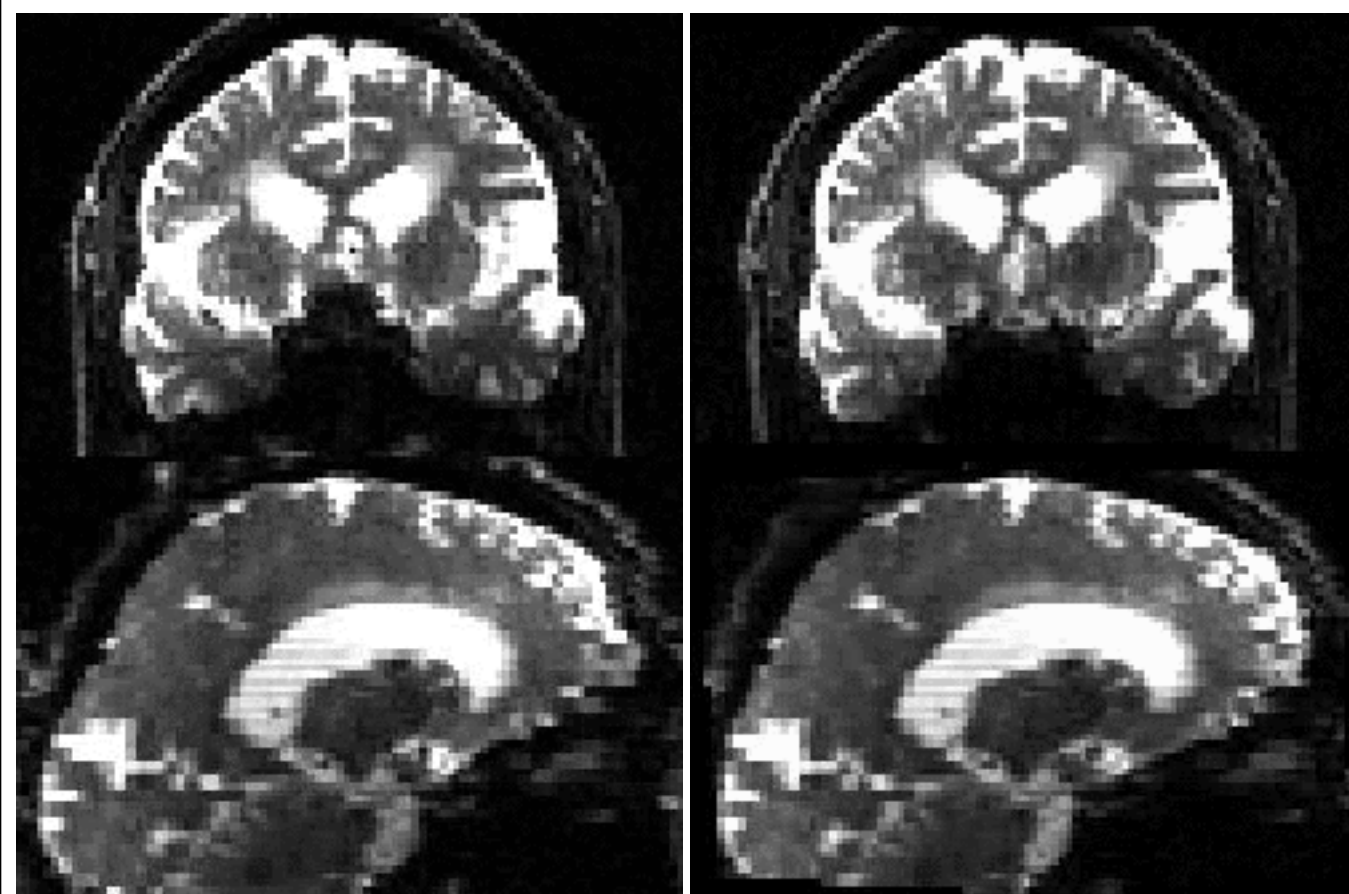


Original data

Problematic elderly subject. Lots of movement induced signal loss and intravolume movement



# Intra-volume movement



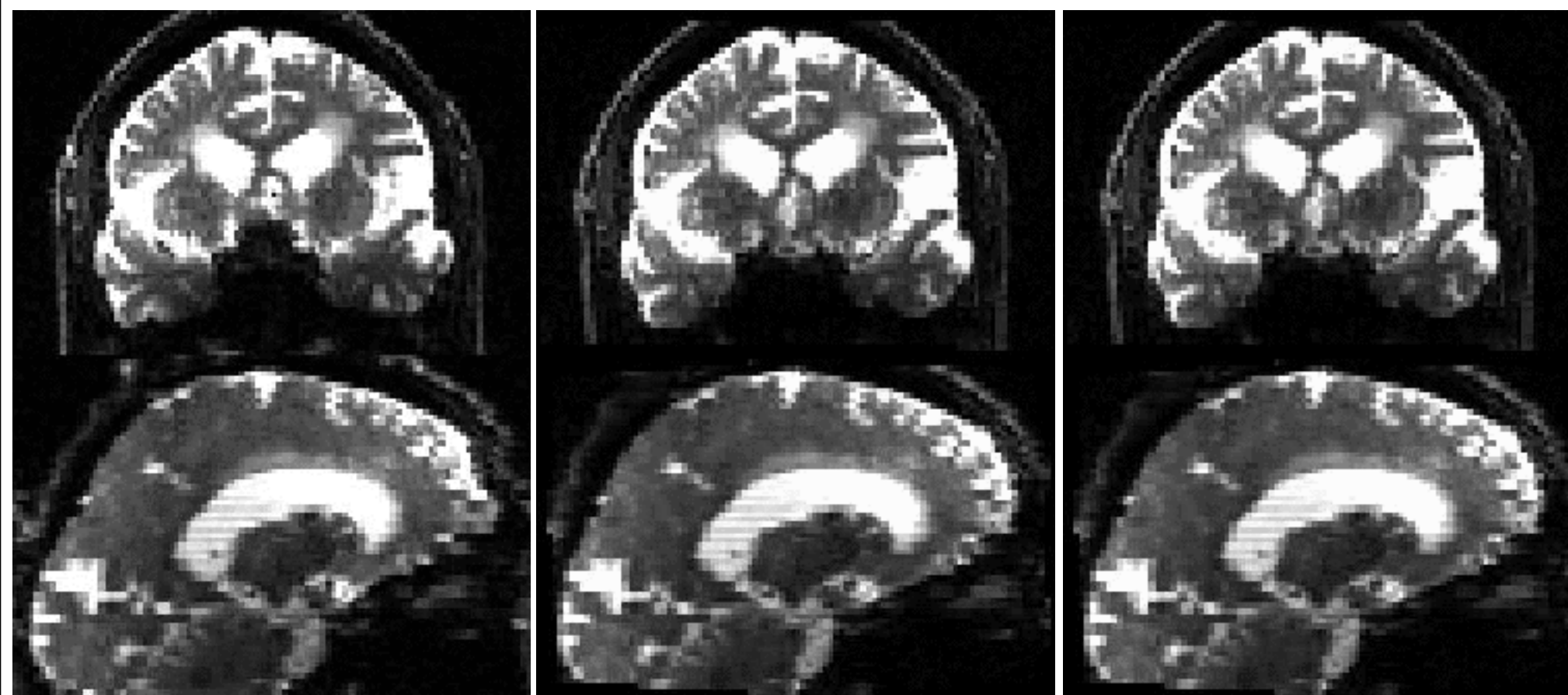
Original data

After correction  
without outlier  
correction

Problematic elderly subject. Lots of movement induced signal loss and intravolume movement



# Intra-volume movement



Original data

After correction  
without outlier  
correction

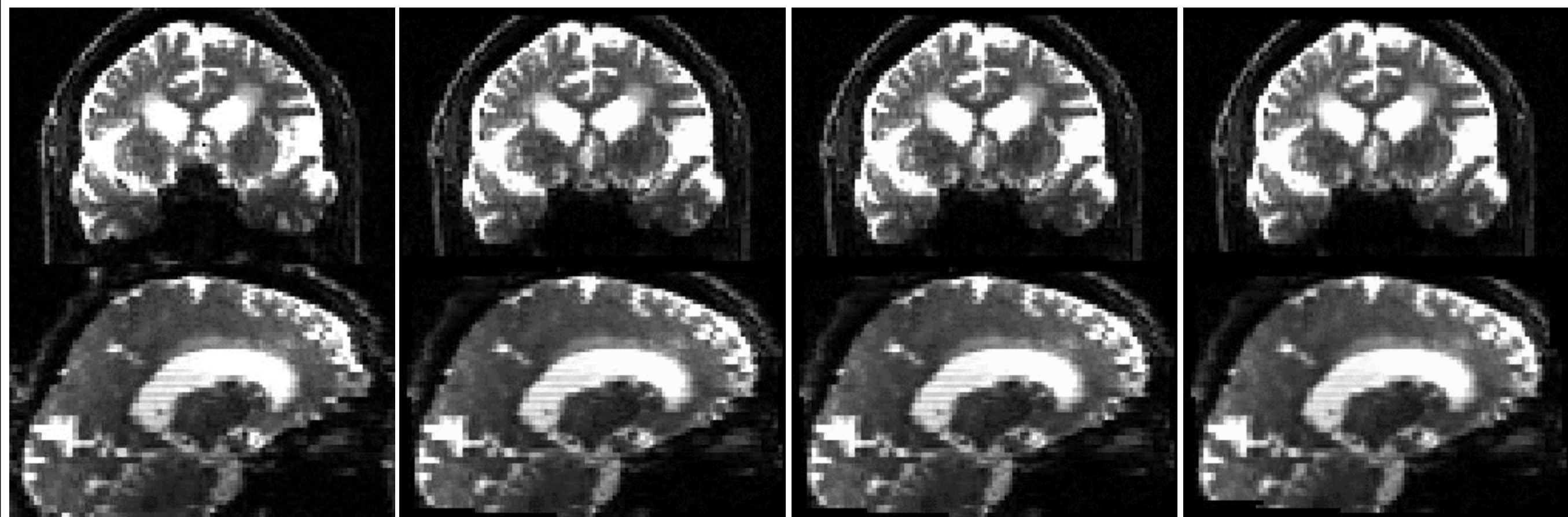
After correction  
with outlier  
replacement

Problematic elderly subject. Lots of movement induced signal loss and intravolume movement





# Intra-volume movement



Original data

After correction  
without outlier  
correction

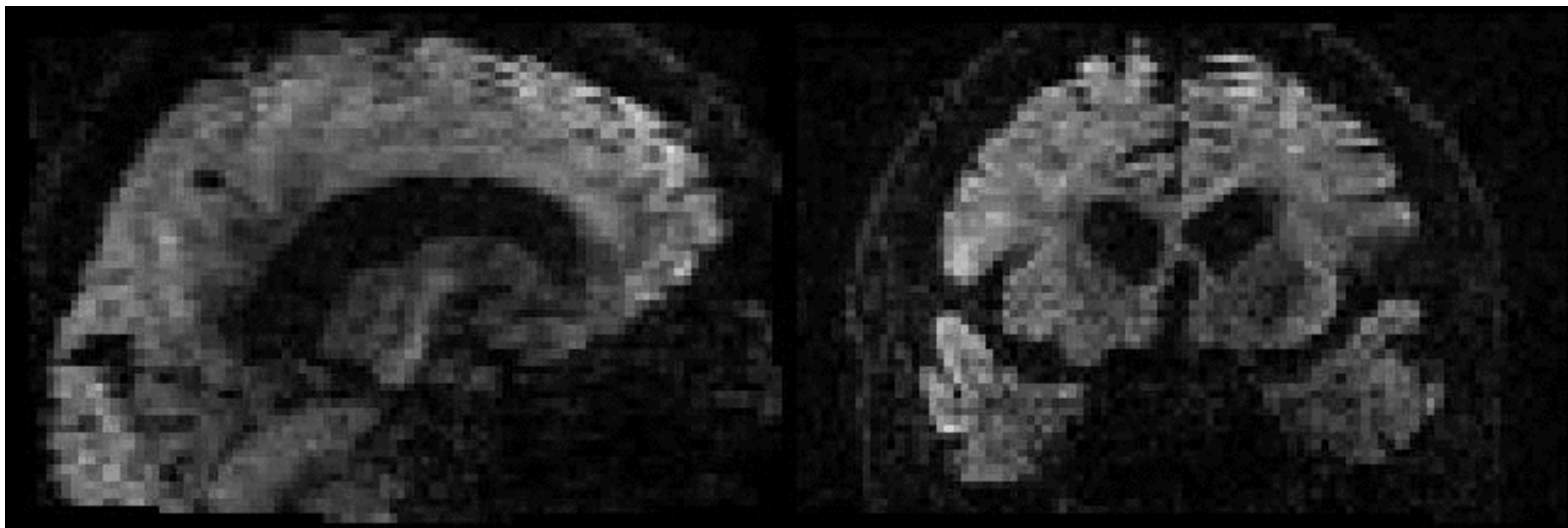
After correction  
with outlier  
replacement

After  
intravolume  
movement  
correction.

Problematic elderly subject. Lots of movement induced signal loss and intravolume movement



# Intra-volume movement



Highlighting the difference between just OLR  
and OLR combined with S2V correction

Problematic elderly subject. Lots of movement  
induced signal loss and intravolume movement





# And also trivial to add to your eddy command

```
eddy --imain=LR_RL --acqp=acqparams.txt  
--index=indx.txt --bvecs=bvecs  
--bvals=bvals --mask=brain_mask  
--topup=my_topup --out=my_eddy --repol  
--mporder=16
```

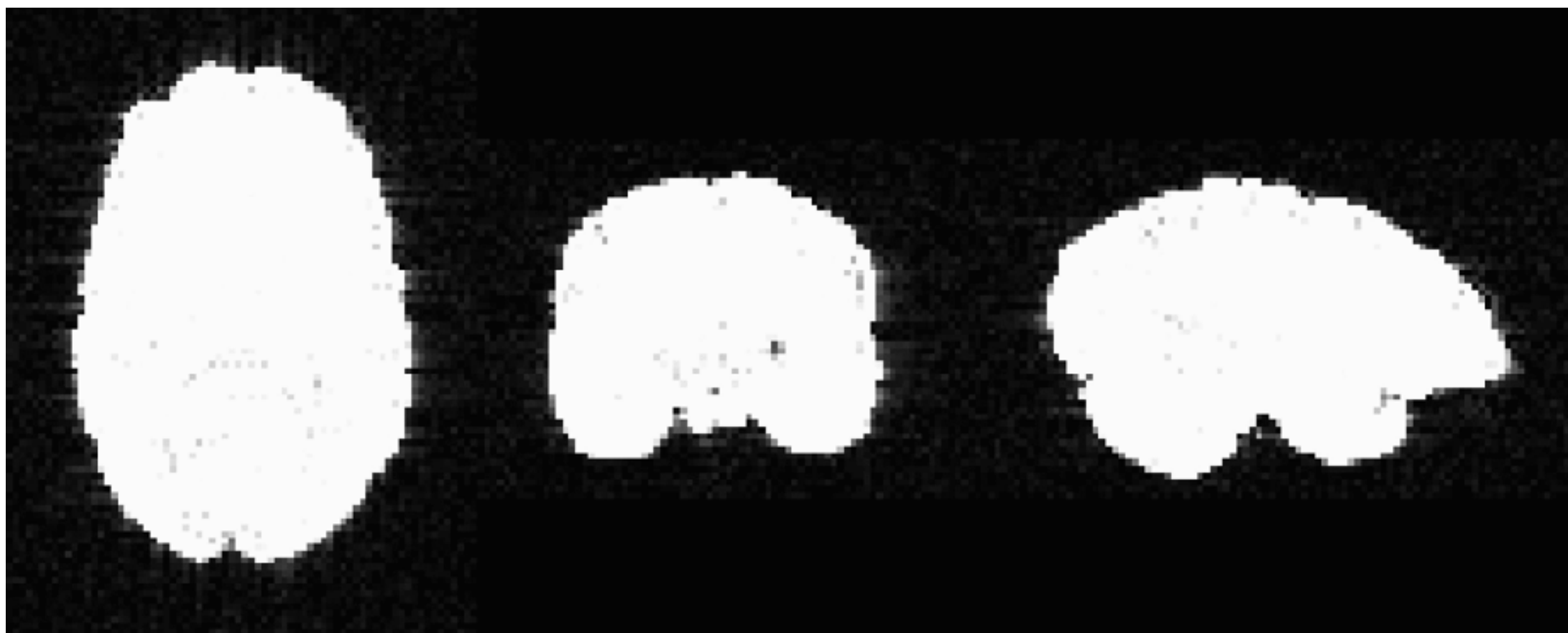


# Outline of the talk

- What is the problem with diffusion data?
- Off-resonance field
- Registering diffusion data
- Practicalities
- Some results
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  - Movement-induced dropout
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  - Susceptibility-by-movement



# Some data with lots of movement

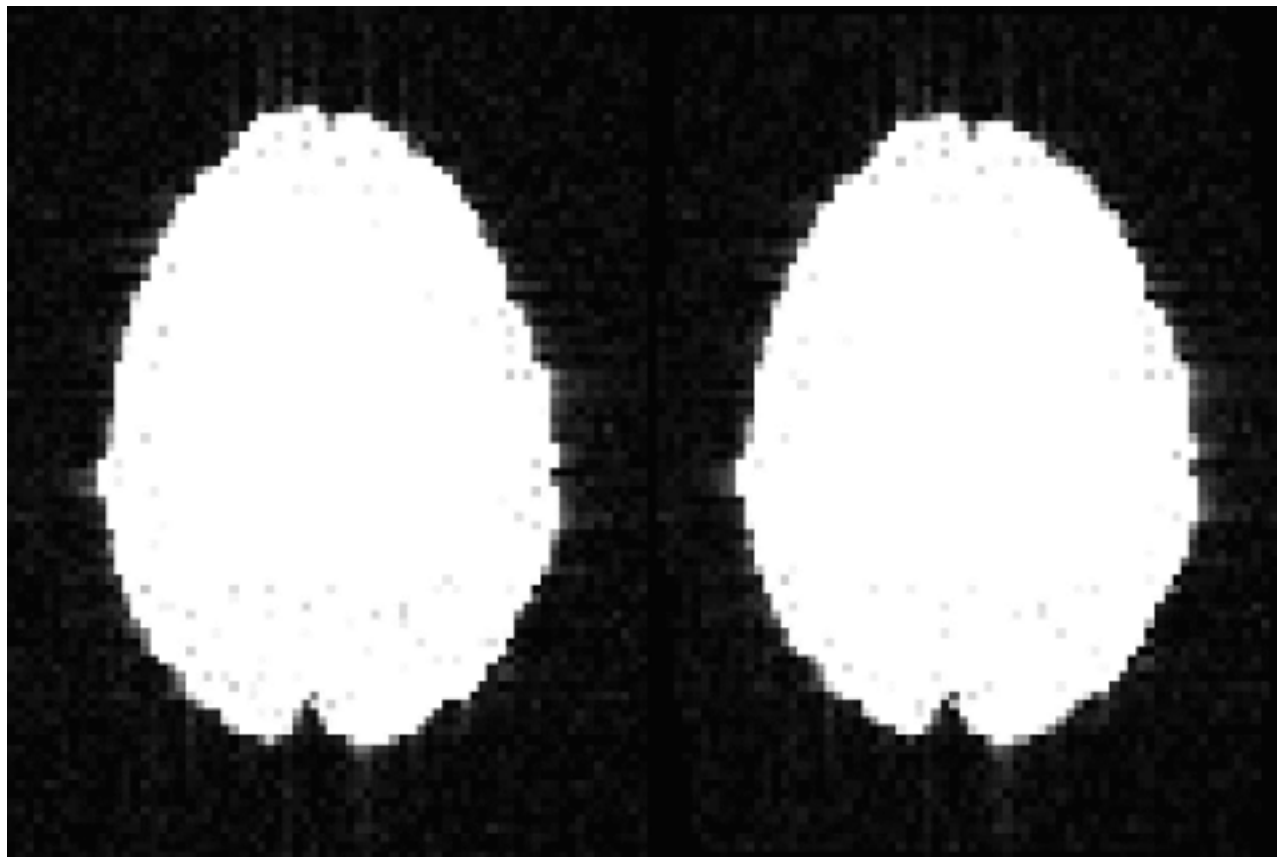




# Some data with lots of movement, aligned with eddy

Before

After





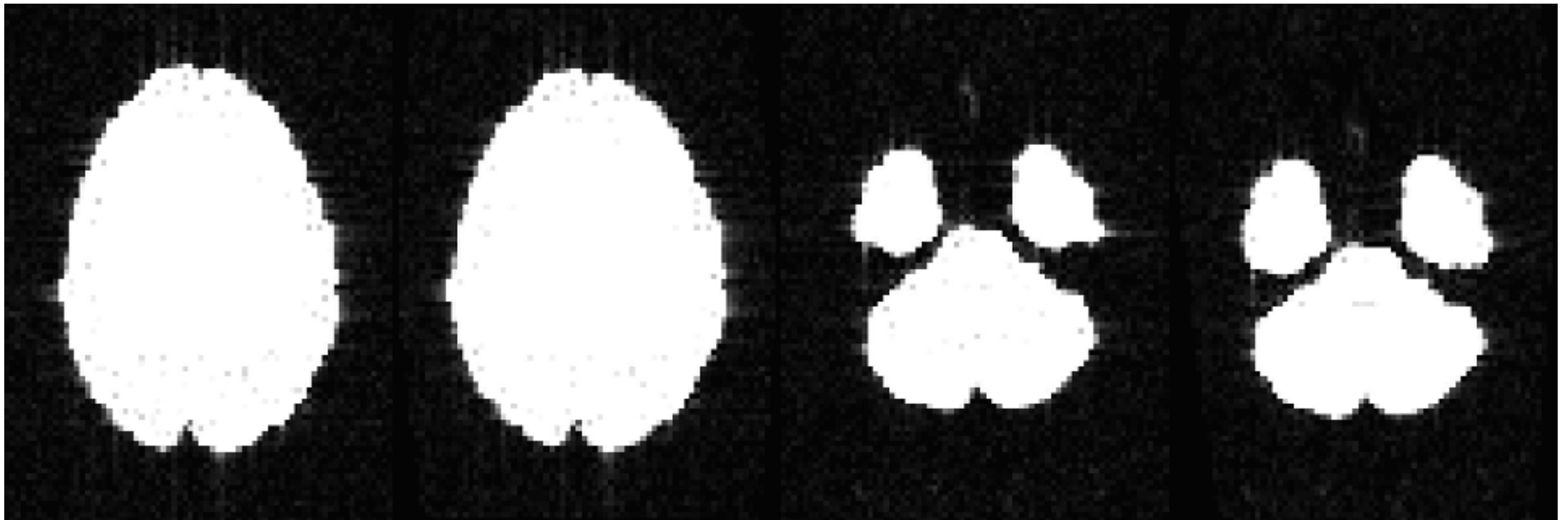
# Some data with lots of movement, aligned with eddy

Before

After

Before

After







# Why is that then?

## Motion-induced Magnetic Field Changes Inside the Brain

Jiaen Liu<sup>1</sup>, Jacco de Zwart<sup>1</sup>, Peter van Gelderen<sup>1</sup>, and Jeff Duyn<sup>1</sup>

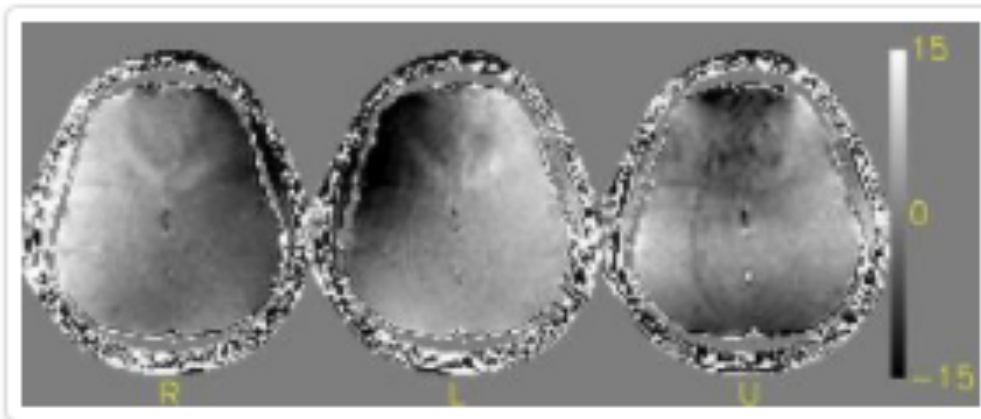


Fig. 1 Changes of field maps in four different positions relative to the field map in the reference position obtained under the “phantom shim” setting. The unit of the field maps is Hz.

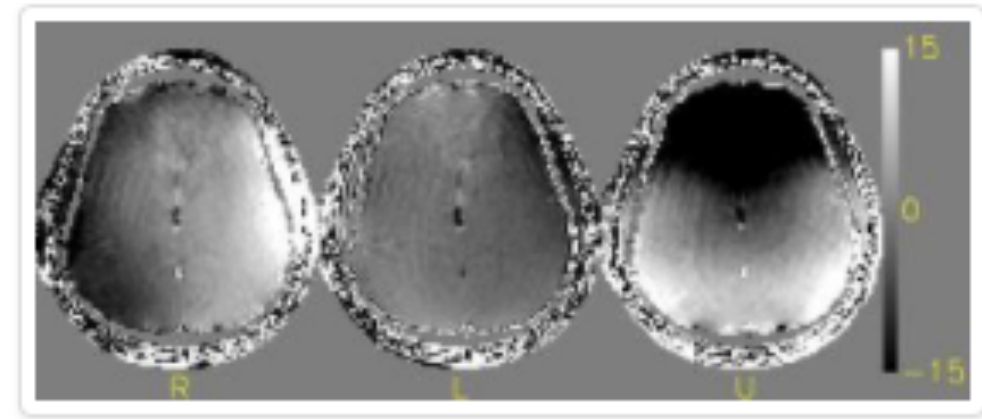


Fig. 2 Changes of field maps in four different positions relative to the field map in the reference position obtained under the “subject shim” setting. The unit of the field maps is Hz.



In case you think that was  
exaggerated



Problematic  
HCP subject.



# Why is that then?

Richard Bowtell

## Will field shifts due to head rotation compromise motion correction?

Aleksandra Sulikowska<sup>1</sup>, Samuel Wharton<sup>1</sup>, Paul M Glover<sup>1</sup>, and Penny A Gowland<sup>1</sup>

<sup>1</sup>Sir Peter Mansfield Magnetic Resonance Centre, University of Nottingham, Nottingham, Nottinghamshire, United Kingdom

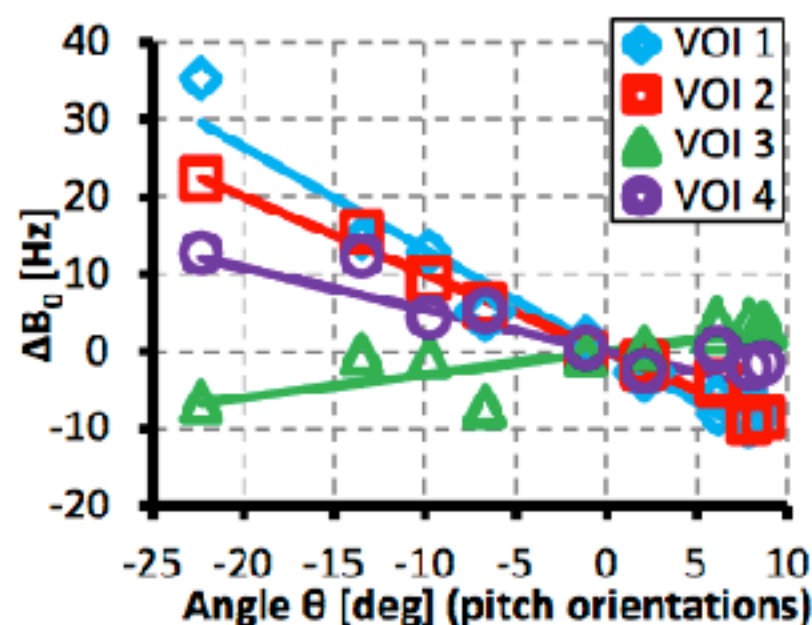


Fig. 3. Figure showing mean field shift in the VOIs during **pitch** rotations.

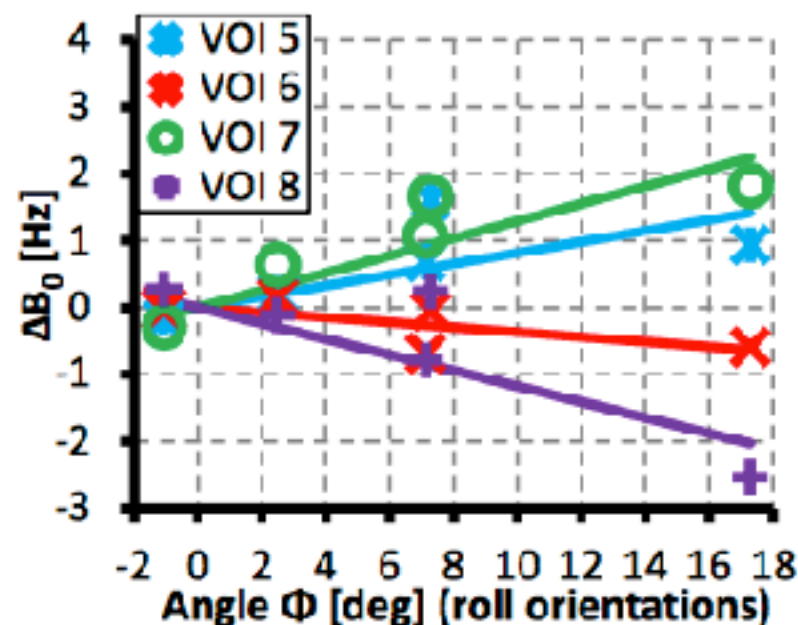


Fig. 4. Figure showing mean field shift in the VOIs during **roll** rotations.

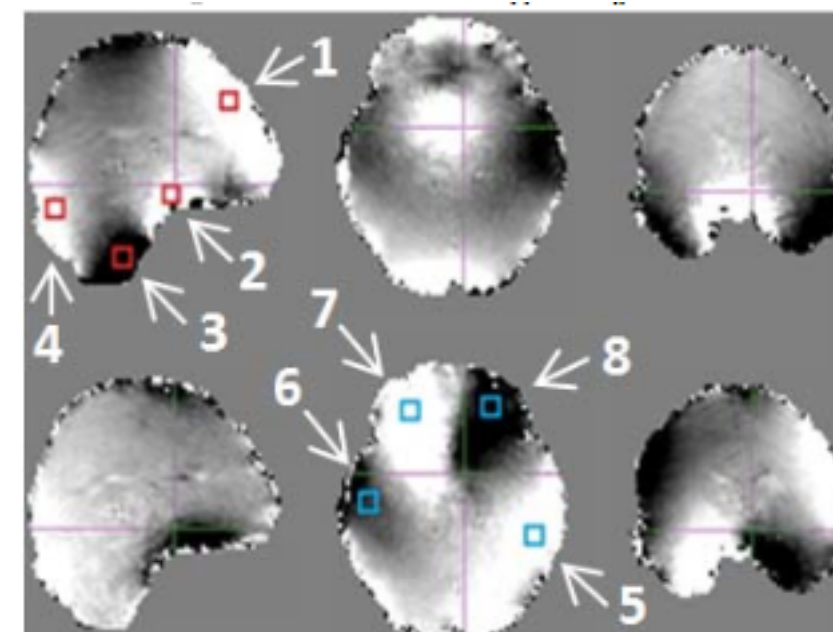


Fig. 2.  $B_0$  field difference maps for 2 head orientations, **TOP**: pitch  $\theta=7.87$  deg, **BOTTOM**: roll  $\Phi=7.13$  deg. Squares indicate VOIs (**red**: volumes 1-4; **blue**: volumes 5-8). Grey scale = -5 Hz to 5 Hz.





# So, maybe we can use a low order Taylor expansion

$\omega_1$	$\approx$	$\omega_0$	$+ \Delta\theta_1$	$\frac{\partial\omega}{\partial\theta}$	$+ \Delta\phi_1$	$\frac{\partial\omega}{\partial\phi}$
$\omega_2$	$\approx$	$\omega_0$	$+ \Delta\theta_2$	$\frac{\partial\omega}{\partial\theta}$	$+ \Delta\phi_2$	$\frac{\partial\omega}{\partial\phi}$
$\vdots$		$\vdots$		$\vdots$		$\vdots$
$\omega_N$	$\approx$	$\omega_0$	$+ \Delta\theta_N$	$\frac{\partial\omega}{\partial\theta}$	$+ \Delta\phi_N$	$\frac{\partial\omega}{\partial\phi}$



# We need a forward model for the observed changes

Volume # 1

Predicted - Observed

$$\approx \overset{0}{\Delta\theta} \left[ \text{template} \odot \text{blur} + \text{mask} \odot \text{blur} \right] + \overset{0}{\Delta\phi} \left[ \text{template} \odot \text{blur} + \text{mask} \odot \text{blur} \right]$$

...

Volume # 6

$$\approx \overset{-5.4}{\Delta\theta} \left[ \text{template} \odot \text{blur} + \text{mask} \odot \text{blur} \right] + \overset{-1.0}{\Delta\phi} \left[ \text{template} \odot \text{blur} + \text{mask} \odot \text{blur} \right]$$

...

Volume # 31

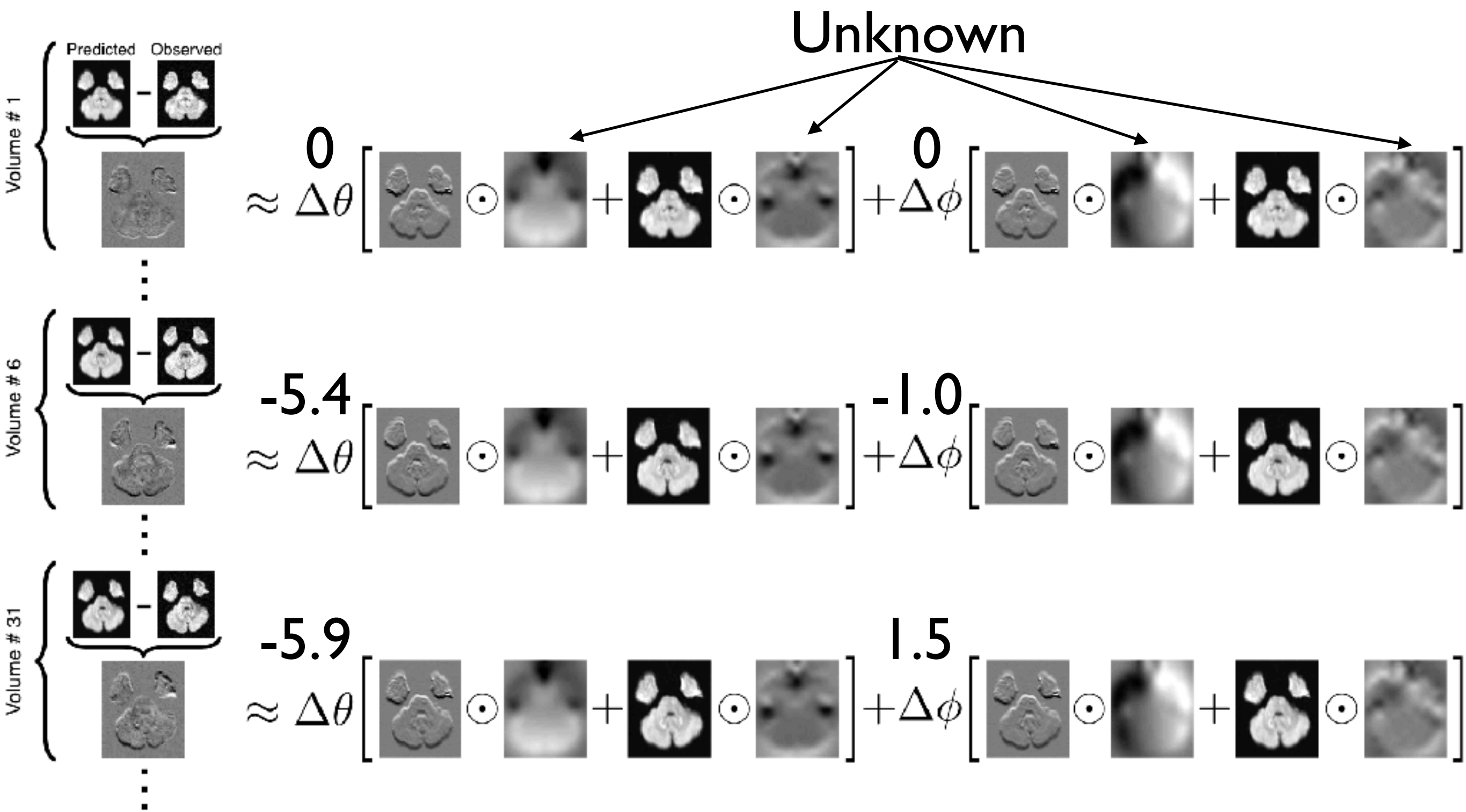
$$\approx \overset{-5.9}{\Delta\theta} \left[ \text{template} \odot \text{blur} + \text{mask} \odot \text{blur} \right] + \overset{1.5}{\Delta\phi} \left[ \text{template} \odot \text{blur} + \text{mask} \odot \text{blur} \right]$$

...





# We need a forward model for the observed changes





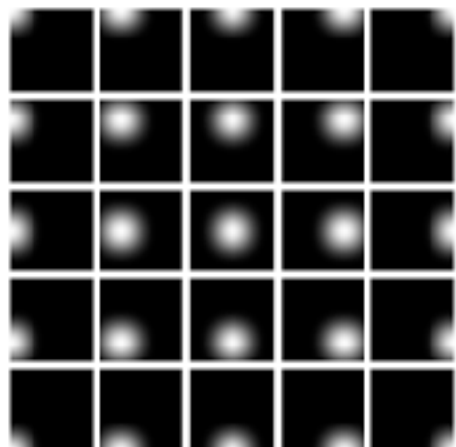
# And then to invert that model to find the unknowns

$$\begin{bmatrix}
 \begin{array}{c} \text{Volume \# 1} \\ \text{Predicted} - \text{Observed} \\ \text{[Brain slice image]} \\ \vdots \\ \text{Volume \# 6} \\ \text{Predicted} - \text{Observed} \\ \text{[Brain slice image]} \\ \vdots \\ \text{Volume \# 31} \\ \text{Predicted} - \text{Observed} \\ \text{[Brain slice image]} \\ \vdots \end{array} \\
 \end{bmatrix}
 =
 \begin{bmatrix}
 \Delta\theta \left[ \text{[Brain slice image]} \odot \mathbf{B} + \text{[Brain slice image]} \odot \mathbf{B}' \right] \Delta\phi \left[ \text{[Brain slice image]} \odot \mathbf{B} + \text{[Brain slice image]} \odot \mathbf{B}' \right] \\
 \vdots \\
 \Delta\theta \left[ \text{[Brain slice image]} \odot \mathbf{B} + \text{[Brain slice image]} \odot \mathbf{B}' \right] \Delta\phi \left[ \text{[Brain slice image]} \odot \mathbf{B} + \text{[Brain slice image]} \odot \mathbf{B}' \right] \\
 \vdots \\
 \Delta\theta \left[ \text{[Brain slice image]} \odot \mathbf{B} + \text{[Brain slice image]} \odot \mathbf{B}' \right] \Delta\phi \left[ \text{[Brain slice image]} \odot \mathbf{B} + \text{[Brain slice image]} \odot \mathbf{B}' \right] \\
 \vdots
 \end{bmatrix}
 \begin{array}{c} \text{Unknown} \\ \begin{bmatrix} \beta_\theta \\ \beta_\phi \end{bmatrix} + \mathbf{e} \end{array}$$



# And then to invert that model to find the unknowns

$$\begin{bmatrix} \text{Volume \# 1} \\ \vdots \\ \text{Volume \# 6} \\ \vdots \\ \text{Volume \# 31} \end{bmatrix} = \begin{bmatrix} \Delta\theta \left[ \text{Basis-set} \odot \mathbf{B} + \text{Basis-set} \odot \mathbf{B}' \right] \Delta\phi \left[ \text{Basis-set} \odot \mathbf{B} + \text{Basis-set} \odot \mathbf{B}' \right] \\ \vdots \\ \Delta\theta \left[ \text{Basis-set} \odot \mathbf{B} + \text{Basis-set} \odot \mathbf{B}' \right] \Delta\phi \left[ \text{Basis-set} \odot \mathbf{B} + \text{Basis-set} \odot \mathbf{B}' \right] \\ \vdots \\ \Delta\theta \left[ \text{Basis-set} \odot \mathbf{B} + \text{Basis-set} \odot \mathbf{B}' \right] \Delta\phi \left[ \text{Basis-set} \odot \mathbf{B} + \text{Basis-set} \odot \mathbf{B}' \right] \\ \vdots \end{bmatrix} \begin{bmatrix} \beta_\theta \\ \beta_\phi \end{bmatrix} + \mathbf{e}$$


 Basis-set



And then to invert that model to find the unknowns

$$\begin{aligned}
 \begin{bmatrix} \text{Volume \# 1} \\ \vdots \\ \text{Volume \# 6} \\ \vdots \\ \text{Volume \# 31} \end{bmatrix} &= \begin{bmatrix} \Delta\theta \left[ \text{Predicted} \odot \mathbf{B} + \text{Observed} \odot \mathbf{B}' \right] \Delta\phi \left[ \text{Predicted} \odot \mathbf{B} + \text{Observed} \odot \mathbf{B}' \right] \\ \vdots \\ \Delta\theta \left[ \text{Predicted} \odot \mathbf{B} + \text{Observed} \odot \mathbf{B}' \right] \Delta\phi \left[ \text{Predicted} \odot \mathbf{B} + \text{Observed} \odot \mathbf{B}' \right] \\ \vdots \\ \Delta\theta \left[ \text{Predicted} \odot \mathbf{B} + \text{Observed} \odot \mathbf{B}' \right] \Delta\phi \left[ \text{Predicted} \odot \mathbf{B} + \text{Observed} \odot \mathbf{B}' \right] \\ \vdots \end{bmatrix} \begin{bmatrix} \beta_\theta \\ \beta_\phi \end{bmatrix} + \mathbf{e} \\
 \mathbf{y} &= \mathbf{X} \mathbf{b} + \mathbf{e} \\
 \hat{\mathbf{b}}^{(k+1)} &= \hat{\mathbf{b}}^{(k)} + \left( \mathbf{X}^T \mathbf{X} \right)^{-1} \mathbf{X}^T \mathbf{y}
 \end{aligned}$$

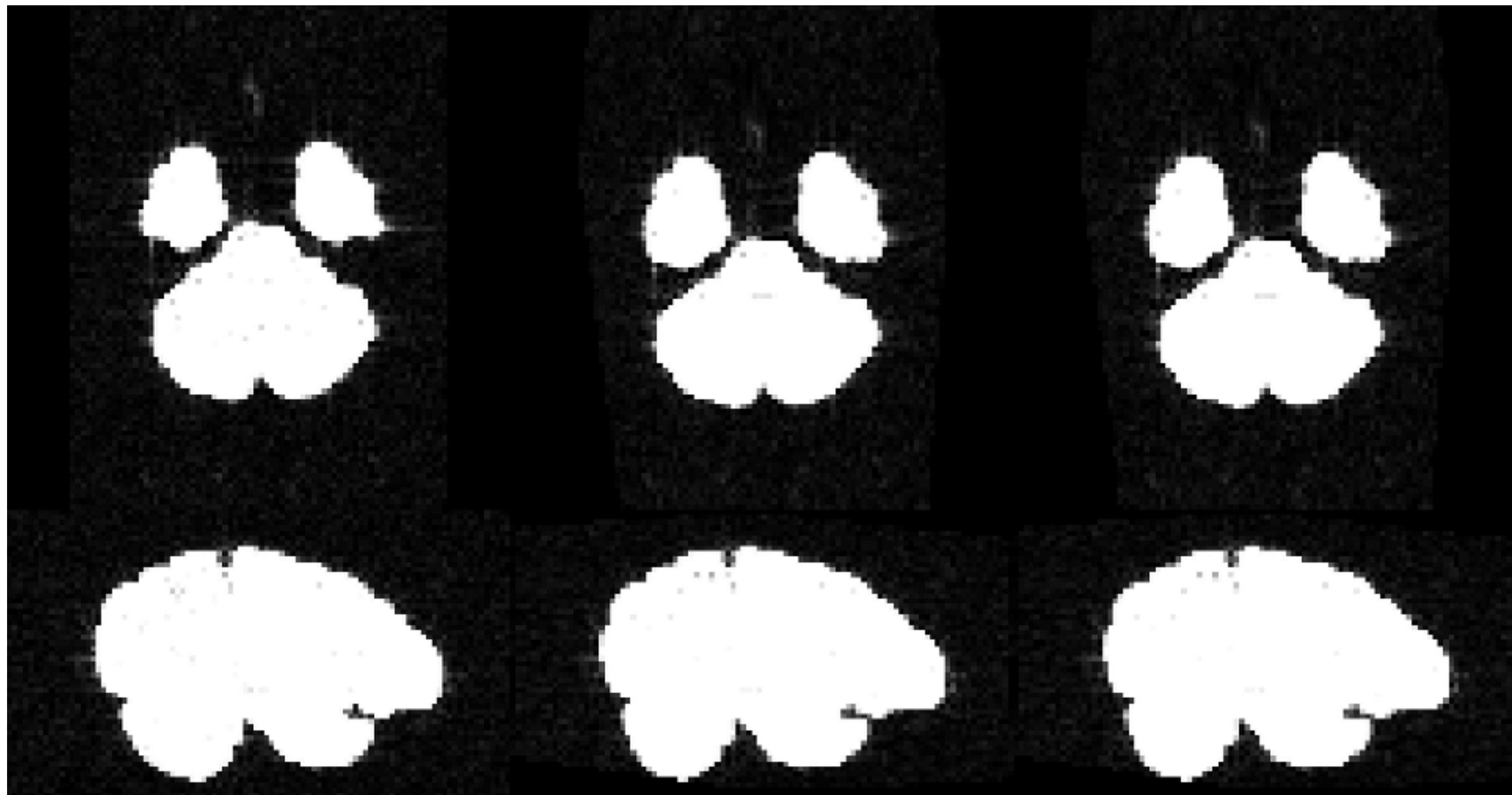


# And now things look a lot better

Before

After

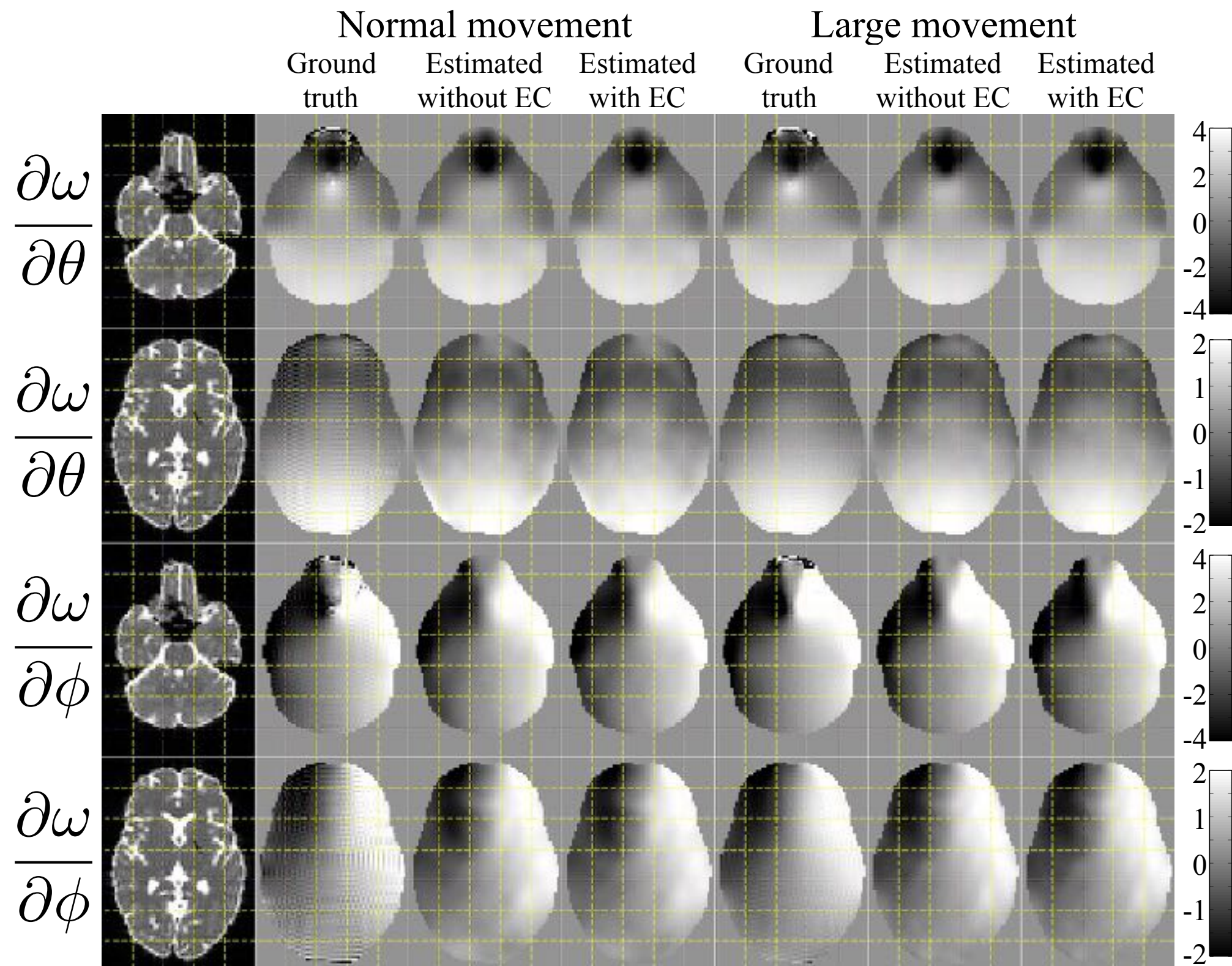
With Susc-by-move







# And this is what the estimated derivative fields look like





# And the problematic HCP subject

