Reconstructing an Increased Number of Simultaneously Excited fMRI Slices

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8/5/2014

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- Introduction
- Single-coil Aliasing Model
- The SPECS Model
- Incorporating Phase Shifted Acquisitions into SPECS
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Introduction

Most multi-band models for accelerating fMRI data acquisition are faced by two limiting factors:

- Acceleration factor, A, limited to no more than the number of coils.
- The origin of a BOLD signal increase within one of several slices aliased together cannot be determined from one measurement.

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- Enables higher acceleration factors by improving the aliasing matrix rank
- Minimal induced correlations

[1]Rowe et al. 2013

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[1]SPECS: Separation of Parallel Encoded Complex-valued Slices

- Enables higher acceleration factors by improving the aliasing matrix rank
- Minimal induced correlations

[2,3]Incorporation of phase shifted acquisitions into the SPECS model:

- Apply various phase shifts to different slices aliased together
- Multiple ways in which each voxel is aliased
- Improves power of detecting activation statistics

[1]Rowe et al. 2013
[2]Rowe et al. 2014 (In prep.)
[3]Setsompop et al. MRM 2013

Single-coil aliasing

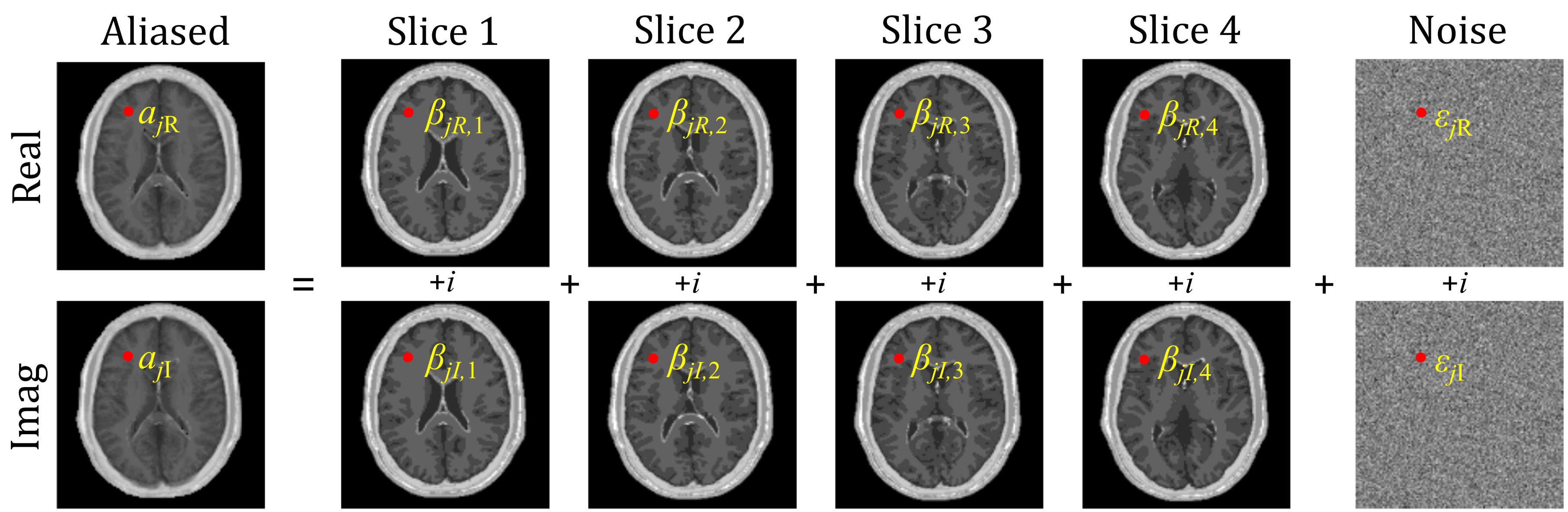
Assuming a homogeneous field, aliasing in a voxel, *j*, is

$$a_{jC} = (\beta_{jR,1} + \beta_{jR,2} + \ldots\beta_{jR,A}) + i(\beta_{jI,1} + \beta_{jI,2} + \ldots\beta_{jI,A}) + (\varepsilon_{jR} + i\varepsilon_{jI})$$

$$= a_{jR} + ia_{jI}$$

$$E[\varepsilon_j] = 0$$

$$\mathrm{cov}(\varepsilon_j) = \sigma^2 I_2$$



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$$= a_{jR} + i a_{jI}$$

In real-valued matrix form:

$$\underset{\substack{2\times 1 \\ \text{Aliased image}}}{\begin{pmatrix} a_{jR} \\ a_{jI} \end{pmatrix}} = \underset{\substack{2\times 2A \\ \text{Aliasing matrix}}}{\begin{pmatrix} 1 & \cdots & 1 & 0 & \cdots & 0 \\ 0 & \cdots & 0 & 1 & \cdots & 1 \end{pmatrix}} \underset{\substack{2A\times 1 \\ \text{True un-aliased images}}}{\begin{pmatrix} \beta_{jR,1} \\ \vdots \\ \beta_{jR,A} \\ \beta_{jI,1} \\ \vdots \\ \beta_{jI,A} \end{pmatrix}} + \underset{\substack{2\times 1 \\ \text{Measurement error}}}{\begin{pmatrix} \varepsilon_{jR} \\ \varepsilon_{jI} \end{pmatrix}}$$

$$a = \left(I_2 \otimes X_A\right) \beta + \varepsilon$$

Single-coil aliasing

At this point, our initial aliasing model is of the form

$$a = \left(I_2 \otimes X_A\right)\beta + \varepsilon = X\beta + \varepsilon$$

The goal is to estimate the true un-aliased voxel values

$$\hat{\beta} = (X'X)^{-1} X'a$$

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When aliasing A slices, the matrix, X, has 2 equations and $2A$ unknowns.

- $(X'X)$ is not square, invertible or of full rank.

We can improve the rank of X by adding $2(A\text{-}1)$ more rows.

Artificial aliasing

If $X = \left(I_2 \otimes X_A\right)$, where $X_A = [1,1,\ldots,1]$, we can add A-1 rows to X_A to make $\begin{bmatrix} X_A \\ C \end{bmatrix}$ square, invertible and full in rank

<u>Orthogonal Coefficients</u>

$$A = 2: \quad C = \begin{bmatrix} -1 & 1 \end{bmatrix}$$

<u>Hadamard Coefficients</u>

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$$A = 2: \quad C = \begin{bmatrix} -1 & 1 \end{bmatrix}$$

$$A = 3: \quad C = \begin{bmatrix} -1 & 0 & 1 \\ 1 & -2 & 1 \end{bmatrix}$$

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$A=4: \quad C=\begin{bmatrix} -3 & -1 & 1 & 3 \\ 1 & -1 & -1 & 1 \\ -1 & 3 & -3 & 1 \end{bmatrix}$	$A=4: \quad C=\begin{bmatrix} 1 & -1 & 1 & -1 \\ 1 & 1 & -1 & -1 \\ 1 & -1 & -1 & 1 \end{bmatrix}$

Artificial aliasing

Adding rows to X gives us additional ways in which the true voxel values in β could be "aliased".

Acquired aliased voxels

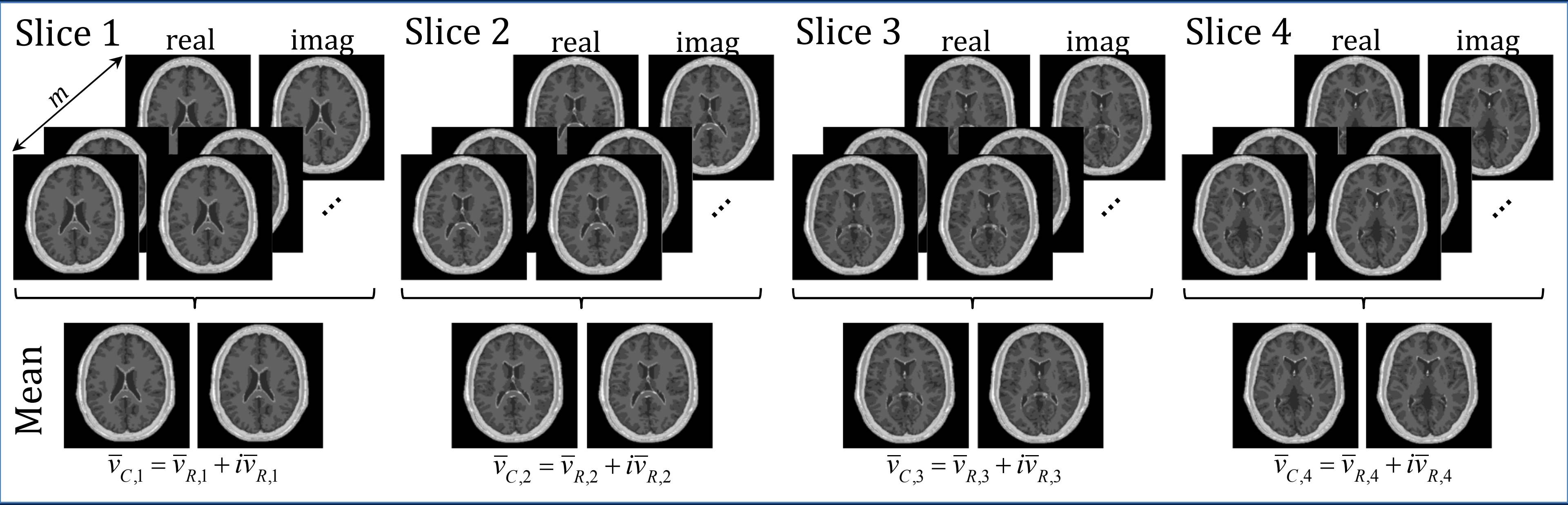
Artificially aliased voxels

$$\begin{pmatrix} a_{jR} \\ ?? \\ a_{jI} \\ ?? \end{pmatrix} = \begin{pmatrix} X_A & 0 \\ C & \\ 0 & X_A \\ & C \end{pmatrix} \beta + \begin{pmatrix} \varepsilon_{jR} \\ ?? \\ \varepsilon_{jI} \\ ?? \end{pmatrix}$$

If we acquire calibration data for each slice, we can use C to artificially alias the slices.

Single-coil calibration data

Acquire a time series of *m* fully sampled complex-valued images for each slice:



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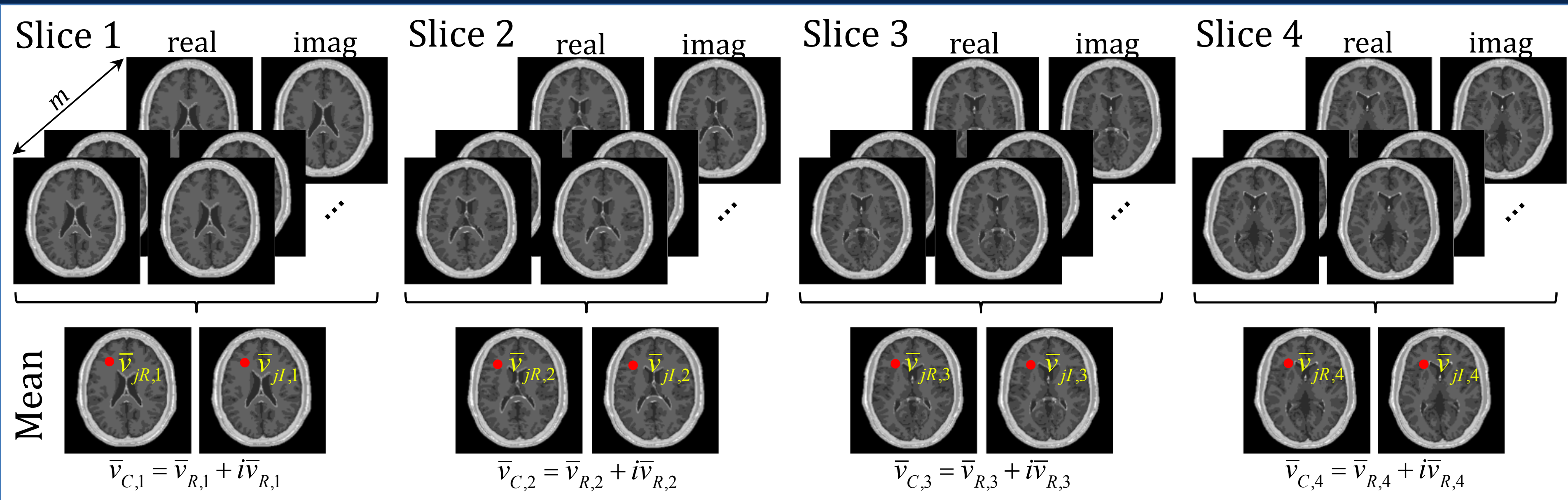

For a voxel *j* in the mean calibration images, we can construct a mean vector

$$\bar{v}_{jC} = \left[\bar{v}_{jC,1}, \bar{v}_{jC,2}, \bar{v}_{jC,3}, \bar{v}_{jC,4} \right]^T$$

The SPECS Model

Incorporating artificially aliased mean calibration voxel values into the model:

Acquired aliased voxels

Artificially aliased voxels

$$\begin{pmatrix} a_{jR} \\ C\bar{v}_{jR} \\ a_{jI} \\ C\bar{v}_{jI} \end{pmatrix} = \begin{pmatrix} X_A & 0 \\ C & \\ 0 & X_A \\ & C \end{pmatrix} \beta + \begin{pmatrix} \varepsilon_{jR} \\ C\eta_{jR} \\ \varepsilon_{jI} \\ C\eta_{jI} \end{pmatrix}$$

$$\underset{2A\times 1}{a} = \underset{2A\times 2A}{X} \underset{2A\times 1}{\beta} + \underset{2A\times 1}{\text{error}}$$

The invertible aliasing matrix allows us to estimate the un-aliased voxel values through a simple inverse: $\hat{\beta} = X^{-1} y$

SPECS Bootstrap approach

To avoid inducing correlations into the un-aliased voxels through the SPECS model, a bootstrapping approach can be used.

Consider the contrast matrices for A=4:

Orthogonal Coefficients

$$A = 4: \quad C = \begin{bmatrix} -3 & -1 & 1 & 3 \\ 1 & -1 & -1 & 1 \\ -1 & 3 & -3 & 1 \end{bmatrix}$$

Assume the covariance of each calibration image is

$$\text{cov}(v_{j,coil}) = \sigma^2$$

Hadamard Coefficients

$$A = 4: \quad C = \begin{bmatrix} 1 & -1 & 1 & -1 \\ 1 & 1 & -1 & -1 \\ 1 & -1 & -1 & 1 \end{bmatrix}$$

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<u>Orthogonal Coefficients</u> <u>Row sum-of-squares (M)</u>

$$A = 4: \quad C = \begin{bmatrix} -3 & -1 & 1 & 3 \\ 1 & -1 & -1 & 1 \\ -1 & 3 & -3 & 1 \end{bmatrix} \rightarrow \begin{bmatrix} 20 \\ 4 \\ 20 \end{bmatrix}$$

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<u>Hadamard Coefficients</u>

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$$A=4: \quad C=\begin{bmatrix} 1 & -1 & 1 & -1 \\ 1 & 1 & -1 & -1 \\ 1 & -1 & -1 & 1 \end{bmatrix} \rightarrow \begin{bmatrix} 4 \\ 4 \\ 4 \end{bmatrix}$$

Averaging M random calibration images with rows of the matrix C will have a covariance

$$\mathrm{cov}(\overline{v}_{j,coil}) = \sigma^2$$

SPECS Bootstrap Statistical Analysis

With the mean and covariance of the data vector,

$$E[a_j]=[a_{jR0},C\overline{v}_{jR0},a_{jI0},C\overline{v}_{jI0}]^T, \quad \Sigma=\text{cov}(a_j)=\sigma^2 I_{2A}$$

the mean and covariance of images reconstructed with a model that employs the bootstrapping approach are

$$E[\hat{\beta}_j]=X^{-1}E[a_j], \qquad \text{cov}(\hat{\beta}_j)=\sigma^2\left(X^{-1}\right)I_{2A}\left(X^{-1}\right)^T$$

Since the aliasing matrix, X, is orthogonal, the theoretical correlation structure induced in $\hat{\beta}_j$ by SPECS is identity.

SPECS Bootstrap Statistical Analysis

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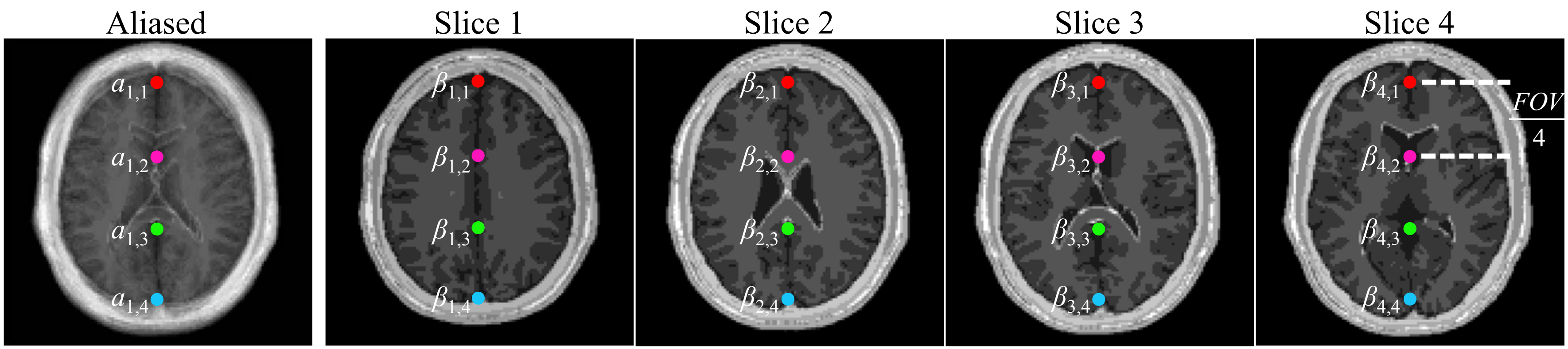
Since the aliasing matrix, X, is orthogonal, the theoretical correlation structure induced in $\hat{\beta}_j$ by SPECS is identity.

Note: If there is a BOLD signal increase (activity) in one of the aliased slices, one cannot determine the origin of the signal increase (which slice) with only one measurement.

Shifted Acquisitions

For a "uniform" acquisition of N_S=4 slices, we can consider a vector of 4 aliased voxels (positioned FOV/4 apart) at once:



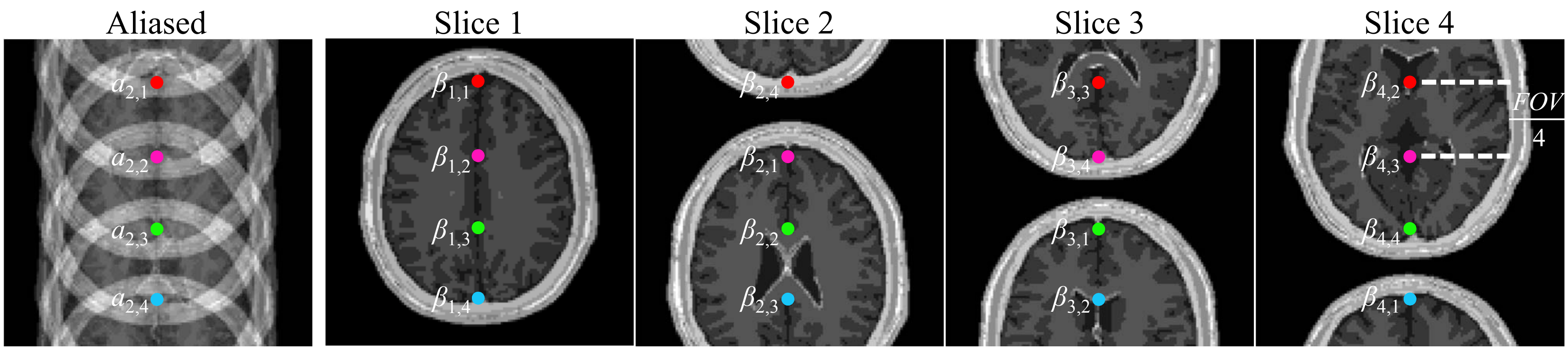
$$\begin{bmatrix} a_{1,1} \\ a_{1,2} \\ a_{1,3} \\ a_{1,4} \end{bmatrix} = a_1 = X_{A1}\beta = \begin{bmatrix} 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \beta_{1,1} \\ \beta_{1,2} \\ \vdots \\ \beta_{2,1} \\ \vdots \\ \beta_{4,4} \end{bmatrix}$$

This is exactly the same as before, only we are now looking at more than one voxel at a time.

[1 Eq with 4 unknowns] $\rightarrow$ [4 Eqs with 16 unknowns] $\rightarrow$ A=4

Shifted Acquisitions

If we shift slices j=1, 2, …N_S=4 in PE by: $(j-1)\dfrac{FOV}{4}$



$$\begin{bmatrix} a_{2,1} \\ a_{2,2} \\ a_{2,3} \\ a_{2,4} \end{bmatrix} = a_2 = X_{A2}\beta = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \beta_{1,1} \\ \beta_{1,2} \\ \vdots \\ \beta_{2,1} \\ \vdots \\ \beta_{4,4} \end{bmatrix}$$

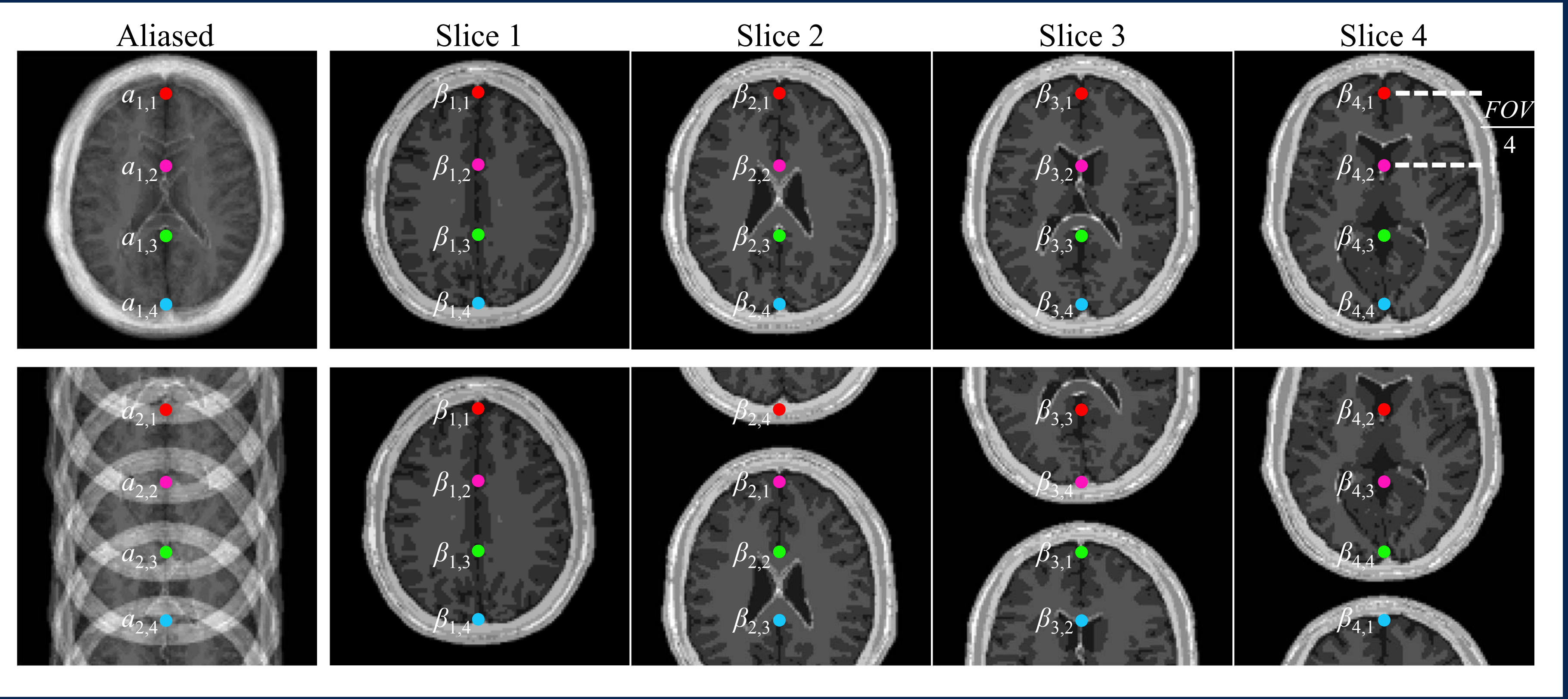
Now have a new way in which the 16 voxels in β can be aliased.

When combined with the uniform aliasing scheme we have:

[1 Eq with 4 unknowns] $\rightarrow$ [8 Eqs with 16 unknowns] $\rightarrow$ A=2

Shifted Acquisitions

Consider the two aliasing patterns at once in a single system



[8 Eqs with 16 unknowns] $\rightarrow A=2$

Shifted Acquisitions

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$$\begin{bmatrix} a_{1,1} \\ a_{1,2} \\ a_{1,3} \\ a_{1,4} \end{bmatrix} = a_1 = X_{A1}\beta = \begin{bmatrix} 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \beta_{1,1} \\ \beta_{1,2} \\ \vdots \\ \beta_{2,1} \\ \vdots \\ \beta_{4,4} \end{bmatrix}$$

$$\begin{bmatrix} a_{2,1} \\ a_{2,2} \\ a_{2,3} \\ a_{2,4} \end{bmatrix} = a_2 = X_{A2}\beta = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \beta_{1,1} \\ \beta_{1,2} \\ \vdots \\ \beta_{2,1} \\ \vdots \\ \beta_{4,4} \end{bmatrix}$$

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$$
\begin{bmatrix} a_{1,1} \\ a_{1,2} \\ a_{1,3} \\ a_{1,4} \\ a_{2,1} \\ a_{2,2} \\ a_{2,3} \\ a_{2,4} \end{bmatrix} = a = \begin{bmatrix} X_{A1} \\ X_{A2} \end{bmatrix} \beta = \begin{bmatrix}
1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \\
1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 \\
0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 \\
0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0
\end{bmatrix} \begin{bmatrix} \beta_{1,1} \\ \beta_{1,2} \\ \vdots \\ \beta_{2,1} \\ \vdots \\ \beta_{4,4} \end{bmatrix}
$$

[8 Eqs with 16 unknowns] $\rightarrow A=2$

Shifted Acquisitions

Consider the two aliasing patterns at once in a single system

$$\begin{bmatrix} a_{1,1} \\ a_{1,2} \\ a_{1,3} \\ a_{1,4} \\ a_{2,1} \\ a_{2,2} \\ a_{2,3} \\ a_{2,4} \end{bmatrix} = a = \begin{bmatrix} X_{A1} \\ X_{A2} \end{bmatrix} \beta = \left[\underbrace{\begin{matrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{matrix}}_{X_1} \quad \underbrace{\begin{matrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{matrix}}_{X_2} \quad \underbrace{\begin{matrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{matrix}}_{X_3} \quad \underbrace{\begin{matrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 \end{matrix}}_{X_4} \right] \begin{bmatrix} \beta_{1,1} \\ \beta_{1,2} \\ \vdots \\ \beta_{2,1} \\ \vdots \\ \beta_{4,4} \end{bmatrix}$$

To incorporate the phase shifted acquisitions into the SPECS model, denote the j^{th} column of the coefficient matrix, C, by C_j to form the new coefficient matrix:

$$C \rightarrow \begin{bmatrix} X_1 \otimes C_1 & X_2 \otimes C_2 & X_3 \otimes C_3 & X_4 \otimes C_4 \end{bmatrix}$$

[8 Eqs with 16 unknowns] $\rightarrow A=2$

Shifted SPECS Model

The original SPECS model is thus updated in three ways:

$$\begin{pmatrix} a_R \\ C\bar{v}_R \\ a_I \\ C\bar{v}_I \end{pmatrix} = \begin{pmatrix} X_A & 0 \\ C & \\ 0 & X_A \\ & C \end{pmatrix} \beta + noise$$

1) New β vector with values from the N_S rows (FOV/N_S apart) in the N_S slices

2) New aliasing matrix

$$\underset{2N_S \times 2N_S}{\begin{bmatrix} X_A \\ C \end{bmatrix}} \rightarrow \underset{\left(2N_S^{\,2} N_{acq} \times 2N_S^{\,2}\right)}{\begin{bmatrix} X_{A1} \\ \vdots \\ X_{AN_{acq}} \\ (X_1 \otimes C_1),(X_2 \otimes C_2),\ldots,(X_{N_S} \otimes C_{N_S}) \end{bmatrix}}$$

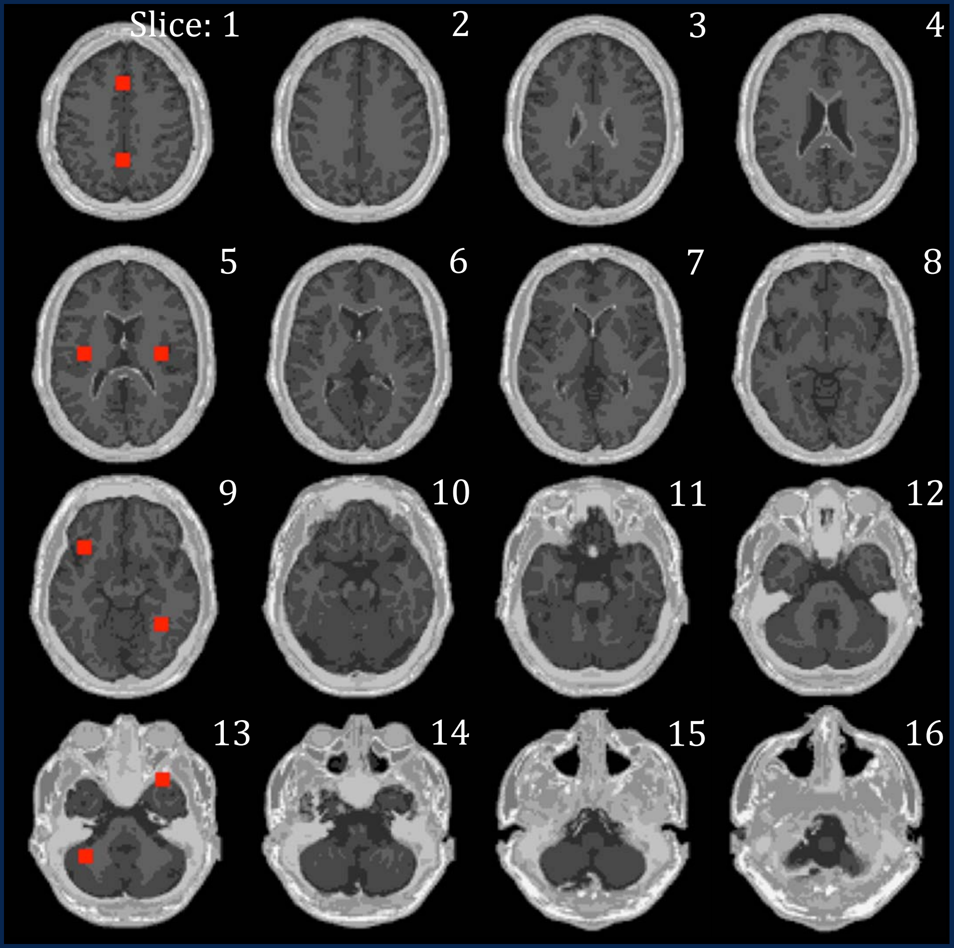
3) Artificially shift and artificially alias random reference images in accordance with shifted aliasing schemes.

$$\text{Acceleration, } A = N_S / N_{acq}$$

Simulation – fMRI Setup

Simulated an fMRI study in N_S=16 (96 × 96) slices

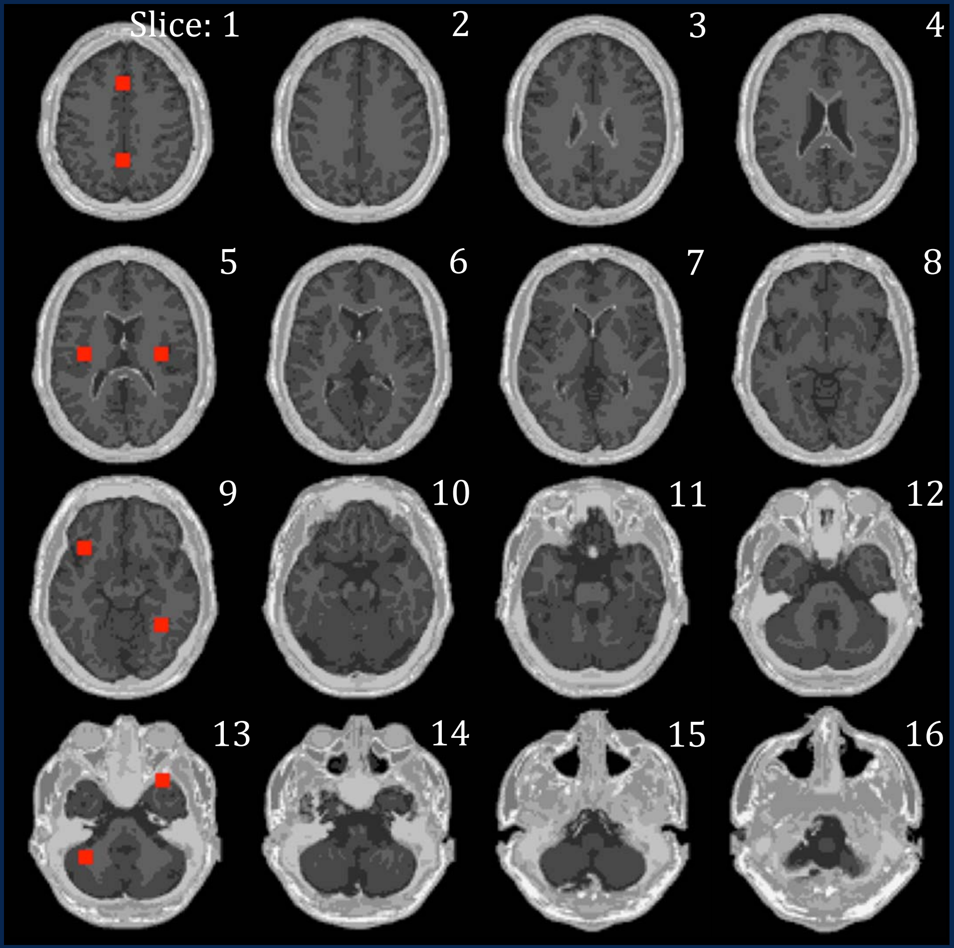
- Max magnitude/SNR = 50
- Phase varied linearly from 0 to π over slices.
- Added $N(0,1)$ noise
- BOLD activity simulated in
  - Slices: 1, 5, 9 and 13
  - 20 epoch block design
  - 15 TRs “on”, 15 TRs “off”
- CNR = 1
- 500 reference images for each slice (non-task)



Simulation - Aliasing

Five data sets simulated with N_{acq} acquisitions and acceleration factors, A, as follows:

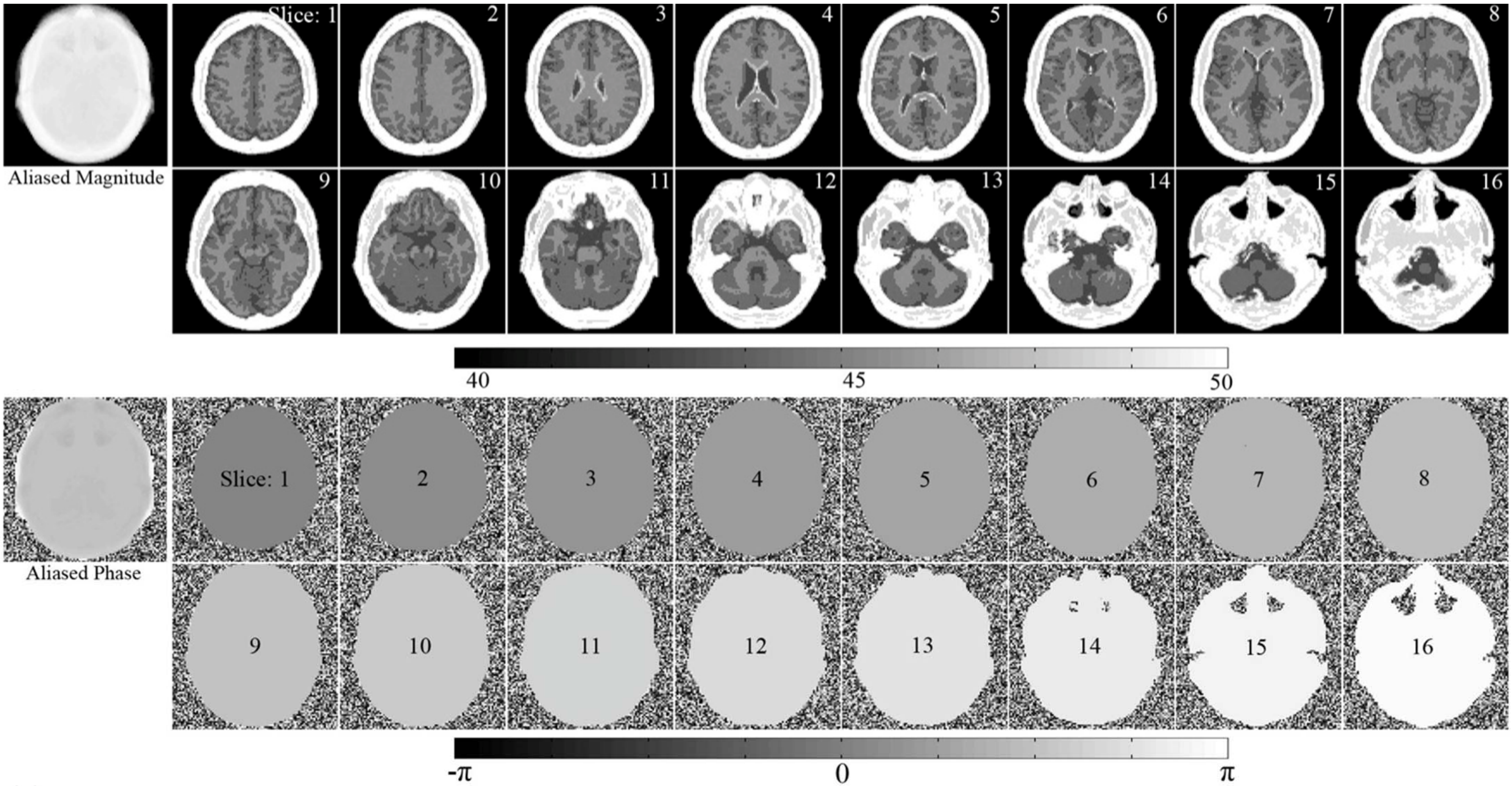
- A=16, (N_{acq}=1)
- A=8, (N_{acq}=2)
- A=4, (N_{acq}=4)
- A=2, (N_{acq}=8)
- A=1, (no aliasing)



For each of acq=1, 2, ... N_{acq} acquisitions, shifts were performed on slice j=1, 2,...16 by: $(acq-1)(j-1)\frac{FOV}{16}$

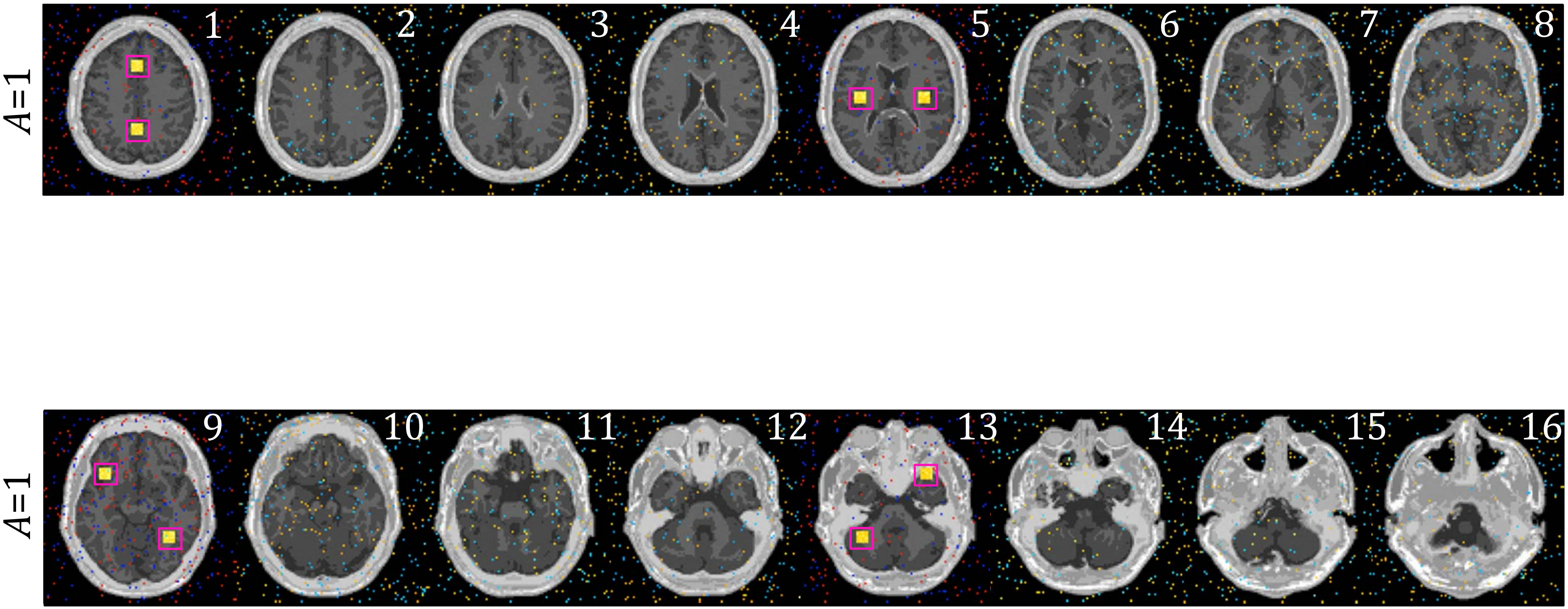
Simulation - Results

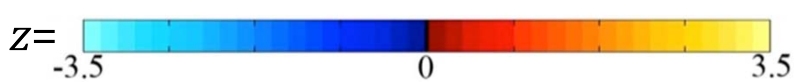
Magnitude and phase images for all reconstructed data sets are indistinguishable, and are thus presented for A=16 (N_{acq}=1).



fMRI Results (A=1, N_{acq}=16)

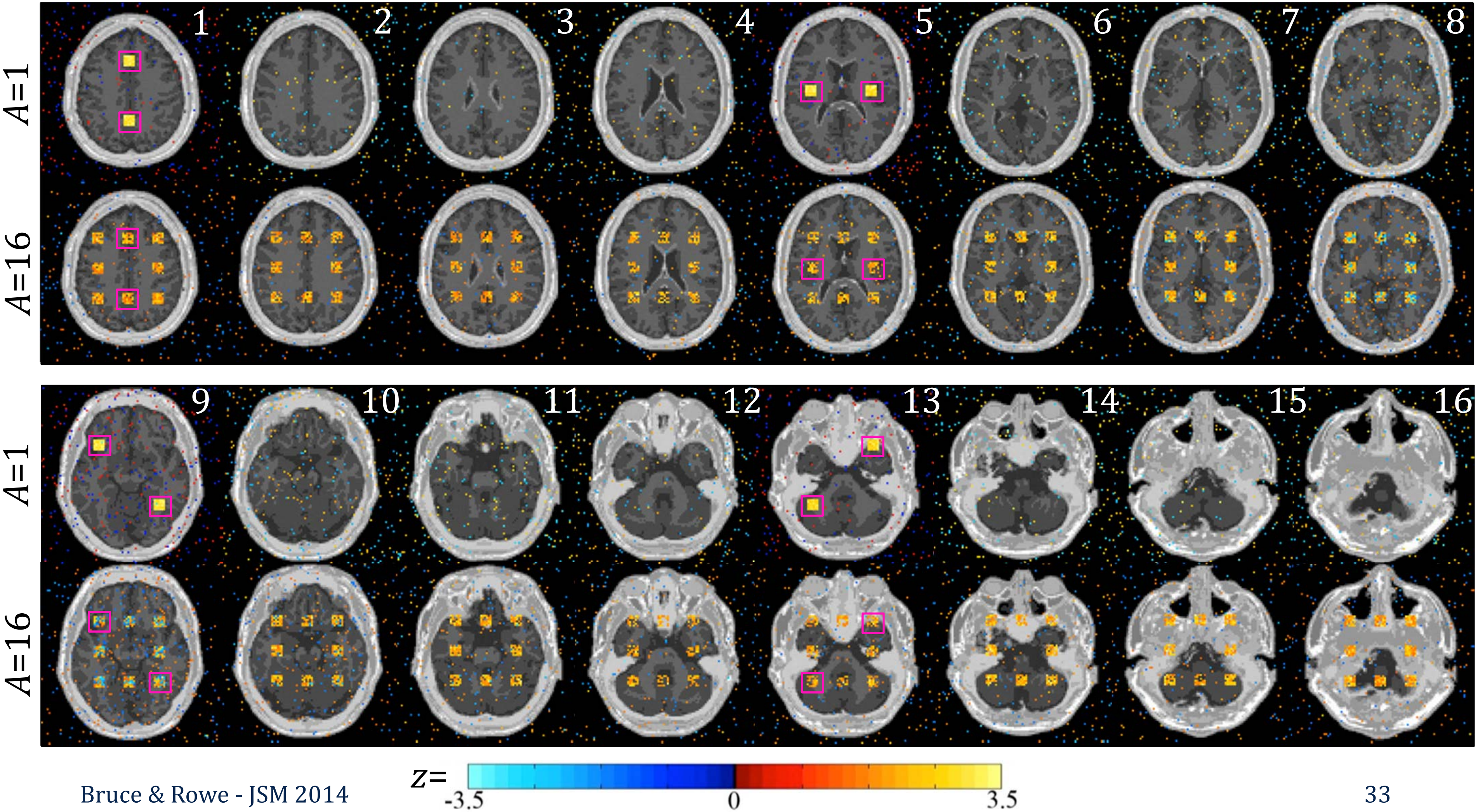
After separation, activation should only be present within the ROIs, otherwise denote false-positives from residual aliasing.





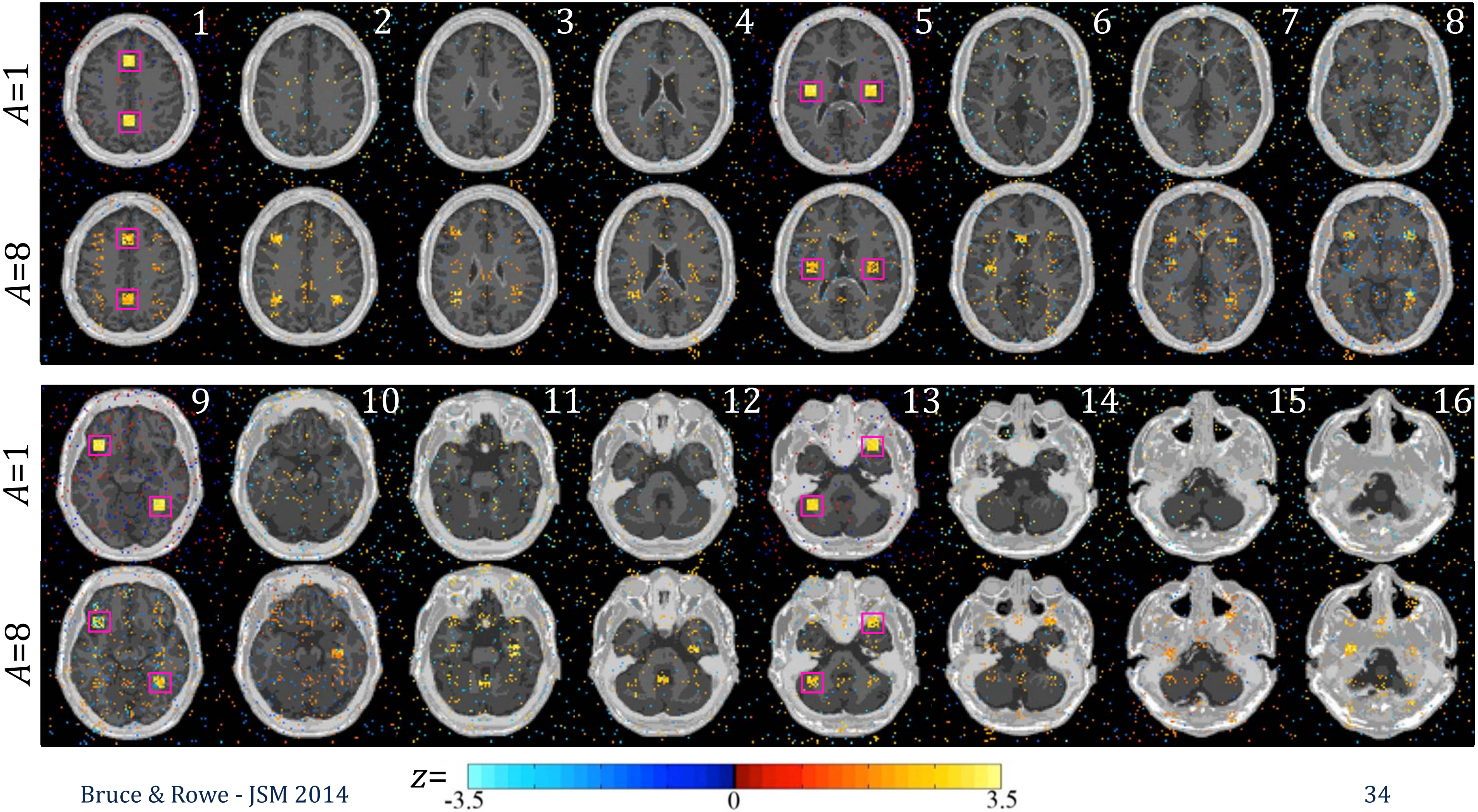
fMRI Results (A=16, N_{acq}=1)

After separation, activation should only be present within the ROIs, otherwise denote false-positives from residual aliasing.



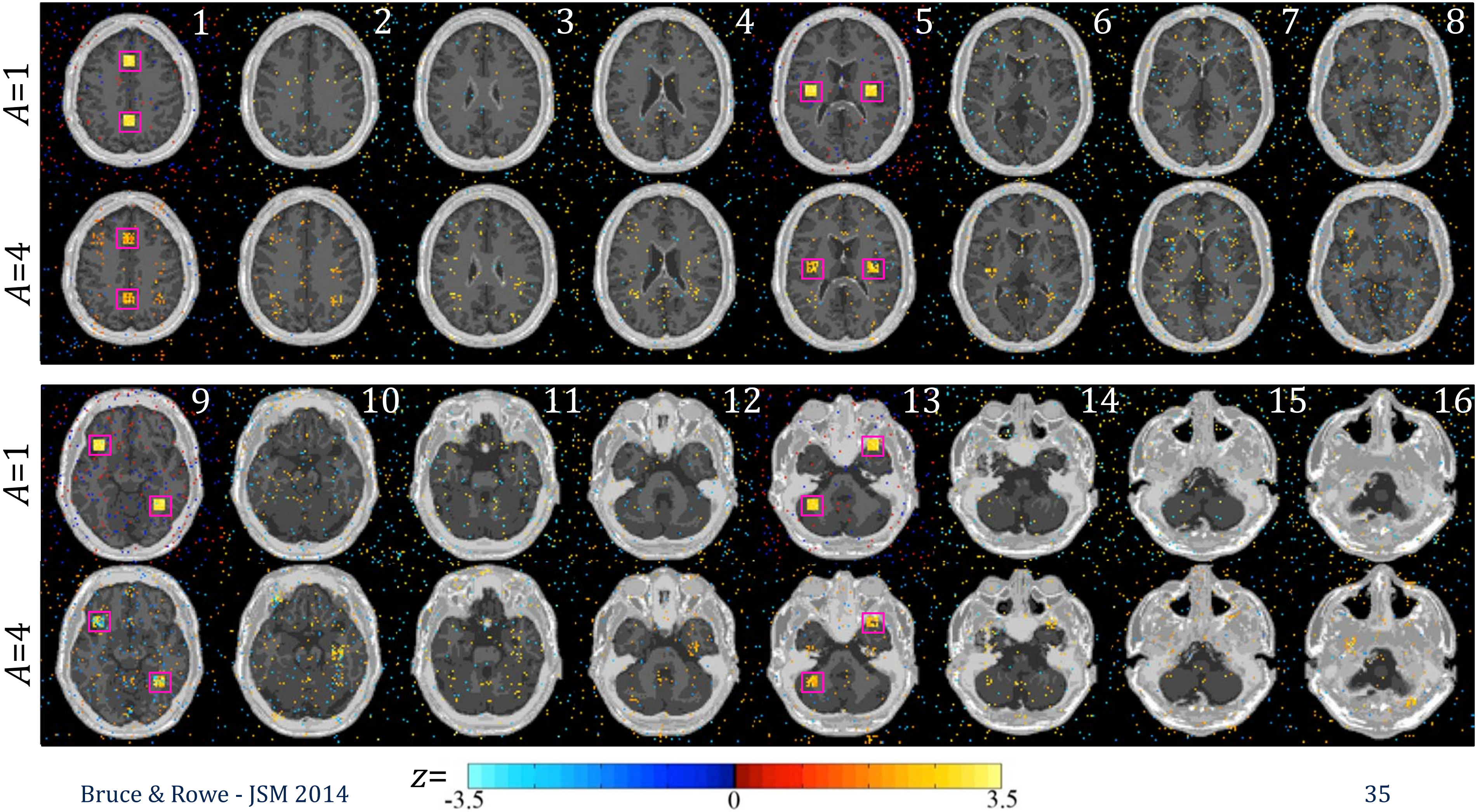
fMRI Results (A=8, N_{acq}=2)

After separation, activation should only be present within the ROIs, otherwise denote false-positives from residual aliasing.



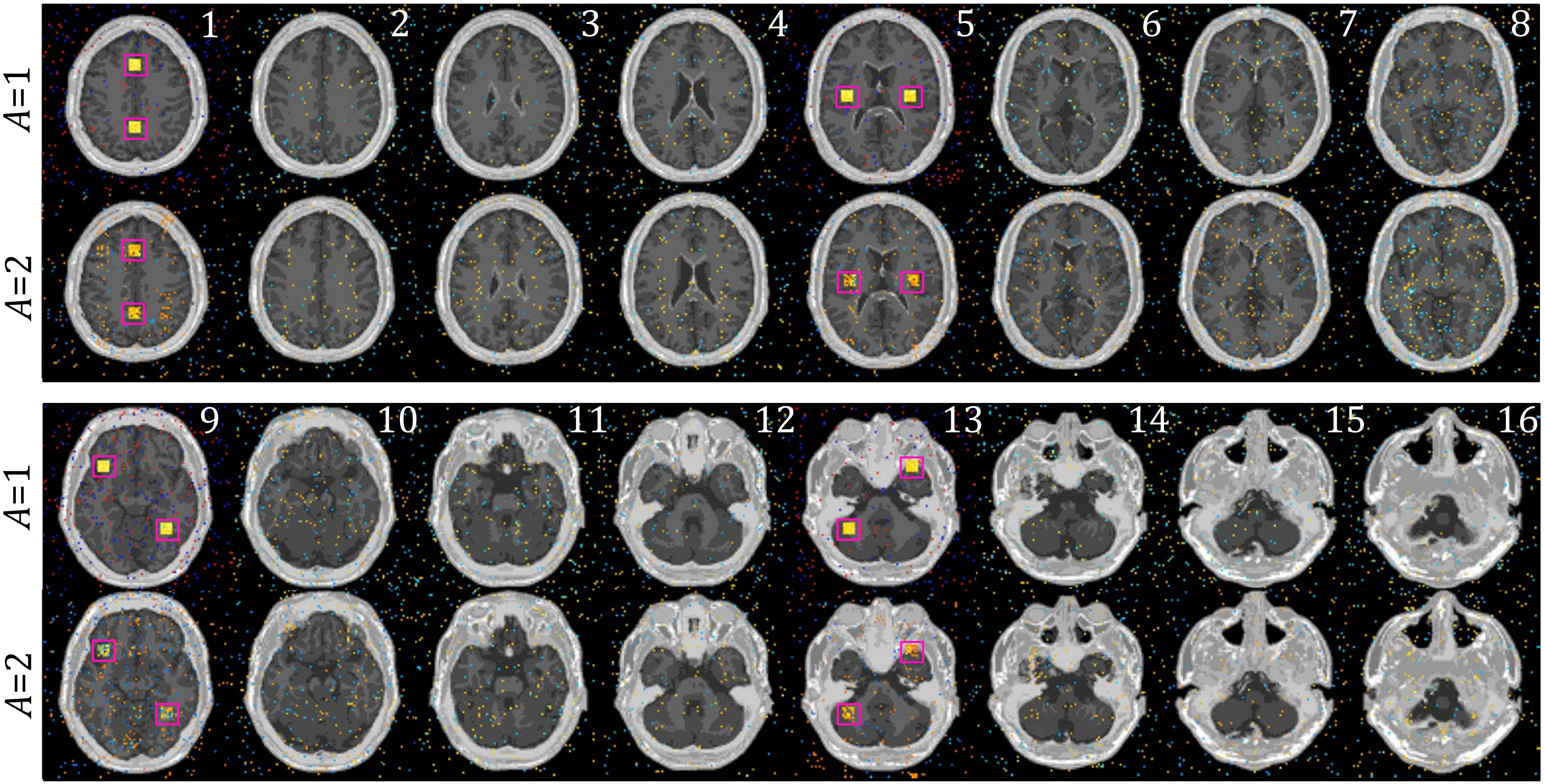
fMRI Results (A=4, N_{acq}=4)

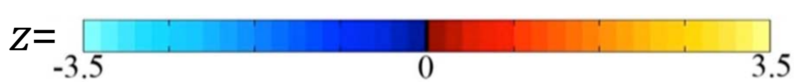
After separation, activation should only be present within the ROIs, otherwise denote false-positives from residual aliasing.



fMRI Results (A=2, N_{acq}=8)

After separation, activation should only be present within the ROIs, otherwise denote false-positives from residual aliasing.





Summary

SPECS incorporates coefficients of orthogonal polynomials and calibration images into the original aliasing model:

- Improves the rank of the aliasing matrix
- Induces no artificial correlation when using Hadamard coefficients
- Acceleration factors can exceed the number of coils (in this case one)

Incorporating multiple phase shifted acquisitions into SPECS:

- Provides multiple ways in which each voxel can be aliased
- Increases the power of detecting activation statistics
- Enables up to four-fold acceleration of fMRI data acquisition with only a single coil

Thank you

Special thanks to collaborators in this work:

- Dr. Daniel B. Rowe, Marquette University,
- Dr. Andrew S. Nencka, MCW
- Dr. James S. Hyde, MCW
- Dr. Andrez Jesmanowicz, MCW