HOW MANY FMRI SCANS ARE NECESSARY AND SUFFICIENT FOR RESTING BRAIN CONNECTIVITY ANALYSIS?

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11.28.18

Background

Resting state fMRI Network
Source: **RFMRI.ORG**

- **Functional connectivity**:

  Temporally correlated neuronal co-activation

- Active during rest – Resting state functional connectivity
- Measured by:

  Low Frequency (< 0:1 Hz) Fluctuations (LFF) of

  Blood Oxygen Level Dependent (**BOLD**) signal

- More suitable for pediatric, aging and disordered population
- Estimation of functional connectivity: **Resting state networks** (RSNs)
- **Analysis**: model driven (SCCA, Graph theory, …) or data driven (PCA, ICA, DL)

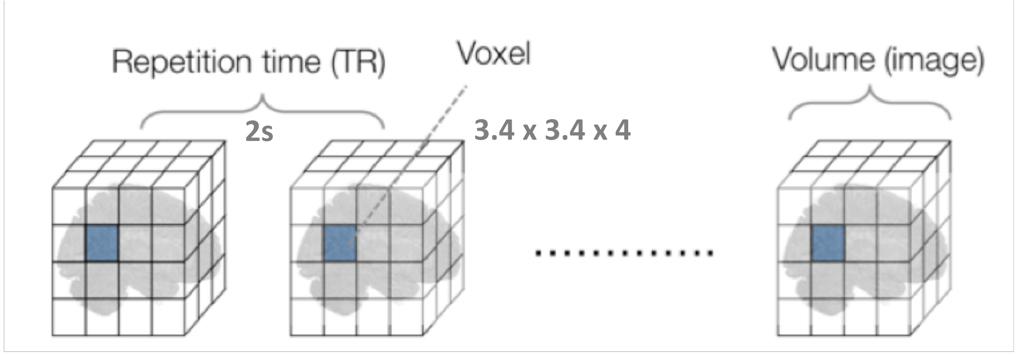
Motivation

- Default scanning period: 5 - 11 minutes
- With time SNR decreases
- Computationally expensive
- Response suppression due to repeated measure
- Reduced subject control
- Difficulty in data collection for diseased population
- <u>Need to investigate whether RSNs can be effectively estimated with a shorter scanning period.</u>

fMRI scan
Source: **radiologyinfo.org**

Data

- **Aging data**
- **14** subjects (8 females + 6 males)
- Mean age = **24** years
- **IRB** approved at UTD and UTSW



- Siemens Allegra **3T** scanner

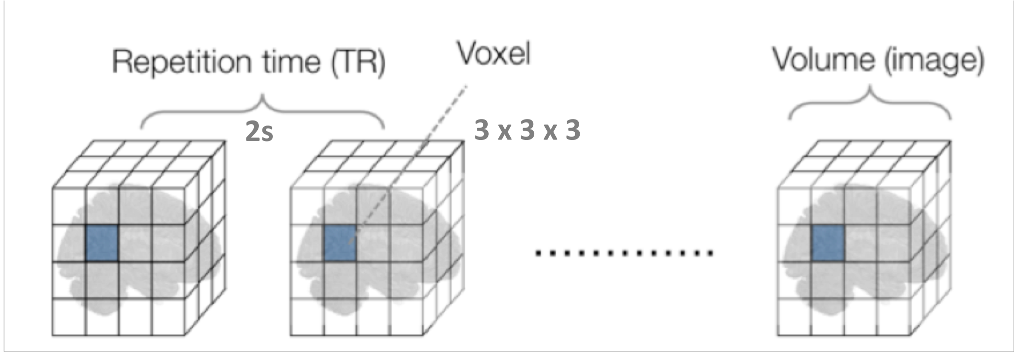
  Anatomical images: MPRAGE sequence: 1 mm isovoxel; sagittal TE=3.7 ms; flip angle = 12^0

- Gradient Echo Planar Images (**EPI**): **120** numbers
- FOV = 220 mm, 64 x 64 matrix, TR/TE = 2000/30 ms; slice thickness of 4 mm.
- Flip angle = 80^0 (to minimize flow weighting)
- 32 slices in the axial plane During the resting-state
- Spatial resolution of voxel as **3.4 x 3.4 x 4** mm^3.

Data

➢ **ADHD data**

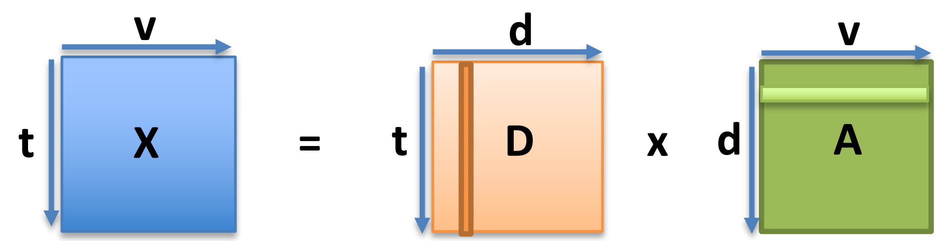
- **40** adolescent subjects
- Age = **7- 21** years
- TR = **2000** ms
- Spatial resolution of voxel as **3 x 3 x 3** mm^3.
- *ADHD-200 consortium*



Data Preprocessing

- **SPM-12** package (http://www.fil.ion.ucl.ac.uk/spm/) on MATLAB 8.1
- Initial **2** scans discarded
- **Motion corrected** and **co-registered** to the anatomical images
- **Normalized** into the **MNI** space.
- **Global signal regression** to remove the noise.
- **Resampled** to 3 mm^3
- **Spatially smoothed** with a Gaussian kernel with FWHM of 5 mm.

Our Approach



- **Dictionary Learning**

- Number of subjects = m
- Number of consecutive scans = n ; $t = nm$ = total number of scans
- Number of voxels = v
- Temporally concatenation to form the data matrix: **X** s.t.

$$\mathbf{X} \in \mathbf{R}^{t \times v}$$

- Decomposition of **X**:

$$\mathbf{X} = \mathbf{D}\,\mathbf{A}$$

- where, $\mathbf{D} \in \mathbf{R}^{t \times d}$ - dictionary of atoms/basis
- rows $\mathbf{a}_{[i]}$ of $\mathbf{A} \in \mathbf{R}^{d \times v}$ - d number of sparse and spatially localized RSNs.

➢ Dictionary Learning

- **Cost function**:

$$\textit{argmin}_{(D,\ A)}\ ||\mathbf{a}_{[i]}||_1 \quad \text{s.t.} \quad \{||\mathbf{X} - \mathbf{DA}||_F\}^2 < \epsilon$$

- $||\ \ ||_1$ - Sparsity promoting function l_1-norm
- $||\ \ ||_F$ - Forbenius norm respectively.
- Jointly non-convex in (**D**, **A**) and hence becomes a NP-hard problem
- Solved using alternative iterations of Dictionary Update (DU) and Sparse Coding (SC)
- The dictionary **D** is undercomplete and projects the low rank structure of rs-fMRI data.

Experiment

➢ Dictionary Learning vs Group P/ICA

- Group-PCA: Eigen value analysis → Noise suppression → MDL criteria → Projection
- Group-ICA: **GIFT** toolbox: Extended Infomax
- DL: Online Dictionary Learning (**ODL**)

➢ Scan sampling

1. First n consecutive scans
2. Random sampling of n number of scans (n is the desired optimum scan)
3. All 120 scans.

➢ Subject sampling

- Subjects with the size of 1; 5; 10 and 14.

Experiment

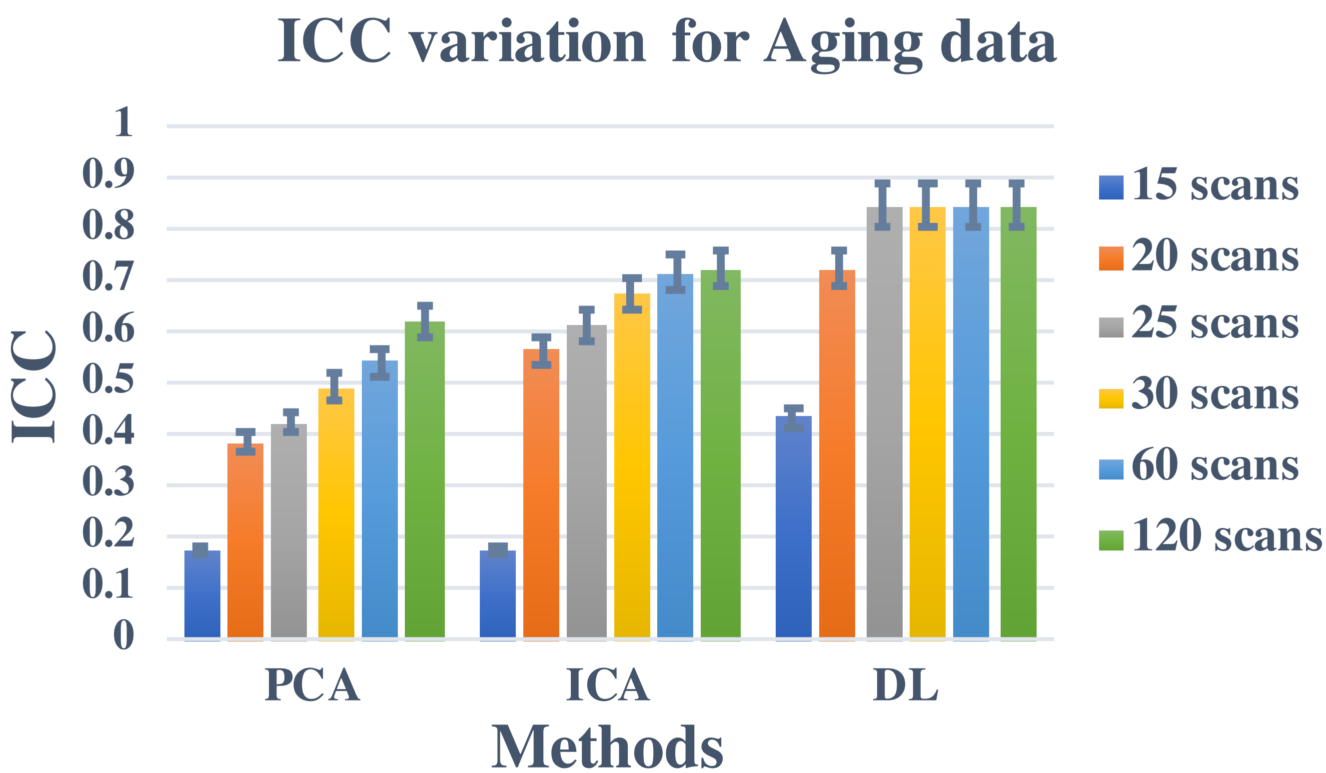
➢ **Reliability**

- Qualitative: by plotting the activated RSNs
- Quantitative: by computing **ICC** (Intra-class Correlation Coefficient)

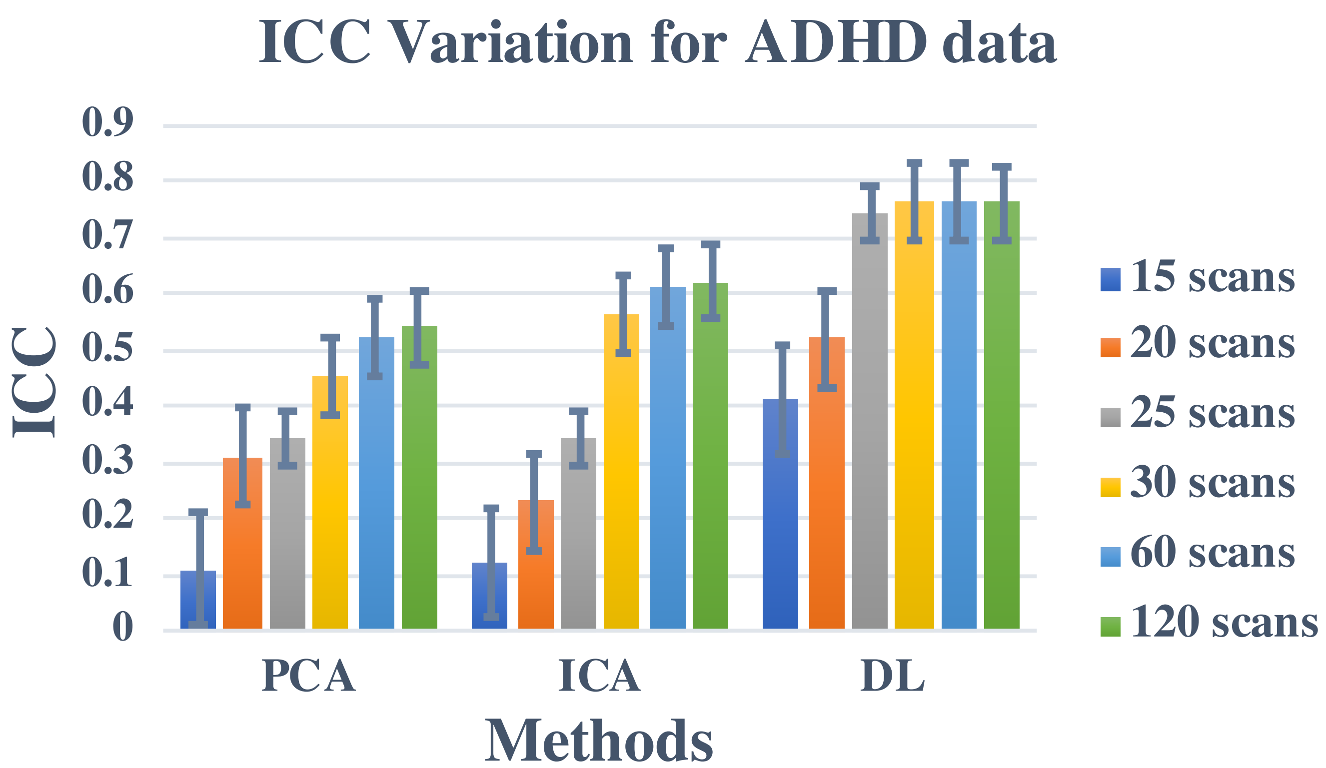
$$\mathbf{ICC} = \frac{\boldsymbol{MSb - MSw}}{\boldsymbol{MSb + (k-1)MSw}}$$

- **MSb** = between-subject mean squares
- **MSw** = within-subject mean squares
- ***k*** is number of fMRI datasets.
- <u>ICC is close to 1 when MSb >> MSw</u>

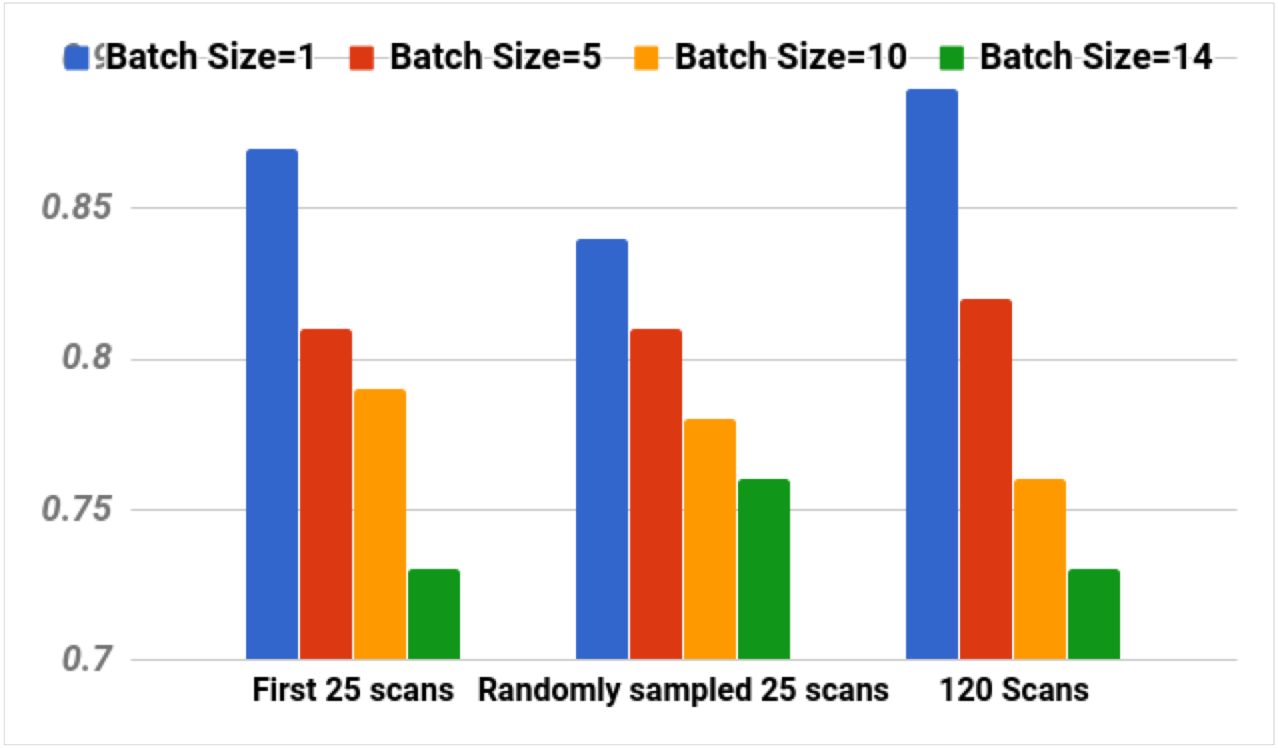
Results : Scan sampling



Results : Scan sampling



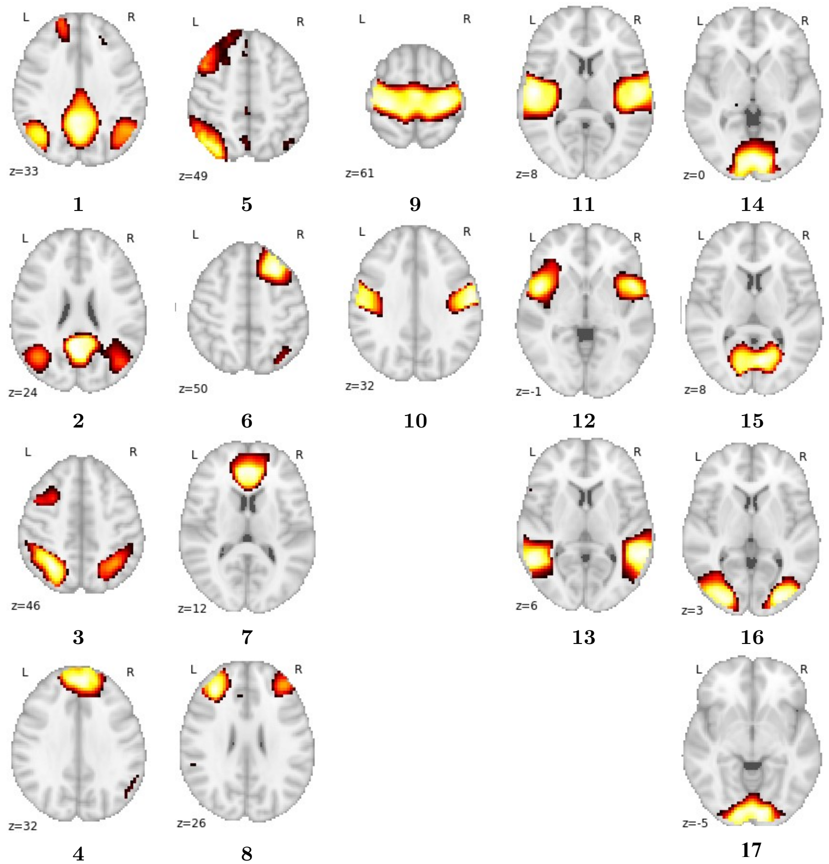
Results : Subject sampling



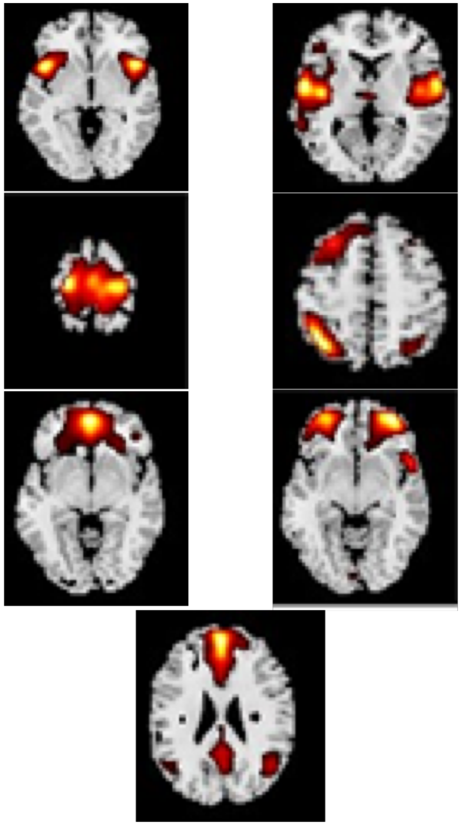
Results : RSN estimation

Method	Number of scans							
	5	10	15	20	25	30	60	120
	Number of functional networks obtained							
Group-PCA	0	0	1	2	4	5	7	9
Group-ICA	0	0	1	5	7	7	15	17
DL	0	3	7	14	17	17	17	17

Results: RSNs with 25 initial scans



DL



ICA

Conclusions

- **A total of 25 number of scans amounting about 1-minute are enough for Dictionary Learning to effectively distinguish distinct resting state networks.**
- High quality spatially localized ICNs with high ICC values can be identified by DL with limited amount of data

PCA < ICA < DL

- Sparsity might be a better constraint for rs-fMRI analysis
- Faster computation
- The neuroscience research in clinical, pediatrics or aging population could greatly benefit with this approach even with limited amount of data.
- <u>Further verification required with varying TR and voxel resolution</u>

Acknowledgments

- NIH-R03 DC013990 (PI: Wang)
- University of Texas System Brain Research grant (PI: Wang)
- Dr. Bart Rypma and Dr. Vinayak Abrol
- IEEE SPS travel grant

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Thank you