Ground-truth "resting-state" signal provides data-driven estimation and correction of scanner distortion

Rajat Kumar[1], Liang Tan[2], Alan Kriegstein[2], Andrew Lithen[1], Jonathan Polimeni[3], Lilianne Mujica-Parodi[1,3], Helmut Strey[1]
1. Stony Brook University, NY; 2. ALA Scientific Instruments, NY; 3. A. A. Martinos Center for Biomedical Imaging, MA; USA.

Motivation and Preliminaries

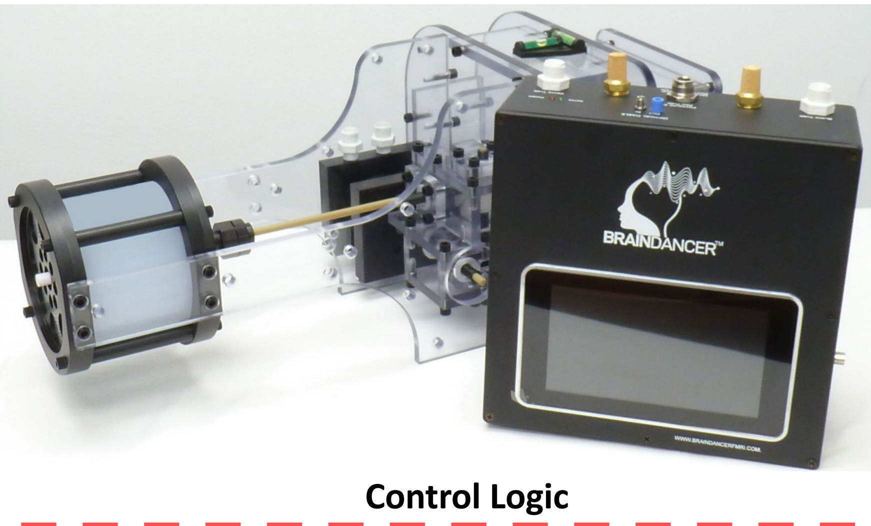
The ability to minimize and correct for scanner-induced distortion of fMRI time-series data addresses a fundamental unmet need in modern task-free ("resting-state") fMRI. For task-based fMRI, subtracting noise from signal is straightforward, since a task activates the brain reliably more under one condition (signal) than another (noise). However, for task-free analyses, the 'baseline' fluctuations themselves also include the 'signal'. In our work, we demonstrate a commercial-grade dynamic phantom, designed to identify systematic scanner-induced noise in time-series data, combined with a deep learning algorithm to correct for the scanner-induced noise. Our deep learning algorithm outperforms conventional machine learning techniques like denoising using the Marchenko-Pastur principal components analysis (MP-PCA). The dynamic phantom not only improves the signal to noise ratio, but can also be used for standardization of protocols and harmonization across scanners.

Scanner Induced Noise in fMRI

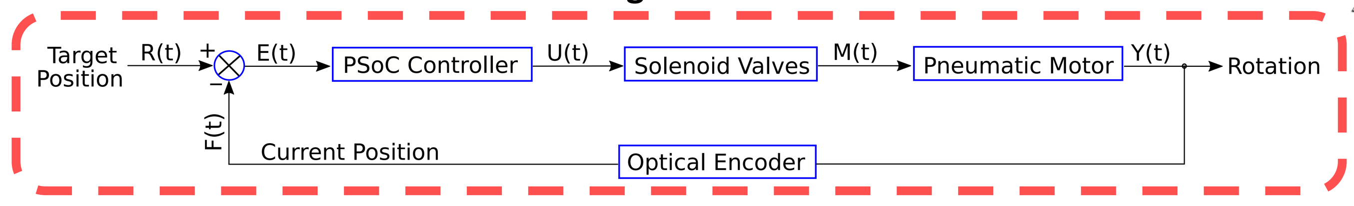
Thermal Noise	Scanner Instability
Signal-independent additive noise.	Signal-dependent multiplicative noise.

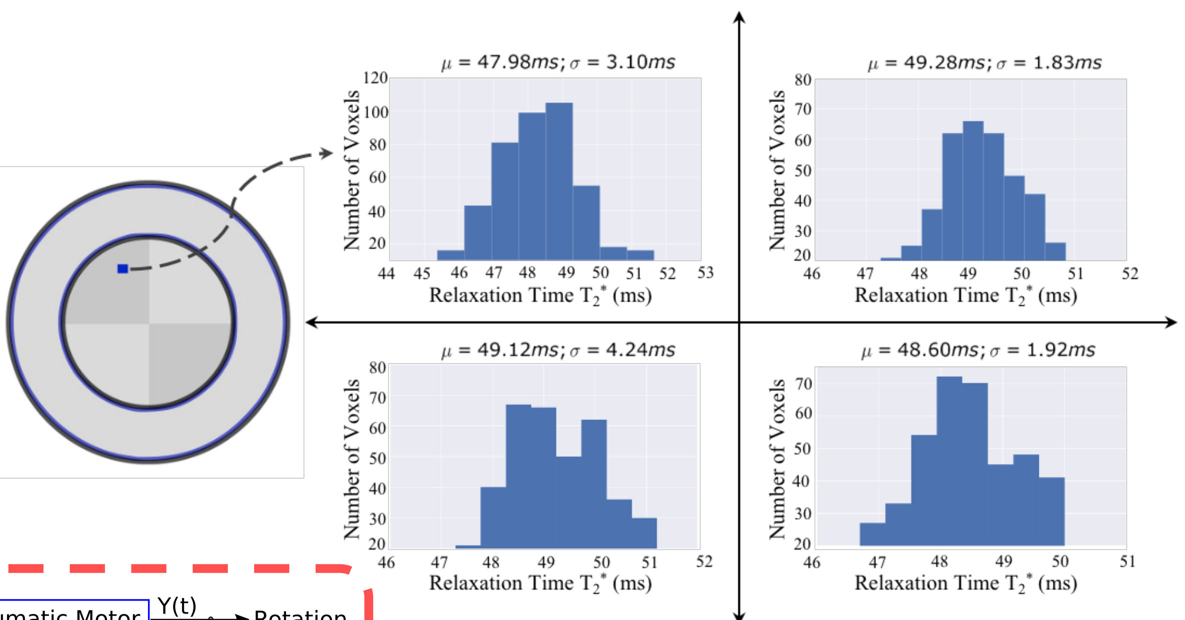
BRAINDancer Dynamic Phantom for Functional MRI

- The phantom consists of two concentric cylinders, with the inner cylinder divided into quadrants and filled with 2 different agarose gel concentrations while the outer cylinder is filled with a single agarose gel concentration.
- The inner cylinder is rotated pneumatically to produce dynamic T2* changes within a voxel, that are matched to typical BOLD amplitudes in human brains.
- The phantom is programmed to produce resting state BOLD-like signals using PSOC microcontroller (controls solenoid valves to drive the pneumatic motor).
- The phantom motion is synchronized to the MR scanner triggers via TTL/serial logic and motion is restricted to 200ms from start of each TR.



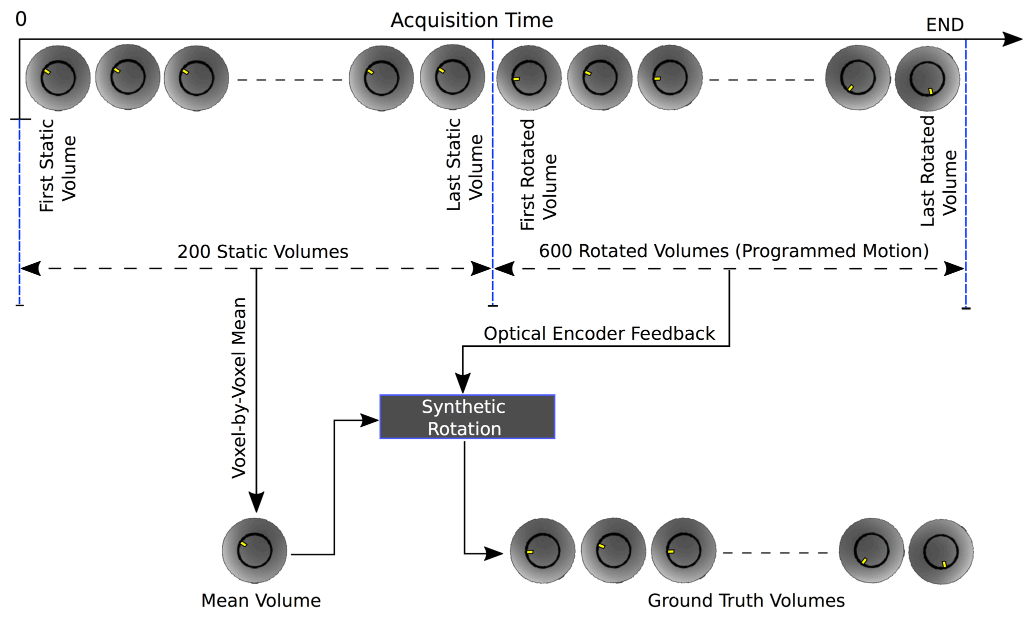
Control Logic



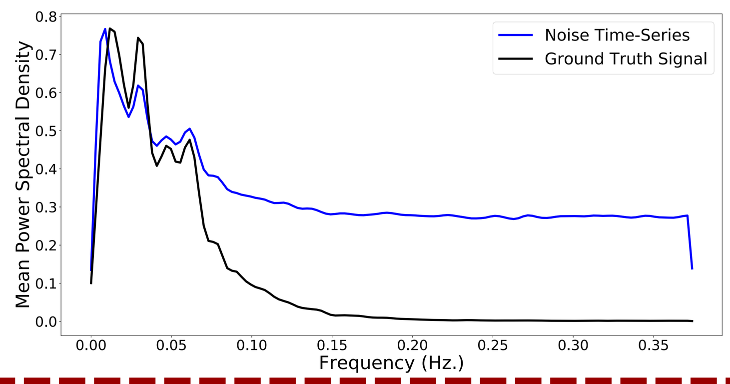


Agarose Gel Characteristics

Noise Estimation, Data Quality Metrics and the Deep Learning Based Denoiser



- For each acquisition, 200 static and 600 rotating volumes are acquired. The static volumes are averaged and then rotated algorithmically to create ground-truth, followed by comparison between scanner output and the ground-truth for obtaining voxelwise noise time series.
- Figure (right) shows **input dependent noise.**



Data Quality Metrics

$$ST-SNR = \frac{Power_{Signal}}{Power_{Noise}}$$

Standardized SNR

- ST-SNR < 1 ➔ Noise Dominates
- ST-SNR > 1 ➔ Signal Dominates

$$DF = \frac{cov(Meas., GT)}{\sigma_{Meas.}\sigma_{GT}}$$

Dynamic Fidelity

- Ranges between 0 – 1.

Nonlinearity Estimation

$$\underbrace{Y(t)}_{\text{Measured fMRI}} = \overbrace{L(t)}^{\text{Linear Function of Ground-Truth}} + \underbrace{F(t)}_{\text{Nonlinear Function of Ground-Truth. Tree nonlinearity estimator.}} + E(t)$$

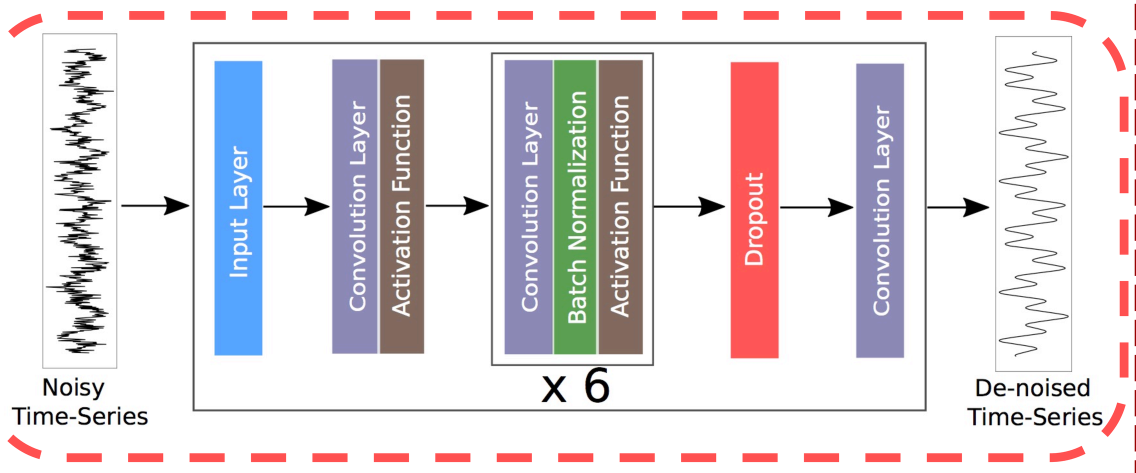
Scanner Instability (Multiplicative Noise)

$$\sigma_{fMRI}^2 = \sigma_{GT}^2 + \sigma_T^2 + \beta^2\sigma_{GT}^2 = \sigma_{GT}^2 + \sigma_{noise}^2$$

$$P\left(Y_{fMRI} \middle| Y_{GT}, \sigma_T, \beta\right) = N(\mu = Y_{GT}, \sigma^2 = \sigma_T^2 + \beta^2 Y_{GT}^2)$$

- We calculated four different data quality metrics using the ground-truth signal (GT), the measured fMRI, and the noise estimates.
- We quantified the ratio of scanner instability to thermal noise using a probabilistic model of the two noise-sources. The scanner instability is signal dependent, whereas background/thermal noise is independent of MR signal intensity.

Denoiser (CNN for temporal denoising)



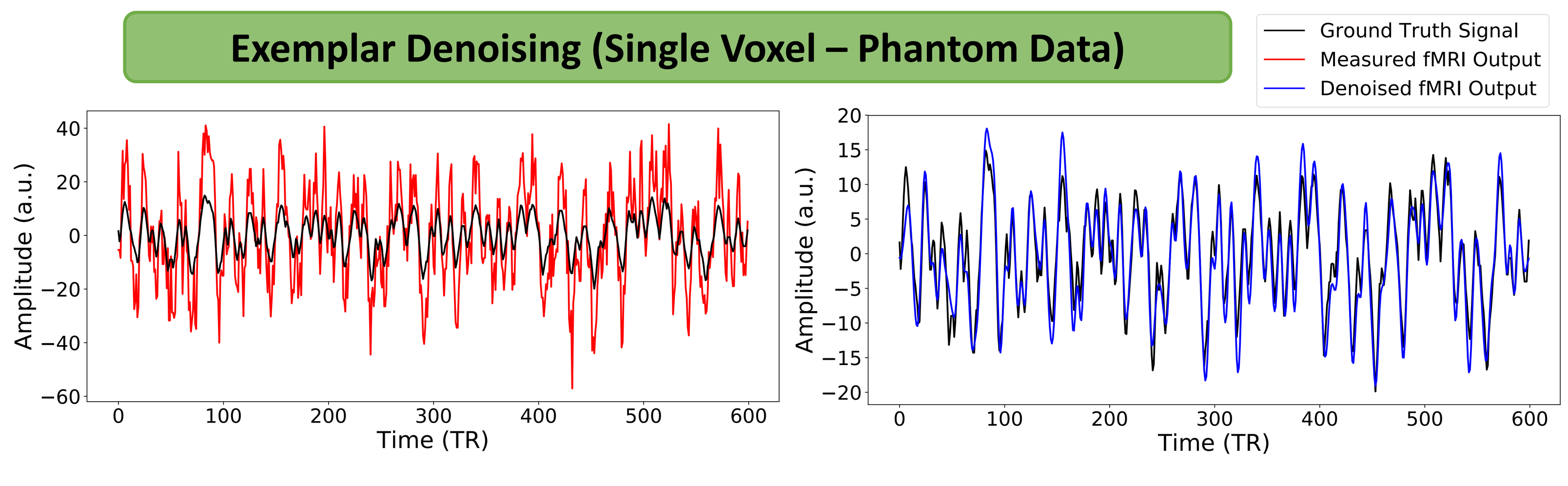
- An end-to-end trainable CNN architecture that uses discriminative denoising to remove noise in the hidden layers.
- Each convolution layer (except the last) contains 18 filters with a kernel size of 9 and a stride of 1. Sigmoid is used as the activation function. A dropout of 0.2 is used in the dropout layer. The last convolution layer contains only one filter. Negative of R-squared between the ground-truth and the denoised time-series used as the loss function (minimize) with Adam optimizer for stochastic optimization.

Scanner-Induced Noise Removal and Improved Detection Sensitivity of Resting-State Networks

Study Design – Phantom and Human Experiments

- Site 1: Only phantom scans.
- Site 2: Data acquired on each scanner in a single session with scan sequence as: Phantom ➔ 3 Human Subjects ➔ Phantom ➔ 3 Human Subjects ➔ Phantom.
- Human subjects viewed a naturalistic stimuli (ecological movie, no audio) while being scanned.

Exemplar Denoising (Single Voxel – Phantom Data)



Data Quality and Denoising Test Data (Phantom Experiments)

Scanner	Data Quality				Instability	Temporal Denoising					
	Fidelity	ST-SNR	Non-Linearity (% of Total Voxels)		Contribution of Total Noise (%)	Bandpass Filter		MP-PCA + Bandpass Filter		CNN	
			Weak	Strong		Fidelity	ST-SNR	Fidelity	ST-SNR	Fidelity	ST-SNR
Site 1: PRISMA 3T	0.38	0.27	18	8	10.06	0.51	0.72	0.53	0.82	0.58	1.5
Site 2: PRISMA 3T	0.32	0.2	25	10	5.7	0.46	0.59	0.51	0.72	0.55	1.44
Site 2: SKYRA 3T	0.33	0.27	32	15	17.15	0.66	0.45	0.49	0.79	0.52	1.37
Site 2: MAGNETOM 7T	0.37	0.34	24	19	17.94	0.47	0.77	0.5	0.88	0.51	1.35

Correction of Scanner Distortion for Human Data

Detection Sensitivity of Resting-State Networks

- **Standard Method**: Spatial Preprocessing + Motion Regression + CompCor + 4mm Smoothing.
- **MP-PCA Denoising**: Standard Method + MP-PCA Denoising.
- **Proposed Method**: Standard Method + CNN Denoising.

		3T PRISMA			3T SKYRA			7T MAGNETOM		
	Subject #	Standard Method	MP-PCA Denoising	CNN Denoising	Standard Method	MP-PCA Denoising	CNN Denoising	Standard Method	MP-PCA Denoising	CNN Denoising
Run 1	Subject 1	2.06	2.22	**2.24**	1.9	2.14	**2.27**	1.89	2.05	**2.25**
	Subject 2	2.25	2.45	**2.55**	2.11	2.39	2.39	2.37	2.61	**2.85**
	Subject 3	2.17	2.36	**2.55**	2.13	2.41	**2.54**	2.32	2.56	**2.78**
Run 2	Subject 1	1.88	2.01	**2.04**	1.95	2.25	**2.38**	2.12	2.24	**2.44**
	Subject 2	2.23	2.46	**2.59**	2.32	2.6	**2.86**	2.22	2.5	**2.63**
	Subject 3	2.1	2.34	**2.45**	2.25	2.52	**2.84**	2.42	2.62	**2.89**
% Improvement			9.06	4.19		13.03	6.78		9.06	8.64
			13.63			20.07			18.74	

- Denoising of human fMRI data for removing scanner-confounds showed an increase in the detection sensitivity of resting-state networks. Here, detection sensitivity refers to the ratio of mean absolute Z-score inside and outside a well-defined resting-state network mask in calculated subject-specific ICA maps. Detection sensitivity >1 indicates higher contrast of voxels-of-interest inside the brain network compared to voxels outside. The higher score is in bold.

Download
Corresponding Manuscript (NeuroImage)
https://bit.ly/2RT9Ats

2511

Commercialization Partner
ALA Scientific Instruments, Inc.

Correspondence: Rajat Kumar, LCNeuro
rajat.kumar@stonybrook.edu

National Institute on Drug Abuse