

Uncovering Hidden Activation Using Model-Free Analysis

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Declaration of Financial Interests or Relationships

Speaker Name: Javier Gonzalez-Castillo

I have no financial interests or relationships to disclose with regard to the subject matter of this presentation.

- **BOLD fMRI time-series are noisy**

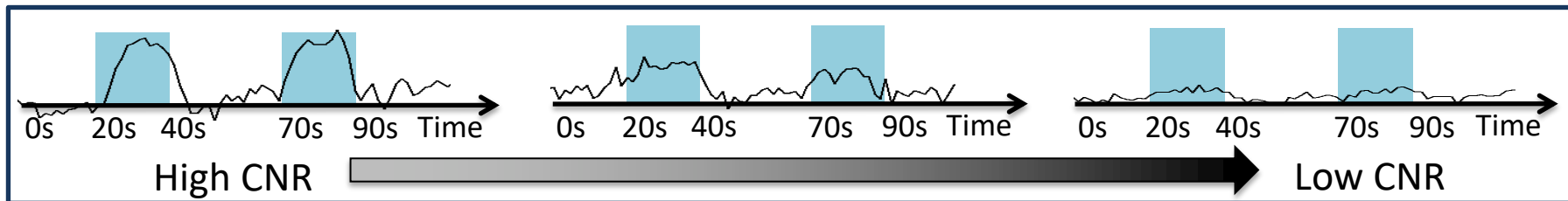


- Thermal Noise
- Signal Drift
- Intensity Inhomogeneity

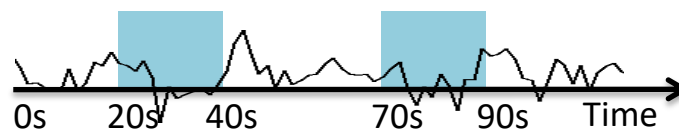
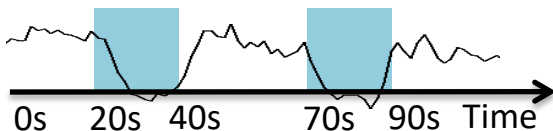


- Head Motion
- Physiological Noise
- Variable Compliance

- **BOLD responses are many times in the same order of magnitude as the noise**

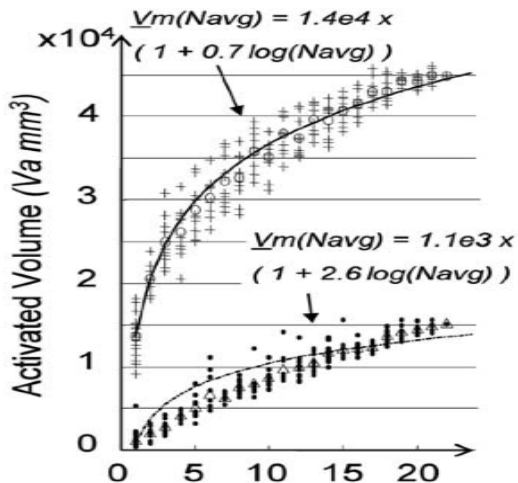


- **BOLD responses vary regionally in shape and timing**



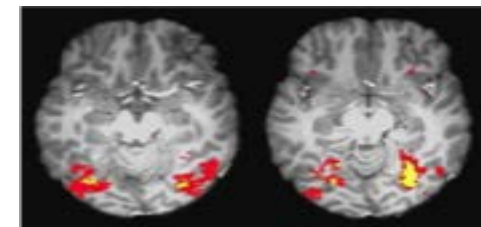
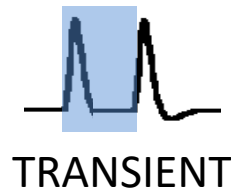
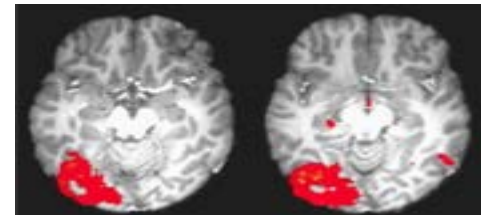
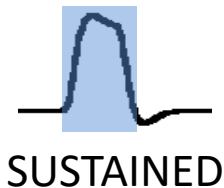
fMRI Activation maps are highly dependent on:

- Available Temporal Signal-to-Noise
- Assumptions on Response Shape and Timing



ACTIVATION VOLUME INCREASES LOGARITHMICALLY WITH NUMBER OF SCANS.

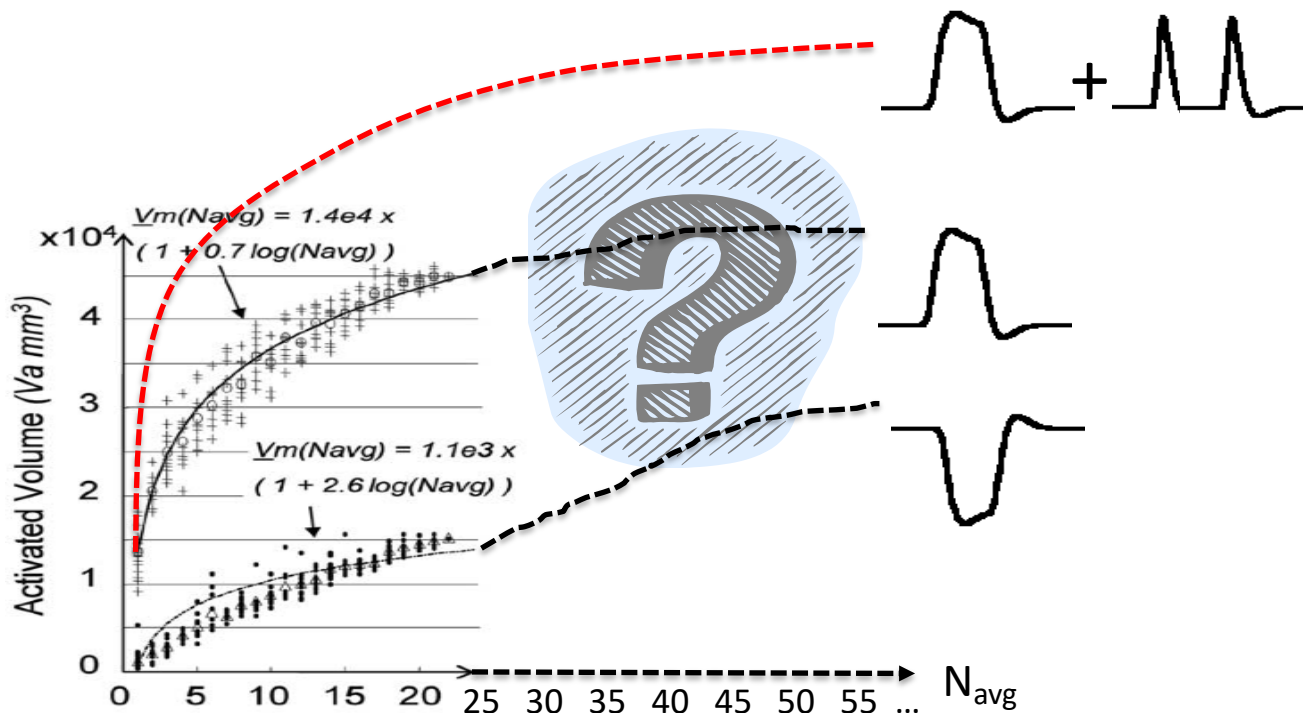
Saad et al., NeuroImage 2003



CONSIDERATION OF ADDITIONAL RESPONSE SHAPES ALLOWS DETECTION OF NEW ACTIVATION SITES

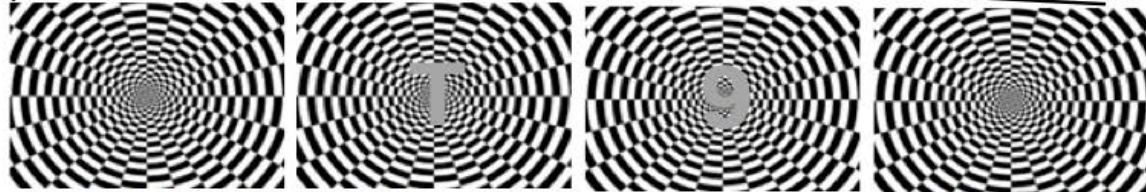
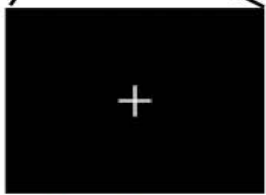
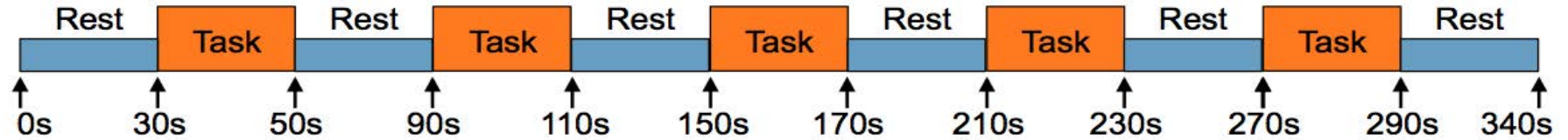
Uludag et al., MRM 2008

To what extent is the sparseness of task-based fMRI activation maps real or a result of noise levels (insufficient CNR) and/or modeling decisions?



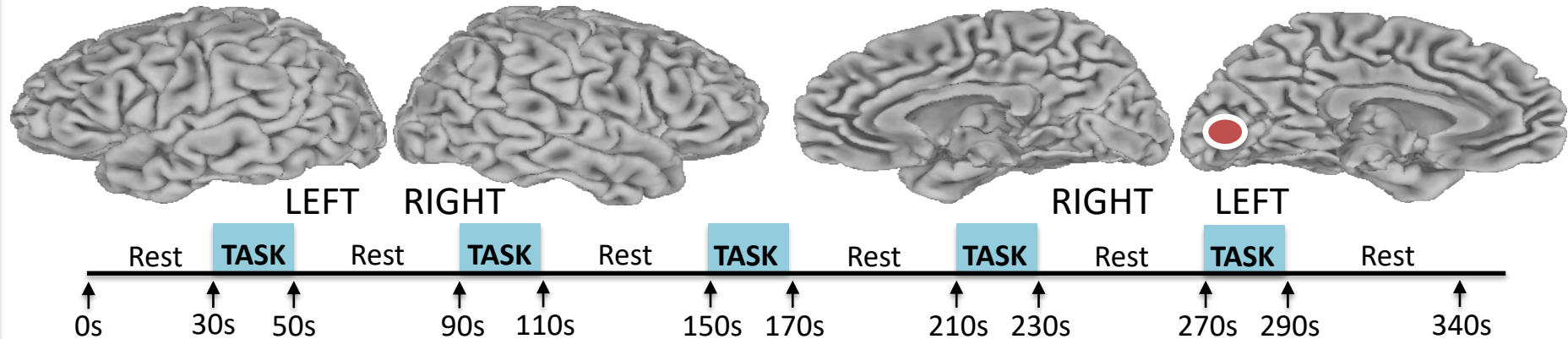


3 Subjects

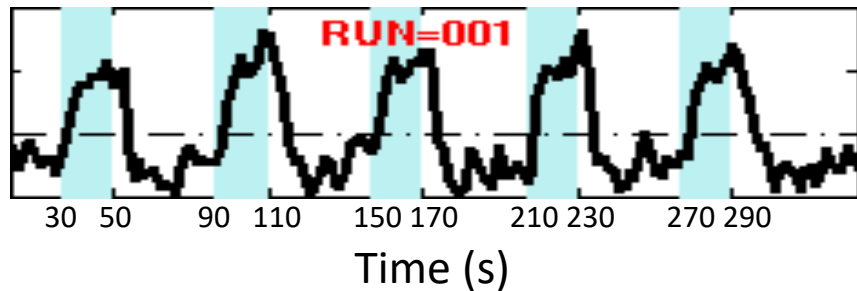


X 100

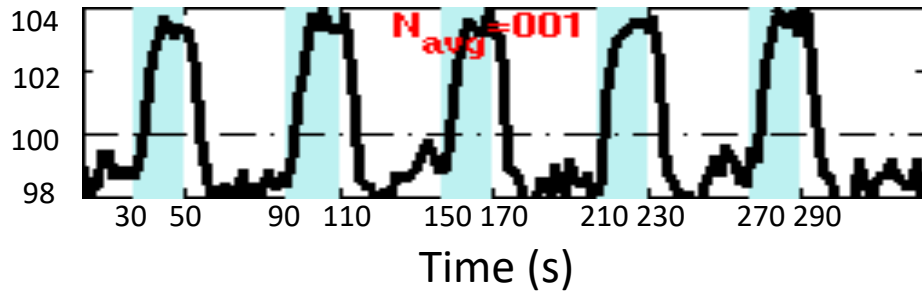
9 HOURS OF FUNCTIONAL DATA PER SUBJECT

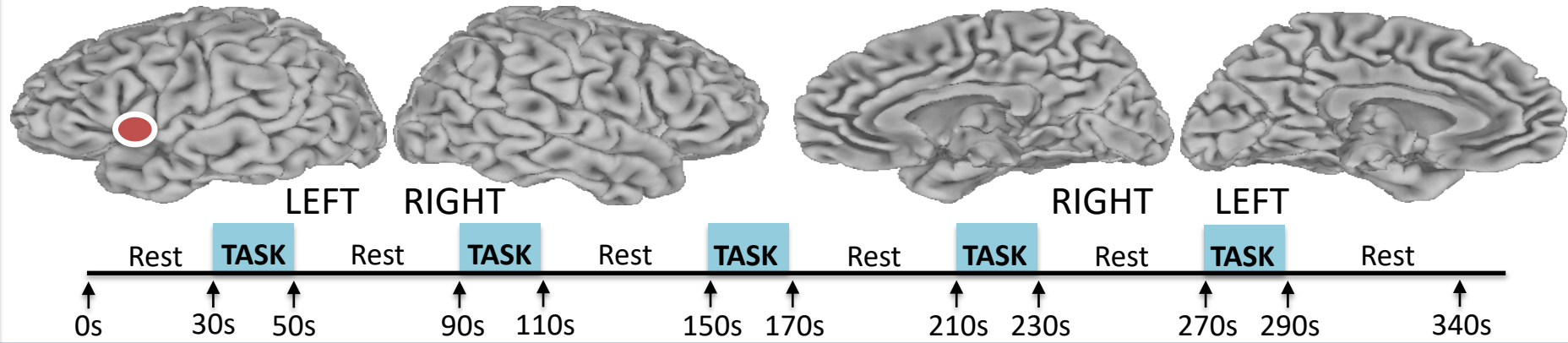


INDIVIDUAL RUNS

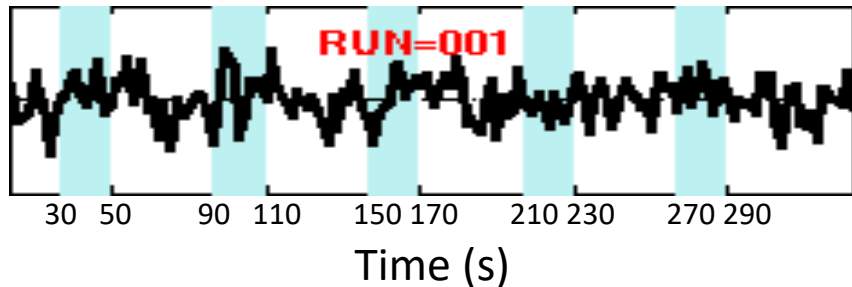


AVERAGING

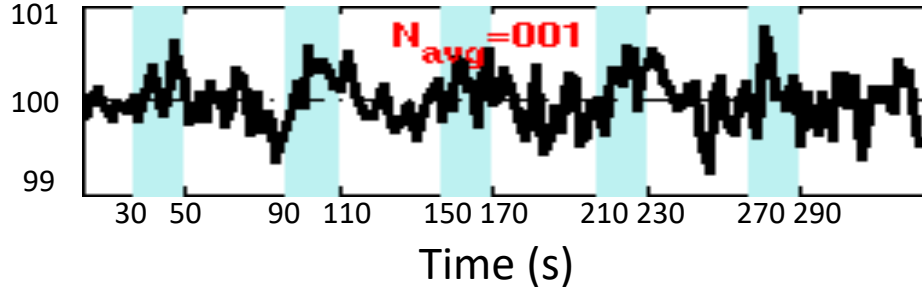


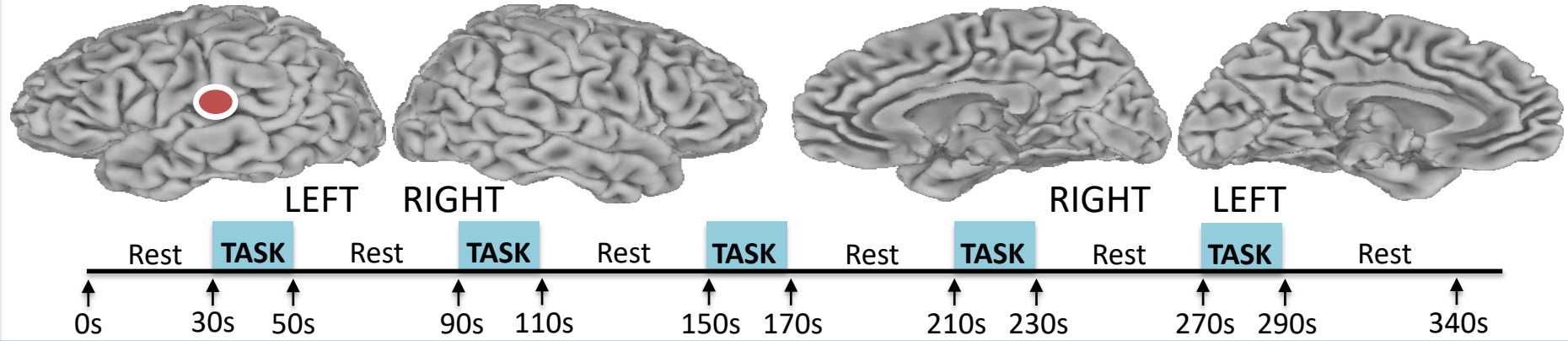


INDIVIDUAL RUNS

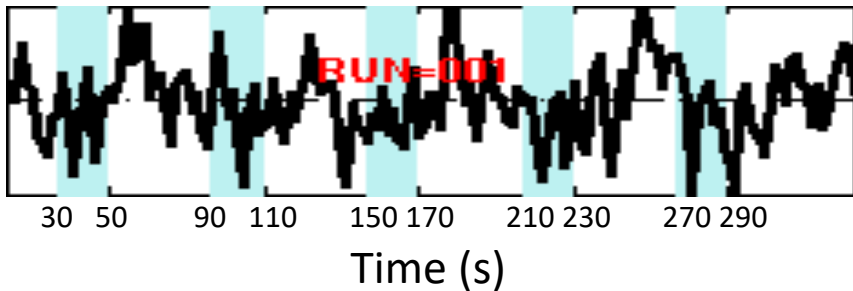


AVERAGING

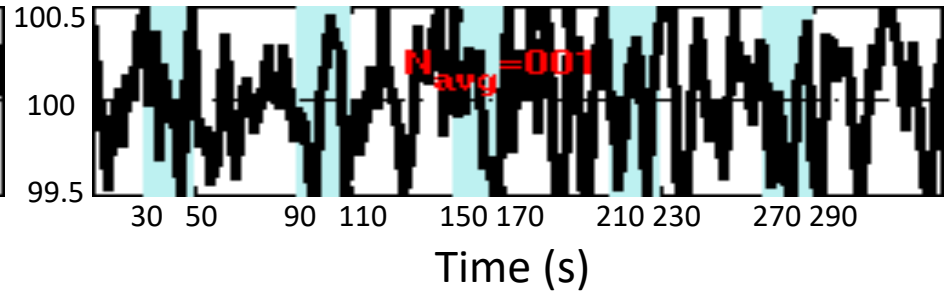


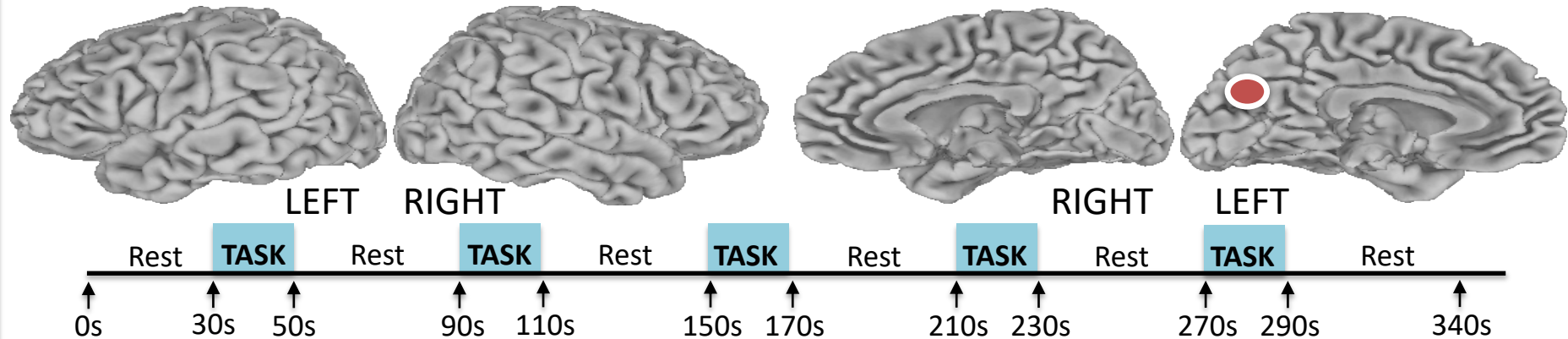


INDIVIDUAL RUNS

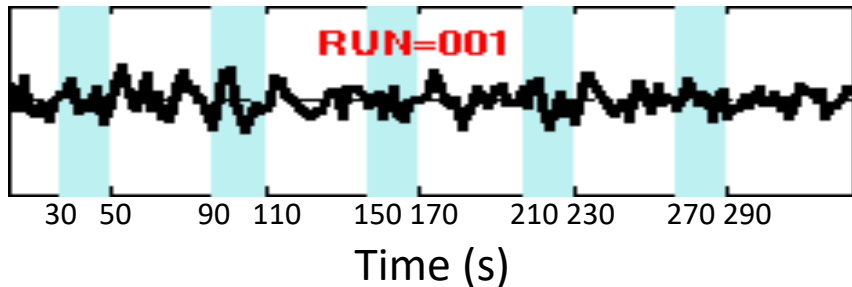


AVERAGING

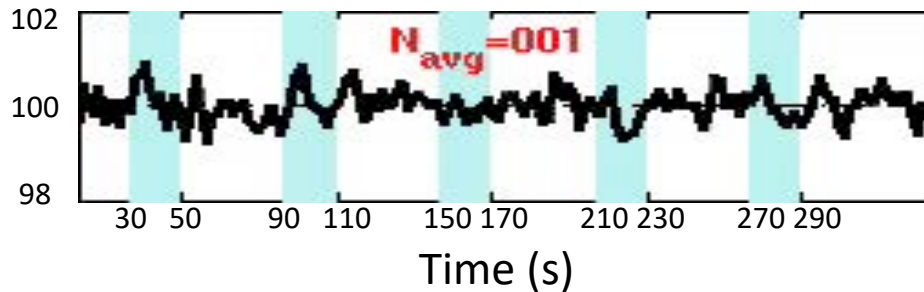




INDIVIDUAL RUNS

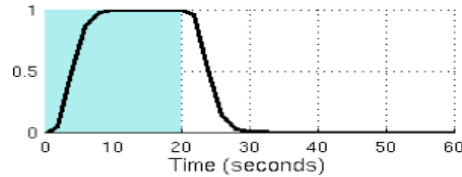
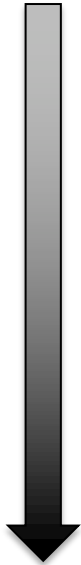


AVERAGING

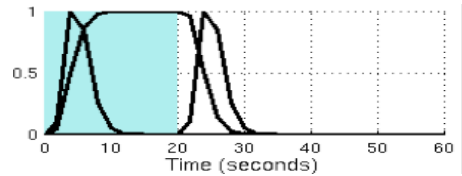


How does this observation translate in terms of volume of activation?

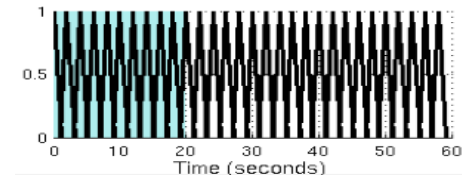
VERSATILITY



**SUSTAINED RESPONSE ONLY
(SUS)**



**ONSET + SUSTAINED +
OFFSET RESPONSE (SUS)**

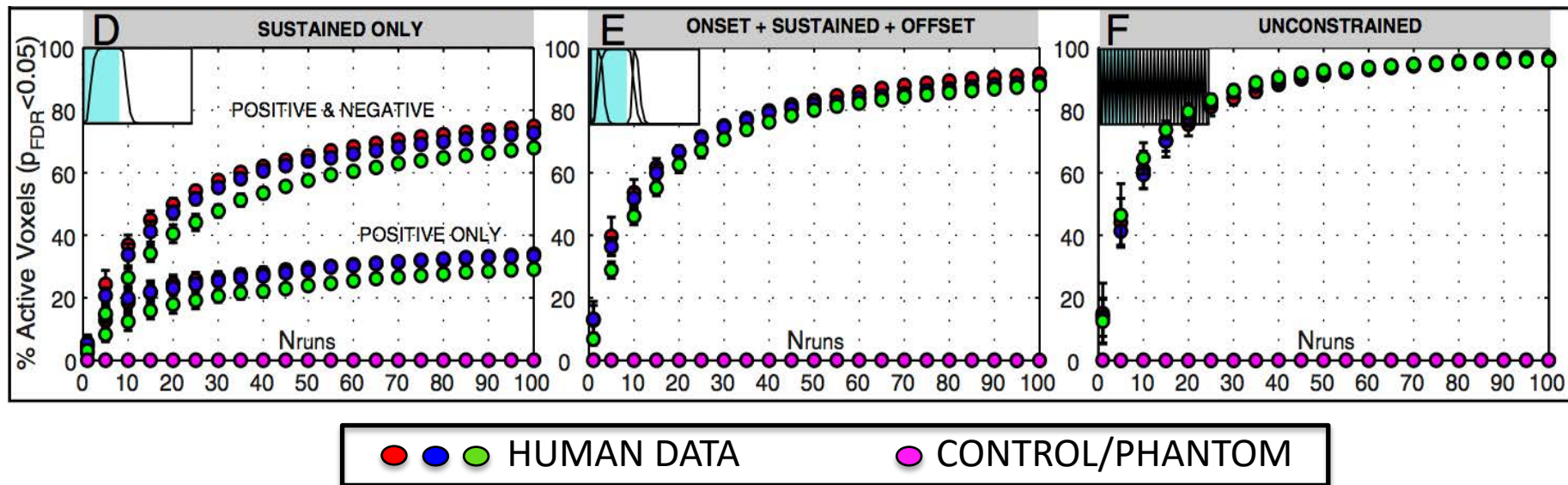


**UNCONSTRAINED MODEL
(UNC)**

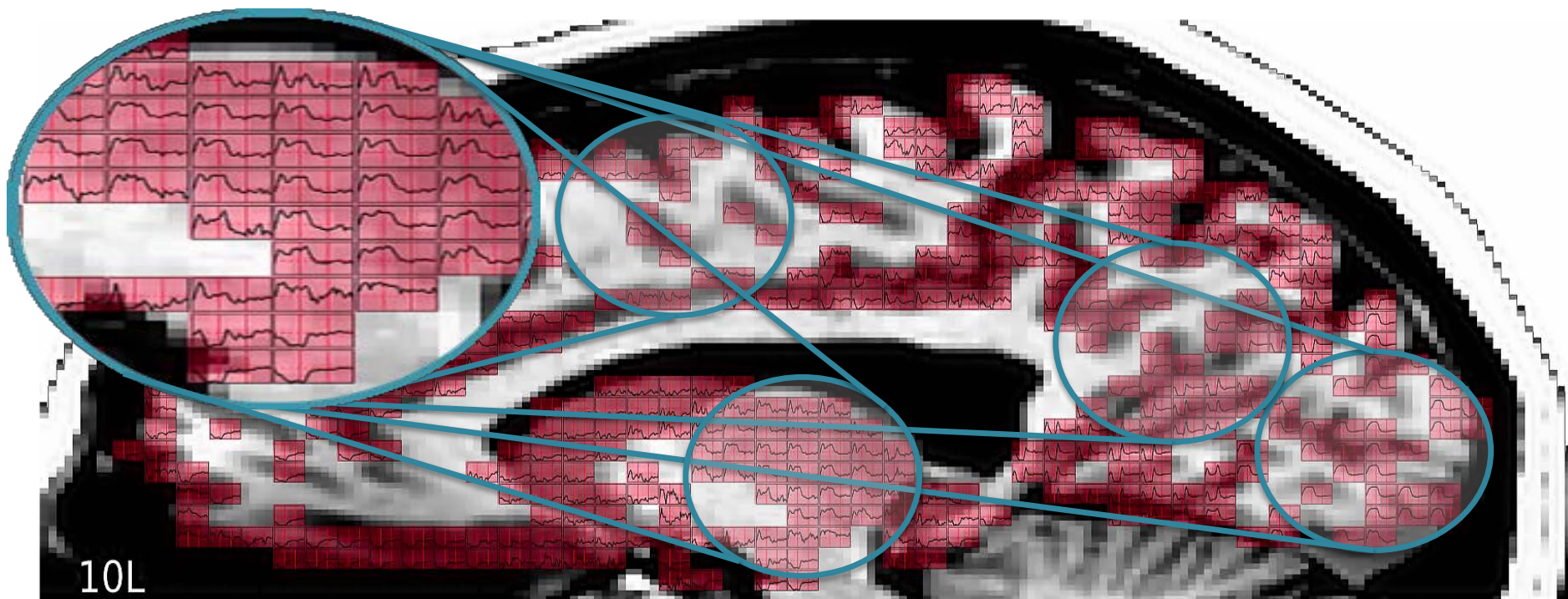
$N_{\text{runs}} = 1, 5, 10, 15, 20, 25, 30, 35 \dots 100$
[10 Permutations per N_{runs} level]



TSNR



- Activation Volume increases considerably between $N_{runs}=5-10$ and $N_{runs}=100$
- Activation Volume increases with versatility of expected response models
- For $N_{runs}=100$, Unconstrained Model & $p_{FDR} < 0.05$ → Active Volume $\approx 95\%$

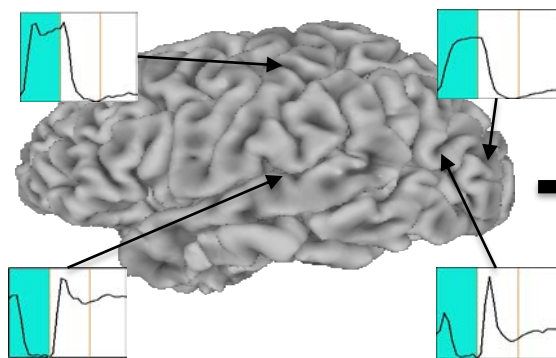


Are these additional responses biologically meaningful?

ARE RESPONSE SHAPES RANDOMLY DISTRIBUTED ACROSS THE BRAIN

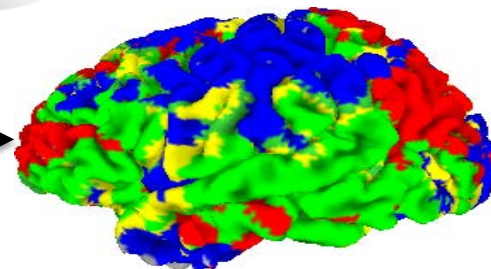
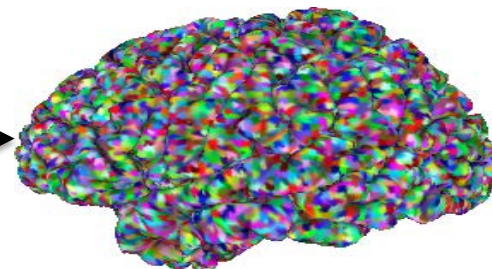
OR

DO THEY CLUSTER IN A FUNCTIONALLY/ANTOMICALLY MEANINGFUL MANNER?

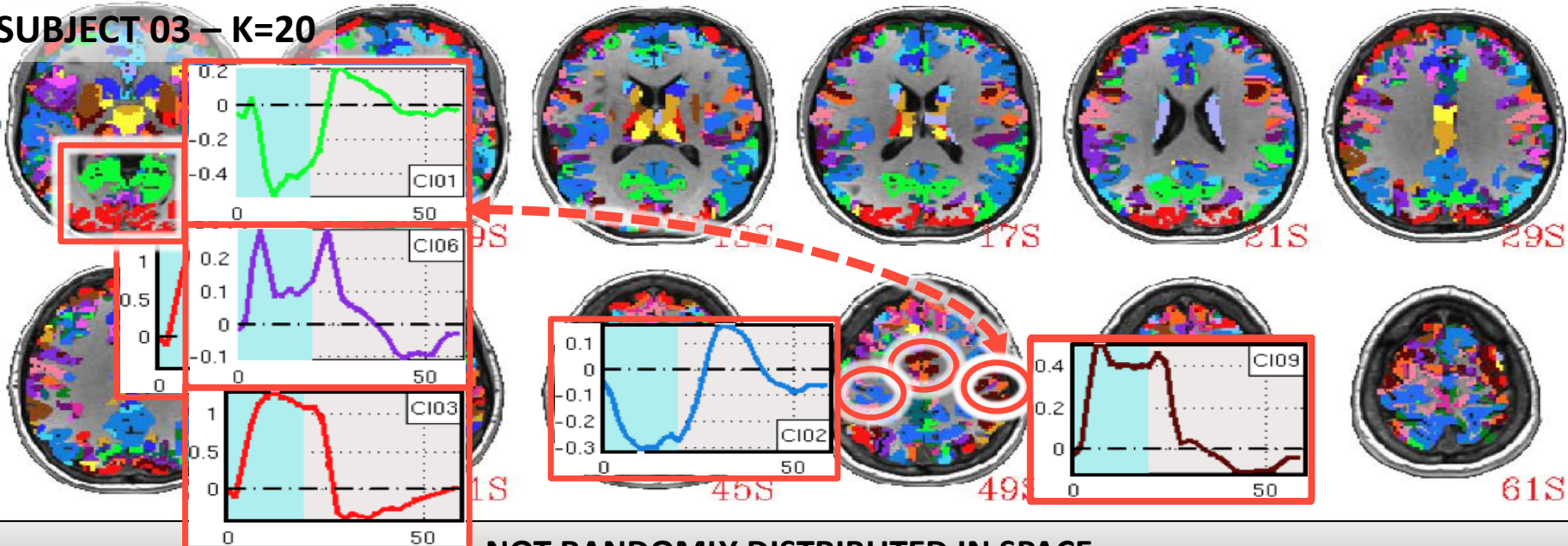


WITHIN-SUBJECT AVERAGED
RESPONSES ACROSS ALL
RUNS AND TRIALS

CLUSTERING



SUBJECT 03 – K=20



NOT RANDOMLY DISTRIBUTED IN SPACE

SYMETRICAL ACROSS HEMISPHERES

FUNCTIONALLY & ANATOMICALLY MEANINGFUL

REPRODUCIBLE PARCELLATION ACROSS SUBJECTS

◆ Advance our understanding of the biological/neuronal significance of the original observation.

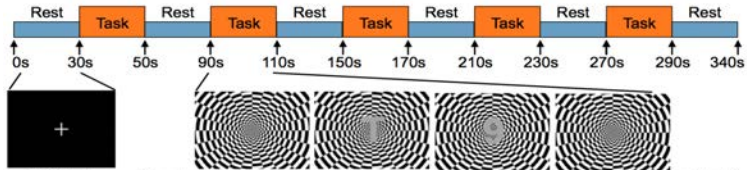
⇒ Vary Cognitive/Stimulation Load across subjects

◆ Reduce

⇒ Reduce

⇒ Modulate

**/STIMULA
LOAD**



X 100

Full FOV Flickering Checkerboard + Letter/Discrimination Task



New Voxel Size = 2x2x2mm | Use a 7T Scanner

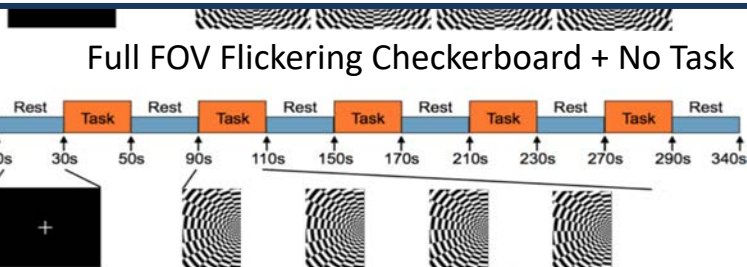
◆ Study

⇒ Power

⇒ Neural

⇒ Original

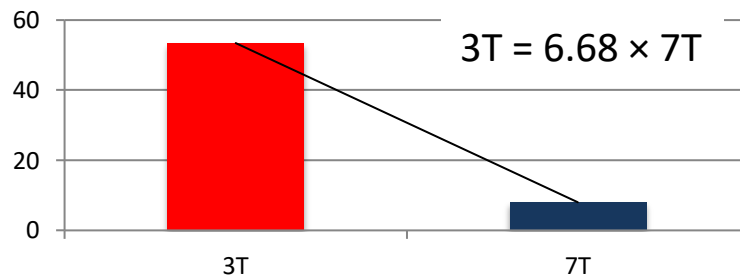
**COGNITIVE
LOAD**



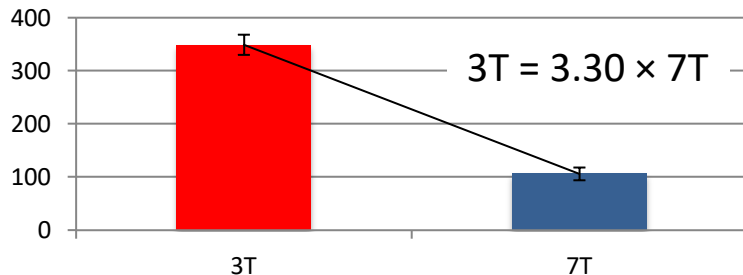
X 100

Full FOV Flickering Checkerboard + No Task

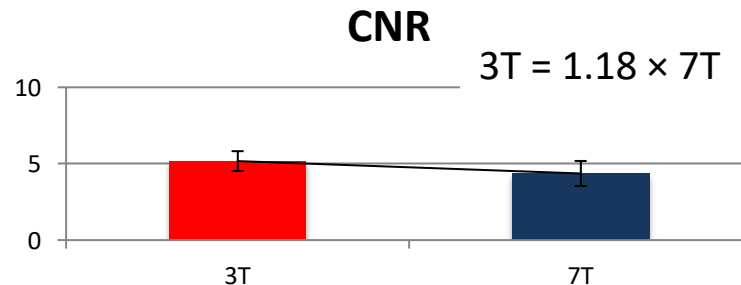
Use a modified version of Harms & Melcher (2003) waveshape index (w) that accounts for negatively sustained responses

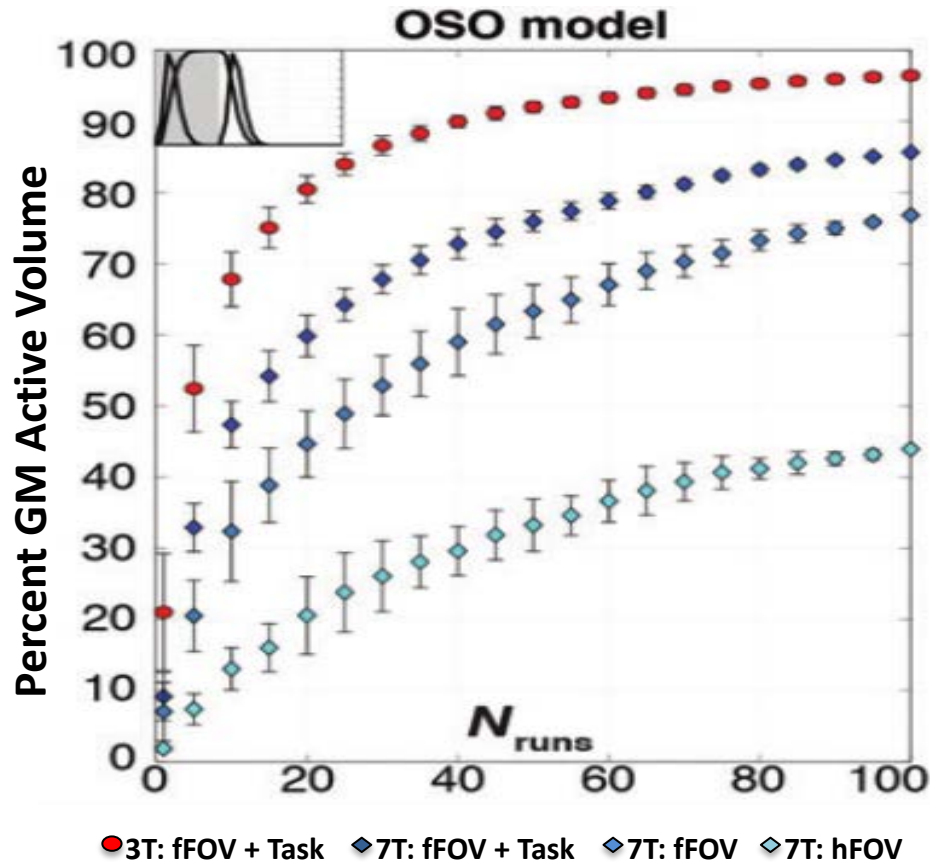
Nominal Voxel Size (mm³)

White Matter TSNR



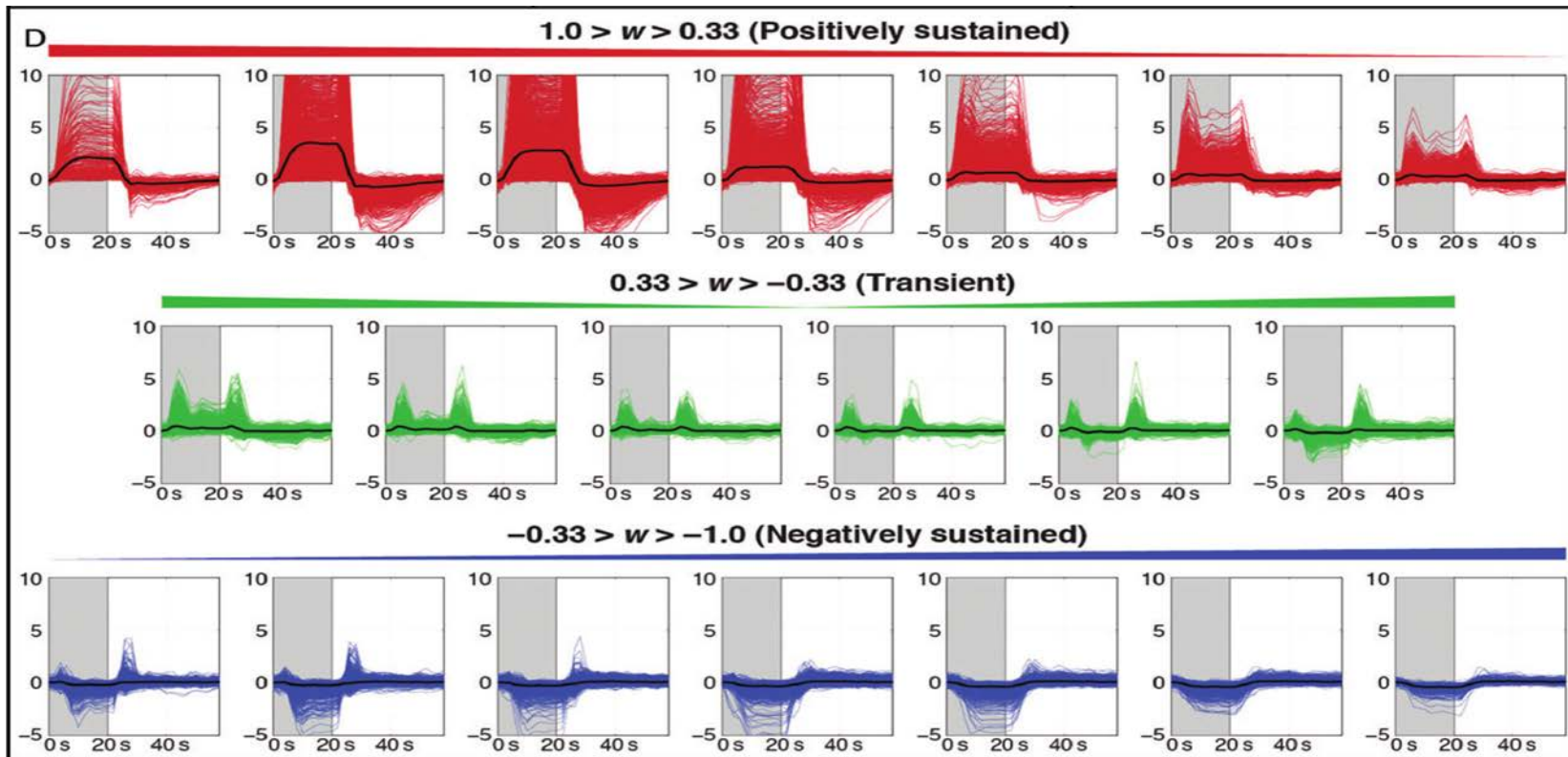
Right Primary Visual Cortex

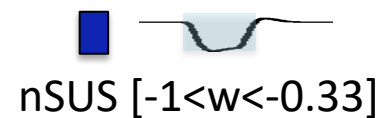
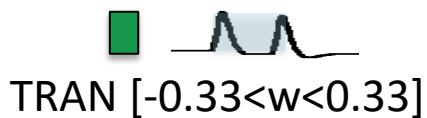
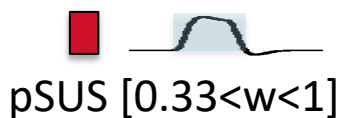




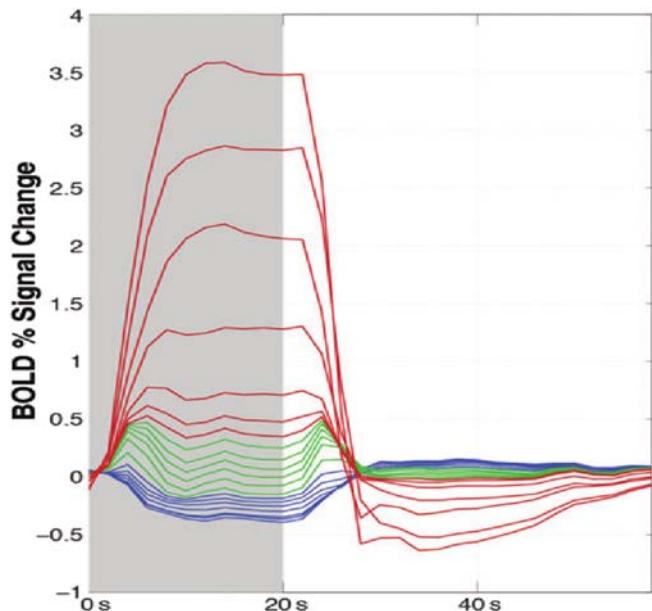
Waveshape Index:

$$w = \frac{\beta_{\text{SUS}}}{|\beta_{\text{SUS}}| + |\beta_{\text{ON}}| + |\beta_{\text{OFF}}|}$$

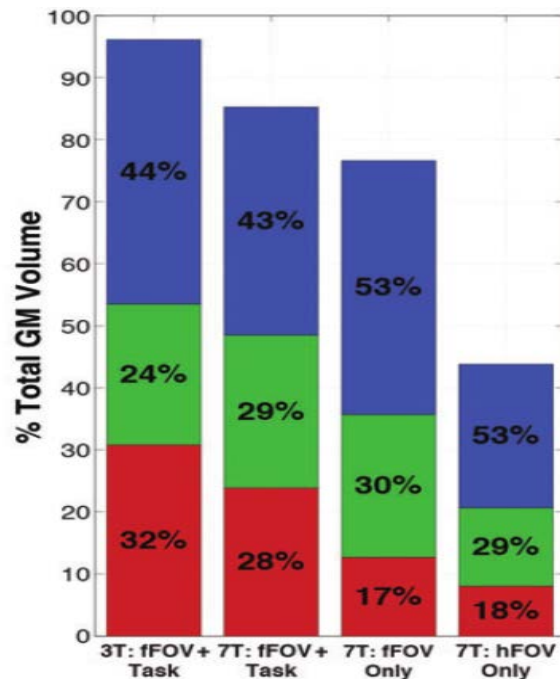
 β_{xx} = Effect size of OSO model
for $N_{\text{runs}}=100$




Average Percent Change vs. Response Type

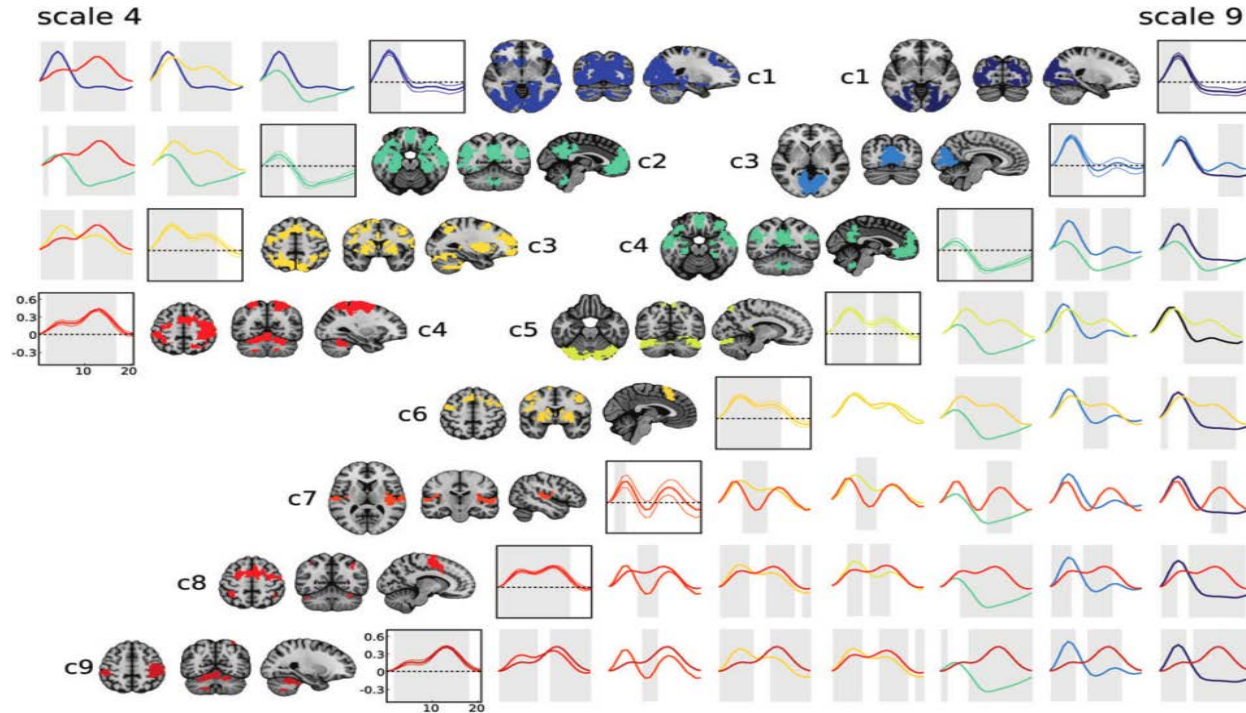


Contribution of each response to activation volume

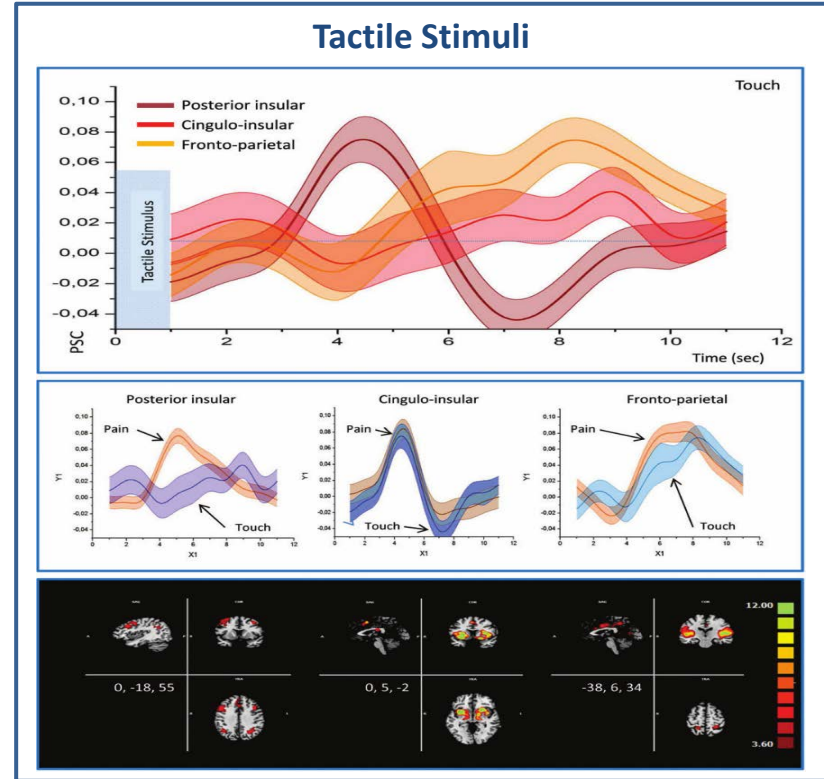
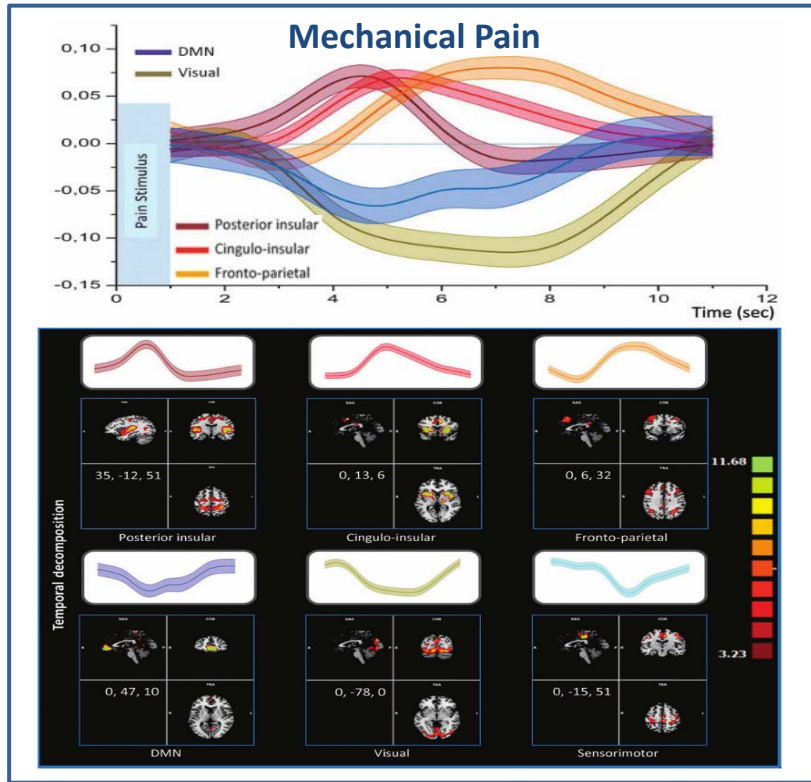


Positively sustained responses have the highest SPC, are the easiest to detect.

Extension to group level in the context of a delayed sequential motor task



“...rich variety of hemodynamic responses elicited by a motor task is systematic enough to decompose the whole human brain into stable task-evoked networks at the group level.”



“Our findings suggest that the areas that respond with stimulus-locked activation to painful stimuli are likely to reflect the activity of different networks, each having different temporal behavior, and possibly, subserving different cognitive functions.”



Spatial ICA reveals functional activity hidden from traditional fMRI GLM-based analyses

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NeuroImage

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NeuroImage 25 (2005) 527–538

Semi-blind ICA of fMRI: a method for utilizing hypothesis-derived time courses in a spatial ICA analysis

J.C. Stevens,^{a,b} K.A. Kiehl,^{a,b} and J.J. Pekar^{c,f}

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Contributive sources analysis: A measure of neural networks' contribution to brain activations

Ewa Beldzik^{a,b,d,*}, Aleksandra Domagalik^{a,d}, Sander Daselaar^c, Magda Wojciech Froncisz^b, Halszka Oginska^a, Tadeusz Marek^{a,d}

Available online at www.sciencedirect.com



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Magnetic Resonance Imaging 25 (2007) 860–868



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Dissecting cognitive stages with time-resolved fMRI data: a comparison of fuzzy clustering and independent component analysis

Alain Smolders^a, Federico De Martino^b, Noël Staeren^b, Paul Scheunders^b, Jan Sijbers^b, Rainer Goebel^b, Elia Formisano^{b,*}

^aVision Lab (Department of Physics), University of Antwerp, Universiteitsplein 1, B-2610 Antwerpen, Belgium

^bDepartment of Cognitive Neuroscience, Faculty of Psychology, Maastricht University, 6200 MD Maastricht, The Netherlands

**MAGNETIC
RESONANCE
IMAGING**

- Simple tasks can significantly modulate on-going BOLD fluctuations across large portions of the brain.
- Traditional analyses can miss more than half of locations affected by task performance.
- Subtle interregional differences in BOLD response contain sufficient information to produce functional parcellations of the whole brain “in action”, which can deviate in some instances from connectivity patterns measured at rest.
- A simple Active/Inactive dichotomy does not capture all information present in the data.

Limitations / Additional Questions

- First, and foremost, the impossibility to unquestionably claim a neuronal origin for all detected hemodynamic responses.

Statistical Significance

<<<<

Biological Significance

<<<<

Neuronal Significance

- Need to better understand “non-traditional” hemodynamic responses.
- Differentiating task-essential regions from task-accessory regions.
- Distinguishing hemodynamic events tightly co-localized to neuronal activity from those that only manifest as a vascular-driven distant echo of true neuronal modulation at a different location.
- How to optimally visualize, interpret and report all this information.

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Section on Functional Imaging Methods

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Daniel Glen
Richard Reynolds
Gang Chen



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Catie Chang



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Vinai Roopchansingh
Souheil Inati
Andy Derbishire

