Quantitative deconvolution of neuronal-related BOLD events with Multi-Echo Sparse Free Paradigm Mapping

Javier González-Castillo, César Caballero-Gaudes, Peter A. Bandettini

Section on Functional Imaging Methods, NIMH, NIH

June 21st, 2018, ISMRM 27th Annual Meeting, Paris, France

JOINT ANNUAL MEETING
ISMRM–ESMRMB
16–21 June 2018

SMRT 27th Annual Meeting 15–18 June 2018
www.smrt.org

Paris Expo Porte de Versailles
Paris, France

Declaration of Financial Interests or Relationships

Speaker Name: Javier González-Castillo

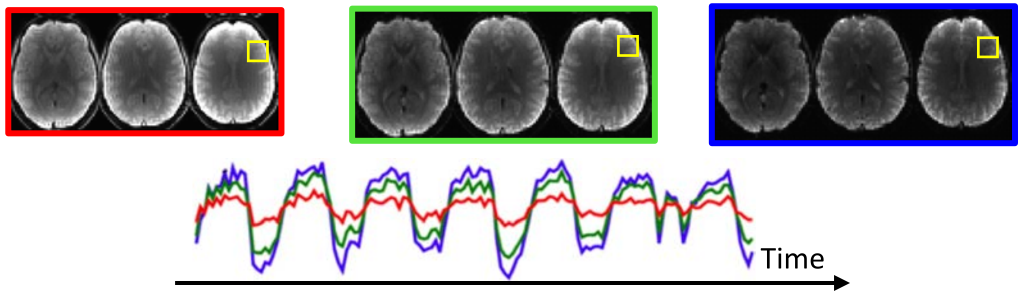
I have no financial interests or relationships to disclose with regard to the subject matter of this presentation.

Multi-Echo fMRI in one slide

SINGLE-ECHO FMRI

- 4D Datasets: 3D (Space) + Time
- One timeseries per voxel acquired at a *TE* aimed to maximize average BOLD contrast across GM.

MULTI-ECHO FMRI



- 5D Datasets: 3D (Space) + *TE* + Time
- N_e traces per voxel, each at a different *TE*
- BOLD contribution to fMRI signal changes with *TE*

MULTI-ECHO SIGNAL MODEL

Assuming a mono-exponential decay model in GRE-EPI, the signal of a voxel x at time t for echo TE_k is given by:

$$s(x,t,TE_k) = S_0(x,t)e^{-R_2^*(x,t)TE_k}$$

Non-BOLD

$$S_0(x,t) = \overline{S_0}(x) + \Delta S_0(x,t)$$

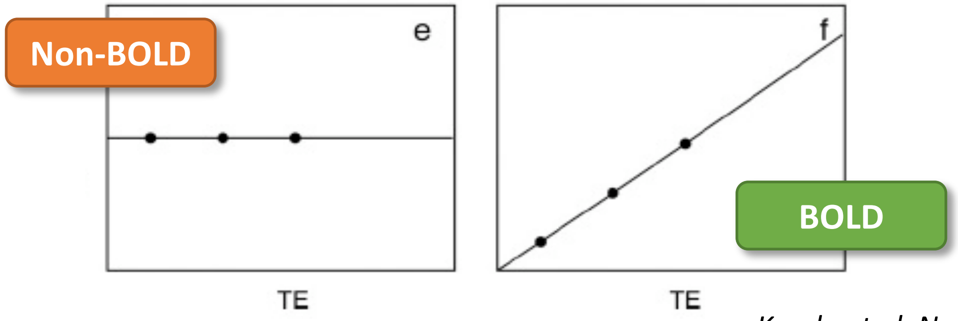
BOLD

$$R_2^*(x,t) = \overline{R_2^*}(x) + \Delta R_2^*(x,t)$$

Following analytical derivation, voxel-wise time series in terms of signal percent change is given by:

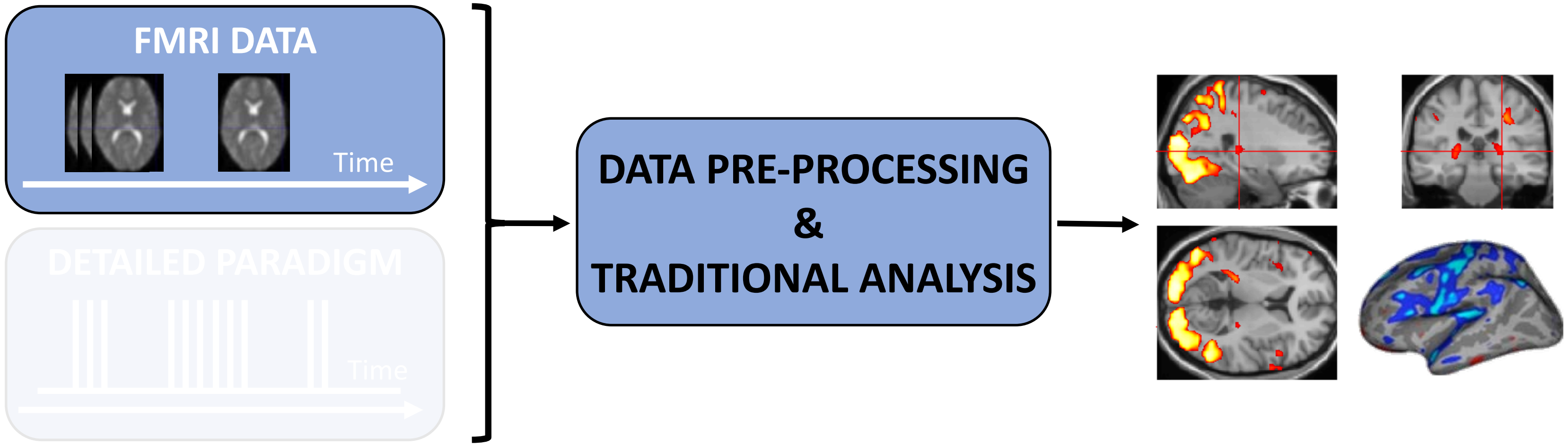
Non-BOLD BOLD

$$\frac{s(x,t,TE_k) - \bar{s}(x,TE_k)}{\bar{s}(x,TE_k)} \approx \Delta\rho(x,t) - \Delta R_2^*(x,t)TE_k$$



Kundu et al. NeuroImage 2017

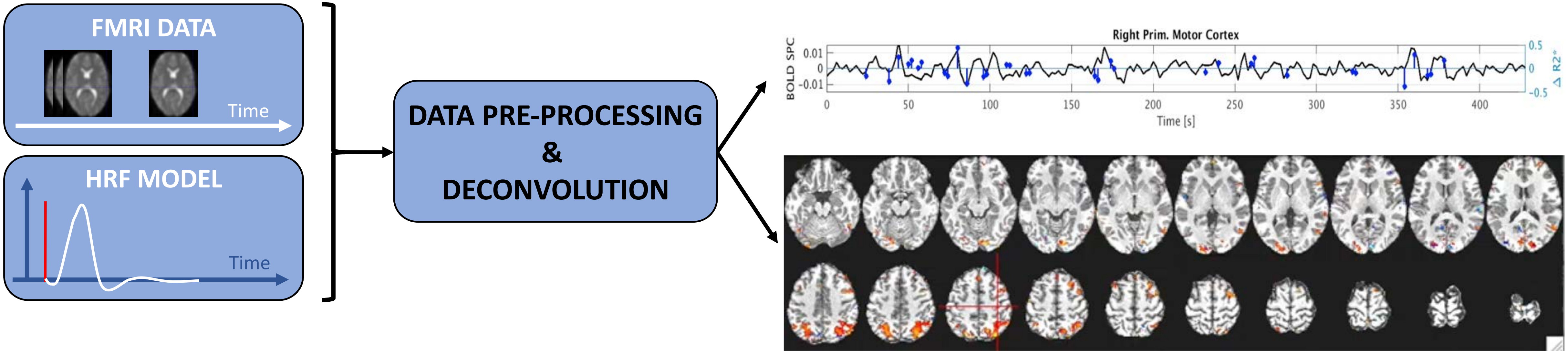
What do deconvolution methods offer to fMRI practitioners



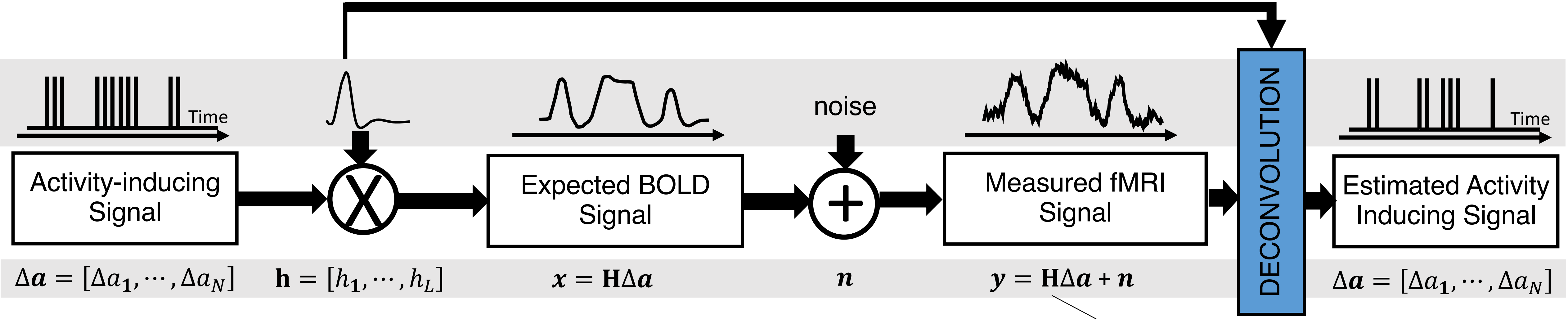
There are experimental scenarios where event timing might be missing:

- Naturalistic paradigms
- Clinical studies (e.g., interictal events)
- Resting State

Deconvolution methods are an alternative in such scenarios:



Deconvolution in Single Echo fMRI



If one assumes the underlying activity-inducing signal to consist of brief, sparse events, then the formulated deconvolution problem can be solved using LASSO regularization:

$$\Delta\hat{\boldsymbol{a}} = \arg\min_{\Delta\boldsymbol{a}} \frac{1}{2}\overbrace{\|\boldsymbol{y} - \mathbf{H}\Delta\boldsymbol{a}\|_2^2}^{\text{Error Minimization Term}} + \underbrace{\lambda\|\Delta\boldsymbol{a}\|_1}_{\text{L1-Norm Regularization (Sparseness)}}$$

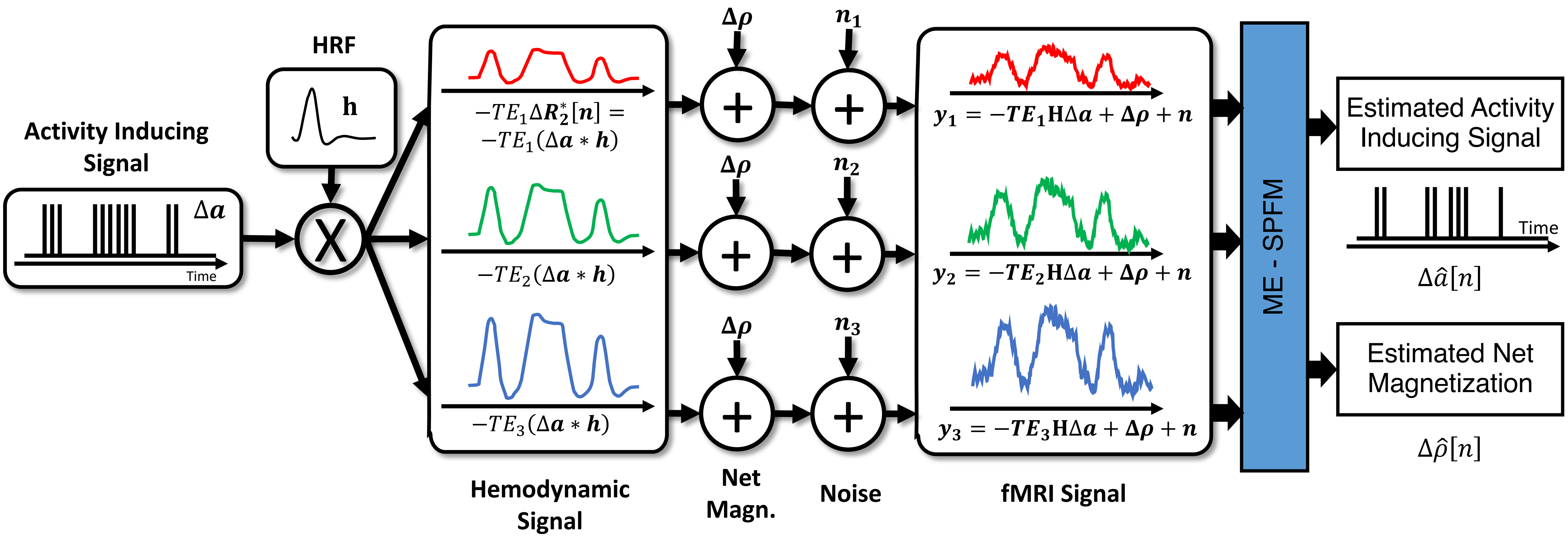
Single Echo Sparse Free Paradigm Mapping Algorithm

AFNI!

3dPFM

Caballero-Gaudes et al. Hum Brain Mapp. 2013

ME Formulation of the Sparse Free Paradigm Mapping Algorithm



$$\bar{y} \stackrel{\text{def}}{=} \begin{bmatrix} y_1 \\ \vdots \\ y_K \end{bmatrix} = \underbrace{\boxed{\begin{bmatrix} \mathrm{I} \\ \vdots \\ \mathrm{I} \end{bmatrix}}}_{\bar{\mathrm{I}}} \Delta\rho - \underbrace{\boxed{\begin{bmatrix} TE_1\mathrm{H} \\ \vdots \\ TE_K\mathrm{H} \end{bmatrix}}}_{\bar{\mathrm{H}}} \Delta a$$

Assuming sparsity in both unknowns, we can solve using LASSO regularization

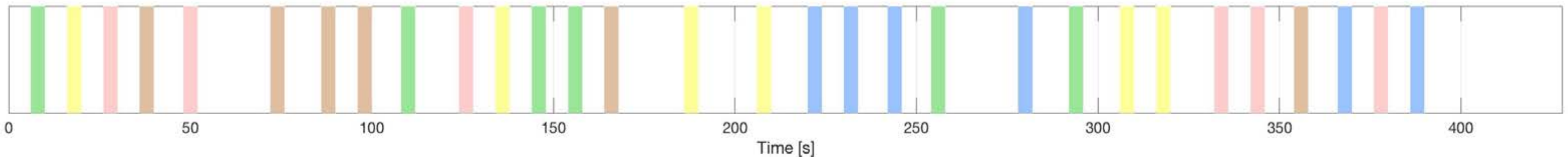
$$\Delta\hat{a}, \Delta\hat{\rho} = \arg\min_{\Delta a, \Delta\rho} \frac{1}{2} \left\| \bar{y} - \bar{\mathrm{H}}\Delta a - \bar{\mathrm{I}}\Delta\rho \right\|_2^2 + \lambda_1 \|\Delta a\|_1 + \lambda_2 \|\Delta\rho\|_1$$

Validation Experiment – Data Acquisition

- 10 Subjects (5M/5F)
- GRE – EPI @ 3T / 32 Channel Coil
- TE = 16.3/32.2/48.1 ms
- TR = 2 seconds
- Resolution = 3 x 3 x 4 mm^3
- ASSET = 2

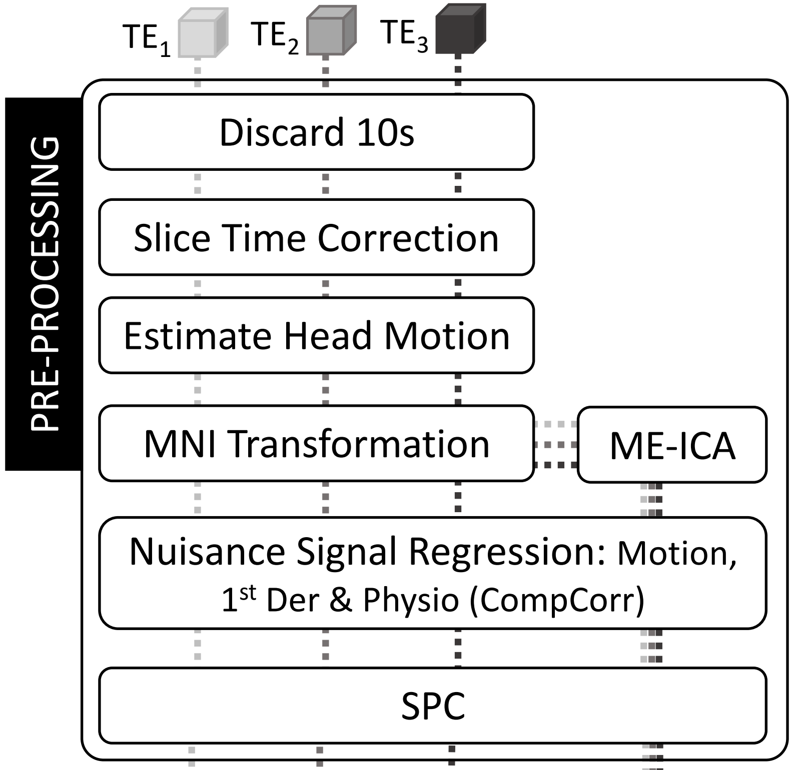
Rapid Event Related with 5 different tasks / 6 trials per task per run / events are approx. 4 seconds long

SCHEMATIC OF ONE FUNCTIONAL RUN

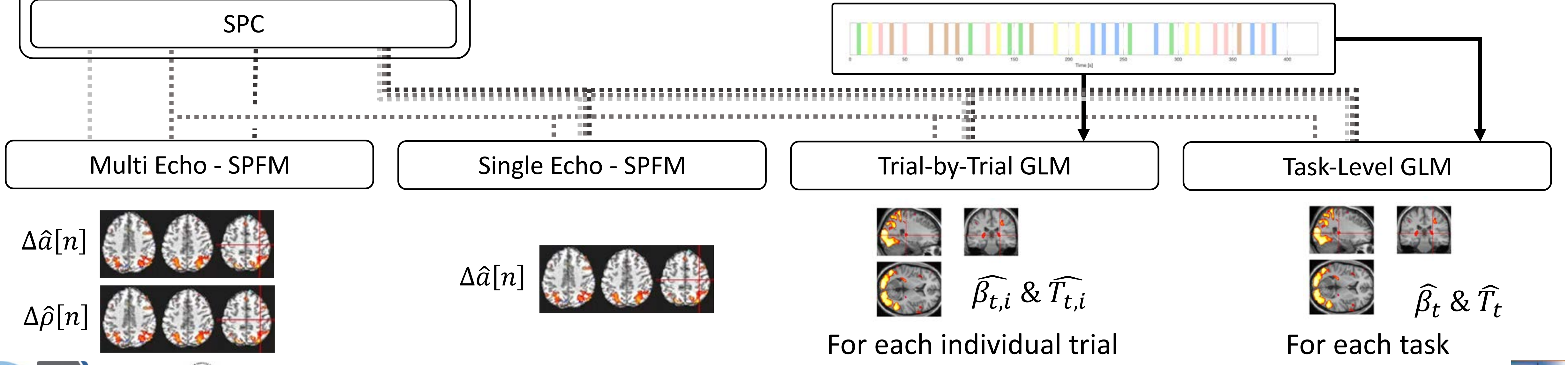


	Listen to an audio clip and select instrument being played from the ones displayed on the screen.
	Passive viewing of dots patterns resembling different types of biological motion.
	Passive viewing of images of houses
	Press button at an approx. rate of 0.5Hz (following a counter on the screen).
READ THIS	Silently read sentences that appear on the screen one word at a time.

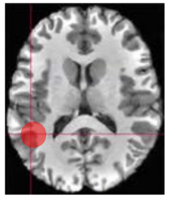
Validation Experiment – Data Analysis



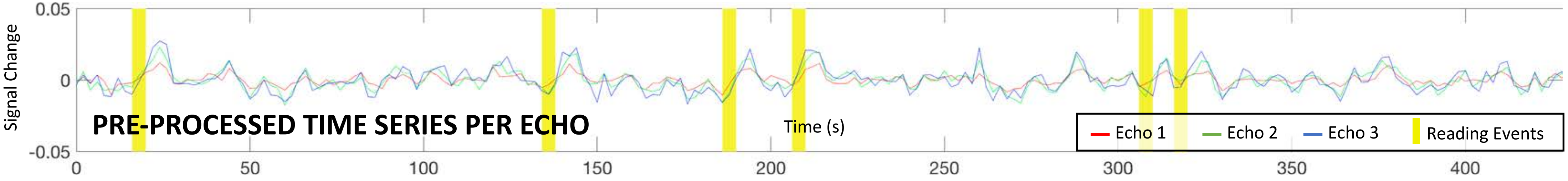
- **ME – SPFM**
  → Newly Proposed Algorithm
- **SE – SPFM**
  → Deconvolution results for original single-echo SPFM algorithm.
- **Trial-by-Trial GLM**
  → ”Best” activation maps for each individual trial
  → Paradigm timing information is available
- **Task – Level Task GLM**
  → GOLD Standard
  → “Best” subject-wise activation map per task type.

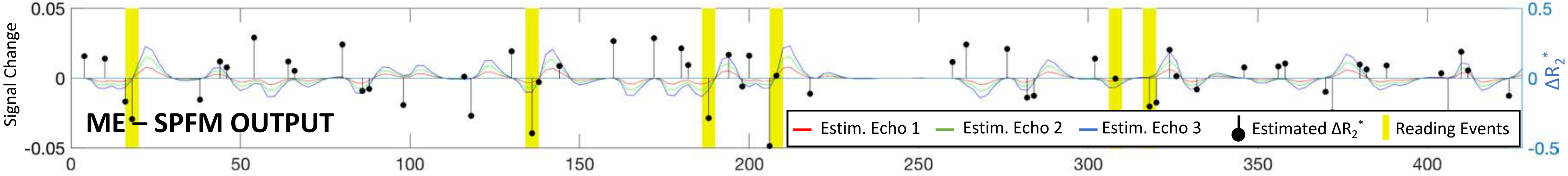


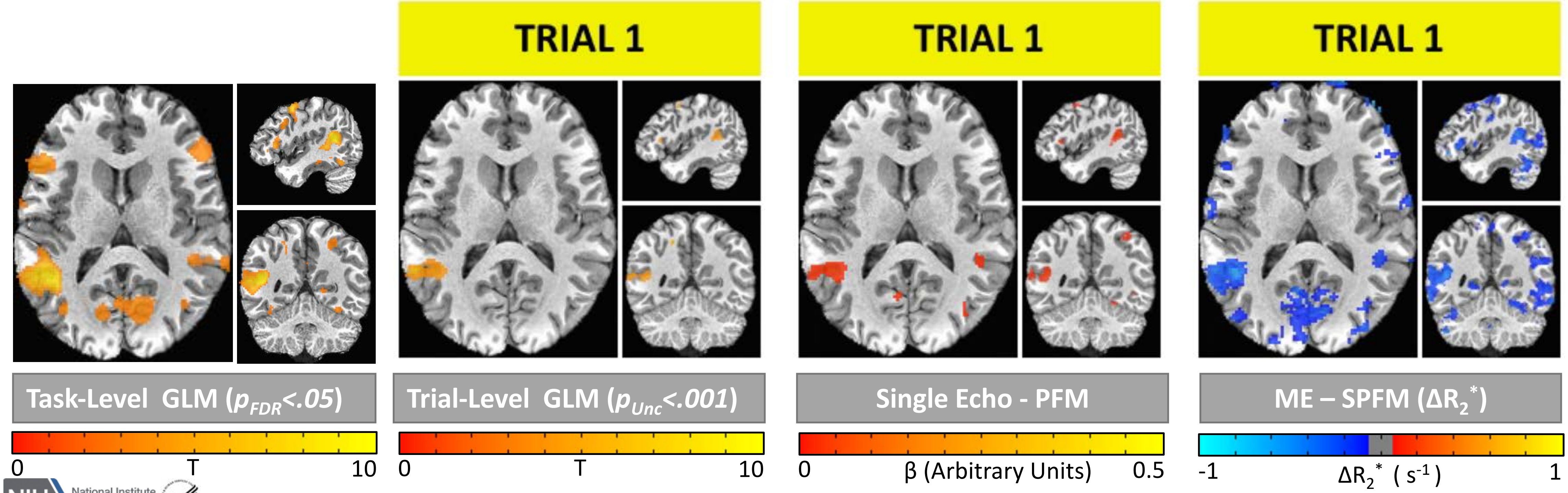
Validation Experiment – Results (I): Sample Subject / Reading Task



READ THIS

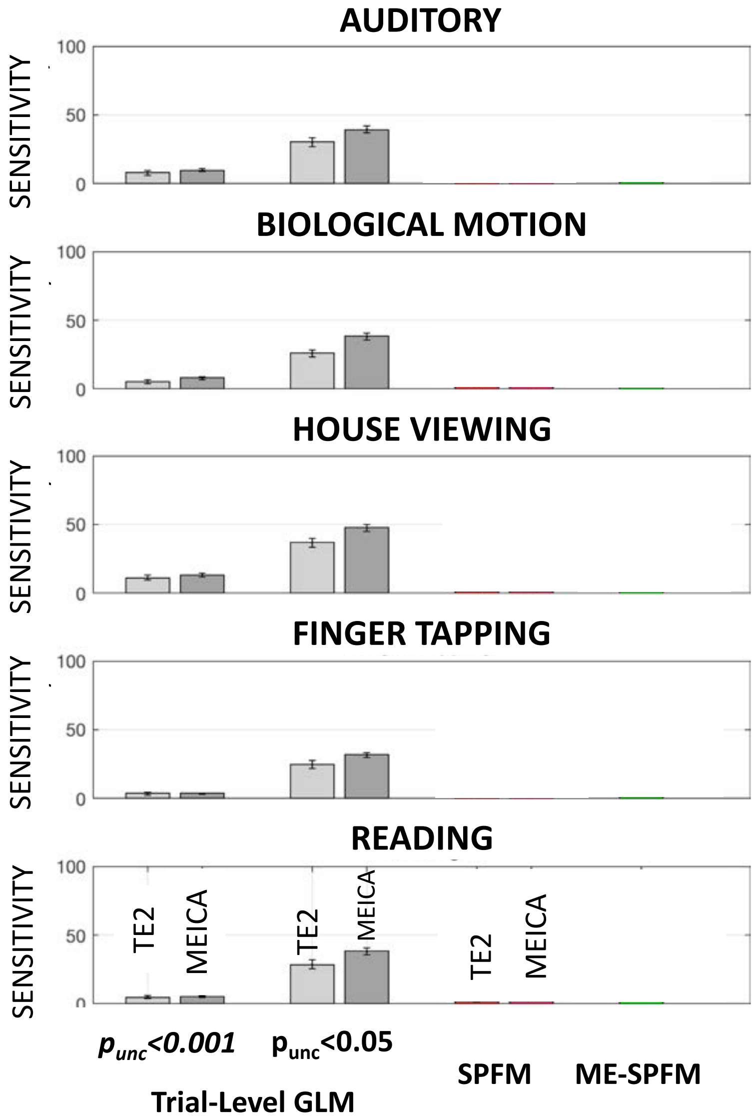




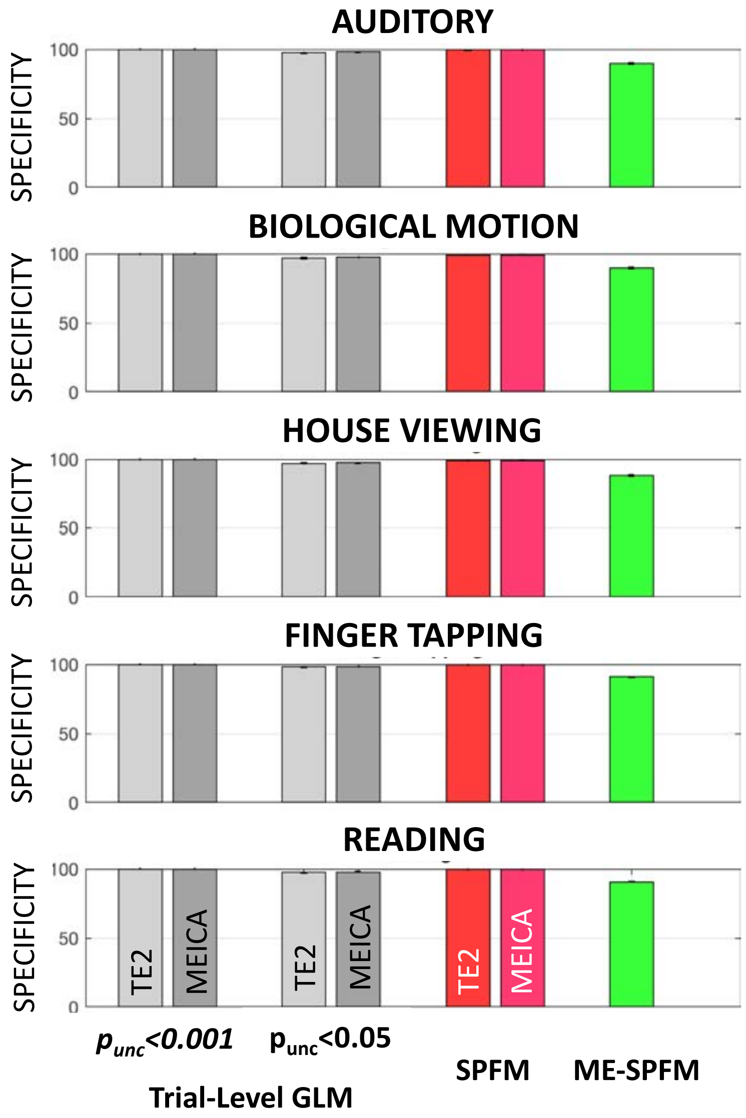


Validation Experiment – Results (III): Sensitivity, Specificity & Dice Coefficient

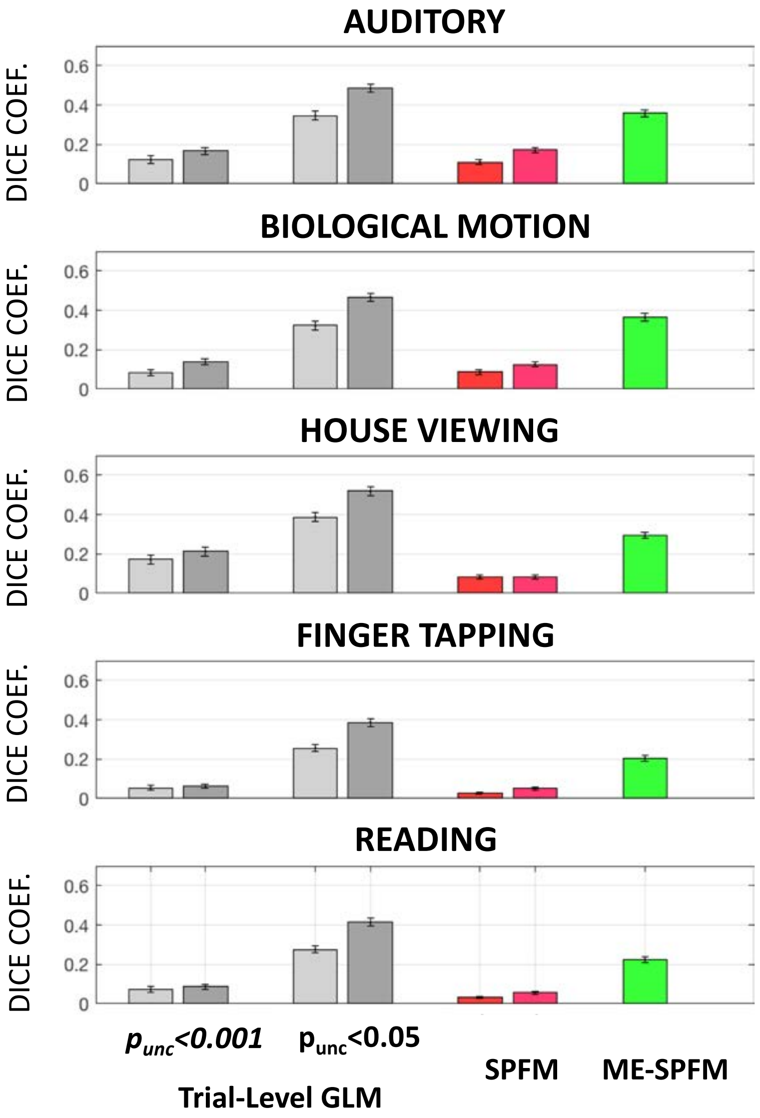
SENSITIVITY vs. TASK-LEVEL GLM



SPECIFICITY vs. TASK-LEVEL GLM

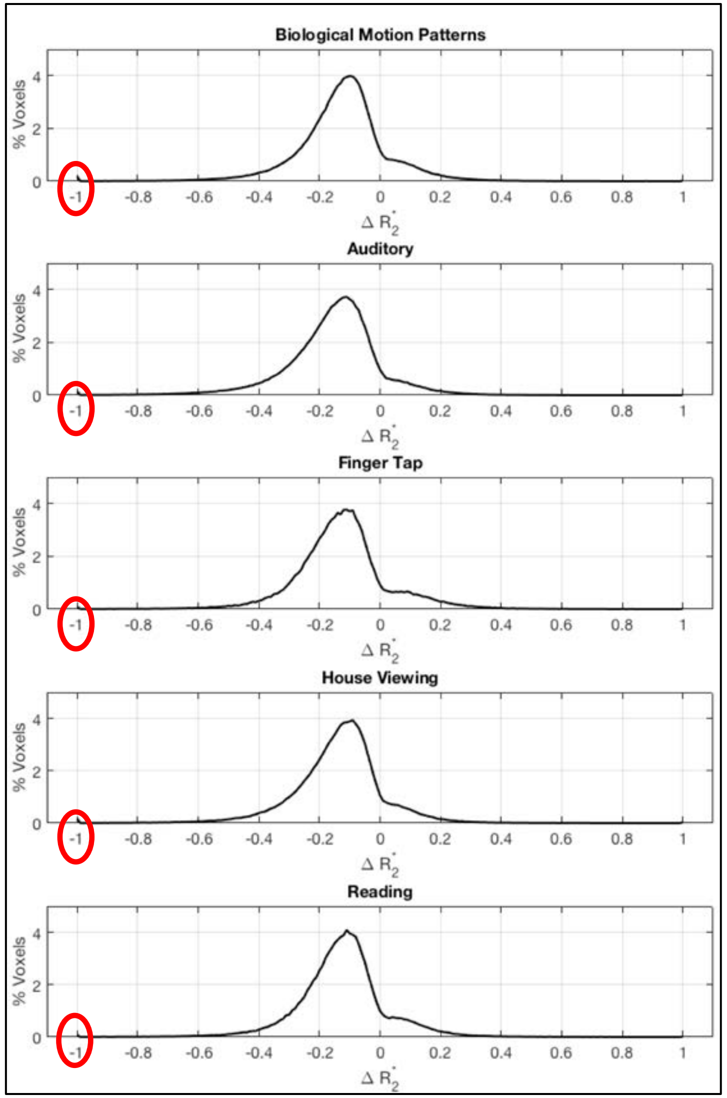


DICE COEFFICIENT

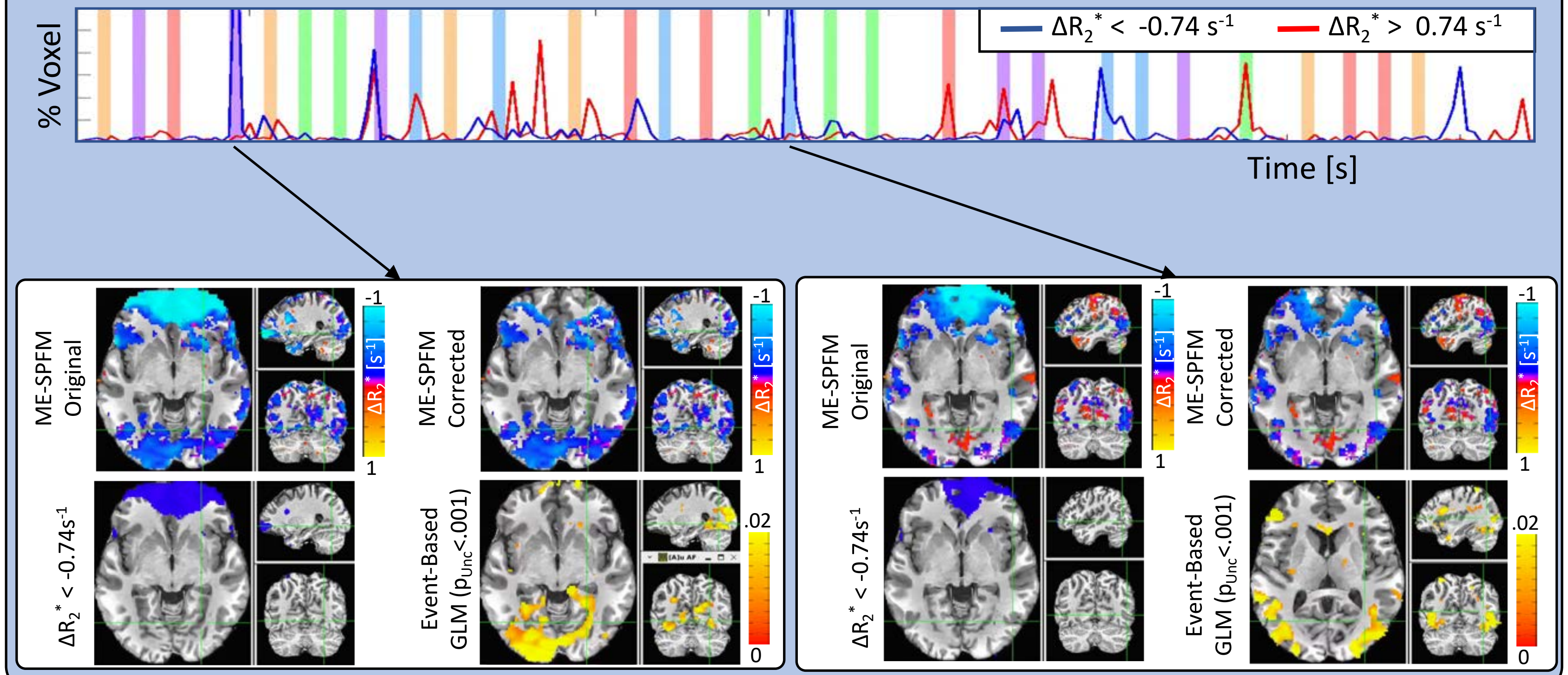


Validation Experiment – Results: Interpretable Units

Distribution of ΔR_2^* in GLM task-level active voxels for each task

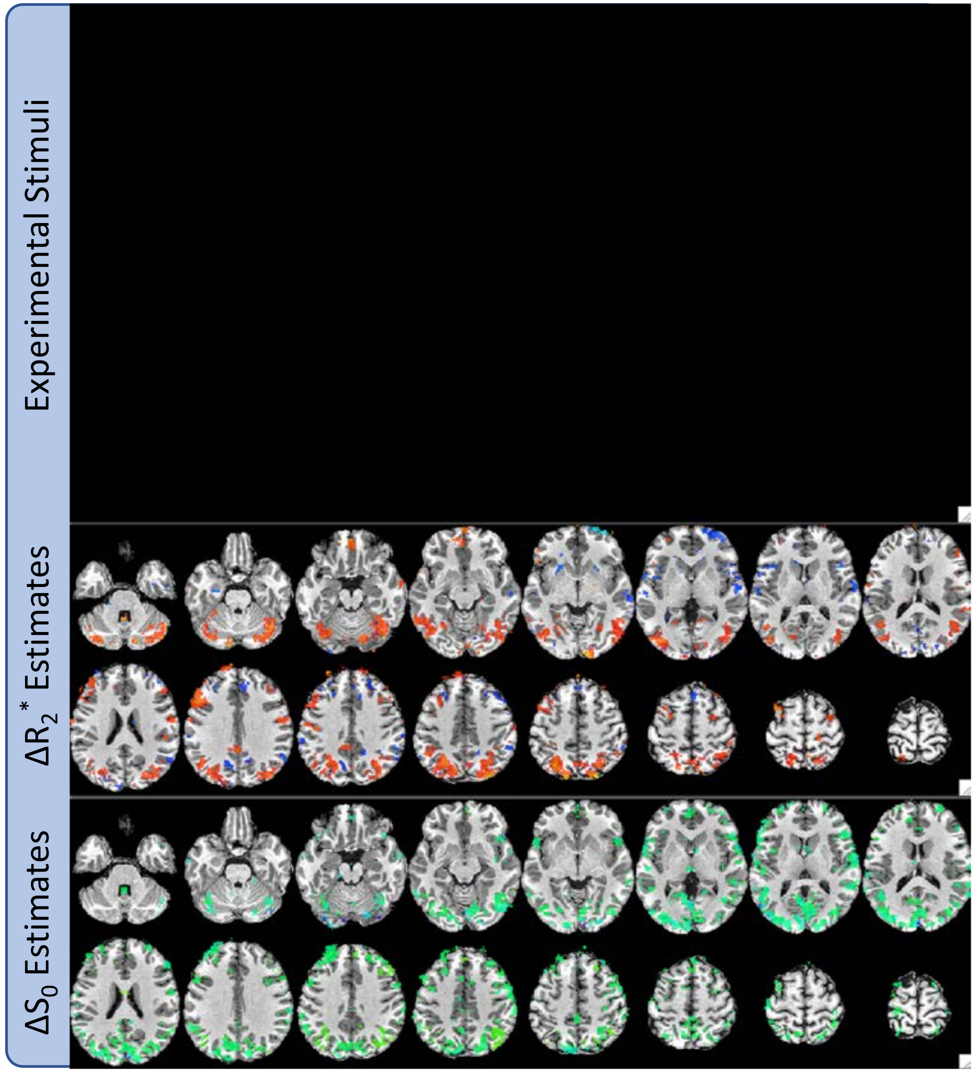


Distribution of ΔR_2^* across all voxels on a volume-by-volume basis



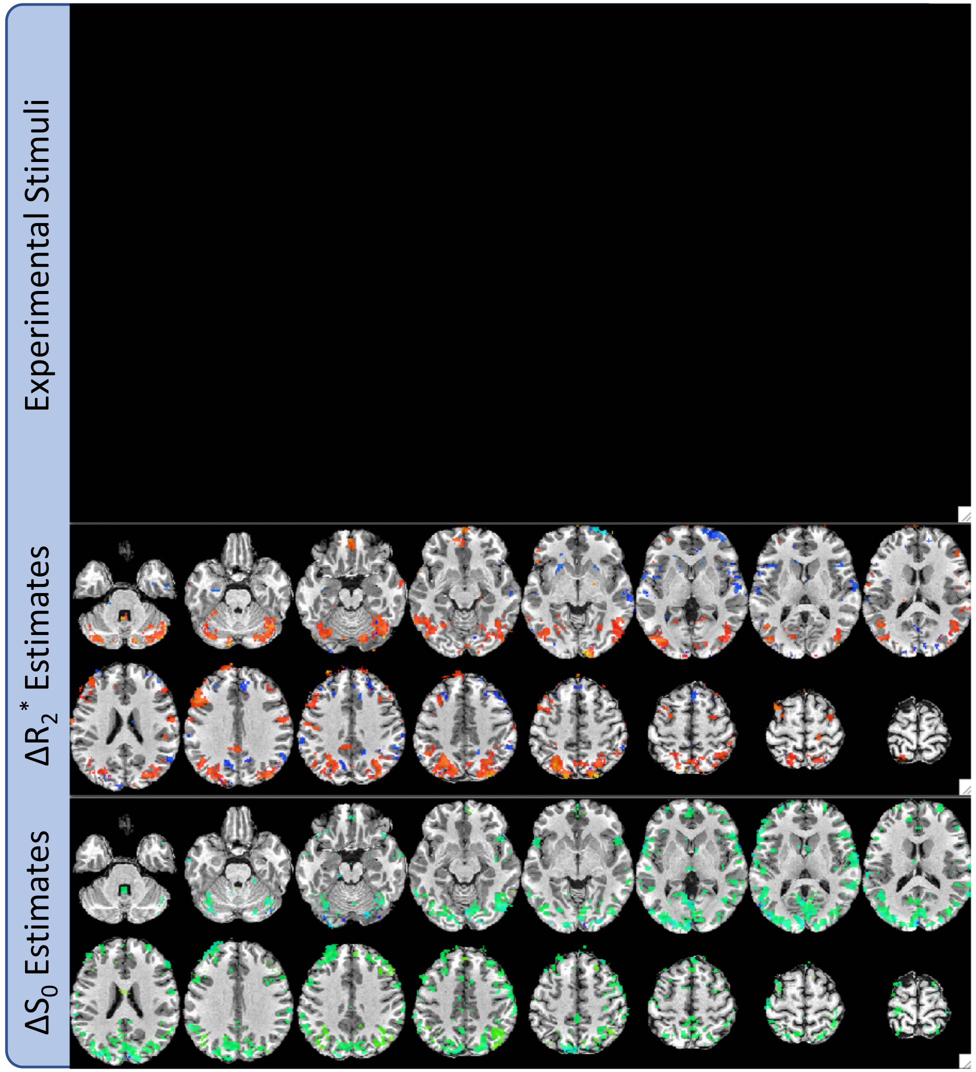
Reference	Region	ROI / Compartment	ΔR_2^* [s^{-1}] @ 3T
W. Van der Zaag et al, NeuroImage, 2009	Motor Cortex	Voxels active across all echoes	-0.98 ± 0.08
		Voxels active at any echo	-0.54 ± 0.03
Donahue et al, NMR in Biomedicine, 2011	Visual Cortex	Total	-0.74 ± 0.05
		Extravascular	-0.52 ± 0.07

Conclusions



- We have introduced a novel deconvolution algorithm for Multi-Echo fMRI (ME-SPFM).
- ME-SPFM can reliably detect individual events without a-priori information about their timing.
- ME-SPFM outperforms its single-echo counterpart in terms of sensitivity and nearly matches GLM-based results.
- ME-SPFM estimates ΔR_2^* with interpretable units [s^{-1}]; which fell within physiologically plausible limits.
- ME-SPFM can help us decipher the dynamic nature of brain activity in naturalistic paradigms, resting-state or clinical applications with unknown event-timing.

Future Work



- Understand the pros/cons of different formulations for the ME deconvolution problem.

	Models	Sparsity
$\Delta\hat{\boldsymbol{a}} = \arg\min_{\Delta\boldsymbol{a}} \frac{1}{2}\lVert\bar{\boldsymbol{y}} - \bar{\mathbf{H}}\Delta\boldsymbol{a}\rVert_2^2 + \lambda\lVert\Delta\boldsymbol{a}\rVert_1$	ΔR_2^*	ΔR_2^*
$\Delta\hat{\boldsymbol{a}}, \Delta\hat{\boldsymbol{\rho}} = \arg\min_{\Delta\boldsymbol{a},\Delta\boldsymbol{\rho}} \frac{1}{2}\lVert\bar{\boldsymbol{y}} - \bar{\mathbf{H}}\Delta\boldsymbol{a} - \bar{\mathbf{I}}\Delta\boldsymbol{\rho}\rVert_2^2 + \lambda_1\lVert\Delta\boldsymbol{a}\rVert_1 + \lambda_2\lVert\Delta\boldsymbol{\rho}\rVert_1$	$\Delta R_2^*, \Delta S_0$	$\Delta R_2^*, \Delta S_0$
$\Delta\hat{\boldsymbol{a}}, \Delta\hat{\boldsymbol{\rho}} = \arg\min_{\Delta\boldsymbol{a}} \frac{1}{2}\lVert\bar{\boldsymbol{y}} - \bar{\mathbf{H}}\Delta\boldsymbol{a} - \bar{\mathbf{I}}\Delta\boldsymbol{\rho}\rVert_2^2 + \lambda\lVert\Delta\boldsymbol{a}\rVert_1$	$\Delta R_2^*, \Delta S_0$	ΔR_2^*

- Explore the limitations of the algorithm in terms of event duration, temporal overlap of events, etc.
- Adapt the method to accommodate spatial heterogeneity in hemodynamic response shape.
- Explore its application to scientifically and clinically relevant scenarios.

Acknowledgements / Questions

Section on Functional Imaging Methods

Peter A. Bandettini
Daniel A. Handwerker
Dave Jangraw
Laurentius Huber
Emily Finn
Yuhui Chai
Natasha Topolski
Harry Hall

Scientific and Statistical Computing Core

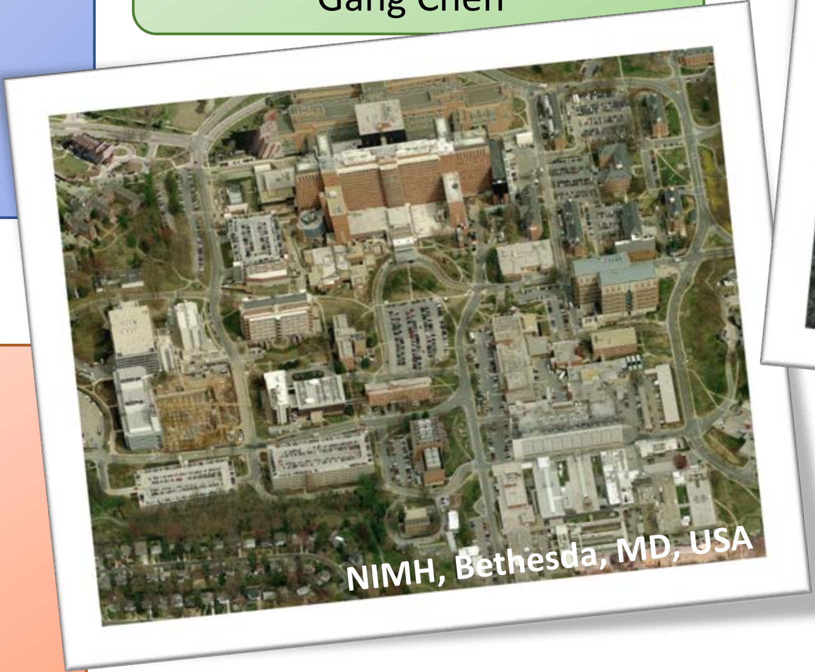
Robert W. Cox
Paul Taylor
Daniel Glen
Richard Reynolds
Gang Chen

Basque Center on Cognition, Brain and Language

César Caballero-Gaudes
Manuel Carreiras

Functional MRI Facility

Sean Marrett
Vinai Roopchansingh
Andy Derbishire
Linquing Li



3dMEPFM will be soon available in AFNI!