Multi-echo EPI for task-based and resting-state fMRI

Javier González-Castillo

Section on Functional Imaging Methods, NIMH, NIH

July 2018, National Institutes of Health, Bethesda, MD

Agenda

❖ WHAT IS MULTI-ECHO (ME) FMRI

❖ BASIC OPERATIONS WITH ME DATA

- Compute static S_o and T_2^* Maps
- Compute voxel-wise time-series of S_o (Non-BOLD) and T_2^* (BOLD)
- Combine echoes to improve SNR/spatially equalize functional contrast
- Echo Time Dependence Analysis

❖ ADVANCE AUTOMATIC DENOISING WITH ME-ICA

- ME-ICA Pipeline
- ME-ICA Outputs
- ME-ICA Web Reporting Tool

❖ EVENT DECONVOLUTION WITH ME-SPFM

- What are fMRI Deconvolution Methods
- ME – Formulation for fMRI Deconvolution based on SPFM
- Example / Validation Experiments

Where to go for additional information…

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Contents lists available at ScienceDirect

NeuroImage

journal homepage: www.elsevier.com/locate/neuroimage

Multi-echo fMRI: A review of applications in fMRI denoising and analysis of BOLD signals

Prantik Kundu[a,*], Valerie Voon[b], Priti Balchandani[a], Michael V. Lombardo[c], Benedikt A. Poser[d], Peter A. Bandettini[e]

[a] Departments of Radiology and Psychiatry, Icahn School of Medicine at Mount Sinai, New York, NY, USA
[b] Behavioral and Clinical Neuroscience Institute, University of Cambridge, Cambridge, UK
[c] Department of Psychology and Center for Applied Neuroscience, University of Cyprus, Nicosia, Cyprus
[d] Department of Cognitive Neuroscience, Maastricht University, Maastricht, NL, The Netherlands
[e] Section on Functional Imaging Methods, National Institute of Mental Health, Bethesda, MD, USA

Intro to ME Signal Model
+ ME-ICA Denoising

2018 IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018)
April 4-7, 2018, Washington, D.C., USA

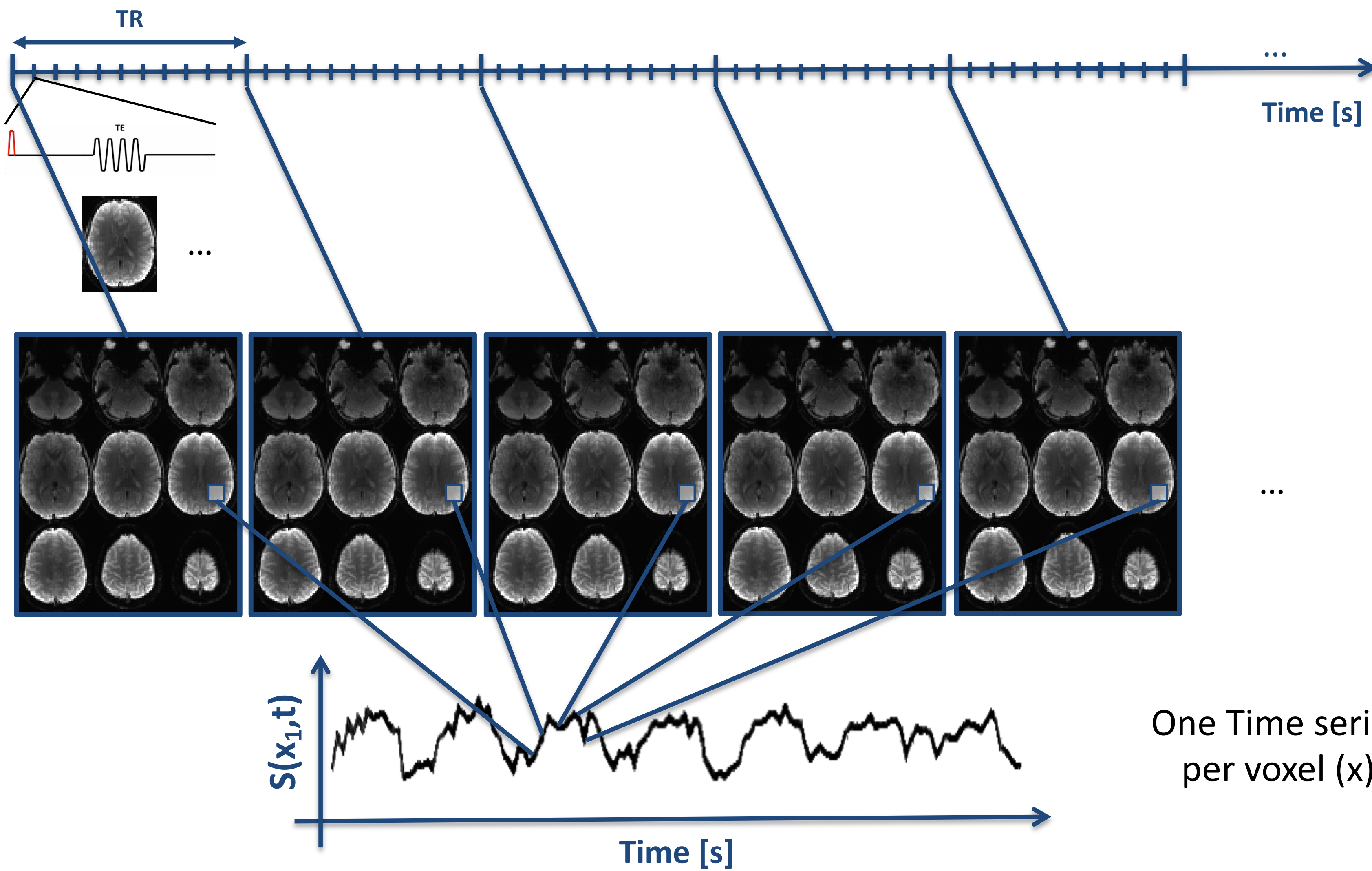
A TEMPORAL DECONVOLUTION ALGORITHM FOR MULTIECHO FUNCTIONAL MRI

César Caballero Gaudes[1], *Peter A. Bandettini*[2,3], *Javier Gonzalez-Castillo*[2]

[1]Basque Center on Cognition, Brain and Language, San Sebastian, Spain
[2]Section on Functional Imaging Methods, NIMH, NIH, Bethesda, MD, USA
[3]Functional MRI Core, NIH, Bethesda, MD, USA

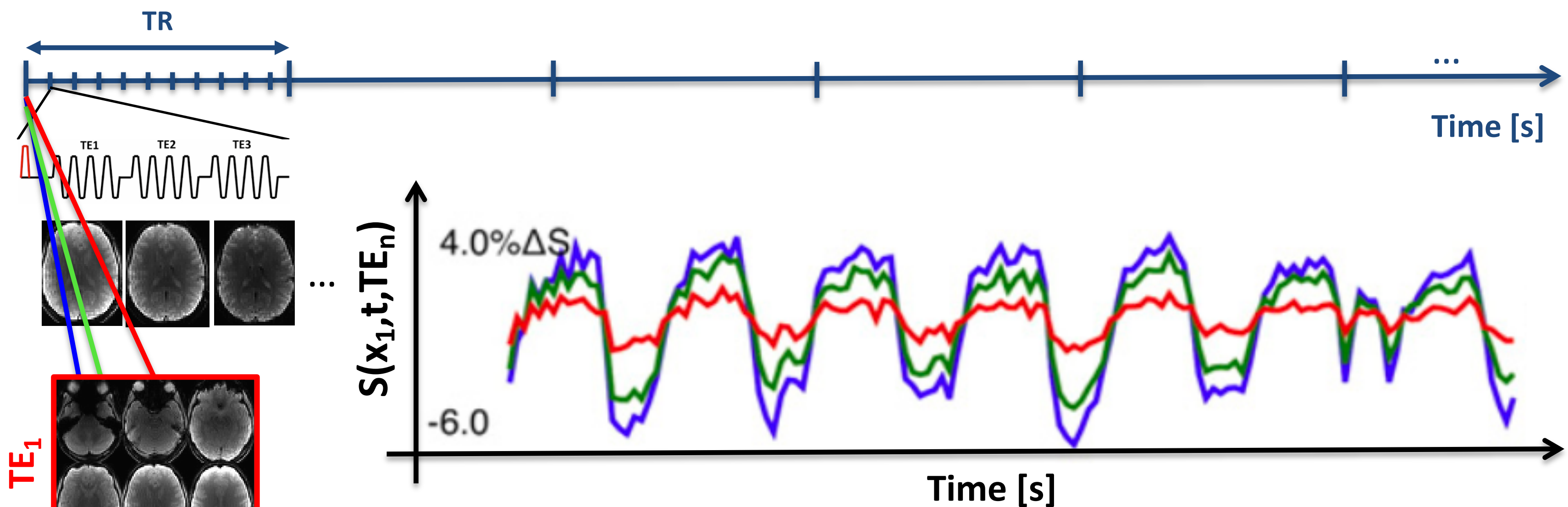
ME Formulation for fMRI
Deconvolution of Sparse Events

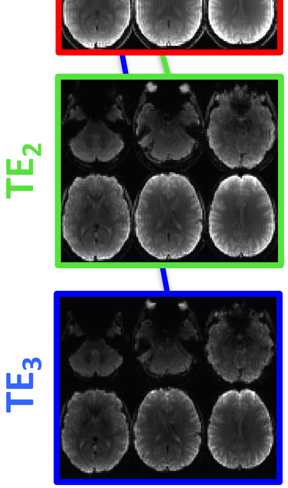
Single-Echo fMRI (a.k.a. Your regular fMRI)



One Time series per voxel (x)

Multi-Echo fMRI

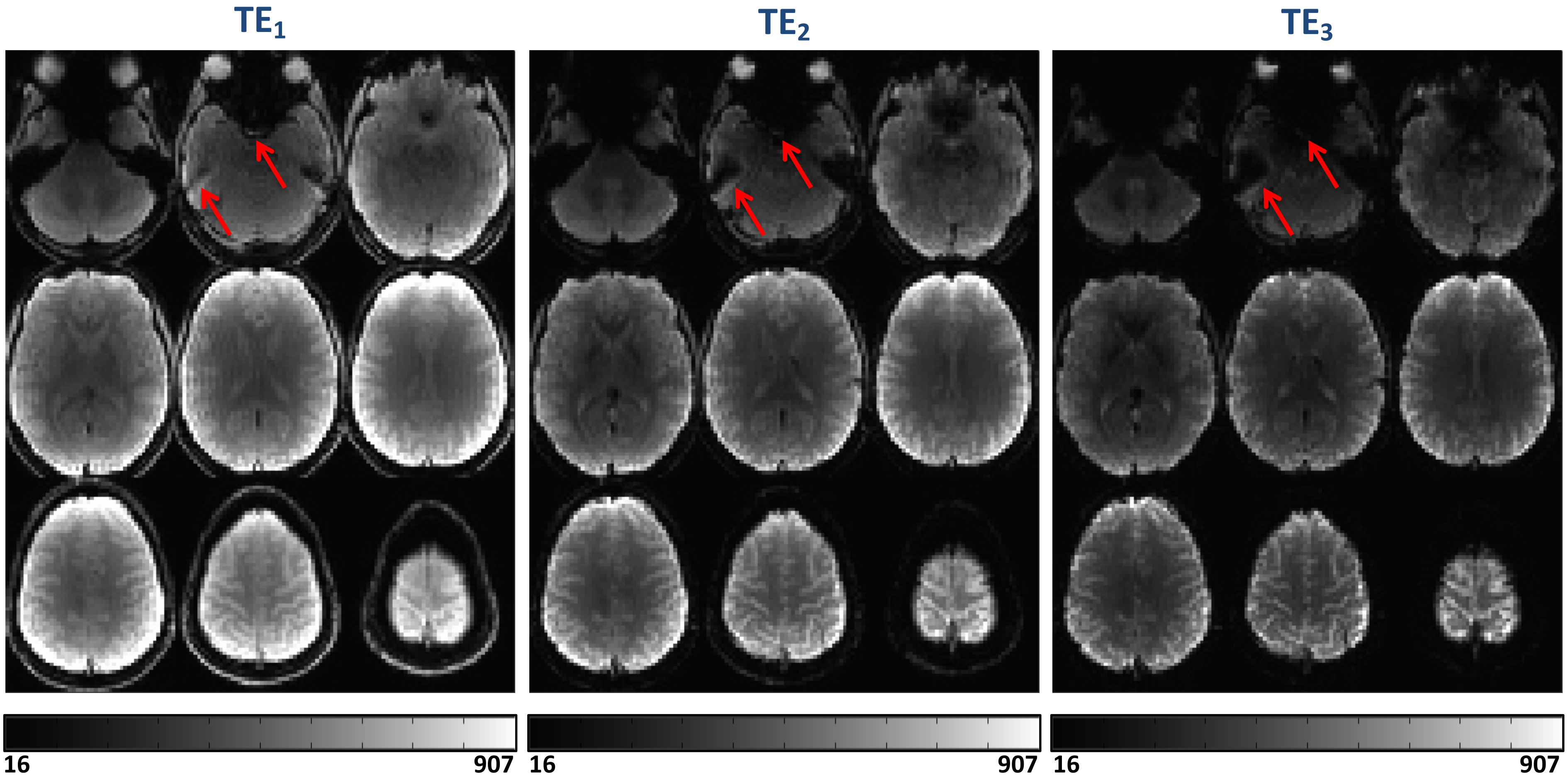




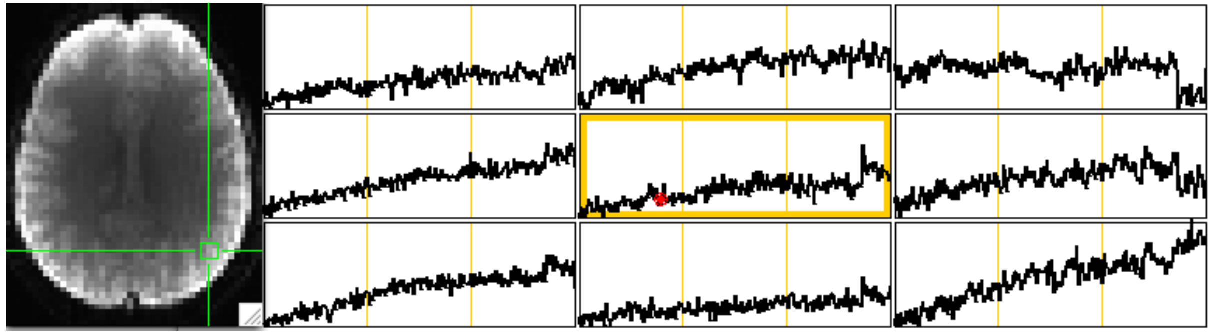
Now, we have N_e (e.g., 3) Time series per voxel, one per echo time (TE_n):

- No SAR cost, as there are no additional excitation pulses.
- Slight lost in temporal resolution (easy to overcome with Multi-Band).
- Slight lost in spatial resolution: to ensure sufficient signal levels in last echo.

Multi-Echo fMRI (II)



Signal Model



Signal in voxel ***x***, at time point ***t***, measured at echo time ***TE***

$$S(x,t,TE) = S_o(x,t)\, e^{-R_2^*(x,t)\cdot TE} \; + \textit{Noise}$$

Captures local fluctuations due to T1 changes (e.g., inflow) and HW instabilities

Captures local fluctuations in field inhomogeneity (including BOLD)

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

$$\Delta S_o(x,t) << \overline{S_o(x)}, \forall x$$

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

$$\Delta R_2^*(x,t) << \overline{R_2^*(x)}, \forall x$$

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How to Compute Spatial Maps of $\overline{S_o}$ and $\overline{T_2^*}$

$$S(x,t,TE) = S_o(x,t)\,e^{-R_2^*(x,t)\cdot TE}$$

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

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

By definition, the average across time of *$\Delta S_o(x,t)$* and *$\Delta R_2^*(x,t)$* are zero, and then it follows that the average signal across time for a given voxel (*x*) and echo time (*TE*) is:

$$\overline{S(x,TE)} = \overline{S_o(x)} \cdot e^{-\overline{R_2^*(x)}\cdot TE}$$

$$\downarrow$$

$$\log\left(\overline{S(x,TE)}\right) = \log\left(\overline{S_o(x)} \cdot e^{-\overline{R_2^*(x)}\cdot TE}\right)$$

$$\downarrow$$

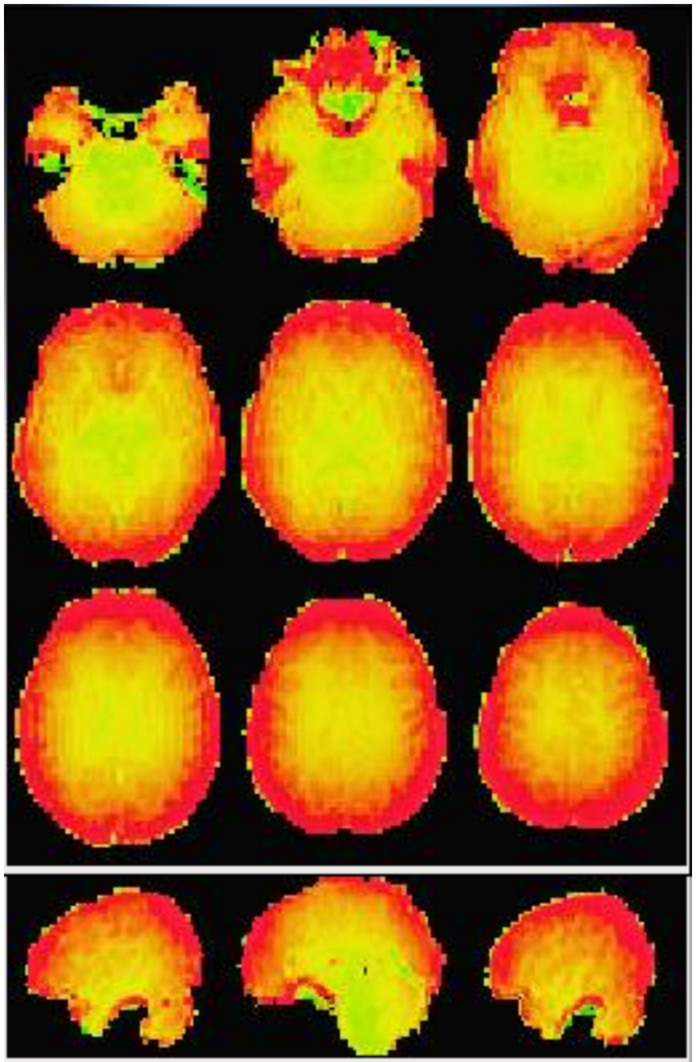
$$\log\left(\overline{S(x,TE)}\right) = -\overline{R_2^*(x)} \cdot TE + \log\left(\overline{S_o(x)}\right)$$

y(x,TE) = a(x) * TE + b(x)

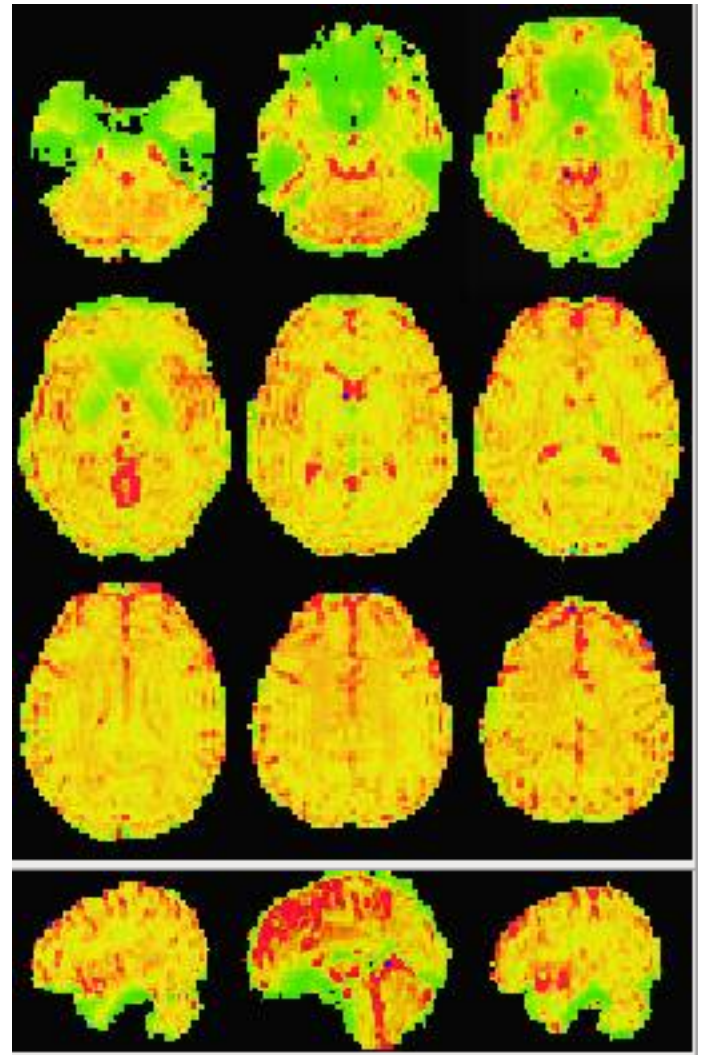
Linear system of equations for 3 echoes

$$\begin{cases} \log\left(\overline{S(x,TE_1)}\right) = -\overline{R_2^*(x)} \cdot TE_1 + \log\left(\overline{S_o(x)}\right) \\ \log\left(\overline{S(x,TE_2)}\right) = \boxed{-\overline{R_2^*(x)}} \cdot TE_2 + \boxed{\log\left(\overline{S_o(x)}\right)} \\ \log\left(\overline{S(x,TE_3)}\right) = -\overline{R_2^*(x)} \cdot TE_3 + \log\left(\overline{S_o(x)}\right) \end{cases}$$

How to Compute Spatial Maps of $\overline{S_o}$ and $\overline{T_2}^*$



Static So Map (s0v.nii)



Static T_2^* Map (t2sv.nii)

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How to Compute Time series of ΔS_o and ΔR_2^* fluctuations

$$S(x,t,TE) = S_o(x,t)\, e^{-R_2^*(x,t)\cdot TE}$$

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

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

$$\overline{S(x,TE)} = \overline{S_o(x)} \cdot e^{-\overline{R_2^*(x)}\cdot TE}$$

$$S(x,t,TE) = \left[\overline{S_o(x)} + \Delta S_o(x,t)\right] \cdot e^{\left[-\overline{R_2^*(x)} + \Delta R_2^*(x,t)\right]\cdot TE} \qquad \textbf{(1)}$$

$$S(x,t,TE) = \overline{S(x,TE)}\left[1 + \frac{\Delta S_o(x,t)}{\overline{S_o(x)}}\right] \cdot e^{-\Delta R_2^*(x,t)\cdot TE} \qquad \textbf{(2)}$$

Using a first order Taylor expansion for the exponential term: $e^{-\Delta R_2^*(x,t)\cdot TE} \approx \left(1 - \Delta R_2^*(x,t)\cdot TE\right)$

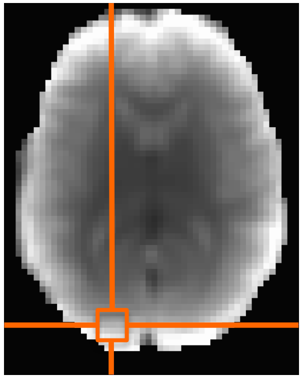
$$S(x,t,TE) \approx \overline{S(x,TE)}\left[1 - \Delta R_2^*(x,t)\cdot TE + \frac{\Delta S_o(x,t)}{\overline{S_o(x)}} - \frac{\Delta R_2^*(x,t)\cdot TE \cdot \Delta S_o(x,t)}{\overline{S_o(x)}}\right] \qquad \textbf{(3)}$$

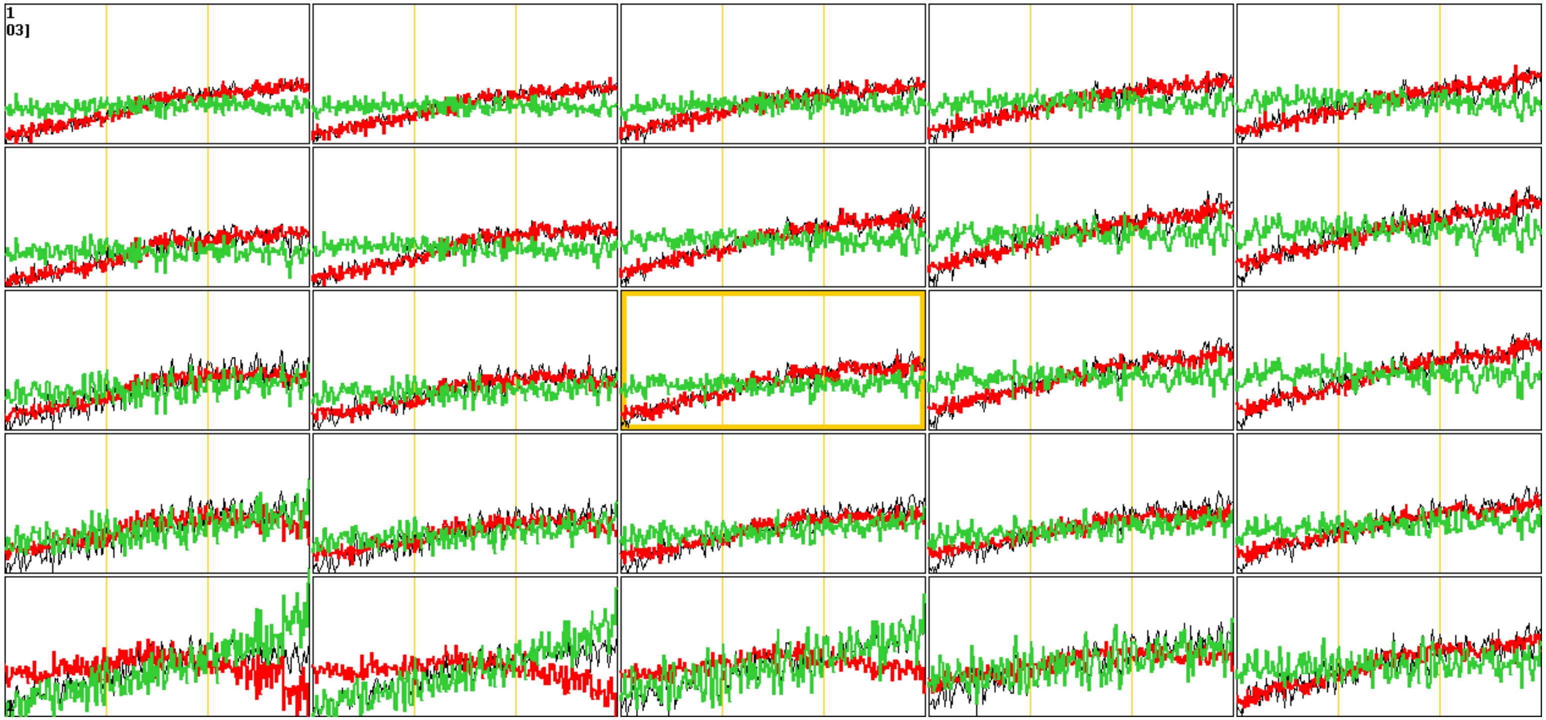
$$S(x,t,TE) \approx \overline{S(x,TE)}\left[1 - \Delta R_2^*(x,t)\cdot TE + \frac{\Delta S_o(x,t)}{\overline{S_o(x)}}\right] \qquad \textbf{(4)}$$

$$\left.\begin{array}{l} \Delta\rho(x,t) = \Delta S_o(x,t) / \overline{S_o(x)} \\ \Delta\kappa(x,t) = \Delta R_2^*(x,t)\cdot \overline{TE} \end{array}\right\} \rightarrow S(x,t,TE) \approx \overline{S(x,TE)} \cdot \left[1 + \Delta\rho(x,t) - \frac{TE}{\overline{TE}}\Delta\kappa(x,t)\right] \qquad \textbf{(5)}$$

$$S(x,t,TE) - \overline{S(x,TE)} \approx \overline{S(x,TE)}\left[\Delta\rho(x,t) - \frac{TE}{\overline{TE}}\Delta\kappa(x,t)\right] \qquad \textbf{(6)}$$

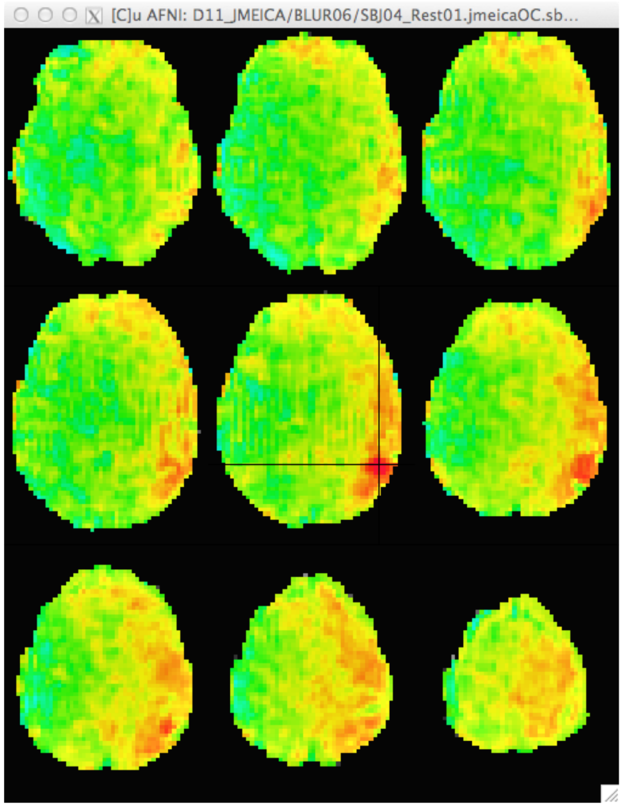
How to Compute Time series of ΔS_o and ΔR_2^* fluctuations



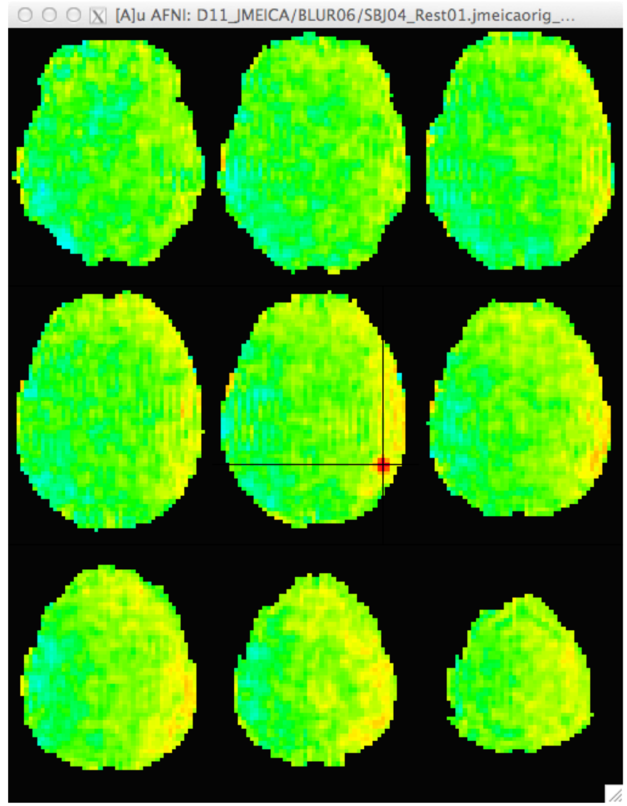


$S(x,t,TE_2)$ — $\Delta S_o(x,t)$ — $\Delta R_2^*(x,t)$

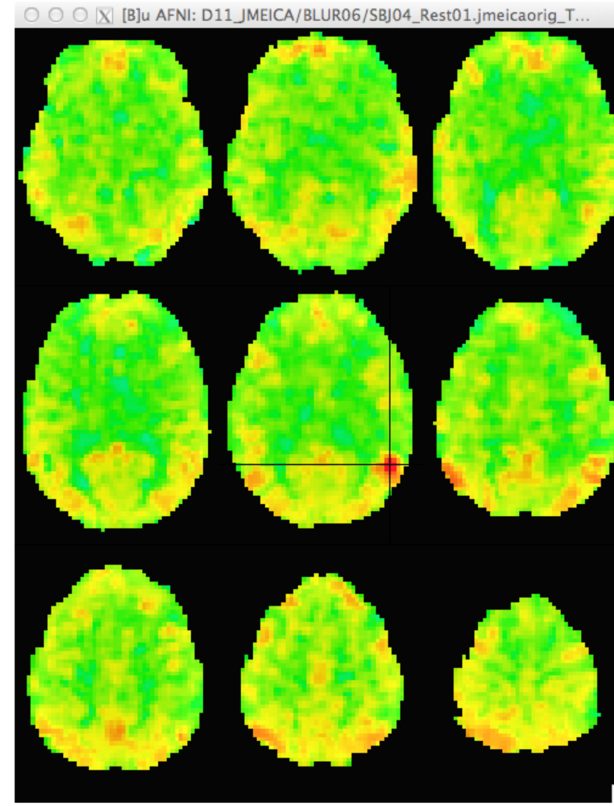
How to Compute Time series of ΔS_o and ΔR_2^* fluctuations



Raw Data



ΔSo



ΔR_2^*

Motion Correction & Smoothing (6mm)
No Filtering | No Detrending

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Combination of Multi-Echo Time series

We have N_e pseudo-concurrent measurements → why not simply combine them to reduce uncorrelated white noise present in each individual measurement?

1. **Simple Summation**

$$\hat{S}(x,t) = \sum_{n=1}^{N} S\left(x,t,TE_n\right)$$

- Noisy data at longer echoes reduce the overall gain in sensitivity.

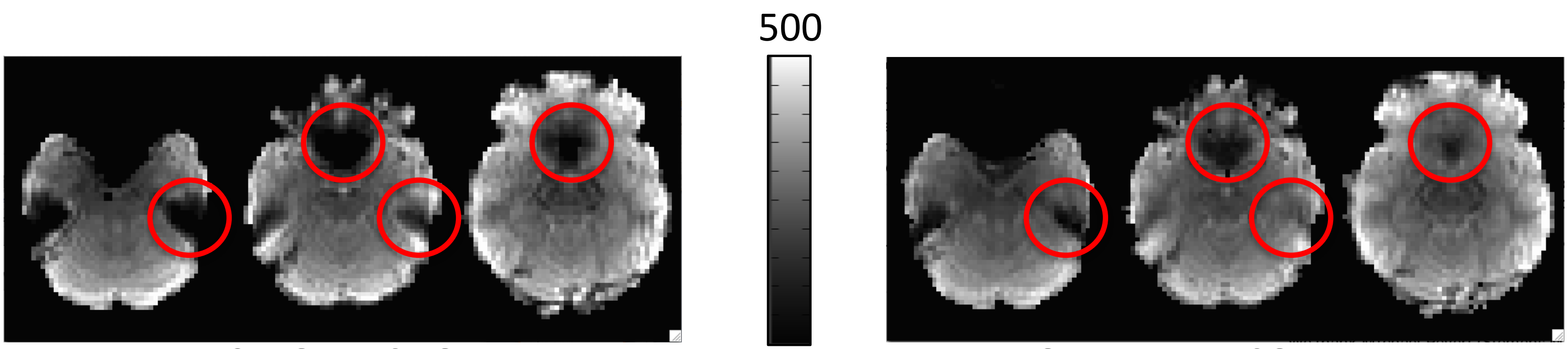
2. **Weighted Summation**

$$\hat{S}(x,t) = \sum_{n=1}^{N} S\left(x,t,TE_n\right) \cdot w_v\left(TE_n\right)$$

$$w_v\left(TE_n\right) = \frac{TE_n e^{-TE_n / T_{2,v}^*}}{\sum_n TE_n \cdot e^{-TE_n / T_{2,v}^*}}$$

- Helps to spatially maximize CNR and also to recover some signal level in regions affected by drop-out.

Posse et al., MRM 1999



SINGLE ECHO **OPTIMALLY COMBINED**

Combination of Multi-Echo Time series

We have N_e pseudo-concurrent measurements, why not simply combine them to reduce uncorrelated white noise present in each individual measurement.

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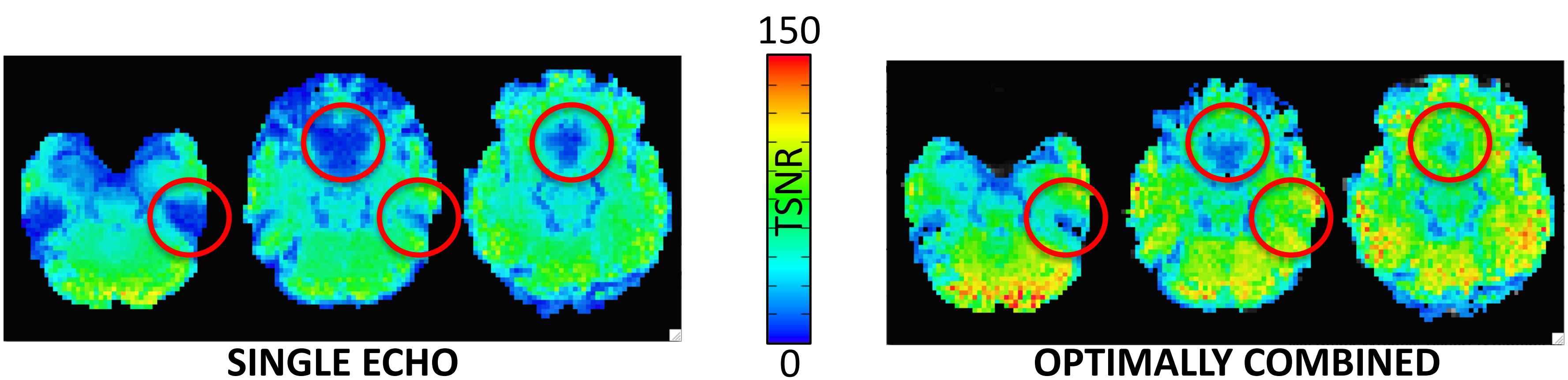
$$w_v\left(TE_n\right)=\frac{TE_n e^{-TE_n/T_{2,v}^*}}{\sum_n TE_n \cdot e^{-TE_n/T_{2,v}^*}}$$

- Optimizes CNR compared to Single Echo.
- Helps to spatially maximize CNR, by helping recover some signal in regions with large drop-outs at regular single echo acquisitions.

Posse et al., MRM 1999



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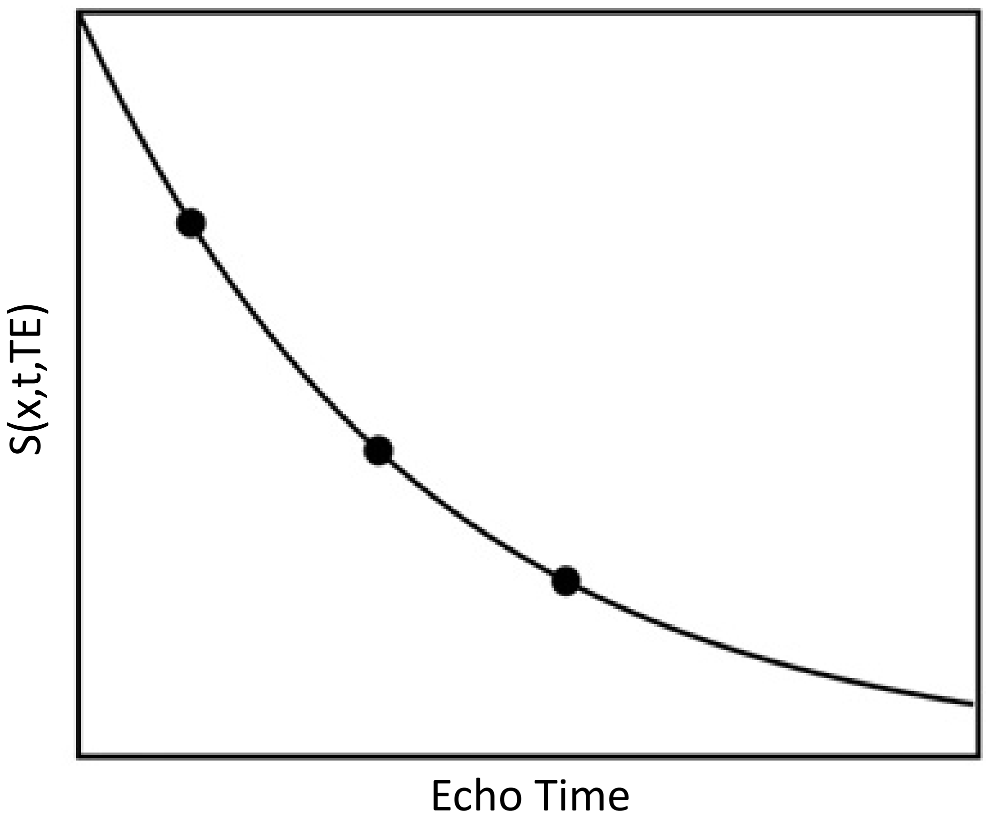
Echo Time (TE) Dependence Analysis

$$S(x,t,TE) = S_o(x,t)e^{-R_2^*(x,t)\cdot TE}$$

Let's assume that a given voxel (x) and time (t) …. So(x,t)=5000 and T2*(x,t)=30ms

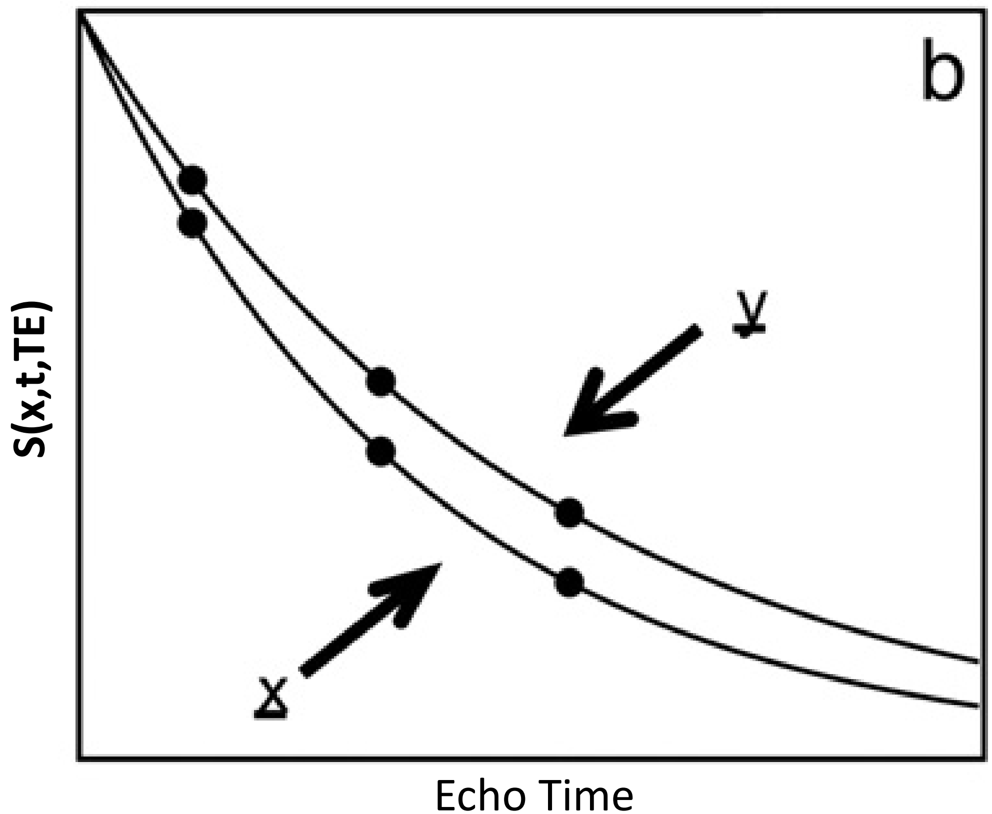


Kundu et al., NeuroImage 2012

Echo Time (TE) Dependence Analysis

$$S(x,t,TE) = S_o(x,t)e^{-R_2^*(x,t)\cdot TE}$$

Let's assume now, that a local change in oxygenation happens (T_2^* effect)

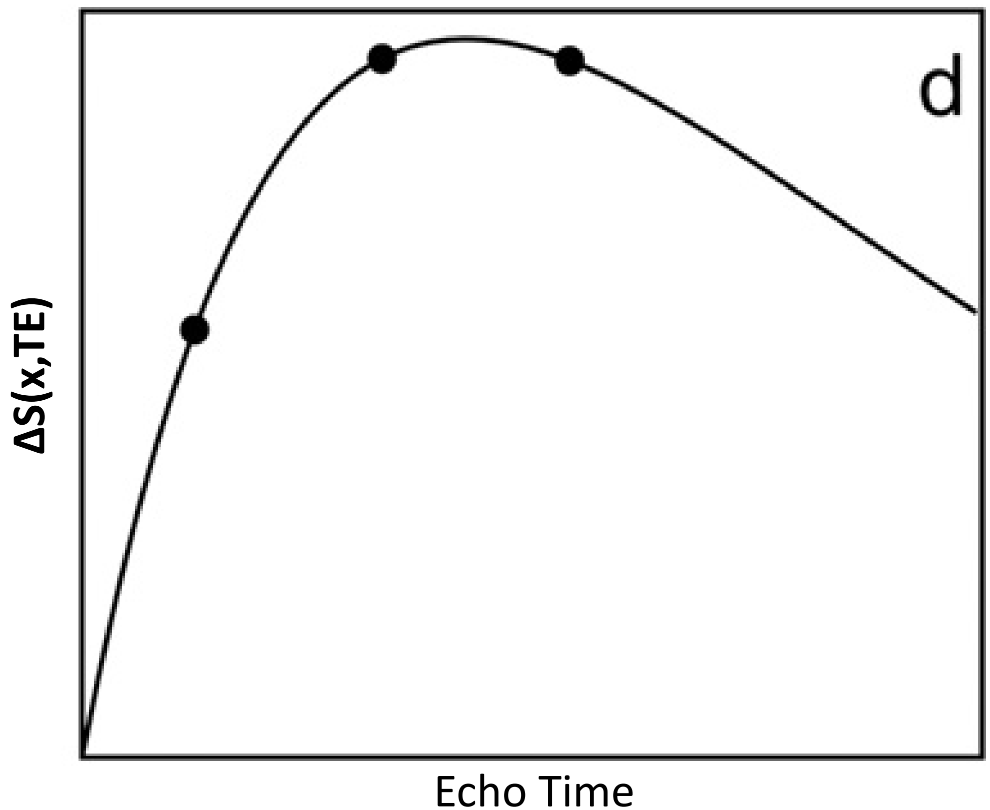


Kundu et al., NeuroImage 2012

Echo Time (TE) Dependence Analysis

$$S(x,t,TE) = S_o(x,t)\, e^{-R_2^*(x,t)\cdot TE}$$

We could then use the difference between two curves to examine which is the optimal TE to maximize BOLD contrast

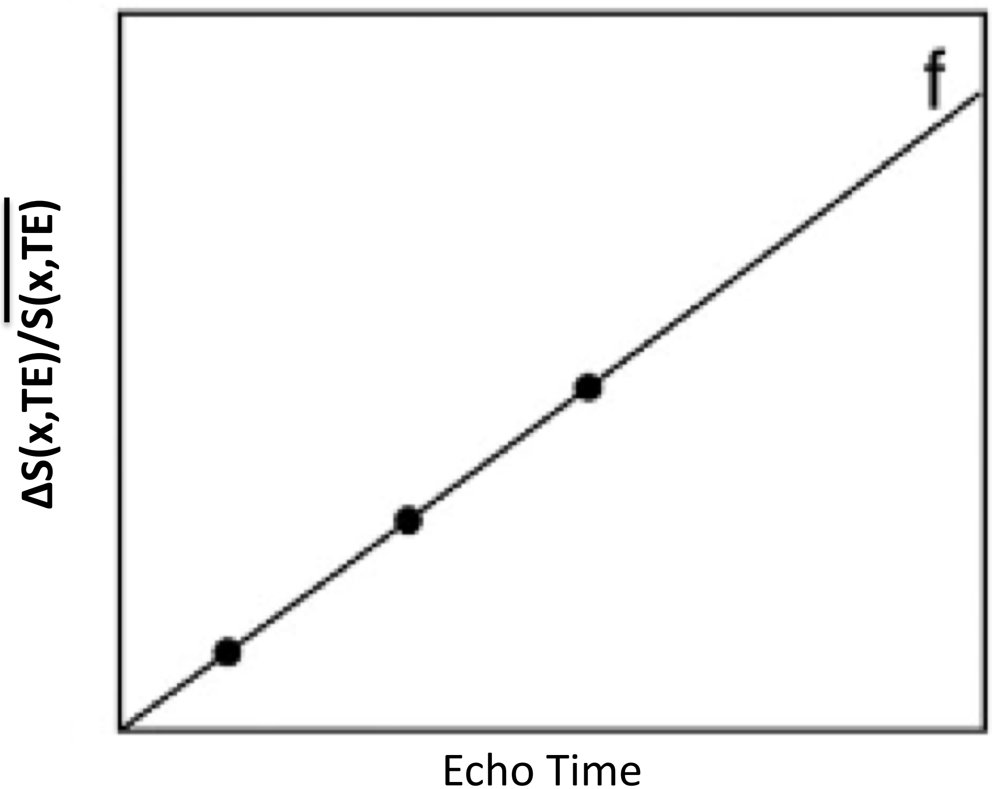


Kundu et al., NeuroImage 2012

Echo Time (TE) Dependence Analysis

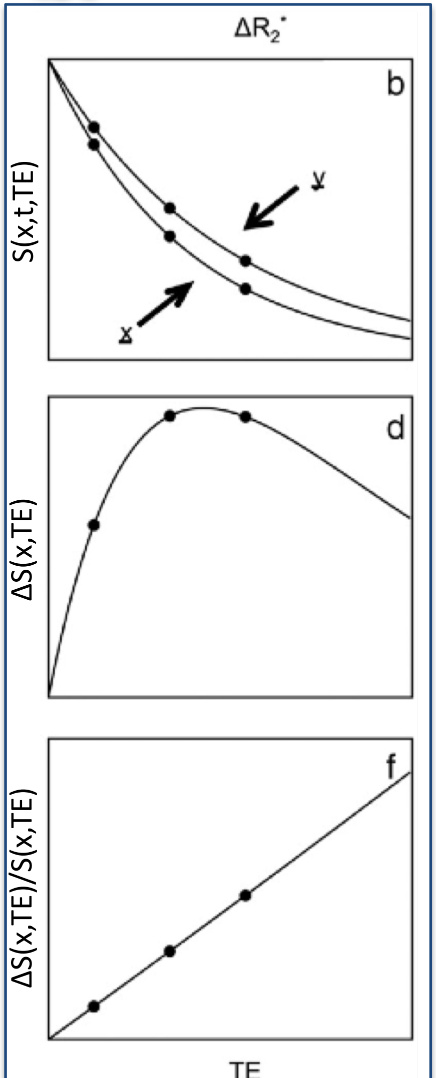
$$S\left(x,t,TE\right)=S_o\left(x,t\right)e^{-R_2^*\left(x,t\right)\cdot TE}$$

Most importantly for our discussion, for T_2^* signal changes, there is a linear relationship between echo time and measured signal (in terms of signal percent change)



Kundu et al., NeuroImage 2012

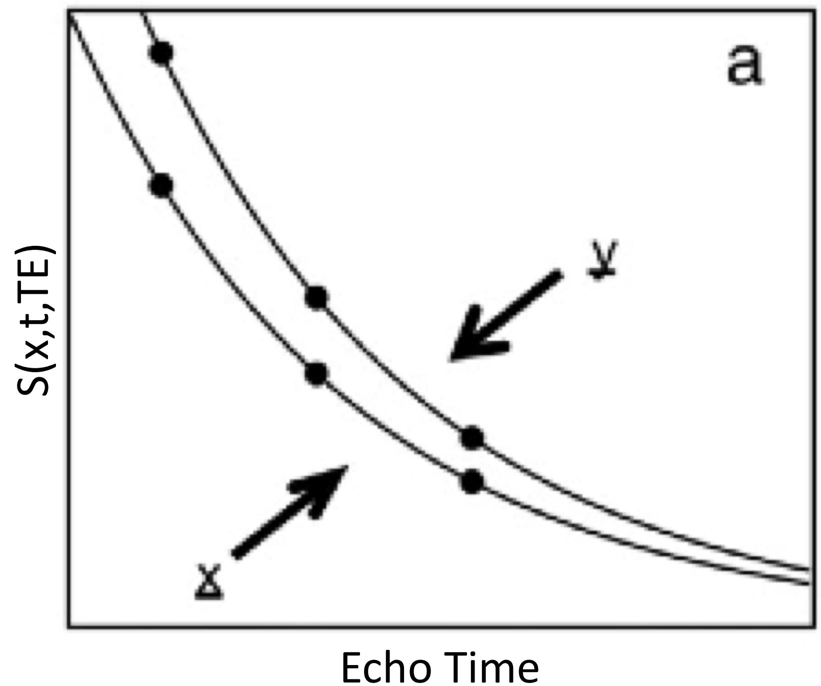
Echo Time (TE) Dependence Analysis



Changes in R2* scale linearly with echo time

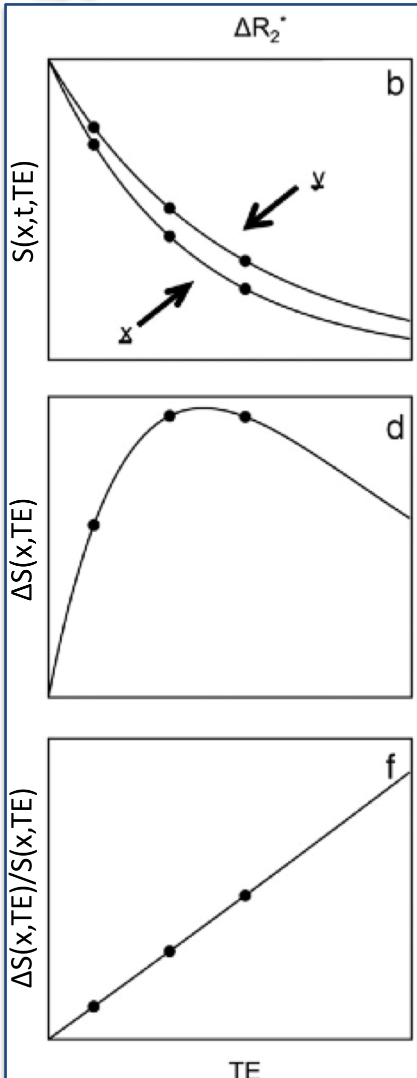
$$S(x,t,TE) = S_o(x,t)\, e^{-R_2^*(x,t)\cdot TE}$$

Let's now examine what happens when there is a change in S_o (T1 effect)



Kundu et al., NeuroImage 2012

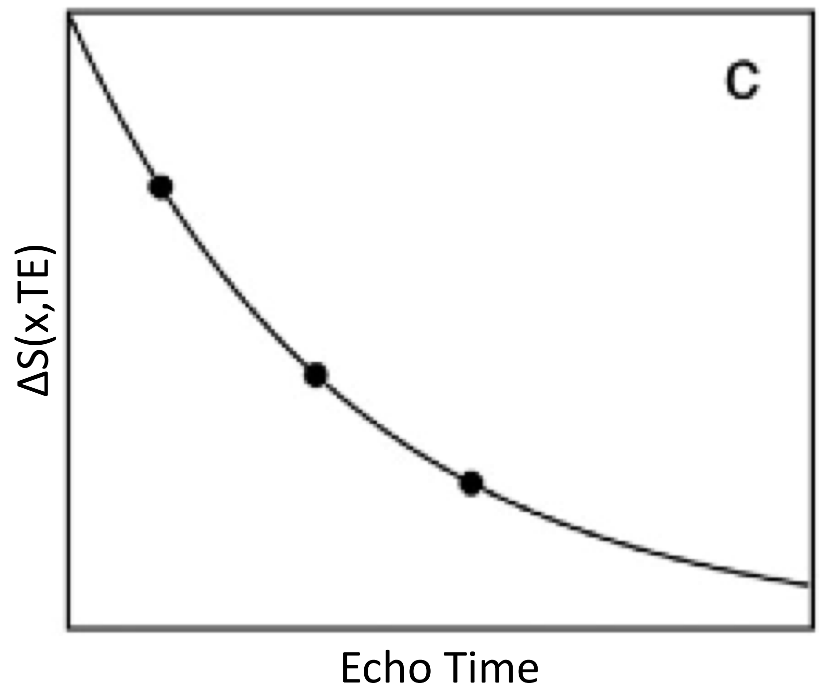
Echo Time (TE) Dependence Analysis



Changes in R2* scale linearly with echo time

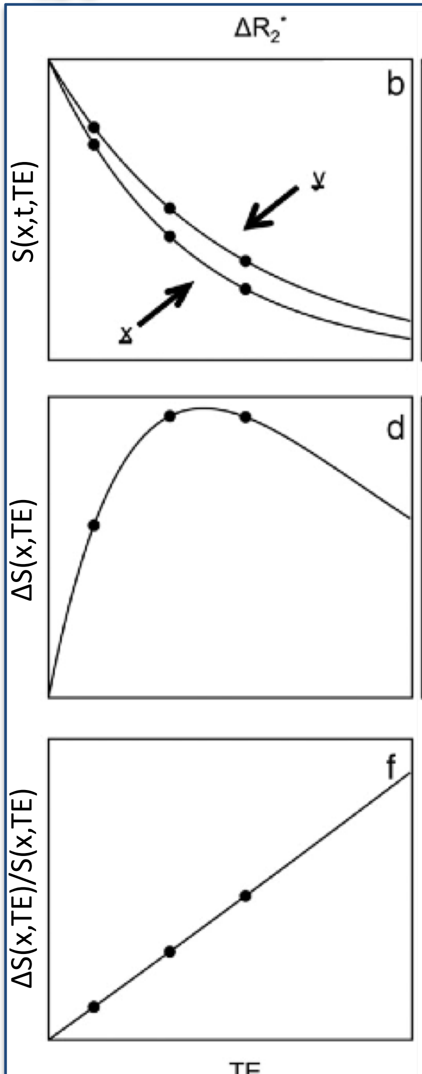
$$S(x,t,TE) = S_o(x,t)\,e^{-R_2^*(x,t)\cdot TE}$$

This time the difference between both curves looks very different



Kundu et al., NeuroImage 2012

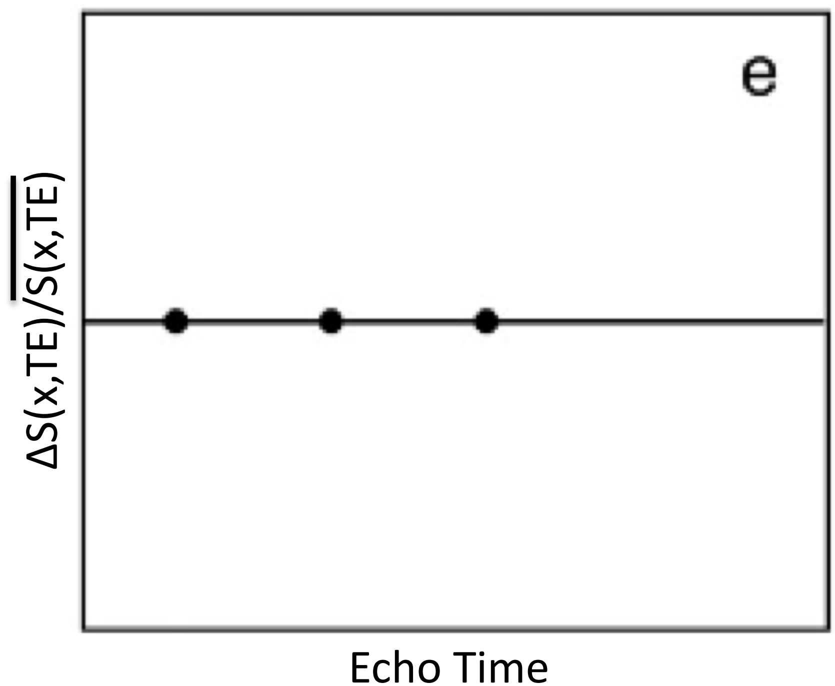
Echo Time (TE) Dependence Analysis



Changes in R2* scale linearly with echo time

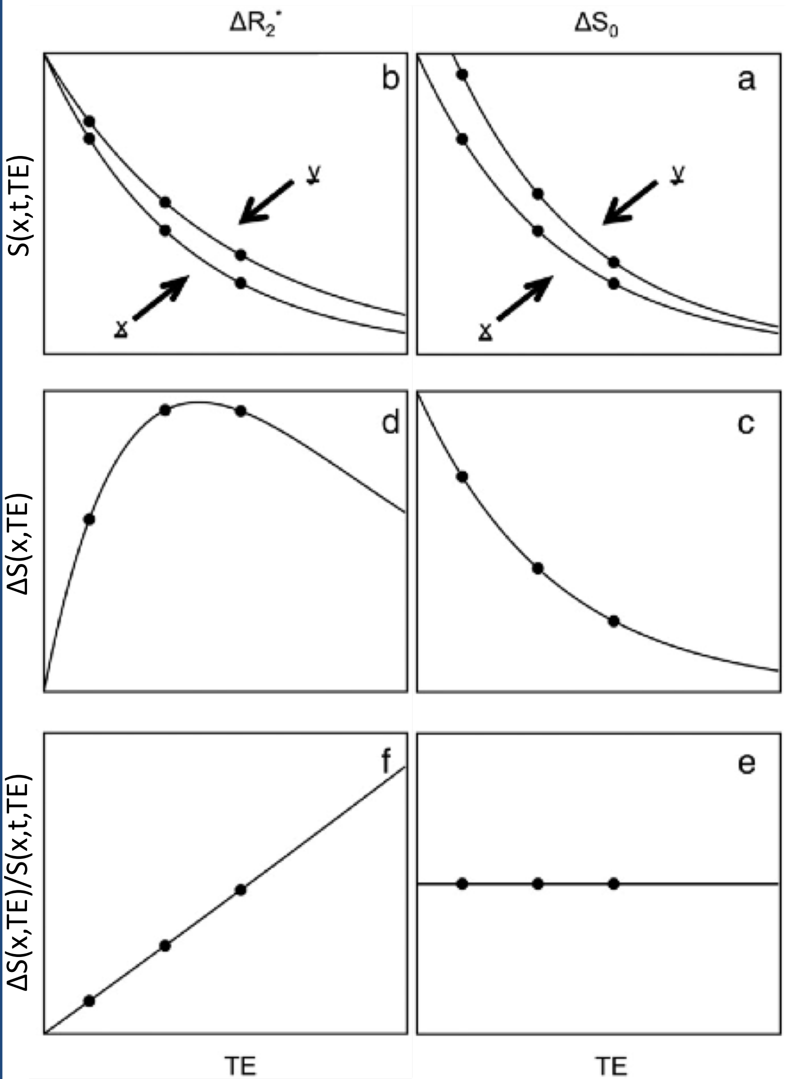
$$S(x,t,TE) = S_o(x,t)\,e^{-R_2^*(x,t)\cdot TE}$$

In term of signal percent change, changes in So have a flat dependence with echo time



Kundu et al., NeuroImage 2012

Echo Time (TE) Dependence Analysis

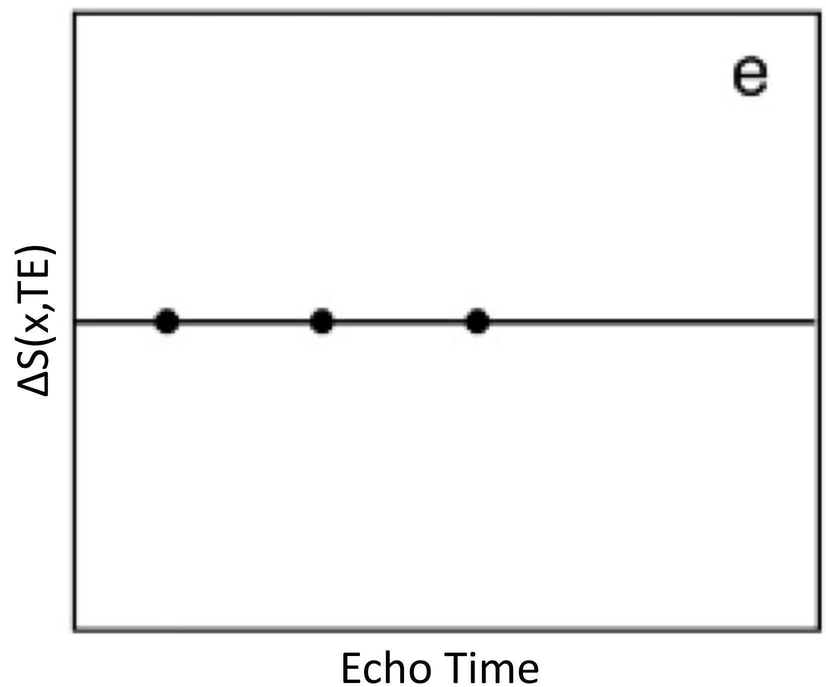


Changes in R2* scale linearly with echo time

Changes in So show a flat dependence with echo time

$$S(x,t,TE) = S_o(x,t)e^{-R_2^*(x,t)\cdot TE}$$

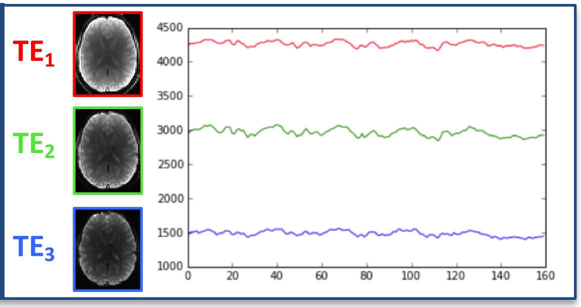
In term of signal percent change, changes in So have a flat dependence with echo time



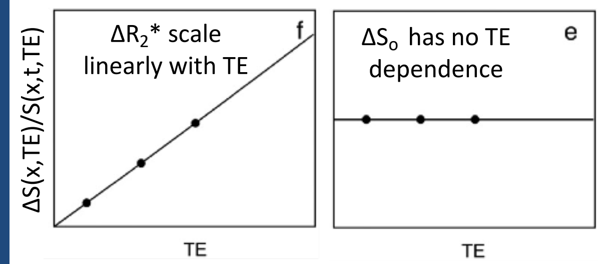
Kundu et al., NeuroImage 2012

Echo Time (TE) Dependence Analysis

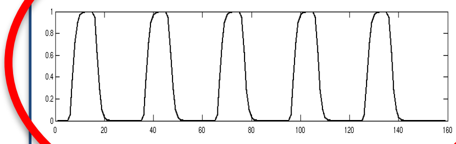
MULTI-ECHO DATASET



TE-DEPENDENCE MODEL

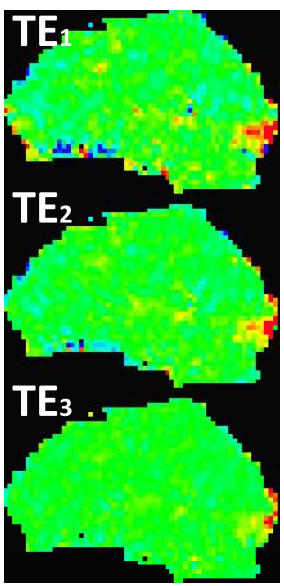


TIMESERIES OF INTEREST

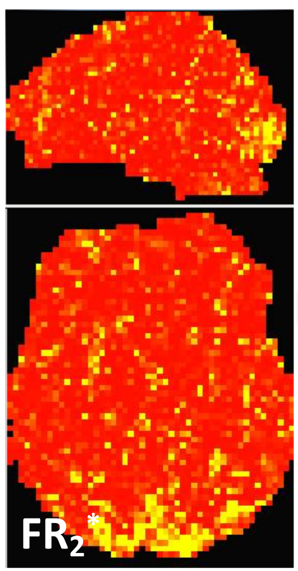


Task Paradigm

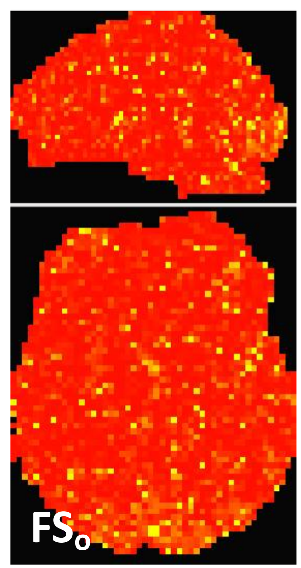
[1] Voxel-wise Fit against all TEs



[2] Voxel-wise Goodness of Fit to R2* Model



[3] Voxel-wise Goodness of Fit to S_0 Model



[4] Compute Avg. Metric for each model

$$\kappa = \sum_{AllVoxels} z_v^2 F_{v,R_2^*} \Big/ \sum_{AllVoxels} z_v^2 = 98.41$$

$$\rho = \sum_{AllVoxels} z_v^2 F_{v,S_o} \Big/ \sum_{AllVoxels} z_v^2 = 26.02$$

Kundu et al., NeuroImage 2012

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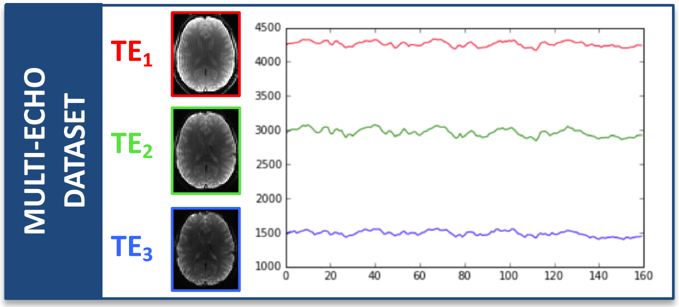
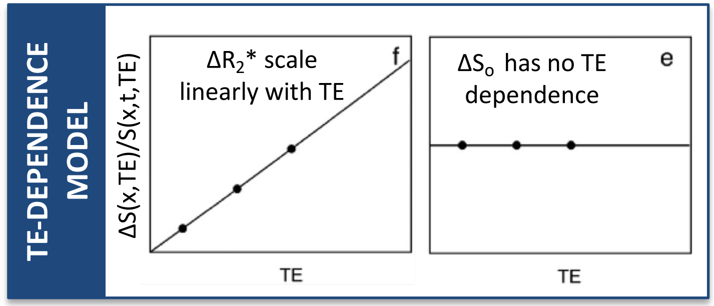
- What are fMRI Deconvolution Methods
- ME – Formulation for fMRI Deconvolution based on SPFM
- Example / Validation Experiments

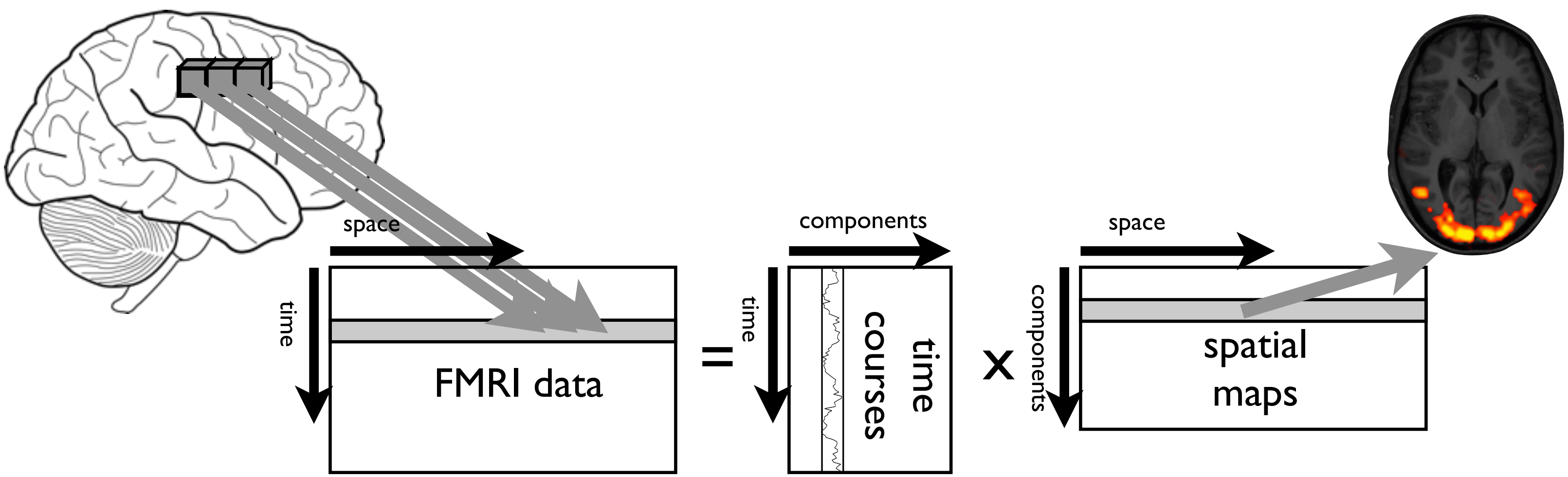
ME-ICA Denoising: Introduction





TIMESERIES OF INTEREST

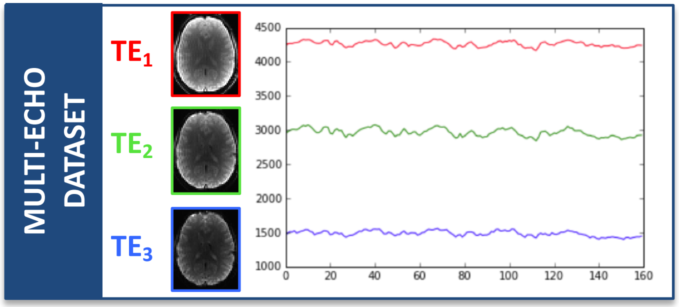
ICA Representative Timeseries

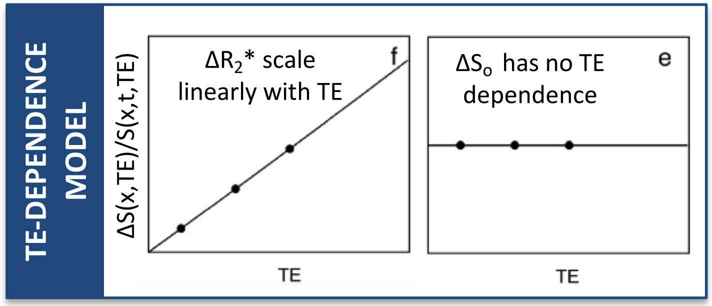


Data is represented as a 2D matrix and decomposed into factor matrices (or modes)

FSL Documentation: http://fsl.fmrib.ox.ac.uk/fslcourse/lectures/melodic.pdf

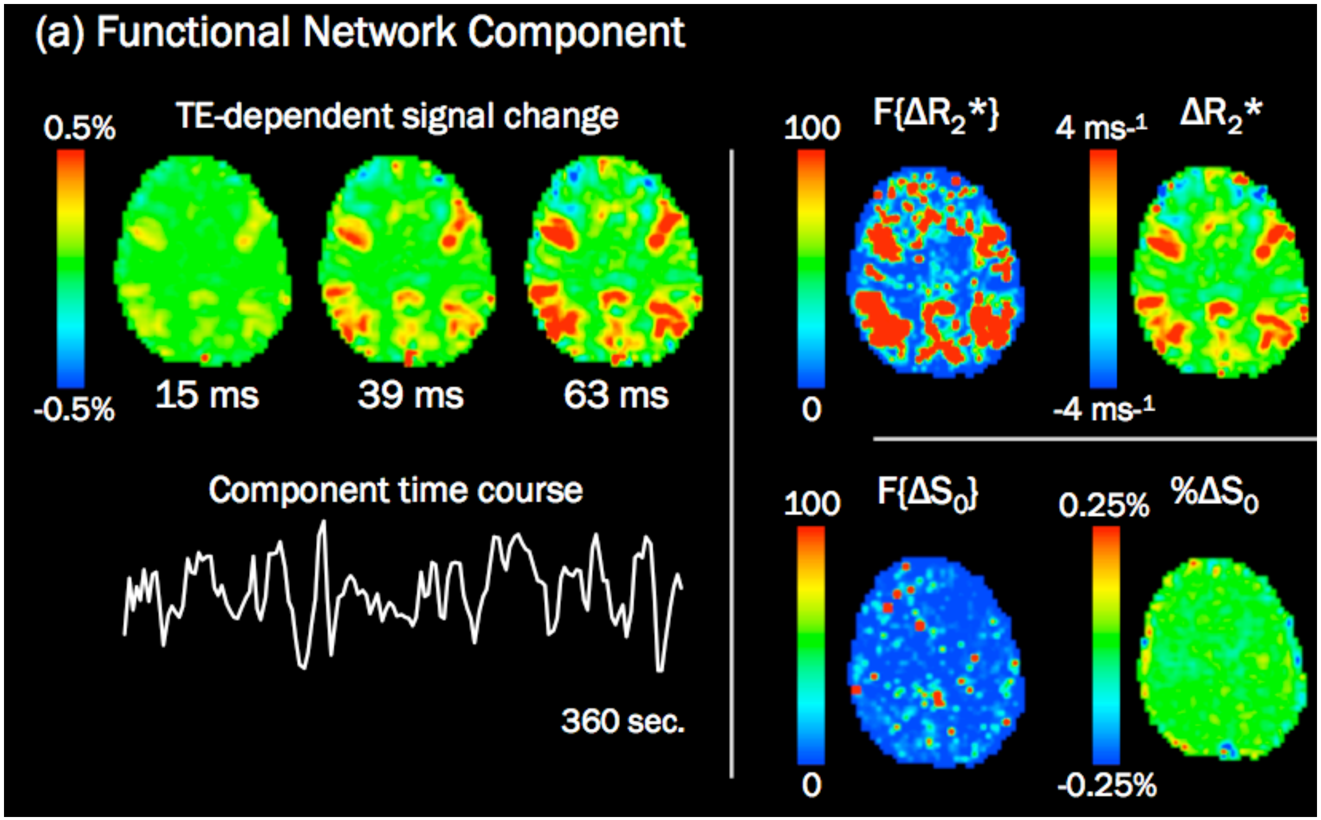
ME-ICA Denoising: Introduction





TIMESERIES OF INTEREST

ICA Representative Timeseries



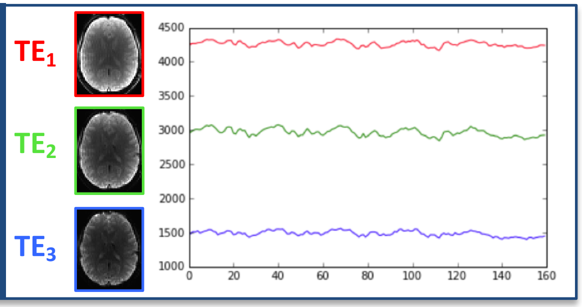
Kappa (κ) = 210

Rho (ρ) = 10

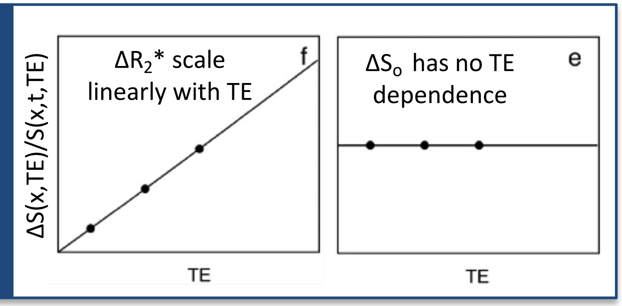
Kundu et al., NeuroImage 2012

ME-ICA Denoising: Introduction

MULTI-ECHO DATASET

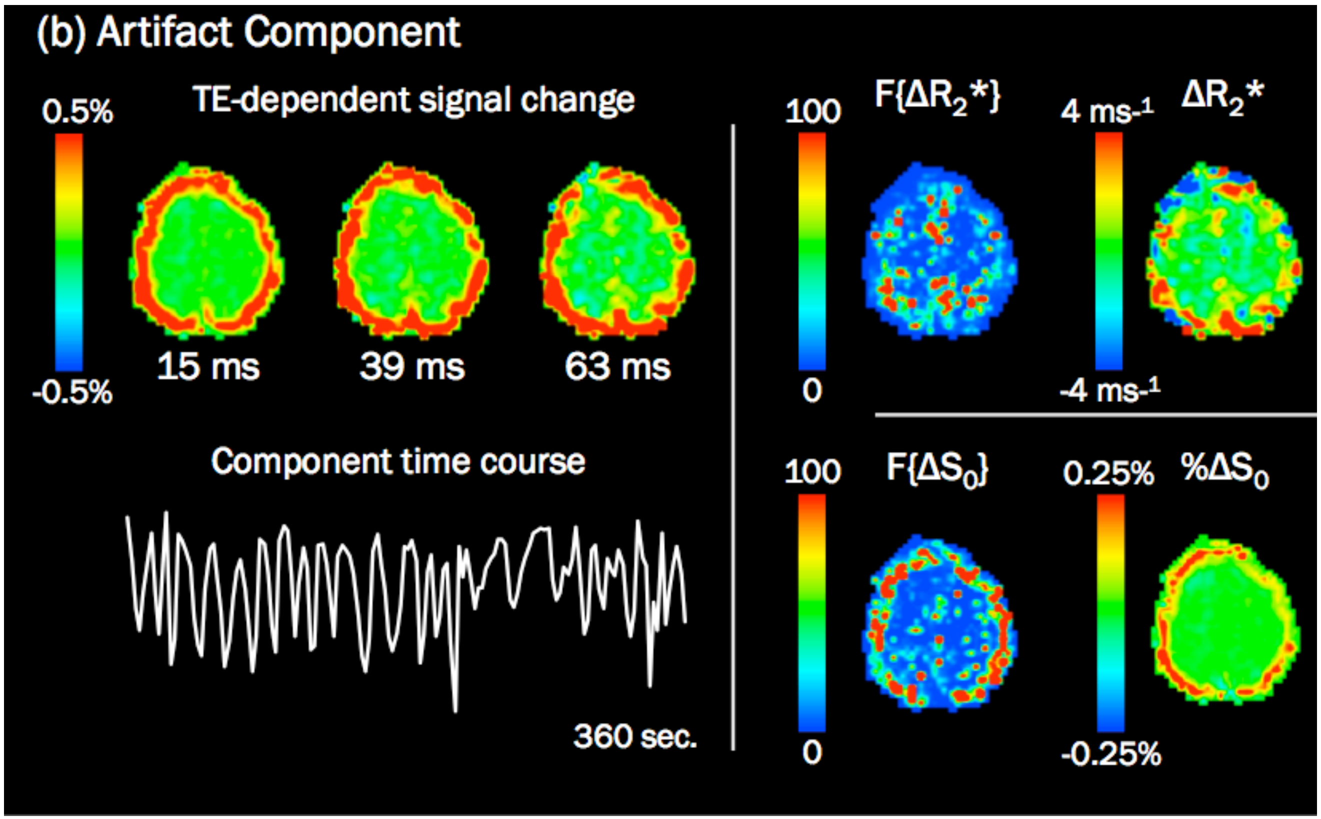


TE-DEPENDENCE MODEL



TIMESERIES OF INTEREST

ICA Representative Timeseries

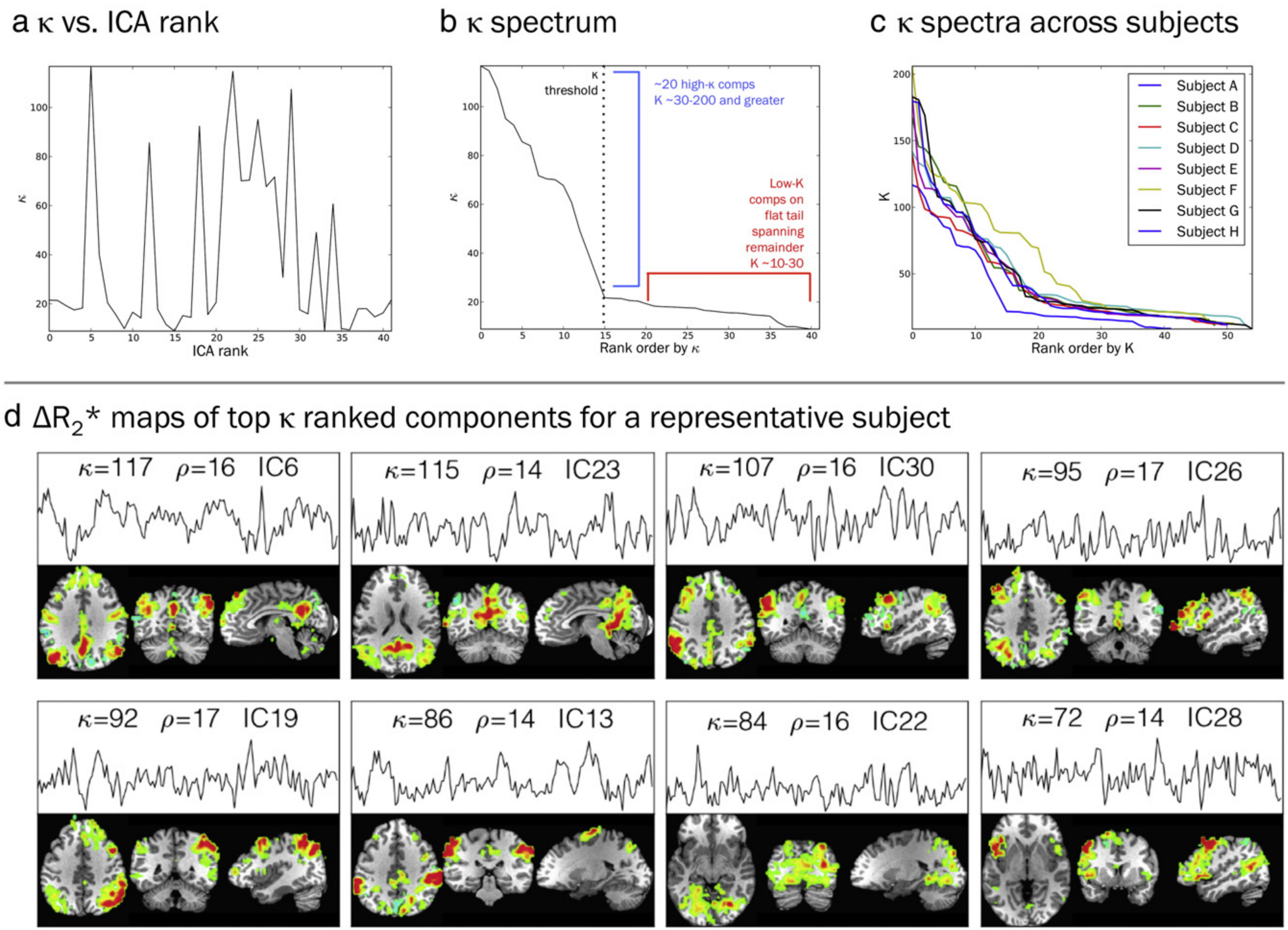


Kappa (κ) = 32

Rho (ρ) = 81

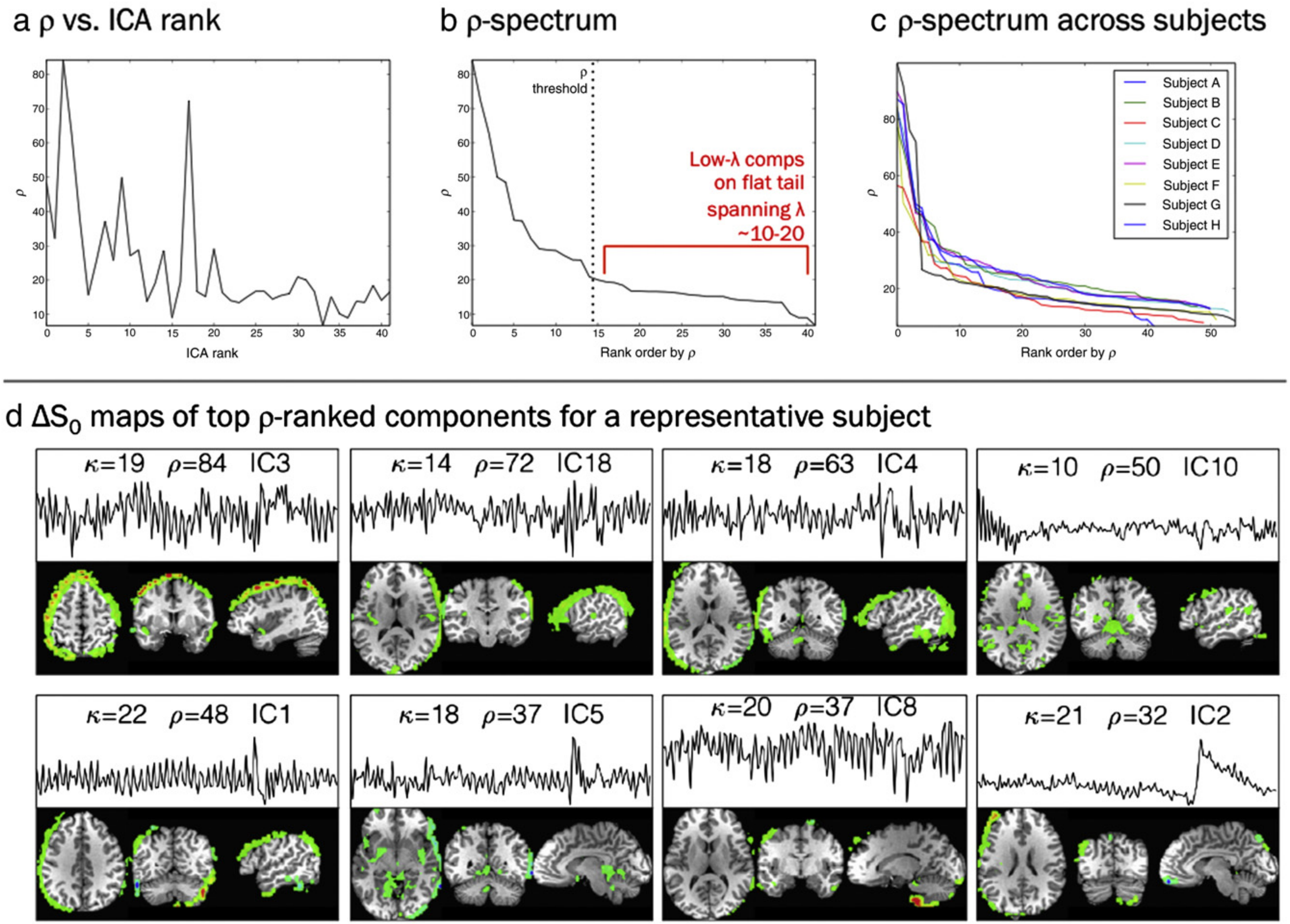
Kundu et al., NeuroImage 2012

ME-ICA Denoising: Introduction



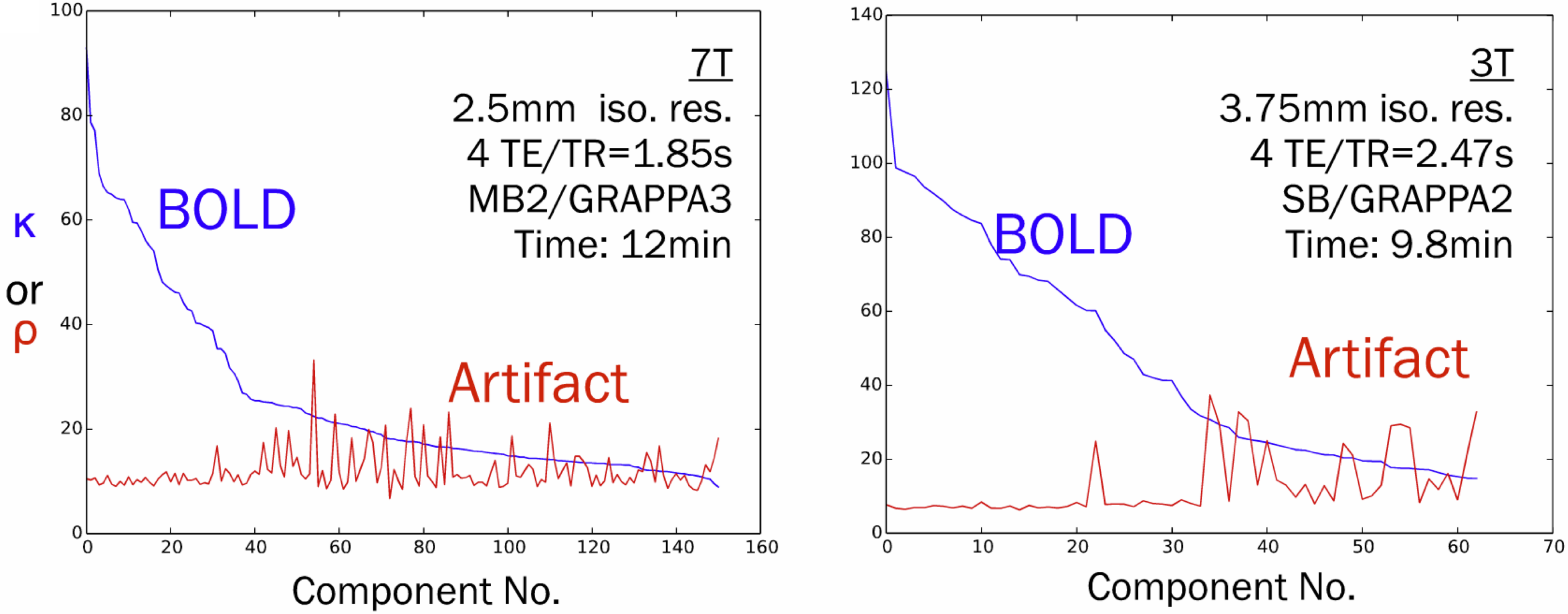
Kundu et al., NeuroImage 2012

ME-ICA Denoising: Introduction



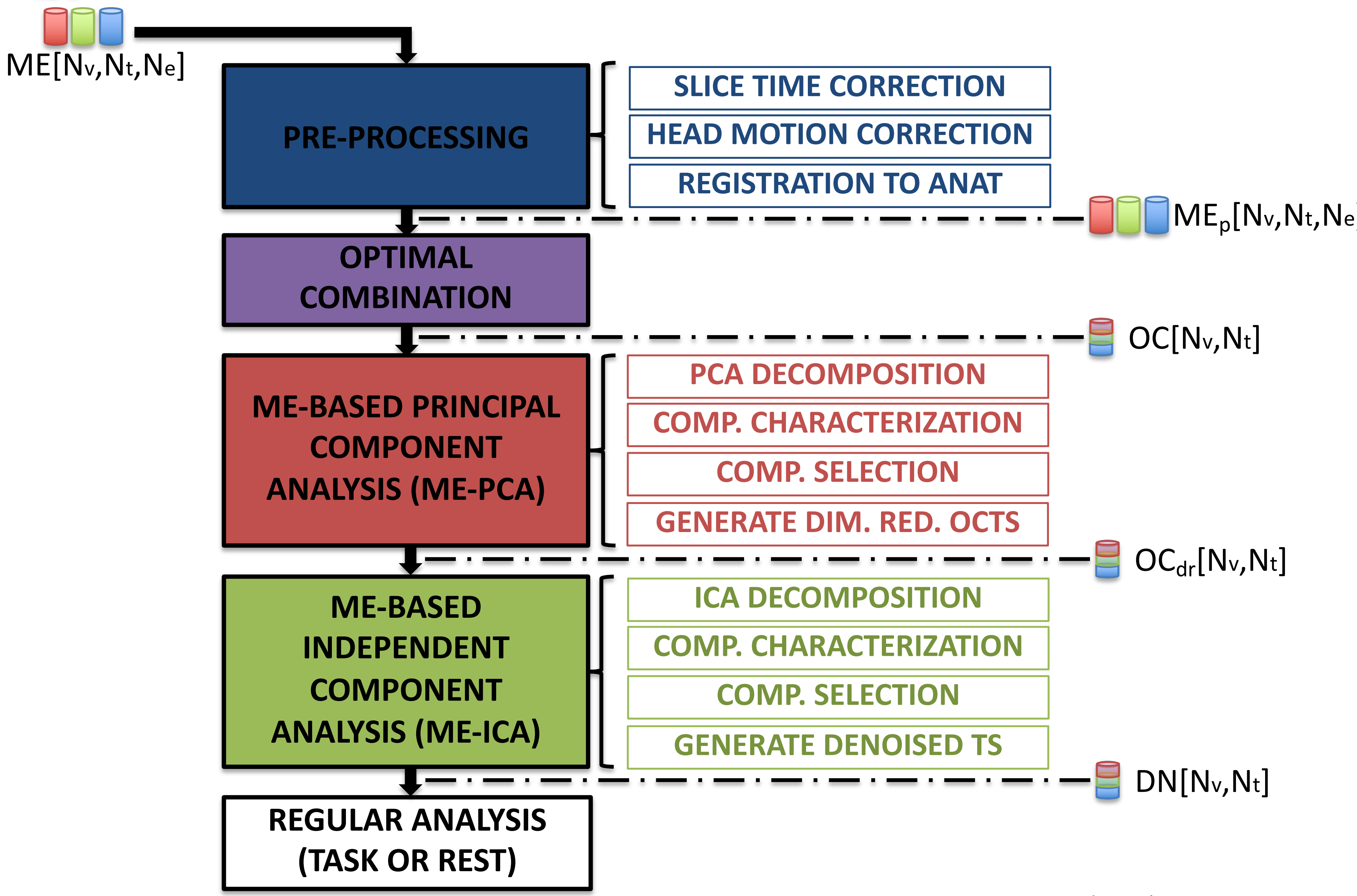
Kundu et al., NeuroImage 2012

ME-ICA Denoising: Introduction



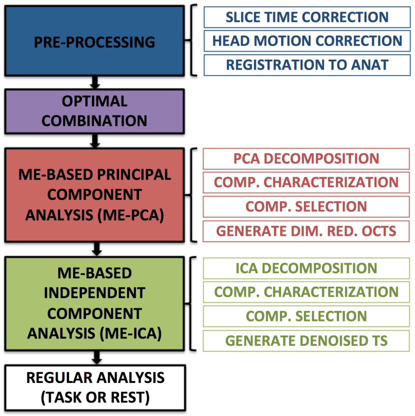
Kundu et al., NeuroImage 2017

ME-ICA Denoising: Pipeline



Kundu et al., NeuroImage 2012

ME-ICA Denoising: Pipeline



ME-PCA

- Uses PCA Decomposition (orthogonality).
- Yet, estimation of model order (Ncomp) is not based on variance, but on κ and ρ thresholds.
  - $\kappa_{thr} = f(\kappa_{elbow}, \kappa_{daw})$; Default $\kappa_{daw} = 10$
  - $\rho_{thr} = f(\rho_{elbow}, \rho_{daw})$; Default $\rho_{daw} = 1$
  - SELECTION RULE: $\kappa > \kappa_{thr}$ are kept
  - SELECTION RULE: $\rho > \rho_{thr}$ are kept

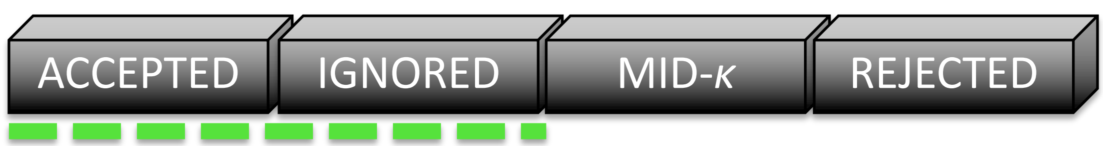
ME-ICA

- Uses fast-ICA algorithm (spatial independence).
- Component Characterization includes:
  - Variance Explained
  - κ (*"BOLD likeliness"*)
  - ρ (*"Non-BOLD likeliness"*)
  - Nvoxels that significantly fit the S_o model
  - Nvoxels that significantly fit the R_2^* model
  - Spatial overlap (D) between ICA map and FR_2^* map
  - Spatial overlap (D) between ICA map and FS_o map
  - Other…

κ, ρ → *If $\kappa_c < \rho_c$ → Discard c*

S_o, R_2^* Nvoxels → *If $N_{so,c} < N_{R2,c}$ → Discard c*

Spatial overlap → *If $D_{so,c} < D_{R2,c}$ → Discard c*



Denoised Time series

Kundu et al., NeuroImage 2012; Kundu et al. 2013 PNAS; Olafsson et al. NeuroImage 2015

ME-ICA Denoising: Primary Inputs / Outputs

INPUTS

- ❑ Minimum: fMRI Datasets for all echoes, echo times
- ❑ Extras: Anatomical, Pre-processing options, kdaw, rdaw,

OUTPUTS

- ❑ T2* Static Map: *t2v.nii*
- ❑ So Static Map: *s0v.nii*
- ❑ Optimally Combined time series: *ts_OC.nii*
- ❑ Denoised time series: *dn_ts_OC.nii*
- ❑ Spatial Maps for all ICA components: *betas_OC.nii*
- ❑ Spatial Maps for Accepted Components only: *betas_hik_OC.nii*
- ❑ Time series for all PCA Components: *mepca_mix.1D*
- ❑ Time series for all ICA Components: *meica_mix.1D*
- ❑ Summary of ICA Decomposition: *comp_table.txt*
  - ❑ List of accepted components
  - ❑ List of rejected components
  - ❑ List of Mid-k components
  - ❑ List of ignored components
  - ❑ Kappa and Rho values for all components
  - ❑ Total Variance Explained by the ICA decomposition

ME-ICA Software available with AFNI: http://afni.nimh.nih.gov/afni
Latest updates available at: https://github.com/ME-ICA

ME-ICA Denoising: Web Reporting Tool

(Ben Gutierrez) available at: https://github.com/BenGutierrez/Meica_Report

Agenda

❖ WHAT IS MULTI-ECHO (ME) FMRI

❖ BASIC OPERATIONS WITH ME DATA

- Compute static S_o and T_2^* Maps
- Compute voxel-wise time-series of S_o (Non-BOLD) and T_2^* (BOLD)
- Combine echoes to improve SNR/spatially equalize functional contrast
- Echo Time Dependence Analysis

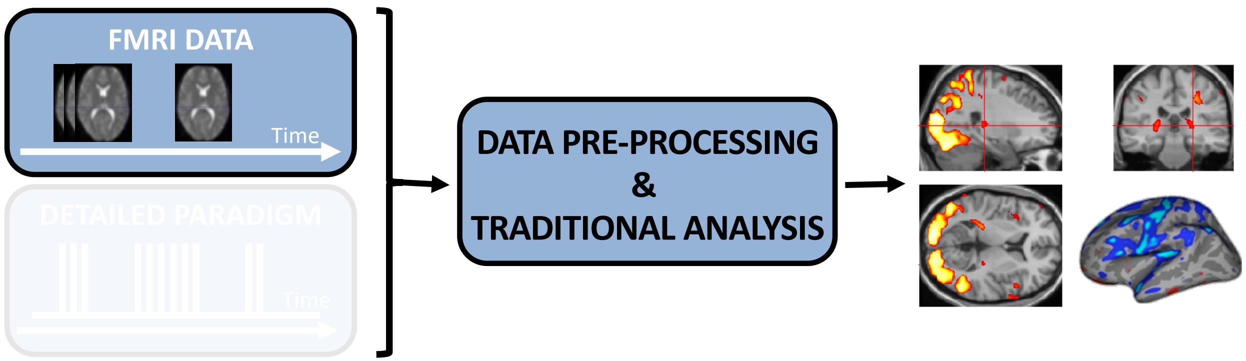
❖ ADVANCE AUTOMATIC DENOISING WITH ME-ICA

- ME-ICA Pipeline
- ME-ICA Outputs
- ME-ICA Web Reporting Tool

❖ EVENT DECONVOLUTION WITH ME-SPFM

- What are fMRI Deconvolution Methods
- ME – Formulation for fMRI Deconvolution based on SPFM
- Example / Validation Experiments

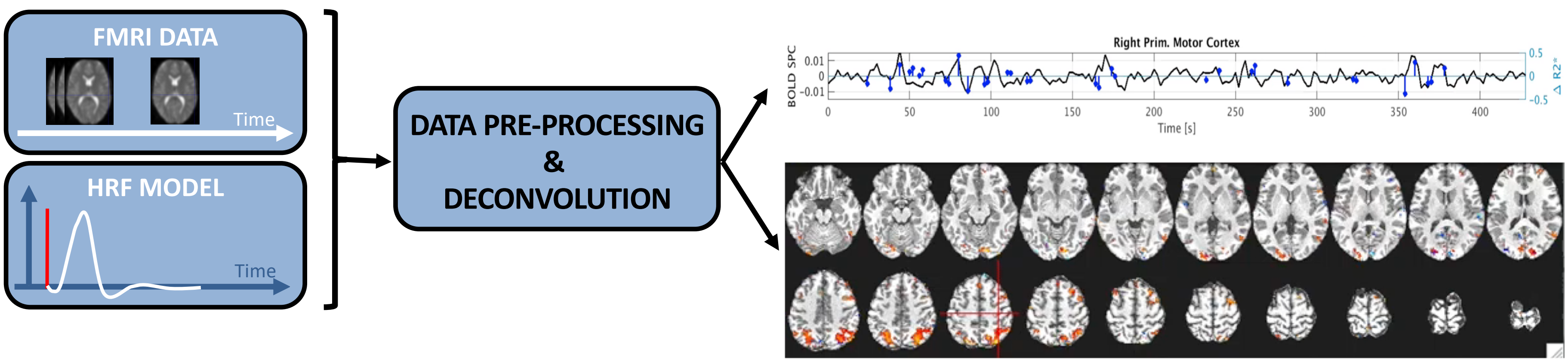
What are deconvolution methods?



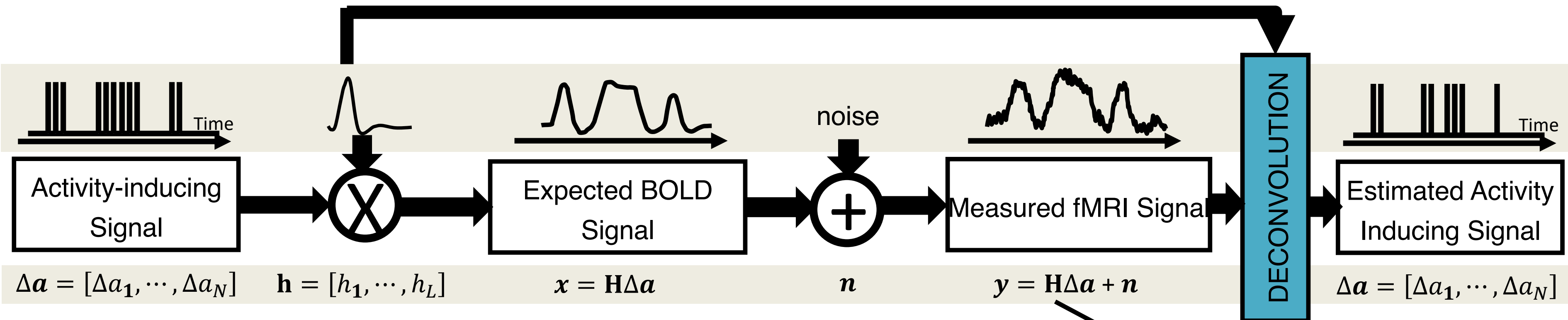
There are experimental scenarios where event timing might be missing:

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

Deconvolution methods are an alternative in such scenarios:



Deconvolution Formulation for Singe-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:

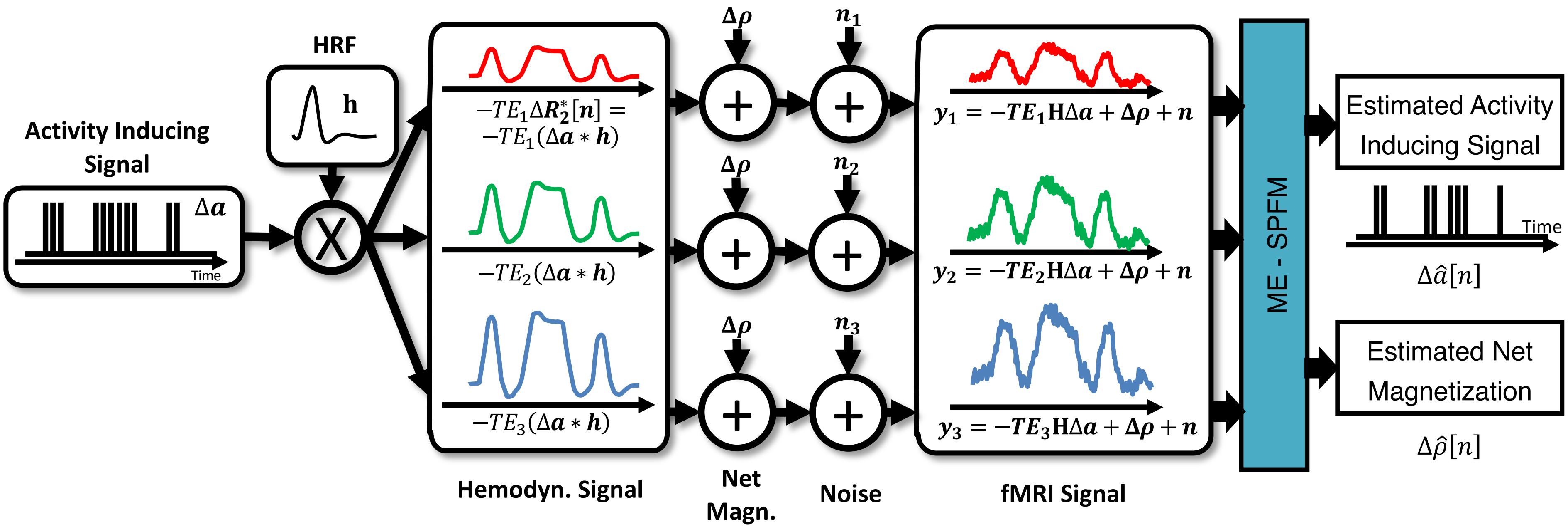
$$\Delta\hat{\boldsymbol{a}} = \arg\min_{\Delta\boldsymbol{a}} \frac{1}{2}\overbrace{\|\boldsymbol{y} - \mathbf{H}\Delta\boldsymbol{a}\|_2^2}^{\text{Error Minimization Term}} + \underbrace{\lambda\|\Delta\boldsymbol{a}\|_1}_{\substack{\text{L1-Norm Regularization} \\ \text{(Sparseness)}}}$$

Single Echo Sparse Free Paradigm Mapping Algorithm

AFNI!

3dPFM

Deconvolution Formulation for Multi-Echo fMRI



$$\overline{\boldsymbol{y}} \stackrel{\text{def}}{=} \begin{bmatrix} \boldsymbol{y}_1 \\ \vdots \\ \boldsymbol{y}_K \end{bmatrix} = \underbrace{\boxed{\begin{bmatrix} \mathrm{I} \\ \vdots \\ \mathrm{I} \end{bmatrix}}}_{\overline{\mathrm{I}}} \boldsymbol{\Delta\rho} - \underbrace{\boxed{\begin{bmatrix} TE_1\mathbf{H} \\ \vdots \\ TE_K\mathbf{H} \end{bmatrix}}}_{\overline{\mathbf{H}}} \boldsymbol{\Delta a}$$

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

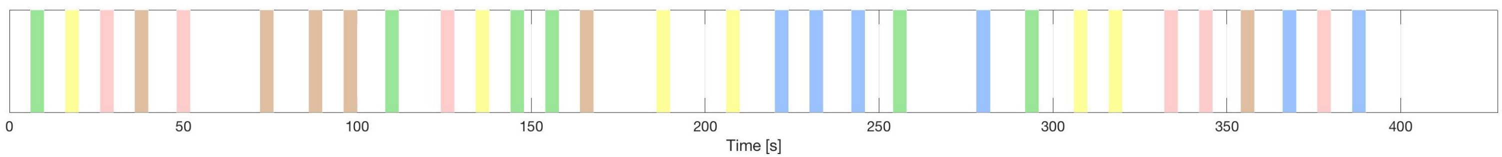
$$\Delta\widehat{\boldsymbol{a}}, \Delta\widehat{\boldsymbol{\rho}} = \arg\min_{\Delta\boldsymbol{a},\Delta\boldsymbol{\rho}} \frac{1}{2}\left\|\overline{\boldsymbol{y}} - \overline{\mathbf{H}}\Delta\boldsymbol{a} - \overline{\mathrm{I}}\Delta\boldsymbol{\rho}\right\|_2^2 + \lambda_1\|\Delta\boldsymbol{a}\|_1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

Validation Experiments – 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.

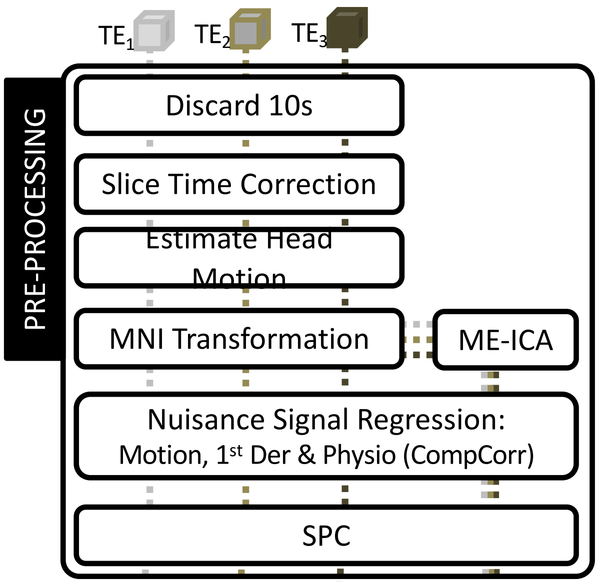
Passive viewing of images of houses

Press button at an approx. rate of 0.5Hz (following a counter on the screen).

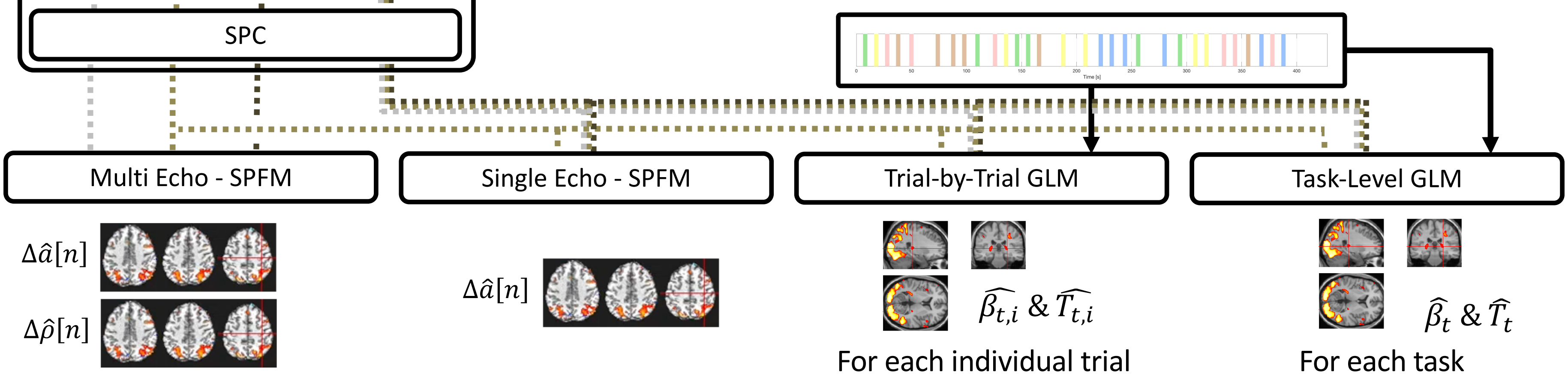
READ THIS

Silently read sentences that appear on the screen one word at a time.

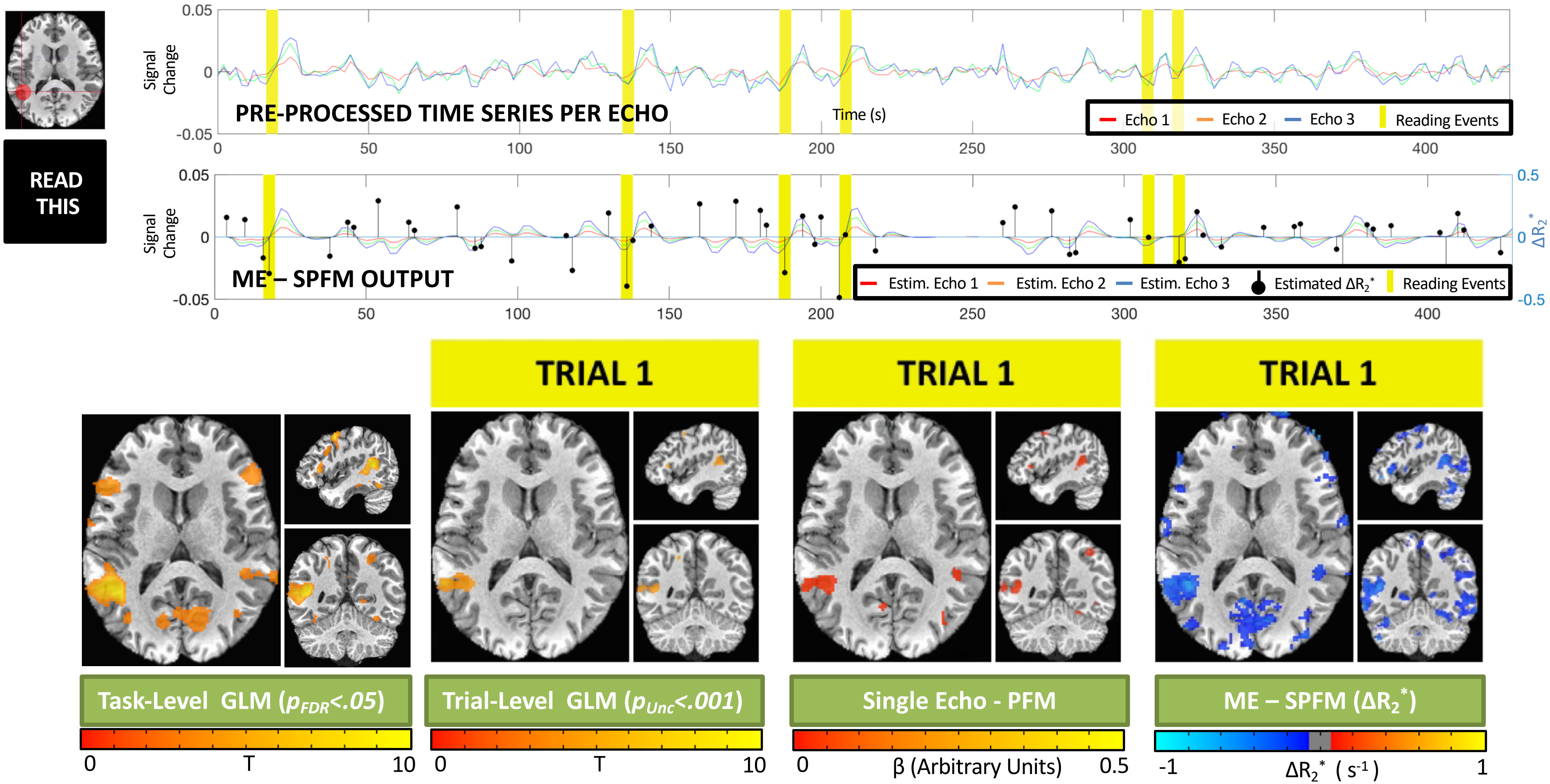
Validation Experiments – Data Analysis



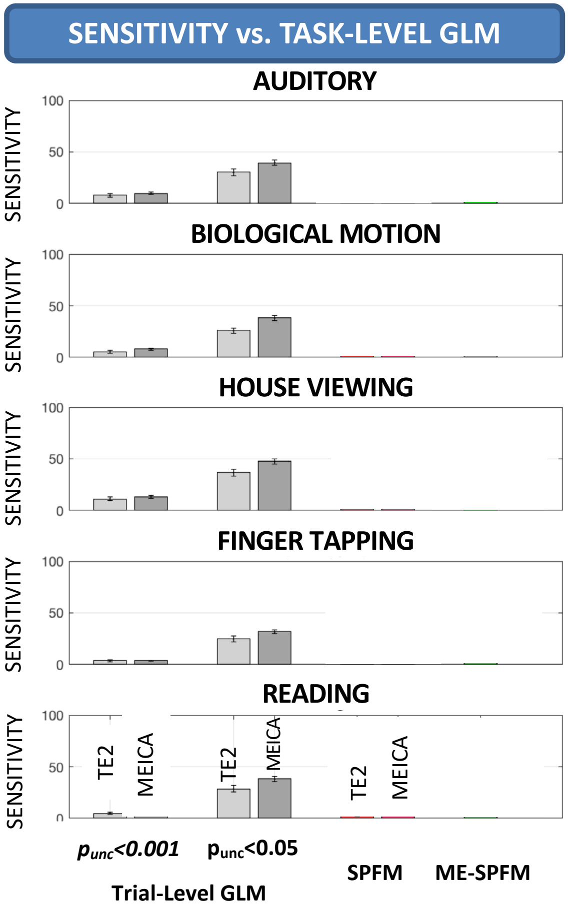
- **<u>ME – SPFM</u>**
  → Newly Proposed Algorithm
- **<u>SE – SPFM</u>**
  → Deconvolution results for original single-echo SPFM algorithm.
- **<u>Trial-by-Trial GLM</u>**
  → ”Best” activation maps for each individual trial
  → Paradigm timing information is available
- **<u>Task – Level Task GLM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

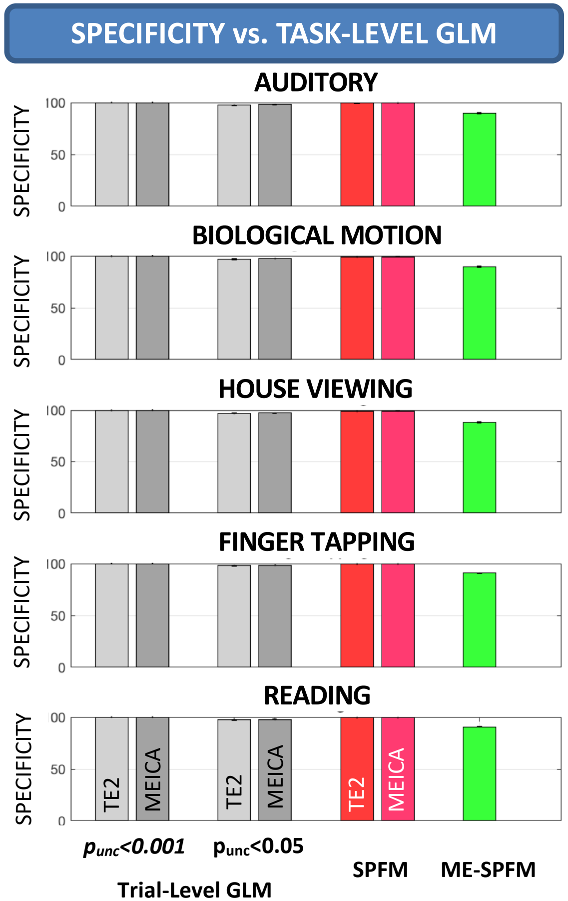


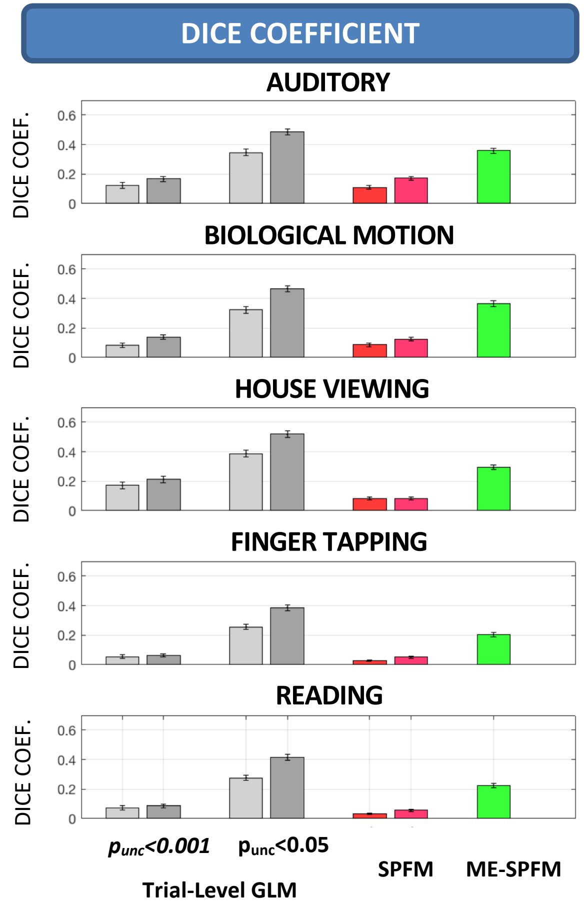
Validation Experiments – Results (I)



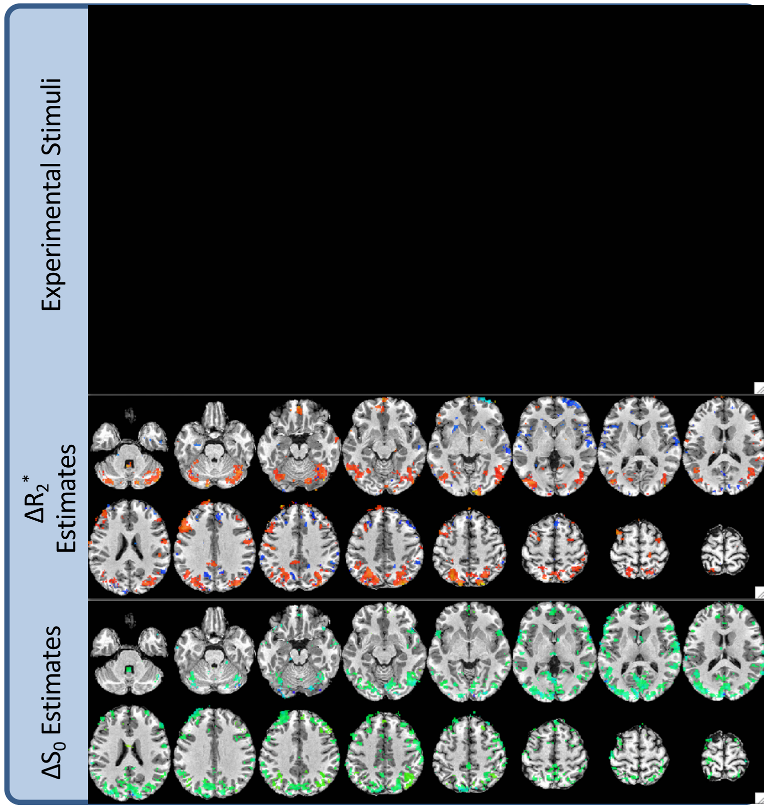
Validation Experiments – Results (2)







ME – Deconvolution – Future Work



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

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

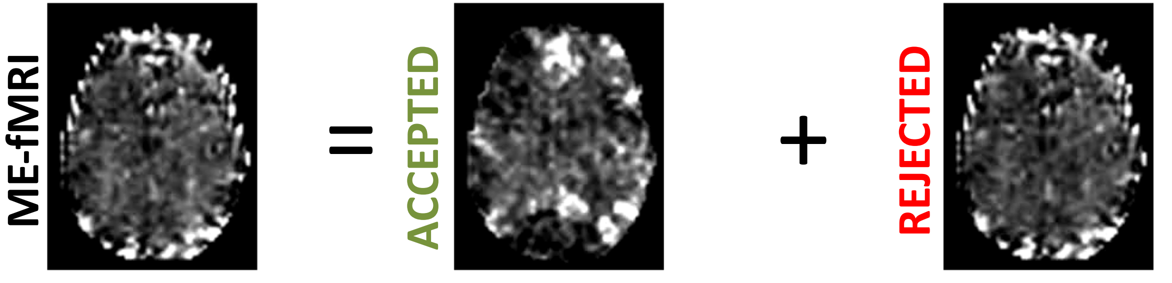
- Explore its application to scientifically and clinically relevant scenarios.

Conclusions

- ❑ Multi-echo fMRI allows to capture additional information with minimal costs in terms of temporal and spatial resolution.

- ❑ Such additional information can be used to:
  - ❑ Increase CNR in drop-out regions (e.g., Optimal Combination of Echoes).
  - ❑ Automatically separate BOLD-like from Non-BOLD-like components (ME-ICA).
  - ❑ Significantly increase the sensitivity of BOLD deconvolution algorithms

- ❑ ME-ICA is a denoising methodology that combines ICA with TE-Dependence Analysis:
  - ❑ Will not clean every single artifact in the data.
  - ❑ Still under development.
  - ❑ Can substantially improve the SNR of the data → Quality of the results.



- ❑ ME-SPFM can help us reliably detect individual BOLD events without a-priori information about their timing.

Acknowledgements/ Questions

Section on Functional Imaging Methods

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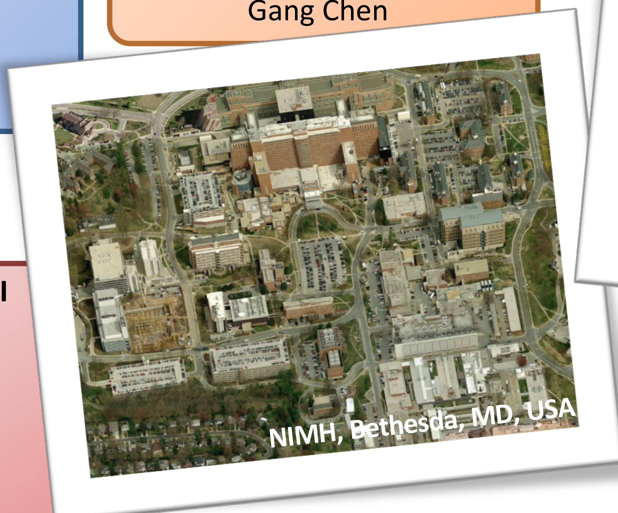

Functional MRI Facility

Sean Marrett
Vinai Roopchansingh
Andy Derbishire
Linquing Li

3dMEPFM will be soon available in AFNI