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

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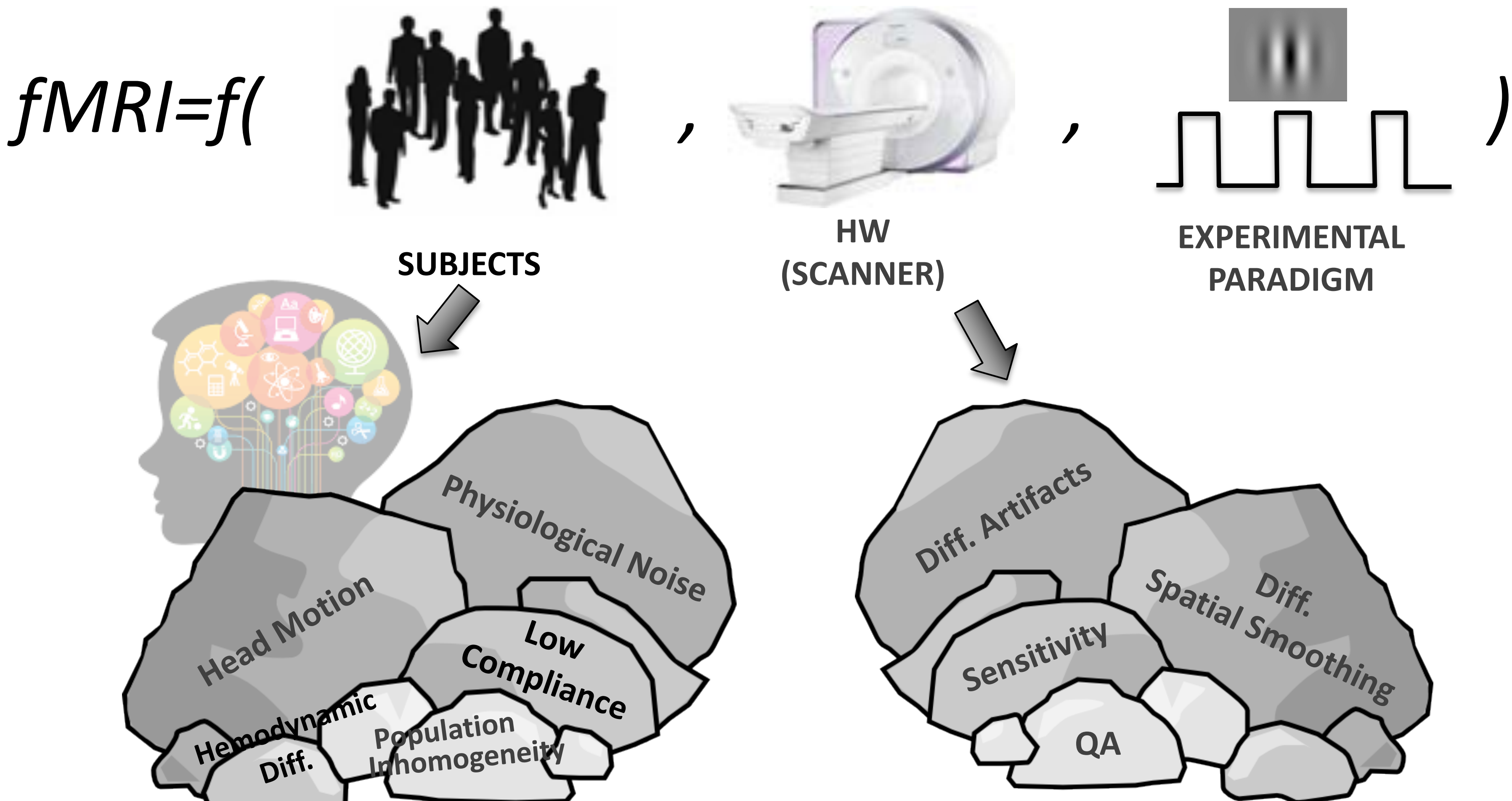
Agenda

- ***Noise sources in fMRI***
- ***Multi-echo fMRI as a Denoising Technique***
- ***ME-ICA Denoising***
- ***ME-ICA Denoising Applications***
- ***Conclusions***

Introduction to fMRI: Noise Sources

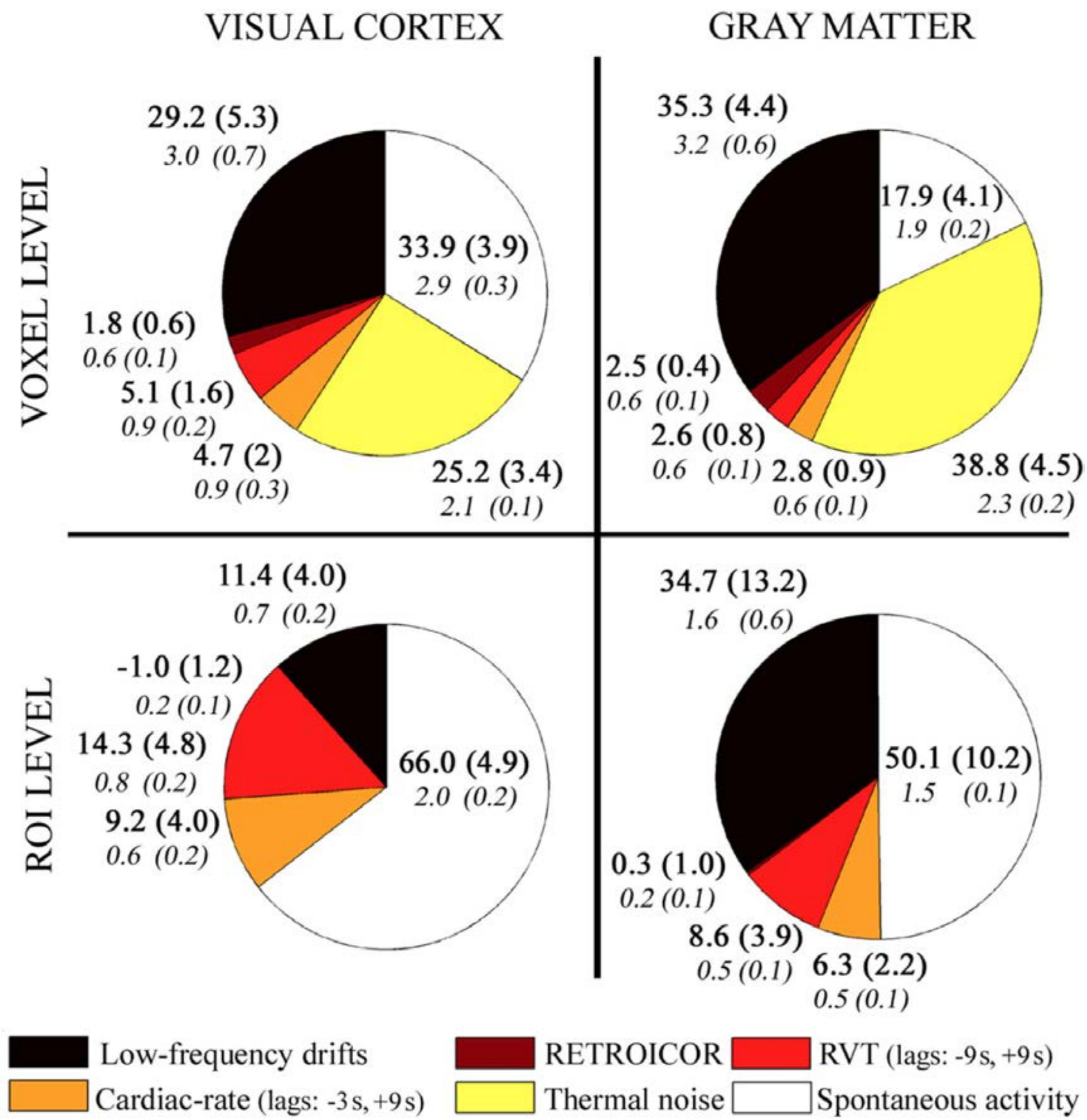


ONLY A SUBSET OF THE SIGNAL WE MEASURE CONTAIN INFORMATION ABOUT NEURONAL PROCESSES

How to best isolate and interpret this extremely valuable component of the fMRI signal?

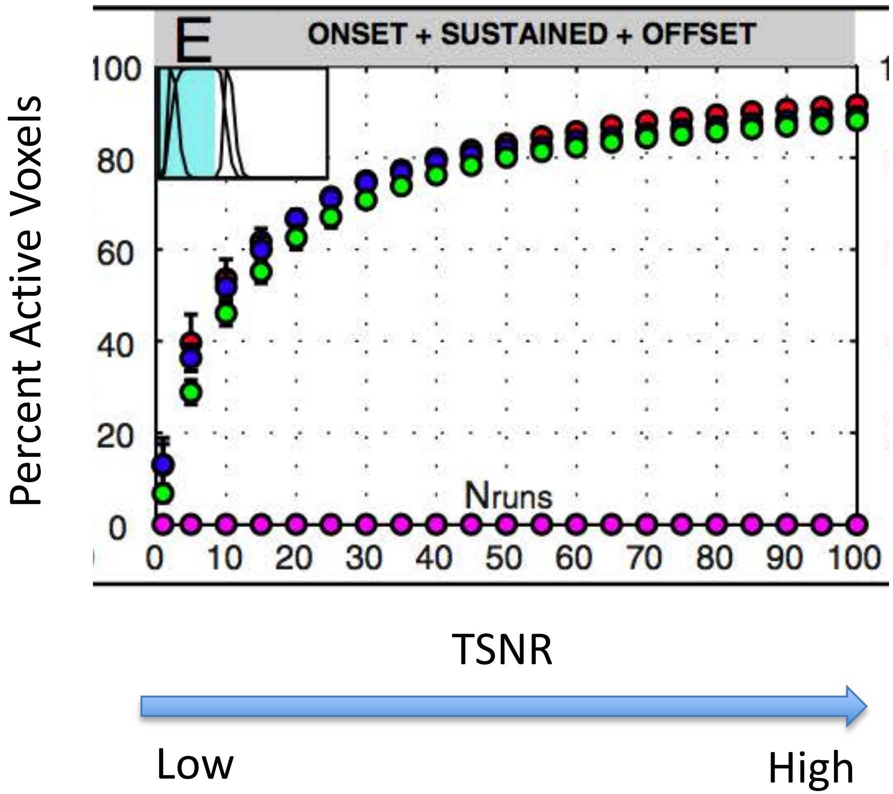
fMRI Datasets have inherently low TSNR

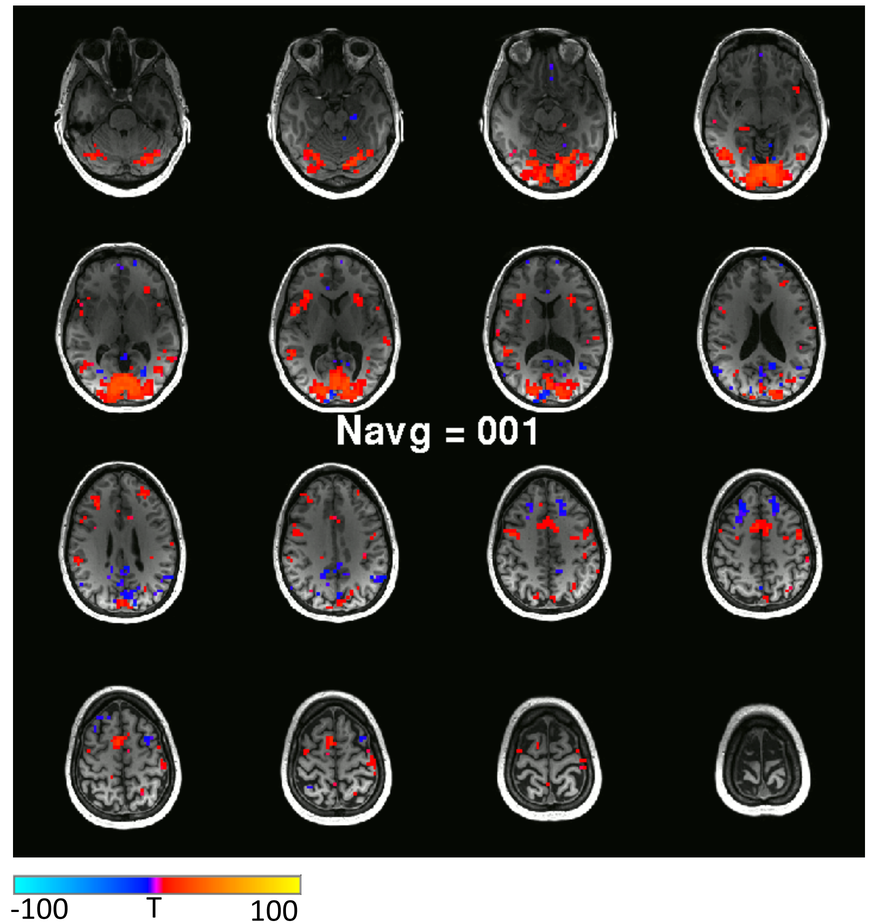
fMRI Time series = Signal of Interest (NEURONAL ORIGN) + Other Fluctuations



Bianciardi et al., Mag Res Imag. 2009

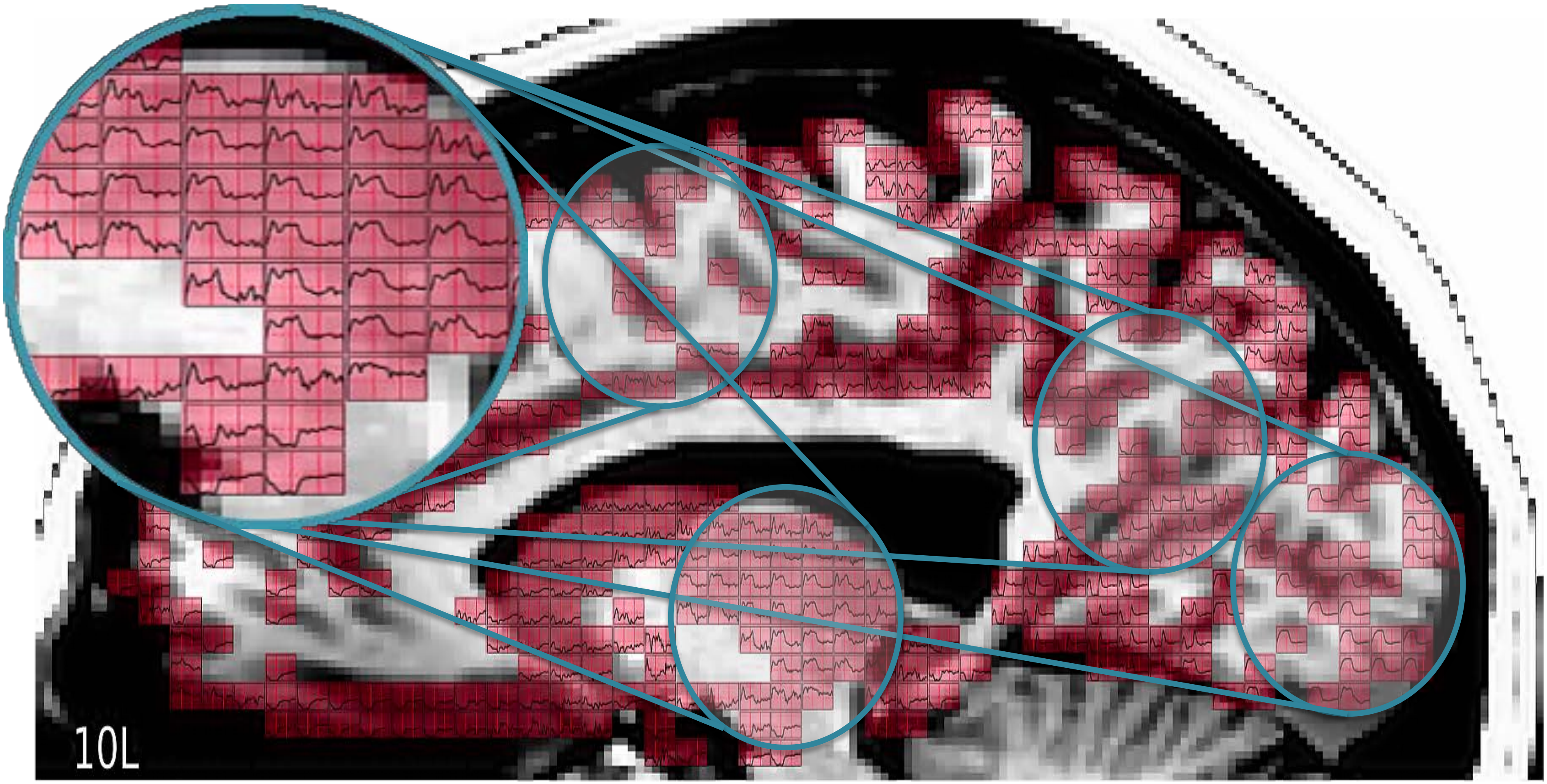
Noise significantly affects detectability of activation





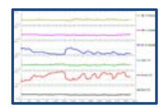
Gonzalez-Castillo et al. PNAS 2012

fMRI contains exquisite detail about distributed brain function



Gonzalez-Castillo et al. PNAS 2012

fMRI Data Pre-processing

NOISE SOURCE		MODEL REGRESSOR	
	Slow Signal Drifts		Legendre Polynomials
	Head Motion		Head Motion Estimates
	Physiological Noise		RETROICOR + RVT
			Lateral Ventricle Regressors
	Localized HW Instabilities		Local WM Regressor

Multi-Echo fMRI & ME-ICA Denoising

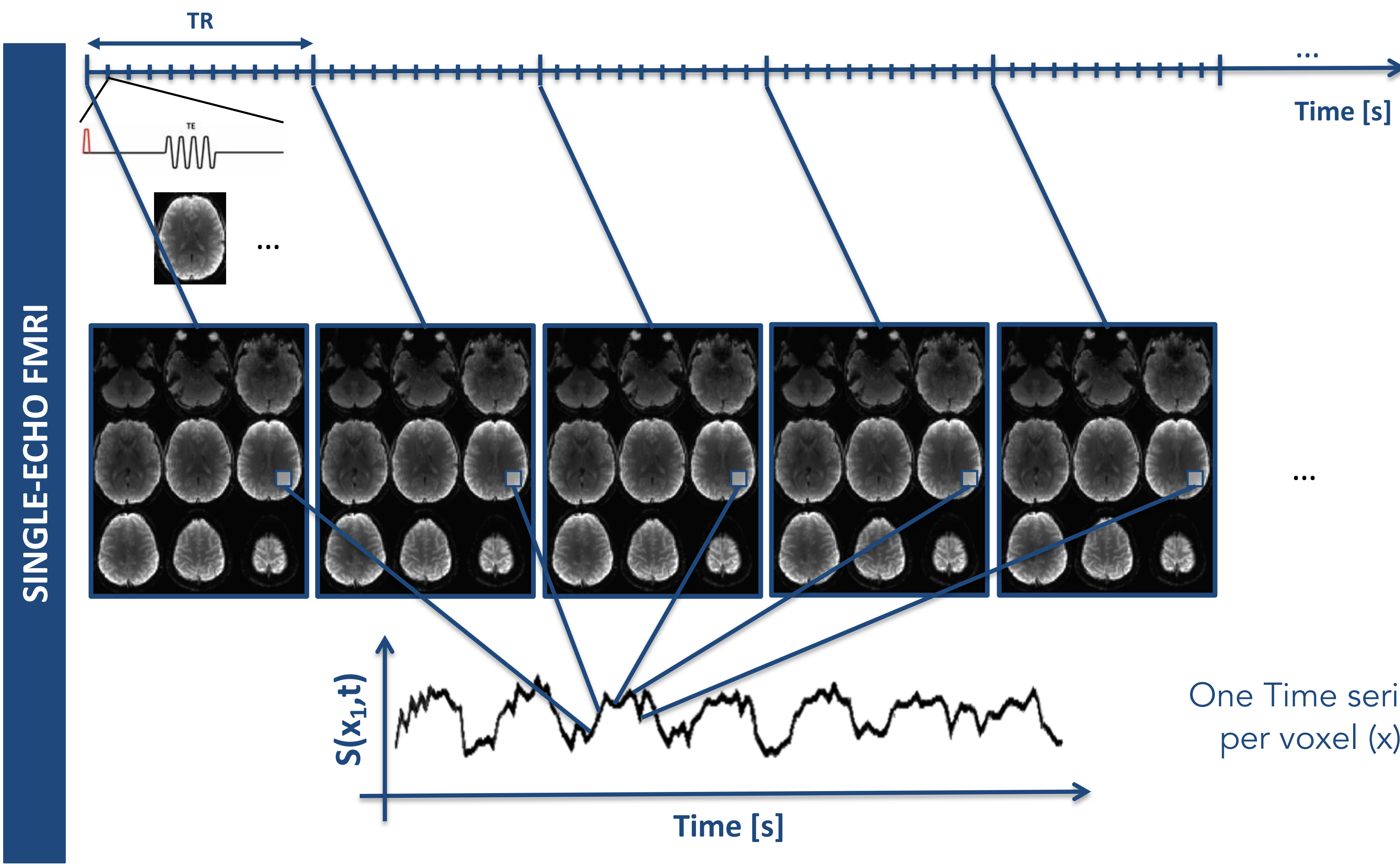
MEICA is not only a pre-processing technique, it also requires data to be acquired differently.

1 MULTI-ECHO DATA ACQUISITION

2 ICA DECOMPOSITION TO OBTAIN SPATIALLY INDEPENDENT SOURCES OF FLUCTUATION IN THE DATA

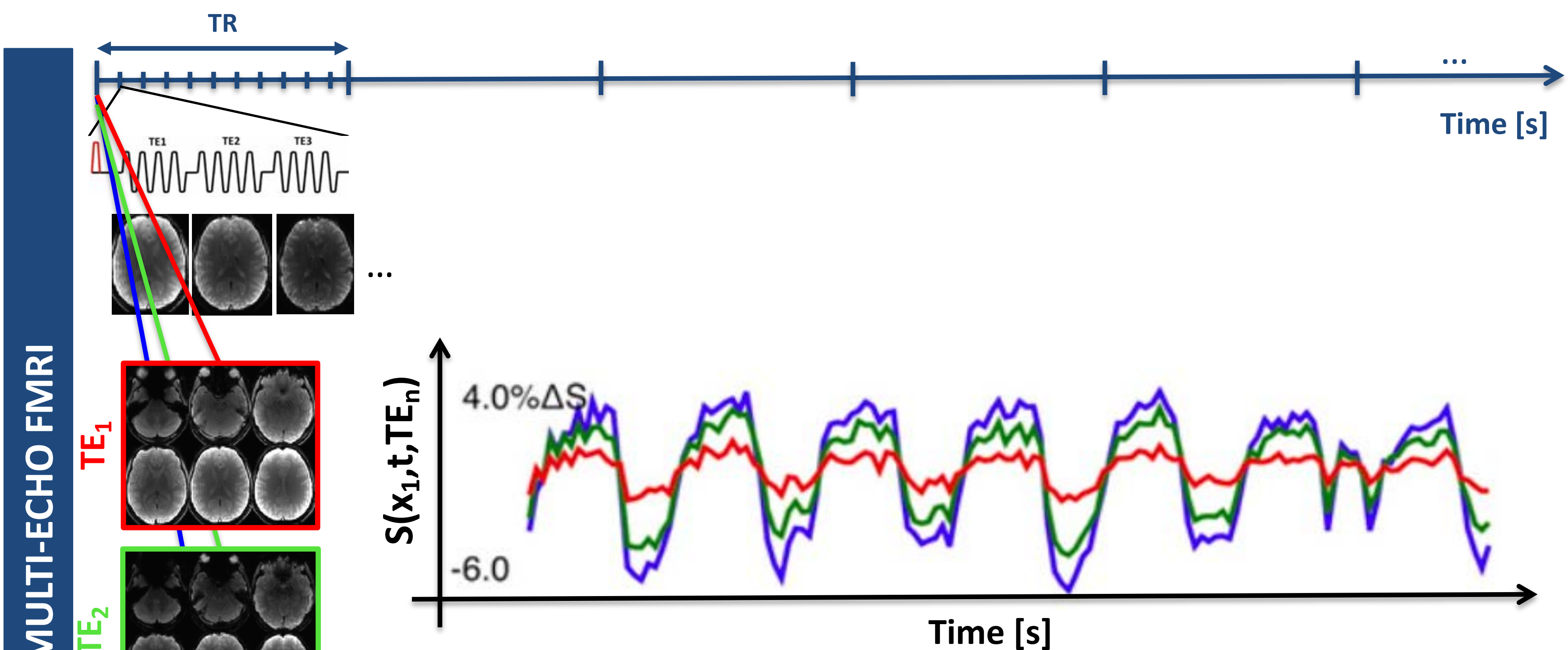
3 AUTOMATIC CLASSIFICATION OF ICA COMPONENTS INTO "GOOD OR BAD" BASED ON A PHYSICALLY INFORMED ECHO-DEPENDENCE MODEL OF THE SIGNALS

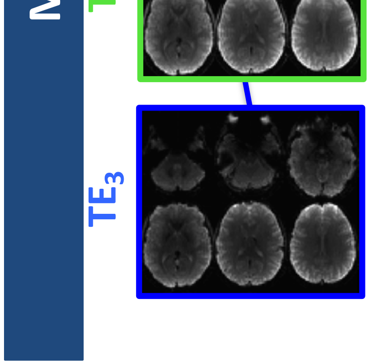
Single-Echo Data Acquisition



One Time series
per voxel (x)

Multi-Echo Data Acquisition

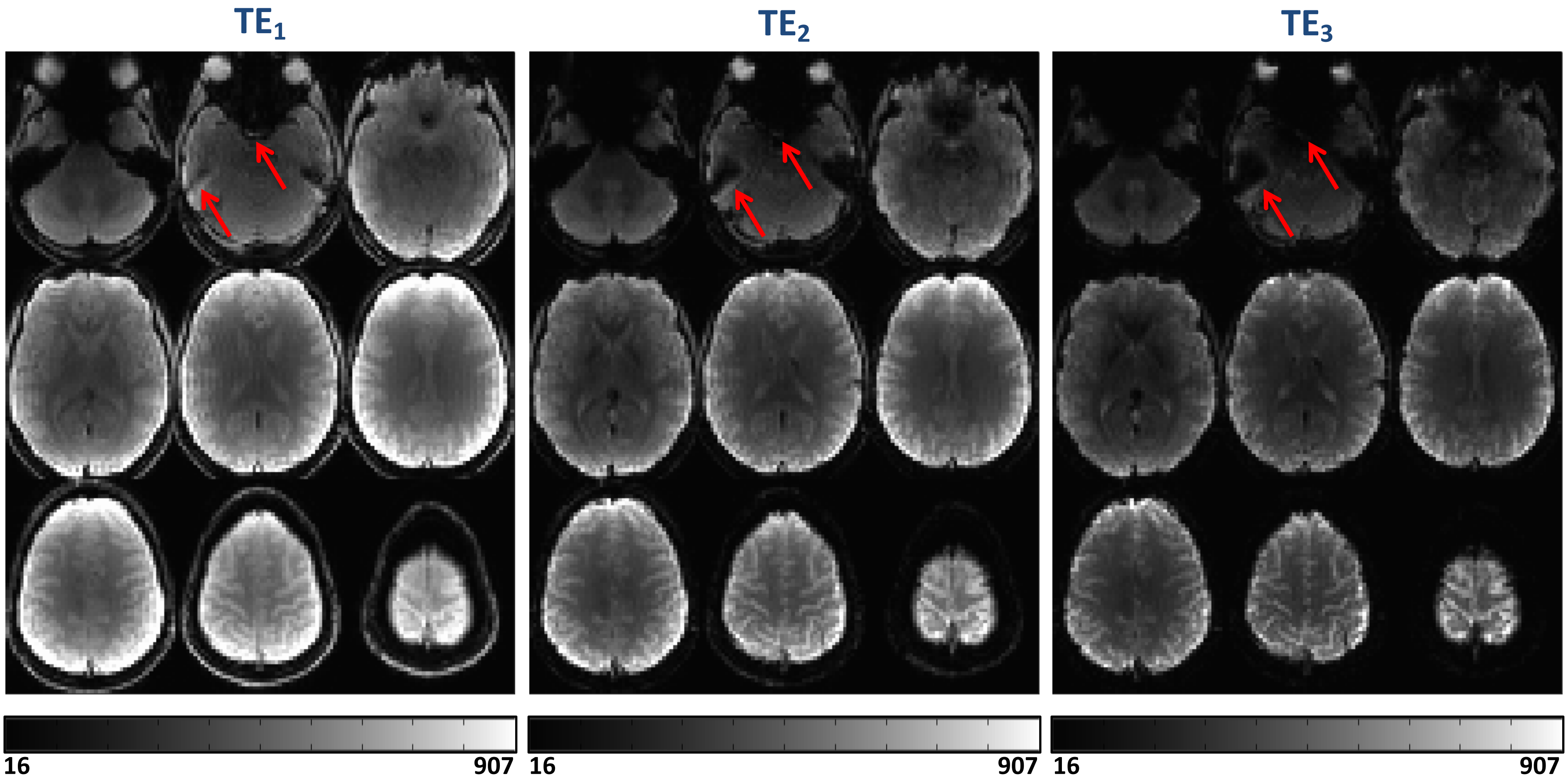




Now you have N_e time series per voxel, one per echo time (TE_n):

- No SAR cost, as there are not additional excitation pulses.
- Slight lost in temporal resolution to fit the third echo.
- Slight lost in spatial resolution to make sure you have signal in last echo.

Multi-Echo Data



Weighted Linear Combinations of Multi-Echo Data

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

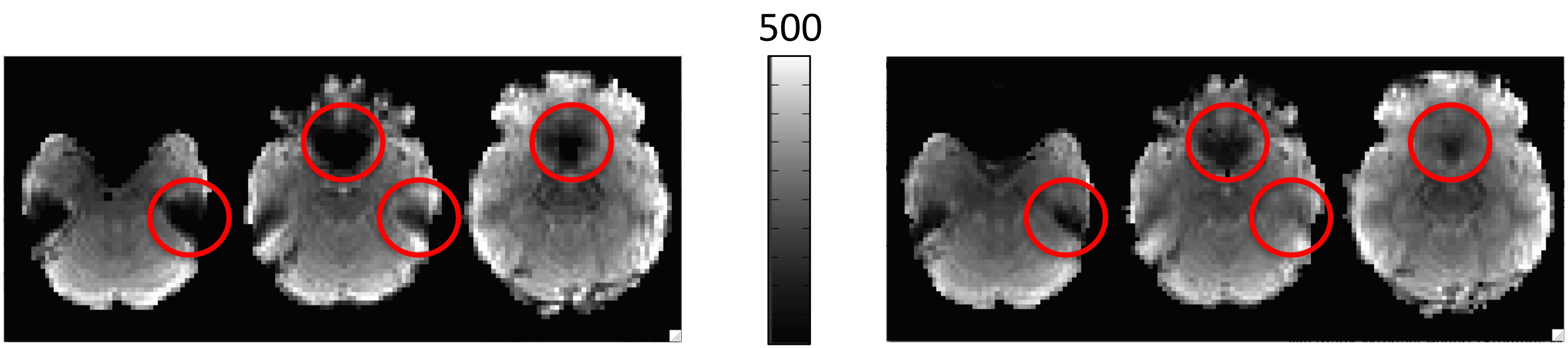
Weighted Summation

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

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

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

Posse et al., MRM 1999



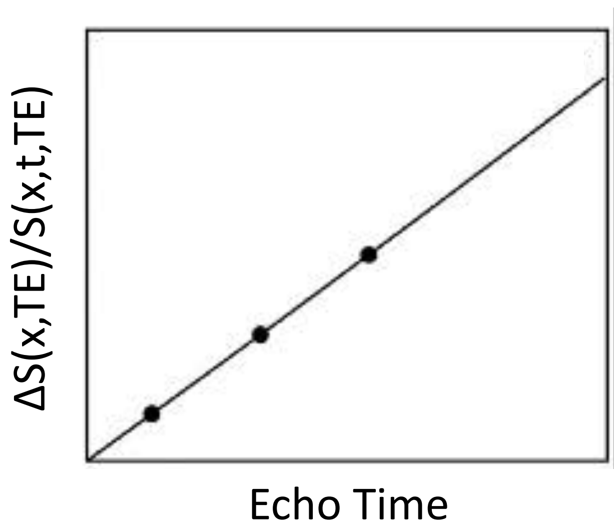
SINGLE ECHO **OPTIMALLY COMBINED**

ME-ICA: Echo-Dependence Model

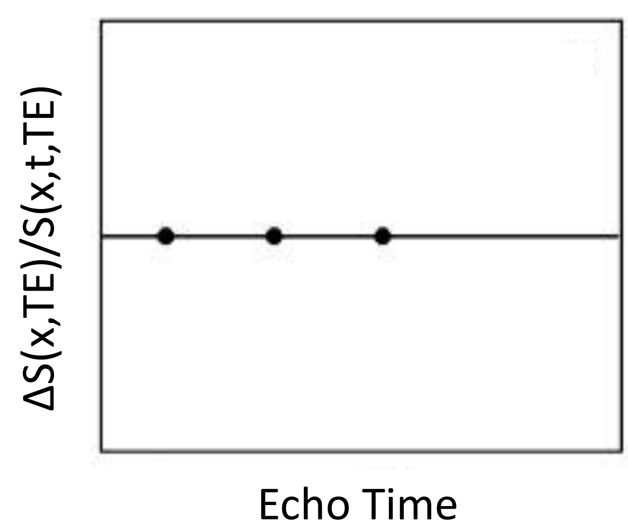
fMRI Data = BOLD-Like Components + Non-BOLD-Like Components

(Neuronal Origin)

(Nuisance/Artifacts)



BOLD-Like Components have a linear dependence with echo time, in terms of signal percent change.

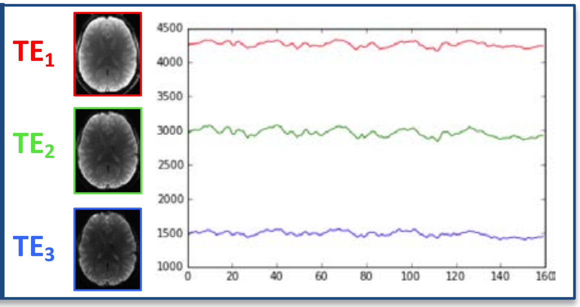


Non-BOLD-Like Components are independent of echo time, in terms of signal percent change

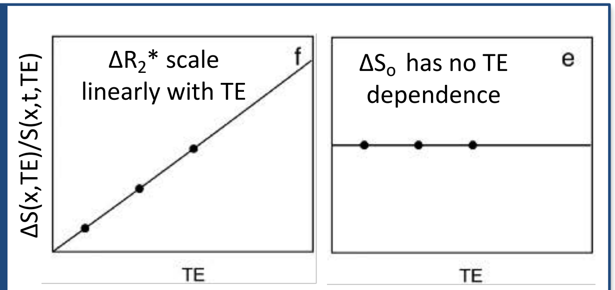
Kundu et al., NeuroImage 2012

Echo Time (TE) Dependence Analysis

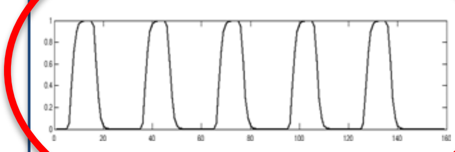
MULTI-ECHO DATASET



TE-DEPENDENCE MODEL

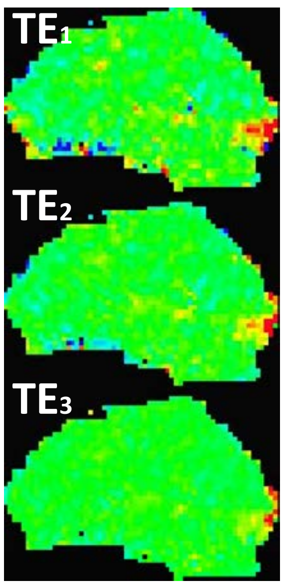


TIMESERIES OF INTEREST

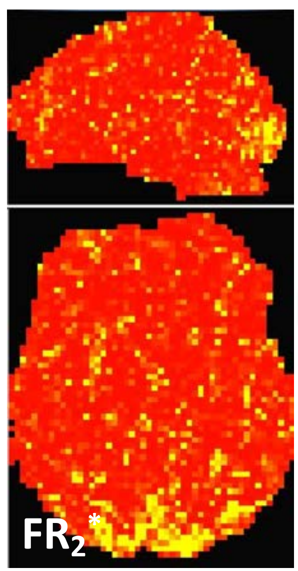


Task Paradigm

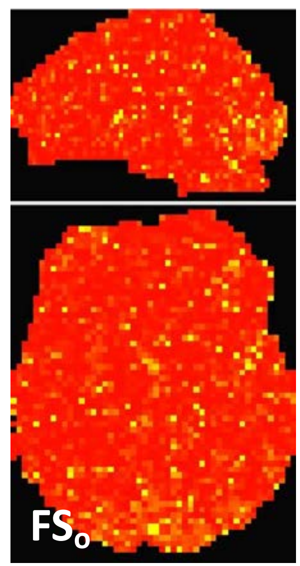
[1] Voxel-wise Fit against all TEs



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



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



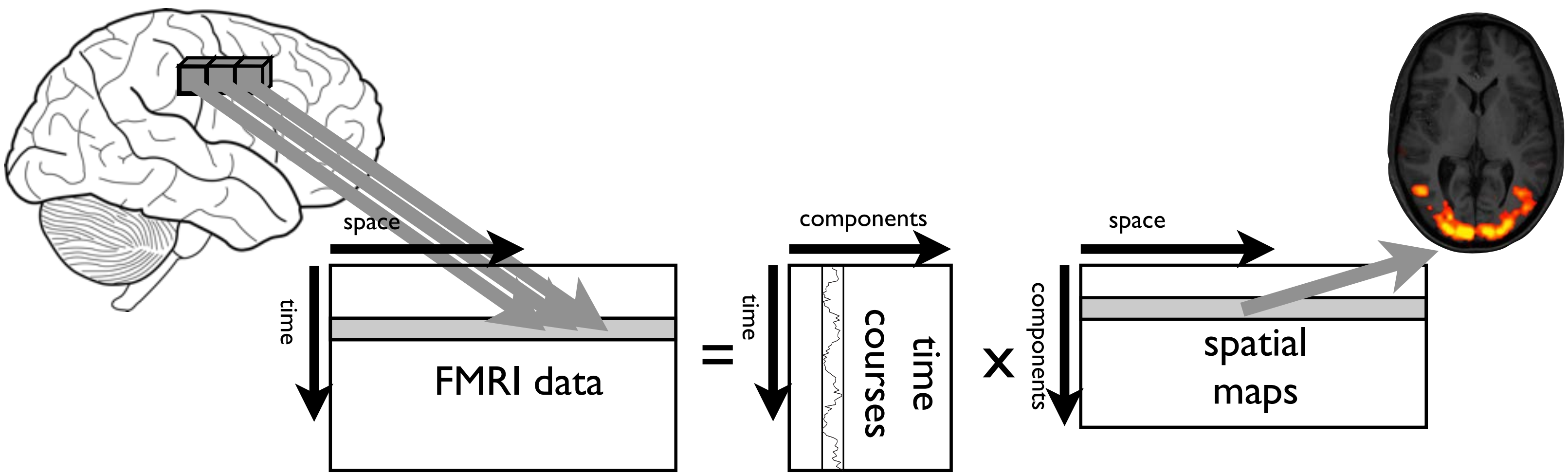
[4] Compute Avg. Metric for each model

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

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

Kundu et al., NeuroImage 2012

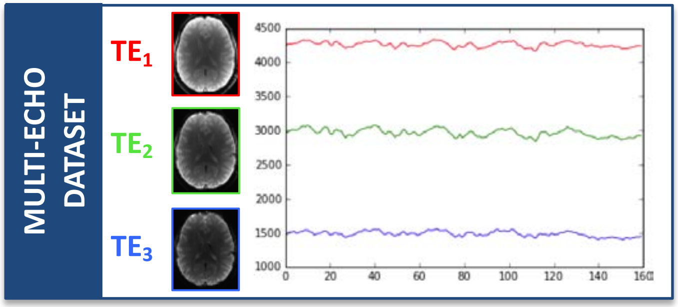
ME-ICA: ICA Decomposition

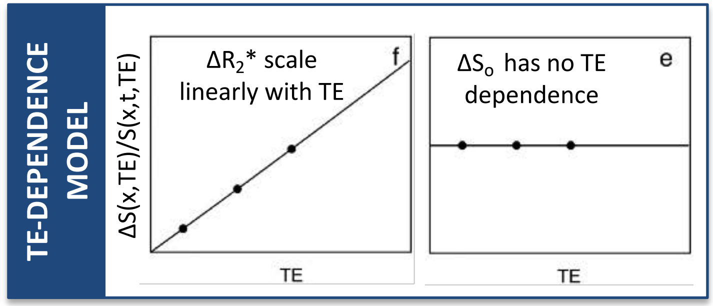


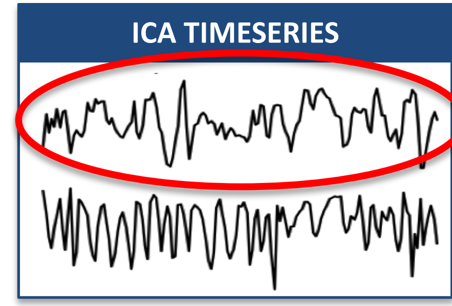
Data is represented as a 2D matrix and decomposed into factor matrices (or modes)

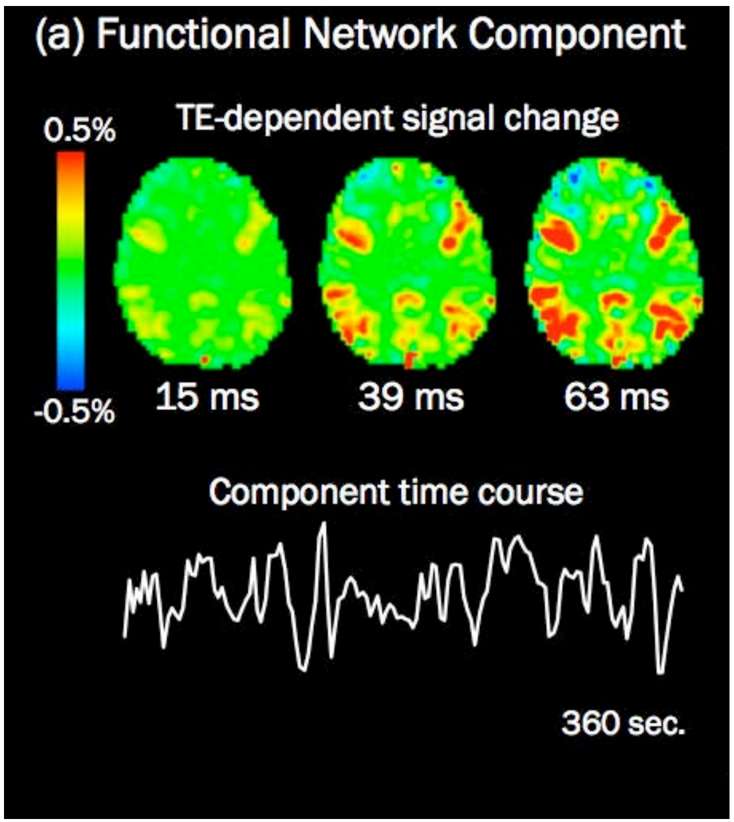
FSL Documentation: http://fsl.fmrib.ox.ac.uk/fslcourse/lectures/melodic.pdf

ME-ICA: How it works







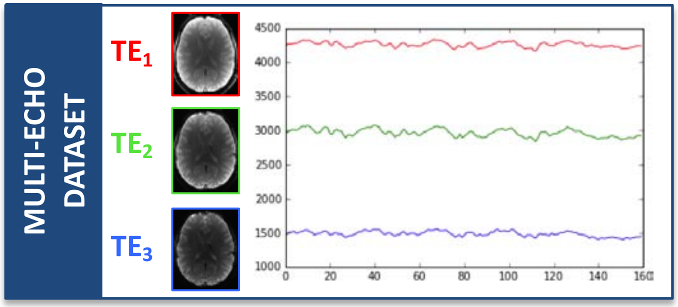


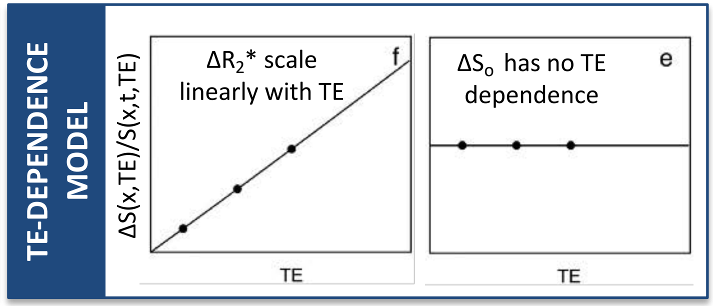
Kappa (κ) = 210

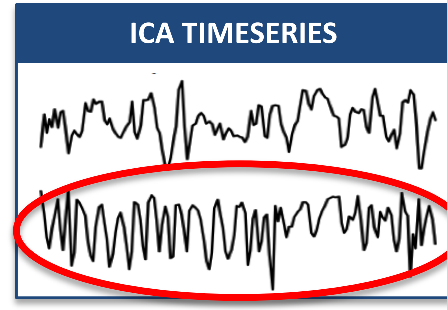
Rho (ρ) = 10

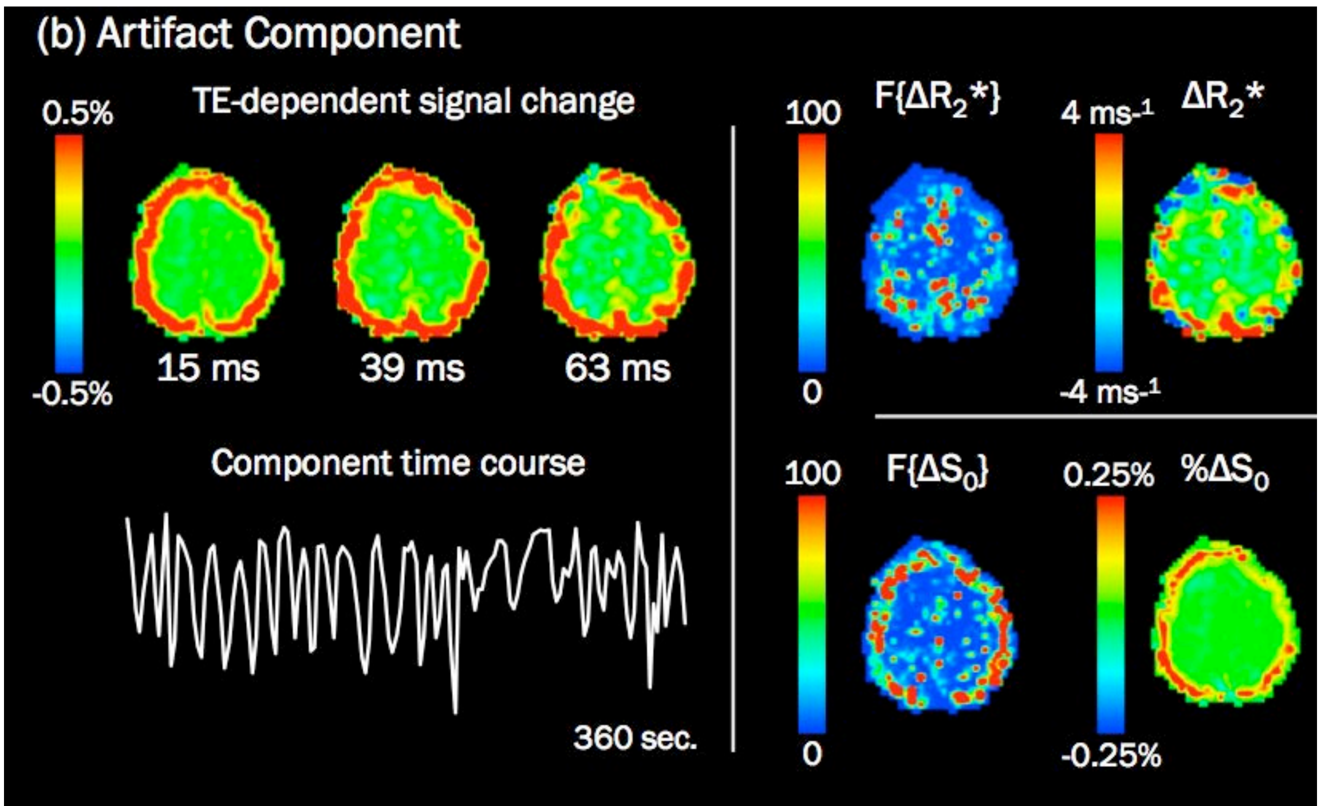
Kundu et al., NeuroImage 2012

ME-ICA: How it works (2)









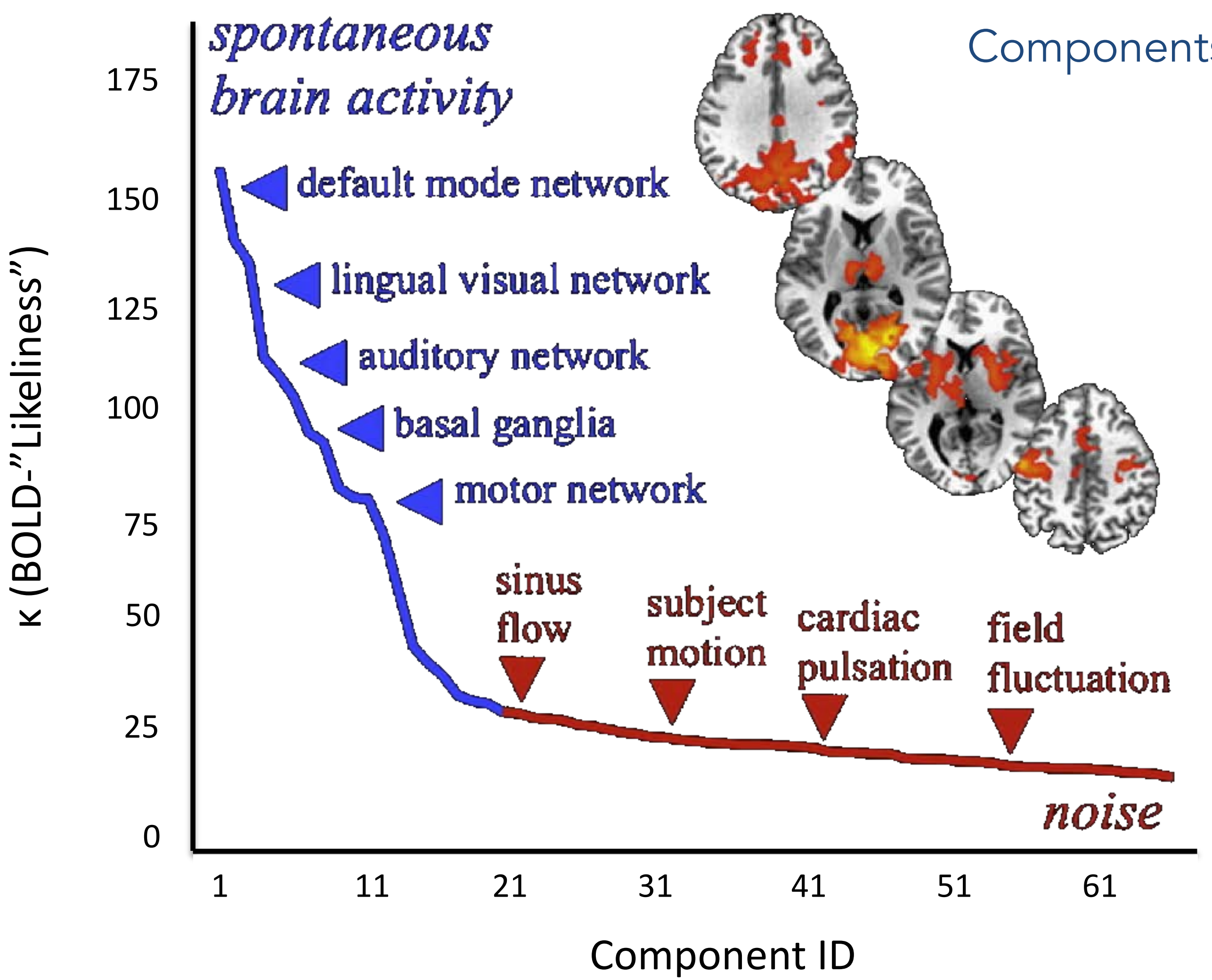
Kappa (κ) = 32

Rho (ρ) = 81

Kundu et al., NeuroImage 2012

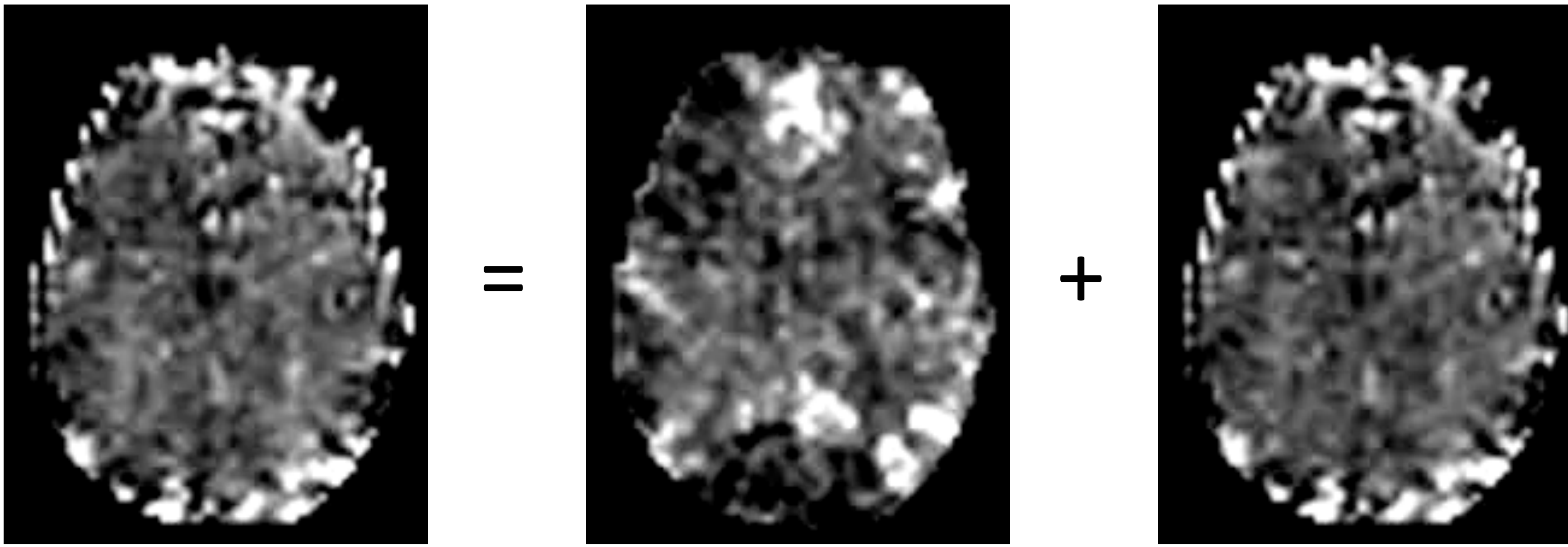
ME-ICA: Outcome

Components sorted by κ



Kundu et al., NeuroImage 2012

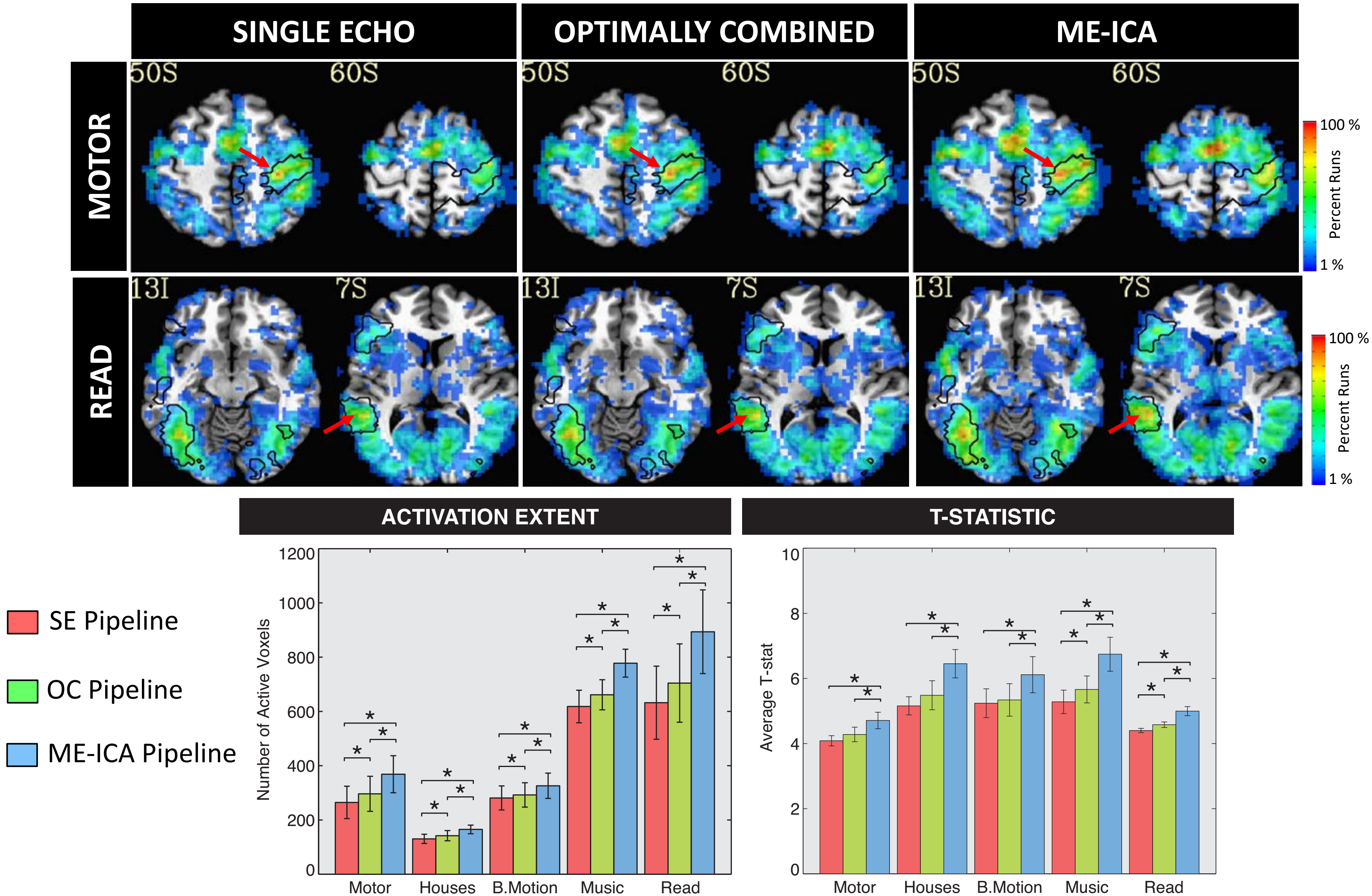
ME-ICA: Outcome



fMRI Timeseries = **BOLD** + **NON BOLD**

Kundu et al., NeuroImage 2012

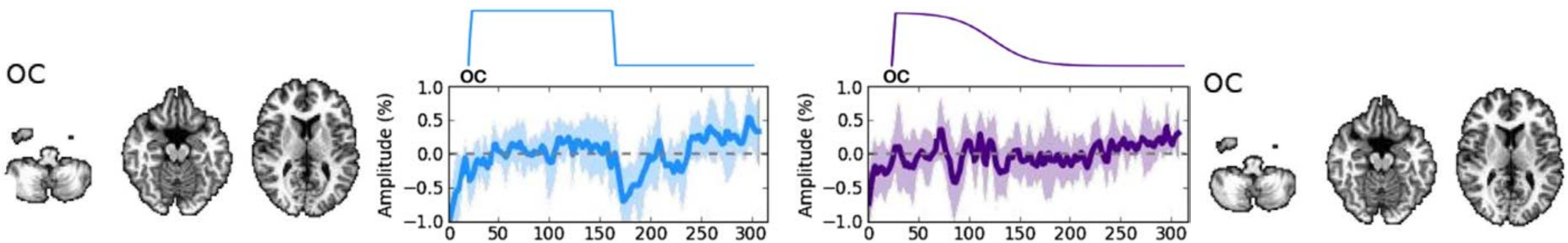
Multi-Echo fMRI – Improvements for task-based data



Gonzalez-Castillo et al., NeuroImage (Under Review)

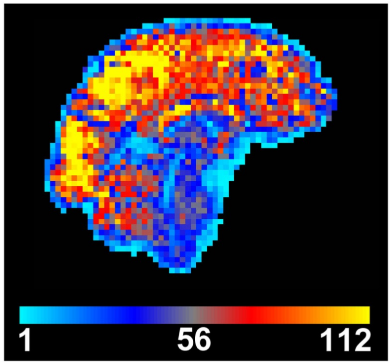
ME-ICA & Ultra-slow Experimental Designs

Detection of activity in very slow paradigms (2 min long blocks)

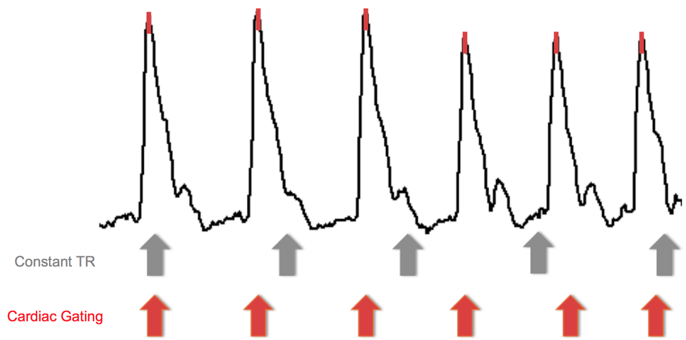


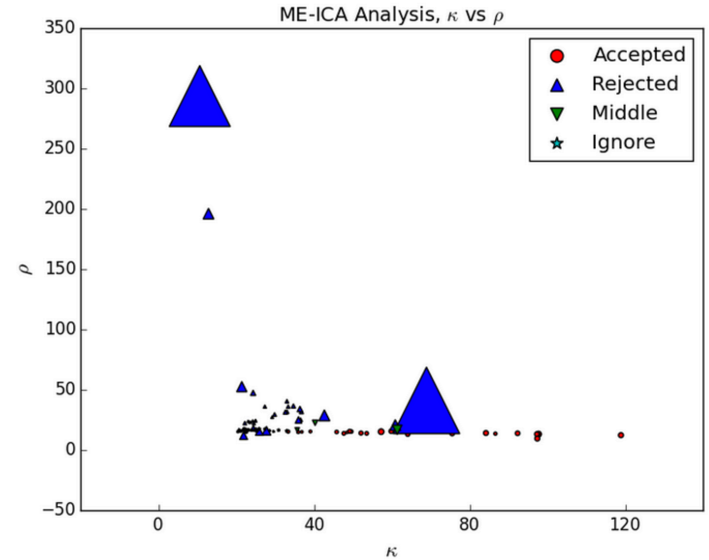
Evans et al., NeuroImage 2015

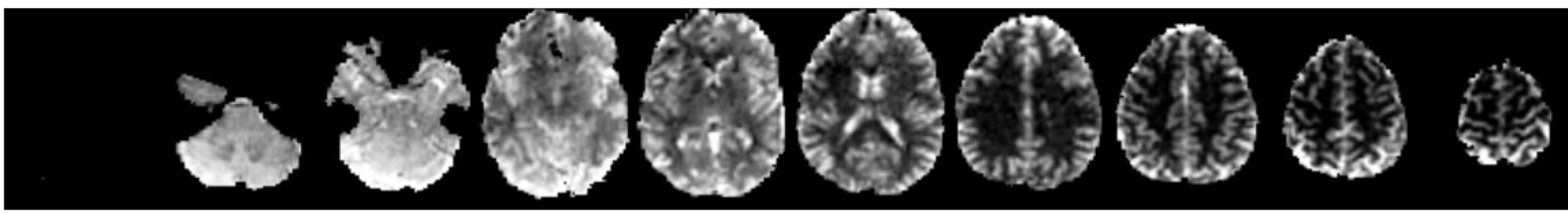
ME-ICA & Cardiac Gated fMRI

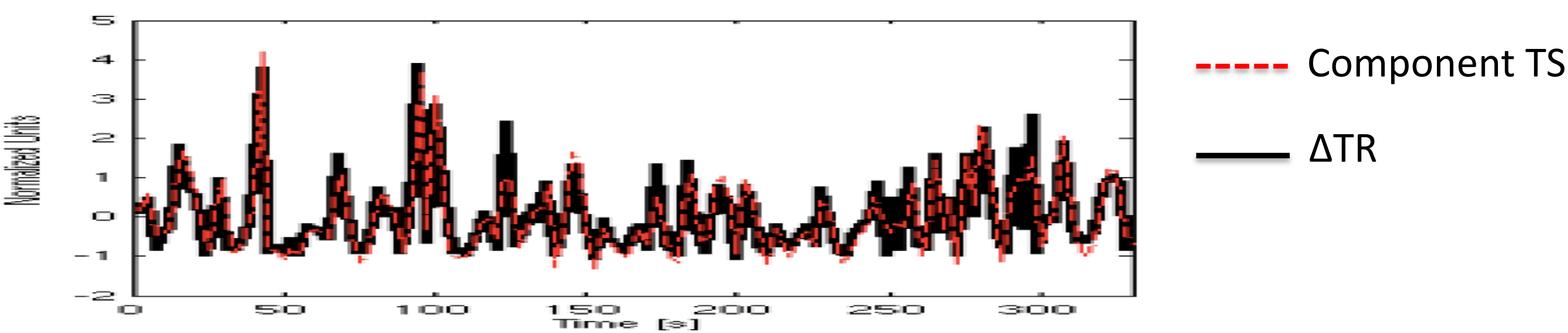


Brooks et al. 2014



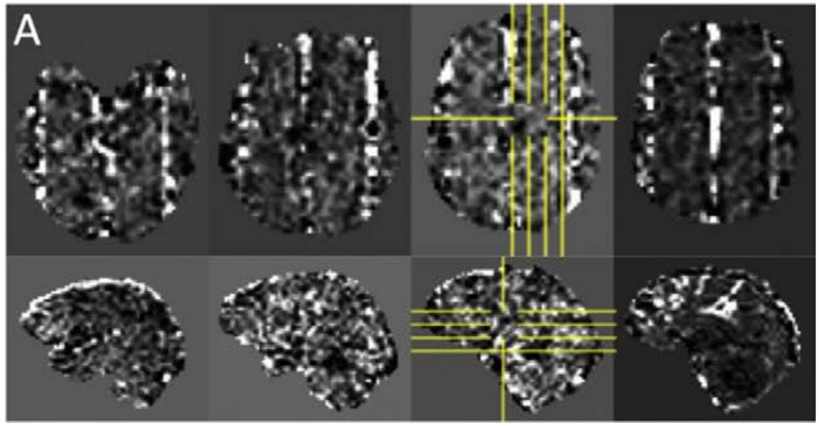




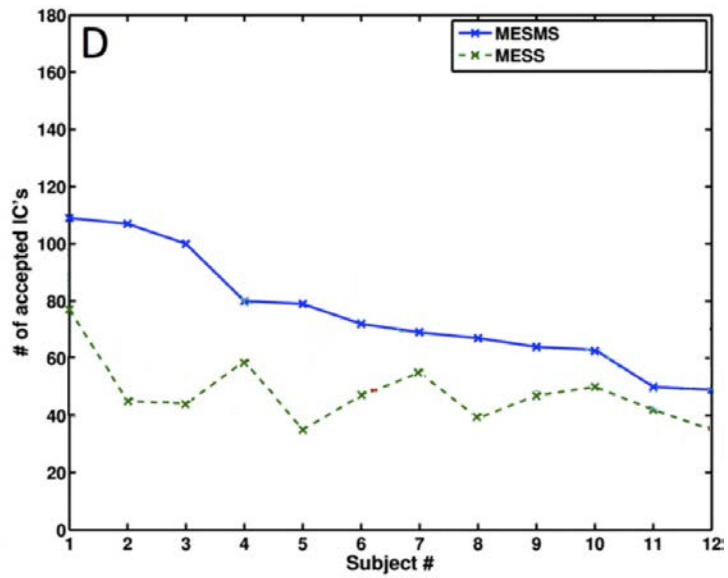


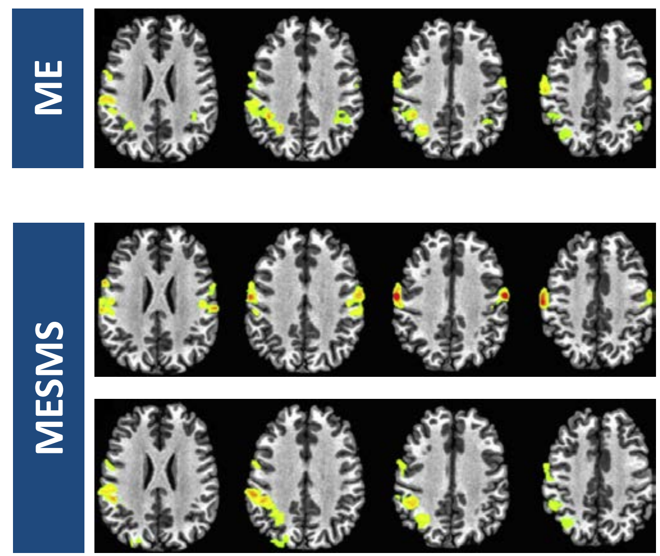
Gonzalez-Castillo et al., NeuroImage (Under Review)

Multi-Echo & Simultaneous Multi-Slice (MESMS)



Non-BOLD Component: MSS Artifact





Number of BOLD-like components significantly larger for MESMS

Olafsson et al., NeuroImage 2015

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).

- ME-ICA is a promising denoising methodology that combines ICA with TE-Dependence Analysis:
  - Can substantially improve the SNR of the data → Quality of the results.
  - Still under development.

Acknowledgements

Section on Functional Imaging Methods

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