



EBRAINS



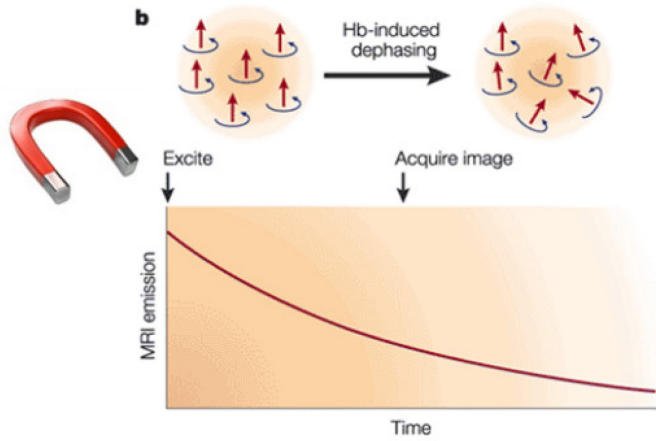
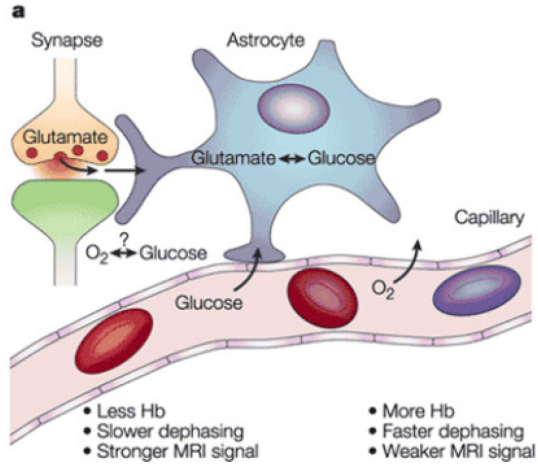
Co-funded by
the European Union

The importance of hemodynamics and blood arrival time in acquiring, analyzing, and modelling fMRI data

N. Colenbier, A. Johri, K. Clauw, G. Wu, G. Ferrazzi, D. Marinazzo

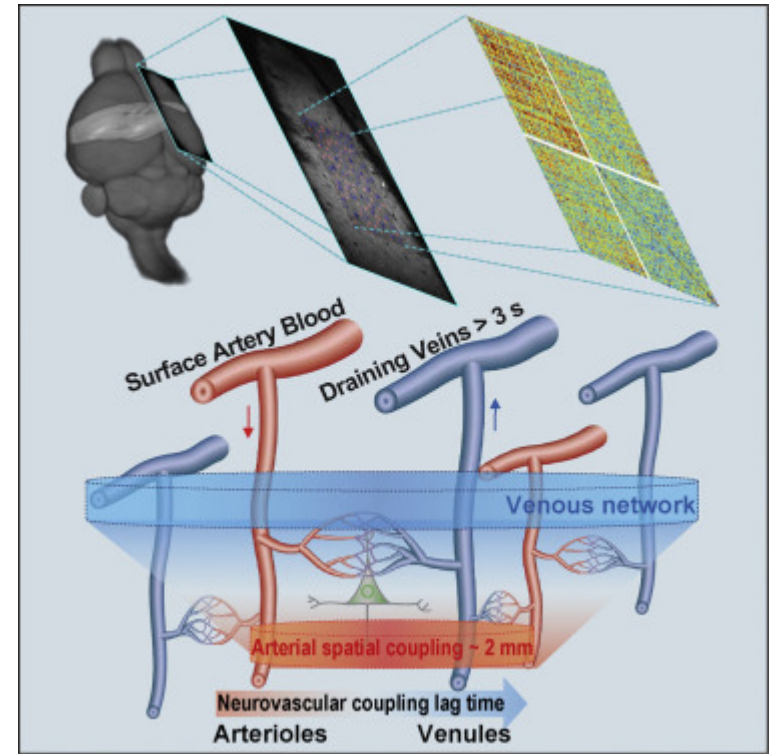
Department of Data Analysis, Ghent University

Through the hemodynamic lens

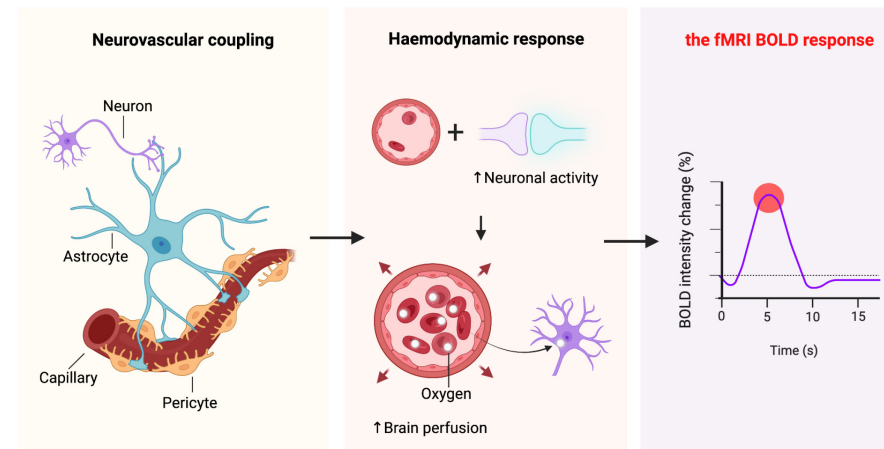


Nature Reviews | Neuroscience

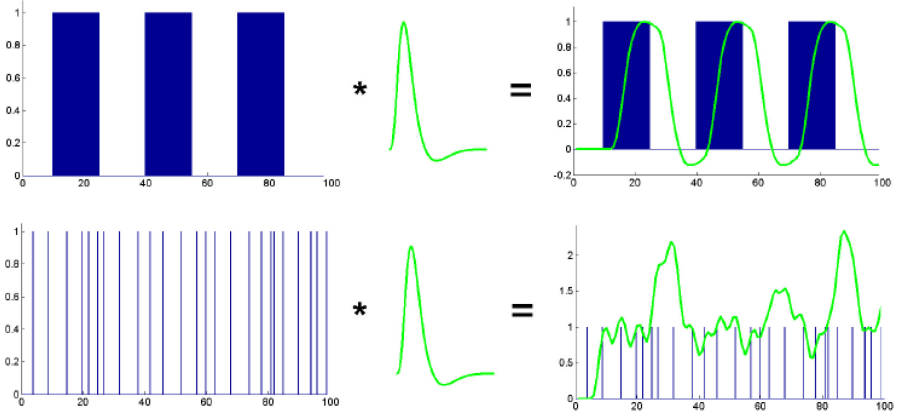
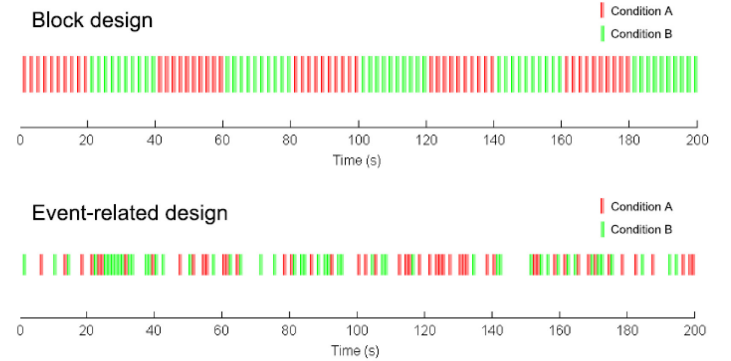
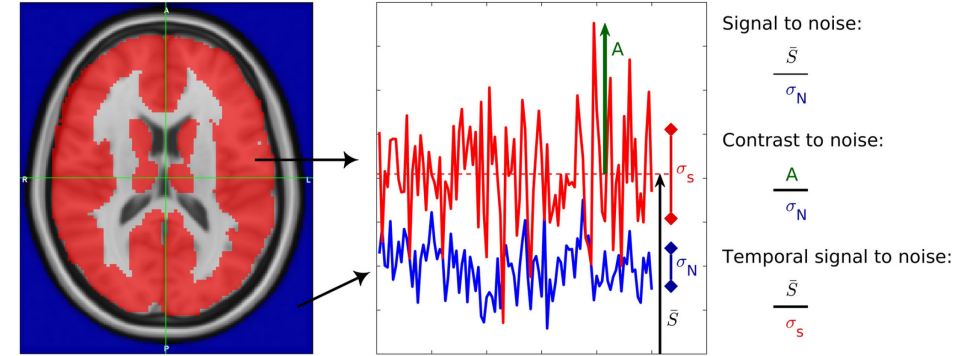
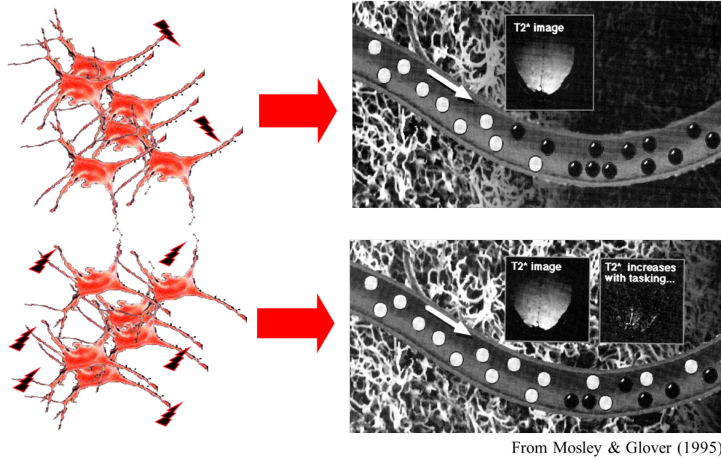
David J. Heeger & David Ress
Nature Reviews Neuroscience 3, 142-151



He et al. *Neuron* 97, 2018



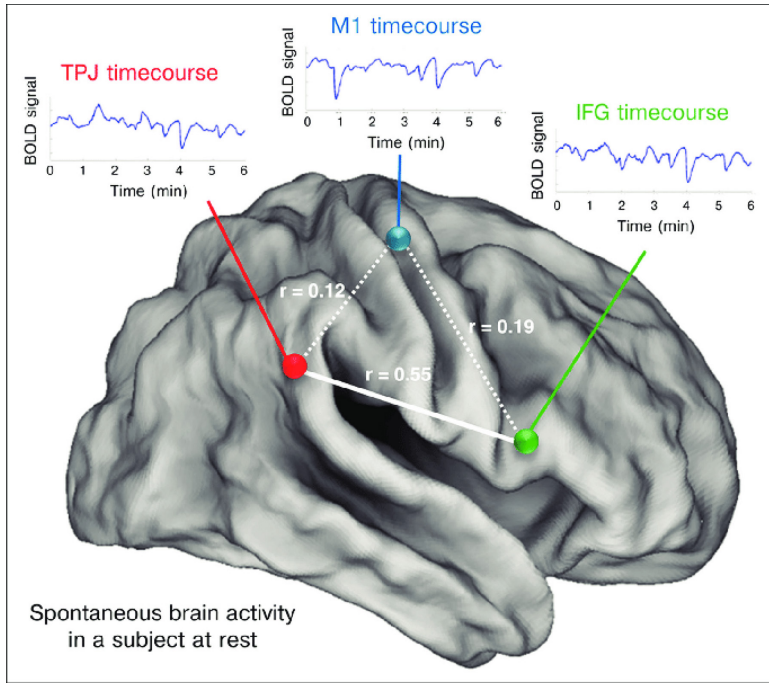
fMRI needs a contrast, and a model for activation ...



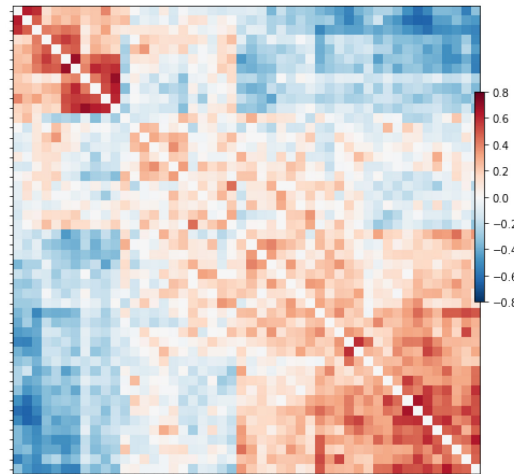
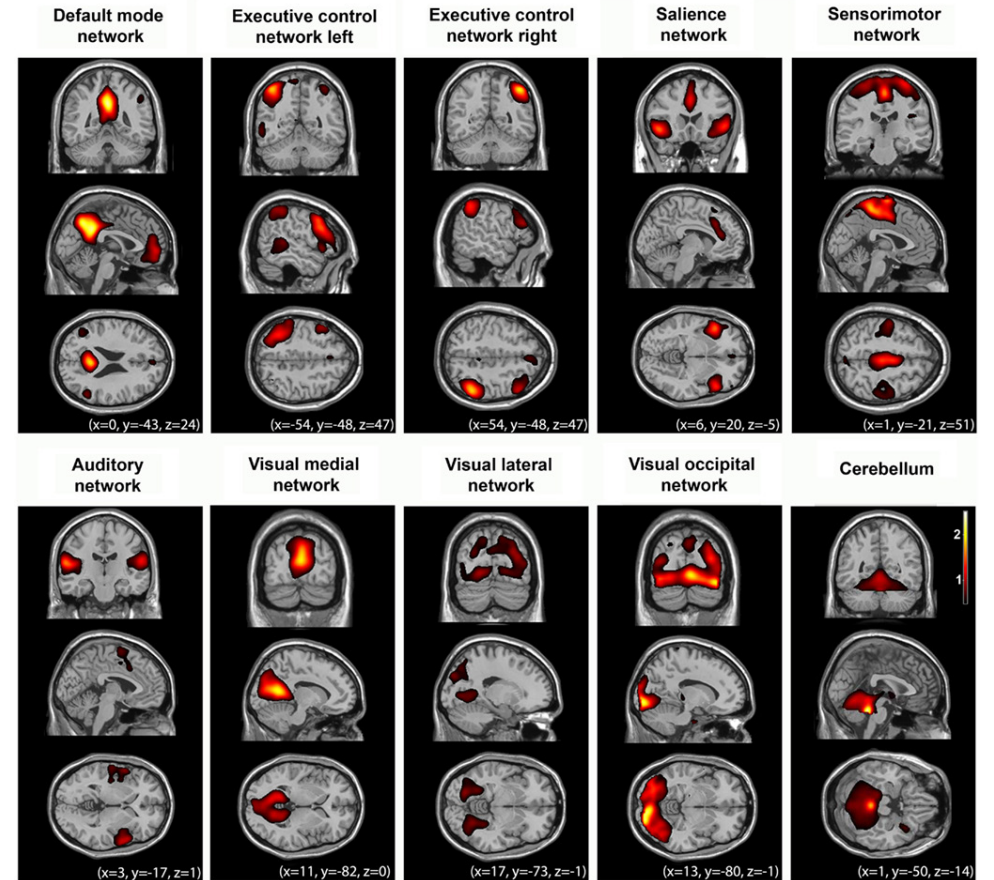
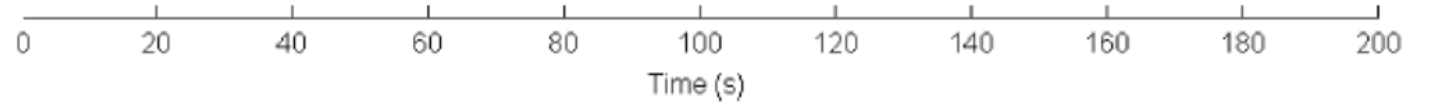
$$Y = X \cdot \beta + \epsilon$$

observed data at a single voxel design matrix estimated parameters error

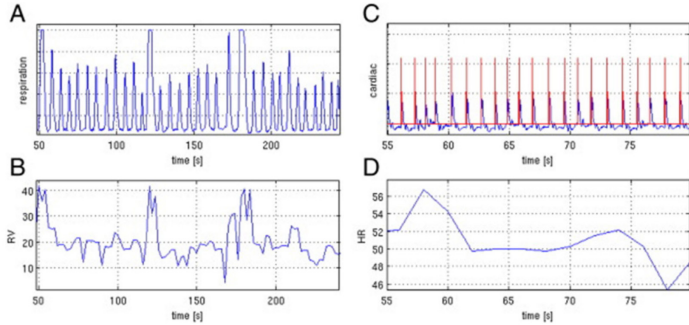
... but BOLD signal also fluctuates on its own



Resting state

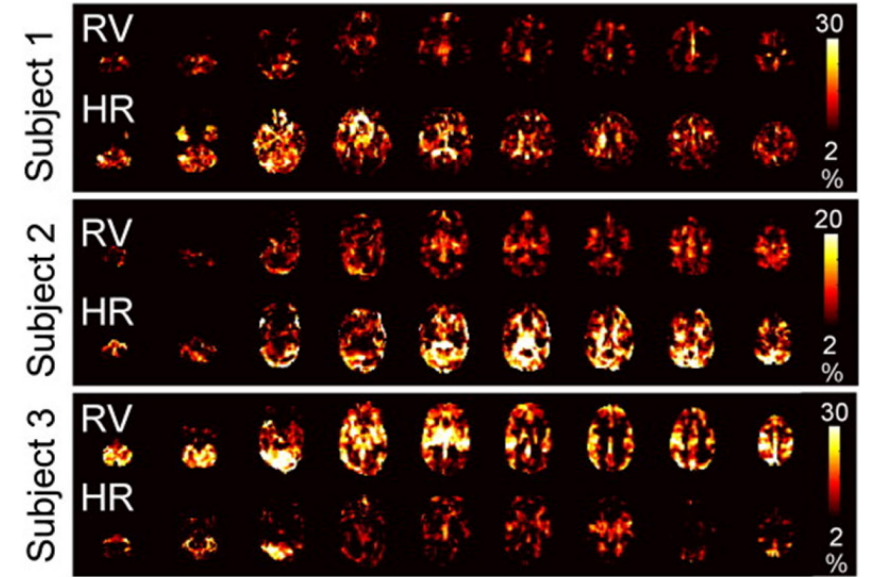
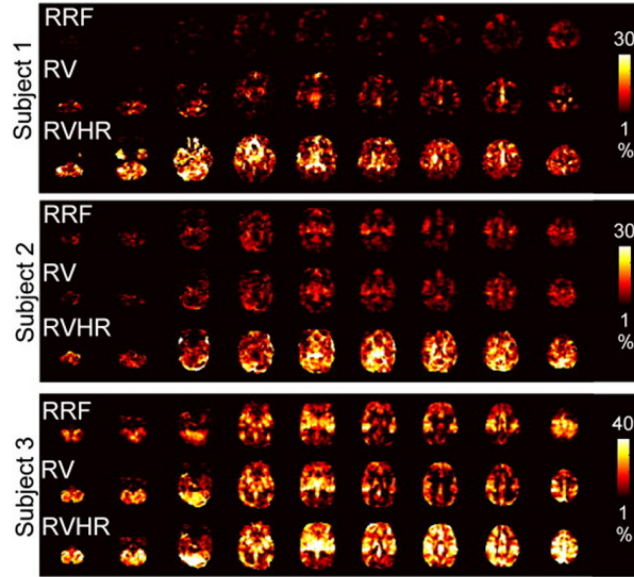


Cardiac and respiratory response function

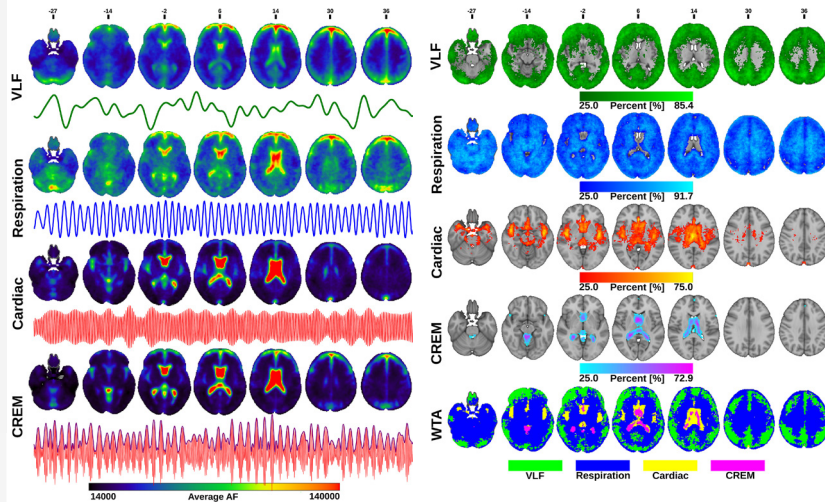


Example of physiological time courses for 1 subject, showing (A) respiration belt measurements, (B) the calculated RV, (C) cardiac cycle with triggers, and (D) the calculated HR. Note that (A, B) are displayed on a different time scale than (C, D).

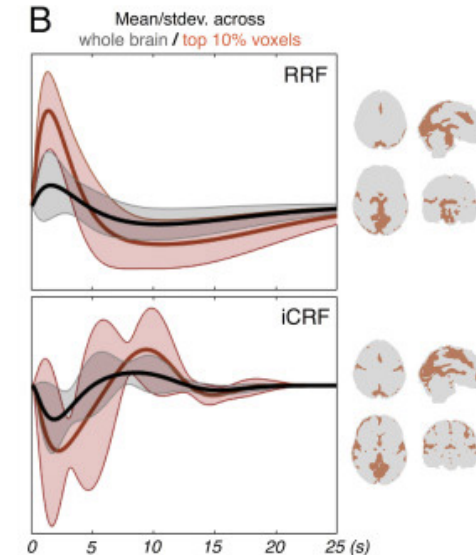
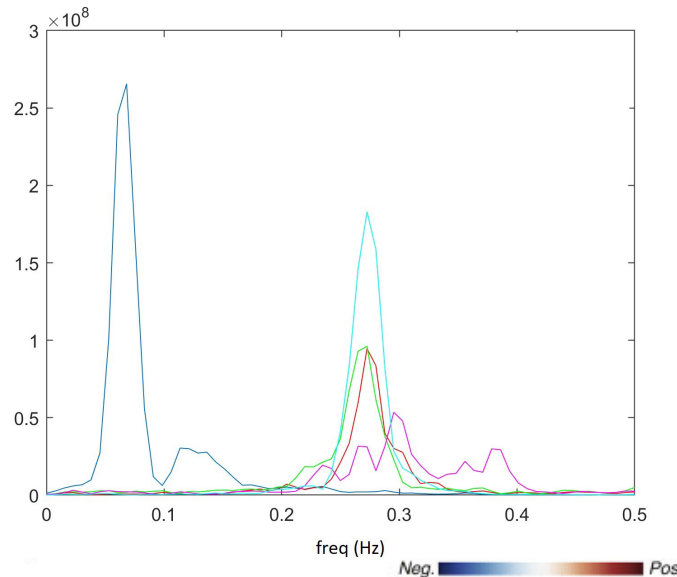
Chang et al. NeuroImage 2009



Chang et al. NeuroImage 2009



Raitamaa et al. HBM 2021

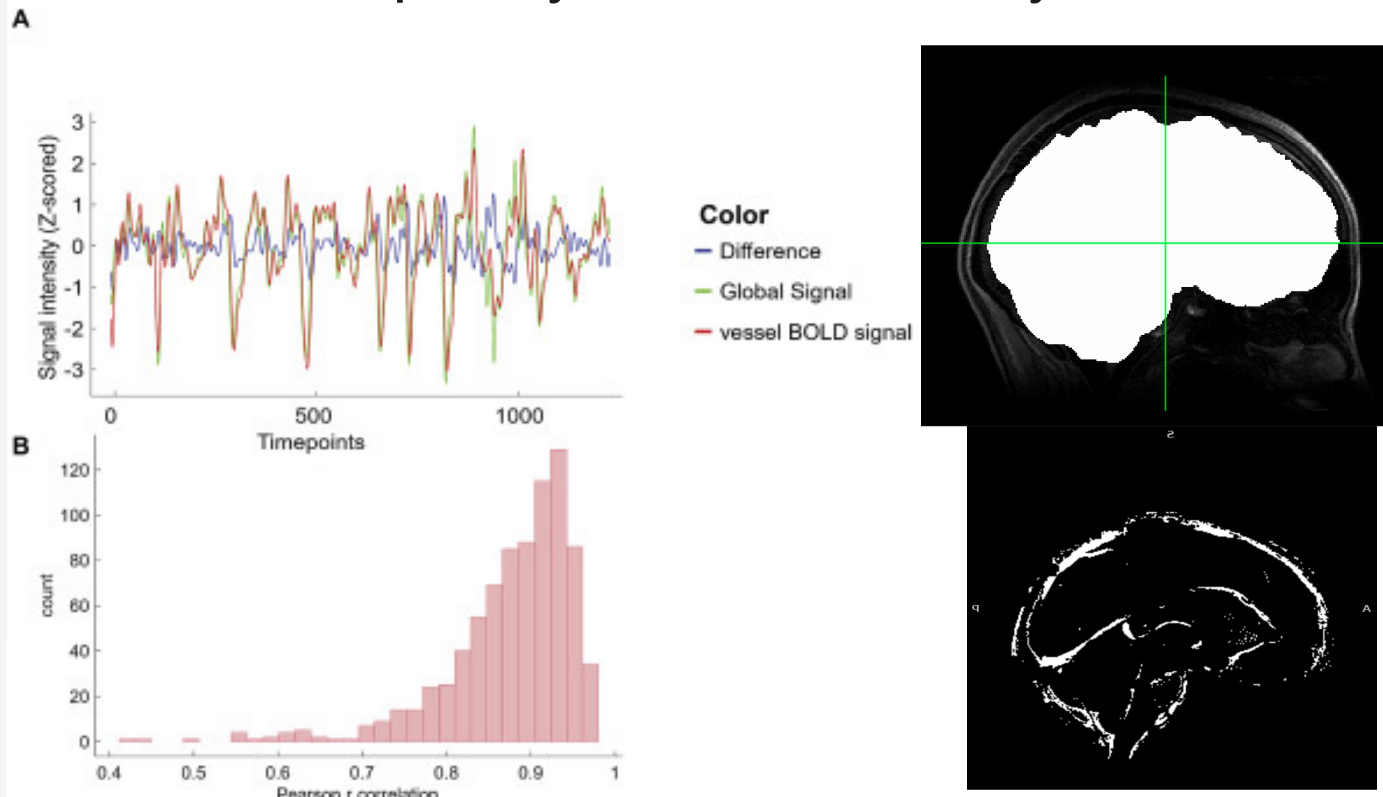


Chen et al. NeuroImage 2020

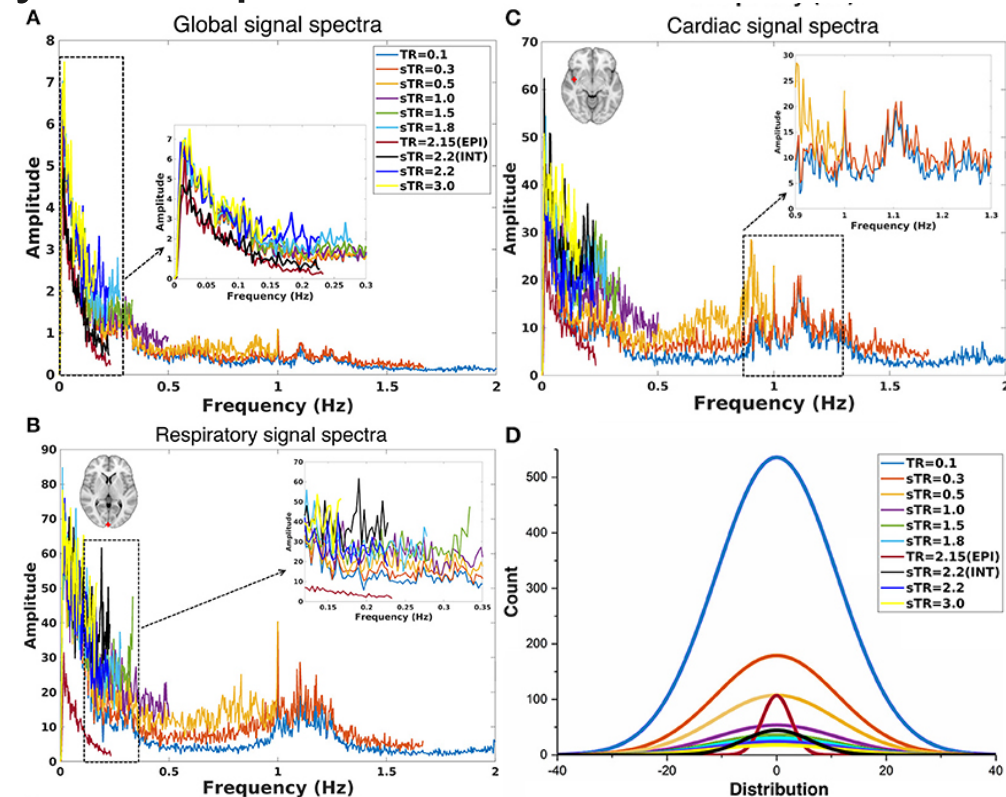


Hemodynamics, heartbeat and respiration are not “just noise”

- Some processing methods claim to “remove” physiological confounders, but this is not possible since physiology literally makes the BOLD signal
- Physiological fluctuations (and/or their aliases) have often the same scale/frequency of neural activity, and similar dynamic patterns

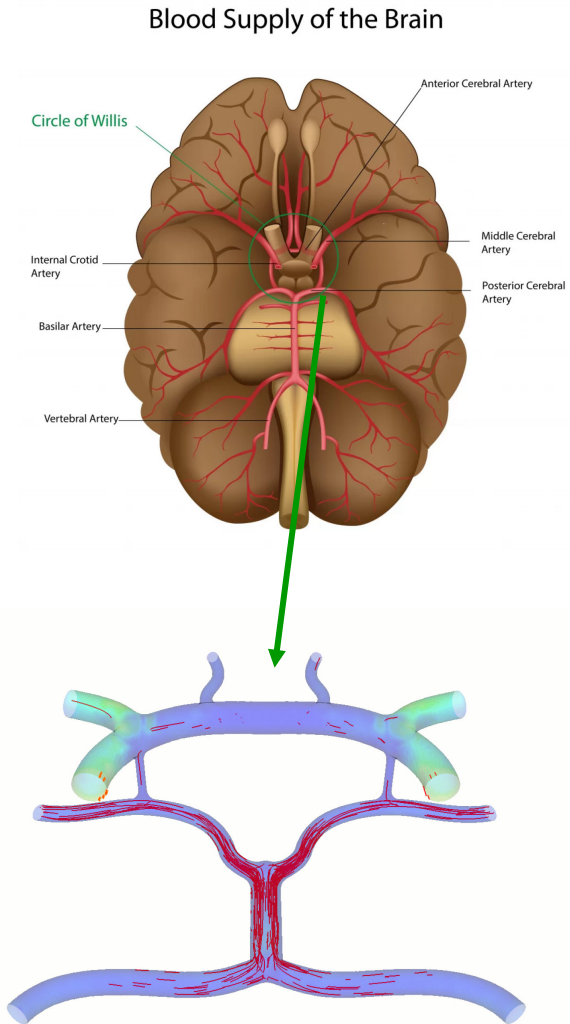


Colenbier et al. Neuroimage 2020

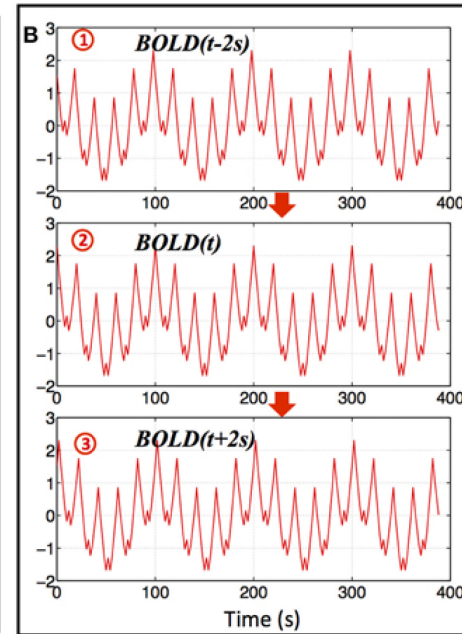
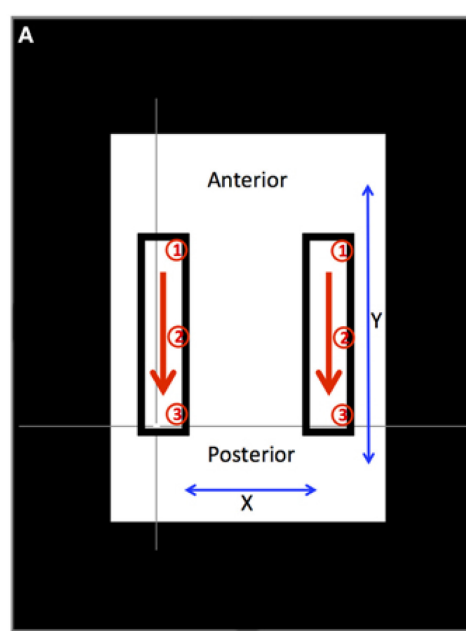


Huotari et al. Front. Neurosci. 2019

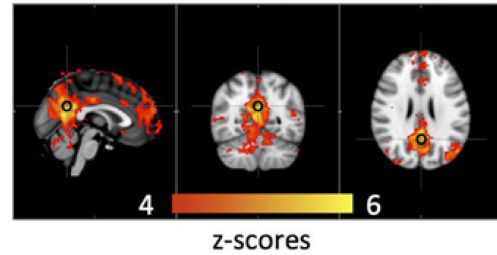
Blood flow



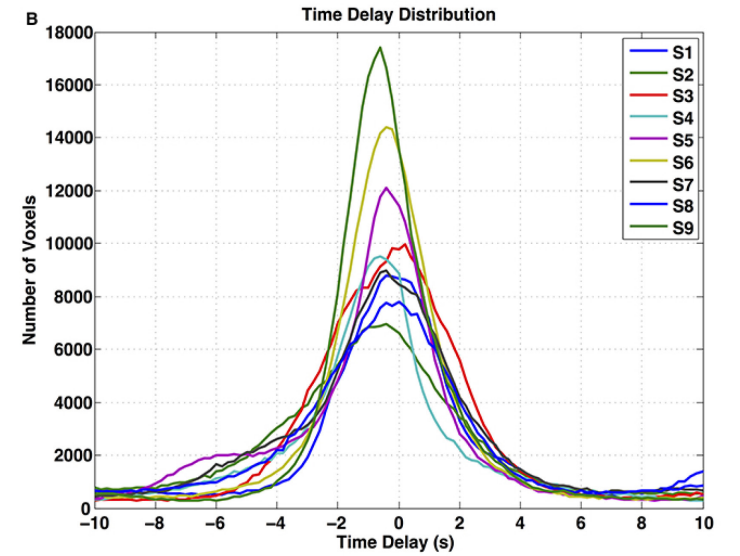
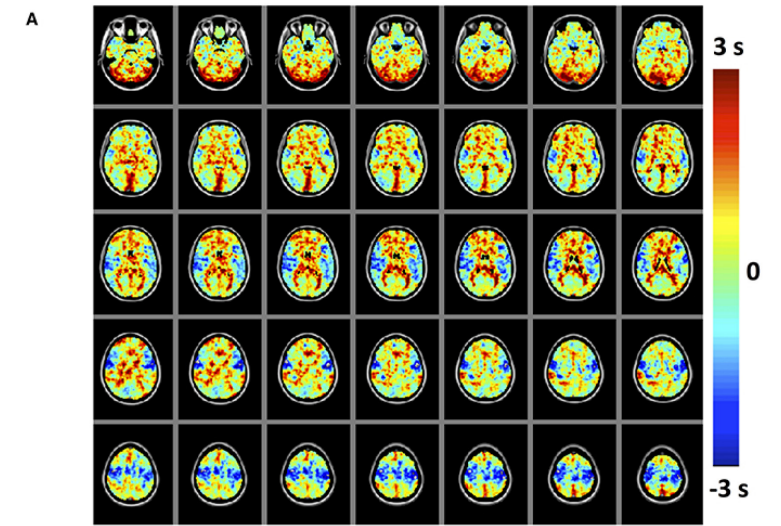
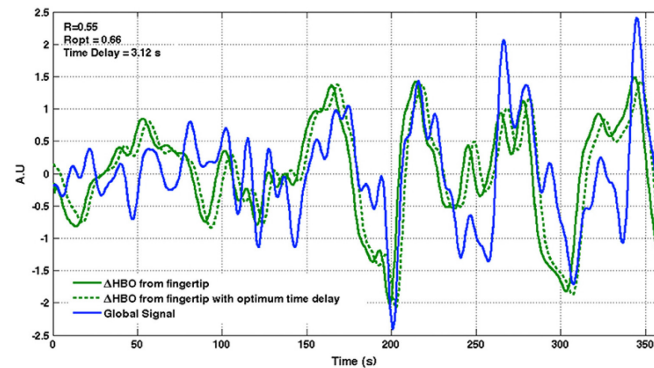
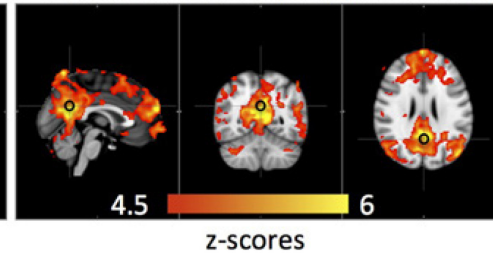
Ansys, 2024



A DMN from seed analysis (real data)



B DMN from seed analysis (synthetic data)



Tong and Frederick Human Brain Mapping 2014
 Tong et al. Front. Hum. Neurosci. 2015
 Erdogan et al. Front. Hum. Neurosci. 2016
 Chen et al. Neuroimage 2020

Blood flow inflates FC estimates

Brain-wide functional connectivity artifactually inflates throughout functional magnetic resonance imaging scans

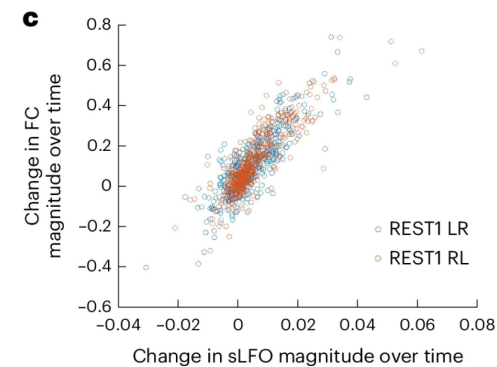
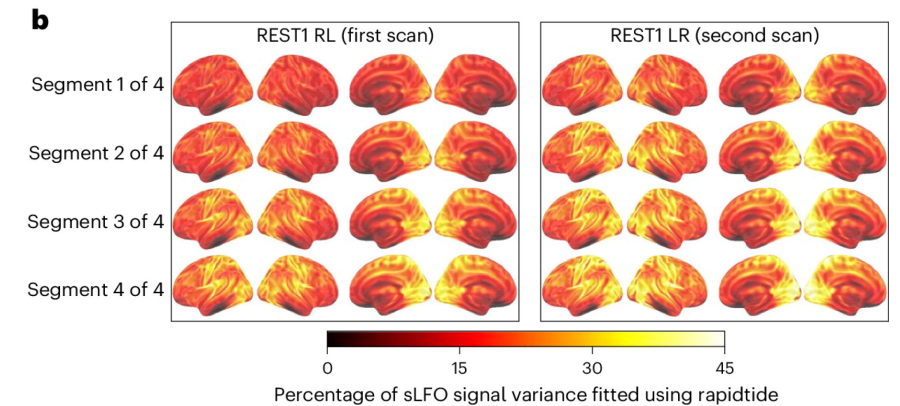
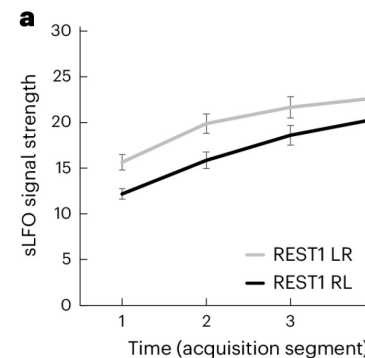
Cole Korponay , Amy C. Janes & Blaise B. Frederick

Nature Human Behaviour **8**, 1568–1580 (2024) | [Cite this article](#)

3132 Accesses | 122 Altmetric | [Metrics](#)

Abstract

Functional magnetic resonance imaging (fMRI) is a central tool for investigating human brain function, organization and disease. Here, we show that fMRI-based estimates of functional brain connectivity artifactually inflate at spatially heterogeneous rates during resting-state and task-based scans. This produces false positive connection strength changes and spatial distortion of brain connectivity maps. We demonstrate that this artefact is driven by temporal inflation of the non-neuronal, systemic low-frequency oscillation (sLFO) blood flow signal during fMRI scanning and is not addressed by standard denoising procedures. We provide evidence that sLFO inflation reflects perturbations in cerebral blood flow by respiration and heart rate changes that accompany diminishing arousal during scanning, although the mechanisms of this pathway are uncertain. Finally, we show that adding a specialized sLFO denoising procedure to fMRI processing pipelines mitigates the artifactual inflation of functional connectivity, enhancing the validity and within-scan reliability of fMRI findings.



Rapidity

Rapidity is a suite of python programs used to perform rapid time delay analysis on functional imaging data to find time lagged correlations between the voxelwise time series and other time series, both in the LFO band (rapidity2) and now in the cardiac band (happy).

python 3.9 | 3.10 | 3.11 | 3.12 | License Apache 2.0 | docs unknown | circleci passing

codecov 35% | DOI 10.5281/zenodo.814990 | NIH R01-NS097512-01A1

Citing rapidtide

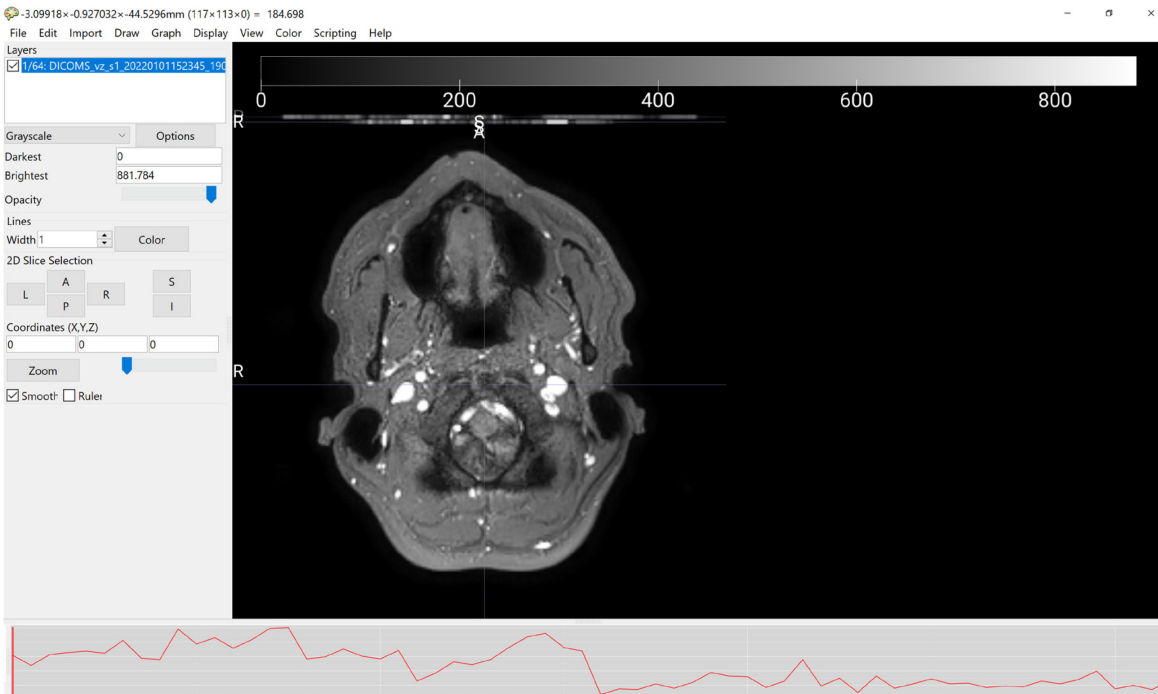
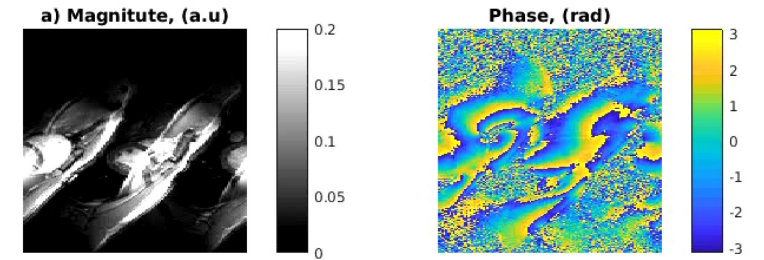
Frederick, B, rapidtide [Computer Software] (2016-2024). Available from <https://github.com/bbfrederick/rapidity>. doi:10.5281/zenodo.814990



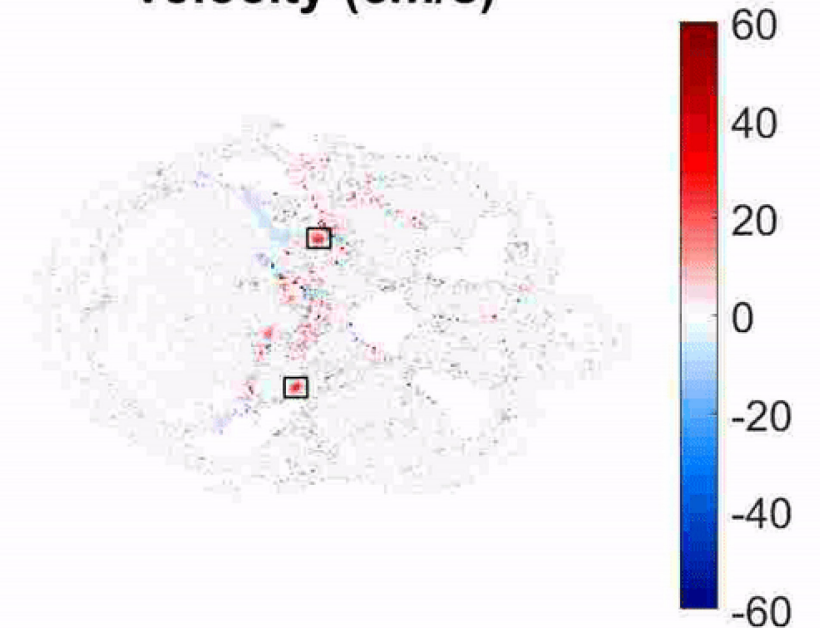
Blood flow velocity in brain plumbing

Autocalibrated multiband CAIPIRINHA with through-time encoding: Proof of principle and application to cardiac tissue phase mapping

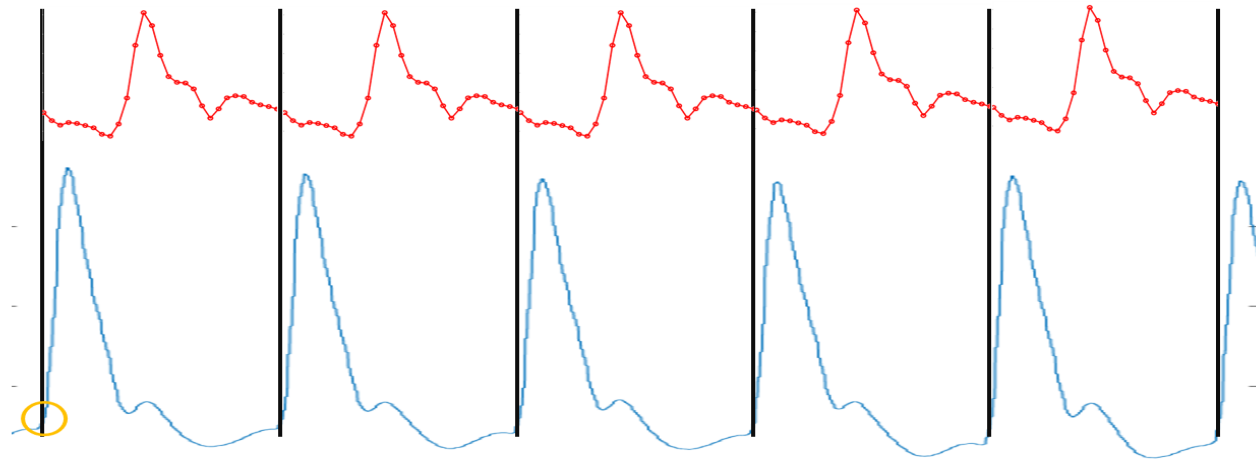
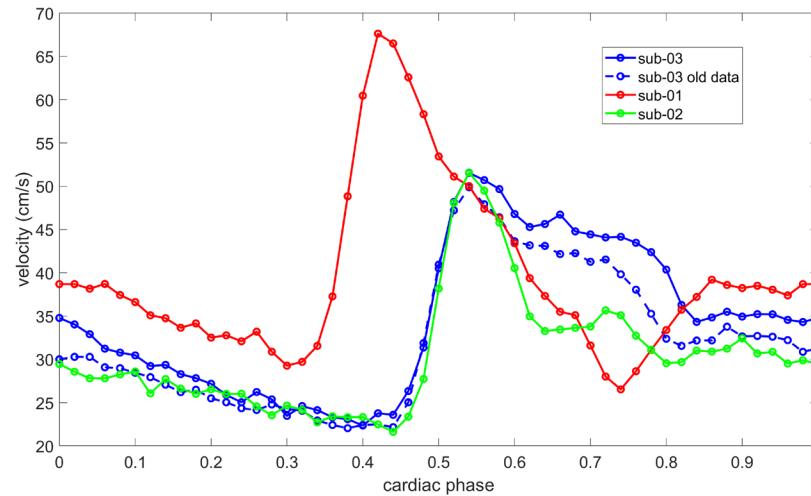
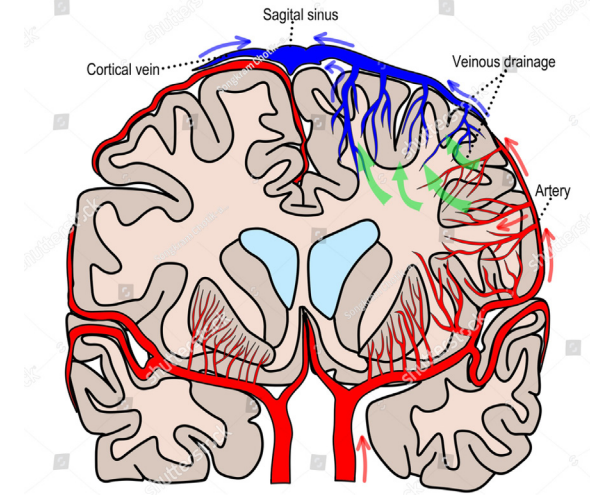
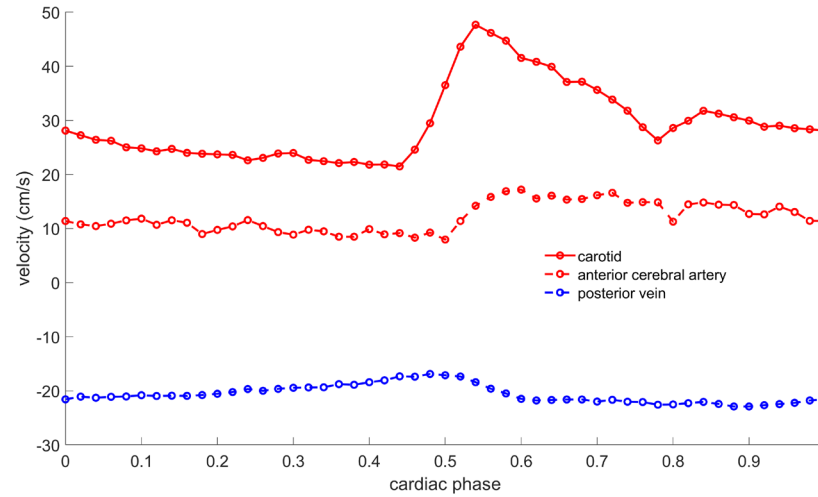
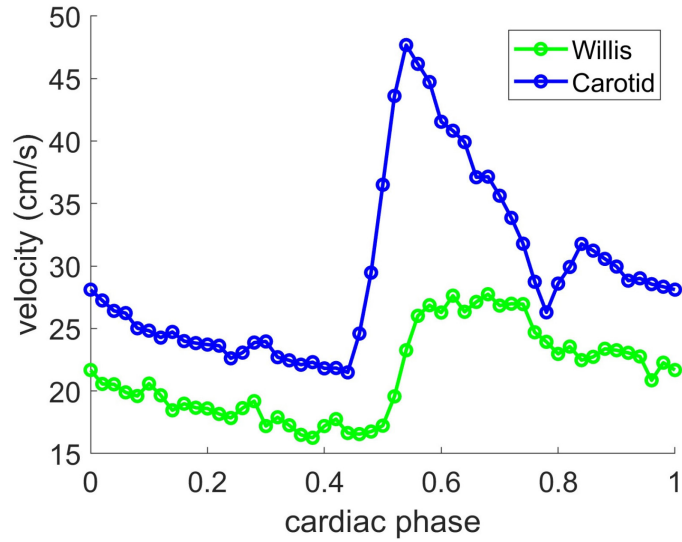
Giulio Ferrazzi ✉, Jean Pierre Bassenge, Clarissa Wink, Alexander Ruh, Michael Markl, Steen Moeller, Gregory J. Metzger, Bernd Ittermann, Sebastian Schmitter



velocity (cm/s)




Blood flow velocity in brain plumbing



A functional role for phase contrast data

September 12 2025

Visual stimulus-evoked blood velocity responses in individual human posterior cerebral arteries measured with dynamic phase-contrast functional MR angiography

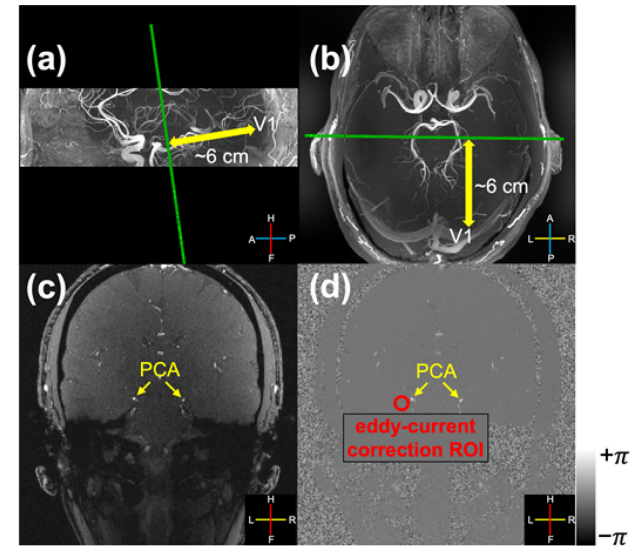
Zhangxuan Hu , Sébastien Proulx, Grant A. Hartung, Daniel E. P. Gomez, Jingyuan E. Chen, Divya Varadarajan, Elif Gökçal, Saskia Bollmann, Can Ozan Tan, M. Edip Gurol, Jonathan R. Polimeni

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[Author and Article Information](#)

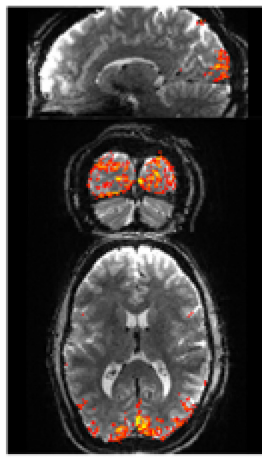
Imaging Neuroscience (2025) 3: IMAG.a.148.

<https://doi.org/10.1162/IMAG.a.148> [Article history](#) 

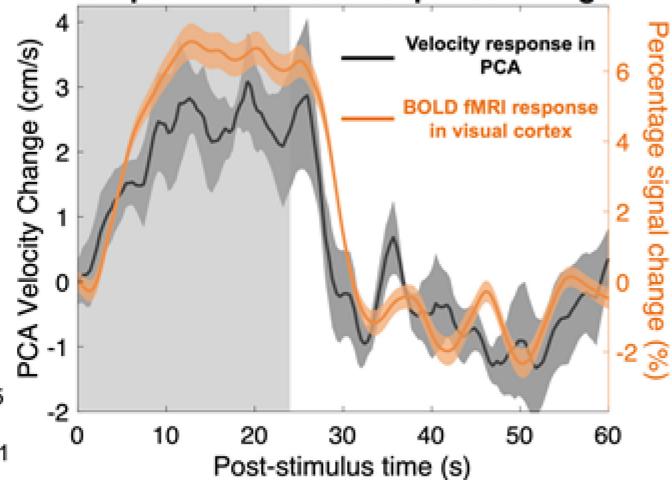


(a) Subject 1 (scanned at 7T)

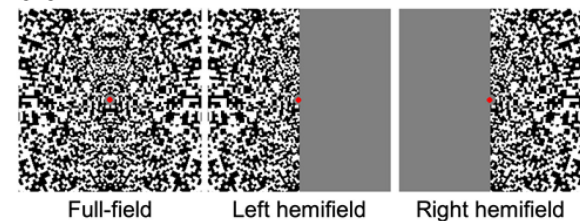
BOLD fMRI activation



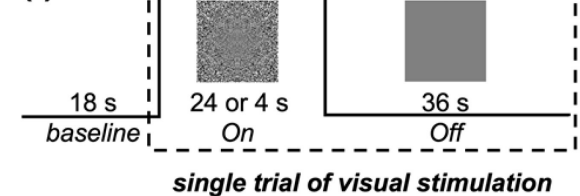
Comparison between response timings



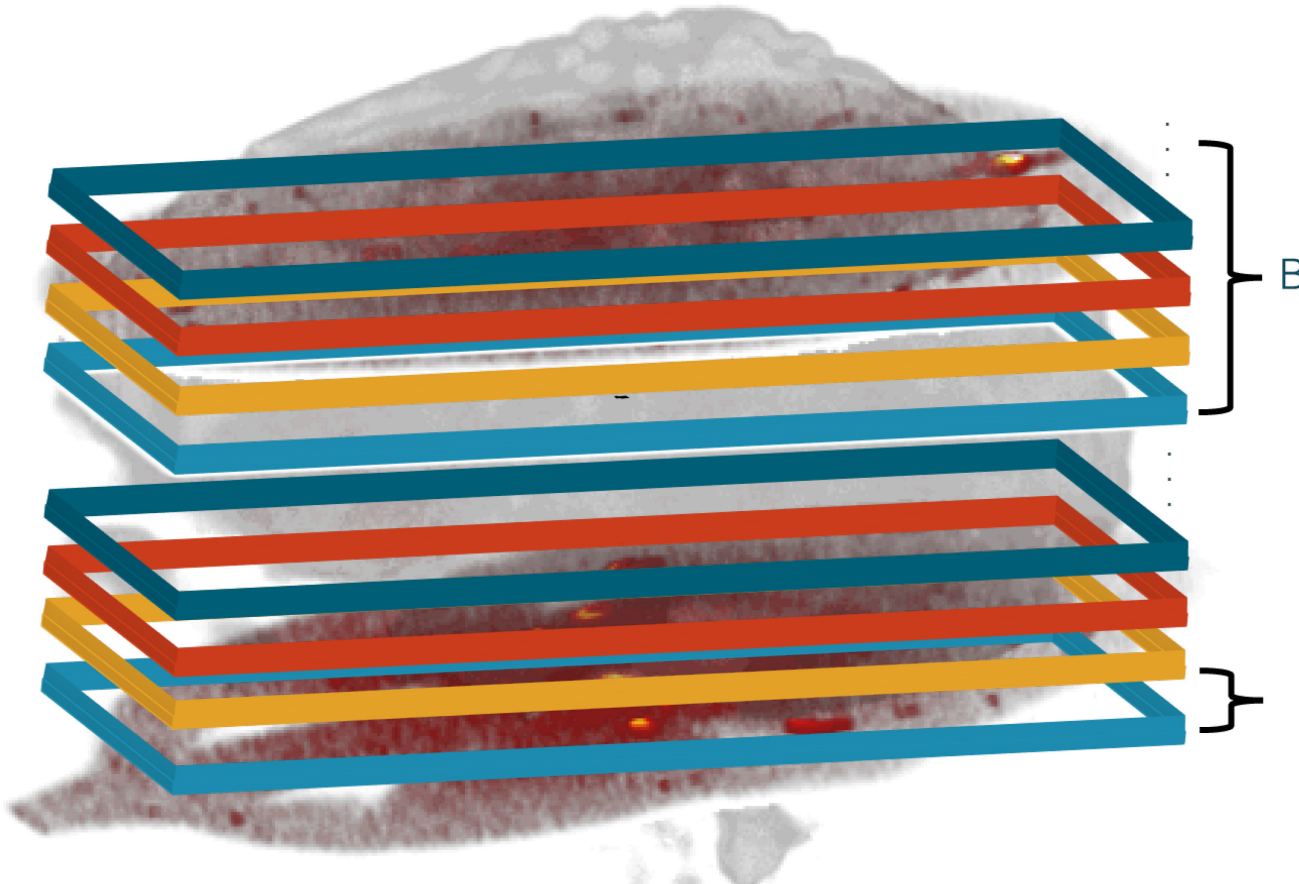
(e)



(f)



Cardiac pulsatility from (multiband) BOLD data



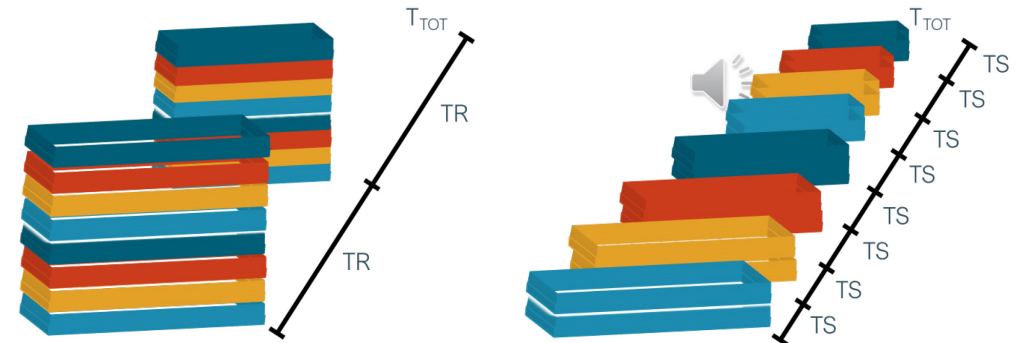
Z [Total slices]

MB [Multiband factor]

$$B = \frac{Z}{MB}$$

B [Number of RF excitations per imaging volume]

TS [Time between excitations]

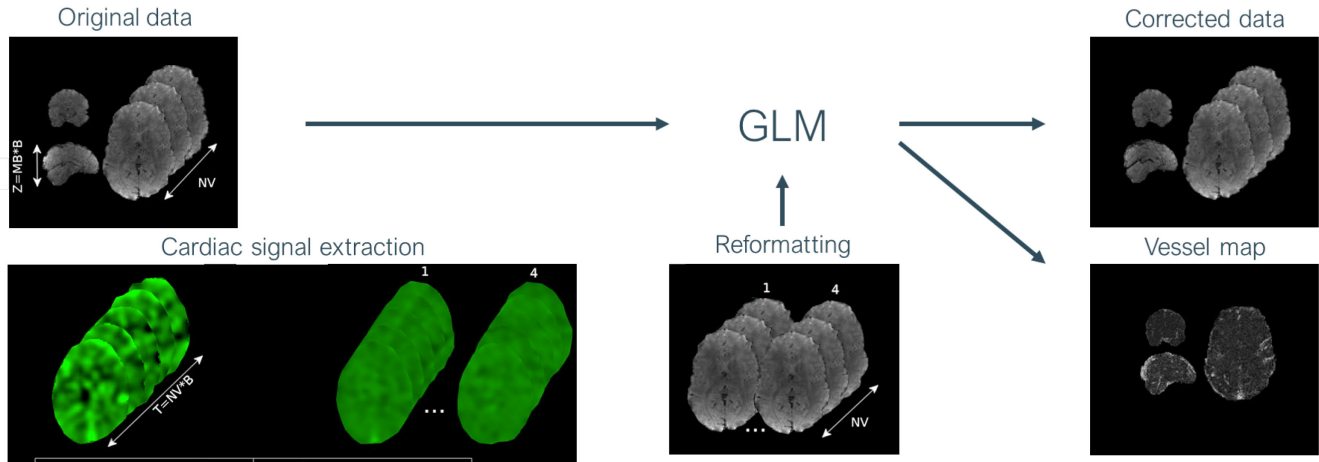


Extraction of the cardiac waveform from simultaneous multislice fMRI data using slice sorted averaging and a deep learning reconstruction filter

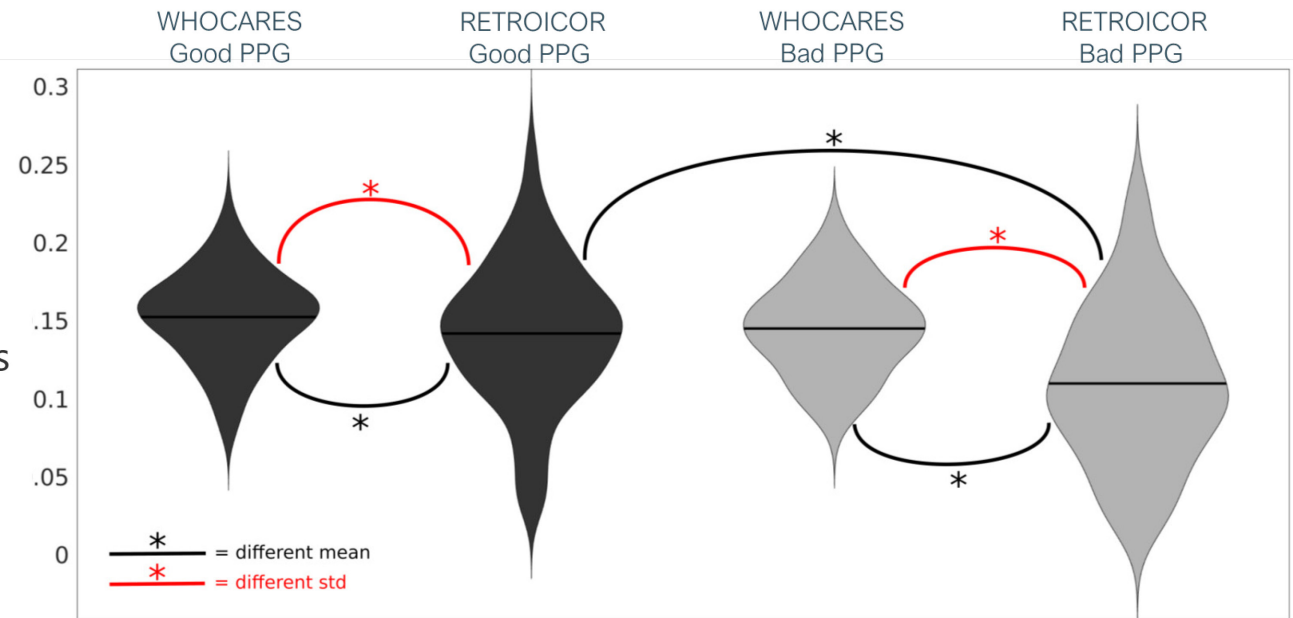
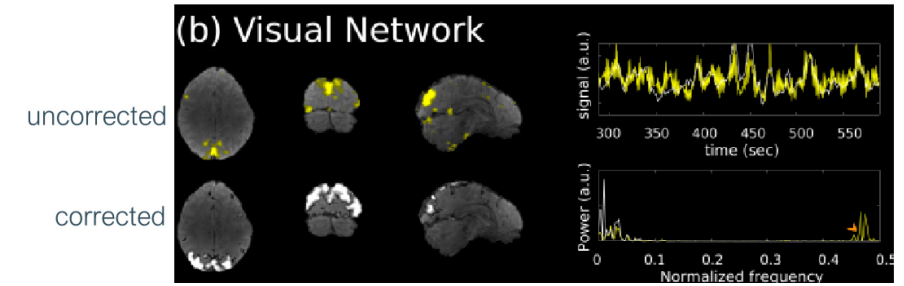
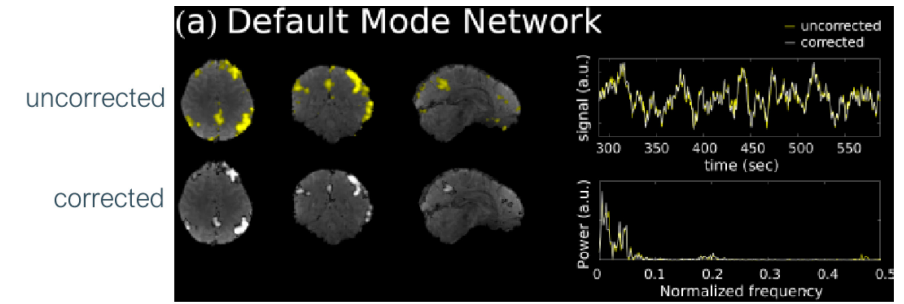
Serdar Aslan^{a,b}, Lia Hocke^{a,b}, Nicolette Schwarz^{a,b}, Blaise Frederick^{a,b}  

data reformatted along slice and temporal domains, then Fourier transformed

Creating a cardiac regressor



Upsample from TR to TS = TR/MB
 Temporal Fourier transform to extract 8 cardiac signal peaks from the hyper-resolved time-series
 Bandpass filters (± 0.2 Hz) isolate each cardiac component; a GLM constructs a voxel-wise cardiac regressor



PAPER • OPEN ACCESS

WHOCARES: WHOLE-brain CARDiac signal REgression from highly accelerated simultaneous multi-Slice fMRI acquisitions

Nigel Colenbier^{6,1} , Marco Marino^{6,1,2} , Giorgio Arcara¹ , Blaise Frederick^{3,4} , Giovanni Pellegrino¹ , Daniele Marinazzo^{1,5} and Giulio Ferrazzi^{7,1}

Published 6 September 2022 • © 2022 The Author(s). Published by IOP Publishing Ltd

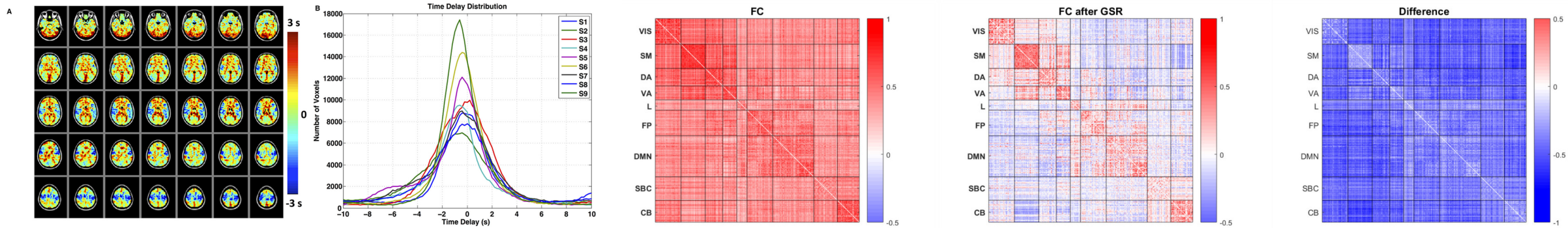
[Journal of Neural Engineering](#), Volume 19, Number 5

Citation Nigel Colenbier et al 2022 *J. Neural Eng.* 19 056006

DOI 10.1088/1741-2552/ac8bff



Blood flow and global signal regression



Brain Connectivity
Volume 2, Issue 1, 1 February 2012, Pages 25-32

Trouble at Rest: How Correlation Patterns and Group Differences Become Distorted After Global Signal Regression (Article)

Saad, Z.S.^a, Gotts, S.J.^b, Murphy, K.^c, Chen, G.^a, Jo, H.J.^a, Martin, A.^b, Cox, R.W.^a

Towards a consensus regarding global resting state functional connectivity

Kevin Murphy^{a, b}, Michael D. Fox^{c, d}

Neuroimage, 2009 Feb 1;44(3):893-905. doi: 10.1016/j.neuroimage.2009.02.001

The impact of global signal regression on resting state functional connectivity

Murphy K¹, Birn RM, Handwerker DA, Jones TB, Bandettini PA

Neuroimage
Volume 146, 1 February 2017, Pages 609-625

Sources and implications of whole-brain resting state functional connectivity

Power, J.D.^a, Plitt, M.^a, Laumann, T.O.^b

Benchmarking of participant-level connectivity strategies for the control of motion artifacts in resting state functional connectivity

Rastko Ciric^a, Daniel H. Wolf^a, Jonathan D. Power^b, David R. Ross^c, Russell T. Shinohara^c, Mark A. Elliott^d, Simon B. Eickhoff^{e, f}, Christof Koch^{g, h}, Danielle S. Bassett^{g, h}, Theodore D. Satterthwaite^{a, i}

Letter

On Global fMRI Signals and Simulations

Jonathan D. Power¹, Timothy O. Laumann², Mark Plitt³, Alex Martin⁴, Steven E. Petersen⁵

Spotlight

Mixed Signals: On Separating Brain Signal from Noise

Lucina Q. Uddin^{1, 2}

To regress out or not? An update on the fMRI global signal debate

Athena Demertzi Organizer

GIGA Institute, University of Liège

Cyclotron Research Center

Liège

Belgium

Monday, Jun 24: 3:15 PM - 4:30 PM

1749

Symposium

COEX

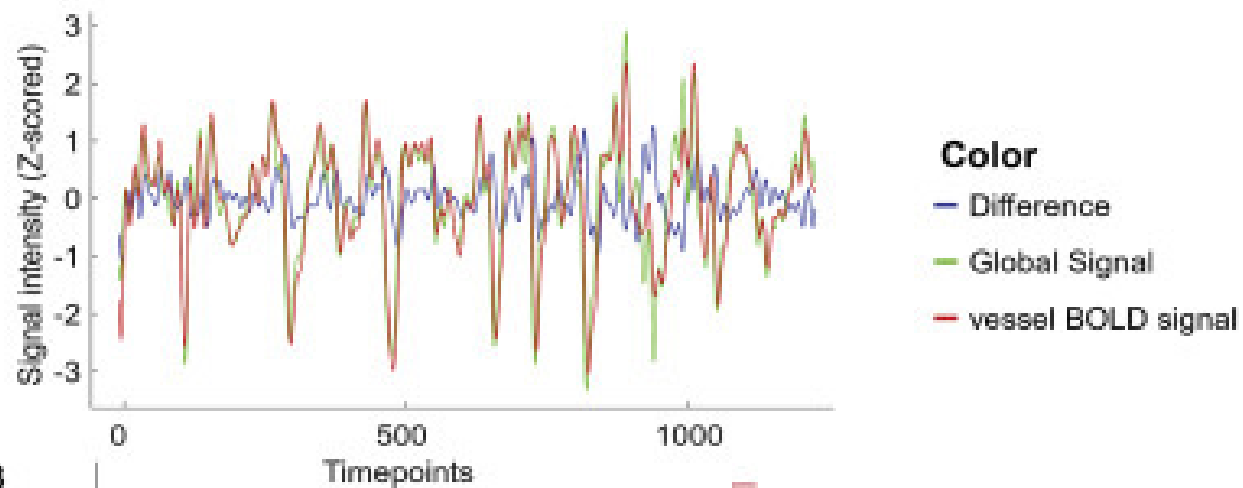
Room: Grand Ballroom 103

We are investigators from different disciplines, who use fMRI as a means to quantify different aspects of cognition and behavior. During the last year, we noticed that our independent studies using fMRI converged on a common topic, the Global Signal (GS). Indicatively, Prof. Uddin shows that the GS topography can be informative across the life span (Li, et al 2019; Nomi et al., 2023), Prof. Van de Ville indicates that GS can mathematically influence dynamic connectivity analyses (Van de Ville et al, 2019), Dr Mortaheb shows that the GS amplitude completes the interpretation of ongoing mental state reports (Mortaheb et al, 2022; 2023), and Prof. Liu's work on the GS aptly contextualizes this work (Liu et al, 2018). Coming together as a panel, we believe that we can provide an updated comprehensive discussion on where we stand methodologically and theoretically on the ongoing debate about the GS as a source of noise or of rich information.

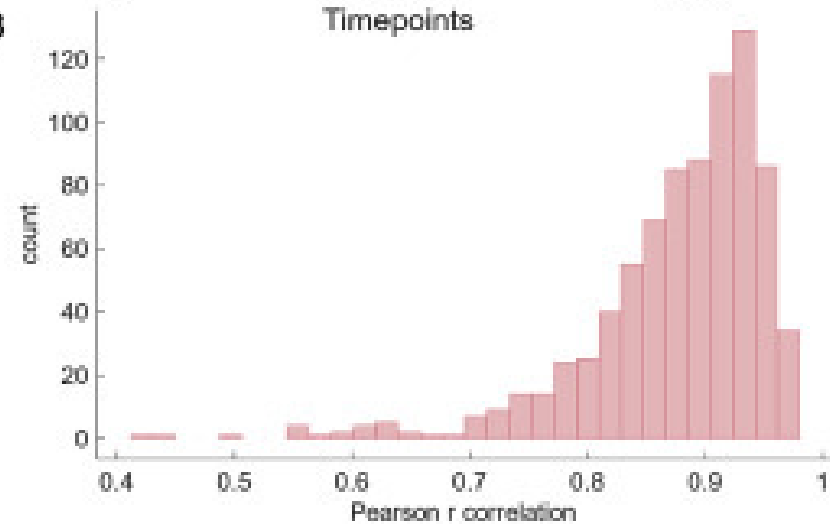


Separating the effects of blood flow and global signal

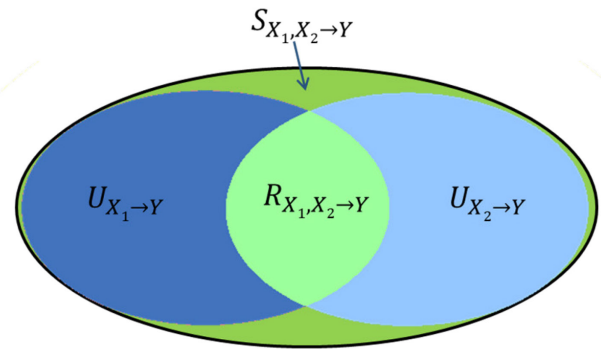
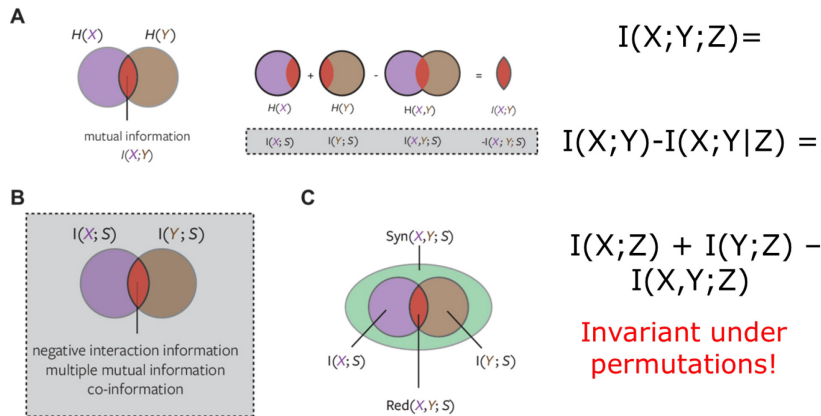
A



B



Partial information decomposition



Distinct non-negative measures of redundancy and synergy, accounting for the possibility that redundancy and synergy may coexist as separate elements of information modification.

The interaction TE is actually a measure of the 'net' synergy manifested in the transfer of information from the two sources to the target.

$$TE_{X_1, X_2 \rightarrow Y} = U_{X_1 \rightarrow Y} + U_{X_2 \rightarrow Y} + R_{X_1, X_2 \rightarrow Y} + S_{X_1, X_2 \rightarrow Y}$$

$$TE_{X_1 \rightarrow Y} = U_{X_1 \rightarrow Y} + R_{X_1, X_2 \rightarrow Y}$$

$$TE_{X_2 \rightarrow Y} = U_{X_2 \rightarrow Y} + R_{X_1, X_2 \rightarrow Y}$$

$$R_{X_1, X_2 \rightarrow Y} = \min\{TE_{X_1 \rightarrow Y}, TE_{X_2 \rightarrow Y}\}$$

PID components cannot be obtained through classic information theory simply subtracting conditional MI terms: one more relation is needed. Shannon information theory does not univocally determine this decomposition

Redundancy can be defined as the minimum of the information provided by each individual source to the target (other recipes exist)

P. Williams and R. D. Beer. "Nonnegative decomposition of multivariate information." arXiv preprint arXiv:1004.2515 (2010).

This choice satisfies the desirable property that the redundant TE is independent of the correlation between the source processes.

PID is particularly relevant when some signals are very similar

Multiscale Information Decomposition: Exact Computation for Multivariate Gaussian Processes

by Luca Faes ^{1,2,*}, Daniele Marinazzo ³ and Sebastiano Stramaglia ^{4,5}

¹ Bruno Kessler Foundation, 38123 Trento, Italy

² BIOtech, Department of Industrial Engineering, University of Trento, 38123 Trento, Italy

³ Data Analysis Department, Ghent University, 9000 Ghent, Belgium

⁴ Dipartimento di Fisica, Università degli Studi Aldo Moro, 70126 Bari, Italy

⁵ Istituto Nazionale di Fisica Nucleare, 70126 Sezione di Bari, Italy

* Author to whom correspondence should be addressed.

Entropy **2017**, *19*(8), 408; <https://doi.org/10.3390/e19080408>

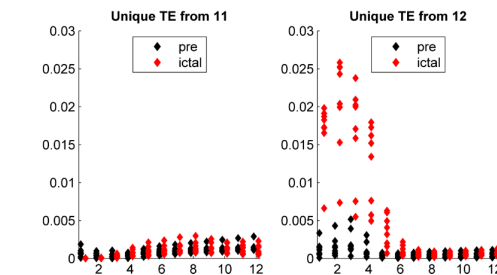
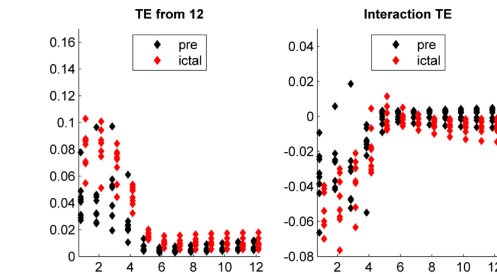
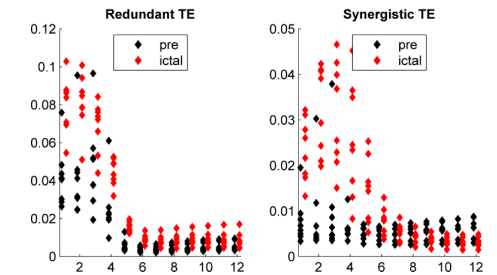
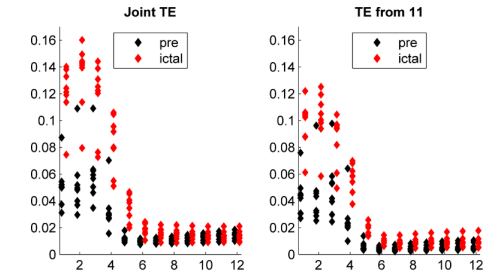
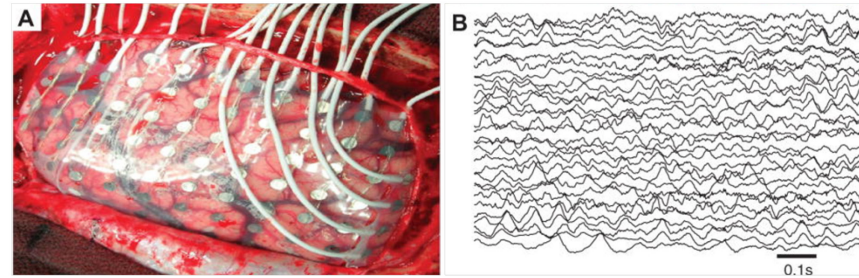


PID vs IID on similar signals

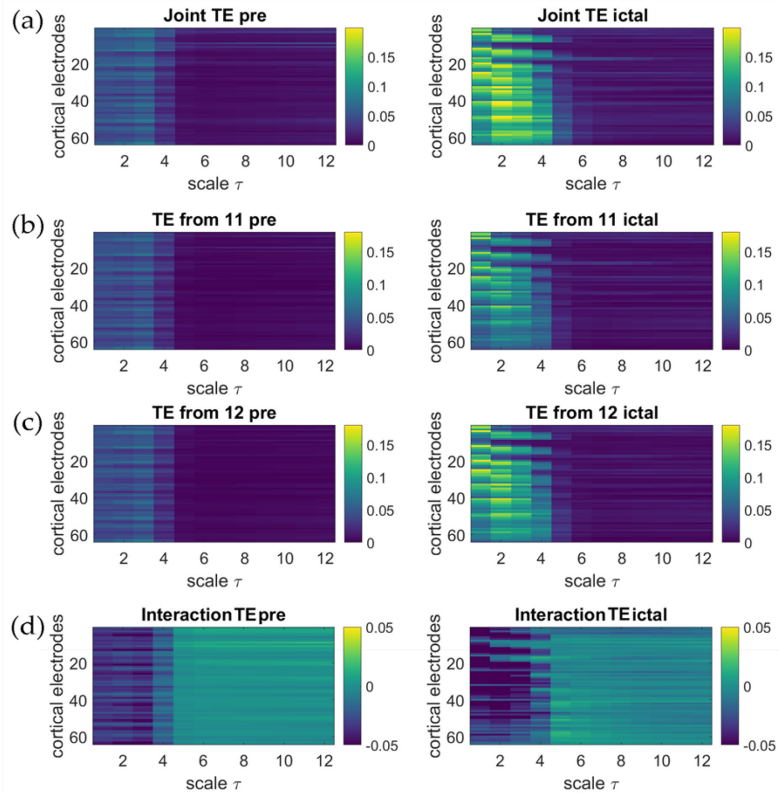
We look at 64 cortical electrodes as targets, and two depth hippocampal electrodes (11 and 12) as drivers

Multiscale Information Decomposition: Exact Computation for Multivariate Gaussian Processes

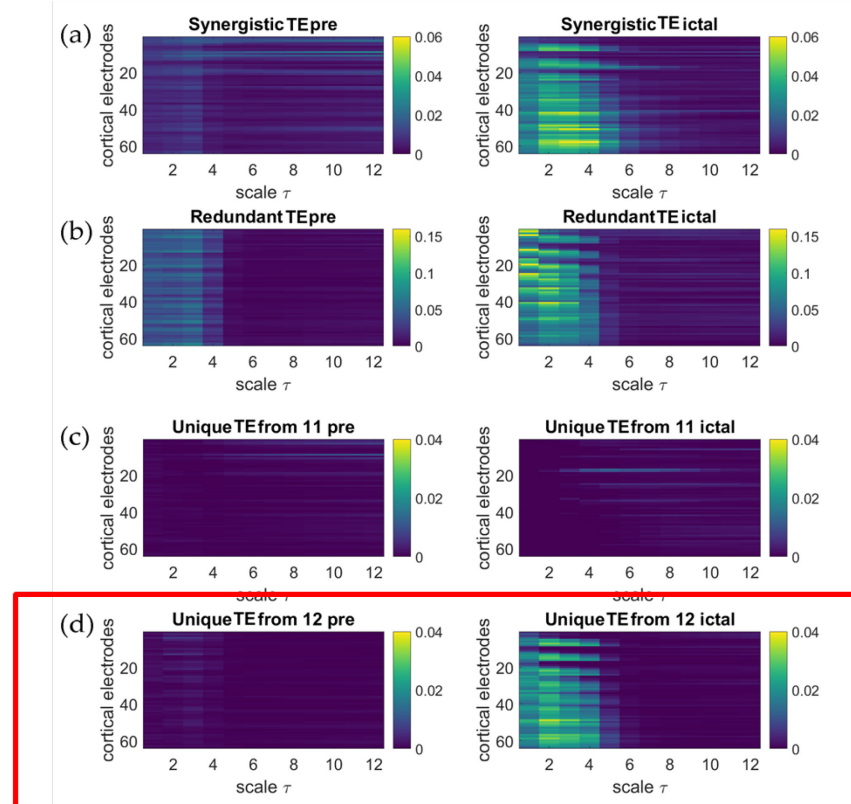
by Luca Faes^{1,2,*}, Daniele Marinazzo³ and Sebastiano Stramaglia^{4,5}



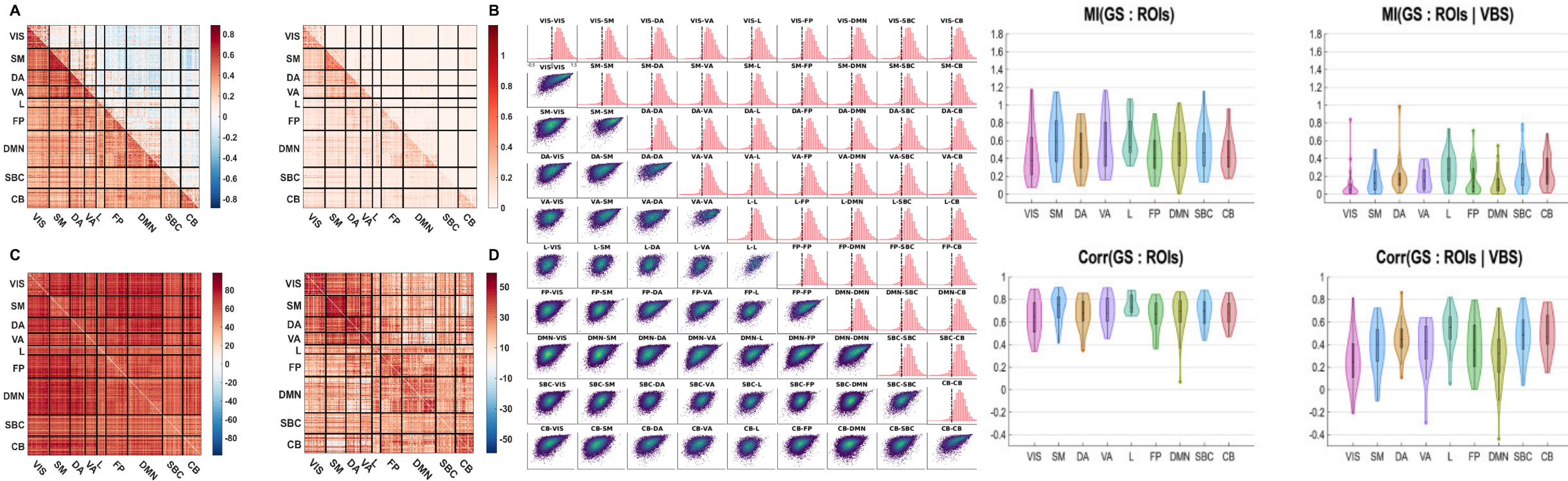
Interaction Information Decomposition (IID)



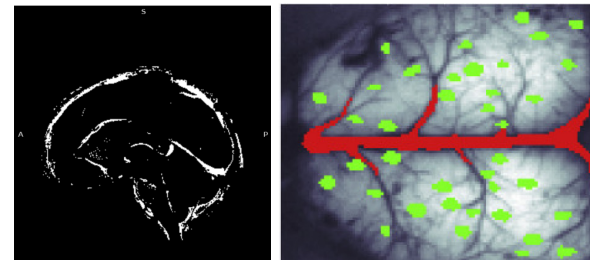
Partial Information Decomposition (PID)



Differential network effect of GSR



Investigate the **JOINT** role of Global Signal and BOLD from vessels towards the different regions in the brain using the framework of Multiscale Partial Information Decomposition, using simultaneous calcium and BOLD recordings in a mouse as a control



NeuroImage
Volume 213, June 2020, 116699



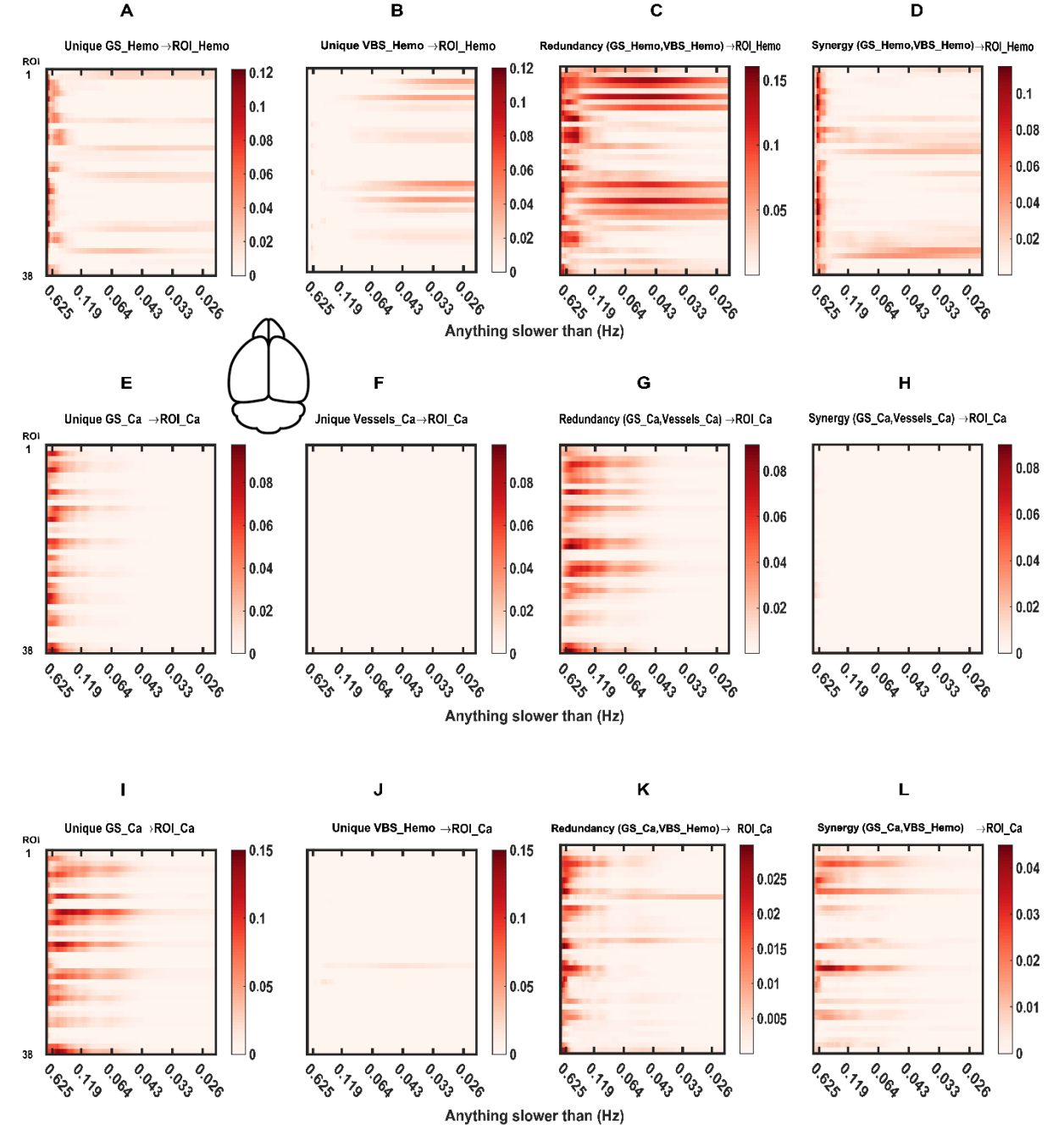
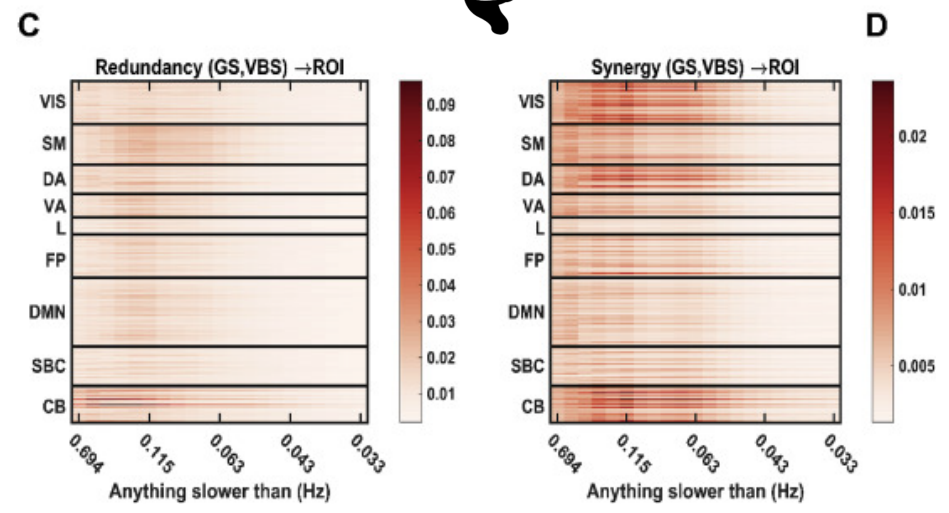
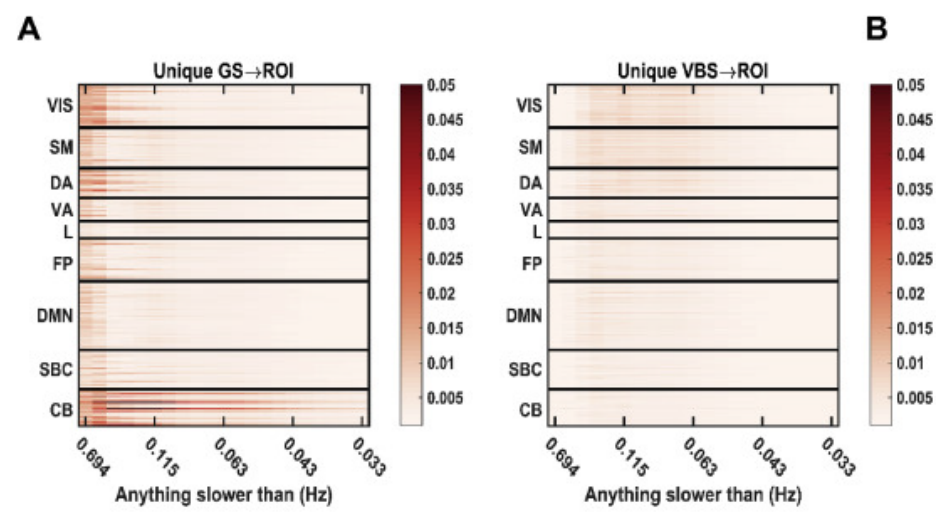
Disambiguating the role of blood flow and global signal with partial information decomposition

Nigel Colenier^{a,*,} Frederik Van de Steen^{a,} Lucina Q. Uddin^{b,} Russell A. Poldrack^{c,} Vince D. Calhoun^{d,*,} Daniele Marinazzo^a

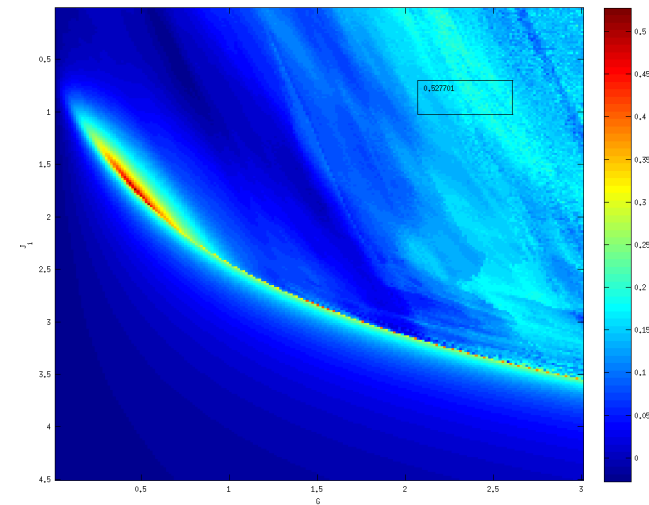
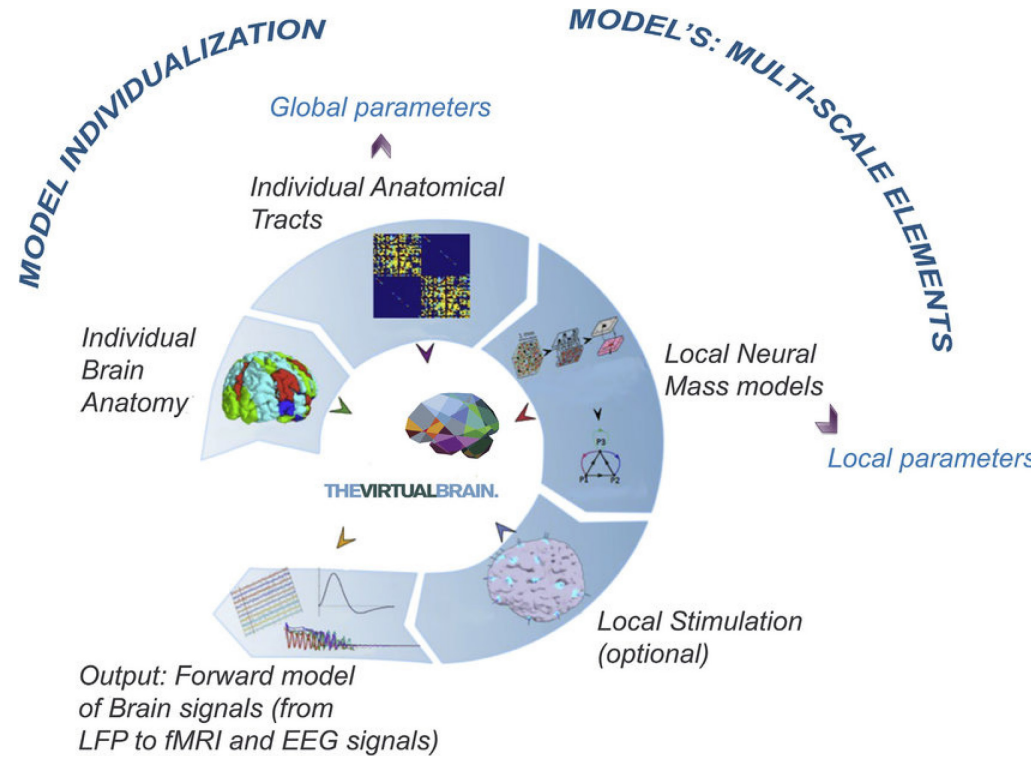
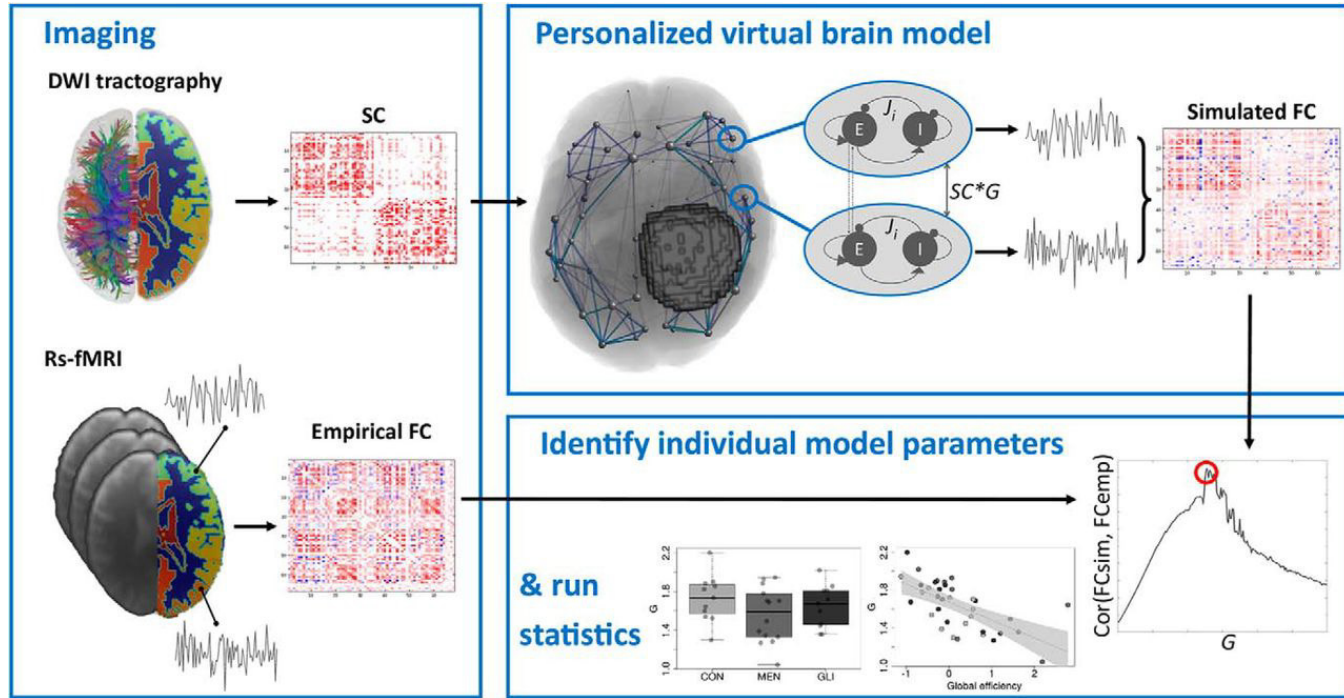




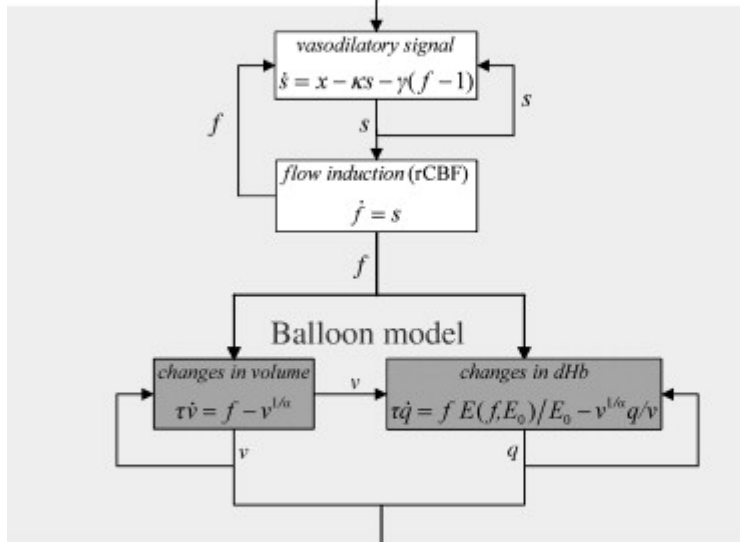
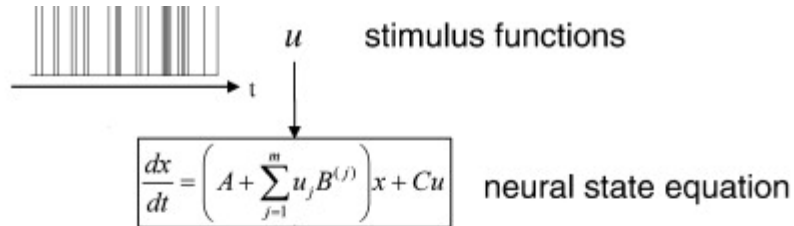
PID (GS, Vessels -> ROI)



The standard way to simulate fMRI data with TVB



Hemodynamics is “modelled” but only as a filter



hemodynamic state equations

```
class BalloonModel(HasTraits):
    ...
    A class for calculating the simulated BOLD signal given a TimeSeries
    object of TVB and returning another TimeSeries object.
    The haemodynamic model parameters based on constants for a 1.5 T scanner.
```

$$\lambda(q, v) = \frac{\Delta S}{S_0} \approx V_0 \left[k_1(1 - q) + k_2 \left(1 - \frac{q}{v} \right) + k_3(1 - v) \right]$$

$k_1 = 4.39_0 E_0 TE$
 $k_2 = \epsilon r_0 E_0 TE$
 $k_3 = 1 - \epsilon$

BOLD signal change equation

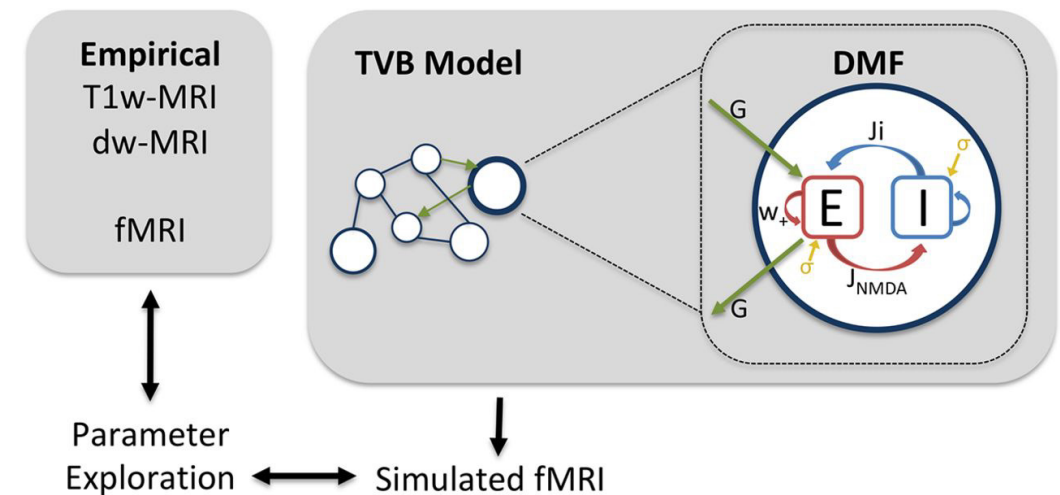


Stephan et al. Neuroimage 2007

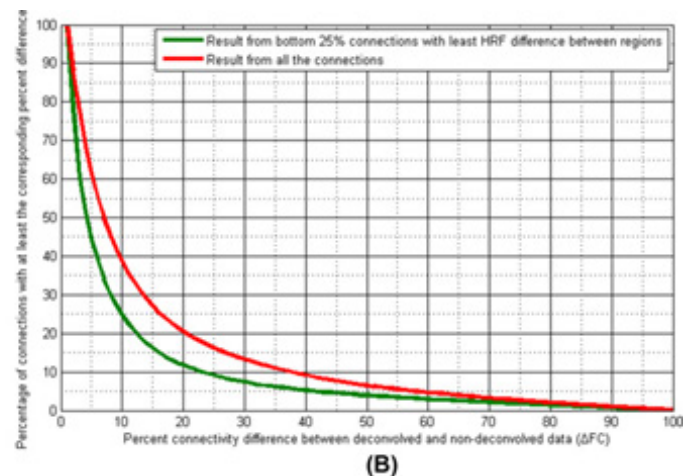
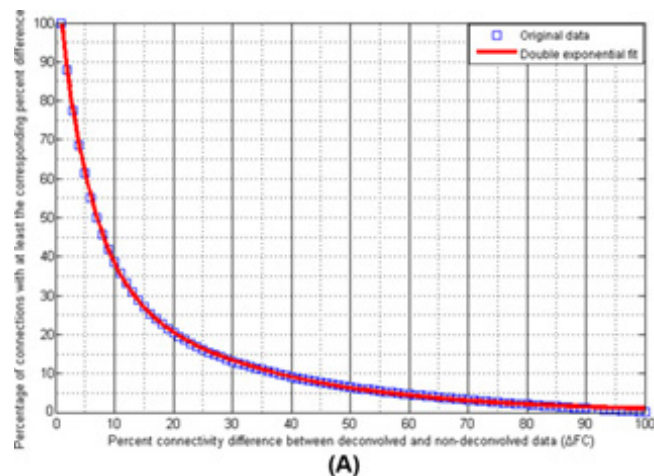
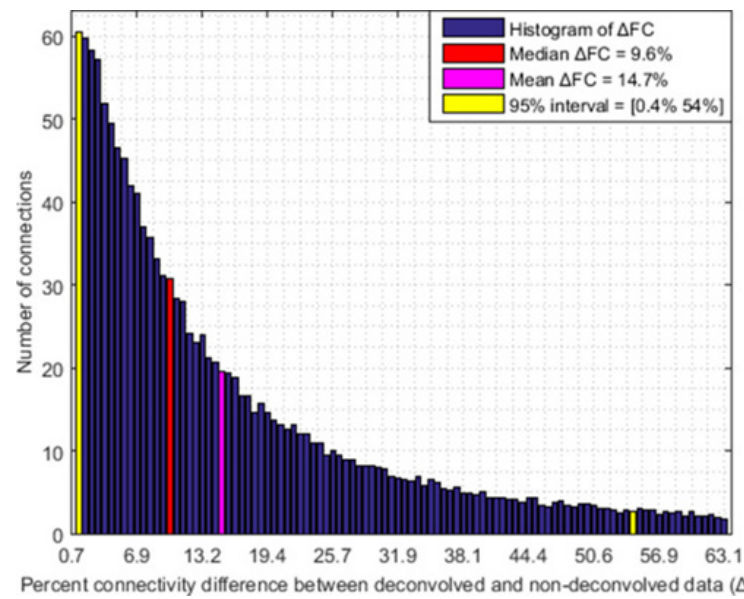
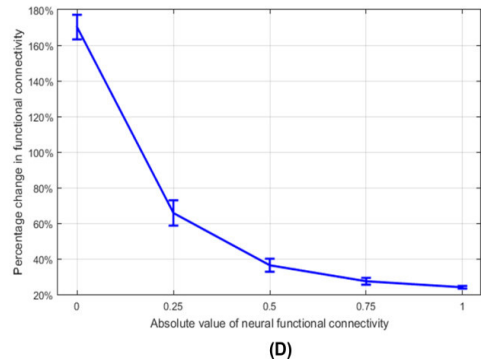
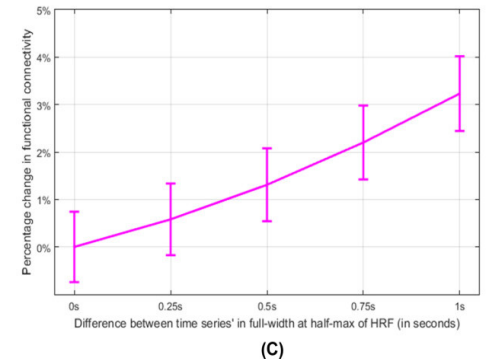
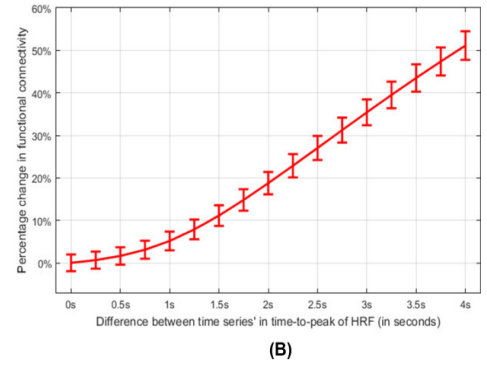
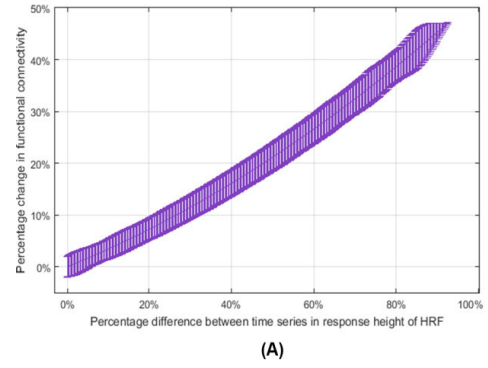
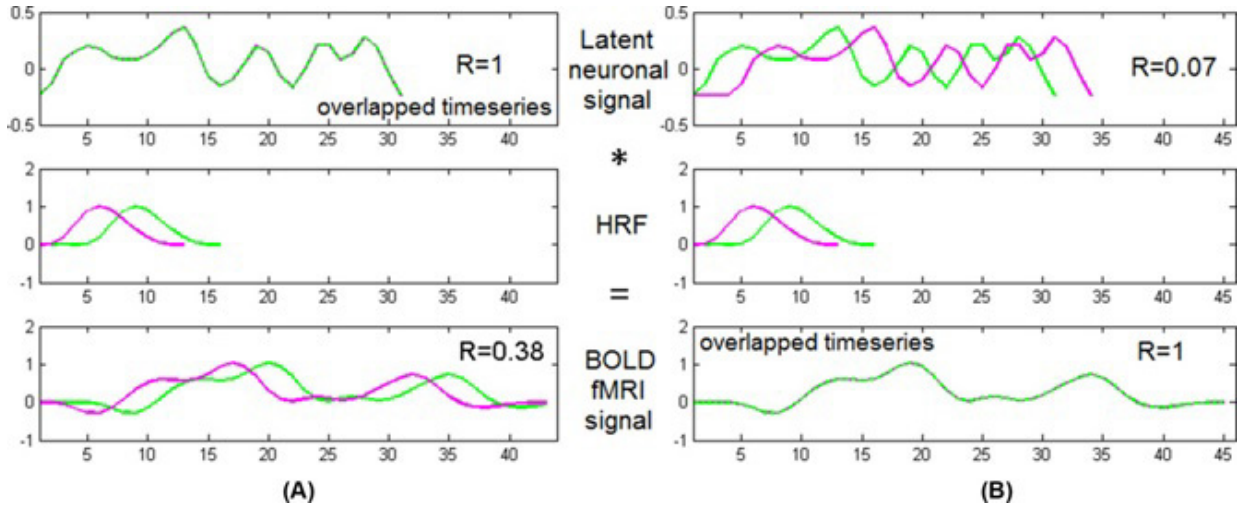
that represents the connections strength, and three synaptic parameters, i.e., the excitatory (NMDA) synapses (J_{NMDA}), the inhibitory (GABA) synapses (J_i), and the recurrent excitation (w_+). The neural activity simulated with TVB was fed into the Balloon-Windkessel hemodynamic model (Stephan et al., 2007) to reconstruct resting-state BOLD fMRI time-courses over 8 min length and compute simulated FC (simFC) and FCD (simFCD). Parameters were adjusted

data, respectively. Each subject's unique structural connectome constrained their personal brain simulation, where local dynamics were represented by the dynamic mean field (DMF) model (Eqs. 1–6; Deco et al., 2014a,b). The simulated local synaptic gating potentials were then fed through the Balloon-Windkessel hemodynamic model, producing simulated fMRI time series. Each subject's simulated fMRI time series was fitted to their functional

sampling frequency $f_s = 100$ Hz. The time step was variable to adapt the integration process and avoid numerical errors or instabilities and the neural mass field was filtered via the Balloon-Windkessel model (Friston et al., 2000) to emulate fMRI time series with repetition time TR set to 2000ms.



Effect of HRF variability on functional connectivity

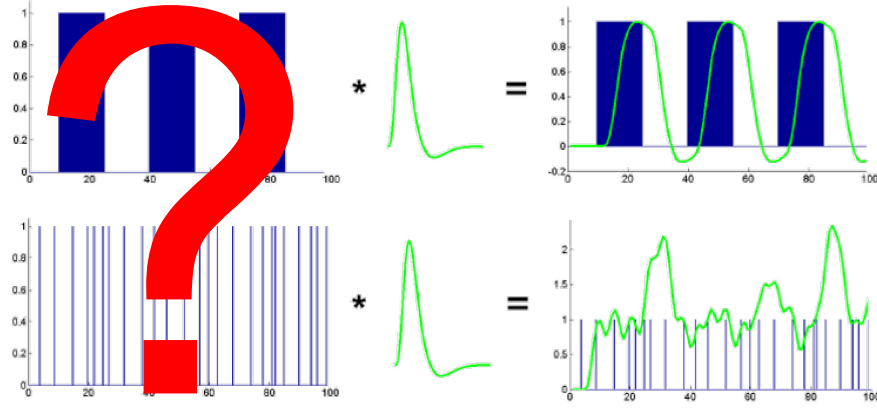




How to address these issues in whole-brain modelling?

- *Simulate all physiology and physiological interactions*
- Use a region- and subject-specific retrieved HRF
- Use physiological variables as covariates/regressors in statistical analyses
- Consider blood arrival time across brain regions

Estimate voxel- and subject-specific HRF from resting state BOLD

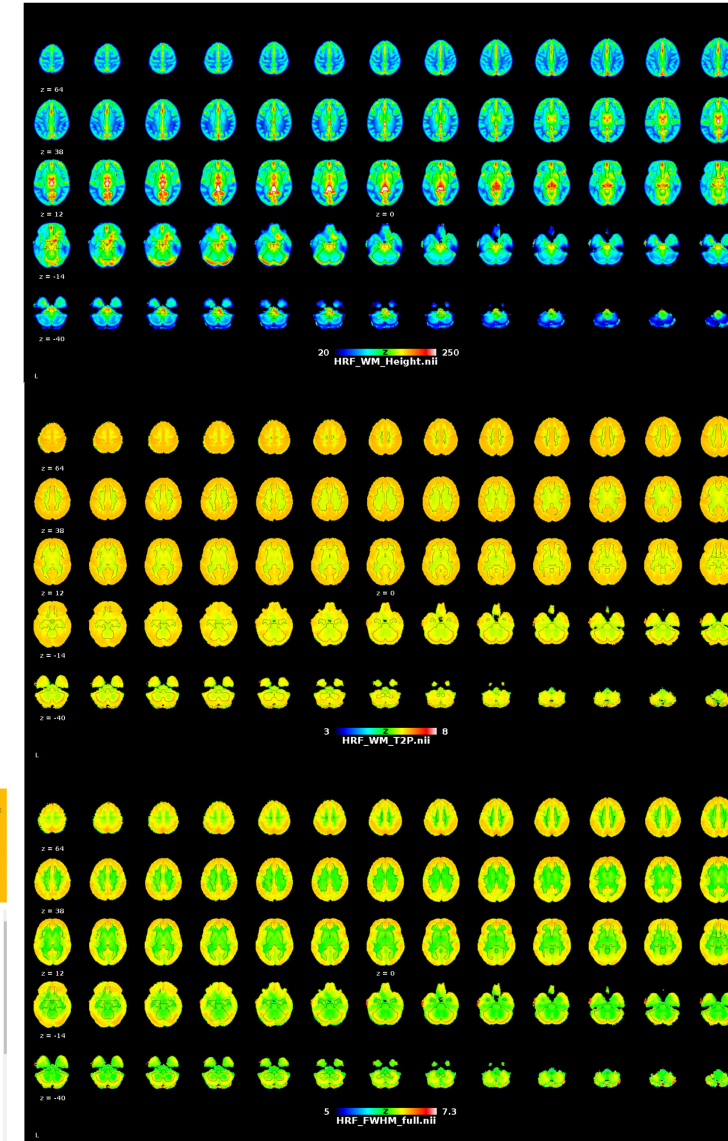
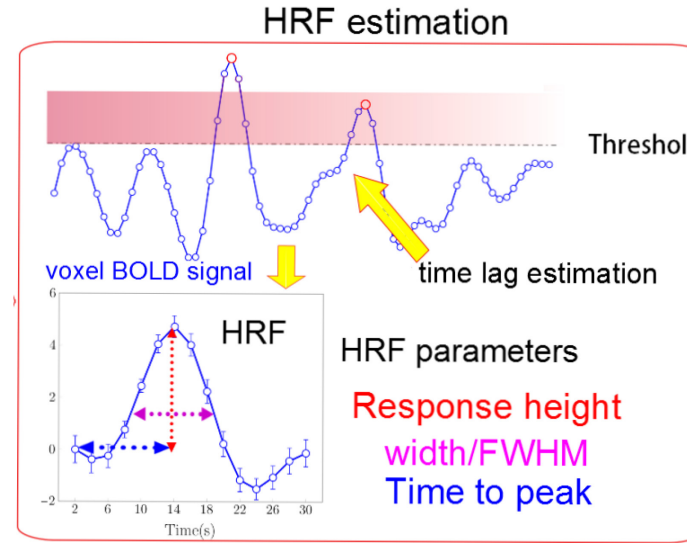


regression model for a single voxel (i):

$$y_i = \beta_0 + \beta_1 x_{1i} + \dots + \epsilon_i$$

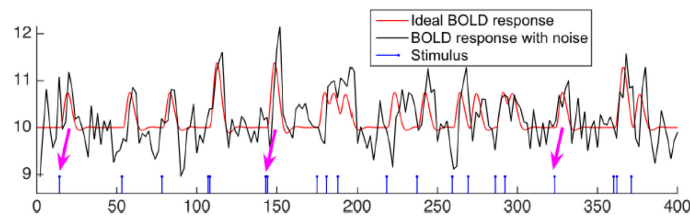
or in words:

(voxel activity) = baseline + $\beta_1 \times$ (timing information) + ... + error



From neuronal pseudo-events to BOLD peaks

we assume the peak of BOLD response lags behind the peak of spontaneous point process event is $L = \kappa \cdot TR/N$ seconds ($0 < L < PST$).



SOFTWARE

Resting state HRF estimation and deconvolution (v1.5.8)

Marinazzo, D.; Wu, G.-R.; Tandon, M.; Johri, A.; Colenbier, N.

Overview

Released: 2021-09-13
 License: The MIT license
 Copyright: 2021 Wu, G.-R., Marinazzo, D.
 Custodians: Marinazzo, D.
 Homepage: <http://bids-apps.neuroimaging.io/rsHRF/>
 Source code: <https://github.com/bids-apps/rsHRF/tree/1.5.8>

Features:

- parallel programming
- commandline interface
- graphical user interface
- desktop environment
- data processing

Application Category: application

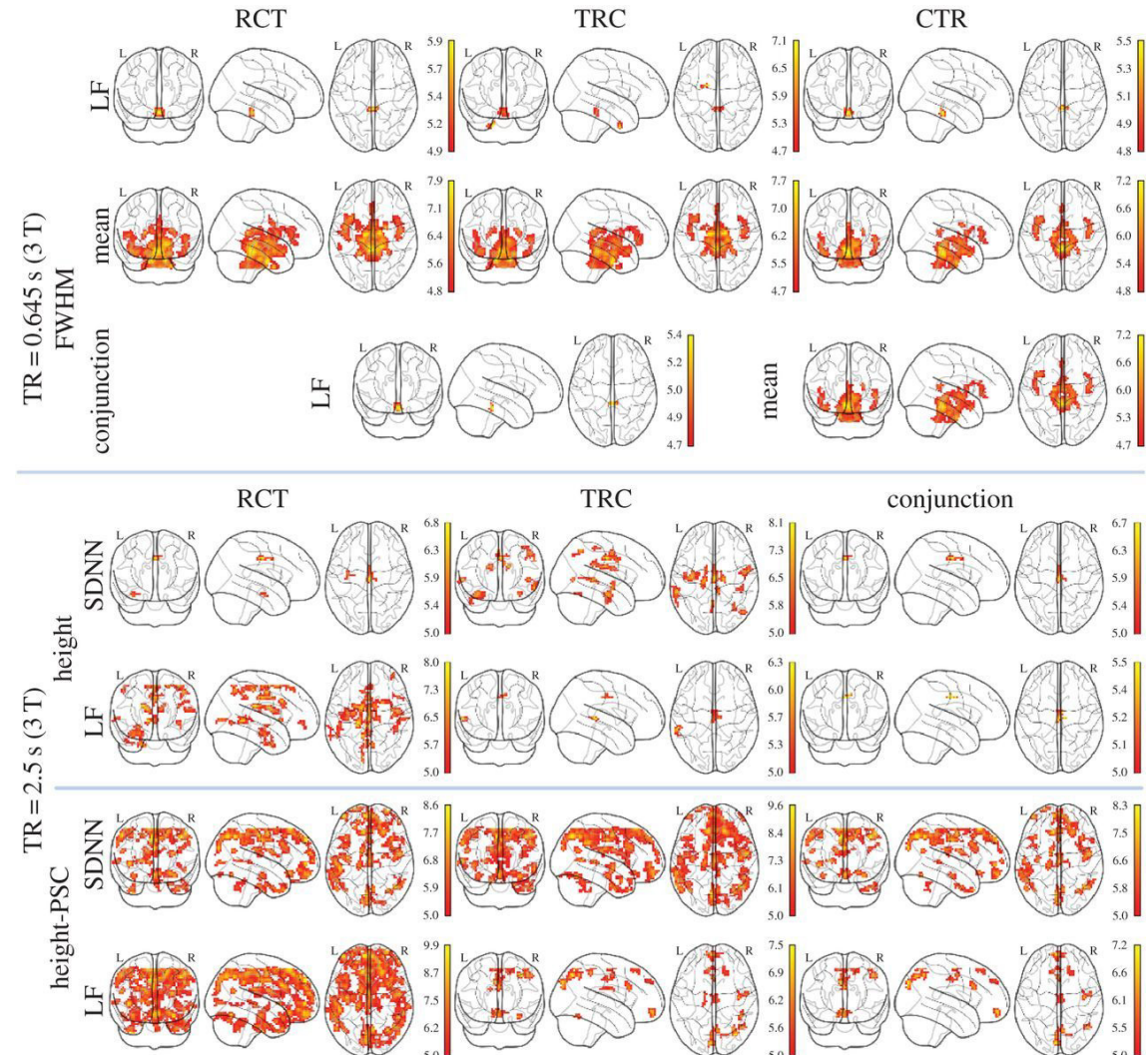
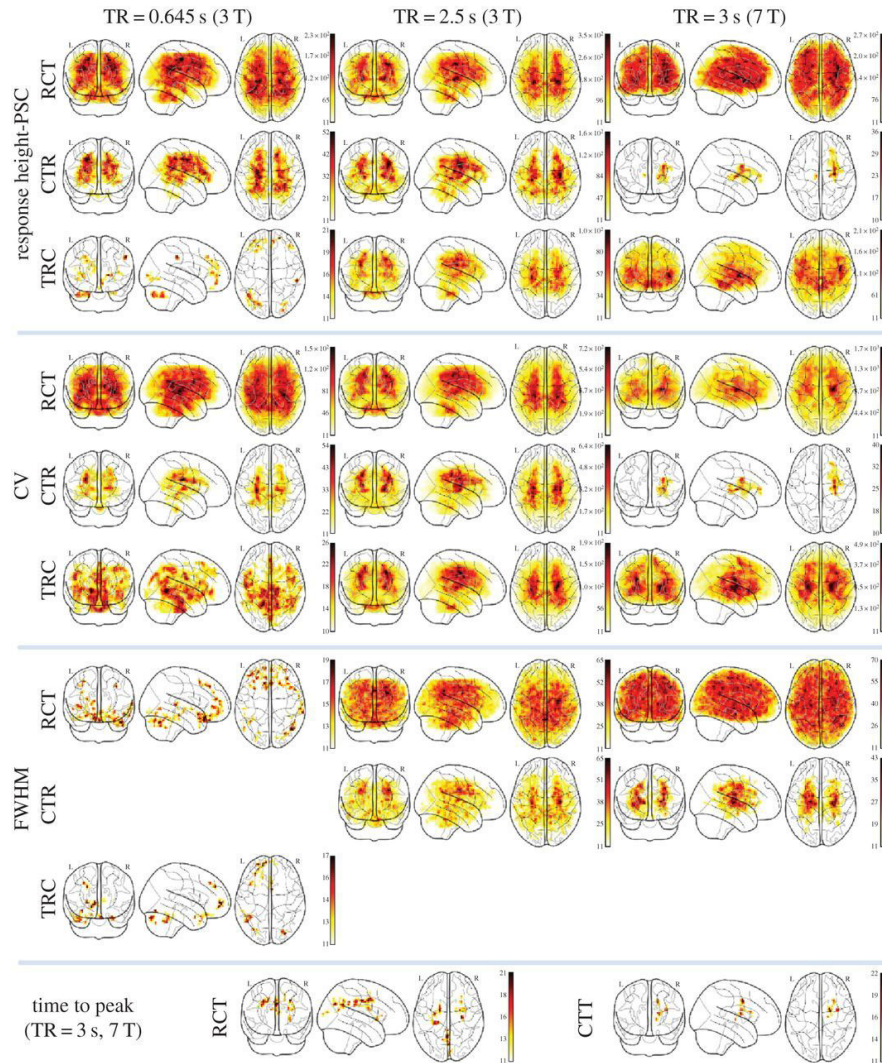
Operating System:

Please alert us at curation-support@ebrains.eu for errors or quality concerns regarding the dataset, so we can forward this information to the Data Custodian responsible.



Processing steps and order impact HRF estimation and correlation with heart rate variability

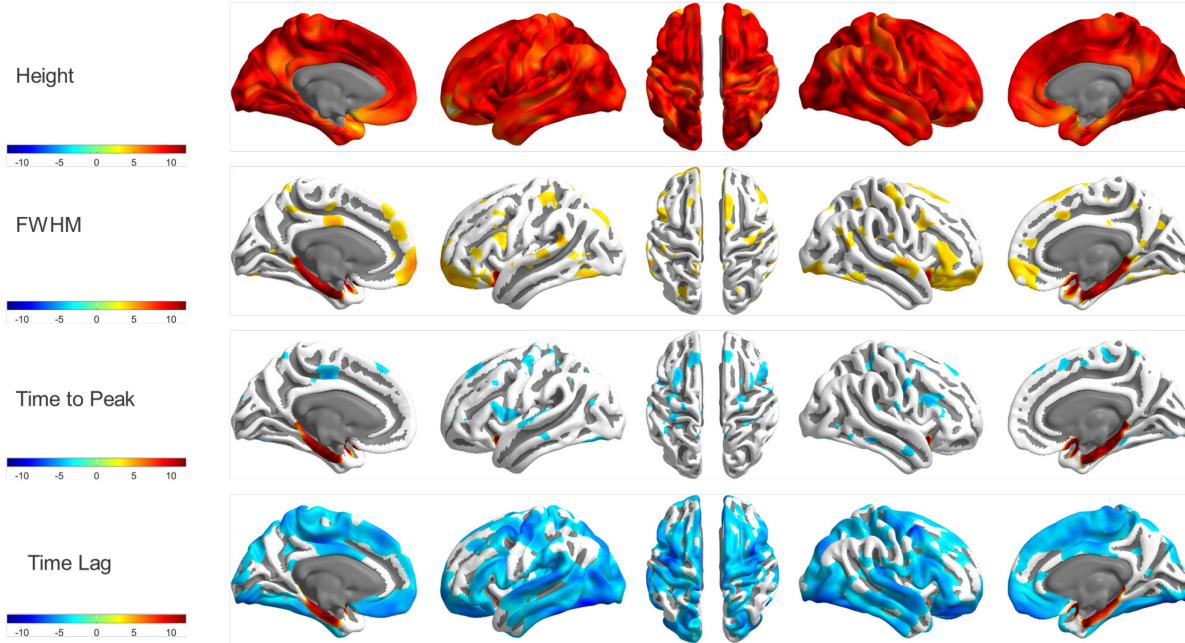
slice timing correction (T), registration (R), physiological correction (C), despiking (D), and normalization (N).



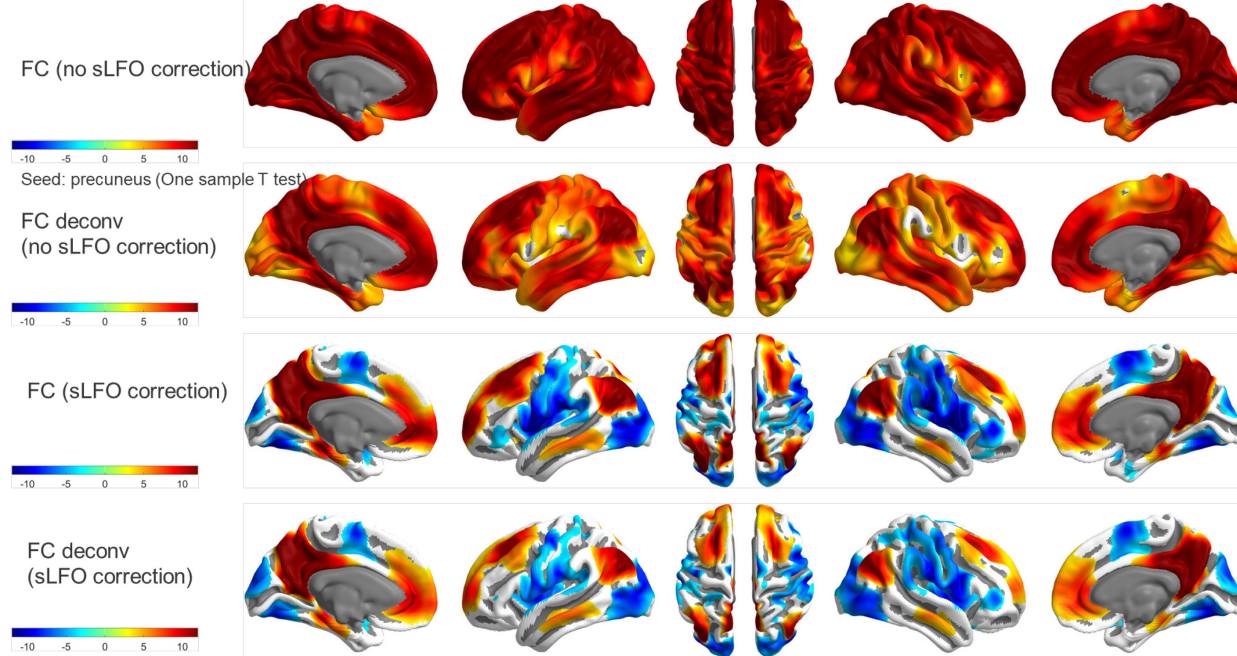


Rapidtide sLFO correction impacts HRF shape and FC

vertex wise $p < 0.001$ (Paired t-Test: no sLFO correction – sLFO correction)



vertex wise $p < 0.001$

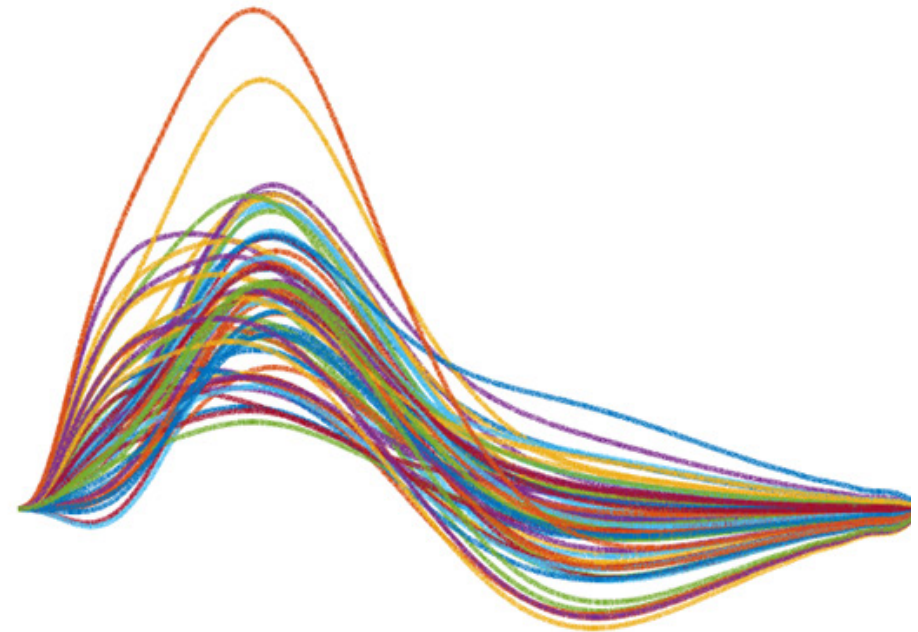
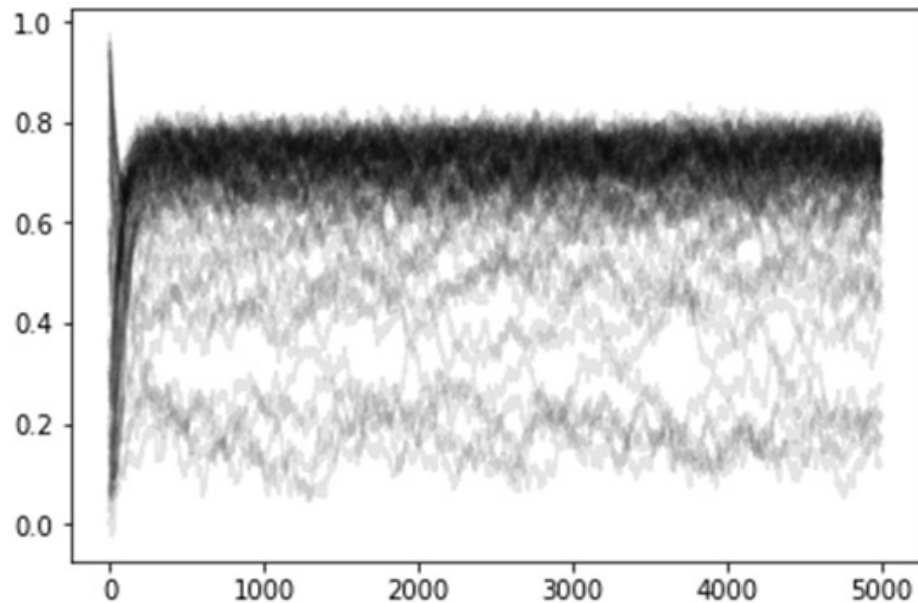




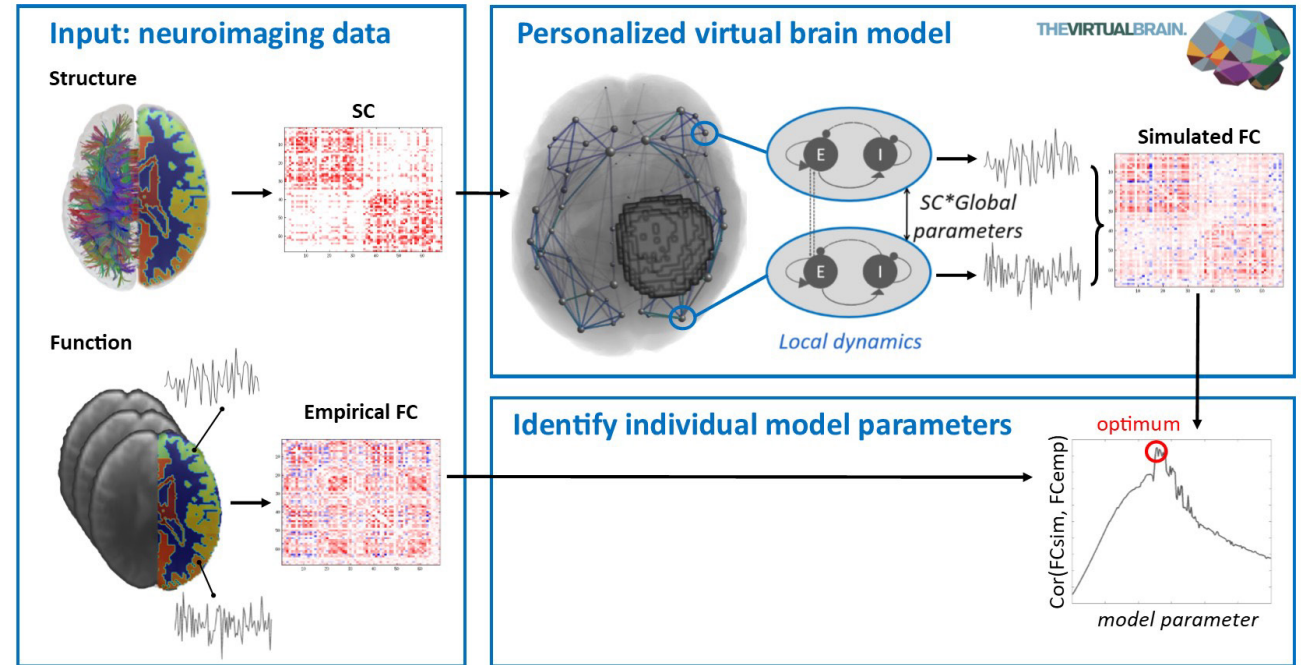
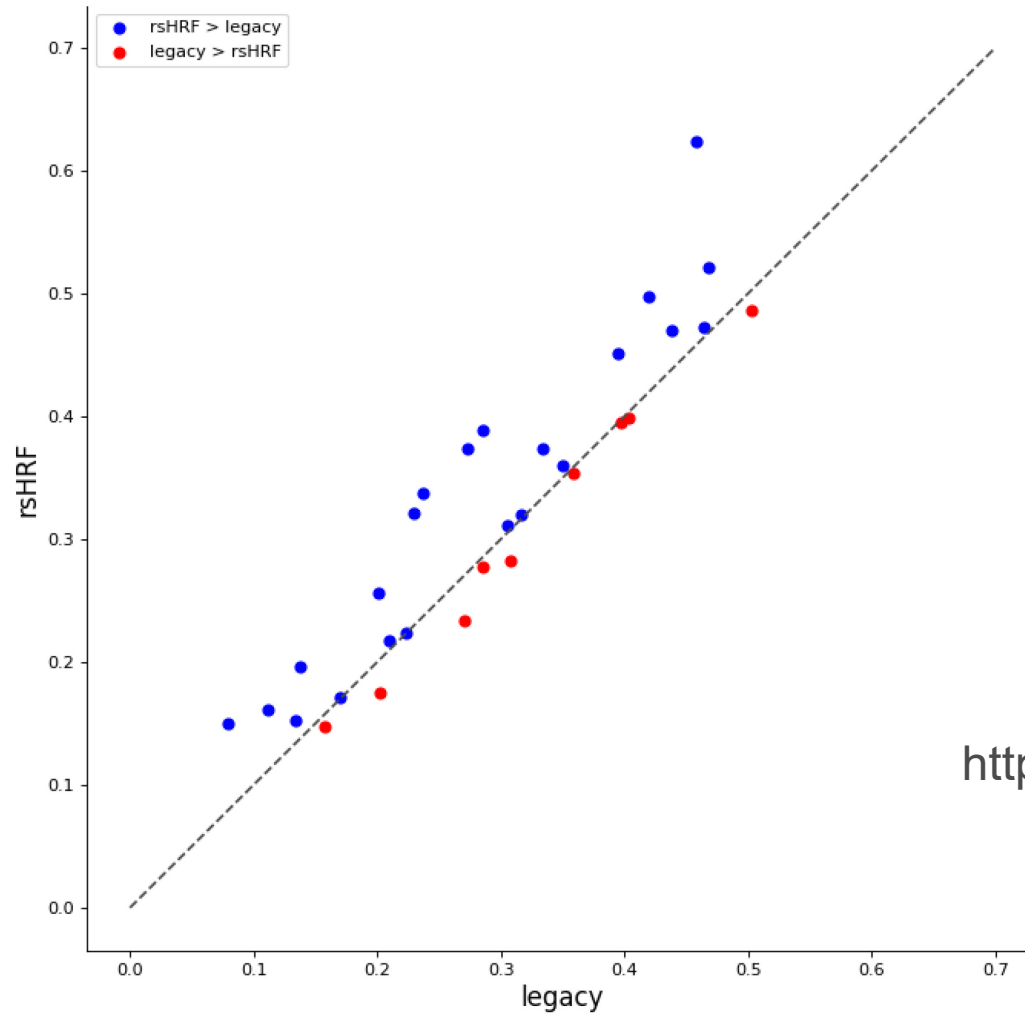
Region- and subject-specific HRF in TVB

For every value in the parameter space exploration

- Obtain the non-averaged (raw) synaptic gating activity with the Wong-Wang model
- ~~Legacy TVB: Map to BOLD through a Balloon-Windkessel model of the HRF~~
- Convolve with personalized region specific HRF, upsampled to model time scale
- Downsample to empirical BOLD
- Obtain simulated FC and compare to empirical FC



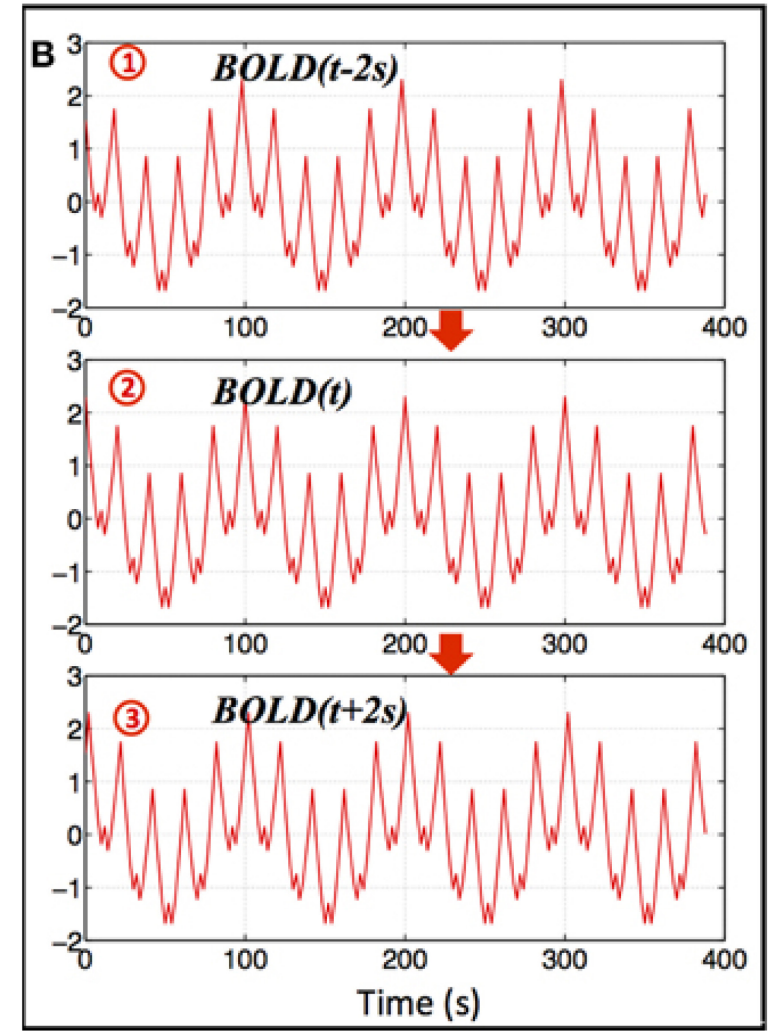
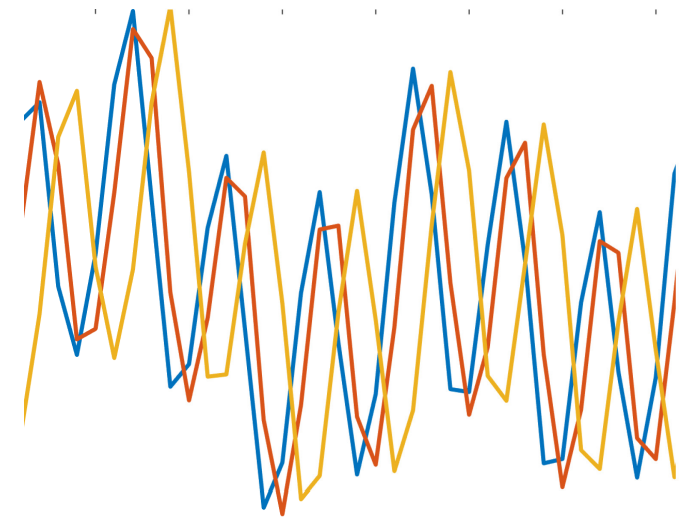
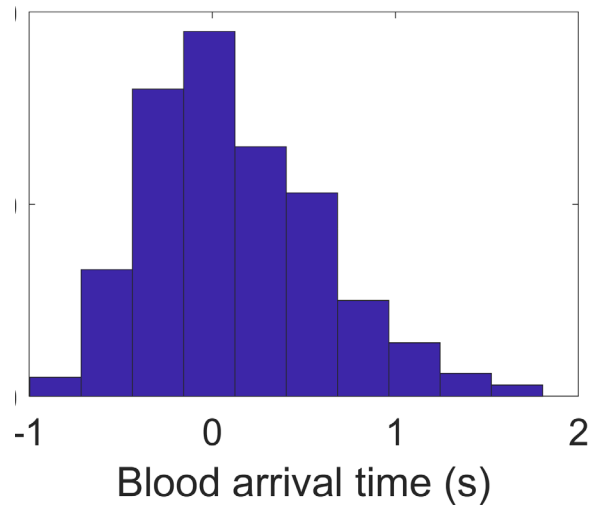
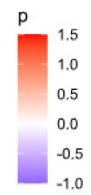
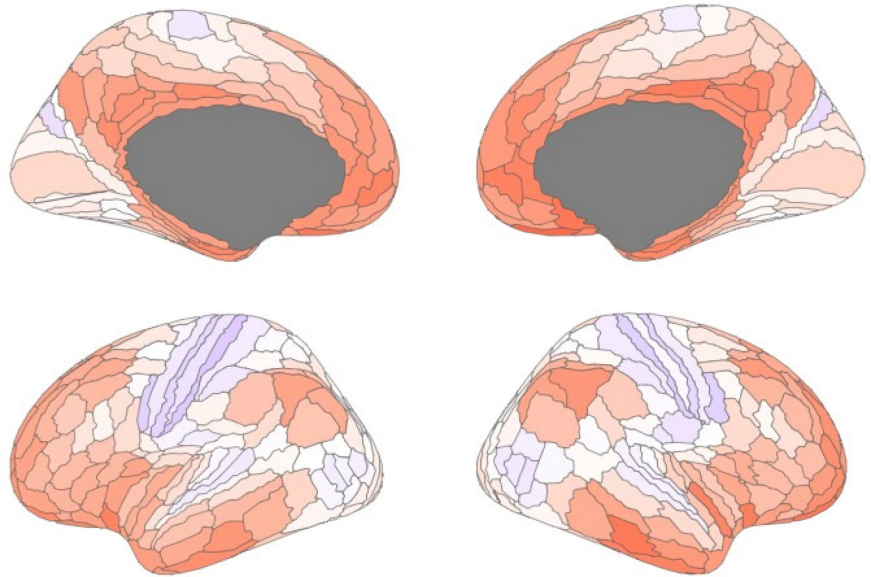
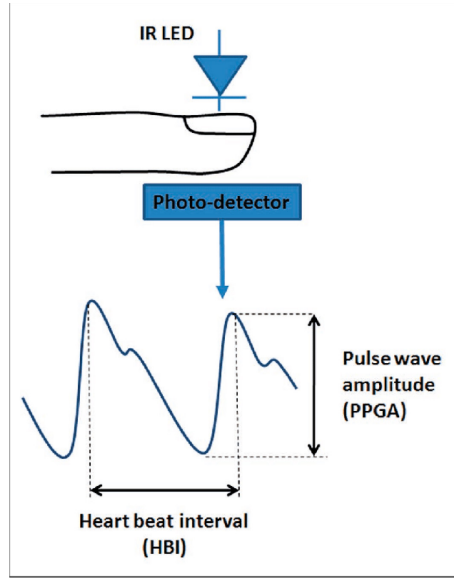
Personalized HRF increases similarity between empirical and simulated FC in a brain tumor fMRI+diffusion dataset



<https://github.com/AmoghJohri/TVB-Tests/blob/master/REPORT.md>

FC from simulation vs FC from delayed copies of the PPU signal (but it could be a completely fake signal FWIW)

Glasser : Blood arrival time (690 subjects)

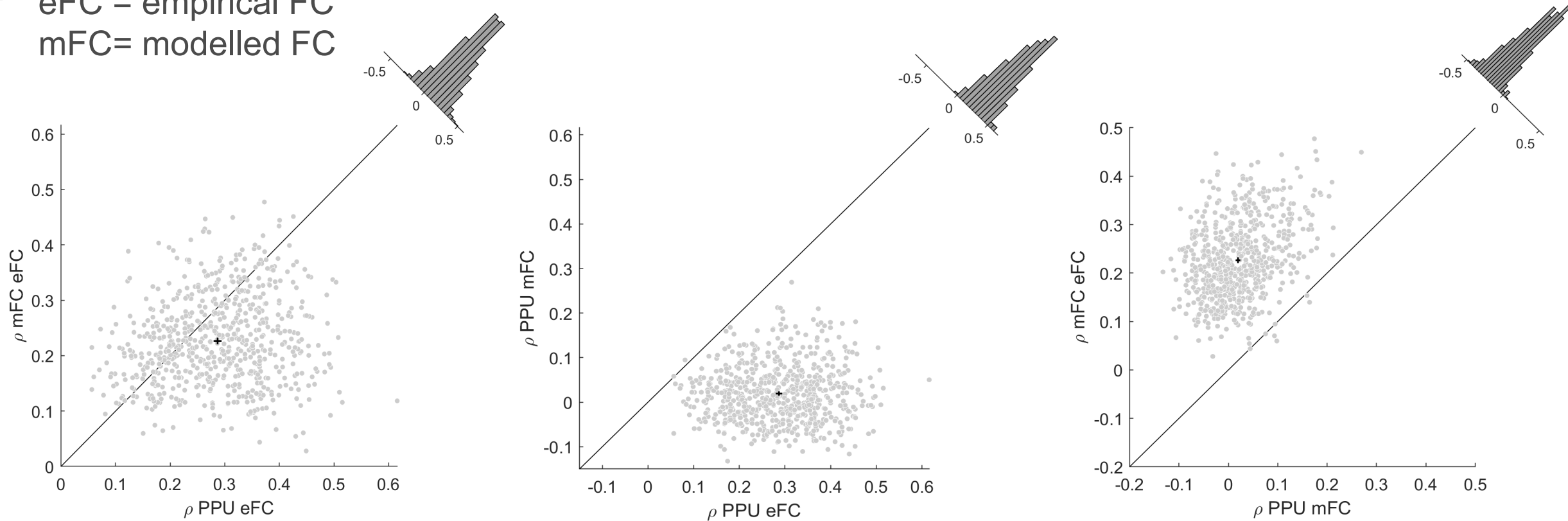


Correlations between differently obtained FC matrices

PPU = PP signal delayed according to BAT

eFC = empirical FC

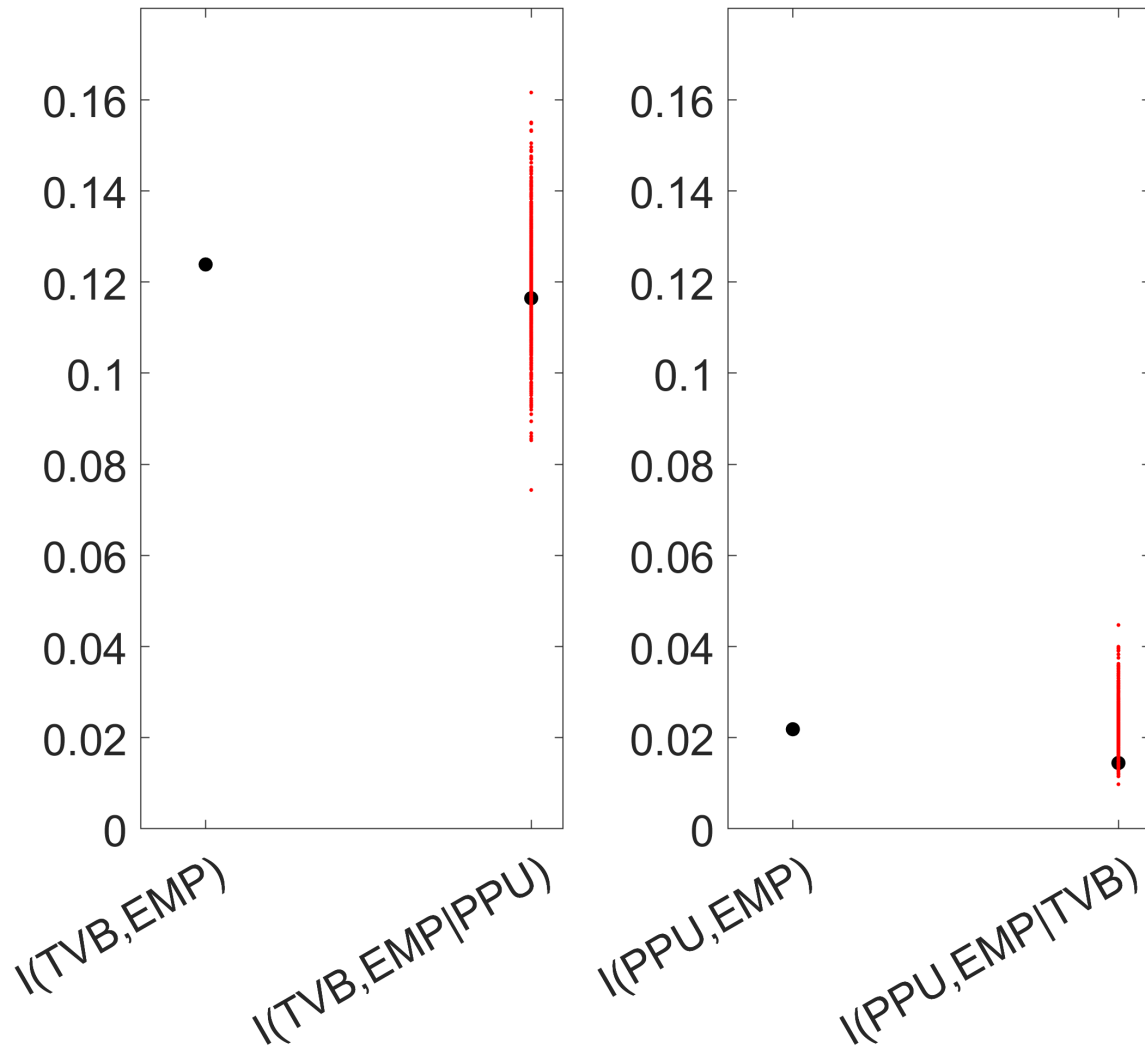
mFC = modelled FC



Delayed PP produces a FC which is slightly more correlated with the empirical FC wrt the legacy TVB model

PP-FC is unrelated to TVB model of FC

No significant interaction effects



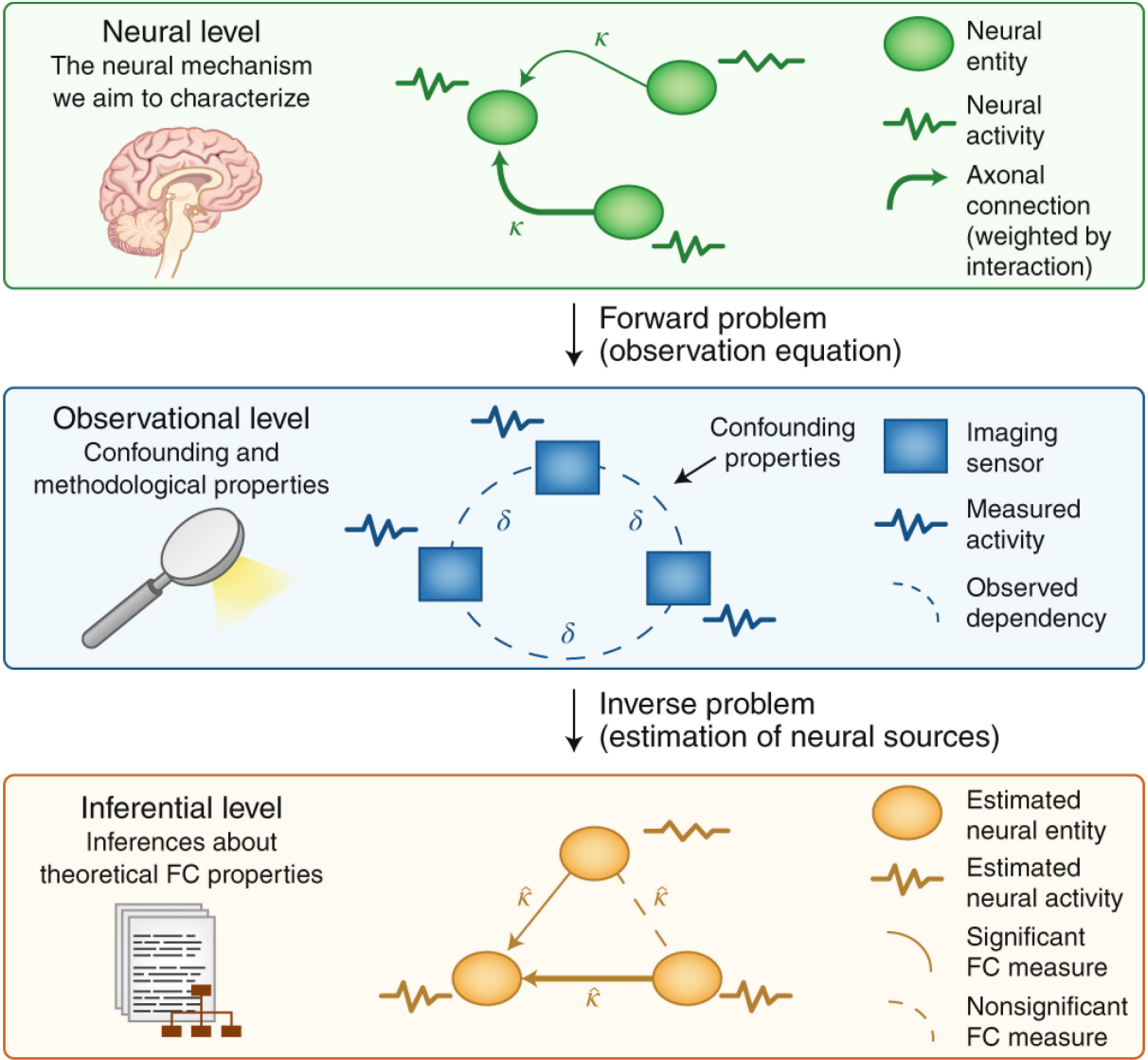
LETTER | OPEN ACCESS

Disentangling high-order effects in the transfer entropy

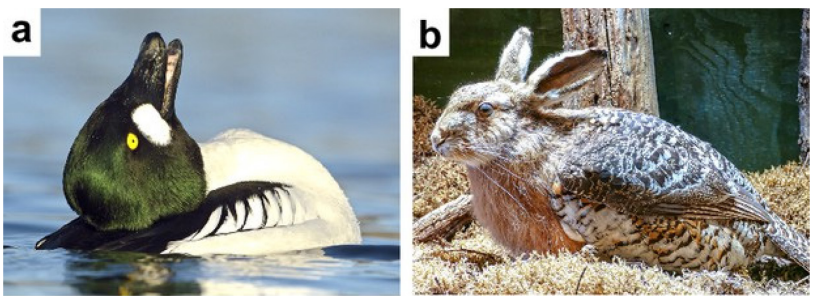
[Sebastiano Stramaglia](#) ¹, [Luca Faes](#) ², [Jesus M. Cortes](#) ^{3,4,5,6}, and [Daniele Marinazzo](#) ⁷



So what?



- Don't forget that we're working in a causal and inferential framework
- In a state space we cannot neglect transfer functions
- Physiology and hemodynamics are non-negligible data features.
- Blood arrival time produces a FC matrix which is as similar to the empirical FC as the one obtained by simulated BOLD data according to empirical SC and biologically inspired model.
- Is this super bad? No, this simply means that all these factors contribute, in a complementary way. And there definitely is a (causal) link between plumbing and neuronal activity in the brain. Still, modulations to FC are certainly also due to modulations in vascularization.
- Keep in mind which empirical FC connectivity matrix are you fitting: physiology and our clumsy strategies to handle it will definitely transform it.
- Maybe fit some data feature other than FC matrix.



Reid et al. 2019

Rubinov 2023



EBRAINS



EBRAINS 2.0

Thank you

daniele.marinazzo@ugent.be



Co-funded by
the European Union

EBRAINS 2.0 has received funding from the European Union's Research and Innovation Program Horizon Europe under Grant Agreement No. 101147319.