For more information, visit the website: https://smoia.github.io/cvr-meica-motion-removal

Improving breath-hold cerebrovascular reactivity mapping with multi-echo BOLD fMRI

Stefano Moia[1], Maite Termenon[1], Eneko Uruñuela[1], Rachael Stickland[2], Molly Bright[2 3], César Caballero-Gaudes[1]

1. Basque Center on Cognition, Brain and Language, Donostia, Spain, 2. Physical Therapy and Human Movement Sciences, Feinberg School of Medicine, Northwestern University, Chicago, IL, 3. Biomedical Engineering, McCormick School of Engineering, Northwestern University, Evanston, IL

Email: **s.moia@bcbl.eu**

To improve breath-hold induced CVR estimation, noisy ICs must be added to the regression model after orthogonalization to the signals of interests and other BOLD-related ICs.

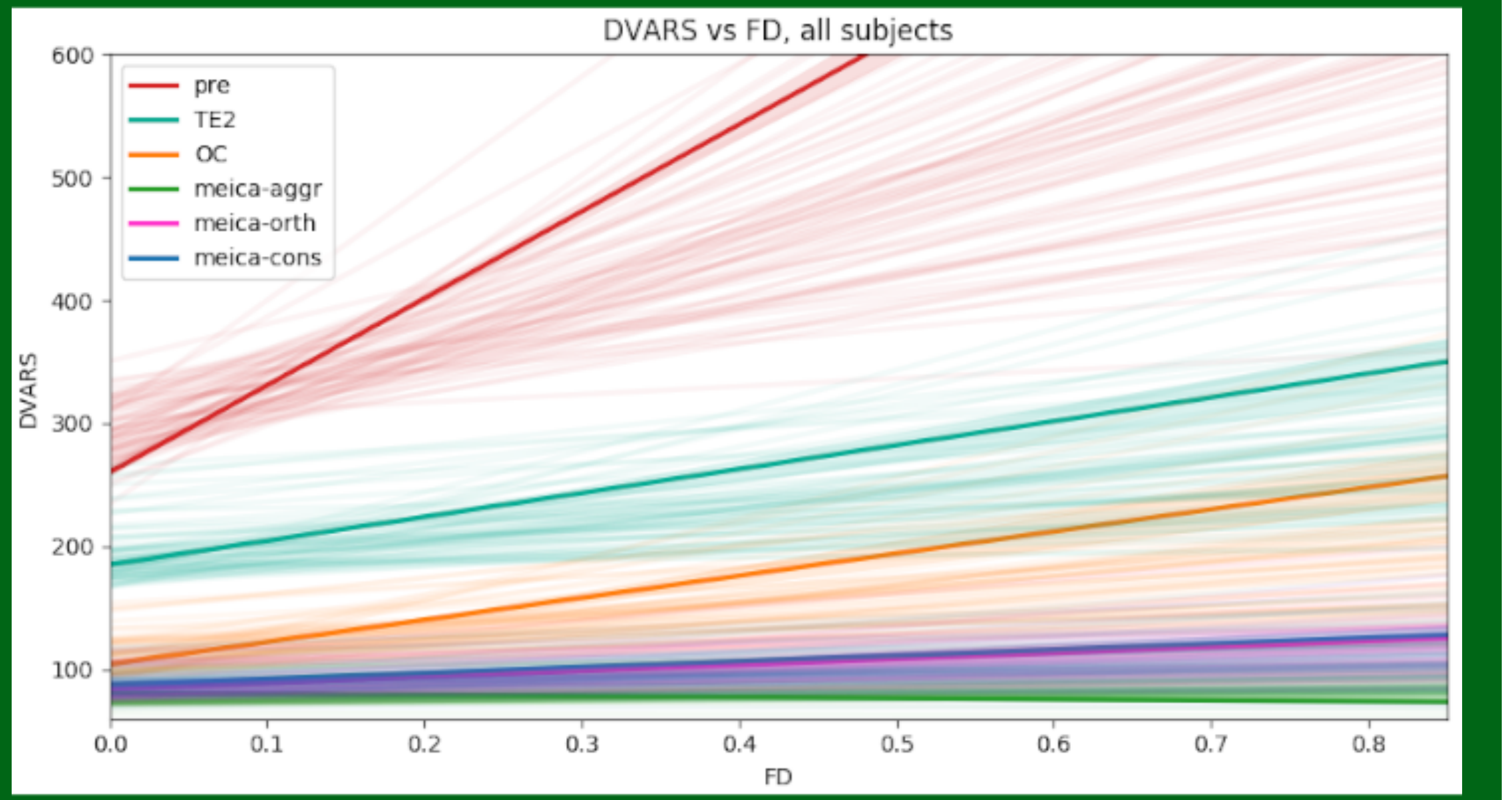

Figure 1. FD vs DVARS of the denoising pipelines for all the subjects. Each transparent line is the linear fit estimated at each session, while the solid line is the linear fit estimated with all the sessions together. Optimal combination of ME data improves motion denoising compared to single echo, ME-ICA is even more effective.

In both figures, ▪ pre: before denoising; ▪ TE2: single echo data; ▪ OC: optimally combined ME data; ▪ meica-aggr: OC data, denoising with "noise" ICs timeseries; ▪ meica-orth: OC data, denoising with "noise" ICs timeseries orthogonalised to CO2 trace; ▪ meica-cons: OC data, denoising with "noise" ICs timeseries orthogonalised to CO2 trace and "signal" ICs.

Background

- Cerebrovascular Reactivity (CVR) can be measured with BOLD functional MRI and induced with Breath-Hold (BH) [1], but BH movement artifacts are time-locked with the vasodilatory signal of interest, introducing bias on CVR estimates.
- Multi-Echo (ME) BOLD fMRI enhances the sensitivity to the BOLD effect by optimally combining the echoes, and enables denoising approaches that have demonstrated to remove non-BOLD (e.g. movement) artefacts effectively [2-5].
- Optimal Combination (OC) of ME time series improves the reliability and repeatability of BH induced CVR mapping [6].
- **Main aim**: Evaluate different denoising variants to clean ME-fMRI data acquired during a BH task, in order to improve Cerebrovascular Reactivity (CVR) estimation.

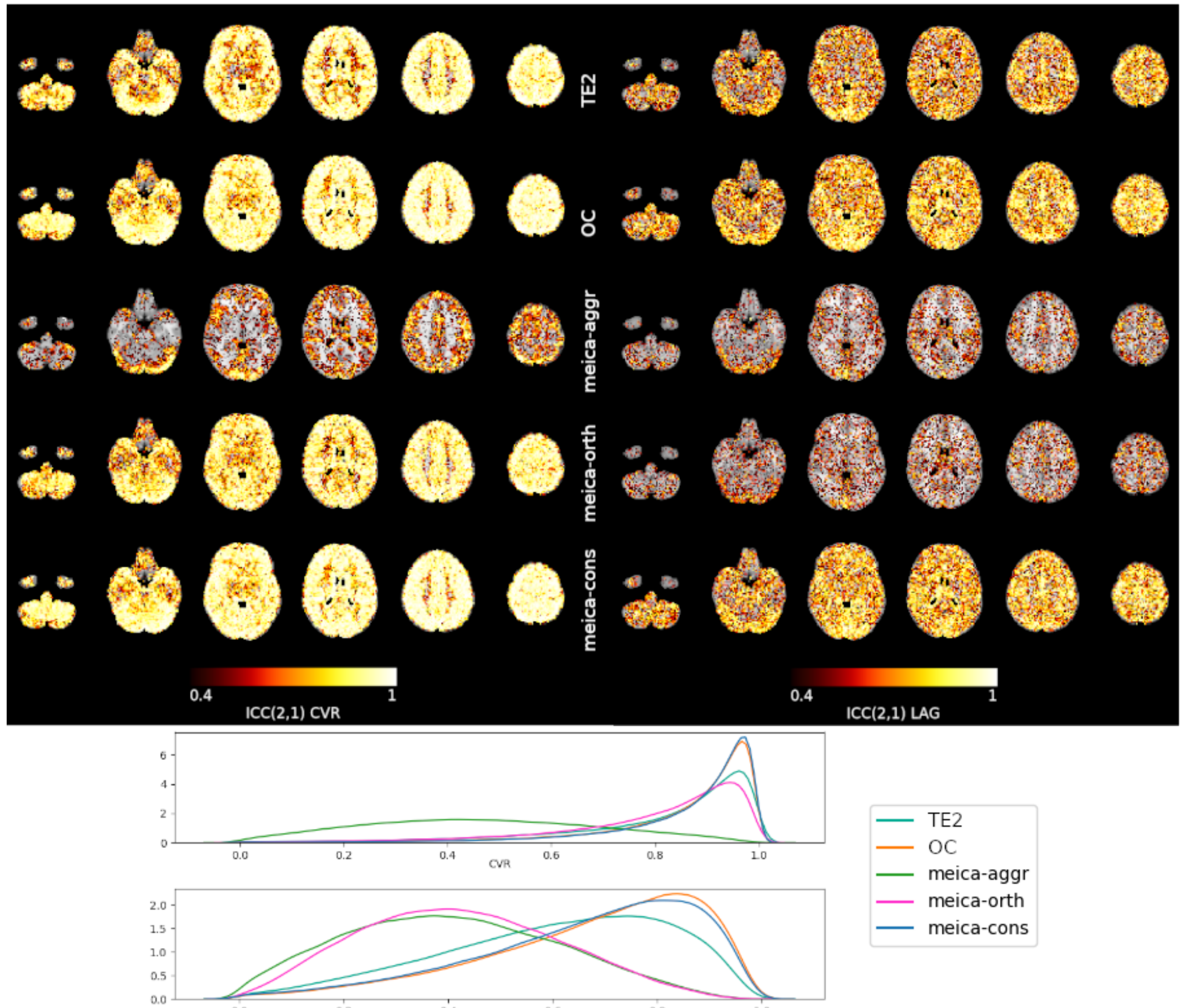

Figure 2. ICC(2,1) of the CVR and lag maps from each pipeline, and its spatial distribution.

Methods

- Seven healthy volunteers underwent 10 MRI sessions in a 3T Siemens PrismaFit scanner, spaced 1-week apart at the same time of day.
- A BH task adapted from [7] was administered at each session while collecting ME-fMRI data. CO_2 levels were measured using a nasal cannula with gas analyzer (ADInstruments) and BIOPAC MP150 system. A T1-w image was collected during each session. The parameters can be found in the website version.
- ME data were decomposed using ICA (tedana [8]), and the ICs were manually classified into "signal" and "noise" ICs (see website).
- In order to obtain CVR and lag maps, data preprocessing and analysis followed the steps described in [9] (OC). The same steps were applied to the second echo volume (echo-2). Additionally, the optimally combined data were analysed using a similar pipeline, but including in the GLM the nuisance regressors: (I) the "noise" ICs timeseries (meica-aggr), or (II) the "noise" ICs timeseries orthogonalised w.r.t. the CO_2 trace (meica-orth), or (III) the "noise" ICs timeseries orthogonalised w.r.t. the CO_2 trace and the "signal" ICs timeseries (meica-cons).
- FD and DVARS [10,11] were computed before realignment (pre) and on the optcom volume, after removal of the reconstructed volume from the nuisance regressors.
- ICC(2,1) was computed using 3dICC (AFNI) [12] on the CVR and lag maps, obtained from the fit of the CO_2 regressor in each of the data analysis pipelines.

Results

- Fig. 1: ME-fMRI with optcom and ME-ICA enhances denoising of motion-related effects (i.e. reduced FD-DVARS correlation), but the type of model with data-driven ICA nuisance regressors is key for denoising performance.
- Fig. 2: OC and meica-cons yield the most reliable CVR and lag maps, while meica-aggr is the least reliable since the effect of interest (CVR) is removed due to high collinearity of motion-related IC components.
- **Overall, meica-cons produces the most reliable CVR maps with improved motion denoising.** However, optimal combination of ME timeseries provides similar results, i.e. improved motion denoise and high reliability of CVR and lag estimation.

More results in the companion website.

Acknowledgements

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