Visit website: https://smoia.github.io/cvr-meica-motion-removal

In tasks with high motion collinearity, noisy ICs must be added to the regression model after orthogonalization to the signals of interests and other BOLD-related ICs.

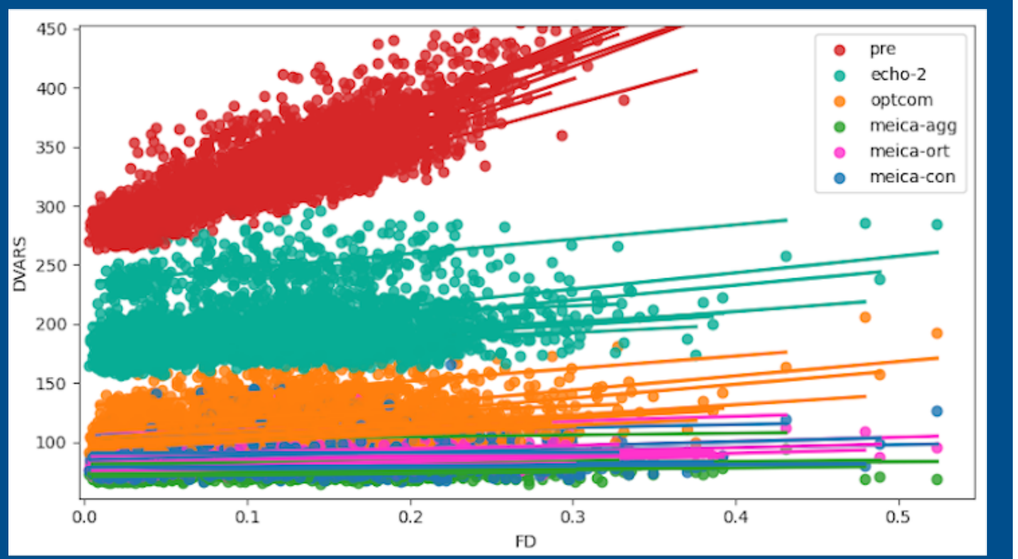

Fig. 1. FD vs DVARS of the denoising pipelines for a representative subject. Each dot is a timepoint, each line a session. Optimal Combination of ME data improves motion denoising compared to single echo, ME-ICA is even more effective.

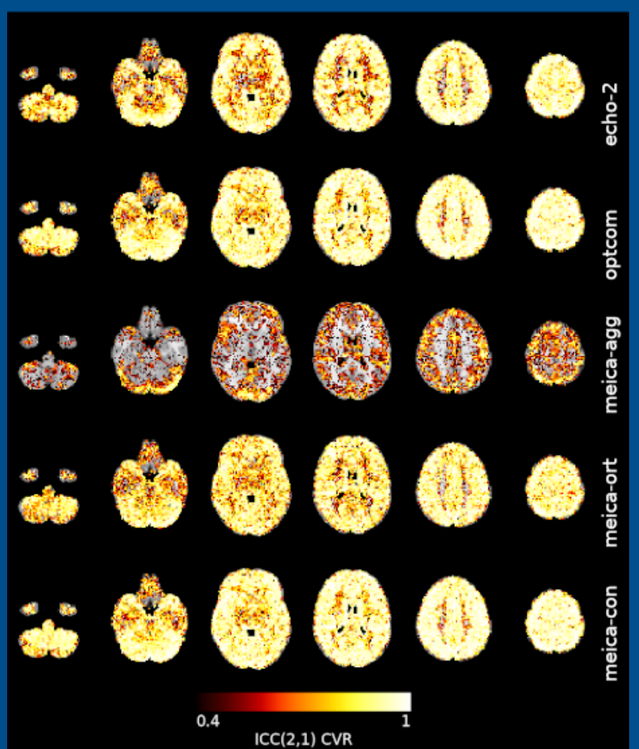

Figure 2. ICC(2,1) of the CVR maps from each pipeline.

In both figures:
- pre: before denoising
- echo-2: single echo data
- optcom: optimally combined (OC) ME data
- meica-agg: OC data, denoising with "noise" ICs timeseries
- meica-ort: OC data, denoising with "noise" ICs timeseries orthogonalised to CO2 trace
- meica-con: OC data, denoising with "noise" ICs timeseries orthogonalised to CO2 trace and "signal" ICs

ICA-based denoising strategies in highly motion correlated tasks with Multi-Echo BOLD fMRI

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Background

- Functional MRI presents different sources of noise.
- Removal of task-correlated noise, such as in a Breath-Holding (BH) paradigms, is particularly challenging due to the tradeoff between effective denoising and signal conservation [1].
- Independent component analysis (ICA) can also be employed to identify noise and use this information during nuisance regression [2].
- Multi-echo fMRI allows increasing the contrast to noise ratio of the signal by optimal combination of the echoes, and identifying non-BOLD sources from BOLD-related components via ME-ICA [3-5].
- **Main aim**: Evaluate different denoising variants to clean ME-fMRI data acquired during a BH task, in order to improve Cerebrovascular Reactivity (CVR) estimation.

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: Optcom and meica-con yield the most reliable CVR 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-con produces the most reliable CVR maps with improved motion denoising.

More results in the companion website.

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 [6] was administered at each session while collecting ME-fMRI data. CO2 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 [3]), and the ICs were manually classified into "signal" and "noise" ICs (see website).
- In order to obtain CVR maps, data preprocessing and analysis followed the steps described in [7] (optcom). 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 CO2 trace (meica-ort), or (III) the "noise" ICs timeseries orthogonalised w.r.t. the CO2 trace and the "signal" ICs timeseries (meica-con).
- FD and DVARS [8,9] 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) [10] on the CVR maps, obtained from the fit of the CO2 regressor in each of the data analysis pipelines.

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