Impact of confound removal strategies on functional connectivity generated from fMRIPrep preprocessed data

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fMRIPrep

version >= 1.4.0

```python
from nilearn.interfaces.fmriprep import load_confounds_strategy

confounds, sample_mask = load_confounds_strategy(
    fmri_filenames, denoise_strategy="simple"
)
```

ni learn

version 0.9.0

Pre-defined methods:

- ➔ `simple` [Fox et al., 2005]
- ➔ `scrubbing` [Power et al., 2012]
- ➔ `compcor` [Behzadi et al., 2007]
- ➔ `ica_aroma` [Pruim et al., 2015]

Selecting a denoising strategy is a key issue when processing fMRI data. We aims to provide a useful reference for ***fMRIPrep users*** *by systematically evaluating the impact of different confound regression strategies. An* ***API to interface with fMRIPrep confounds*** *is now in* ***nilearn****.*

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See full draft of the paper:
https://simexp.github.io/fmriprep-denoise-benchmark/

Background

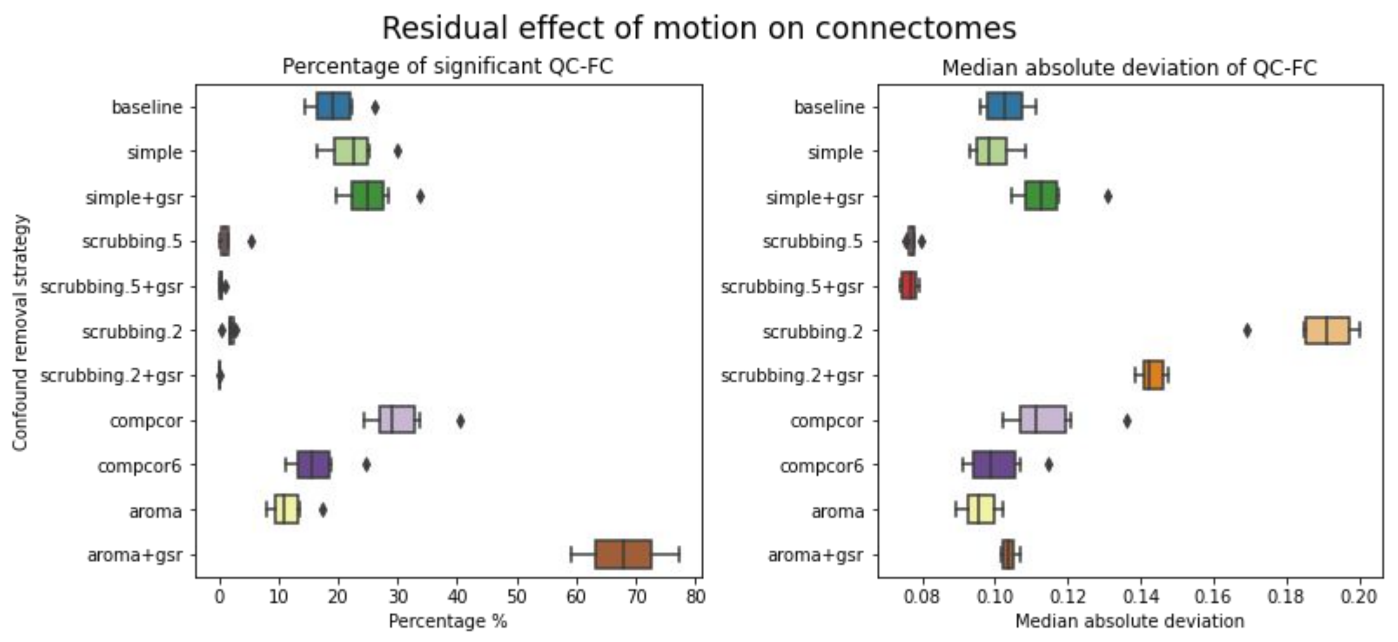
- fMRIPrep offers a wide range of confound regressors to choose from to denoise data.
- We used curated confound selection based on the literature and generate performance benchmarks.

Aim: replicate the finding in the confound literature on functional connectivity with fMRIPrep outputs.

Data processing

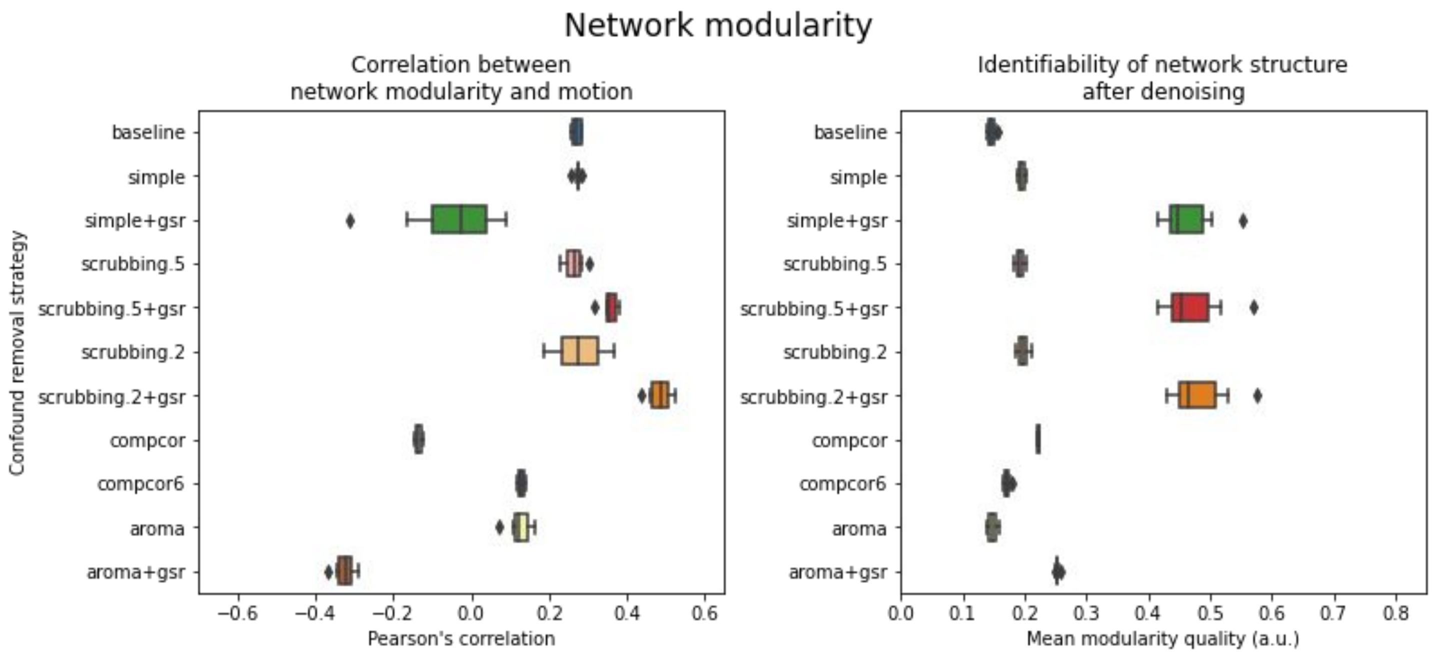
- Dataset: OpenNeuro ds000228 (33 adult / 122 kids)
- Preprocessing: `fMRIPrep LTS20.2.1`
- Confound removal strategies: see Table below.
- Atlases for time series extraction
  - MIST atlas [Urchs *et al.*, 2019] *Showing results using 64+ ROI **
- All post-fMRIPrep processes were built from `nilearn`.

For results on all atlases used in the benchmark, please see the paper.



Strategies with GSR display higher residual motion.

Lower median absolute deviation is better.

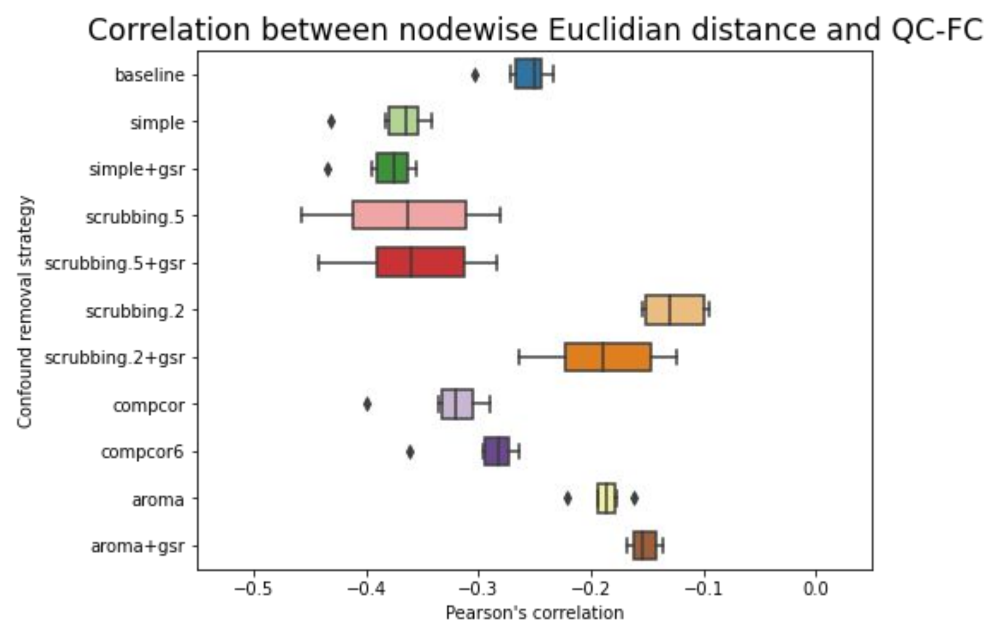


Close to zero is better performance.

All performs similarly except GSR.

Metrics

- **Quality control / functional connectivity (QC-FC [Power et al., 2015])**
  Correlation between functional connectivity and mean framewise displacement.
- **Distance-dependent effects of motion on connectivity [Power et al., 2012]**
  Correlation between node-node euclidean distance and QC-FC
- **Network modularity [Satterthwaite et al., 2012]**
  Detectable network in the functional connectome. If confound regression reduces modularity, the confound removes too much real signal.



Close to zero is better performance.

Results

- `scrubbing.*` and `aroma` performs better than the `baseline` in **QC-FC**.
- `scrubbing.2` and `aroma` performs better than the `baseline` in eliminating **distance dependency of motion**.
- `simple` performs close or better than `baseline` in **QC-FC** and **network modularity**.
- Use of `compcor` (include all components up to 50% variance) risks reintroducing noise.
- All results related to `gsr` did not perform as expected comparing to the past literatures [Ciric et al., 2017], [Parkes et al., 2018].

Discussions

- Code used for **global signal** extraction in fMRIPrep and signal cleaning in nilearn requires further investigation.
- `aroma` performs well but it is achieved at the cost of **decrease in degrees of freedom** and a higher computational cost. (See [Ciric et al., 2017] Figure 5).

Conclusions

- `simple` is sufficient general approach.
- `scrubbing.*` and `aroma` are valid choices, depending on the number of time points and the analysis methods.

Table. Confound strategies and related `load_confounds` options

strategy	image	high_pass	motion	wm_csf	global_signal	scrub	fd_thresh	compcor	n_compcor	ica_aroma	demean
baseline	desc-preproc_bold	True	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	True
simple	desc-preproc_bold	True	full	basic	N/A	N/A	N/A	N/A	N/A	N/A	True
simple+gsr	desc-preproc_bold	True	full	basic	basic	N/A	N/A	N/A	N/A	N/A	True
scrubbing.5	desc-preproc_bold	True	full	full	N/A	5	0.5	N/A	N/A	N/A	True
scrubbing.5+gsr	desc-preproc_bold	True	full	full	basic	5	0.5	N/A	N/A	N/A	True
scrubbing.2	desc-preproc_bold	True	full	full	N/A	5	0.2	N/A	N/A	N/A	True
scrubbing.2+gsr	desc-preproc_bold	True	full	full	basic	5	0.2	N/A	N/A	N/A	True
compcor	desc-preproc_bold	True	full	N/A	N/A	N/A	N/A	anat_combined	all	N/A	True
compcor6	desc-preproc_bold	True	full	N/A	N/A	N/A	N/A	anat_combined	6	N/A	True
aroma	desc-smoothAROMAnonaggr_bold	True	N/A	basic	N/A	N/A	N/A	N/A	N/A	full	True
aroma+gsr	desc-smoothAROMAnonaggr_bold	True	N/A	basic	basic	N/A	N/A	N/A	N/A	full	True

*Low number of parcels covering large region are more susceptible to motion with functional connectivity measures.