Framewise displacement (FD)

This measure indexes the movement of the head from one volume to the next, and is calculated as the sum of the absolute values of the differentiated realignment estimates (by backwards differences) at every timepoint (Power et al., 2012). FD for the first volume of a run is 0 by convention. The purpose of this measure is to index head movement, not to precisely calculate or model it.

Framewise displacement (FD) calculations

Differentiating head realignment parameters across frames yields a six dimensional timeseries that represents instantaneous head motion. To express instantaneous head motion as a scalar quantity we used the empirical formula, $FD_i = |\Delta d_{ix}| + |\Delta d_{iy}| + |\Delta d_{iz}| + |\Delta \alpha_i| + |\Delta \beta_i| + |\Delta \gamma_i|$, where $\Delta d_{ix} = d_{(i-1)x} - d_{ix}$, and similarly for the other rigid body parameters $[d_{ix} \ d_{iy} \ d_{iz} \ \alpha_i \ \beta_i \ \gamma_i]$. Rotational displacements were converted from degrees to millimeters by calculating displacement on the surface of a sphere of radius 50 mm, which is approximately the mean distance from the cerebral cortex to the center of the head.

- From Power et al. (2012): "After studying the plots of dozens of healthy adults, values of **0.5 mm for framewise displacement** and **0.5% ΔBOLD for DVARS** were chosen to represent values well above the norm found in still subjects."
- Fair et al. (2013) used an even more stringent FD cut-off of 0.2 mm and DVARS cut-off of 0.4%

Quality Check for fMRI data

Soyeon Kim, Mina Kwon





Quality Check with Cocoanlab pipeline!

Emotional Face Matching Task (EFAT) data

Steps

Behavior data

- Accuracy

Anatomical data

- Raw data

Functional data

- Outlier detection (spiking)
- Realignment (motion outliers)
- Coregistration

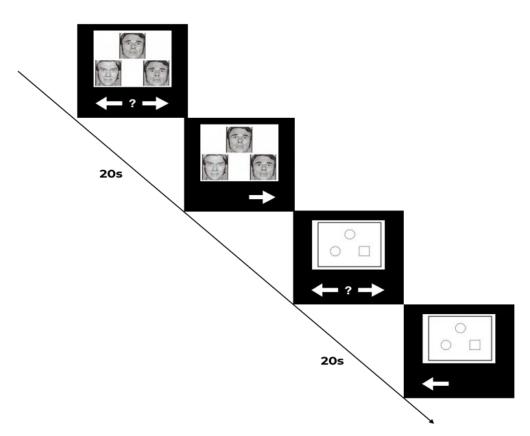


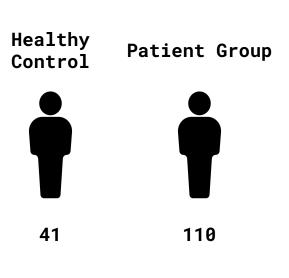
Tips

Making checklist!

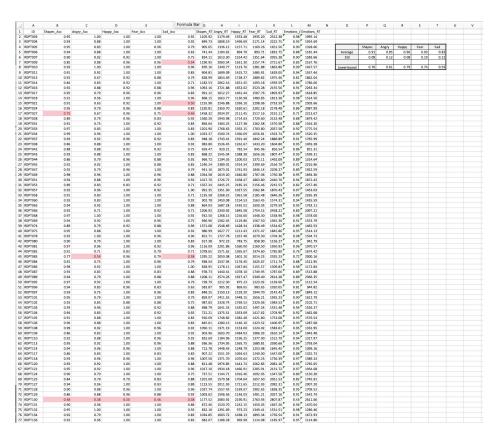
			Quality	Checkl	ist - Co	coanlal	<u> </u>				
Subject			- Guarry	Done?	Pass/Fail V	%Spikes ▼	Global SNR	FD	▼	Notes	~
RDPT003	behavior		accuracy	~							
	func	run-01	outlier detection (spiking)	~		1.64	299.36				
			realignment (motion outliers)	~				0.05			
			coregistration	•							
		run-02	outlier detection (spiking)	,		1.23	276.47				
			realignment (motion outliers)	,				0.06			
			coregistration	,							
RDPT004	behavior		accuracy	Ś							
	func	run-01	outlier detection (spiking)	,		2.05	567.39				
			realignment (motion outliers)	•				0.04			
			coregistration	,							
		run-02	outlier detection (spiking)	·		3.69	356.87				
			realignment (motion outliers)	~				0.05			
			coregistration	~							
RDPT005	behavior		accuracy	~							
	func	run-01	outlier detection (spiking)	,		4.92	400.38				
			realignment (motion outliers)	,				0.07			
			coregistration	,							
		run-02	outlier detection (spiking)	,		4.51	277.81				
			realignment (motion outliers)	~				0.09			
			coregistration	,							
RDPT006	behavior		accuracy	>							
	func	run-01	outlier detection (spiking)								
			realignment (motion outliers)	>				0.07			
			coregistration								
		run-02	outlier detection (spiking)								
			realignment (motion outliers)	>	×			0.25			
			coregistration								
RDPT007	behavior		accuracy	•							
	func	run-01	outlier detection (spiking)	~		5.33	432.92				
			realignment (motion outliers)	,				0.09			
			coregistration	Ÿ							
		run-02	outlier detection (spiking)	,		3.28	363.77				
			realignment (motion outliers)	,				0.09			

EFAT data





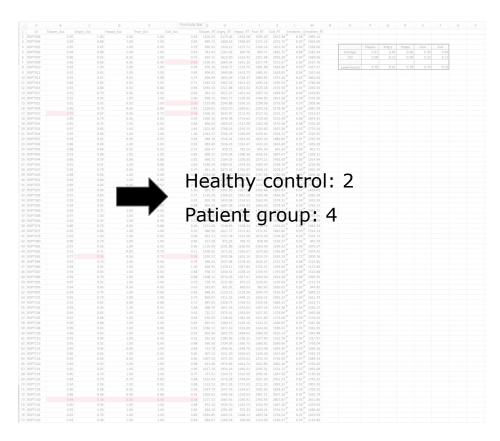
Behavior data



accuracy

- lower than Mean 2*SD
- 3 or more

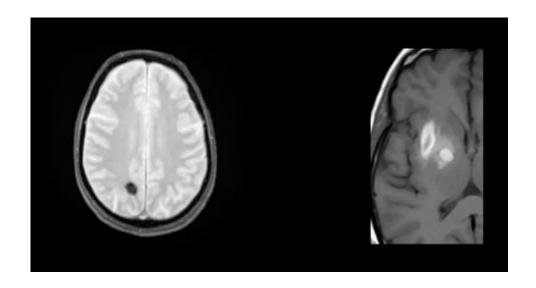
Behavior data



accuracy

- lower than Mean 2*SD
- 3 or more

Artifacts in raw images



→ coregistration

Steps



Functional images OC (outlier detection) b1: Make directories b2: implicit mask and mean images

· create an implicit mask image

· save mean images and SBRef (before preproc) as png in gc directories

b3: outlier detection

PART 2 (b1-b3)

· outlier detection based on 1) mahalanobis distance across global mean for slices and spatial STD for slices, as in scn session spike id.m 2) root-mean-square successive differences between images

PART 3 (b4-b6)

Functional images

Slice timing, motion, distortion correction

b4: slice timing correction

- · It works with multi-band sequence
- · It reads the actual acquisition timing from dicom header

b5: motion correction (realignment)

- It uses the first functional image or SBRef (you can choose) as a reference.
- It saves 6 movement parameters for each run

b6: distortion correction (using FSL's topup)

PART 4 (b7-b8)

Structural and functional images Coregistration, normalization, smoothing

b7: coregistration

· coregistration between T1 and mean functional images or SBRef image (you can choose).

b8: normalization

- segmentation of the coregistered T1 image using SPM12's tissue probability map (TPM.nii)
- · warping segmented (and coregistered) T1 image to MNI template
- · applying the warping parameter to the functional images

PART 5 (b9-b10)

Functional images Smoothing and ICA-AROMA

b9: smoothing

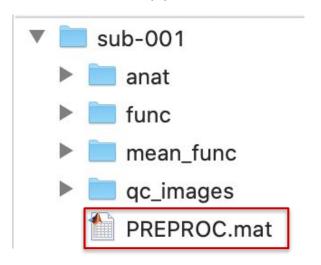
· smoothing functional images with the FWHM 5 mm smoothing kernel.

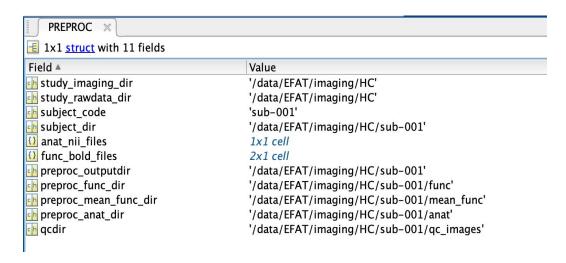
b10: ICA-AROMA

- · A data-driven method to identify and remove motion-related independent components from functional MRI data.
- · https://github.com/rhr-pruim/ICA-AROMA

Steps

```
%% PART3:
% B-1. Preproc directories
SY_b1_preproc_directories(subject_code, study_imaging_dir, run_n, func_tasks); %'forced_save', 'no_save'
```





Steps

PART 2 (b1-b3)

Functional images QC (outlier detection)

b1: Make directories

b2: implicit mask and mean images

- create an implicit mask image
- save mean images and SBRef (before preproc) as png in gc directories

b3: outlier detection

 outlier detection based on 1) mahalanobis distance across global mean for slices and spatial STD for slices, as in scn_session_spike_id.m 2) root-mean-square successive differences between images

PART 3 (b4-b6)

Functional images

Slice timing, motion, distortion correction

b4: slice timing correction

- · It works with multi-band sequence
- It reads the actual acquisition timing from dicom header.

b5: motion correction (realignment)

- It uses the first functional image or SBRef (you can choose) as a reference.
- · It saves 6 movement parameters for each run

b6: distortion correction (using FSL's topup)

PART 4 (b7-b8)

Structural and functional images

Coregistration, normalization, smoothing

b7: coregistration

 coregistration between T1 and mean functional images or SBRef image (you can choose).

b8: normalization

- segmentation of the coregistered T1 image using SPM12's tissue probability map (TPM.nii)
- warping segmented (and coregistered) T1 image to MNI template
- applying the warping parameter to the functional images

PART 5 (b9-b10)

Functional images Smoothing and ICA-AROMA

b9: smoothing

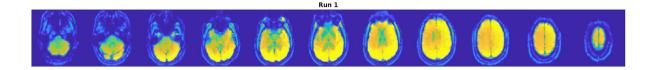
smoothing functional images with the FWHM 5 mm smoothing kernel.

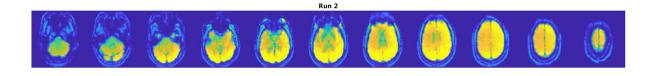
b10: ICA-AROMA

- A data-driven method to identify and remove motion-related independent components from functional MRI data.
- · https://github.com/rhr-pruim/ICA-AROMA

Steps

```
%% B-2. Implicit mask and save means
% This step creates an implicit mask image (implicit_mask.nii) and also
% saves mean images and SBRef as png in qc directories
humanfmri_b2_functional_implicitmask_savemean(preproc_subject_dir);
```





Steps

PART 1 (a1-a4) — DICOM to NIFTI in a NDS format a1s, key sectory a2: Standard a3 (c) a1 rieldma

PART 2 (b1-b3)

Functional images QC (outlier detection)

b1: Make directories

b2: implicit mask and mean images

- · create an implicit mask image
- save mean images and SBRef (before preproc) as png in qc directories

b3: outlier detection

 outlier detection based on 1) mahalanobis distance across global mean for slices and spatial STD for slices, as in scn_session_spike_id.m 2) root-mean-square successive differences between images

PART 3 (b4-b6)

Functional images

Slice timing, motion, distortion correction

b4: slice timing correction

- · It works with multi-band sequence
- It reads the actual acquisition timing from dicom header.

b5: motion correction (realignment)

- It uses the first functional image or SBRef (you can choose) as a reference.
- · It saves 6 movement parameters for each run

b6: distortion correction (using FSL's topup)

PART 4 (b7-b8)

Structural and functional images

Coregistration, normalization, smoothing

b7: coregistration

 coregistration between T1 and mean functional images or SBRef image (you can choose).

b8: normalization

- segmentation of the coregistered T1 image using SPM12's tissue probability map (TPM.nii)
- warping segmented (and coregistered) T1 image to MNI template
- applying the warping parameter to the functional images

PART 5 (b9-b10)

Functional images Smoothing and ICA-AROMA

b9: smoothing

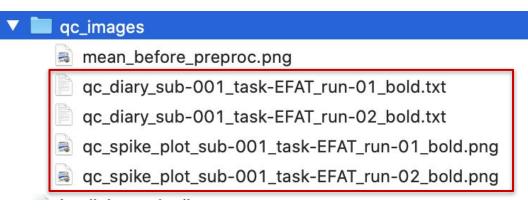
smoothing functional images with the FWHM 5 mm smoothing kernel.

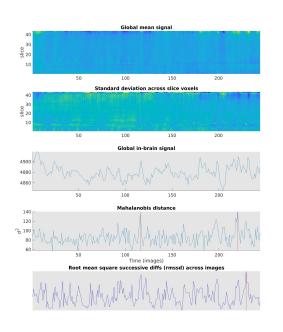
b10: ICA-AROMA

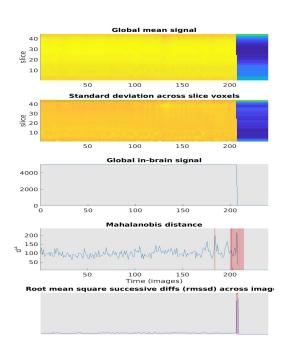
- A data-driven method to identify and remove motion-related independent components from functional MRI data.
- · https://github.com/rhr-pruim/ICA-AROMA

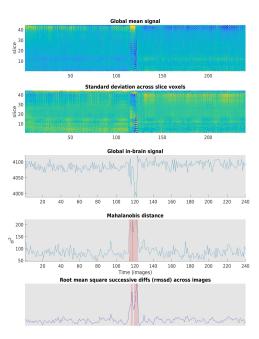
```
%% B-3. Spike identification

% Detecting outliers based on mahalanobis distance across global mean for
% slices and spatial STD for slices, and also RMSSD (root-mean-squared
% successive differences) between images
humanfmri_b3_spike_id(preproc_subject_dir);
```









```
qc_diary_sub-003_task-EFAT_run-01_bold.txt
                                      %Spikes: 3.28 Global SNR (Mean/STD): 363.94
Session
              8 Potential outliers
       8 global/mahal outlier covariates to covariates field.
Added
Added
       8 global/mahal outlier covariates to covariates field.
Outliers in RMSSD images:
                           0%, 6 imas.
                          qc_diary_sub-042_task-EFAT_run-01_bold.txt
Session
              8 Potential outliers
                                                       Global SNR (Mean/STD): 108.76
                                       %Spikes: 3.33
       8 global/mahal outlier covariates to covariates field.
Added
        8 global/mahal outlier covariates to covariates field.
Added
Outliers in RMSSD images:
                           0%, 7 imas.
```

```
Gegatiang Sub-O03 task-EFAT run-O1 bold.txt

Session 1: 8 Potential outliers %Spikes: 3.28 Global SNR (Mean/STD): 363.94

Added 8 global/mahal outlier covariates to covariates field.

Added 8 global/mahal outlier covariates to covariates field.

Outliers in RMSSD images: 0%, 6 il%Spike? Global SNR?

No absolute standard!

Outliers in RMSSD images: %Spikes: 3.33 Global SNR (Mean/STD): 108.76

Added 8 global/mahal outliers %Spikes: 3.33 Global SNR (Mean/STD): 108.76

Added 8 global/mahal outlier covariates to covariates field.

Outliers in RMSSD images: 0%, 7 imgs.
```

```
gc_diary_sub-003_task-EFAT_run-01_bold.txt

Session 1: 8 Potential outliers %Spikes: 3.28 Global SNR (Mean/STD): 363.94

Added 8 global/mahal outlier covariates to covariates field.

Added 8 global/mahal outlier covariates field.

Outliers in RMSSD images: 09 images: Patient group: 5

Qc_diary_sub-042_task-EFAT_run-01_bold.txt

Session 1: 8 Potential outliers %Spikes: 3.33 Global SNR (Mean/STD): 108.76

Added 8 global/mahal outlier covariates to covariates field.

Added 8 global/mahal outlier covariates to covariates field.
```

Steps

PART 2 (b1-b3)

Functional images QC (outlier detection)

b1: Make directories

b2: implicit mask and mean images

- · create an implicit mask image
- save mean images and SBRef (before preproc) as png in gc directories

b3: outlier detection

 outlier detection based on 1) mahalanobis distance across global mean for slices and spatial STD for slices, as in scn_session_spike_id.m 2) root-mean-square successive differences between images

PART 3 (b4-b6)

Functional images

Slice timing, motion, distortion correction

b4: slice timing correction

- · It works with multi-band sequence
- It reads the actual acquisition timing from dicom header.

b5: motion correction (realignment)

- It uses the first functional image or SBRef (you can choose) as a reference.
- · It saves 6 movement parameters for each run

b6: distortion correction (using FSL's topup)

PART 4 (b7-b8)

Structural and functional images

Coregistration, normalization, smoothing

b7: coregistration

 coregistration between T1 and mean functional images or SBRef image (you can choose).

b8: normalization

- segmentation of the coregistered T1 image using SPM12's tissue probability map (TPM.nii)
- warping segmented (and coregistered) T1 image to MNI template
- applying the warping parameter to the functional images

PART 5 (b9-b10)

Functional images Smoothing and ICA-AROMA

b9: smoothing

smoothing functional images with the FWHM 5 mm smoothing kernel.

b10: ICA-AROMA

- A data-driven method to identify and remove motion-related independent components from functional MRI data.
- · https://github.com/rhr-pruim/ICA-AROMA

Motion artifacts

```
%% B-5. Motion correction
% It uses the first functional image or SBRef as a reference
% It saves 6 movement parameters for each run
use st corrected data = false;
use sbref = false:
SY humanfmri b5 motion correction(preproc subject dir, use st corrected data, use sbref);
                                                              qc_images
          T1 MEMPRAGE 1.0mm p2 RMS
                                                              mean_before_preproc.png
         BOLD Minn 2mm SMS3p2 TR2006 SBRef
                                                              mean r func bold.png
               goes with this scan 🕓
        91BOLD Minn 2mm SMS3p2 TR2000
                                                                 gc diary sub-001 task-EFAT run-01 bold.txt
                                                                 gc_diary_sub-001_task-EFAT_run-02_bold.txt
        [10] BOLD_Minn_2mm_SMS3p2_TR2000_SBRef
                                                                gc_mvmt_sub-001_task-EFAT_run-01_bold.png
        [11] BOLD Minn 2mm SMS3p2 TR2000
                                                              gc_mvmt_sub-001_task-EFAT_run-02_bold.png
        [12] BOLD_Minn_2mm_SMS3p2_TR2000_SBRef
                                                              ac spike plot sub-001 task-EFAT run-01 bold.png
```

gc spike plot sub-001 task-EFAT run-02 bold.png

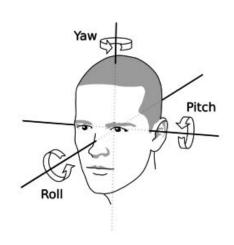
[13] BOLD_Minn_2mm_SMS3p2_TR2000

6 motion parameters

- x, y, z, pitch, roll, yaw

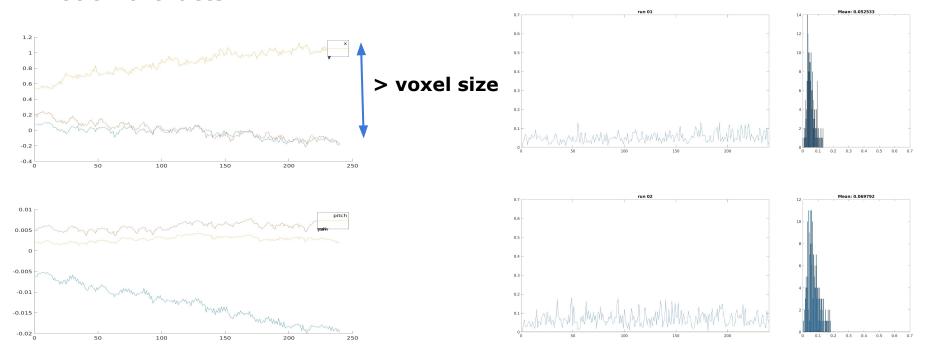
Framewise Displacement

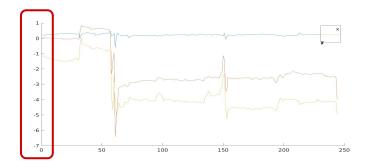
- > 0.2mm

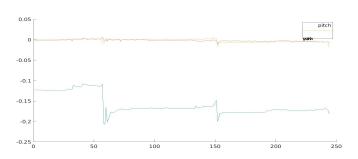


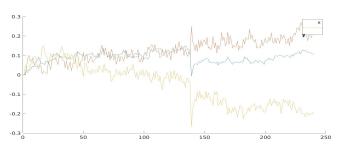


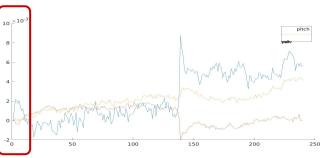






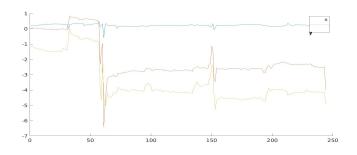


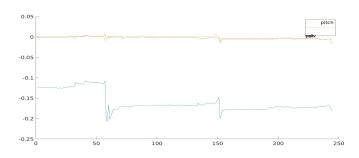


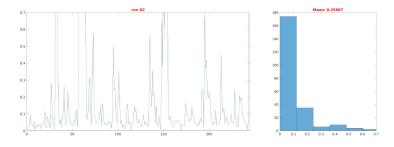






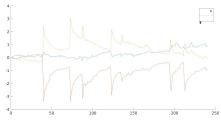


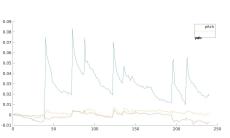


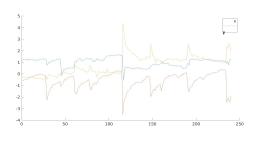


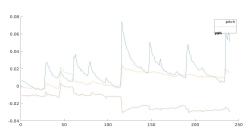


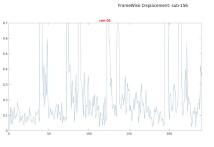


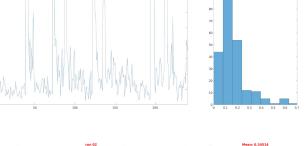


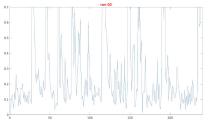


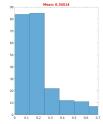




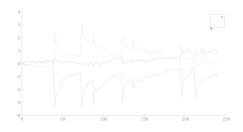


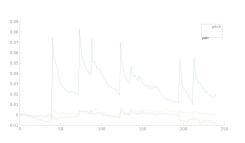




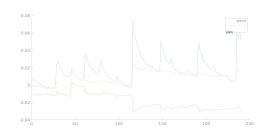


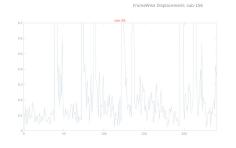


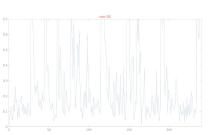














Steps

PART 1 (a1-a4) — DICOM to NIFTI in a NDS format a 13. a kg a ectory a 2: \$5 a frail a 3 a kg a l

PART 2 (b1-b3)

Functional images QC (outlier detection)

b1: Make directories

b2: implicit mask and mean images

- · create an implicit mask image
- save mean images and SBRef (before preproc) as png in gc directories

b3: outlier detection

 outlier detection based on 1) mahalanobis distance across global mean for slices and spatial STD for slices, as in scn_session_spike_id.m 2) root-mean-square successive differences between images

PART 3 (b4-b6)

Functional images

Slice timing, motion, distortion correction

b4: slice timing correction

- · It works with multi-band sequence
- It reads the actual acquisition timing from dicom header.

b5: motion correction (realignment)

- It uses the first functional image or SBRef (you can choose) as a reference.
- · It saves 6 movement parameters for each run

b6: distortion correction (using FSL's topup)

PART 4 (b7-b8)

Structural and functional images Coregistration, normalization, smoothing

b7: coregistration

coregistration between T1 and mean functional images or SBRef image (you can choose).

b8: normalization

- segmentation of the coregistered T1 image using SPM12's tissue probability map (TPM.nii)
- warping segmented (and coregistered) T1 image to MNI template
- applying the warping parameter to the functional images

PART 5 (b9-b10)

Functional images Smoothing and ICA-AROMA

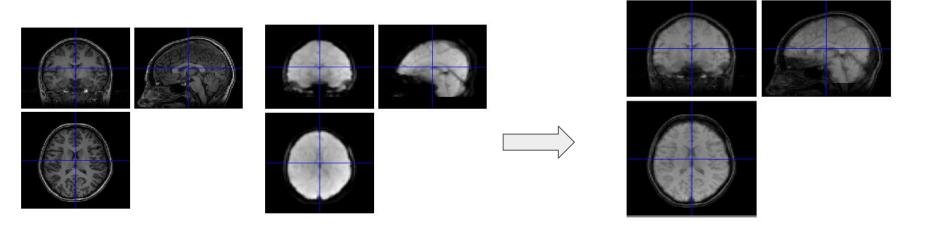
b9: smoothing

smoothing functional images with the FWHM 5 mm smoothing kernel.

b10: ICA-AROMA

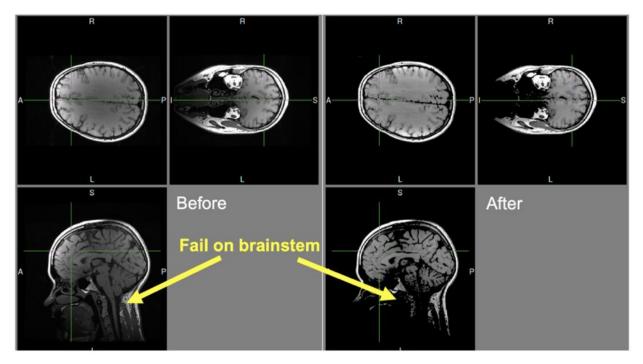
- A data-driven method to identify and remove motion-related independent components from functional MRI data.
- · https://github.com/rhr-pruim/ICA-AROMA

Co-registration



Anatomical image

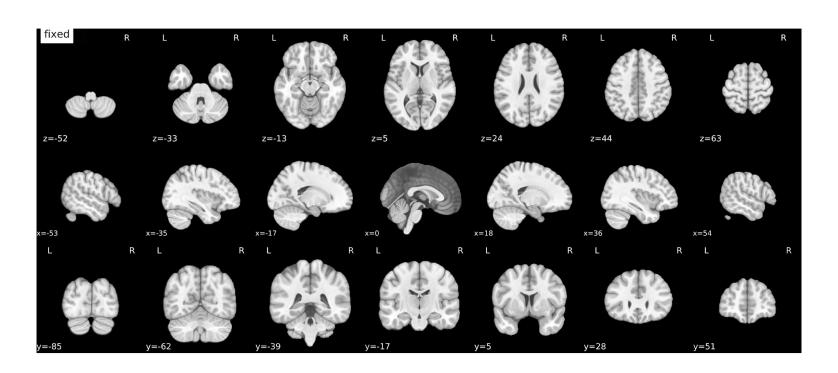
Homogeneity correction



Skull stripping

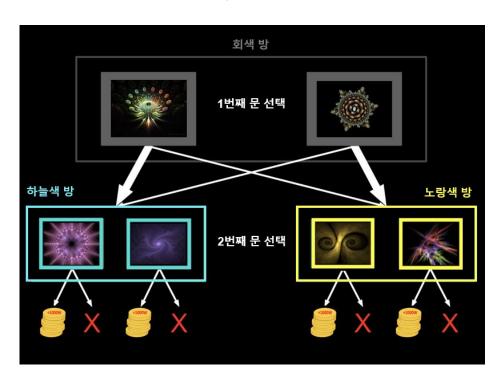


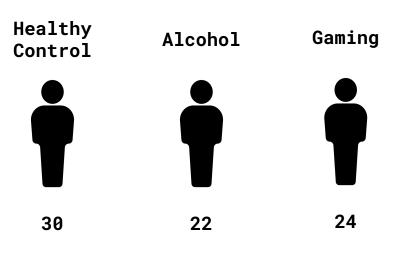
T1 Normalization



Quality Check with fmriprep output!

Two-step (yonsei) data





Steps

Behavior data

Parameters

Functional data

- co-registration
- Outlier detection with motion index

Anatomical data

- Homogeneity Check
- Skull Stripping
- T1 Normalization
- surface reconstruction

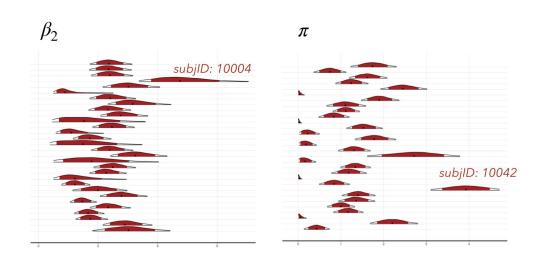


Behavior data

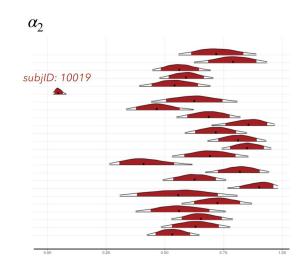
Behavior data

3 outliers

Posterior distribution: Healthy



Posterior distribution: Gaming



Things to check with fmriprep!

Anatomical data

1. Homogeneity & Skull stripping check file name: * seg brainmask.svg

2. T1 Normalization (T1 to MNI registration)

file name: *_t1_2.svg

3. Surface reconstruction

file name: *_reconall.svg

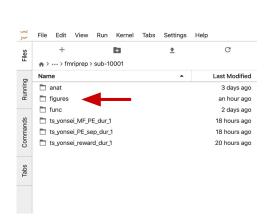
Functional data

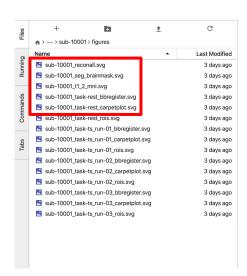
1. co-registration

file name: *_bbregister.svg

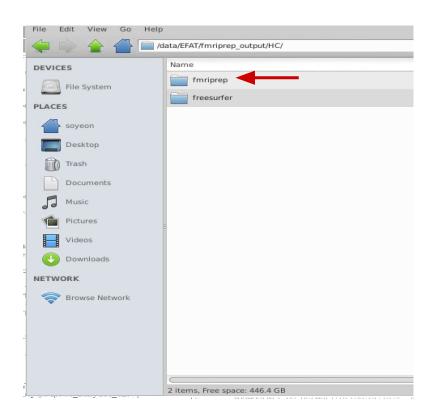
2. outlier detection (with motion index)

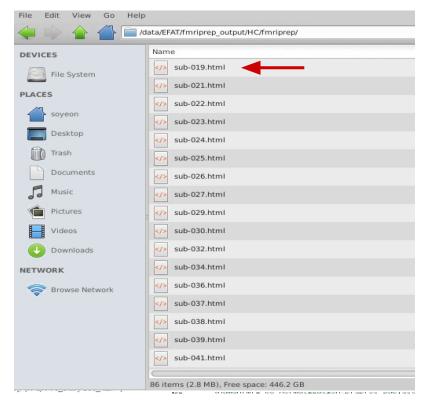
file name: *_carpetplot.svg



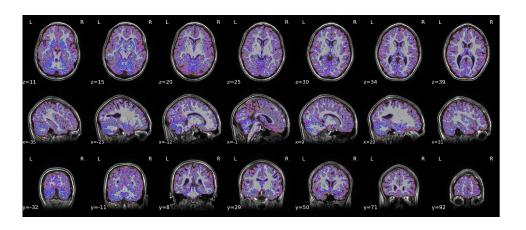


Where to go?



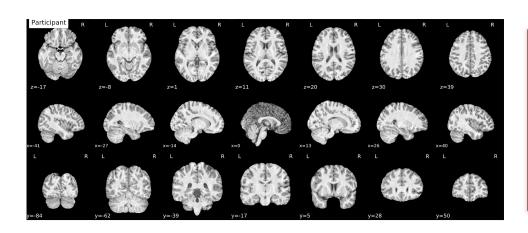


1. Homogeneity & Skull stripping check



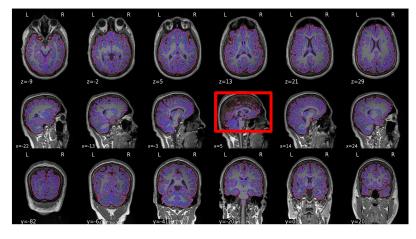
- 1) homogeneity: visually check if color of brain is homogeneous. Filter out those with holes etc.
- 2) Skull segmentation: Visually check if brain is properly segmented.

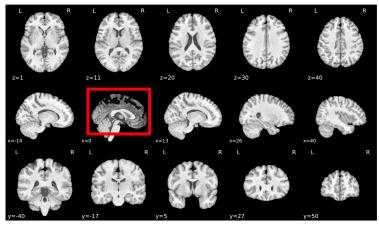
2. T1 Normalization (T1 to MNI registration)



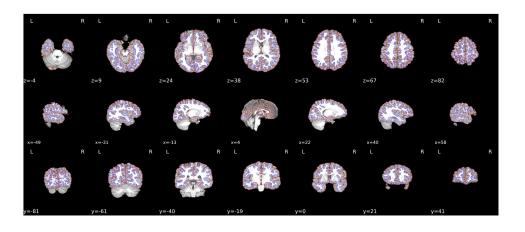
⇒ visually check if T1 image and MNI is matched!

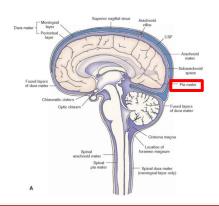






3. Surface reconstruction





Surfaces (white matter and pial) reconstructed with FreeSurfer overlaid on the participant's T1w template

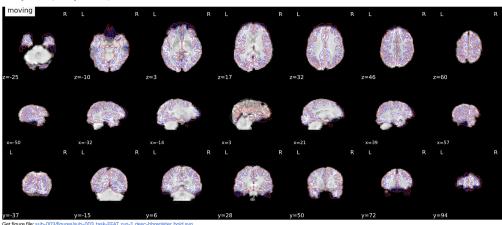
⇒ visually check if red line (pia mater) & blue line (white matter) is correctly drawn

Functional image

Co-registration (EPI to T1 image)

Alignment of functional and anatomical MRI data (surface driven)

bbreqister was used to generate transformations from EPI-space to T1w-space. Note that Nearest Neighbor interpolation is used in the reportlets in order to highlight potential spin-history and other artifacts, whereas final images are resampled using Lanczos interpolation.



Get figure file: sub-003/figures/sub-003_task-EFAT_run-1_desc-bbregister_bold.svg

fixed: T1w-space

red line: Pia mater

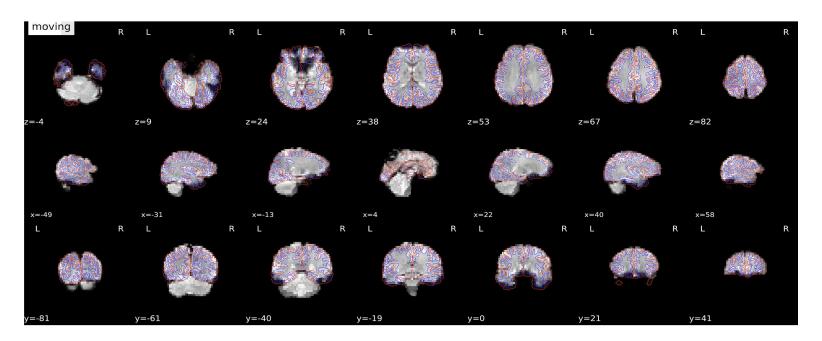
blue line: white matter

moving: EPI-space

⇒ visually check if the lines are aligned with **EPI-space!**



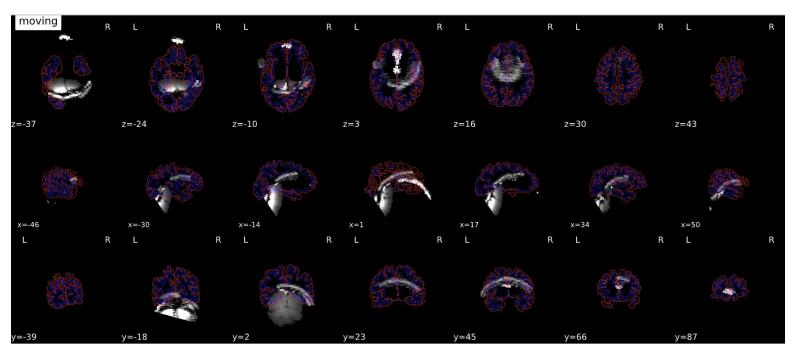
1. Co-registration (EPI to T1 image)



file name: *bbregister_bold.svg



1. Co-registration (EPI to T1 image)



file name: *bbregister_bold.svg

2. Outlier Detection (with 'framewise displacement; FD')

Outlier detection. These confounds can be used to detect potential outlier time points - frames with sudden and large motion or intensity spikes. framewise_displacement | is a quantification of the estimated bulk-head motion calculated using formula proposed by [Power2012]; dvars - the derivative of RMS variance over voxels (or DVARS) [Power2012]; std dvars - standardized DVARS; non_steady_state_outlier_XX - columns indicate non-steady state volumes with a single 1 value and 0 elsewhere (i.e., there is one non_steady_state_outlier_XX column per outlier/volume). Detected outliers can be further removed from time series using methods such as: volume censoring - entirely discarding problematic time points [Power2012], regressing signal from outlier points in denoising procedure, or including outlier points in the subsequent first-level analysis when building the design matrix. Averaged value of confound (for example, mean framewise displacement) can also be added as regressors in group level analysis [Yan2013]. Spike regressors for outlier censoring can also be generated from within fMRIPrep using the command line options --fd-spike-threshold and --dvars-spike-threshold (default: FD > 0.5 mm or DVARS > 1.5). Spike regressors are stored in separate motion outlier XX columns.

DVARS (DV)

This measure indexes the change in signal intensity from one volume to the next, and is calculated as the root mean square value of the differentiated BOLD timeseries (by backwards differences) within a spatial mask at every timepoint (Smyser et al., 2010). DV for the first volume of a run is set to zero by convention. This paper usually presents DV calculated over the whole-brain mask but it can be calculated over any collection of voxels. Gray matter DV (DV $_{GM}$), which closely parallels whole-brain DV (DV $_{GS}$), is presented at several points in the manuscript where indicated (e.g., after global signal regression has made it pointless to plot mean global signal but still informative to plot mean gray matter signal, we use DV $_{GM}$ instead of DV $_{GS}$ so that the same set of voxels is being examined.)

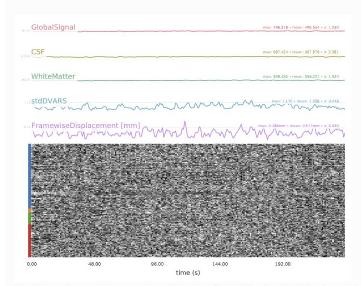
DVARS calculations

DVARS (D referring to temporal derivative of timecourses, VARS referring to RMS variance over voxels) indexes the rate of change of BOLD signal across the entire brain at each frame of data. To calculate DVARS, the volumetric timeseries is differentiated (by backwards differences) and RMS signal change is calculated over the whole brain. DVARS is thus a measure of how much the intensity of a brain image changes in comparison to the previous timepoint (as opposed to the global signal, which is the average value of a brain image at a timepoint). The global measure of signal change is

$$\mathrm{DVARS}(\Delta I)_i = \sqrt{\left\langle \left[\Delta I_i \left(\overrightarrow{x}\right)\right]^2 \right\rangle} = \sqrt{\left\langle \left[I_i \left(\overrightarrow{x}\right) - I_{i-1} \left(\overrightarrow{x}\right)\right]^2 \right\rangle}$$

where, as before, $I_i(\vec{x})$ is image intensity at locus \vec{x} on frame i and angle brackets denote the spatial average over the whole brain. A computationally important detail

The visual reports provide several sections per task and run to aid designing a denoising strategy for subsequent analysis. Some of the estimated confounds are plotted with a "carpet" visualization of the BOLD time series [Power2016]. An example of these plots follows:



The figure shows on top several confounds estimated for the BOLD series: global signals ('GlobalSignal', 'WM', 'GM'), standardized DVARS ('stdDVARS'), and framewise-displacement ('Framewise-Displacement'). At the bottom, a 'carpetplot' summarizing the BOLD series. The color-map on the left-side of the carpetplot denotes signals located in cortical gray matter regions (blue), subcortical gray matter (orange), cerebellum (green) and the union of white-matter and CSF compartments (red).

Criterion

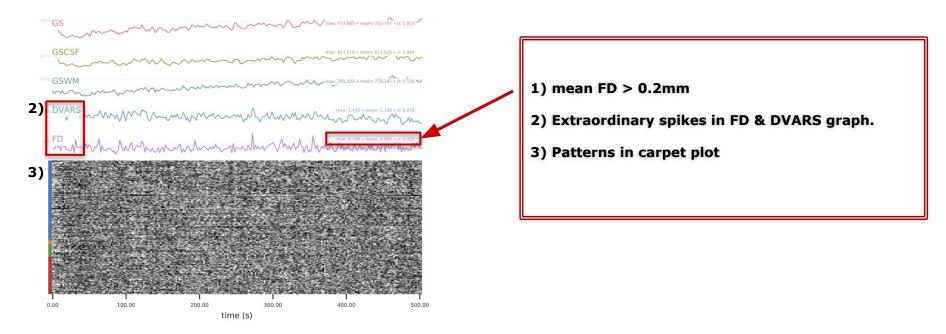
- stdDVARS > 0.4 ~ 0.5% △BOLD
- mean FD > 0.2mm ~ 0.5 mm

FD: Difference between frames across time **DVARS**: Difference between each voxel across time

- D: referring to temporal derivative of timecourses
- VARS: referring to RMS variance over voxels
- → provide a single estimated head motion parameter for each time point

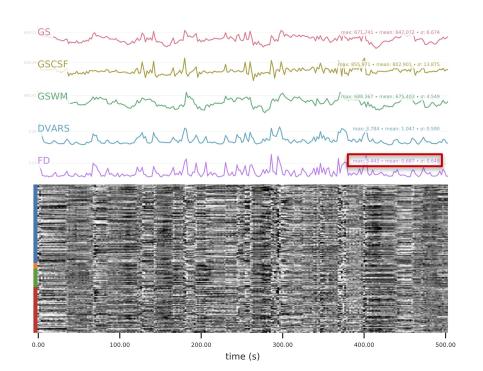
https://fmriprep.readthedocs.io/en/stable/outputs.html#functional-derivatives

2. Outlier Detection (with 'framewise displacement; FD')





2. Outlier Detection (with 'framewise displacement; FD')

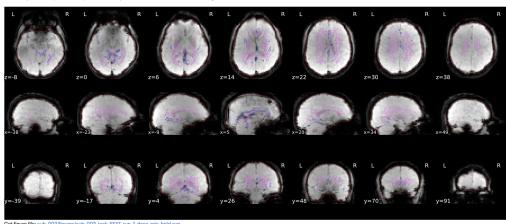


BOLD signal (red) aCompCor mask (magenta): additional noise components calculated using anatomical tCompCor mask (blue contour): additional noise components calculated using temporal

- * CompCor: component based noise correction method
- ⇒ Check what?????

Brain mask and (temporal/anatomical) CompCor ROIs

Brain mask calculated on the BOLD signal (red contour), along with the masks used for a/tCompCor. The aCompCor mask (magenta contour) is a conservative CSF and white-matter mask for extracting physiological and movement confounds. The fCompCor mask (blue contour) contains the top 5% most variable voxels within a heavily-eroded brain-mask,



Get figure file: sub-003/figures/sub-003_task-EFAT_run-1_desc-rois_bold.svg

Checking it with fmriprep output!

Outlier detection. These confounds can be used to detect potential outlier time points - frames with sudden and large motion or intensity spikes.

- framewise_displacement is a quantification of the estimated bulk-head motion calculated using formula proposed by [Power2012];
- dvars the derivative of RMS variance over voxels (or DVARS) [Power2012];
- std dvars standardized DVARS;
- non_steady_state_outlier_XX columns indicate non-steady state volumes with a single 1
 value and 0 elsewhere (i.e., there is one non_steady_state_outlier_XX column per outlier/volume).

Detected outliers can be further removed from time series using methods such as: volume *censoring* - entirely discarding problematic time points [Power2012], regressing signal from outlier points in denoising procedure, or including outlier points in the subsequent first-level analysis when building the design matrix. Averaged value of confound (for example, mean framewise_displacement) can also be added as regressors in group level analysis [Yan2013]. *Spike regressors* for outlier censoring can also be generated from within *fMRIPrep* using the command line options

---fd-spike-threshold and --dvars-spike-threshold (default: FD > 0.5 mm or DVARS > 1.5).

Spike regressors are stored in separate motion_outlier_XX columns.

```
Name

sub-003_desc-reconall_T1w.svg
sub-003_desc_svg
sub-003_desc_svg
sub-003_task_EFAT_run-1_desc_bbregister_bold.svg
sub-003_task_EFAT_run-1_desc_compcorvar_bold.svg
sub-003_task_EFAT_run-1_desc_compcorvar_bold.svg
sub-003_task_EFAT_run-1_desc_compcorvar_bold.svg
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sub-003_task_EFAT_run-1_desc_rois_bold.svg
sub-003_task_EFAT_run-2_desc_bbregister_bold.svg
sub-003_task_EFAT_run-2_desc_compcorvar_bold.svg
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sub-003_task_EFAT_run-2_desc_compcorvar_bold.svg
sub-003_task_EFAT_run-2_desc_compcorvar_bold.svg
```

Variance explained by t/aCompCor components

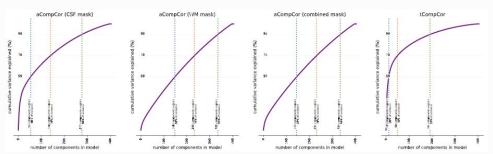
The cumulative variance explained by the first k components of the t/aCompCor decomposition, plotted for all values of k. The number of components that must be included in the model in order some fraction of variance in the decomposition mask can be used as a feature selection criterion for confound regression.

Functional data

Noise components computed during each CompCor decomposition are evaluated according to the fraction of variance that they explain across the nuisance ROI. This is used by fMRIPrep to determine whether each component should be saved for use in denoising operations: a component is saved if it contributes to explaining the top 50 percent of variance in the nuisance ROI. fMRIPrep can be configured to save all components instead using the command line option

—return-all-components

. fMRIPrep reports include a plot of the cumulative variance explained by each component, ordered by descending singular value.



The figure displays the cumulative variance explained by components for each of four CompCor decompositions (left to right: anatomical CSF mask, anatomical white matter mask, anatomical combined mask, temporal). The number of components is plotted on the abscissa and the cumulative variance explained on the ordinate. Dotted lines indicate the minimum number of components necessary to explain 50%, 70%, and 90% of the variance in the nuisance mask. By default, only the components that explain the top 50% of the variance are saved.

Behzadi (2007) https://www.ncbi.nlm.nih.gov/pubmed/17560126

Framewise displacement (FD)

This measure indexes the movement of the head from one volume to the next, and is calculated as the sum of the absolute values of the differentiated realignment estimates (by backwards differences) at every timepoint (Power et al., 2012). FD for the first volume of a run is 0 by convention. The purpose of this measure is to index head movement, not to precisely calculate or model it.

- From Power et al. (2012): "After studying the plots
 of dozens of healthy adults, values of 0.5 mm for
 framewise displacement and 0.5% ABOLD for
 DVARS were chosen to represent values well above
 the norm found in still subjects."
- Also removed 1 TR before and 2 TRs after bad frame
- Fair et al. (2013) used an even more stringent FD cut-off of 0.2 mm and DVARS cut-off of 0.4%

Framewise displacement (FD) calculations

Differentiating head realignment parameters across frames yields a six dimensional timeseries that represents instantaneous head motion. To express instantaneous head motion as a scalar quantity we used the empirical formula, $FD_i = |\Delta d_{ix}| + |\Delta d_{iy}| + |\Delta d_{iz}| + |\Delta \alpha_i| + |\Delta \beta_i| + |\Delta \gamma_i|$, where $\Delta d_{ix} = d_{(i-1)x} - d_{ix}$, and similarly for the other rigid body parameters $[d_{ix} \ d_{iy} \ d_{iz} \ \alpha_i \ \beta_i \ \gamma_i]$. Rotational displacements were converted from degrees to millimeters by calculating displacement on the surface of a sphere of radius 50 mm, which is approximately the mean distance from the cerebral cortex to the center of the head.

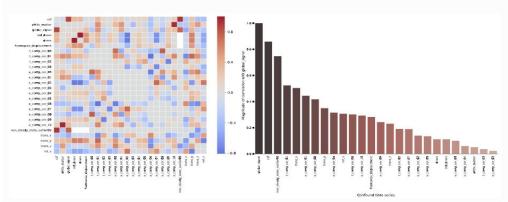
only large movements are sought. After studying the plots of dozens of healthy adults, values of 0.5 for framewise displacement and 0.5% ABOLD for DVARS were chosen to represent values well above the norm found in still subjects (see Figure S5 for examples of still subjects).

Realizing the artifactual contributions of micromovements to R-fMRI findings, Power and colleagues recently called for the rigorous scrubbing of any time frames in which micromovements occur, as well as their neighboring time points, proposing framewise displacement (FD) > 0.2mm as the threshold for frame removal (Power et al., 2012a, b). Recent work has suggested that the combination of scrubbing and modeling based approaches brings about the greatest reduction in motion-induced artifact (Power et al., 2012b, Satterthwaite et al., 2013) – this combination can be accomplished in a single, integrated regression model (i.e., by modeling motion parameters and spike regressors for each scrubbed time point).

Power (2012) https://www.sciencedirect.com/science/article/pii/S1053811911011815

https://fmriprep.readthedocs.io/en/stable/outputs.html#functional-derivatives

Also included is a plot of correlations among confound regressors. This can be used to guide selection of a confound model or to assess the extent to which tissue-specific regressors correlate with global signal.



The left-hand panel shows the matrix of correlations among selected confound time series as a heat-map. Note the zero-correlation blocks near the diagonal; these correspond to each CompCor decomposition. The right-hand panel displays the correlation of selected confound time series with the mean global signal computed across the whole brain; the regressors shown are those with greatest correlation with the global signal. This information can be used to diagnose partial volume effects.

Left: correlation matrix of selected confound time series

Right: correlation of selected confound time series with the mean global signal (regressors with greatest correlation wer shown)

Results after Quality Check

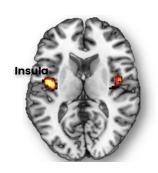
QC results

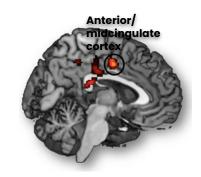
EFAT data

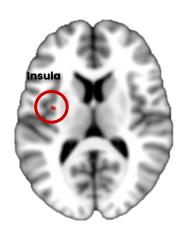
PASS	FAIL		
	behavior	spike & movement	coregistration
108	6	34	2

Second Level Results

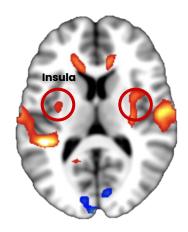
angry > shapes contrast

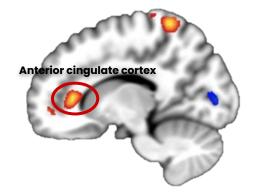








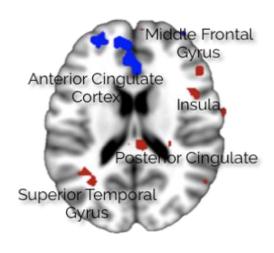


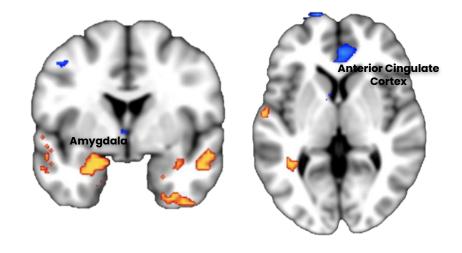


<After>



Machine Learning Results









<After>

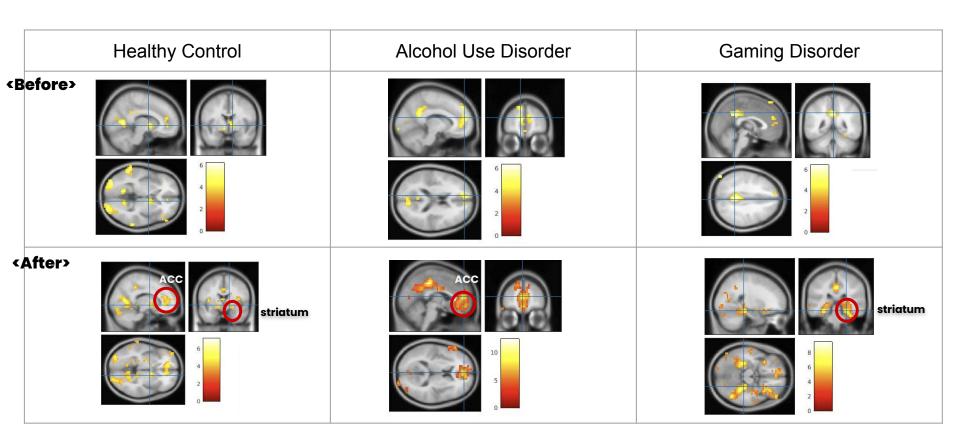
QC results

Two step task (yonsei) data

PASS	FAIL		
	behavior	spike & movement	signal loss
47	3	21	3

	FAIL	PASS	total
НС	11	19	30
AUD	9	13	22
GD	9	15	24
sum	29	47	76

QC results reward vs non reward (p < 0.001)



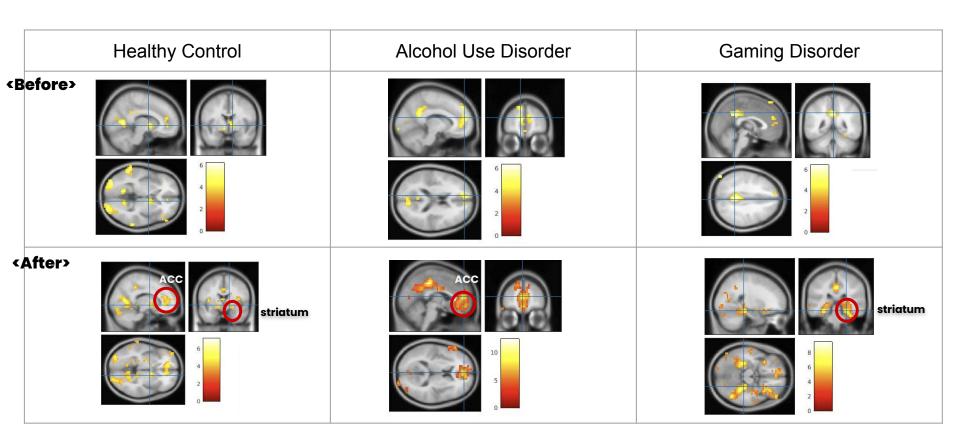
QC results

Two step task (yonsei) data

PASS	FAIL		
	behavior	spike & movement	signal loss
47	3	21	3

	FAIL	PASS	total
НС	11	19	30
AUD	9	13	22
GD	9	15	24
sum	29	47	76

QC results reward vs non reward (p < 0.001)



QC results reward prediction error (p < 0.001)

