





Preprocessing & denoising of fMRI data

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Plan

- Simple fMRI pre-processing pipeline in 2018
- Signal fluctuations or noise
- Motion related noise & denoising in GLM
- Denoising based on external physiological signals
- TAPAS Physio Toolbox
- Denoising based on PCA of noise regions signals
- Example of results
- Questions to be addressed
- Next step: Multi-Echo acquisitions
- Conclusion & references





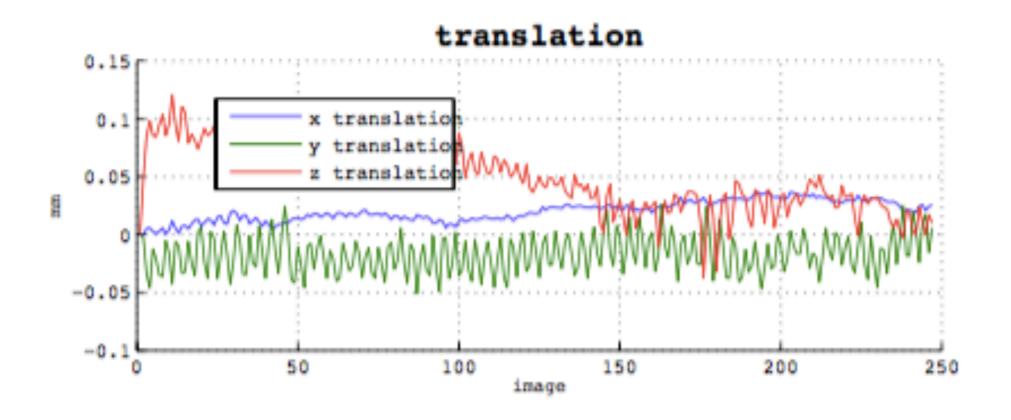
Simple fMRI pre-processing pipeline (2018)

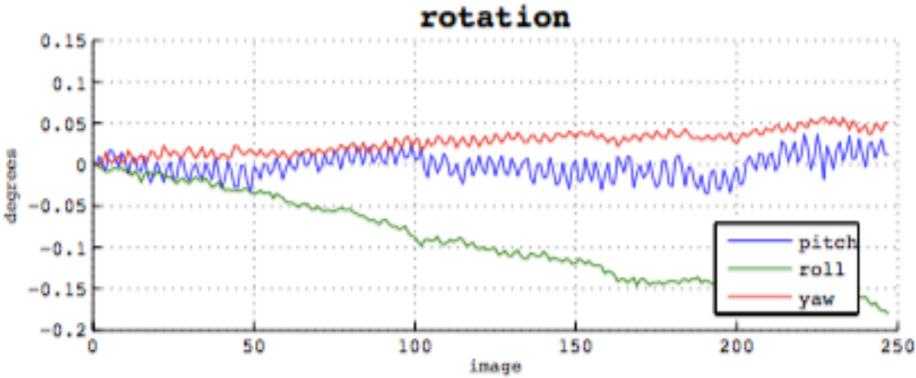
- * Check of the data: quality, coregistration, ...
- * Fielmap computation -> Voxel Displacements Map
- * Realign & unwarp
- * Coregistration of anatomical data to functional data
- * Spatial Normalisation to the MNI space (DARTEL)
- * Spatial smoothing

Nota : the slice timing step is often skipped because of the interpolation problems and is no more really useful thanks to short TRs (≈ 1 sec)



Motion parameters estimates









EPI Multi-bande sequences

- → Very short TR (≈ 1 sec)
- → Small voxels (≈ 2.5 mm iso)
- → High SNR (multi-channel receiving coils)

→Artefacts seem to be more visibles than with older MRI systems





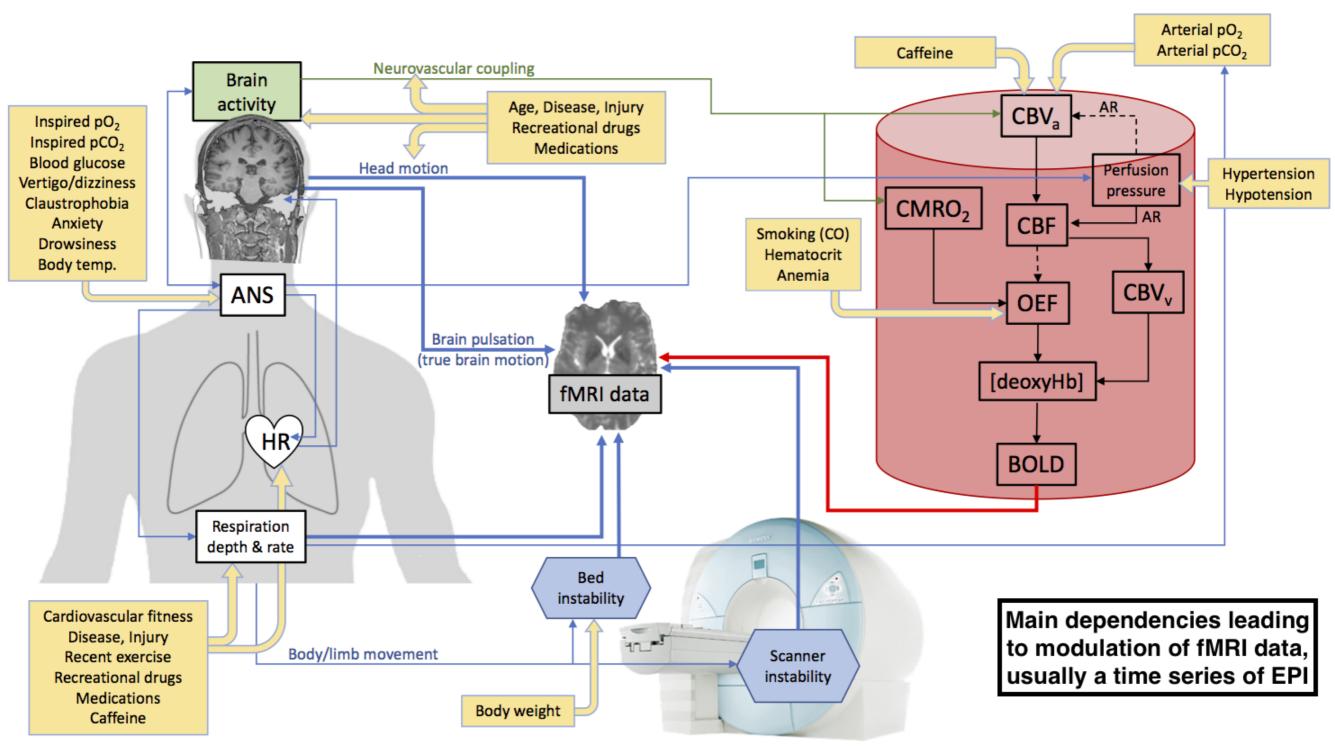
Different sources of noise:

- Head motion
- Cardiac pulsatility -> motion (global) & inflow (local)
- Respiratory induced changes

 change of B0 in the head
- Draining veins
- Slow drifts
- Hardware related instabilities







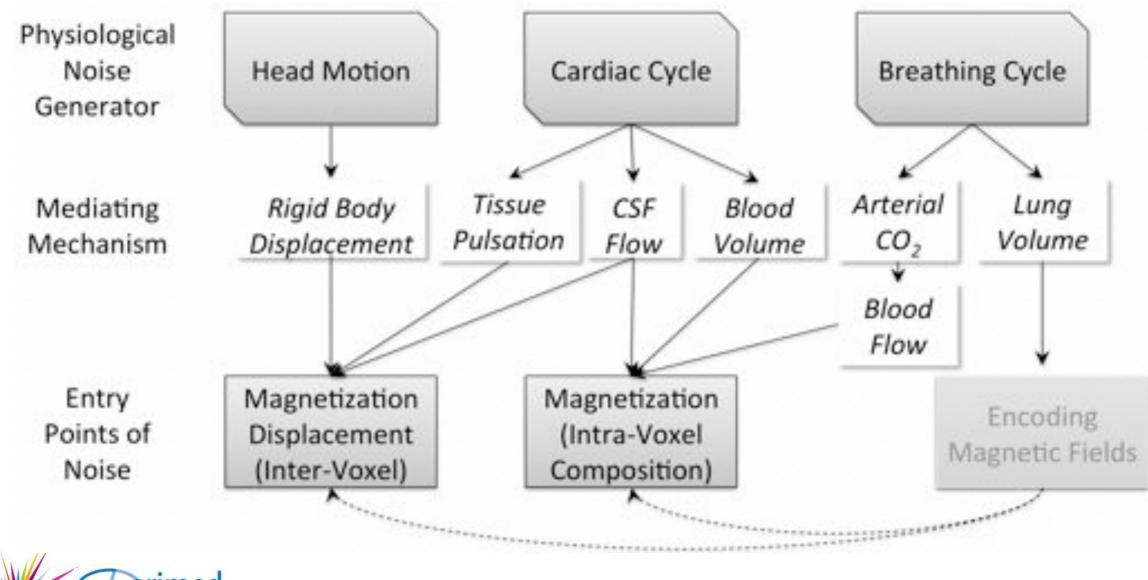




<u>Different sources of noise:</u>

- Head motion
- Cardiac pulsatility

 motion (global) & inflow (local)
- Respiratory induced changes ightarrow change of B0 in the head





Motion-related noise

- The best solution is to limit the head motion of the subject during the data acquisition:
 - compliant & trained subjects: mock-scanner is useful!





Motion-related noise

- The best solution is to limit the head motion of the subject during the data acquisition:
 - compliant & trained subjects
 - good head restraint: inflating pads (already available)
 - or the ultimate solution : https://caseforge.co/







Motion-related noise

- The best solution is to limit the head motion of the subject during the data acquisition:
 - compliant & trained subjects
 - good head restraint
 - on-line head motion monitoring :
 - feedback to the subject in case of problematic motion
 - and/or run longer acquisitions

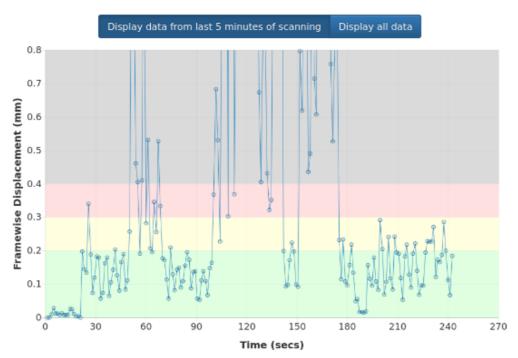


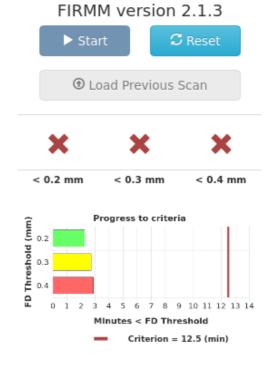


FIRMM: Real-time head motion analysis



loggle patient info table





Summary									
Series	Description	Frames	TR (sec)	Time (min)	< 0.2 mm (min) (%)	< 0.3 mm (min) (%)	< 0.4 mm (min) (%)		
15	AUDIO_RUN1_PERC	182	1.224	3:42	1:57 (52.7%)	2:25 (65.4%)	2:35 (69.8%)		
10	task-rest_bold	15	1.224	0:18	0:18 (100.0%)	0:18 (100.0%)	0:18 (100.0%)		
9	task- rest_bold_SBRef	1	1.224	0:01	0:01 (100.0%)	0:01 (100.0%)	0:01 (100.0%)		

Collected Low Movement Frames							
	< 0.2 mm	< 0.3 mm	< 0.4 mm				
Good Time (min) (%)	2:17 (56.6%)	2:45 (68.2%)	2:55 (72.2%)				
Good Frames	112	135	143				
Bad Frames	86	63	55				

Predicted	Duration	to Scan	Criteria
	< 0.2 mm	< 0.3 mm	< 0.4 mm
Minutes to	20:53	16:47	15:14





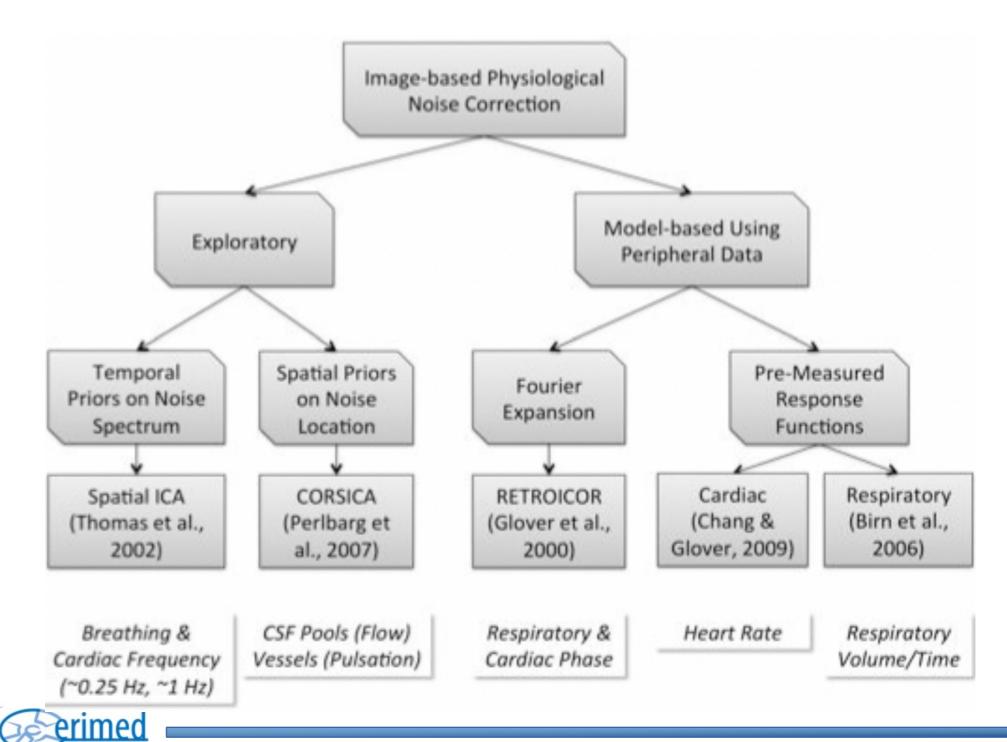
Denoising motion-related noise

- 1/ Motion correction : Realignment pre-processing
 - classical rigid-body volume correction
 - or slice by slice: SLOMOCO (Ball & Lowe 2014), to be tested
- 2/ Modelisation of motion-reated artifacts: in GLM, 6, 12, 24 or 36 nuisance regressors: realignment parameters time series (rp(t)), their squared time series (rp^2(t)), plus one or two temporal derivatives ((rp(t-1)) (Friston & al, 1996)
- 2bis/ Modelisation of artifacted scans (head jerks, transitory problem): censoring (1 regressor per outlier scan). See Artifact Detection Tools (ART) for example.





- Denoising physiological noise based on external recordings
- Data-driven denoising methods of physiological noise

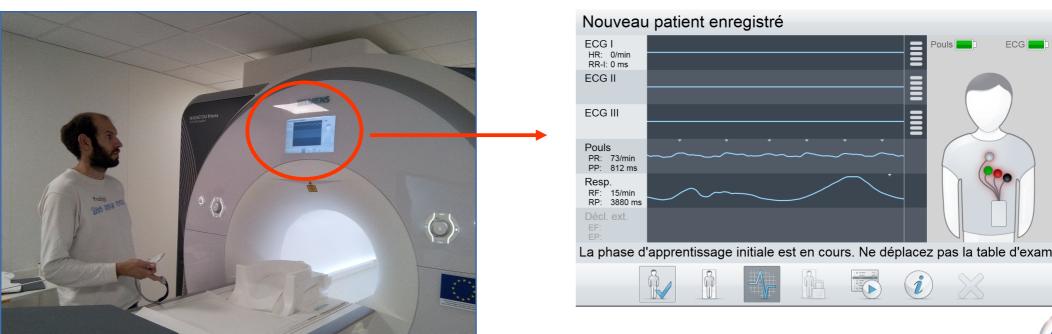




- Denoising physiological noise based on external recordings
 - Respiration cycle: pneumatic belt
 - Cardiac pulse: Photo-Plethysmo-Graph (PPG)







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Denoising physiological noise based on external recordings

In RETROspective Image CORrection (RETROICOR, Glover et al., 2000), the quasi-periodic physiological noise time series is modelled by means of a low-order Fourier series with time-varying cardiac and respiratory phases, which are fit to the data as nuisance regressors and removed.





- Denoising physiological noise based on external recordings

The same physiological recordings can also be employed to reduce low-frequency BOLD fluctuations related to varying cardiac and respiratory rates

- Heart Rate Variability (HRV)
- Respiration Volume Time series (RVT)
- Assuming that the relationship between the HRV and RVT fluctuations and the BOLD signal follows a linear model
 → nuisance regressors obtained by convolving the HRV and RVT time series with a respiratory response function (Birn et al., 2008) and cardiac response function (Chang et al., 2009)



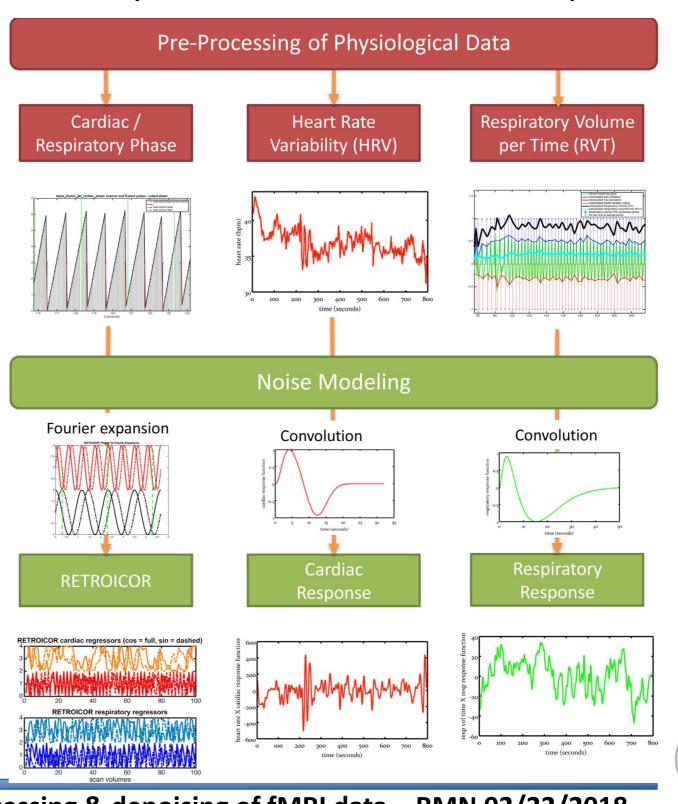


Denoising physiological noise based on external recordings
 2/ Nuisance regressors (RETROICOR, HRV, RVT)

TAPAS Physio Toolbox

The PhysIO Toolbox for Modeling Physiological Noise in fMRI Data Kasper & al.

J of Neuroscience Methods 276 (2017) 56-72





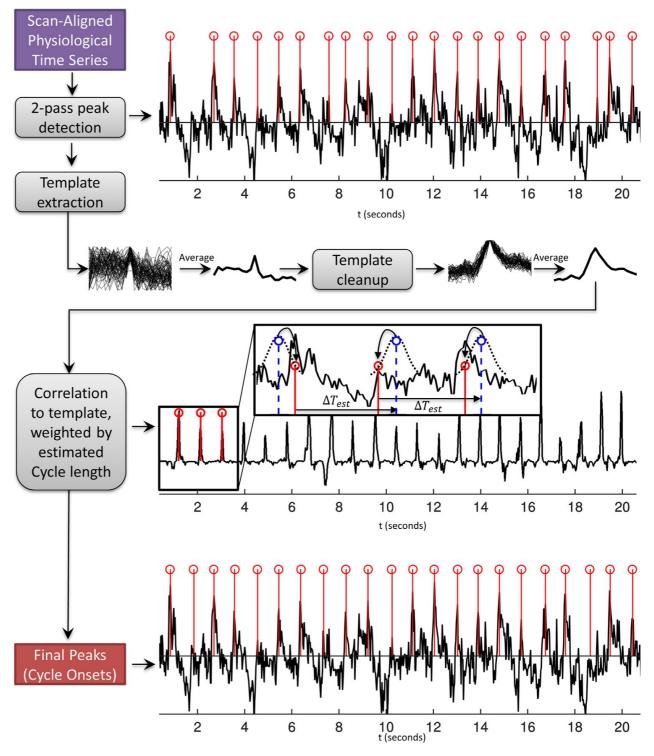


Denoising physiological noise based on external recordings
 1/ Physiological Peak Detection Algorithm

TAPAS Physio Toolbox

The PhysIO Toolbox for Modeling Physiological Noise in fMRI Data Kasper & al.

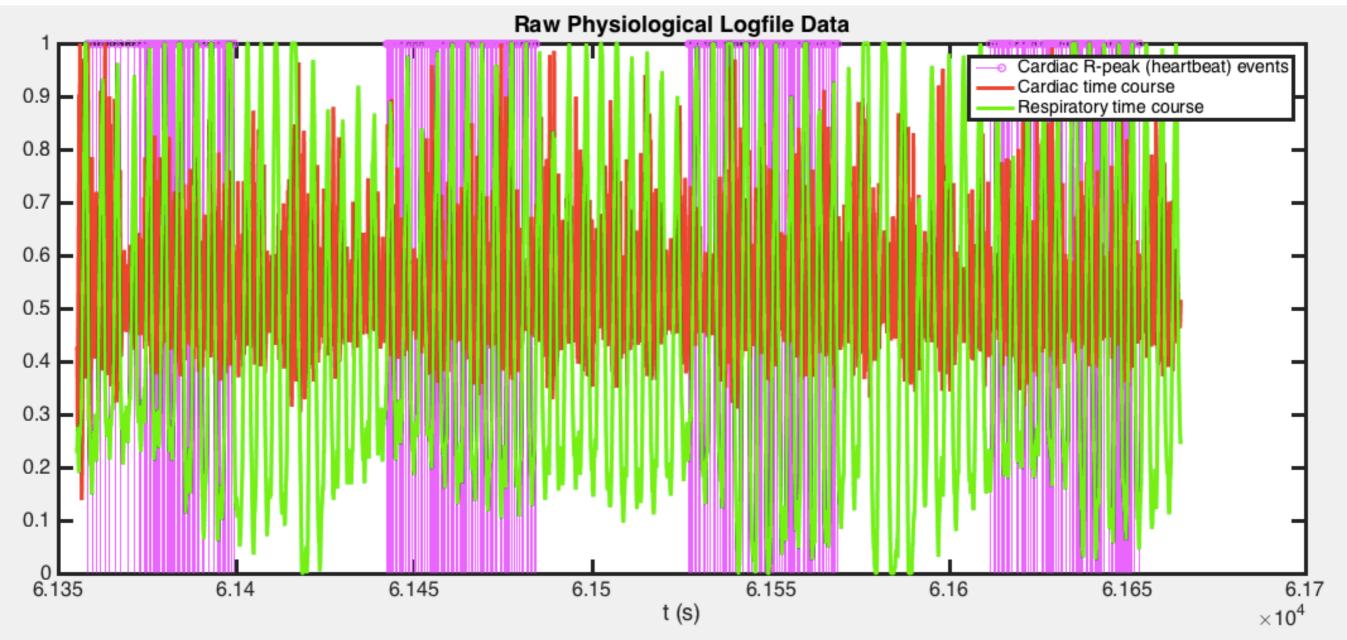
J of Neuroscience Methods 276 (2017) 56-72







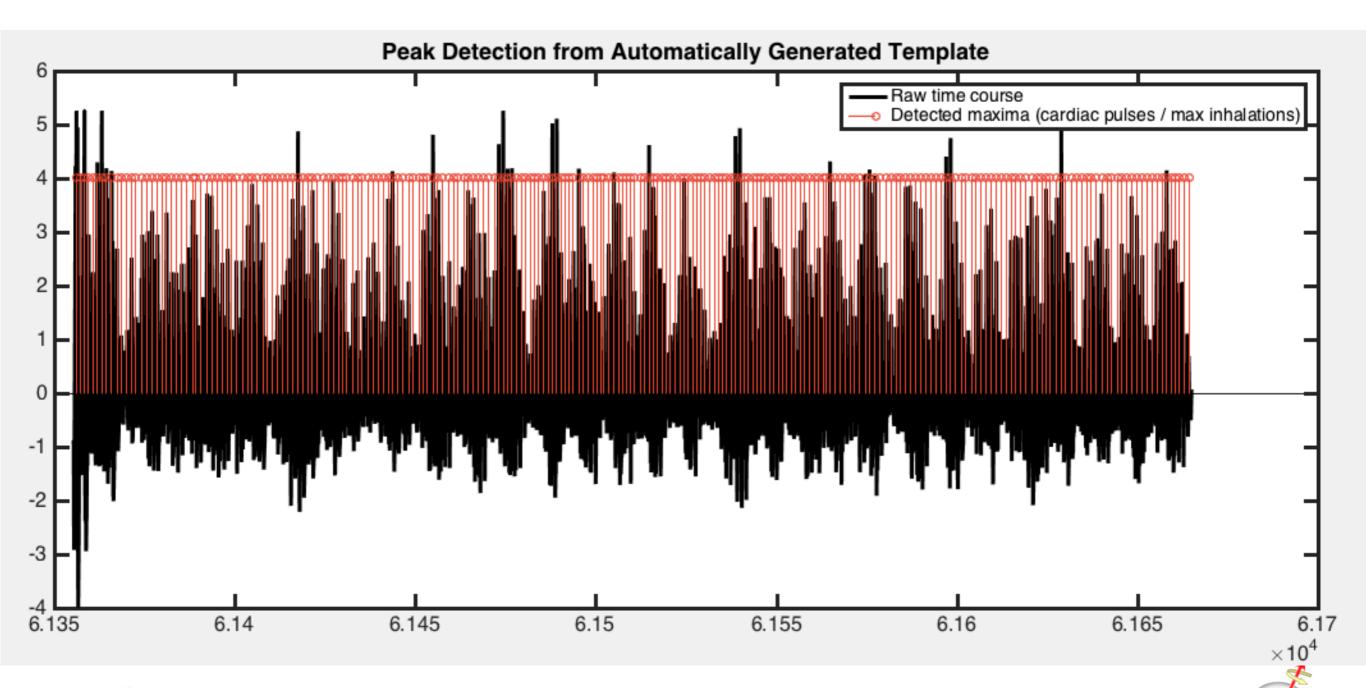
Denoising physiological noise based on external recordings
 1/ Preprocessing of physiological data



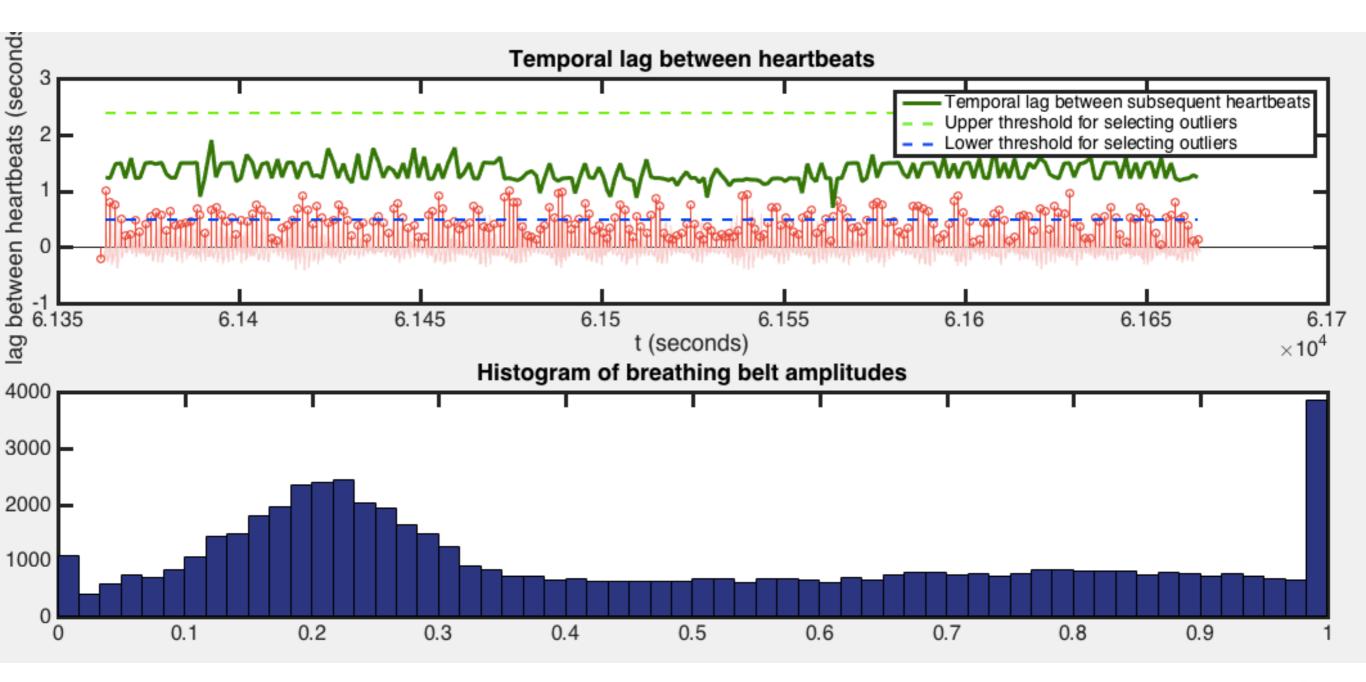




Denoising physiological noise based on external recordings
 1/ Preprocessing of physiological data



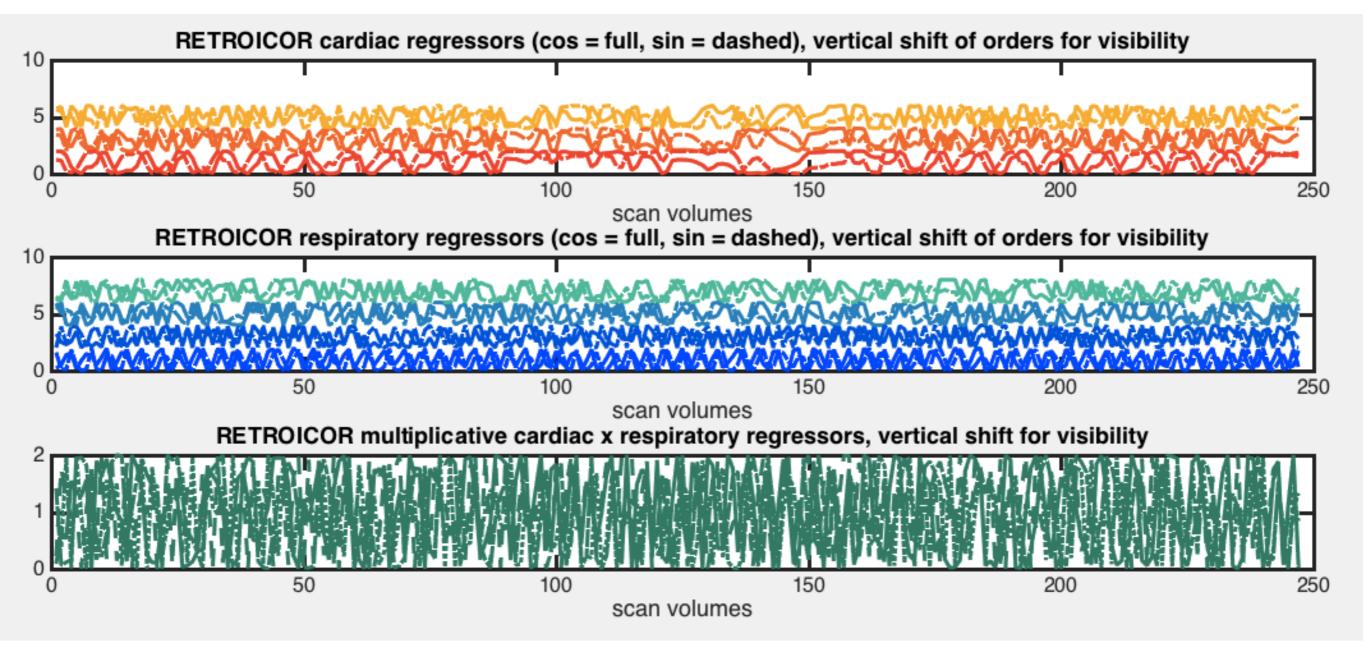
Denoising physiological noise based on external recordings
 1/ Preprocessing of physiological data







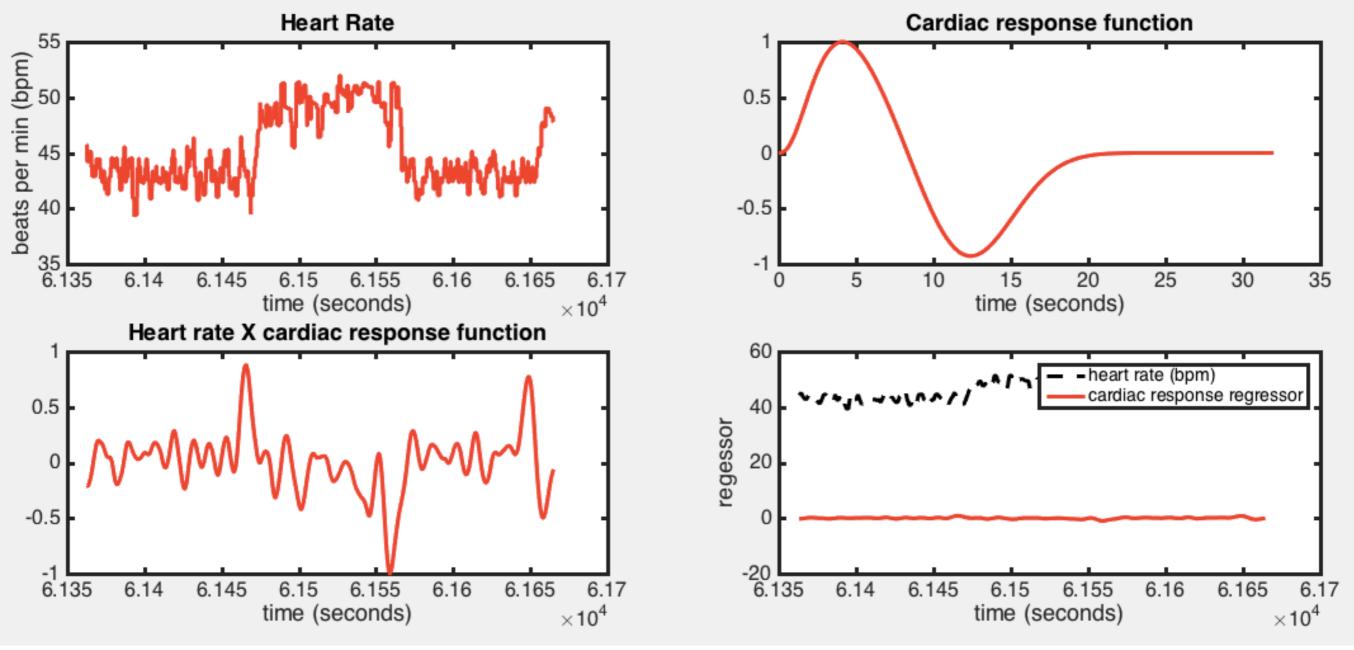
Denoising physiological noise based on external recordings
 2/ Nuisance regressors : RETROICOR







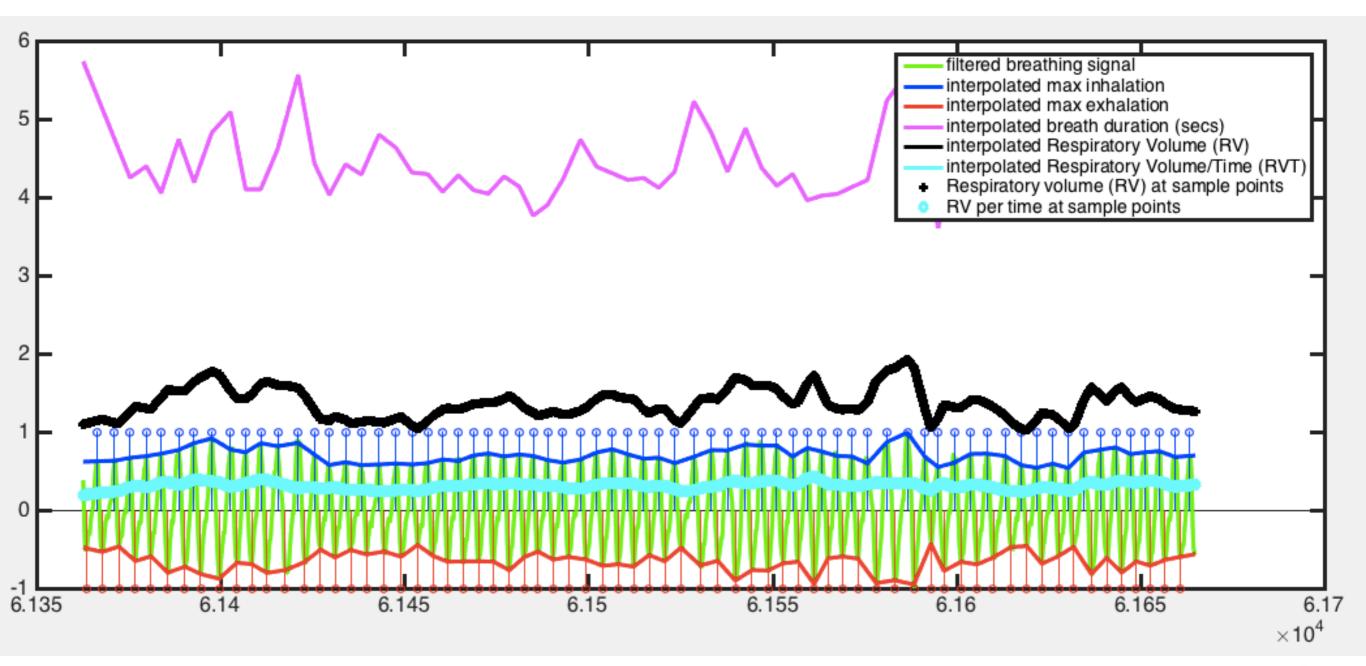
Denoising physiological noise based on external recordings
 2/ Nuisance regressors : HRV x CRF







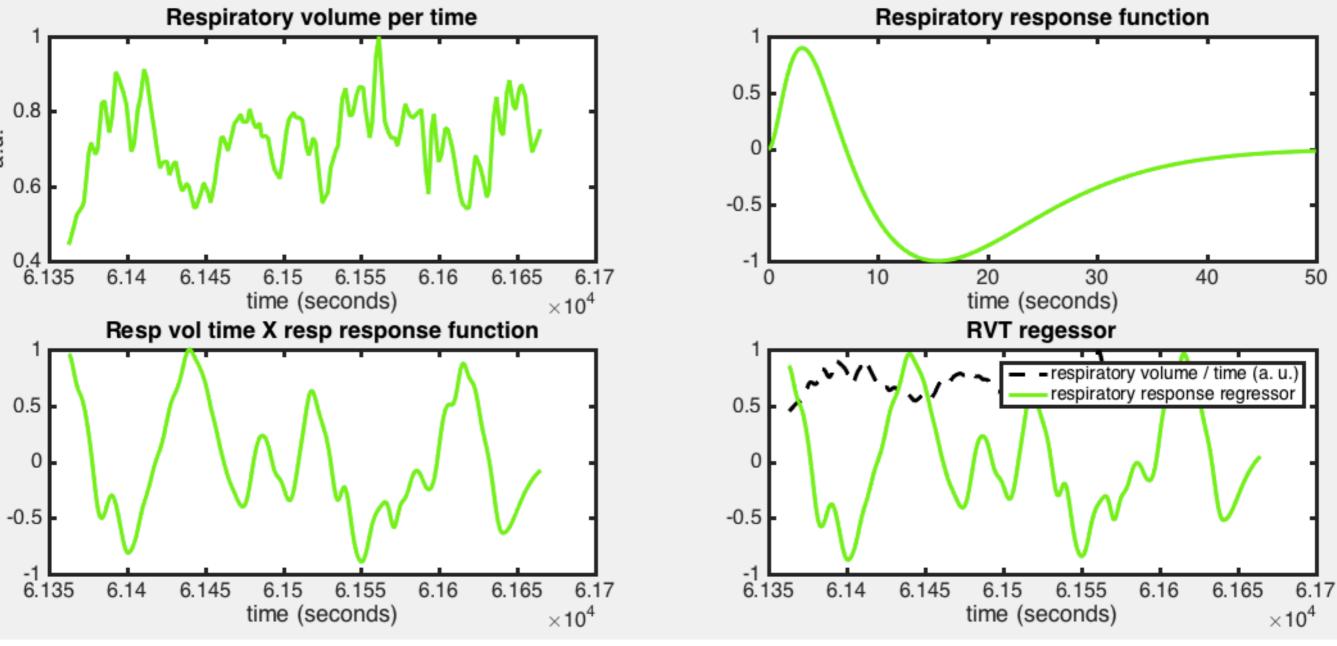
Denoising physiological noise based on external recordings
 2/ Respiratory Volume per Time (RVT)







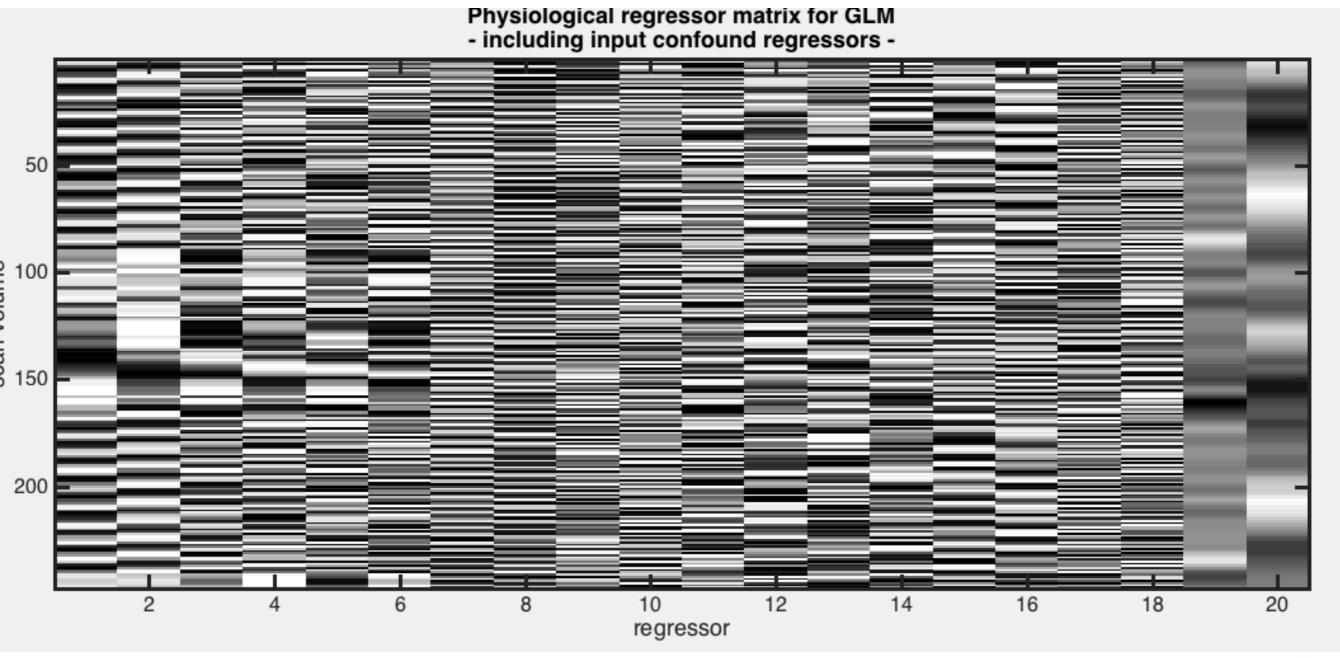
Denoising physiological noise based on external recordings
 2/ Nuisance regressors: RVT x RRF







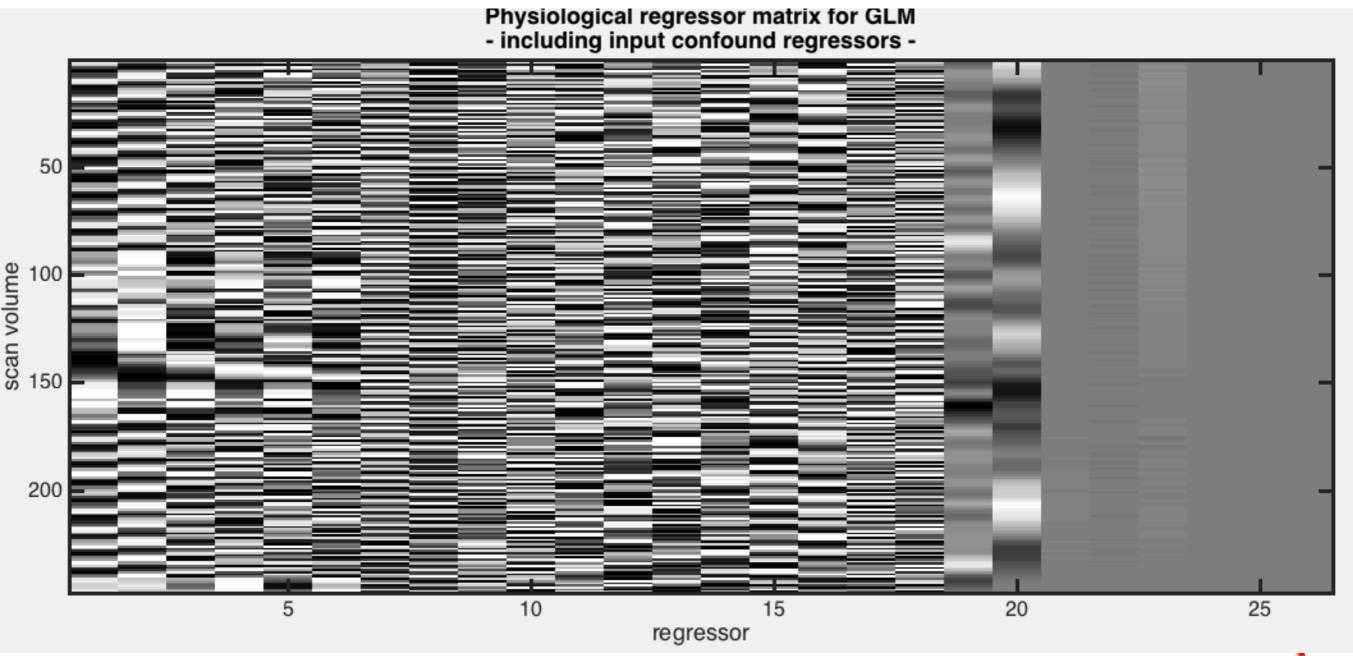
Denoising physiological noise based on external recordings
 2/ Nuisance regressors (RETROICOR, HRV, RVT)







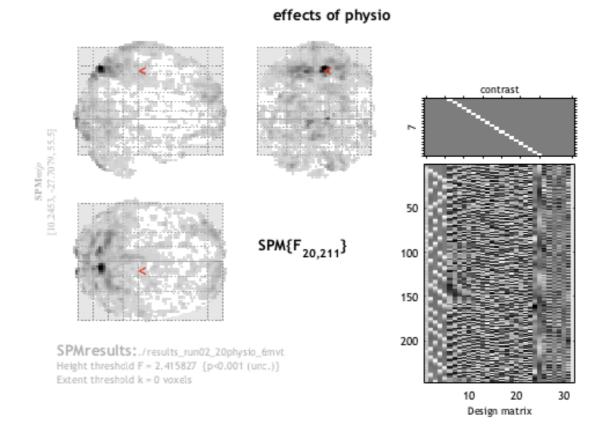
Denoising physiological noise based on external recordings
 2/ Nuisance regressors (RETROICOR, HRV, RVT) + 6 mvts

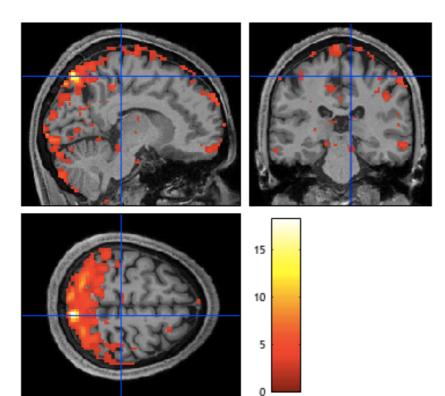






- Denoising physiological noise based on external recordings





Effects of physio nuisance regressors





Denoising physiological noise based on external recordings

SPMF6,211}

SPMF6,211

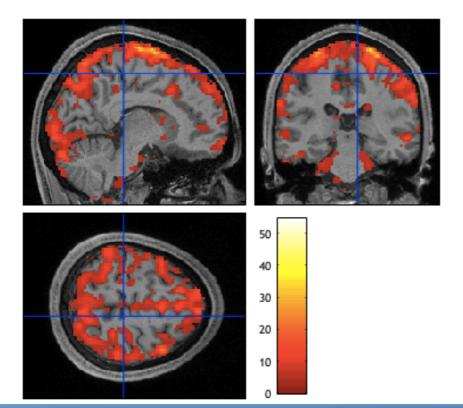
SPMF6,211

100

150

SPMresults:./results_run02_20ptysio_6mvt
Height threshold F = 3,910795 {p-0.001 (unc.)}
Extent threshold k = 0 voxels

10 20 30
Design matrix



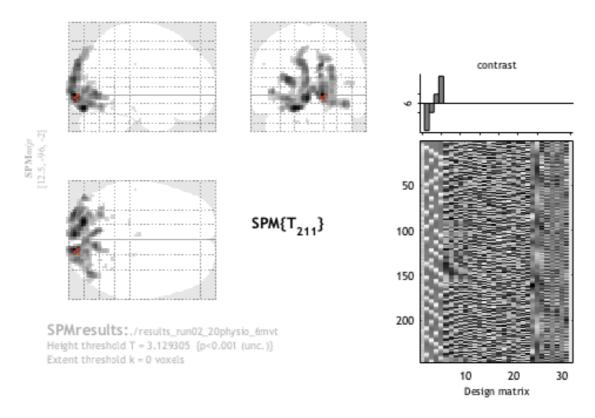
Effects of movement parameters

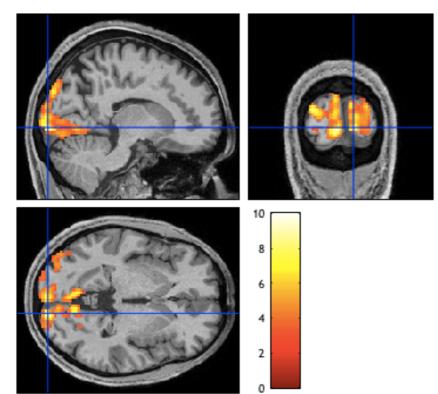


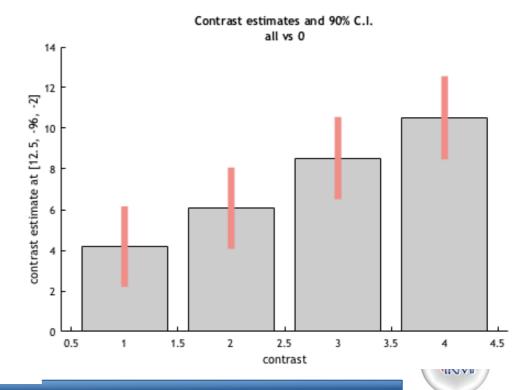


- Denoising physiological noise based on external recordings

Parametric_effects_contrast_visual





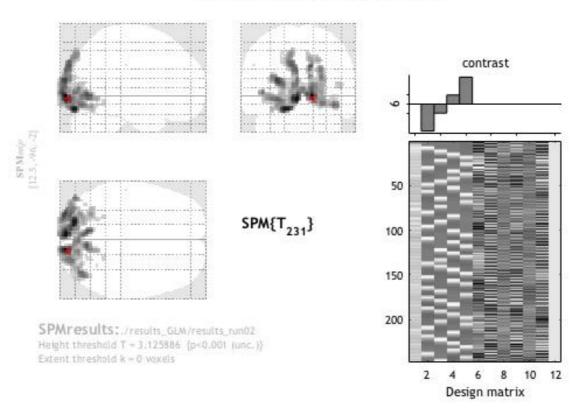


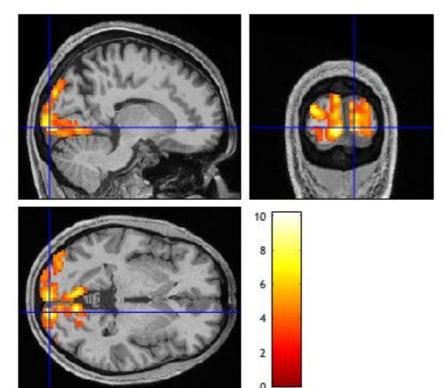


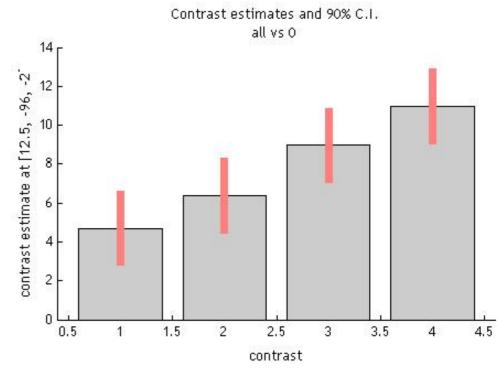
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« Good » subject ≈ identical than without physio denoising

Parametric_effects_contrast_visuel



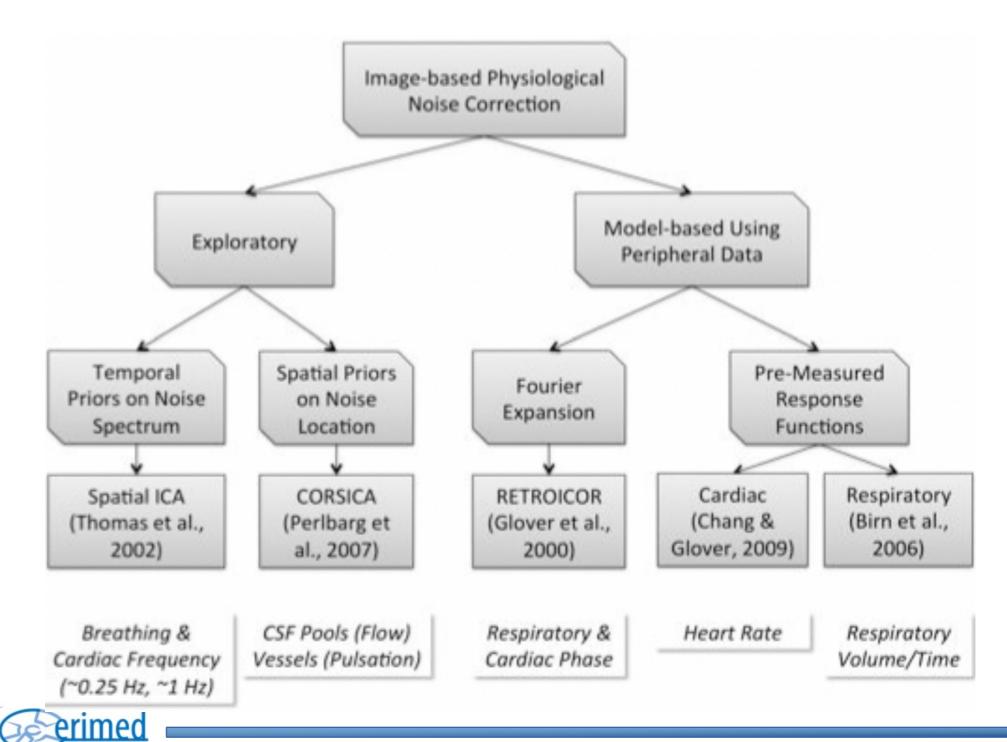








- Denoising physiological noise based on external recordings
- Data-driven denoising methods of physiological noise





- Data-driven denoising methods of physiological noise
 - based on **Principal Component Analysis (PCA)** of noise regions signals : white matter (WM) & Cerebro-Spinal Fluid (CSF)
 - CompCor (Behzadi et al., 2007)
 - based on Independent Component Analysis (ICA)
 - temporal ICA: PESTICA (Beall and Lowe, 2007)
 - spatial ICA: CORSICA (Perlbarg & al, 2007)
 - spatial ICA: ICA-AROMA (Pruim & al, 2015) & FIX-ICA (Salimi-Khorshidi & al, 2014): available in FSL
- → Determine nuisance regressors for the GLM analysis



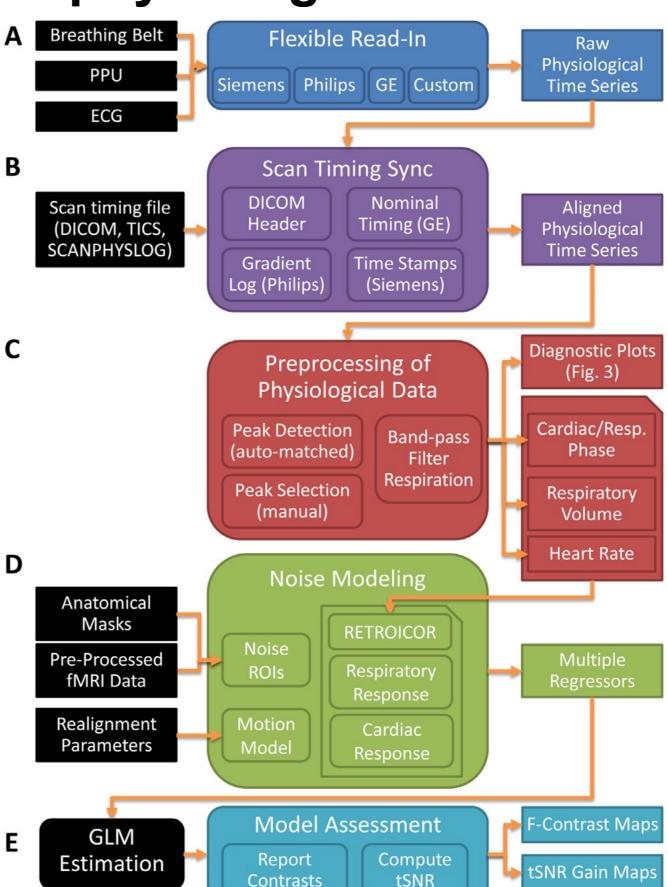


- Data-driven denoising methods of physiological noise
 Based on Principal Component Analysis (PCA)
 - Selection of noise regions signals :
 - Thresholding the tissues volume fraction map (at 0.99)
 - Performing a map erosion by two pixels
 - → minimizing the effect of partial voluming with other tissue types.
 - Extraction of EPI non-smoothed data in the noise regions
 - Principal Component Analysis (PCA) on these EPI data





Denoising motion & physiological-related noise





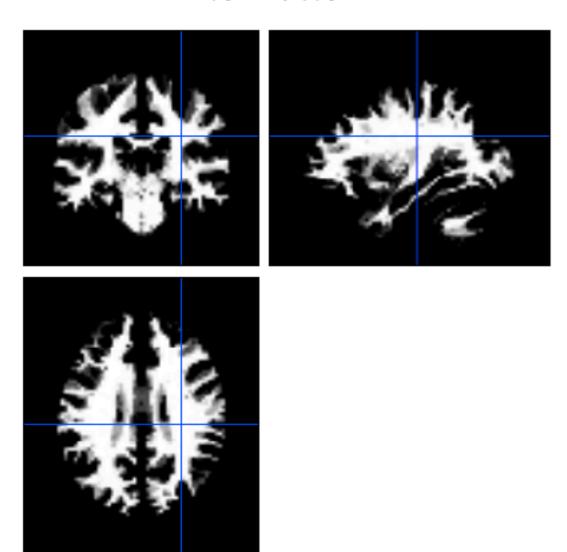
The PhysIO Toolbox for Modeling Physiological Noise in fMRI Data Kasper & al.

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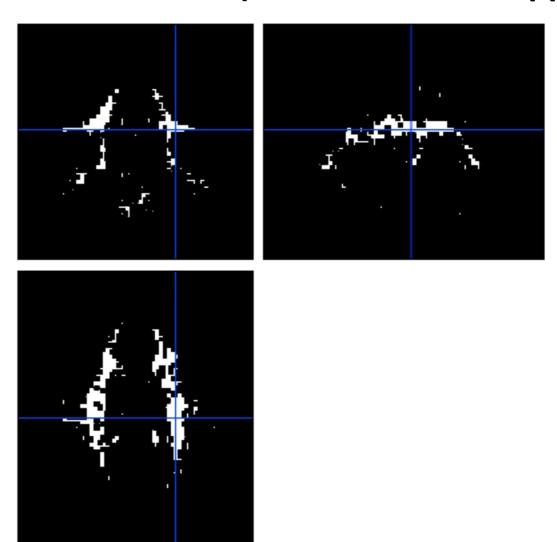


- Masks/tissue probability maps characterizing where noise resides: ROI 1

White Matter



White Matter (thresholded & cropped)

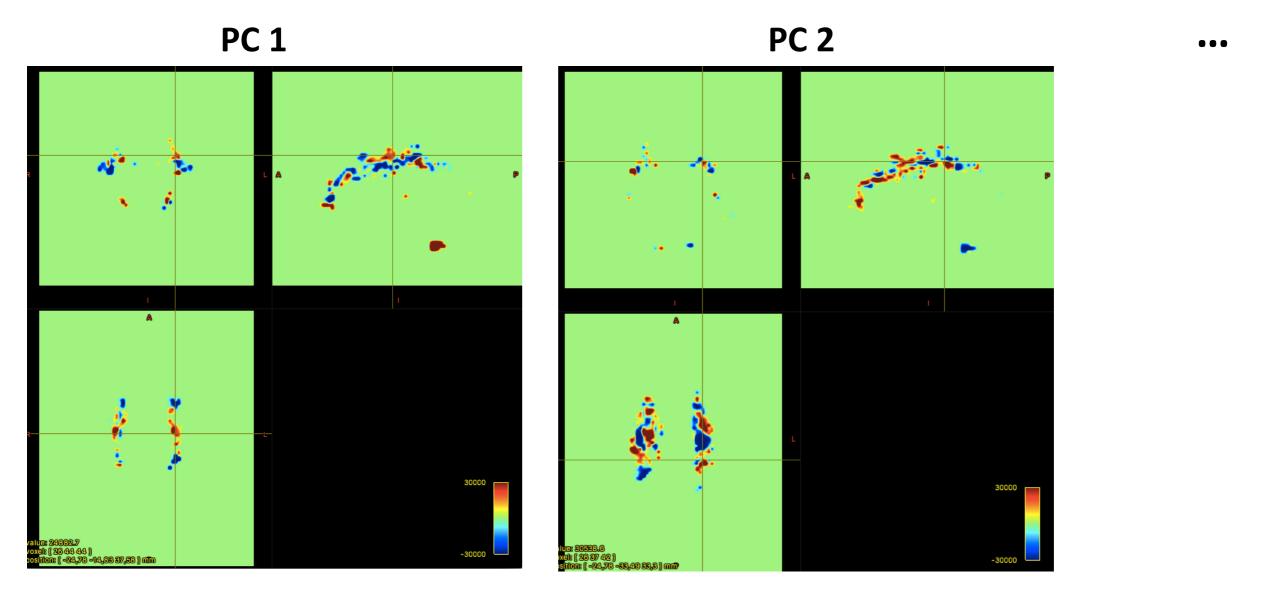






 Principal Component Analysis (PCA) of <u>non-smoothed EPI data</u> in WM (thresholded & cropped)

→ N Principal Spatial Components in WM

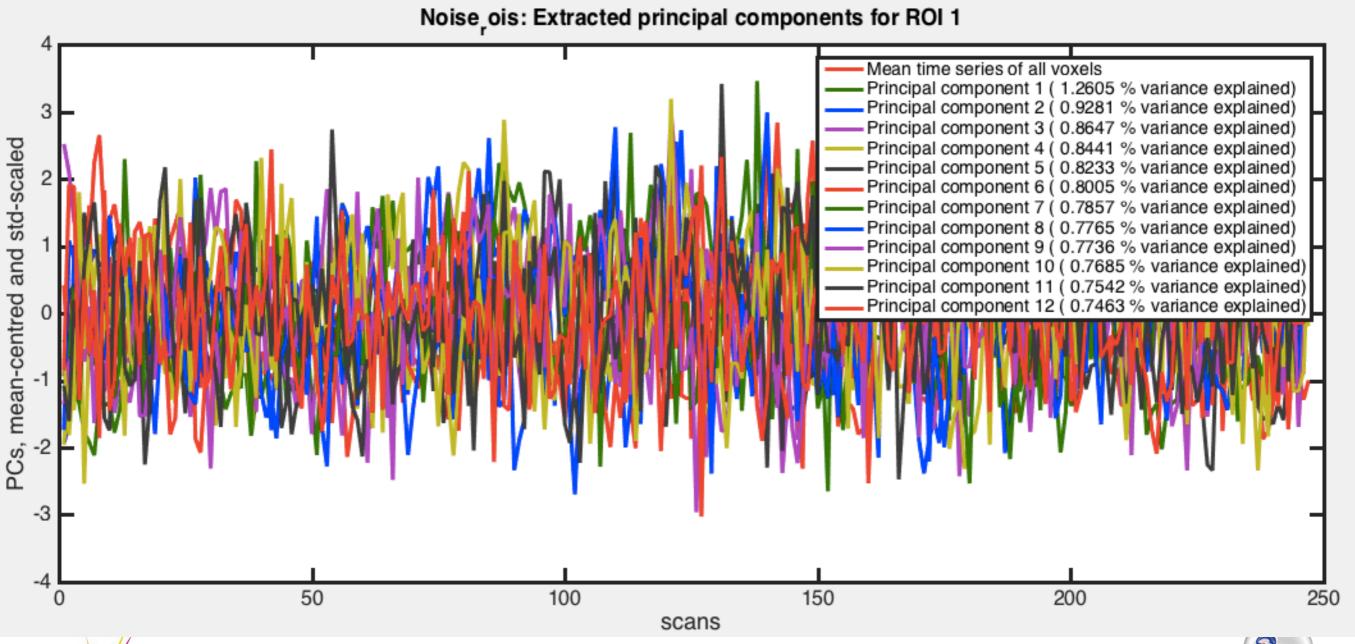






 Principal Component Analysis (PCA) of <u>non-smoothed EPI data</u> in WM (thresholded & cropped)

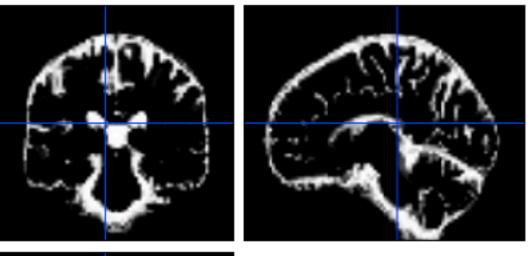
→ N Temporal Components : nuisance regressors

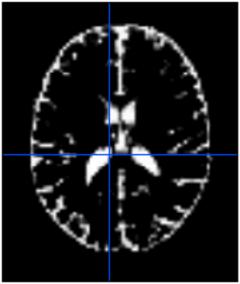




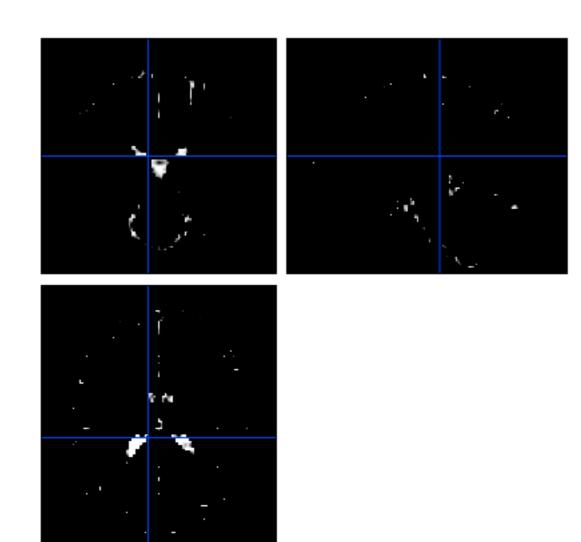
- Masks/tissue probability maps characterizing where noise resides: ROI 2

Cerebro-Spinal Fluid (CSF)





CSF (thresholded)

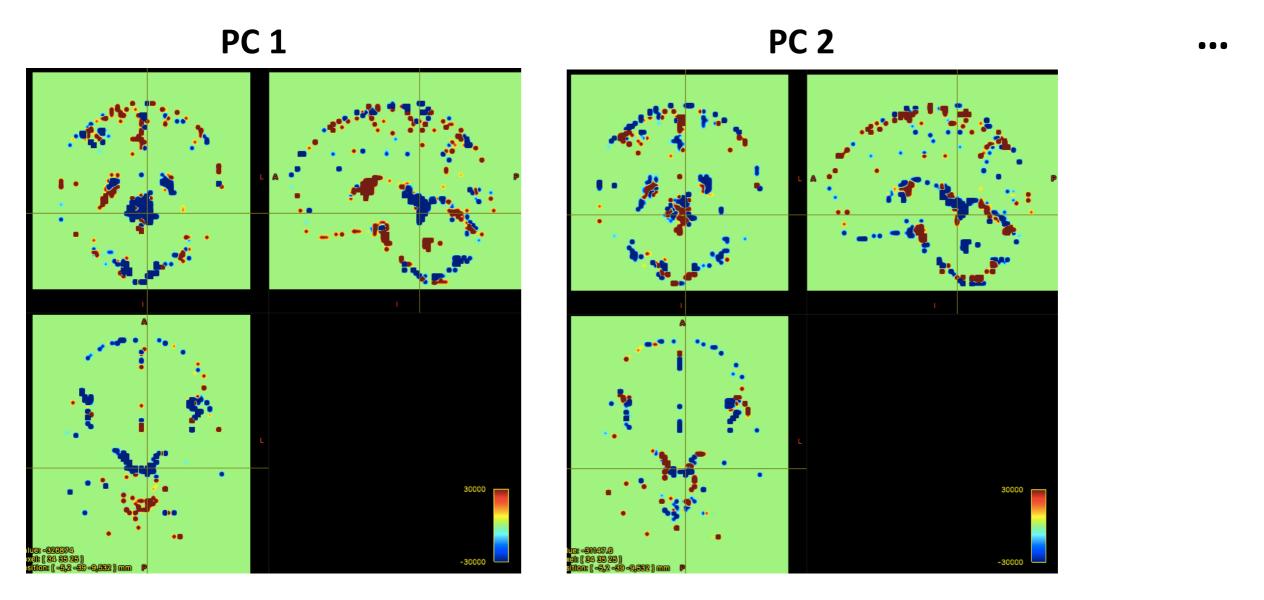






- Principal Component Analysis (PCA) of non-smoothed EPI data in CSF

→ N Principal Spatial Components in CSF

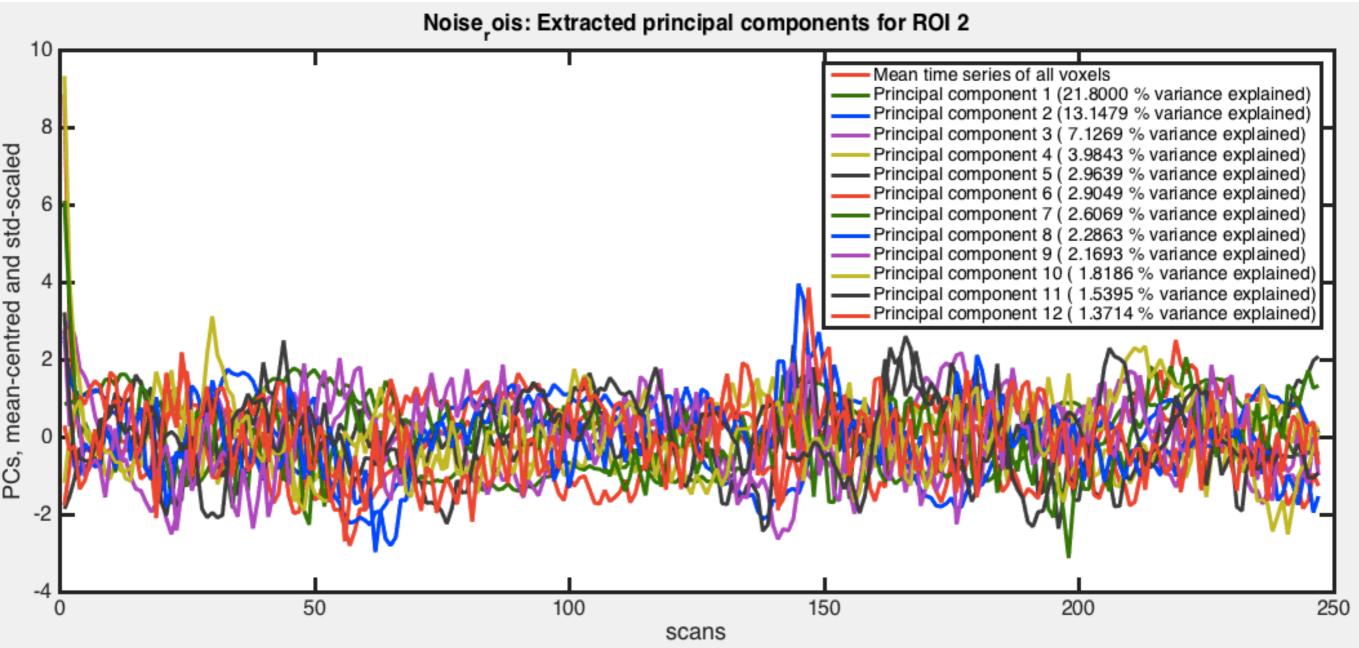






- Principal Component Analysis (PCA) of non-smoothed EPI data in CSF

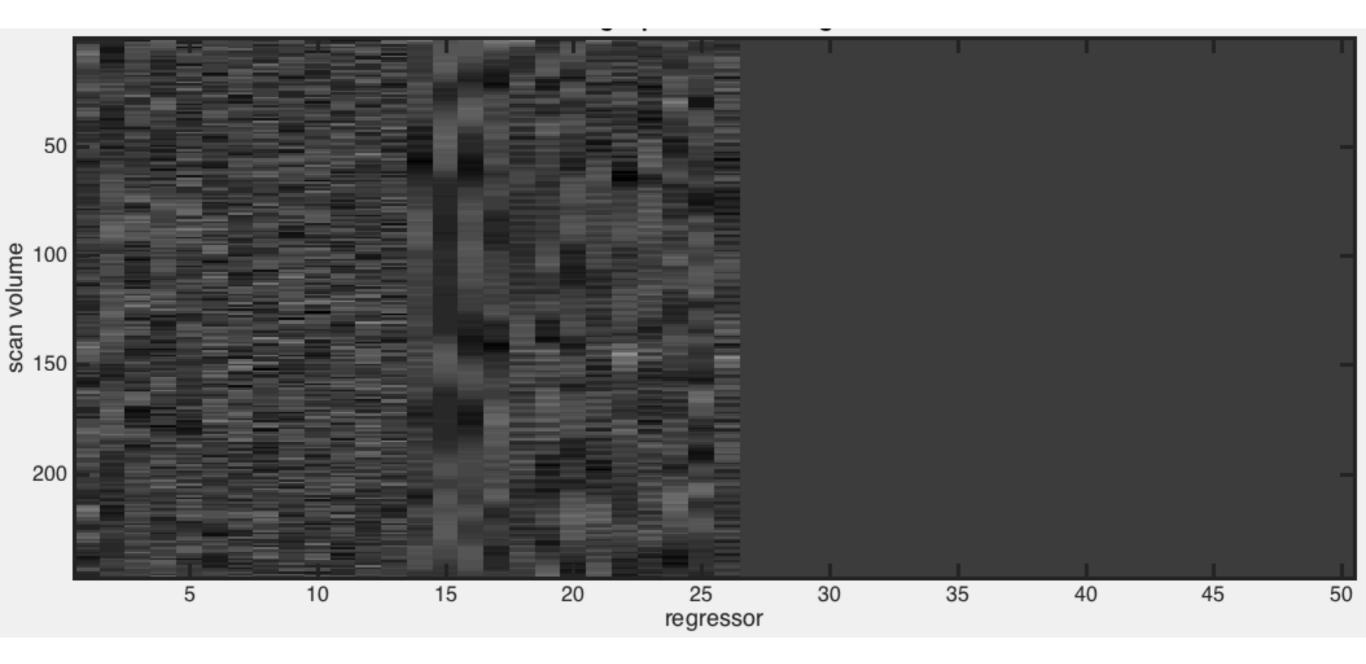
→ N Temporal Components : nuisance regressors







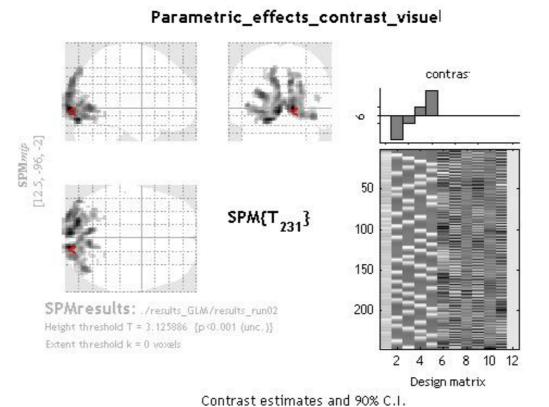
- 12 PCs + 1 mean for WM, 12 PCs + 1 mean for CSF, 24 movement parameters

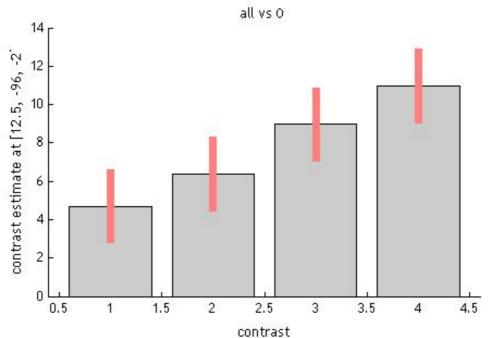






Only 6 realign parameters



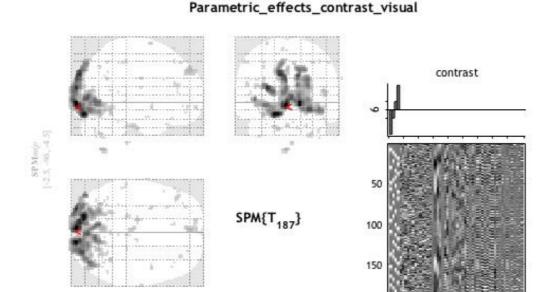






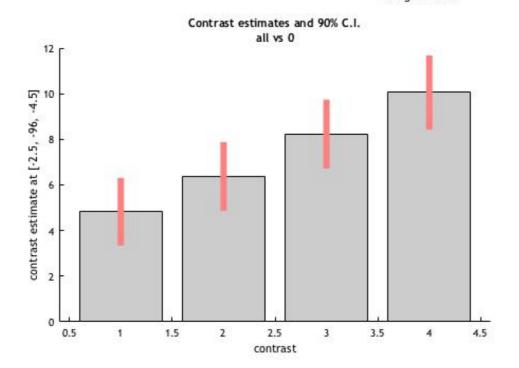


- 12 PCs + 1 mean for WM, 12 PCs + 1 mean for CSF, 24 movement parameters



Height threshold T = 3.134385 {p<0.001 (unc.)}

Extent threshold k = 0 voxels



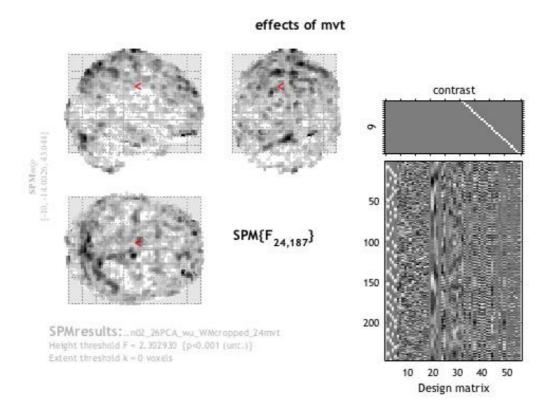
 \rightarrow T max = 11.65

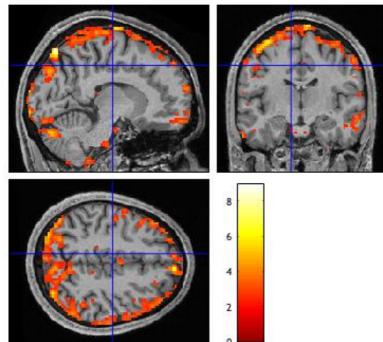


30 40

Design matrix

- 12 PCs + 1 mean for WM, 12 PCs + 1 mean for CSF, 24 movement parameters



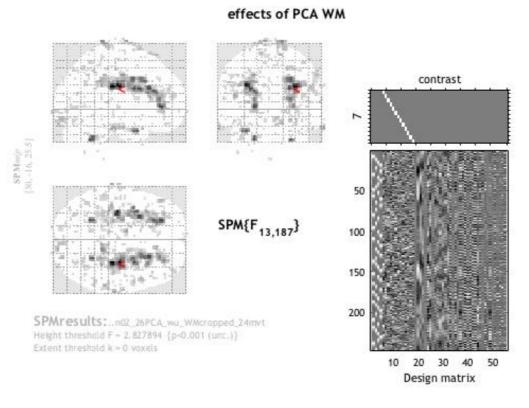


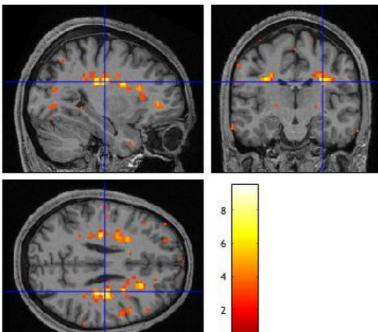
Effects of movement parameters





- 12 PCs + 1 mean for WM, 12 PCs + 1 mean for CSF, 24 movement parameters



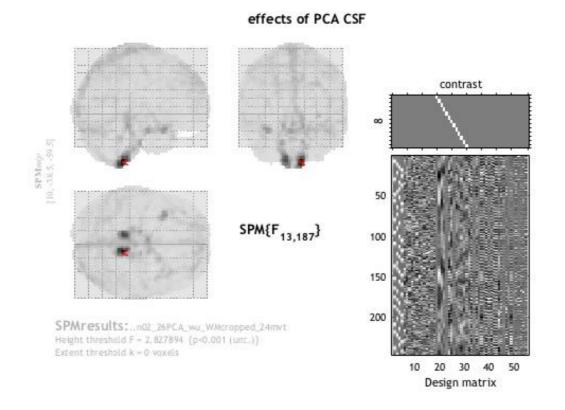


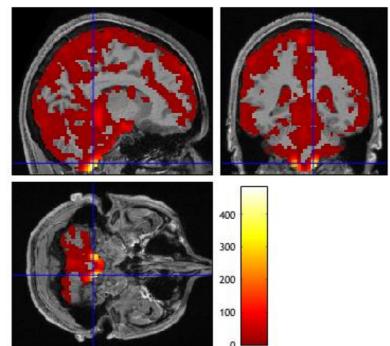
Effects of WM nuisance regressors





- 12 PCs + 1 mean for WM, 12 PCs + 1 mean for CSF, 24 movement parameters





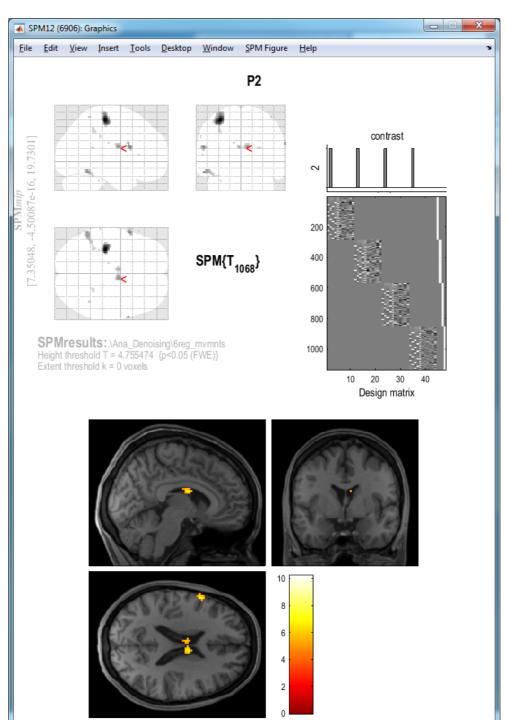
Effects of CSF nuisance regressors





- Other example : non-null contrast [1 0 0 ...], old subject, right hand stimulation

6 nuisance regressors : realign parameters rp(t)

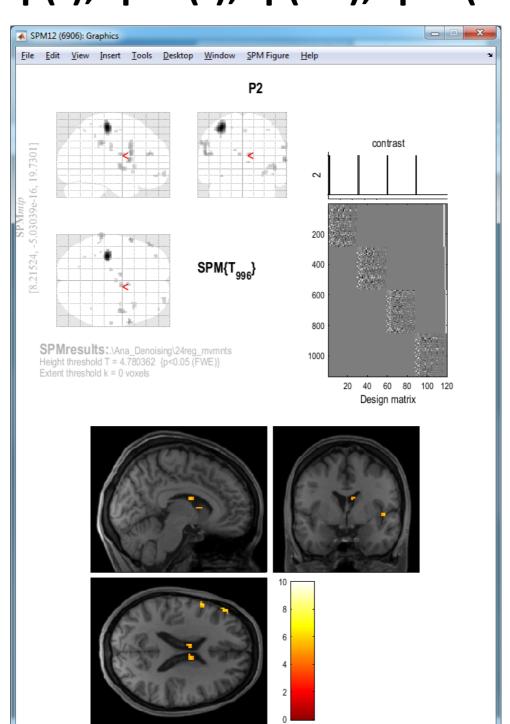






- Other example : non-null contrast [1 0 0 ...], old subject, right hand stimulation

24 nuisance regressors: rp(t), rp^2(t), rp(t-1), rp^2(t-1)

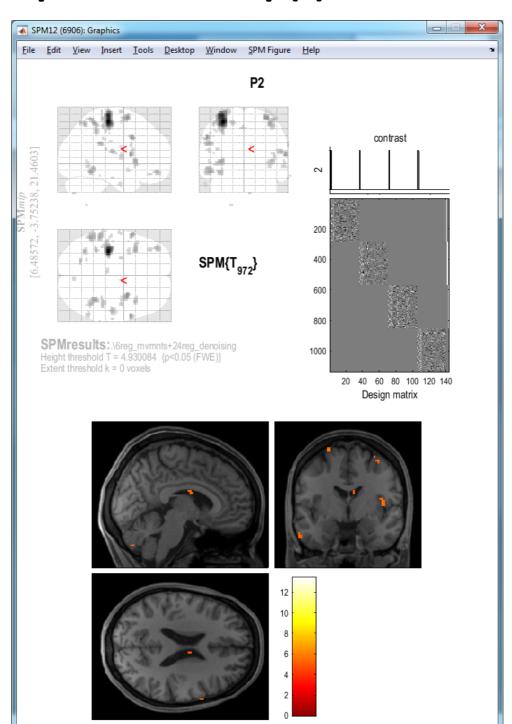






- Other example: non-null contrast [1 0 0 ...], old subject, right hand stimulation

30 nuisance reg: 6 realign parameters rp(t) + 12 PCA WM + 12 PCA CSF

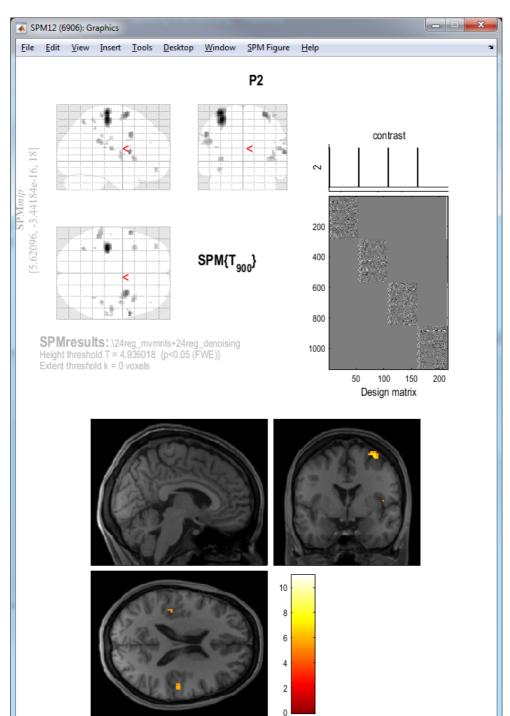






- Other example: non-null contrast [1 0 0 ...], old subject, right hand stimulation

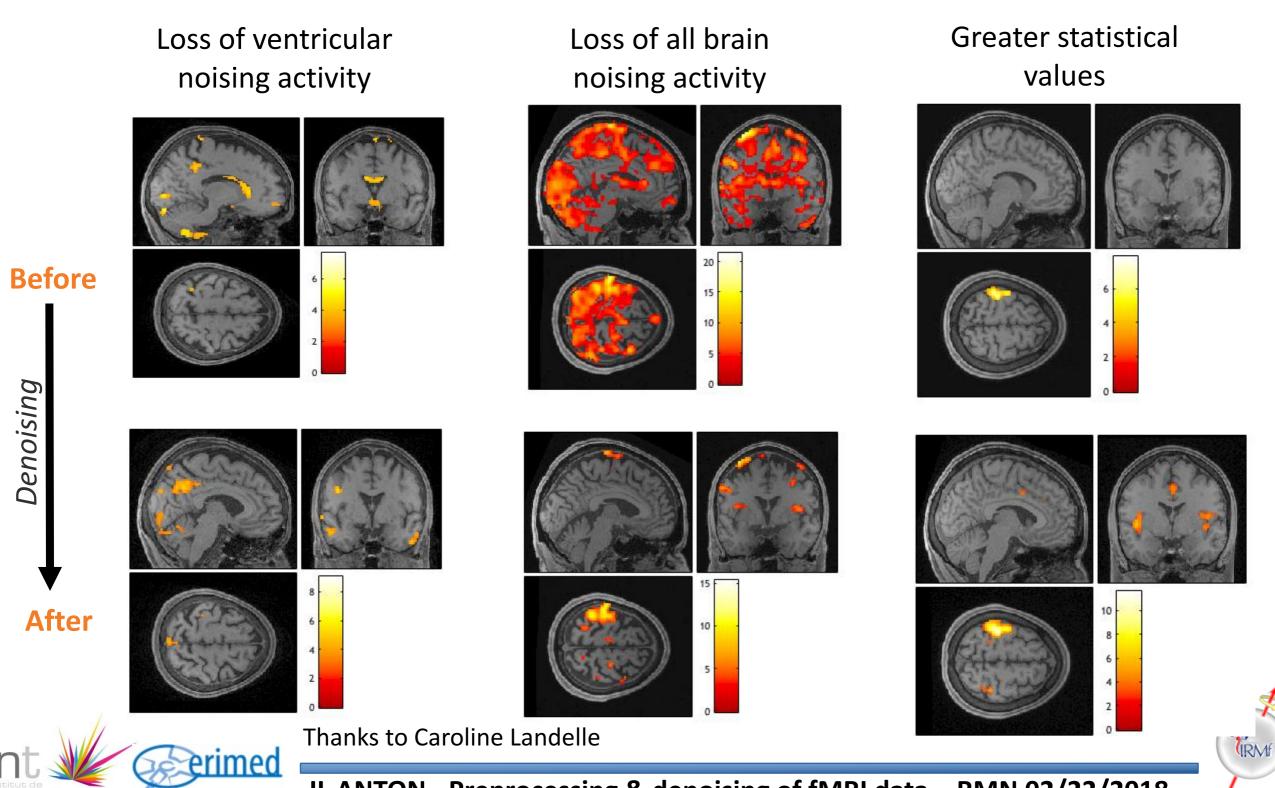
48 nuisance reg: rp(t), rp^2(t), rp(t-1), rp^2(t-1) + 12 PCA WM + 12 PCA CSF



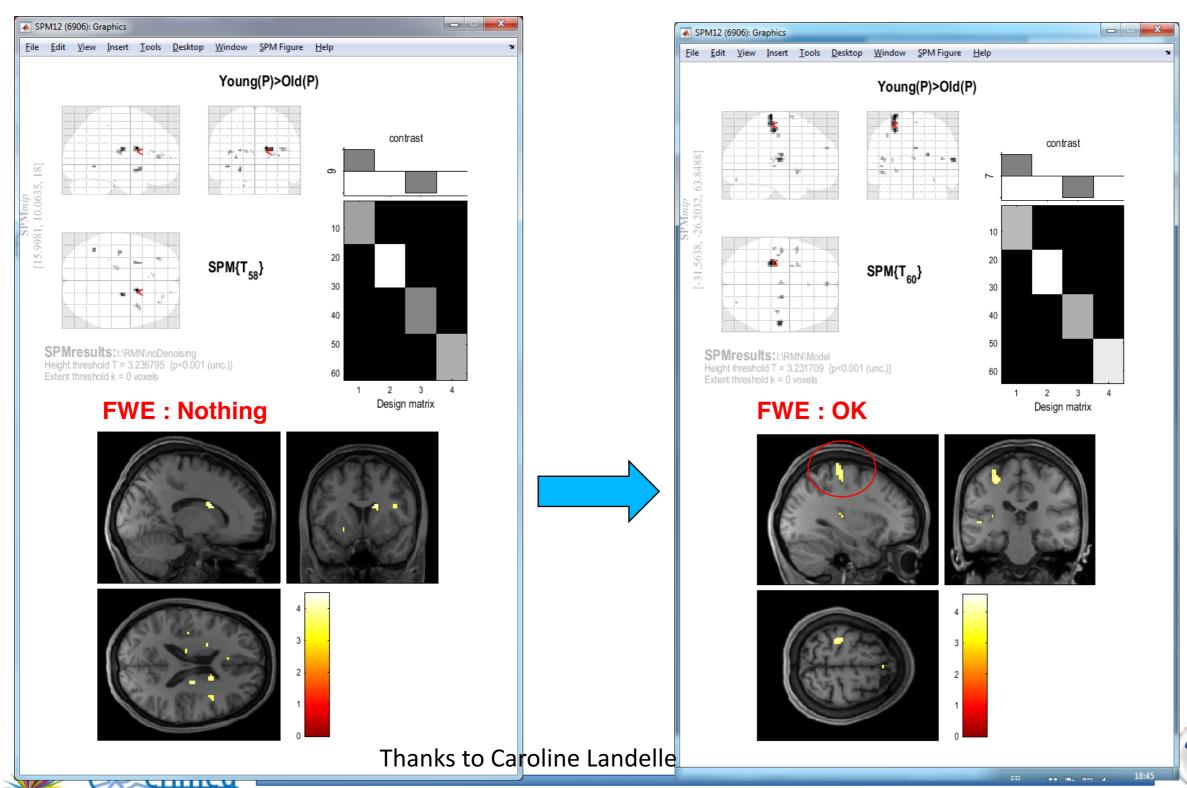




→ For some subjects, the denoising with 48 nuisance regressors
 (rp(t), rp^2(t), rp(t-1), rp^2(t-1), 12 PCA WM, 12 PCA CSF) is very efficient



- For inter-group comparison, the denoising with 48 nuisance regressors (rp(t), rp^2(t), rp(t-1), rp^2(t-1), 12 PCA WM, 12 PCA CSF) is very efficient



neurosciences

Data-driven denoising methods of physiological noise

Based on Principal Component Analysis (PCA) of noise regions signals: white matter (WM) & Cerebro-Spinal Fluid (CSF)

→ Questions :

- Precise definition of noise region signals (minimizing the effect of partial voluming with other tissue types)
- PCA to be performed on non-smoothed EPI data
- Number of PCs for each tissue? % of variance explained?
- Need to orthogonalize the nuisance regressors from the task-related regressors





Data-driven denoising methods of physiological noise

Based on Independent Component Analysis (ICA)

- temporal ICA: PESTICA (Beall and Lowe, 2007)
- spatial ICA: CORSICA (Perlbarg & al, 2007)
- spatial ICA: ICA-AROMA (Pruim & al, 2015) & FIX-ICA (Salimi-Khorshidi & al, 2014): available in FSL

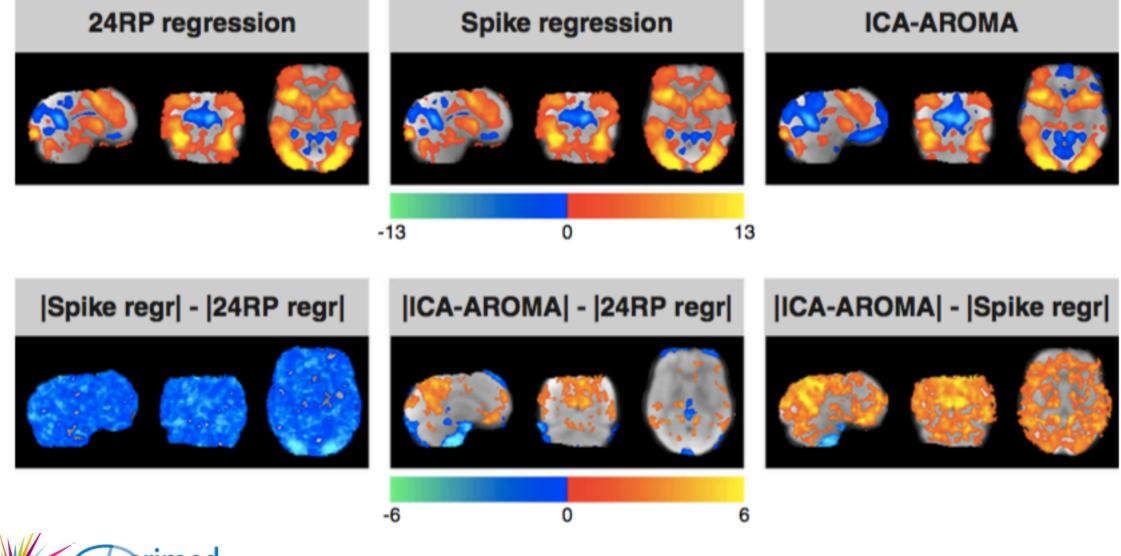
→ Question :

Choice of the components to be removed to the EPI data?





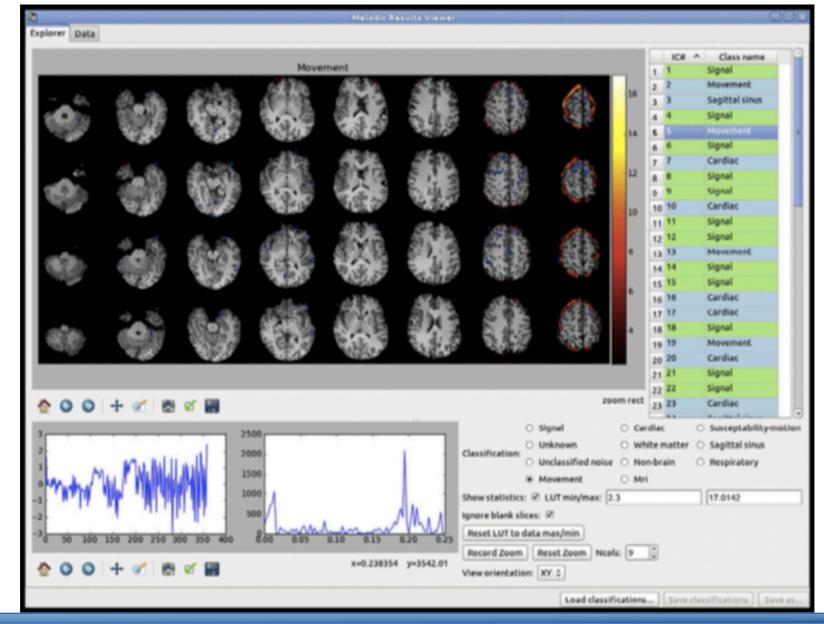
- Data-driven denoising methods of physiological noise
 Based on Independent Component Analysis (ICA)
 - ICA-AROMA (Pruim & al, 2015) : available in FSL
 - > remove motion-related ICA components from FMRI data







- Data-driven denoising methods of physiological noise
 Based on Independent Component Analysis (ICA)
- FIX-ICA (Salimi-Khorshidi & al, 2014): available in FSL
 → aims to auto-classify ICs into "good" vs "bad" components







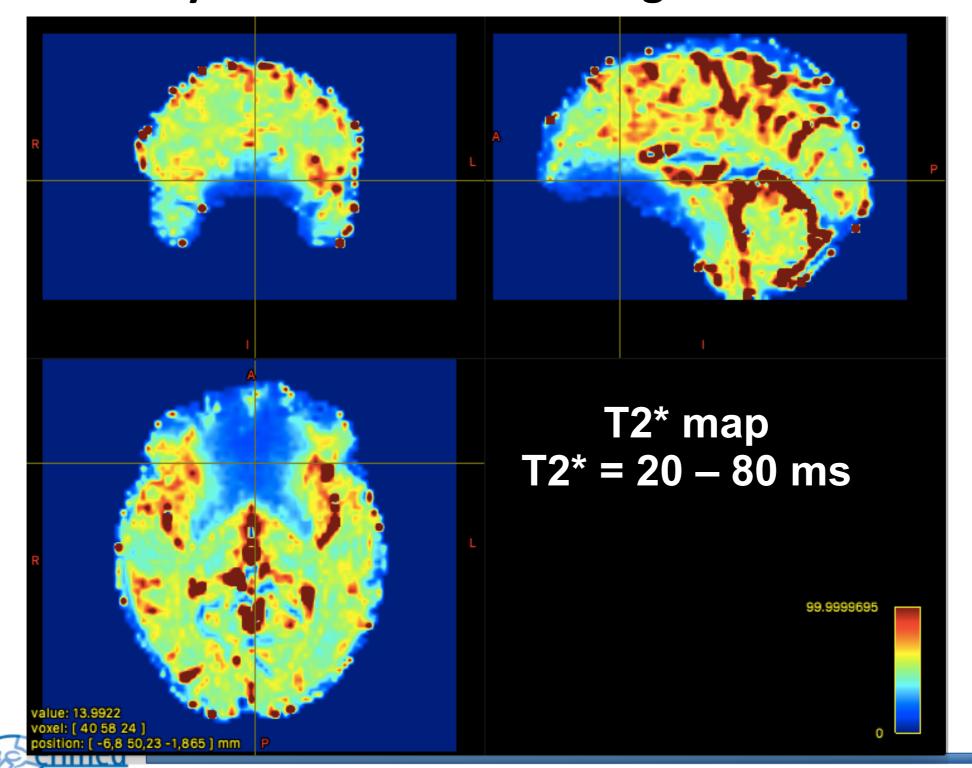
- Data-driven denoising methods of physiological noise Based on Independent Component Analysis (ICA)
- FIX-ICA (Salimi-Khorshidi & al, 2014): available in FSL
 → aims to auto-classify ICs into "good" vs "bad" components

Example: FMRIB's ICA-based Xnoiseifier – FIX (FSL)
 http://www.fmrib.ox.ac.uk/analysis/FIX-training/fix_eg.html



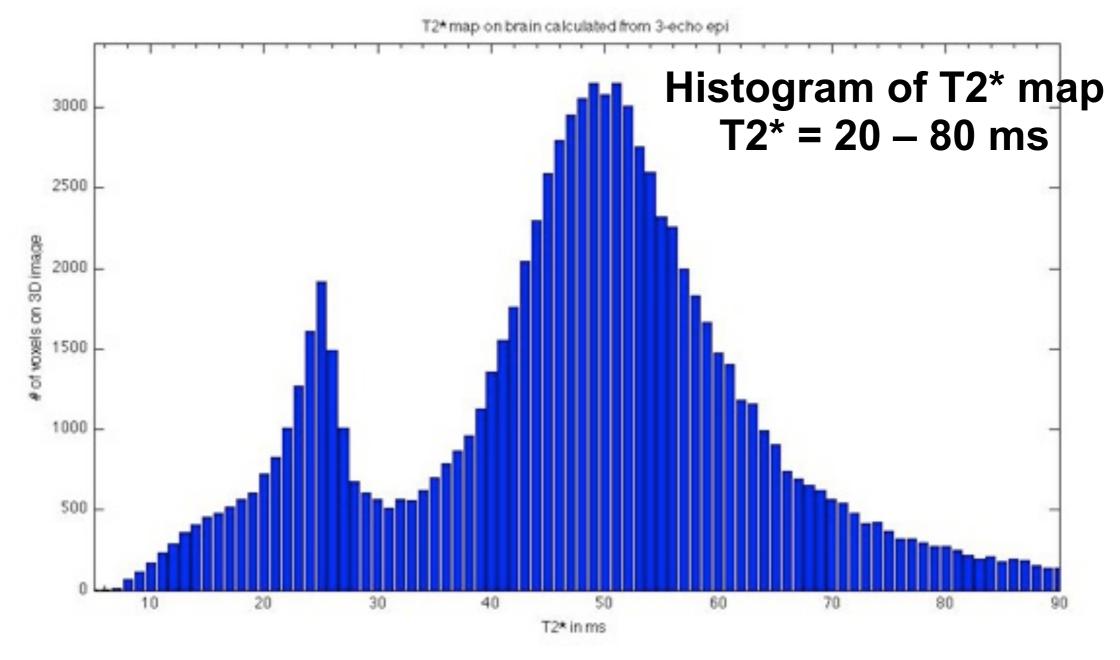


 A single-echo EPI (TE ≈ 30 ms) is sub-optimal because of the huge variability of T2* across brain regions



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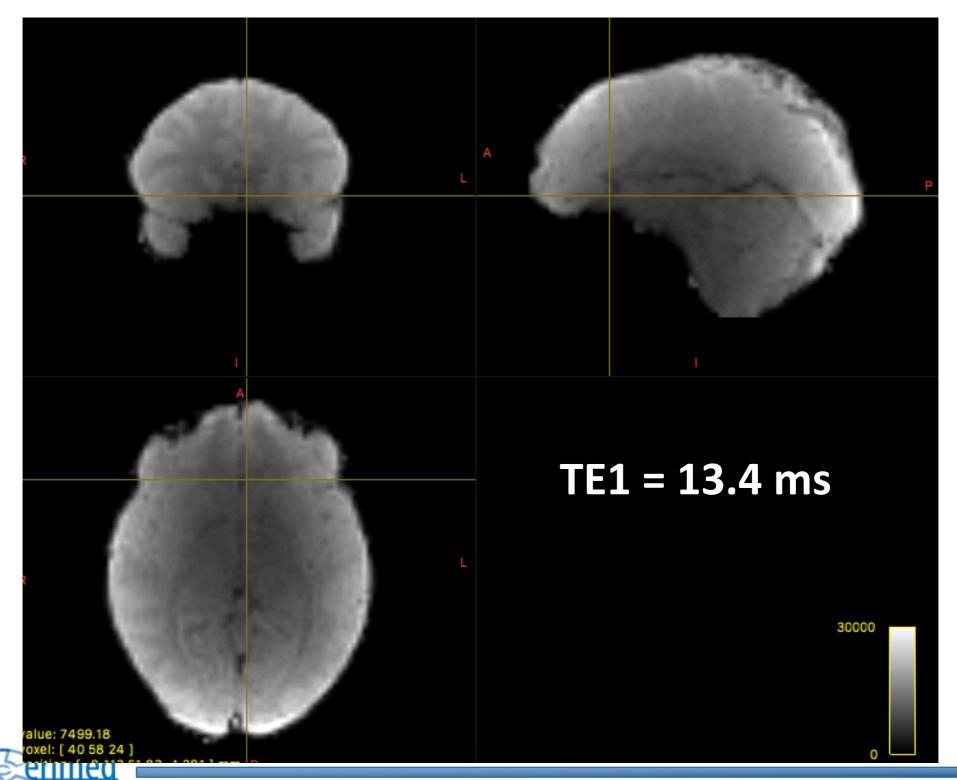
 A single-echo EPI (TE ≈ 30 ms) is sub-optimal because of the huge variability of T2* across brain regions





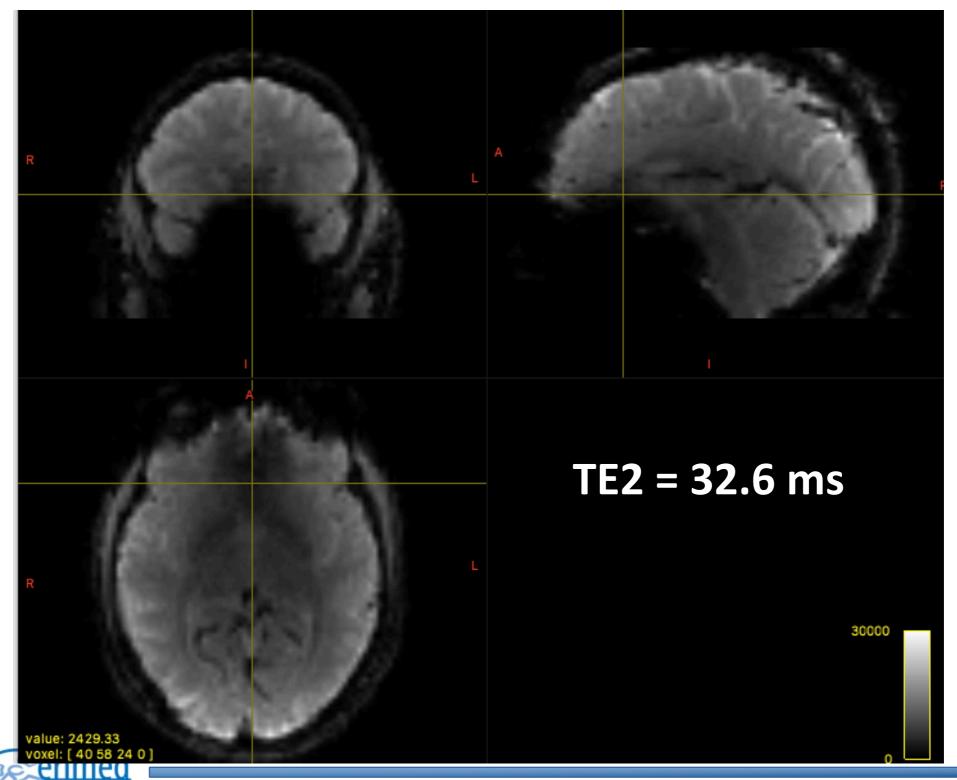


- EPI Multi-bande Multi-Echo (MB 3 ME 3, iPAT 2, TR 1425 ms)



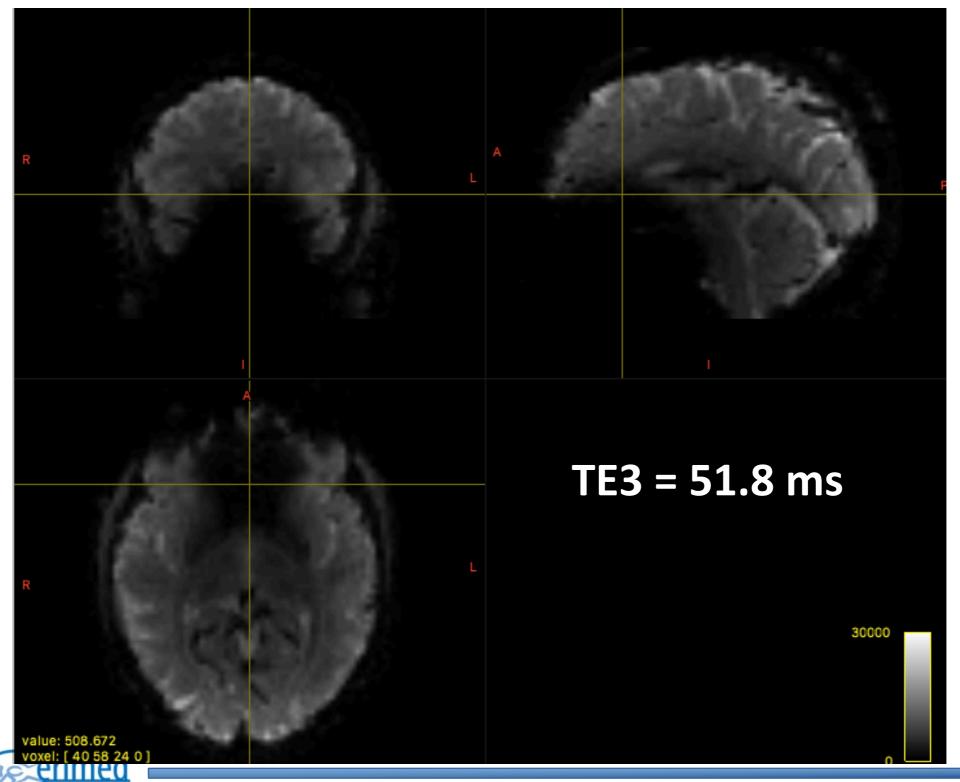


- EPI Multi-bande Multi-Echo (MB 3 ME 3, iPAT 2, TR 1425 ms)





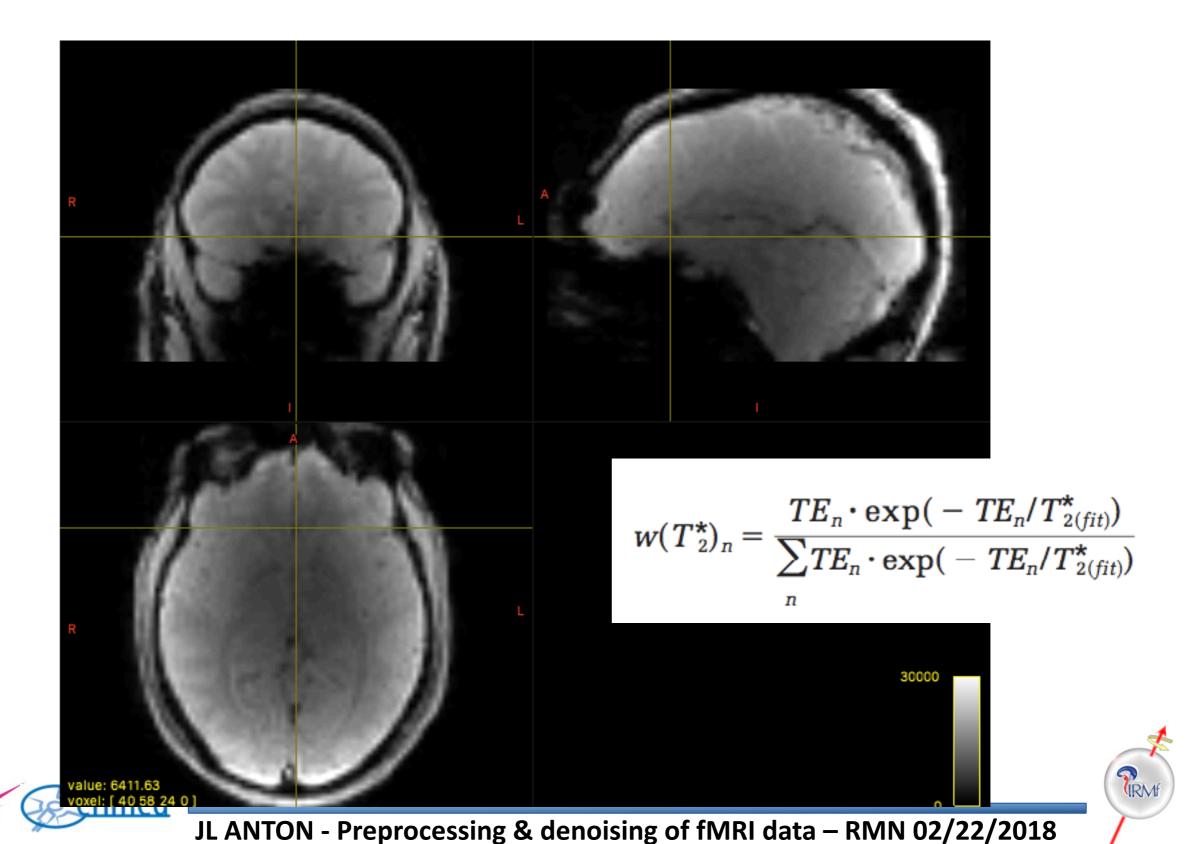
- EPI Multi-bande Multi-Echo (MB 3 ME 3, iPAT 2, TR 1425 ms)





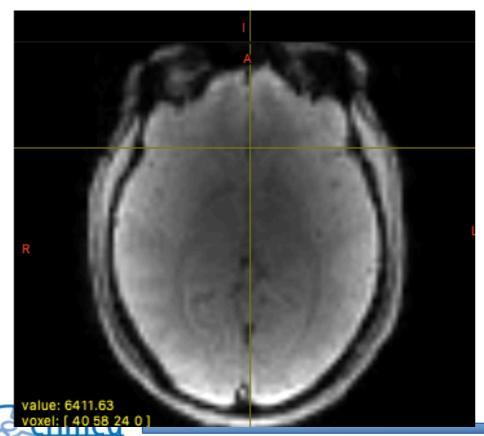
JL ANTON - Preprocessing & denoising of fMRI data - RMN 02/22/2018

--> 1/ Multi-Echo combination (Poser & al, 2006)



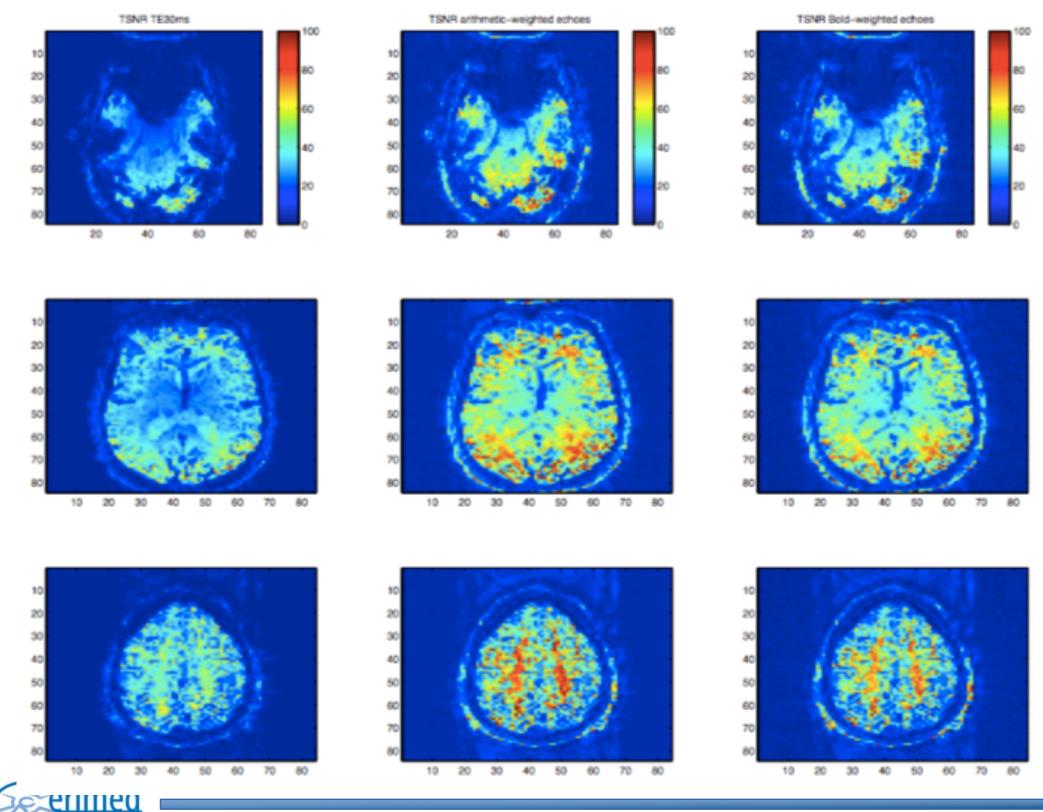
→ 1/ Multi-Echo combination (Poser & al, 2006)

Multi-echo fMRI offers clear advantages for imaging brain regions such as the orbitofrontal cortex and inferior temporal lobes, which are prone to susceptibility distortions and signal dropouts





→ 1/ Multi-Echo combination (Poser & al, 2006)



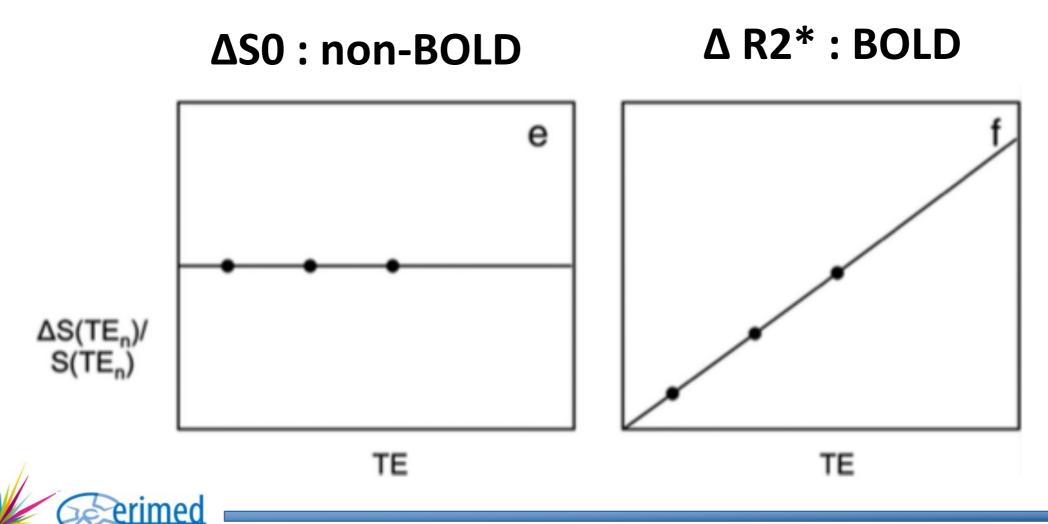
- → 2/ Multi-Echo acquisitions for denoising
- Signals can be recorded at a short TE which is assumed to have minimal T2*- weighting and mainly sensitive to fluctuations in the net magnetization S0.
- → The short TE signal can then be regressed out from time series acquired at a longer TE that is optimized for BOLD sensitivity (Bright and Murphy, 2013; Buur et al., 2008).



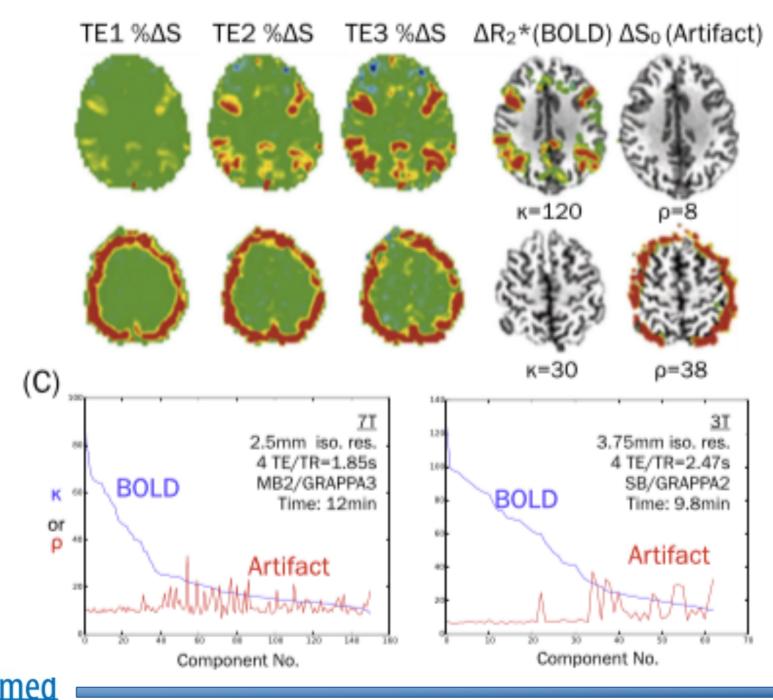


→ 2/ Multi-Echo acquisitions for denoising Kundu et al. (2012) proposed a multi-echo denoising strategy based on independent component analysis (ME- ICA).

This method exploits the fact that BOLD components must exhibit a linear dependence with TE, whereas non-BOLD components must exhibit no dependence with TE.



- > 2/ Multi-Echo acquisitions for denoising
 Kundu et al. (2012) proposed a multi-echo denoising strategy based on independent component analysis (ME- ICA).





General Conclusion

- Denoising BOLD fMRI data is crucial!

It has to be done with a lot of care ...





References

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Methods for cleaning the BOLD fMRI signal

César Caballero-Gaudes^a,*, Richard C. Reynolds^b



- PhysIO Toolbox

Journal of Neuroscience Methods 276 (2017) 56–72



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The PhysiO Toolbox for Modeling Physiological Noise in fMRI Data







