



Physiological Confounds in fMRI

13/06/24

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NIH National Institute of Mental Health

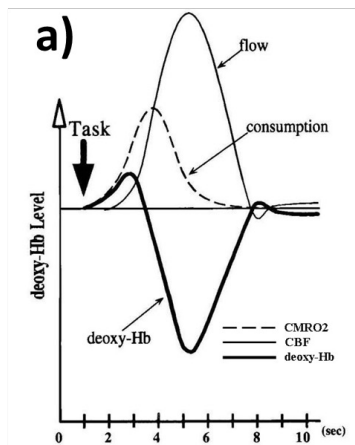
Confounds? or Noise? and Neuronal Activity? or Brain Activity?

- What is the definition of the Noise?
 - Anything doesn't fit to a model
 - Non-task related variability
 - Just anything looks like this →

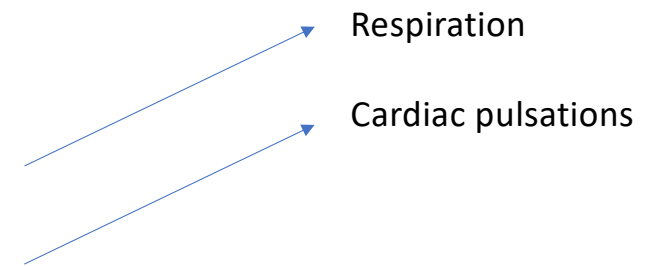


Functional MRI

- T2*-weighted imaging sensitive to paramagnetic deoxyhaemoglobin concentration in the blood
- Blood-oxygenation level dependent (BOLD) effect



Glover et.al 1999

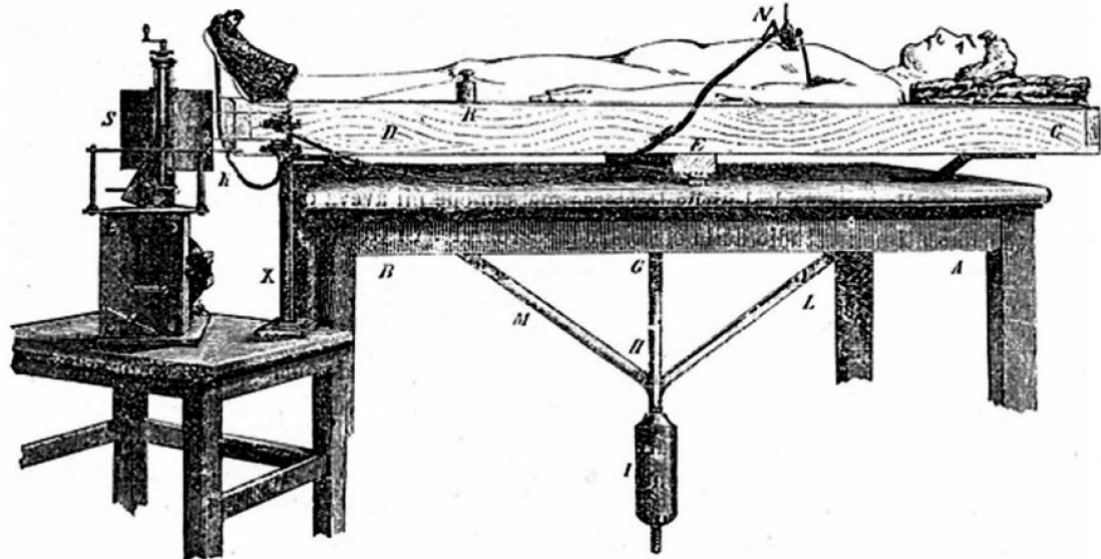


The man who weighed thoughts

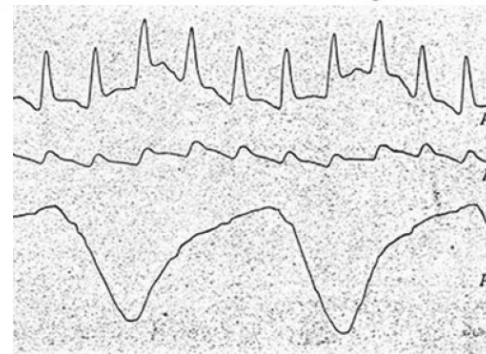
Early cerebral blood flow (CBF) measurements



Angelo Mosso (1846 -1910)

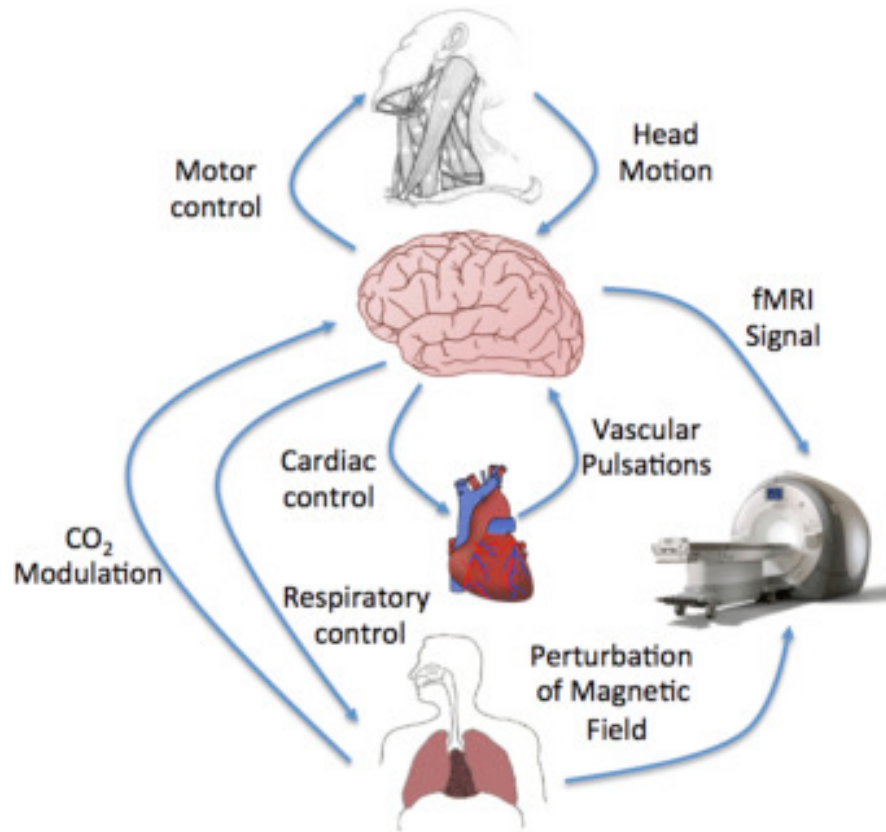


Turin - Italy



Mosso et.al 1880

Potential noise sources in fMRI



Liu TT, Neuroimage 2016

- Noise

- Hardware related
- Physiological
- Motion

- Hardware related

- Scanner drift
- Thermal noise

- Motion

- Respiration related
- Cardiac related
- Task related
- Other head motion

- Physiological

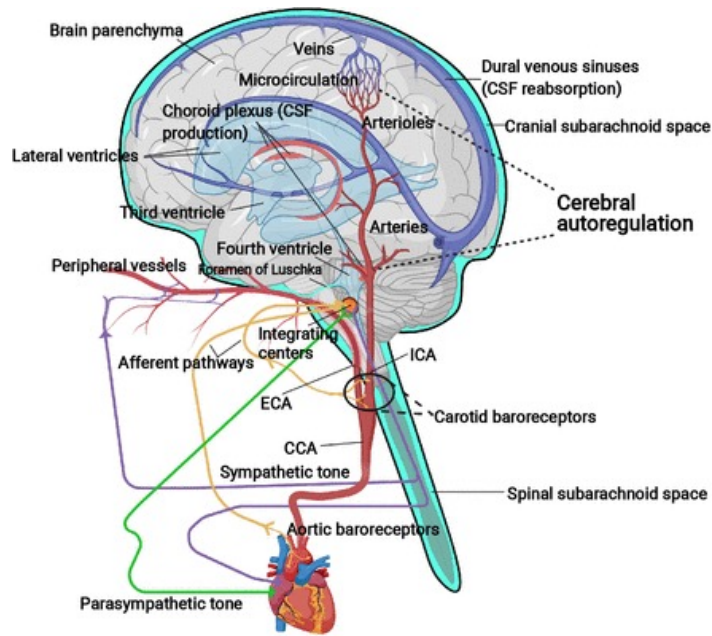
- Respiration

- Time-locked
- B₀-field
- CO₂
- Blood flow

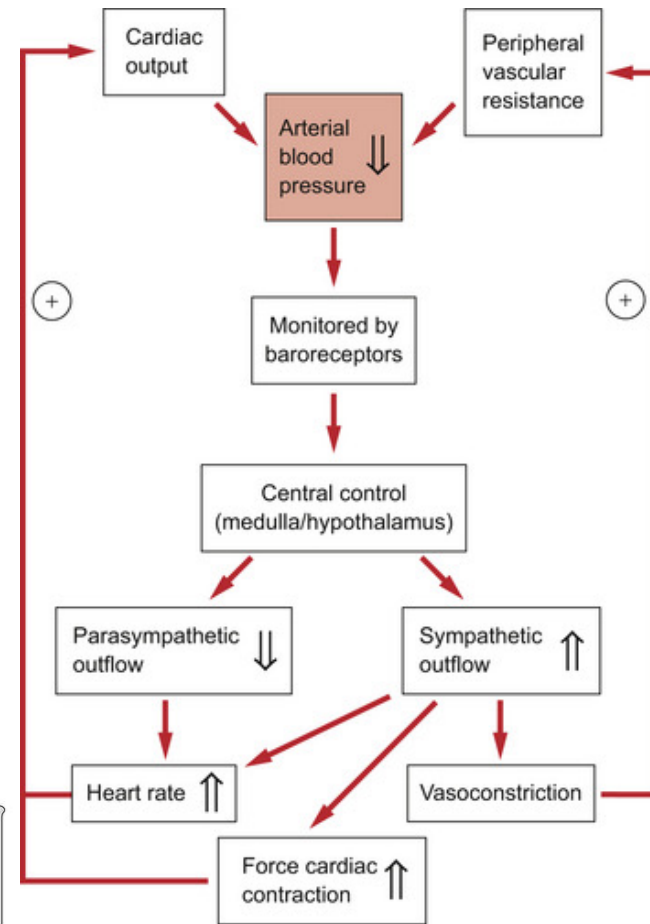
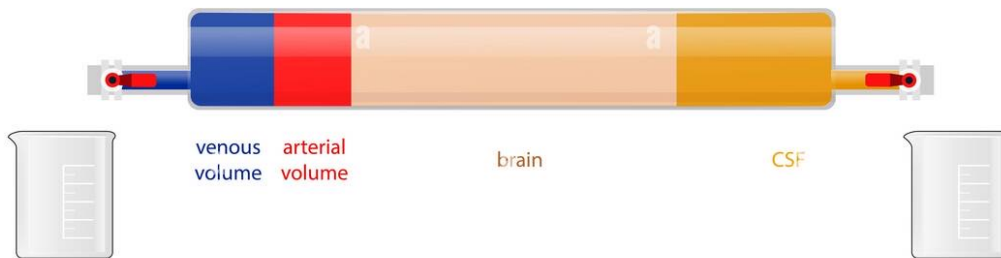
- Cardiac

- Time-locked
- Motion-related
- Blood flow

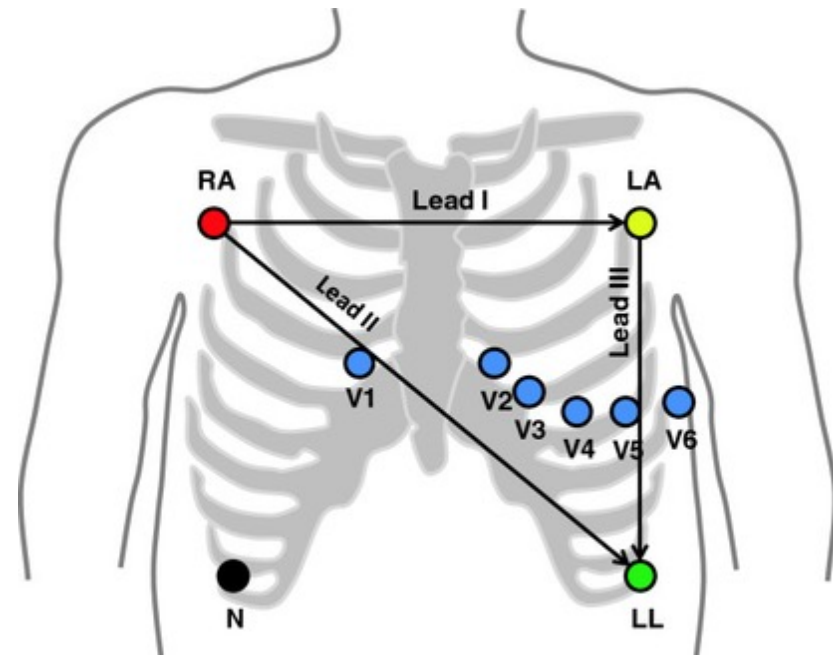
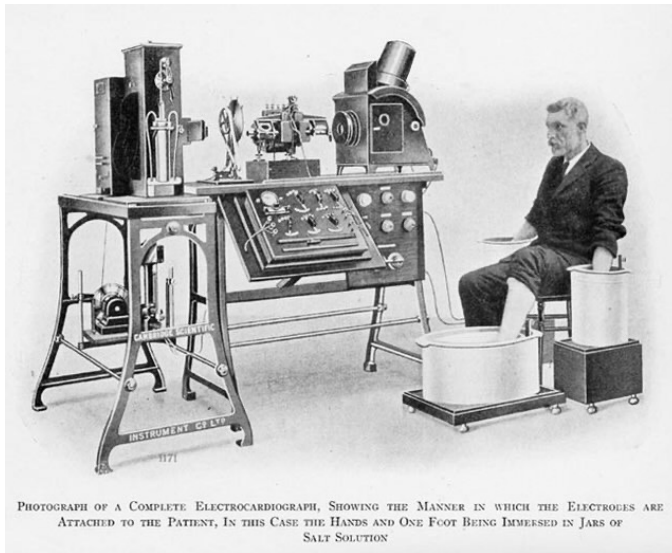
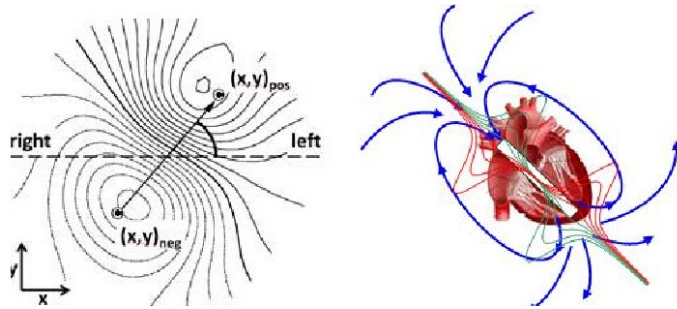
Potential noise sources in fMRI



Garcia et, al.2021



How do we measure physiological signals? Cardiac activity

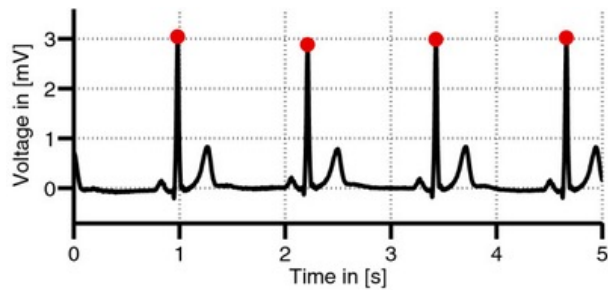


How do we measure physiological signals?

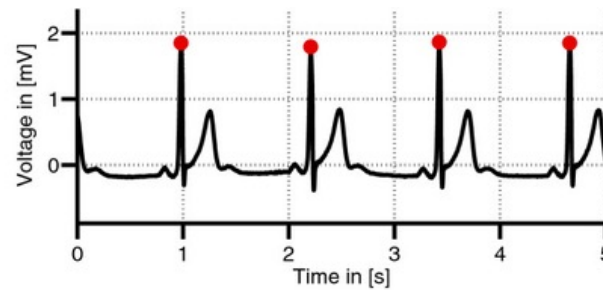


How do we measure physiological signals?

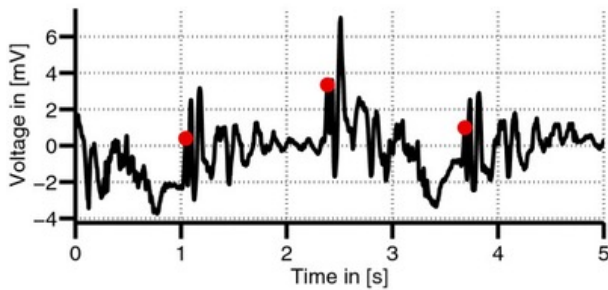
- ECG inside MRI
- The magneto-hydrodynamic effect : the motion of the blood



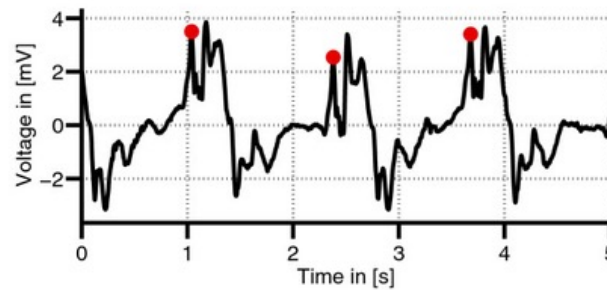
(a) Lead II, outside



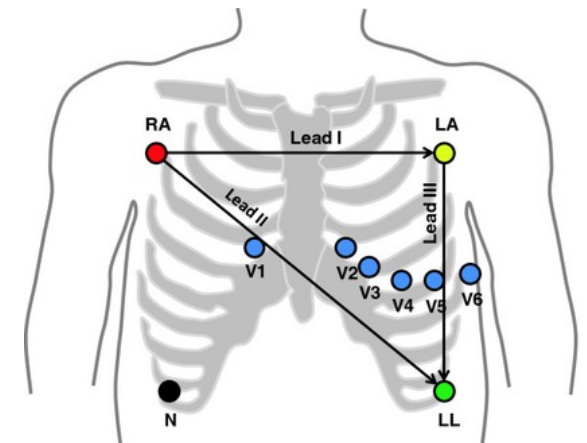
(b) Lead V3, outside



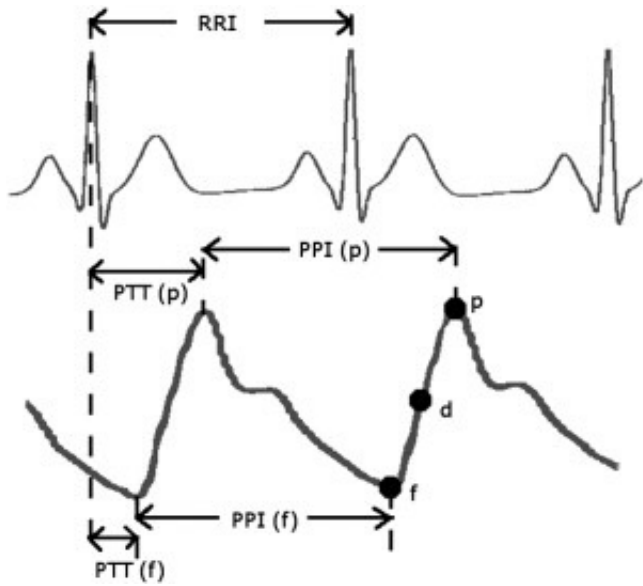
(c) Lead II, inside, Ff



(d) Lead V3, inside, Ff



Pulse Oximeter



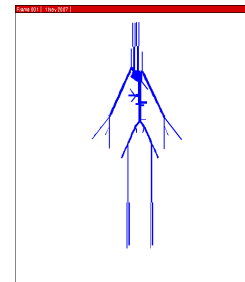
Schäfer et, al.2012

How accurate is pulse rate variability as an estimate of heart rate variability?

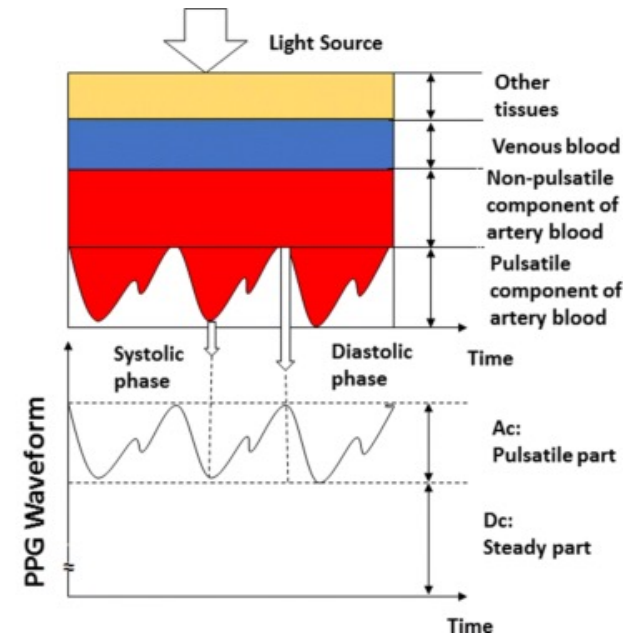


ECG

Pulse

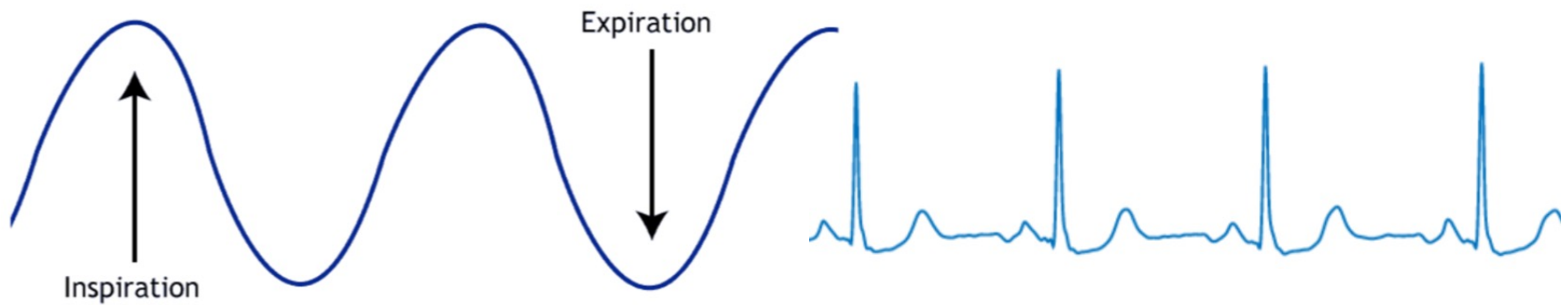


<http://haemod.uk/nektar>

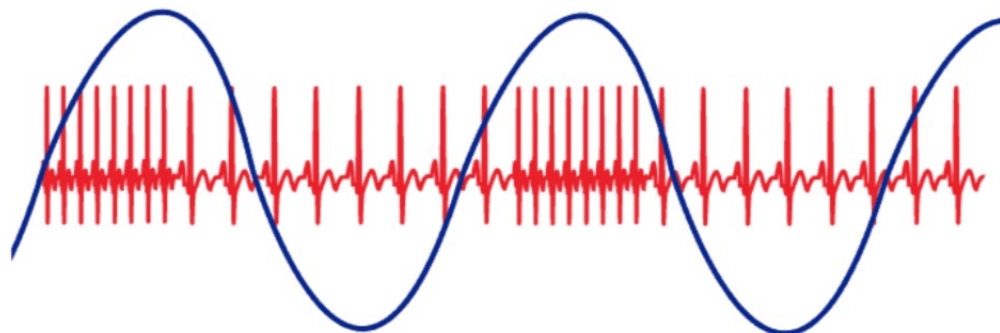


What are the characteristics of physiological signals?

Periodicity



Variability & Interaction

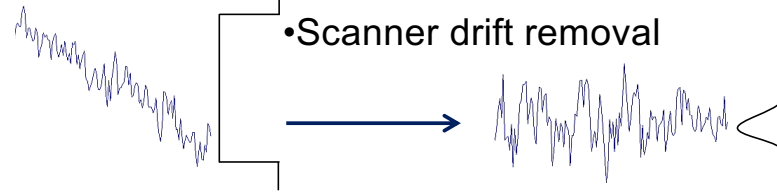


Functional MRI

Preprocessing

- fMRI images are not ready to do statistics on them.
- They need to be “conditioned”

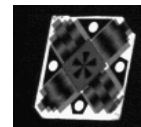
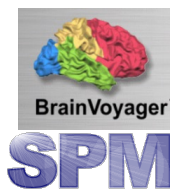
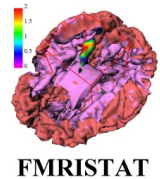
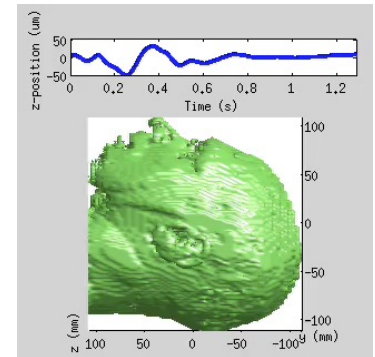
- Baseline wander correction
- Trend removal
- Scanner drift removal



- Physiological noise correction
- Skull stripping
- Spectral filtering
- Smoothing

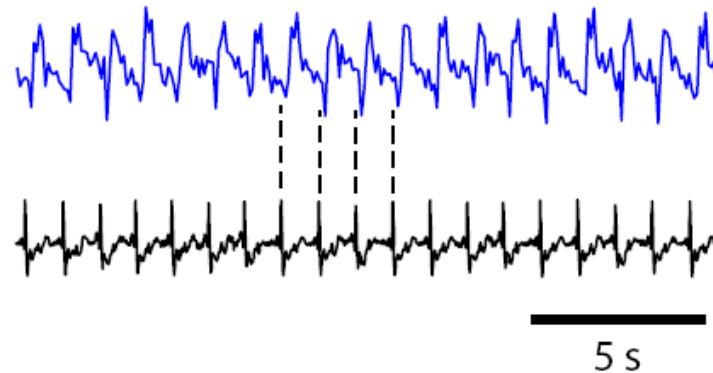
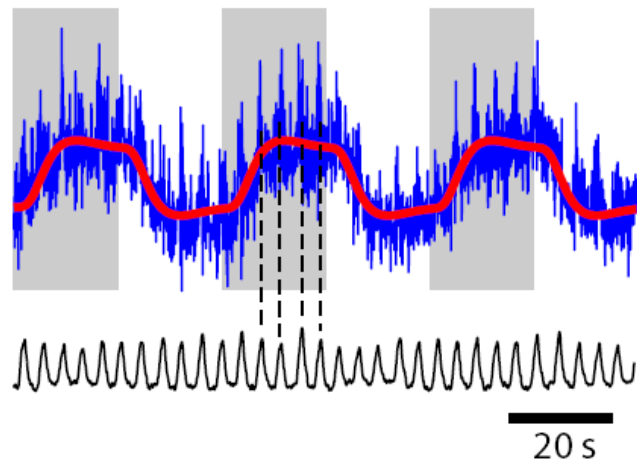
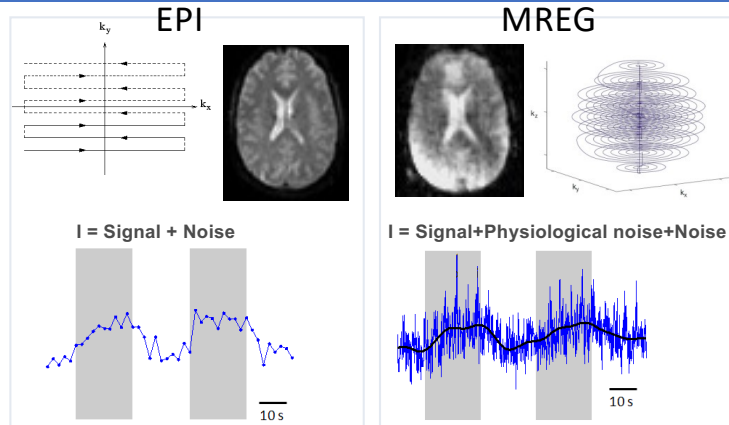


- Image alignment
- Registration
- Motion Correction



Improving temporal resolution

Fast fMRI

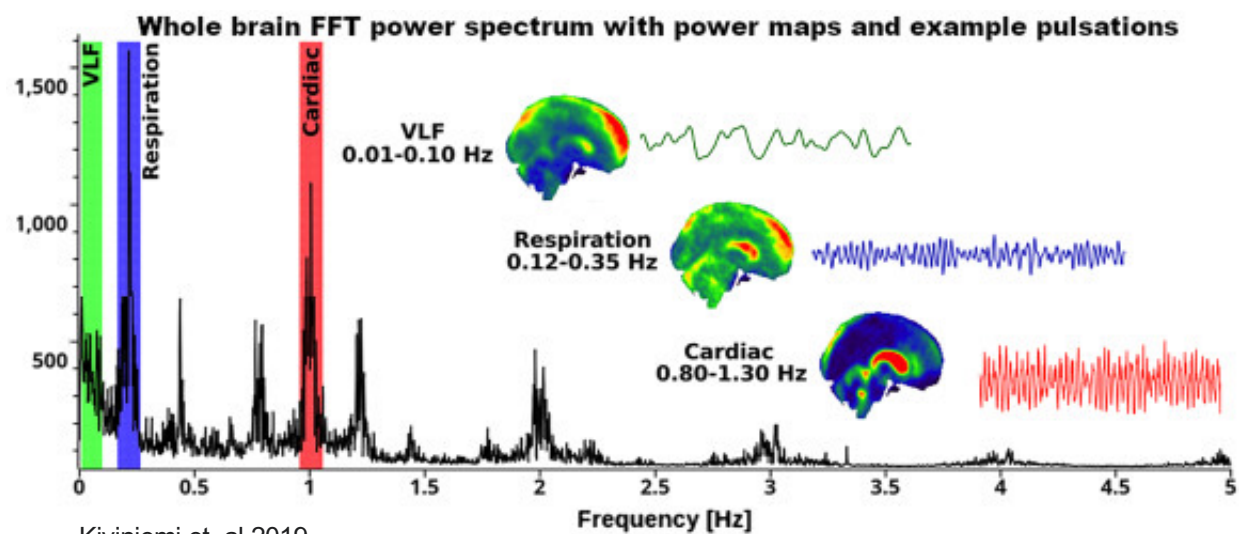


•Fast fMRI opens new application areas

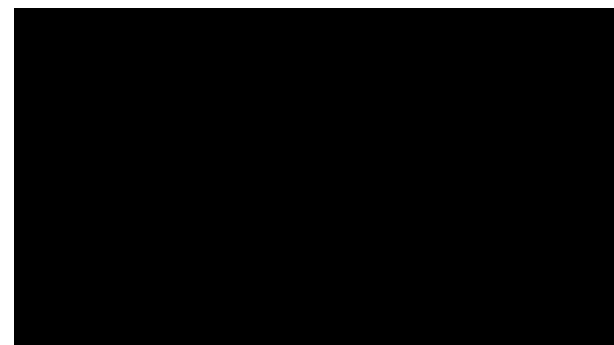
- Improved detectability of the patterns
- Dynamic connectivity mapping
- Lag thread analysis
- **Physiological noise removal**

Improving temporal resolution

Fast fMRI

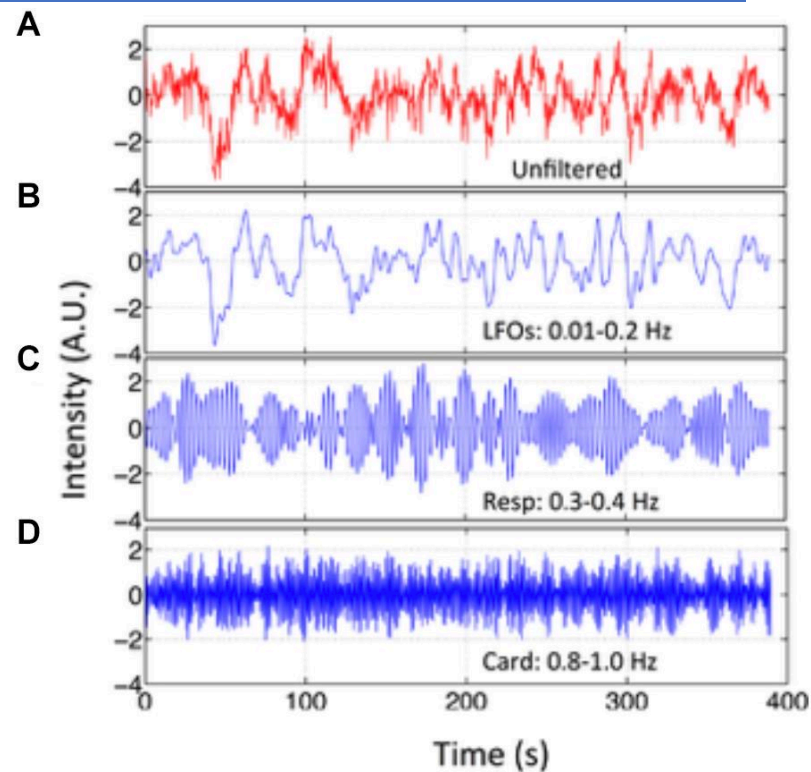
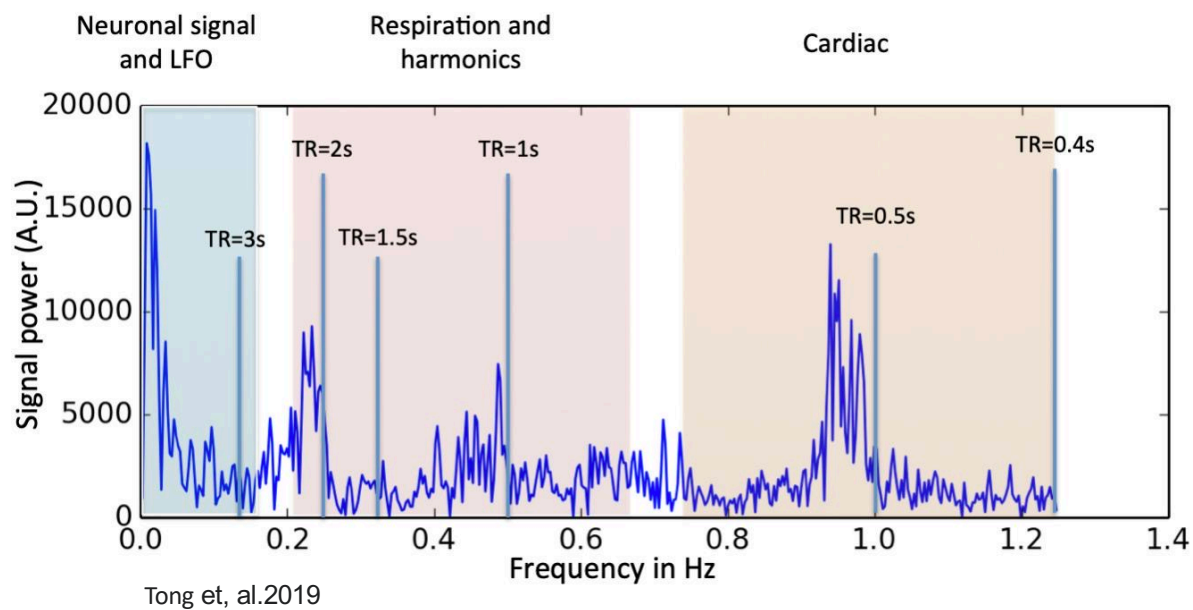


Kiviniemi et, al.2019



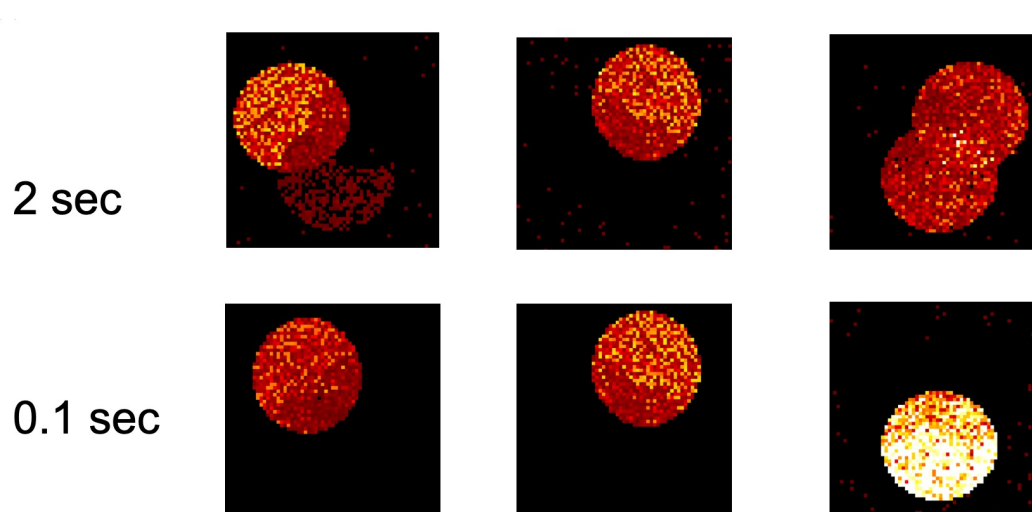
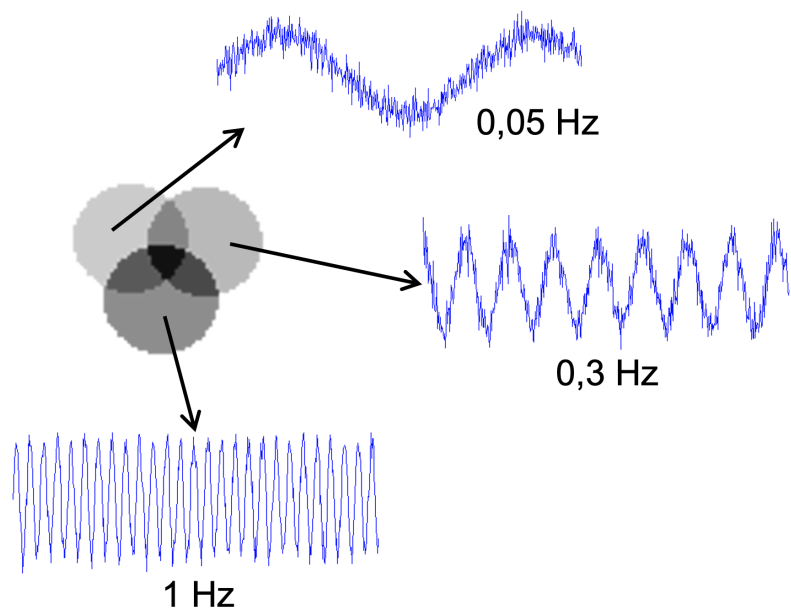
Improving temporal resolution

Fast fMRI



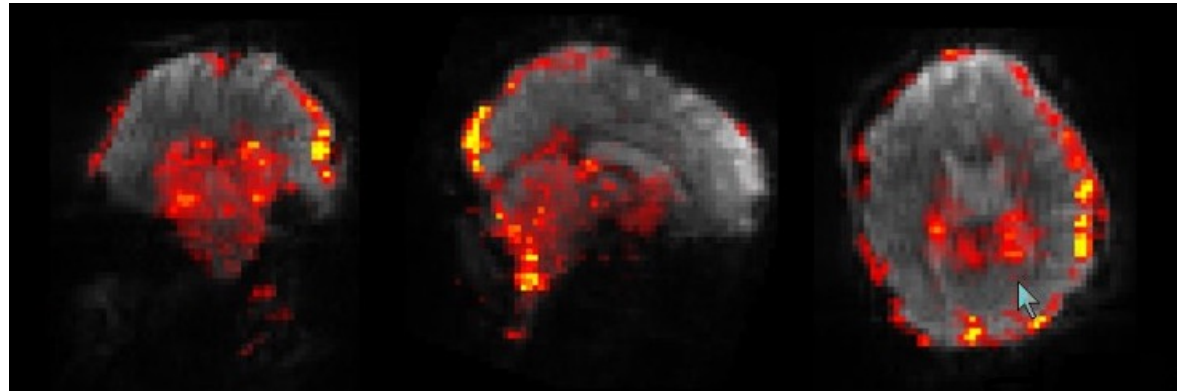
Improving temporal resolution

Fast fMRI

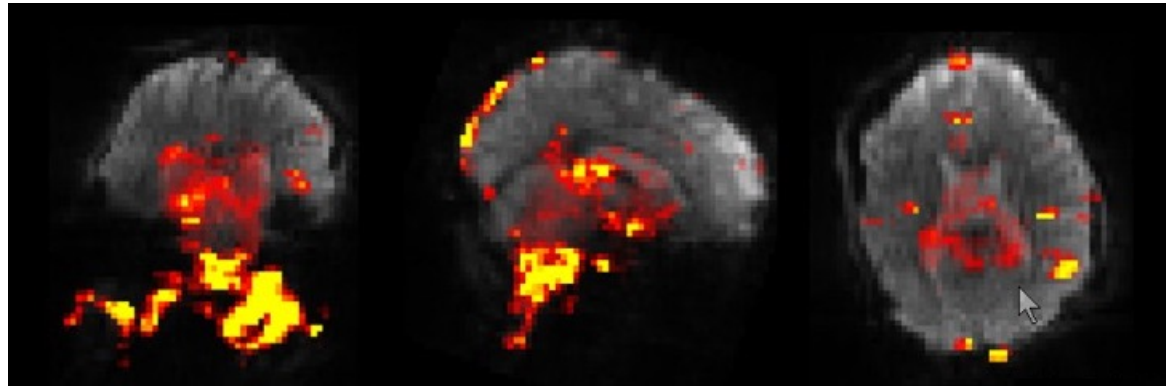


What are the characteristics of physiological signals ?

Respiratory 0.3 Hz



Cardiac 1.3 Hz



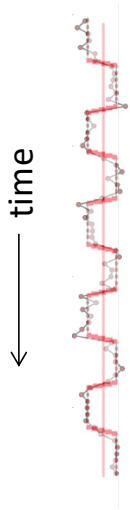
How to denoise fMRI data?

- Modeling task paradigm carefully
- Measuring potential confounds externally
- Regressing them from fMRI time series

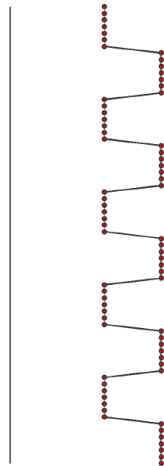
General Linear Model (GLM)

$$\mathbf{Y} = \mathbf{X} \cdot \boldsymbol{\beta} + \boldsymbol{\varepsilon}$$

Observed data Design matrix Parameters Error



=



.

$$\begin{bmatrix} \beta_0 \\ \beta_1 \end{bmatrix}$$

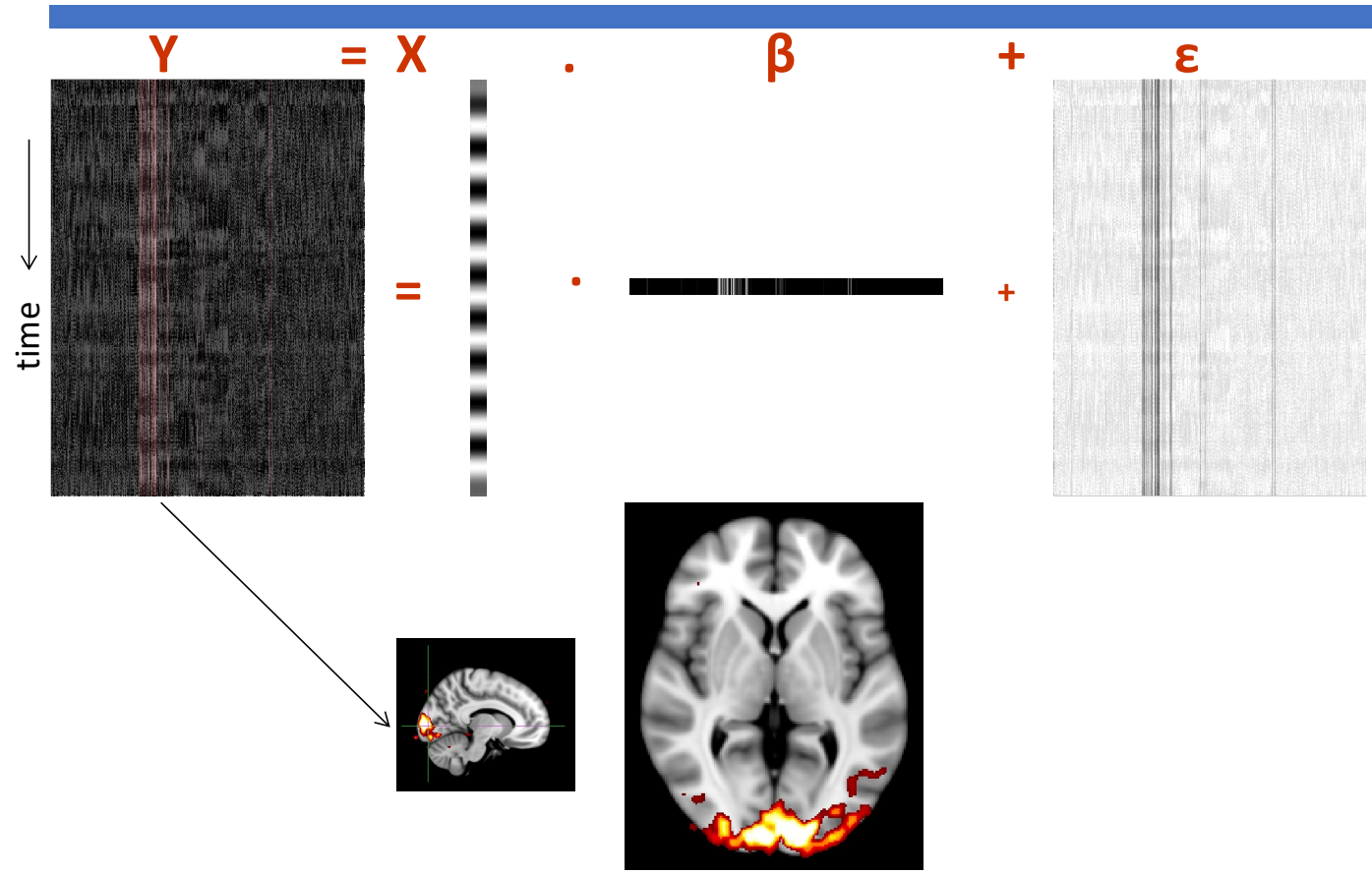
+



$$\boldsymbol{\beta} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{Y}$$

(2xn) (nx2) (2xn) (nx1)

General Linear Model (GLM)



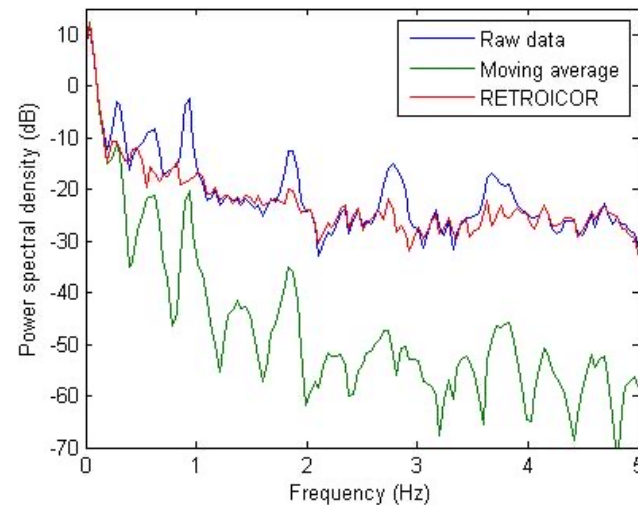
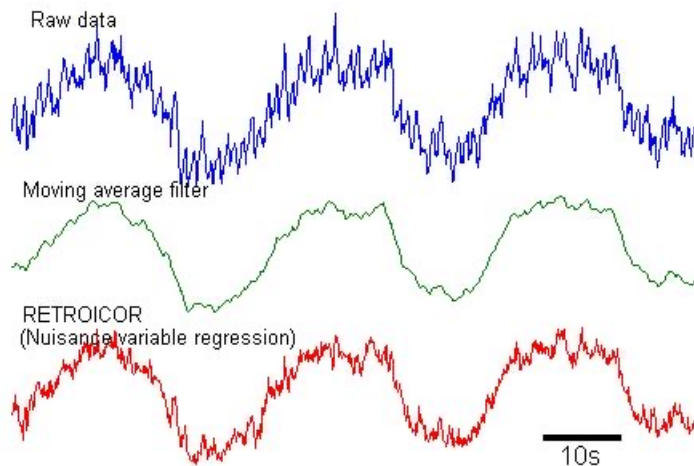
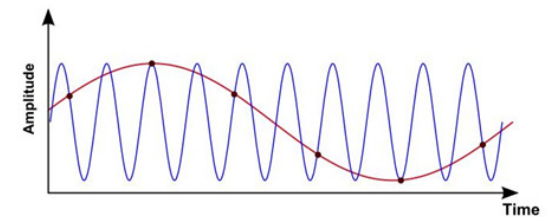
How to denoise fMRI data?

Moving average filter (Lin et al., 2011; Posse et al., 2012)

Removes high frequencies and affects noise properties

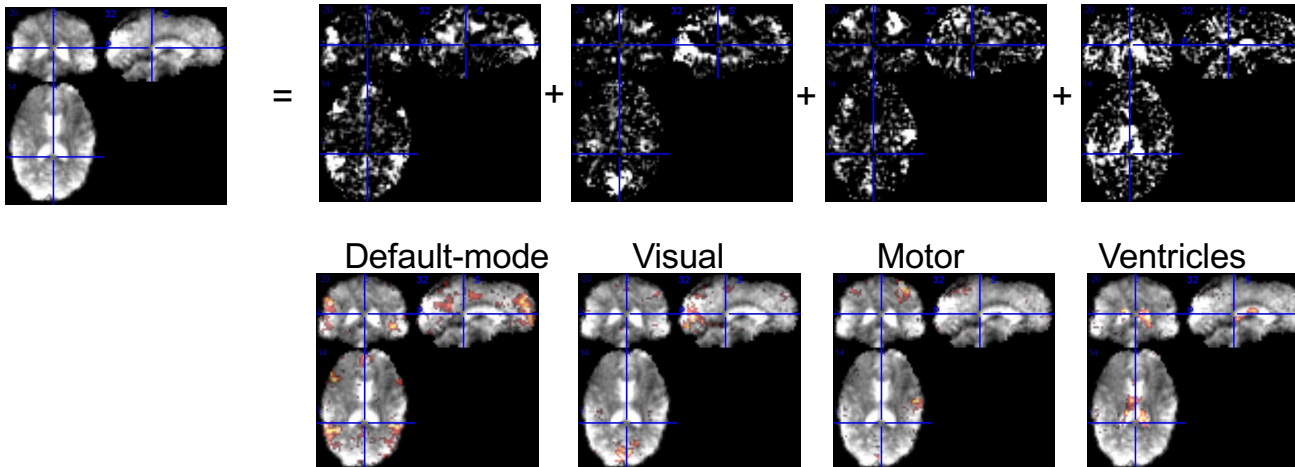
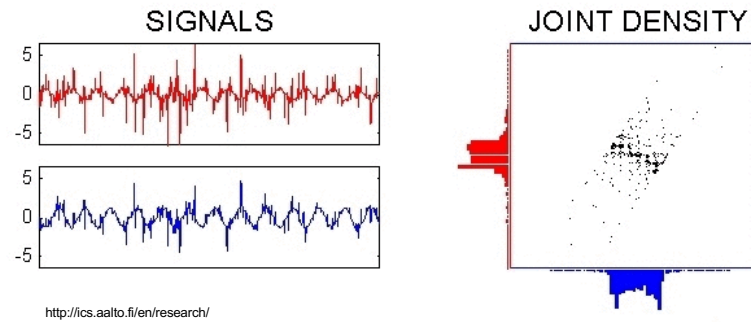
Artefact modeling (Glover et al., 2000; Lund et al., 2006)

Model noise as high-order autoregressive process

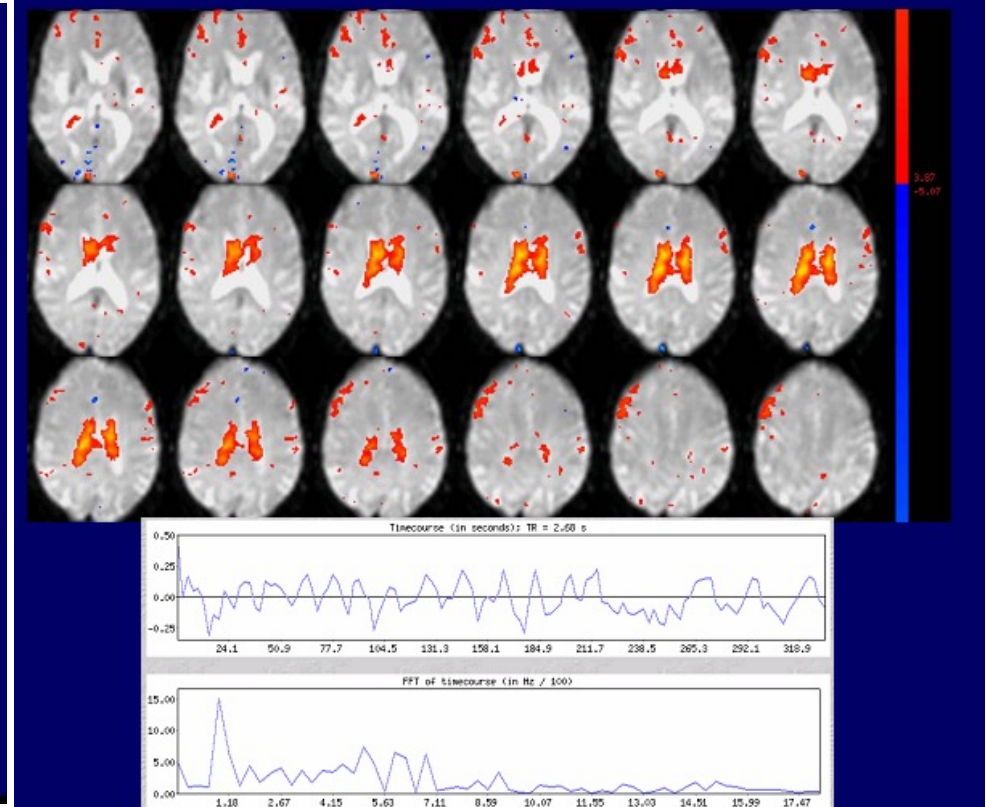
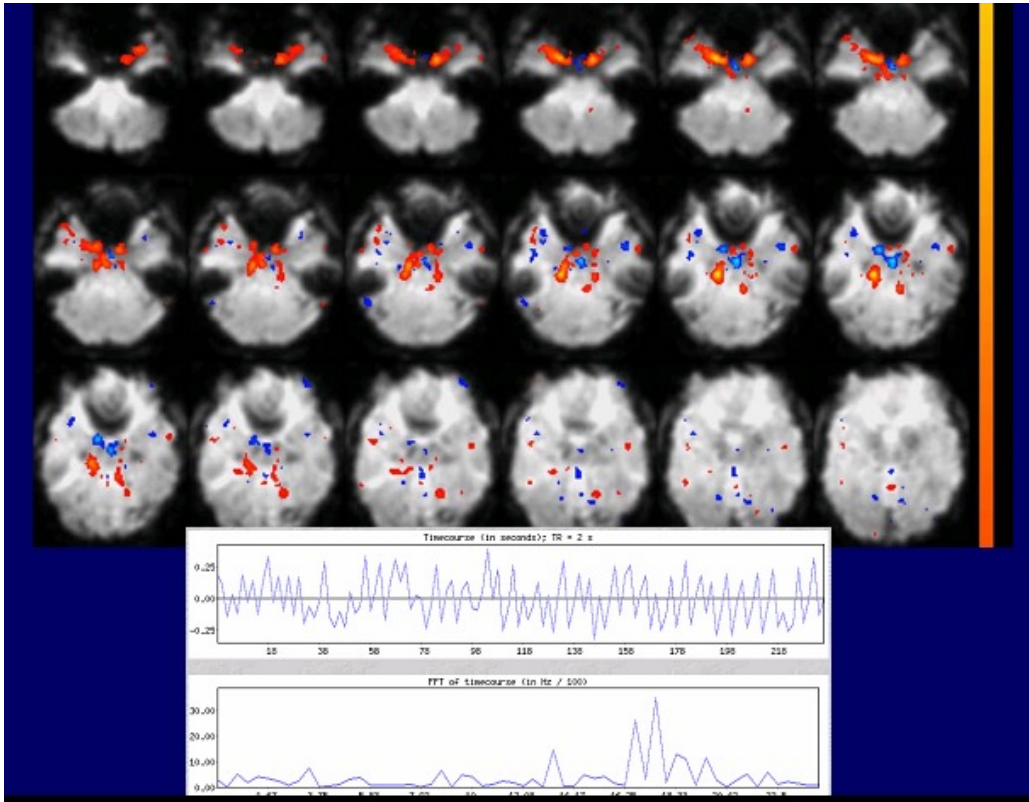


Independent Component Analysis

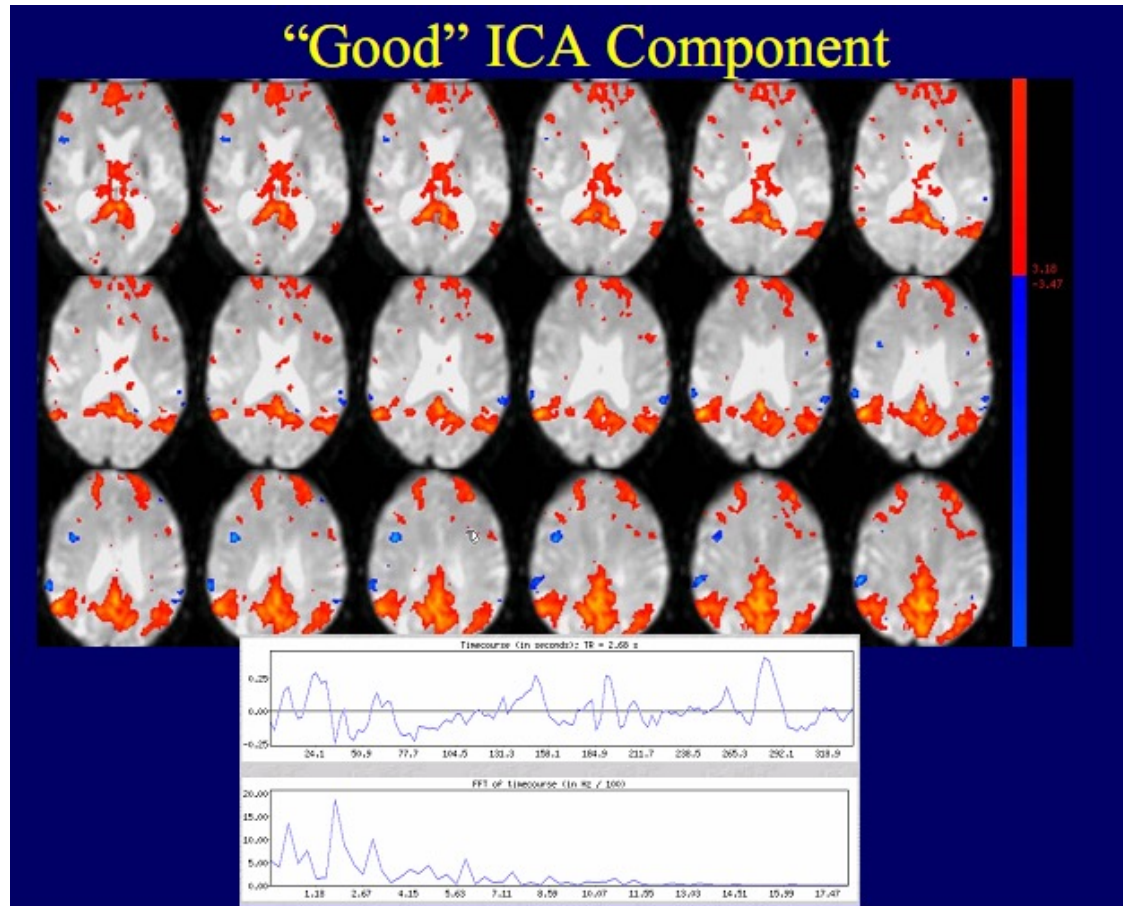
- ICA is the mathematical approach that performs this so-called “blind source separation”
- In fMRI: at each time point, we measure a mixture of unknown functional networks (as well as artifacts)
- Networks fluctuate and are thus mixed differently at each time point



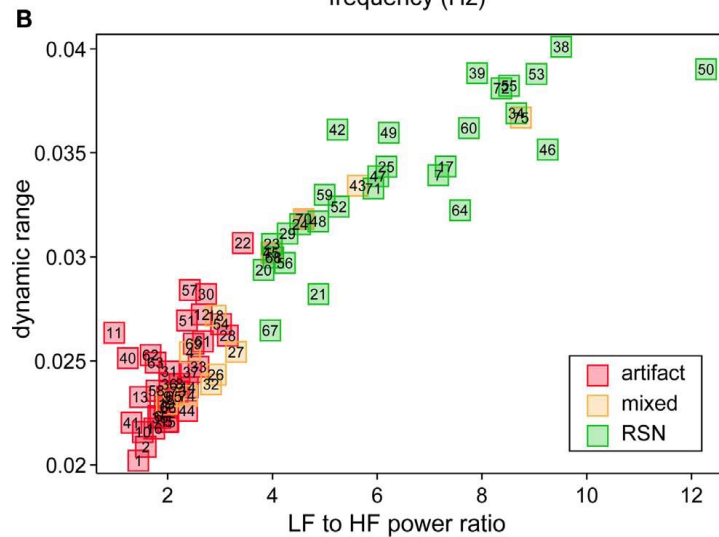
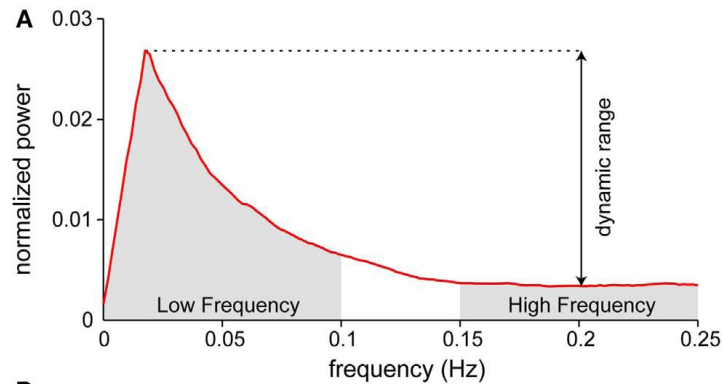
Bad components?



Good components?



How to denoise fMRI data?

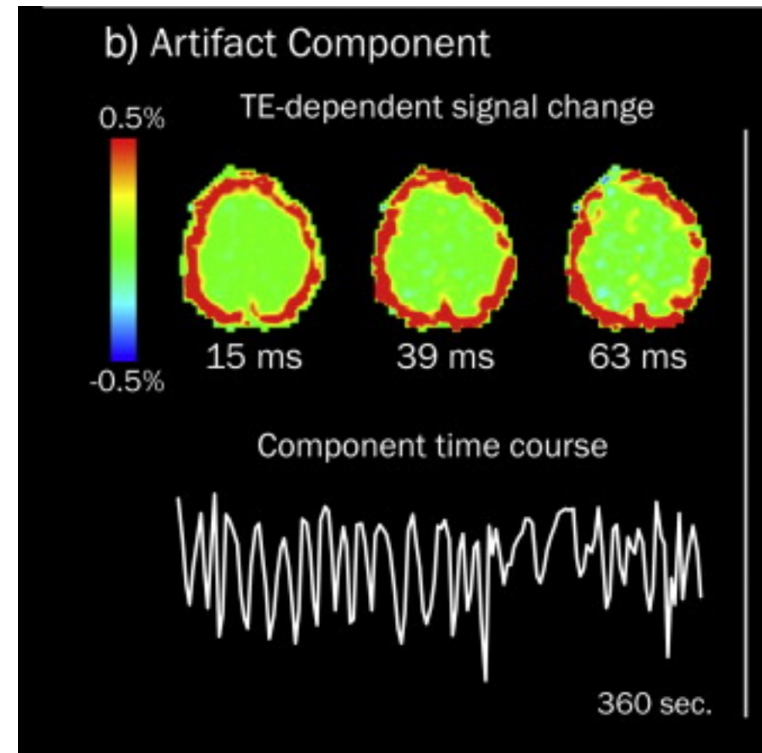
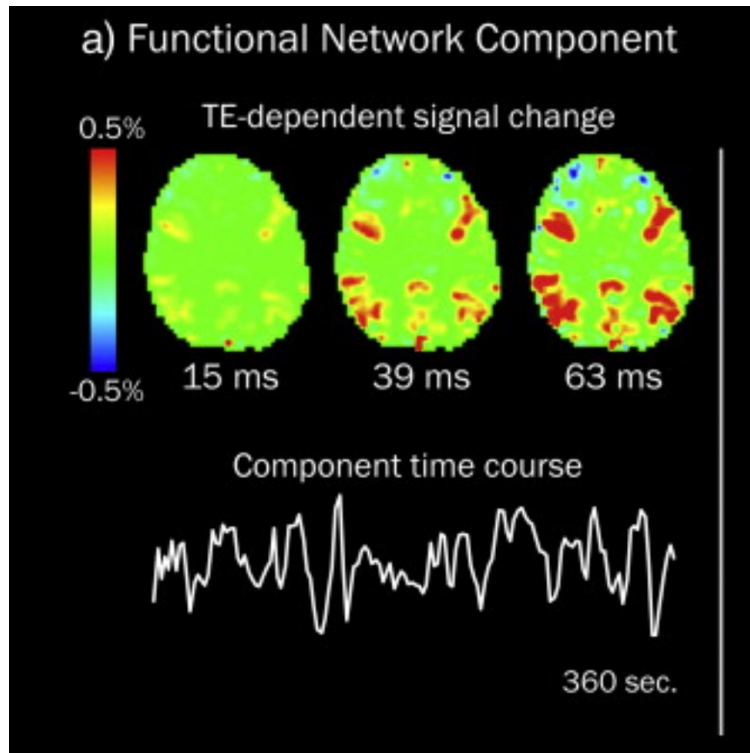


fALFF

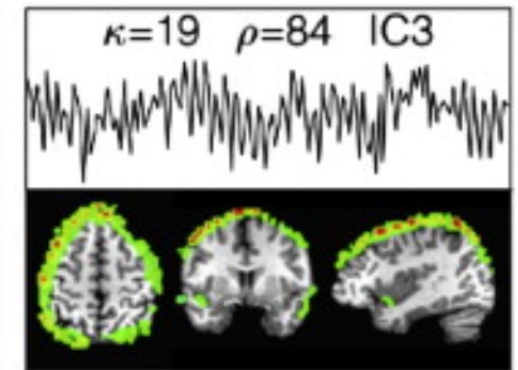
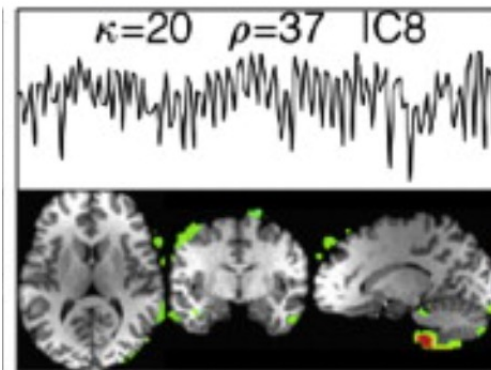
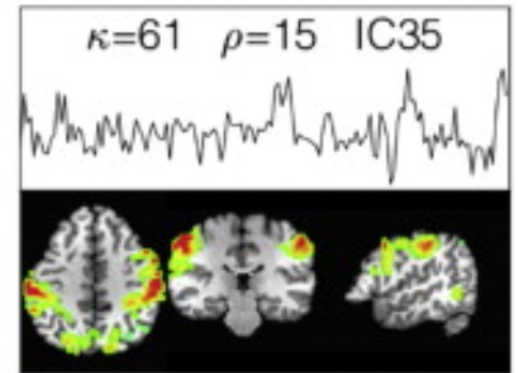
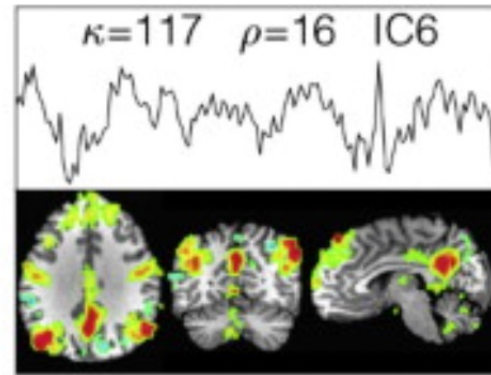
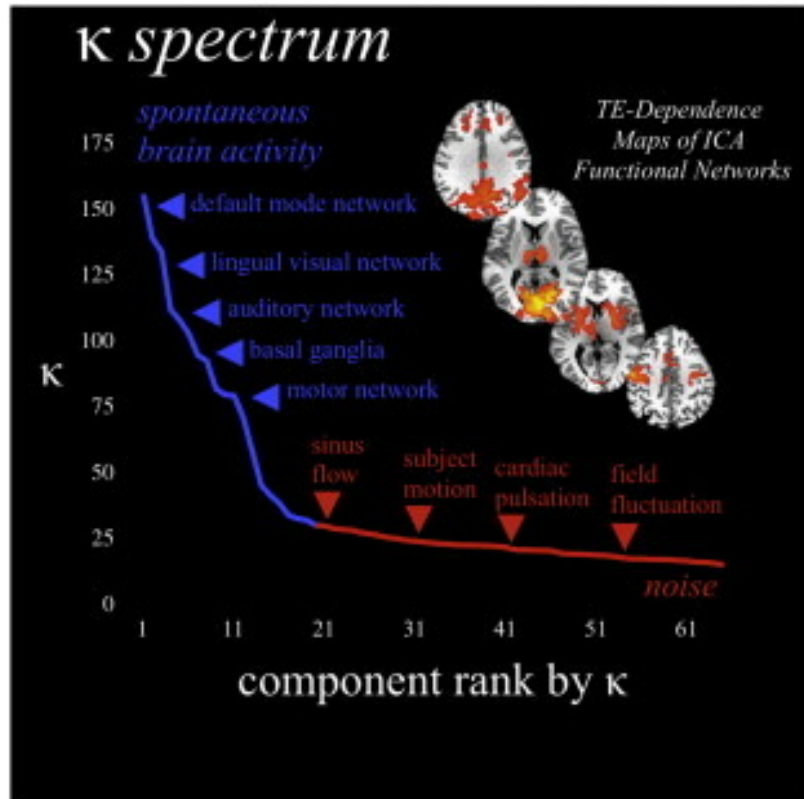
fractional amplitude of
lowfrequency fluctuations

summing the oscillatory
amplitudes across the typical
0.01-0.08 Hz range, then
dividing by the amplitude sum
across 0-0.25 Hz

Multi-Echo EPI



Multi-Echo EPI



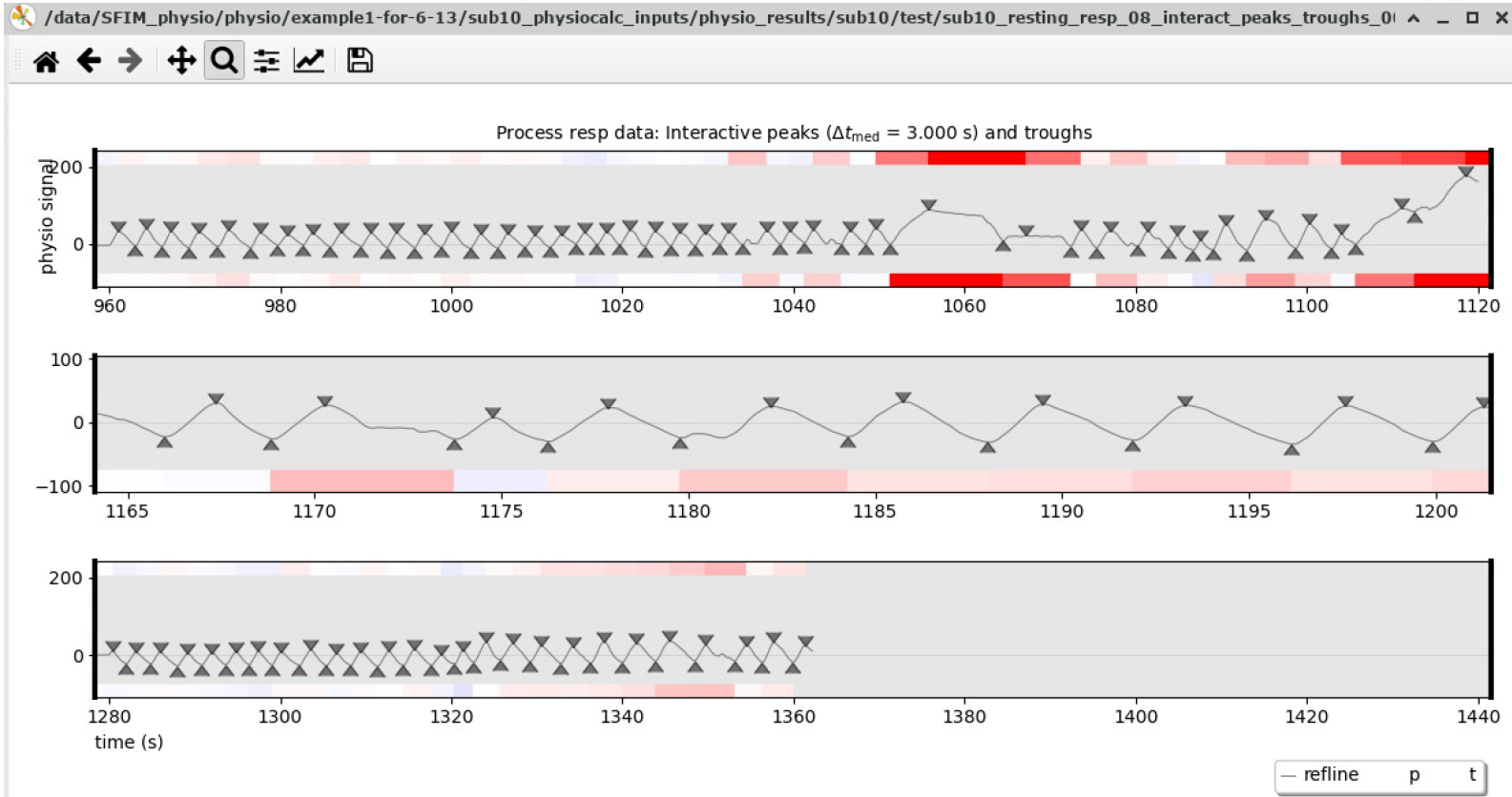


AFNI physio_calc.py

```
physio_calc.py \
  -card_file      sub-001_ses-01_task-rest_run-1_physio-ECG.txt \
  -resp_file      sub-001_ses-01_task-rest_run-1_physio-Resp.txt \
  -freq           500 \
  -dset_tr        0.1 \
  -dset_nt        219 \
  -dset_nslice    33 \
```

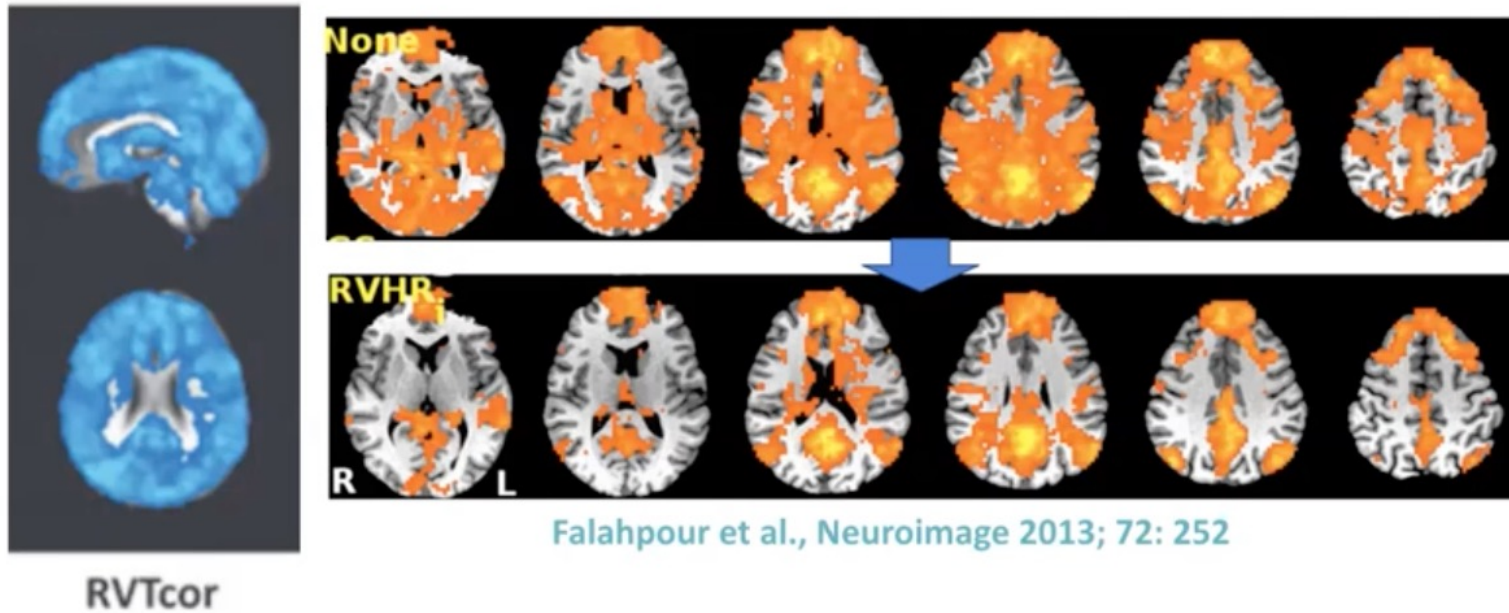
```
afni_proc.py -subj_id bp10 \
  -blocks tcat despiked tshift align tlrc volreg mask scale regress \
  -radial_correlate_blocks tcat volreg \
  -copy_anat /data/akinb2/allbp/bp10/anat/anatSS.bp10.nii \
  -anat_has_skull no \
  -anat_follower_ROI aaseg anat /data/akinb2/allbp/fsurfs/bp10/SUMA/aparc.a2009s+aseg.nii.gz \
  -anat_follower_ROI aaseg epi /data/akinb2/allbp/fsurfs/bp10/SUMA/aparc.a2009s+aseg.nii.gz \
  -tcat_remove_first_trs 0 \
  -dsets /data/akinb2/allbp/bp10/rest.nii \
```

AFNI physio_calc.py



RVT

Higher functional connectivity (PCC seed) without RVT correction

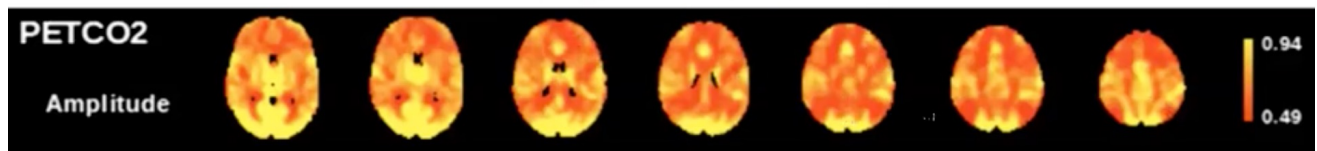
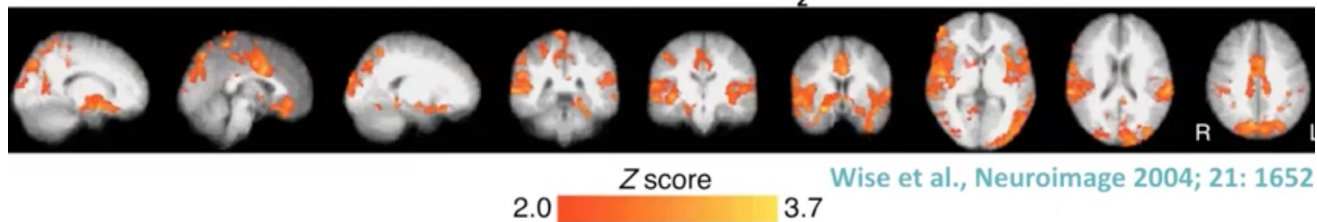


Birn et al. Brain Connectivity 2014; 4: 511

Regions related to end-tidal CO₂

- The contributions by RVT and CO₂ only partially overlap^{1,2}
- CO₂ fluctuations produce network patterns that mimic functional networks³

Strength of association between CO₂ and rs-fMRI signal



Golestani et al., Neuroimage 2015; 104: 266

1. Chang et al. Neuroimage 2009; 47: 1381
2. Golestani et al., Neuroimage 2015; 104: 266
3. Bright et al., Neuroimage 2020; 116970

43

43

> [Neuroimage](#). 2020 Aug 15;217:116907. doi: 10.1016/j.neuroimage.2020.116907. Epub 2020 May 6.

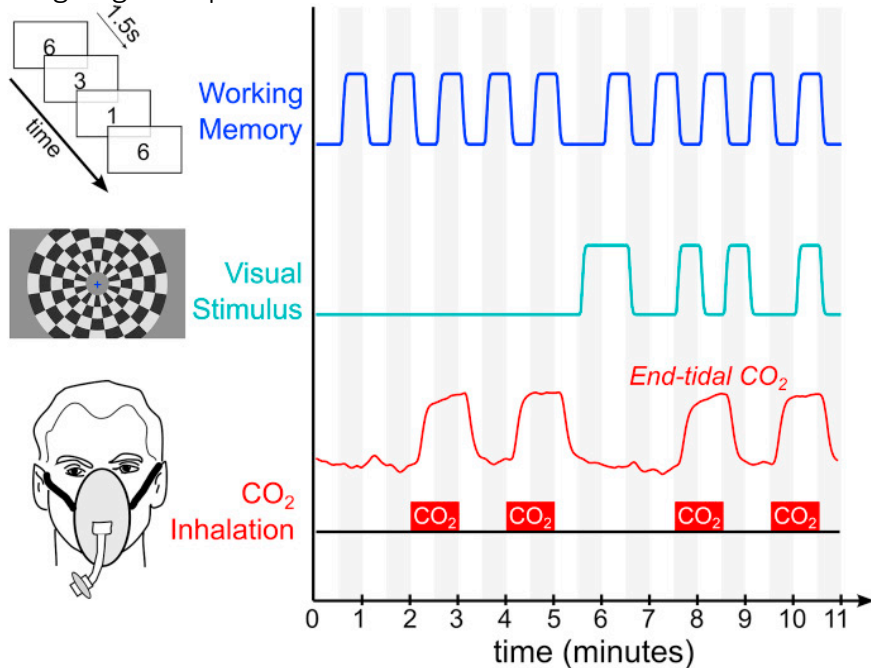
Vascular physiology drives functional brain networks

Molly G Bright ¹, Joseph R Whittaker ², Ian D Driver ³, Kevin Murphy ²

Affiliations + expand

PMID: 32387624 PMCID: [PMC7339138](#) DOI: [10.1016/j.neuroimage.2020.116907](#)

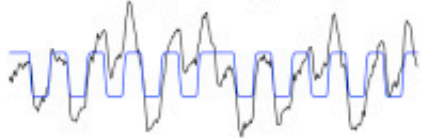
Designing an experiment with distinct tasks



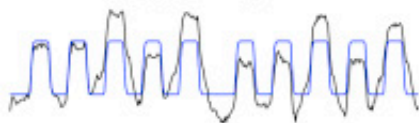
Designing an experiment with distinct tasks

Step 1
Identify neuronal networks using temporal correlations

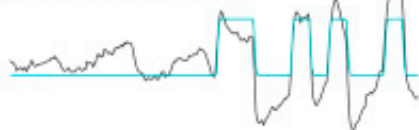
Maximum negative correlation with Working Memory task



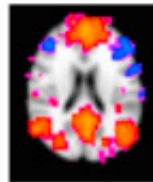
Maximum positive correlation with Working Memory task



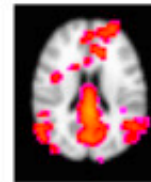
Maximum positive correlation with Visual stimulus



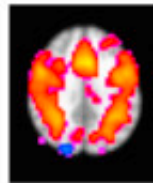
Default Mode Network



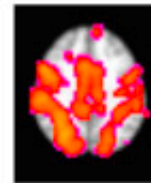
overlap
= 0.34



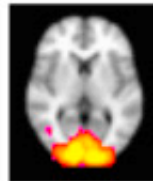
Task Positive Network



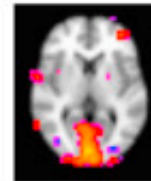
overlap
= 0.48



Visual Network

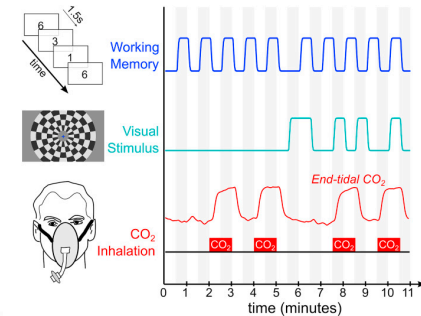


overlap
= 0.29



Step 2
Identify similar network using spatial overlap

Step 3
Analyze time-series of spatially similar networks



Some take home messages

- Always look at your data
- Always acquire physiology
- Physiological confounds might be both noise or signal
- Design a task paradigm that helps to disentangle sources of signals
- Design a processing pipeline that helps to delineate the activity

Thanks for your attention!

