Interactions of Preprocessing Steps

Nathan Churchill

Technical University of Denmark, Cognitive Systems

Baycrest Hospital, Rotman Research Institute

Preprocessing Interactions in fMRI

- Complex interactions between preprocessing and experimental design choices:
  - **Effects of subject** (young/old, healthy/clinical)
  - **Effects of task design** (block/event/rest)
  - **Interactions between preprocessing steps**
- Many potential interactions – some are more important than others
- I will focus on 3 preprocessing “case studies”

Case studies

(1) Correcting residual motion:
effects of subject and task design

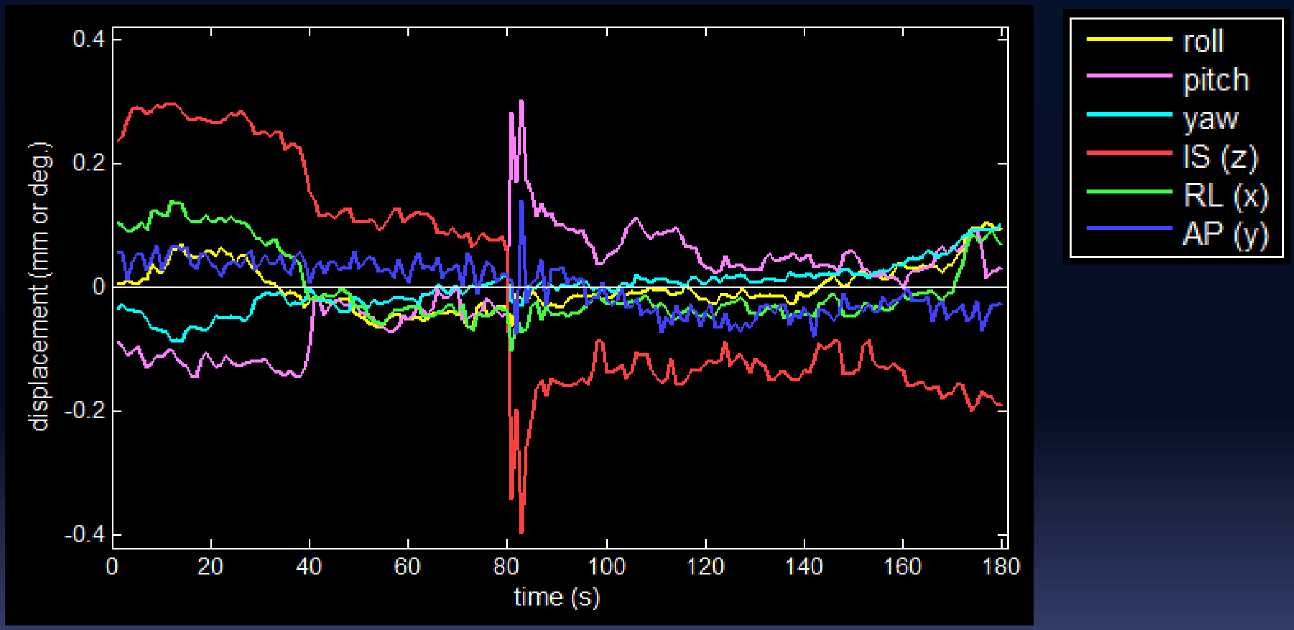
(2) Correcting physiological noise:
effects of task design

(3) Ordering of preprocessing steps
interactions between steps

(4) Conclusions and recommendations

Correcting residual motion

- **MPR**: regression of 6 rigid-body motion parameters (sometimes derivatives and/or quadratic terms)
- Corrects for non-rigid, non-linear motion effects

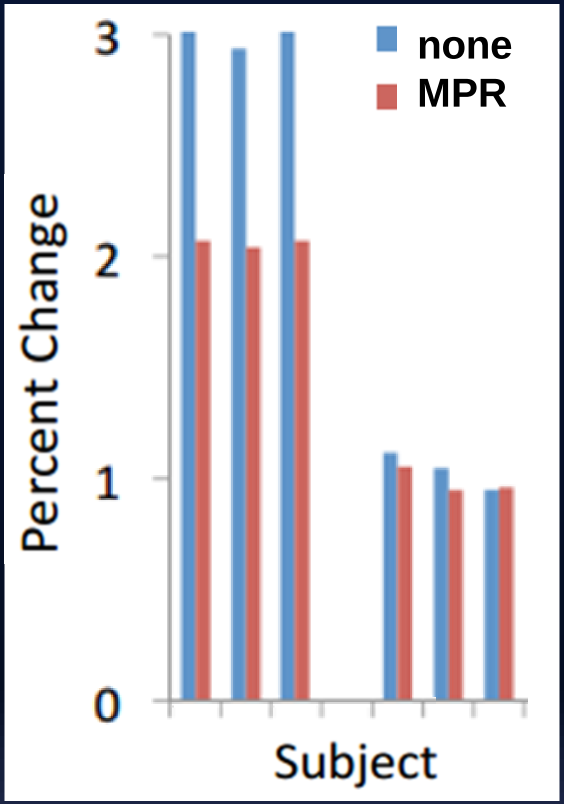


Correcting residual motion

- MPR effects depend on:

- Signal vs. motion variance
  - For **high signal / low motion**, MPR reduces signal power

- Correlation of task and motion
  - **Low correlation**: MPR increases signal
  - **High correlation**: MPR reduces signal

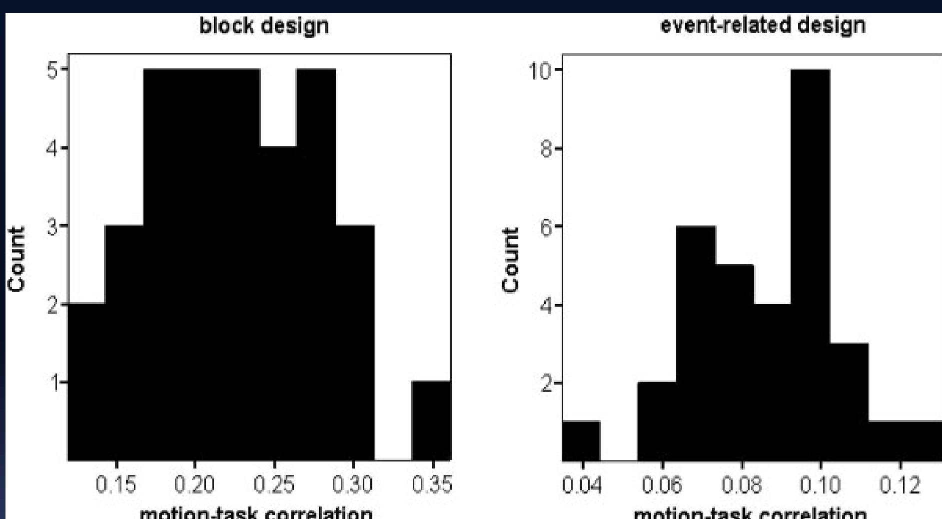


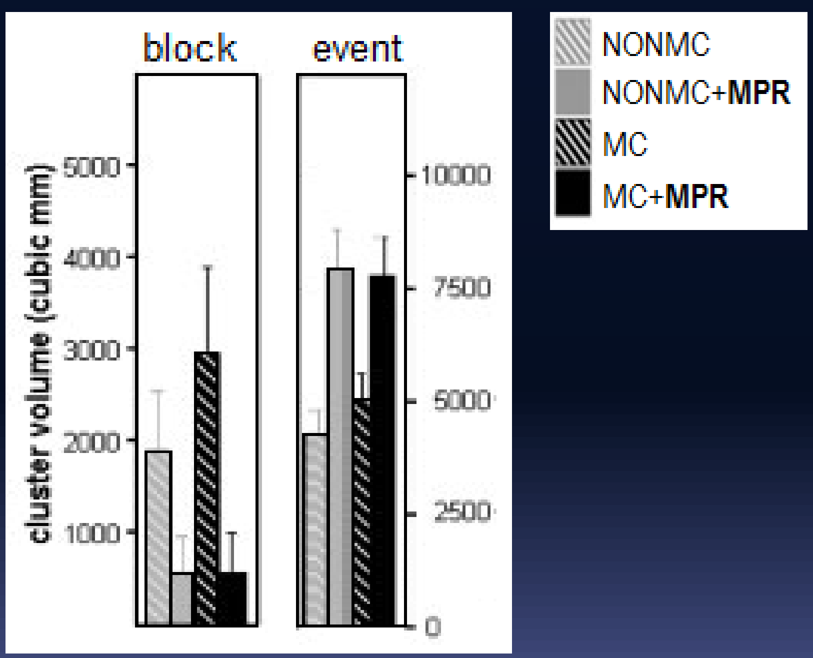
(Ollinger et al., 2009)

(Bullmore et al., 1999; Johnstone et al., 2006; Ollinger et al., 2009; Churchill et al., 2012)

Task Design interactions: block vs. event

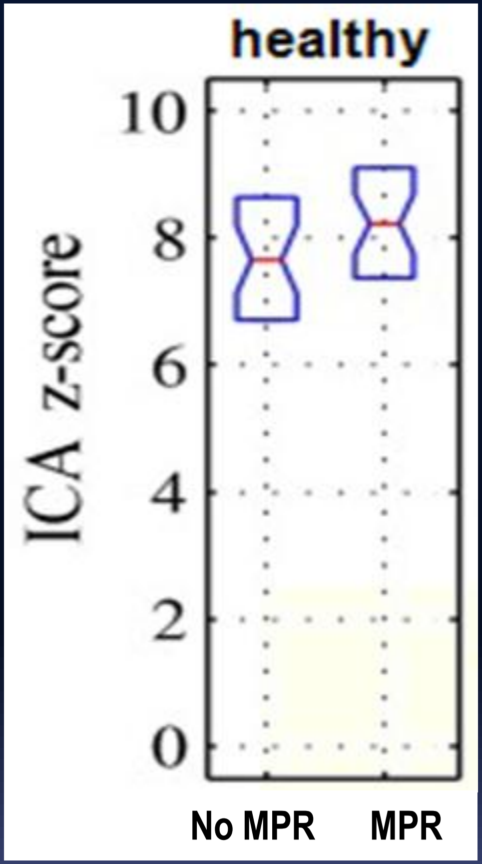
- MPR reduces sensitivity of Block tasks; strong signal, higher task-motion correlations (Johnstone et al., 2006).
- Also shown in pipeline optimization of Block data (Churchill et al., 2012)





Task Design interactions: resting-state

(Andronache et al., 2013)



*includes band-pass filter

- **Resting state**:

  less sensitive to MPR, particularly in young, healthy adult populations

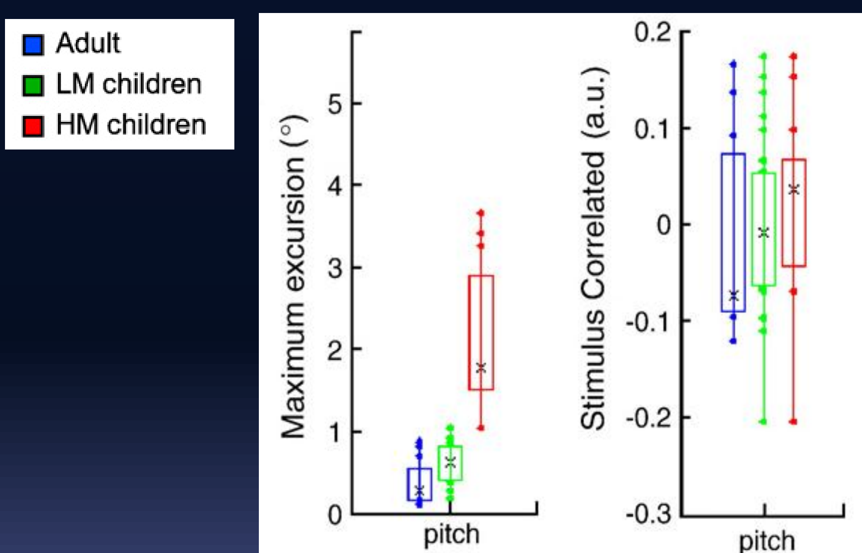
  (Gavrilescu et al., 2004; Weissenbacher et al., 2009; Shirer et al., 2013; Andronache et al., 2013)

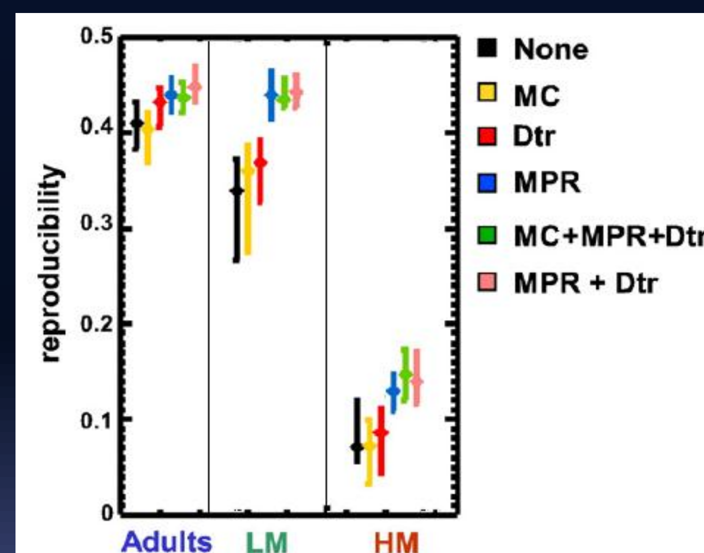
- Motion tends to be lower

- No task-correlation issues

Subject group interactions: age effects

- <u>Aging and child populations</u>: major increases in motion amplitude, but usually ***not*** task correlation (D'Esposito et al, 1999; Seto et al, 2001; Yuan et al, 2009; Evans et al, 2010; Power et al, 2012)
- MPR improves reliability of activation patterns (Evans et al, 2010)

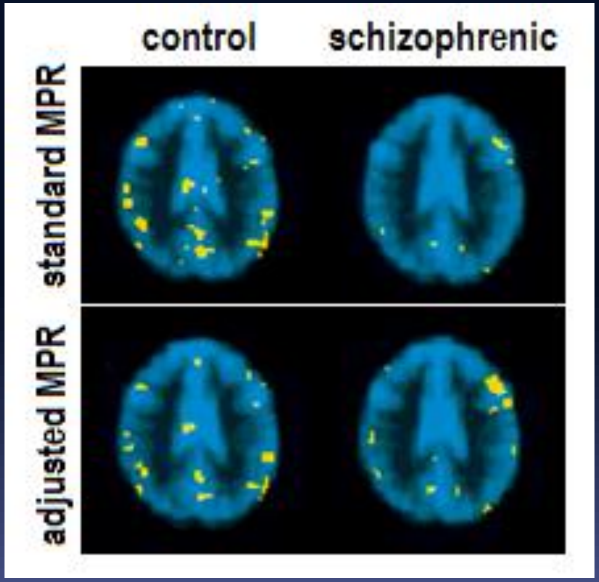




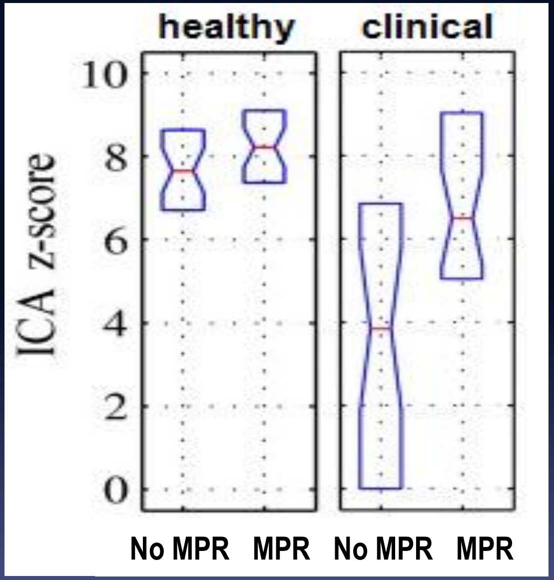
Subject group interactions: clinical groups

- Clinical populations: motion amplitude greater than age-matched controls. Often significant task-correlation (Bullmore et al., 1999; Seto et al., 2001; Lemieux et al., 2007; Andronache et al., 2013)
- MPR has mixed effects on signal detection:

TASK (Bullmore et al., 1999)



REST (Andronache et al., 2013)



Correcting residual motion: Summary

- Effect of residual motion correction depends on (1) signal vs. motion amplitude, (2) task-motion correlation
  - Improves: low signal/high motion; uncorrelated to task
  - Detrimental: high signal/low motion; task correlation
- Effects are both group- and subject-dependent

Case studies

(1) Correcting residual motion:
effects of subject and task design

(2) Correcting physiological noise:
effects of task design

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Correcting physiological noise

- Remove fluctuations in BOLD signal driven by:
  - Cardiac cycle
  - Respiratory cycle
  - Slow modulations **in cardiac/respiratory rates**

- Modeled by:
  - External measures of cardiac and respiratory rates (e.g. RETROICOR*****, RVHR******)
  - Data-driven models (e.g. PCA, ICA)

* (Glover et al., 2000) ** (Chang et al., 2009)

Correcting physiological noise

- Physiology and brain function form a feedback system
- **Autonomic Nervous System** (ANS) regulates blood pressure, respiration, pupil dilation, etc.

- From the localized…
  - ANS linked to cognitive domains
  - Self-monitoring, emotion, conflict assessment

- To the global…
  - Cardiac and Respiratory rates increase with effort
  - Thus, physio. modulations correlate with task stimuli

(Foster & Harrison, 2004; de Munck et al., 2008; Birn et al., 2009; Iacovella & Hasson, 2011)

Task Design interactions - localized

- Regression of autonomic measures (e.g. RVHR) can remove ANS-linked activations.
- Potential interaction in studies of self-regulation, conflict resolution, emotional processing

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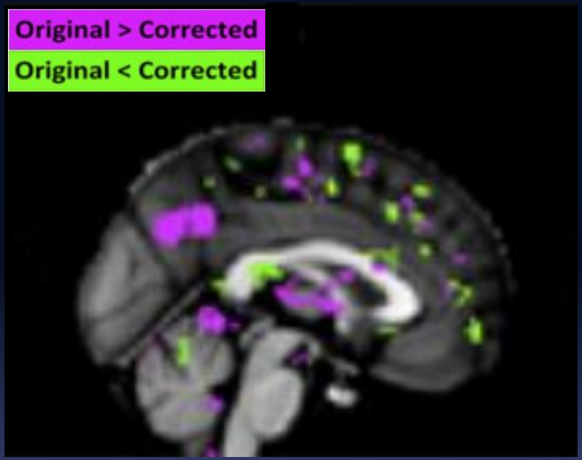
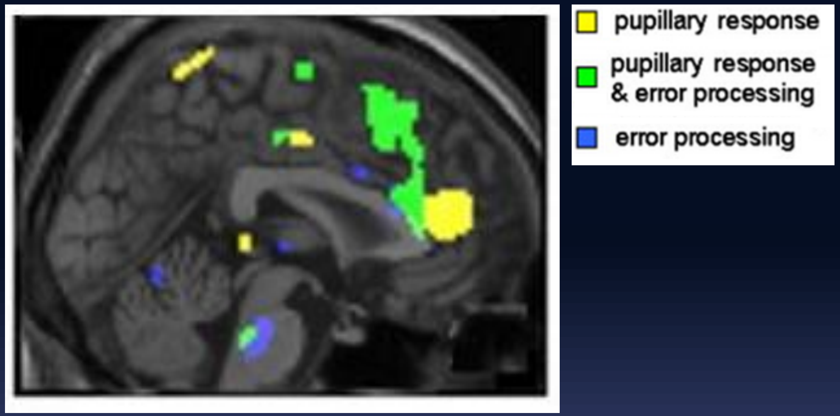
Drug treatment (morphine)



(Khalili-Mahaniet al., 2013)

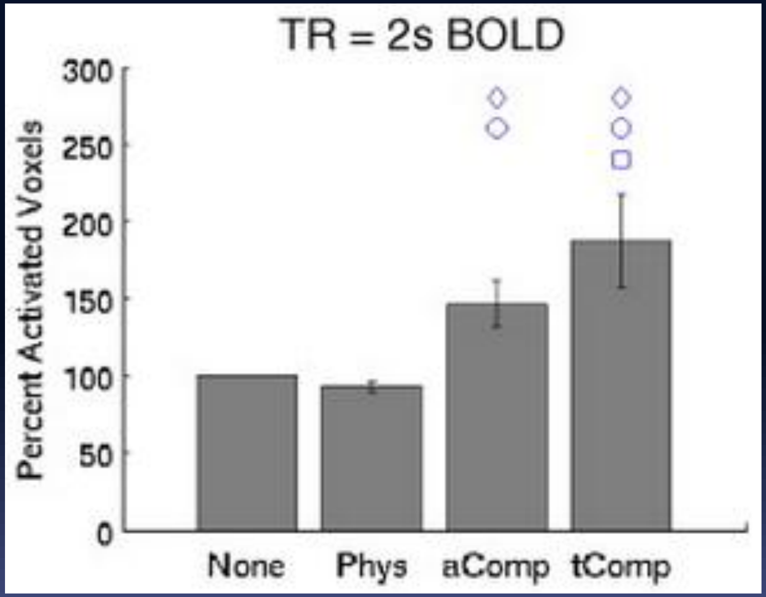
Stroop task



(Critchley et al., 2005)

Task Design interactions - global

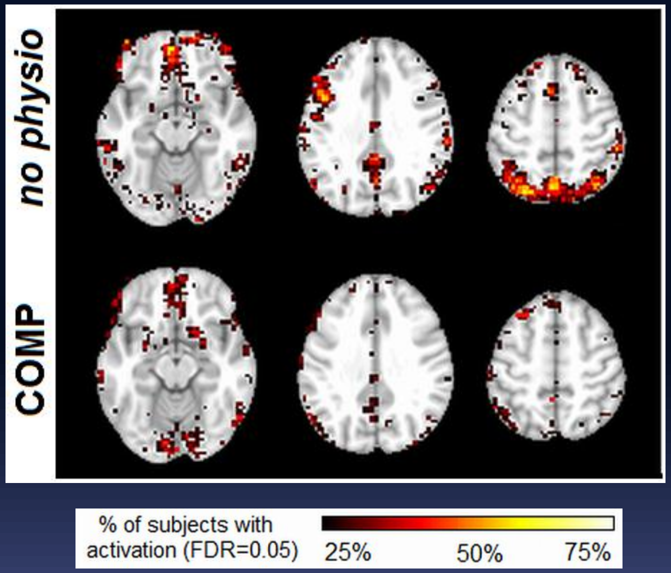
- Data-driven physio. correction is very sensitive to task modulation effects
- **CompCor** significantly improves signal detection for a simple visual paradigm task

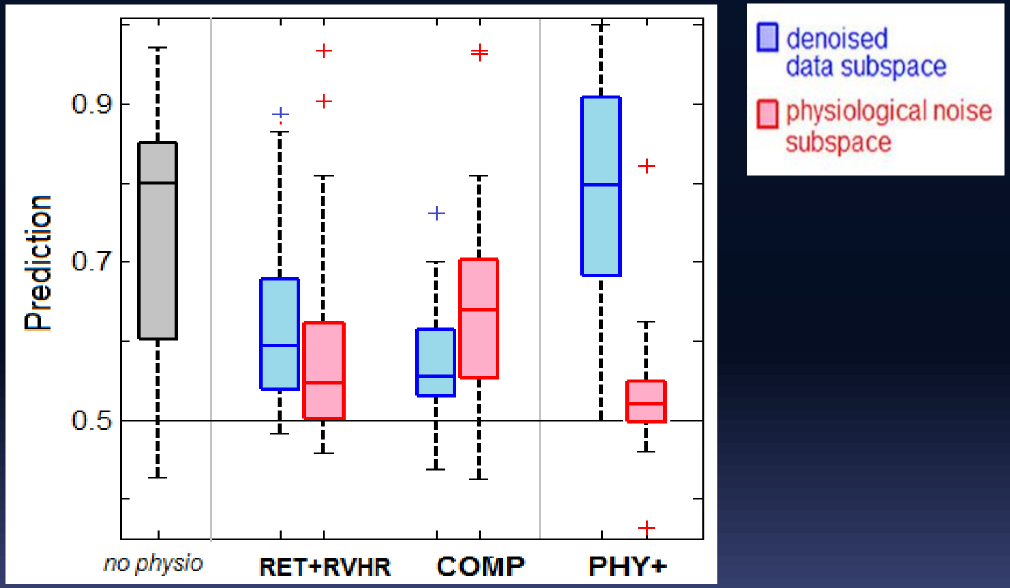


(Behzadi et al., 2007)

Task Design interactions - global

- **CompCor** is detrimental for a task with:
  - complex, spatially distributed BOLD response
  - High-effort, executive control (associated with ANS)





(Churchill & Strother, 2013)

Correcting physio. noise: Summary

- Regression using physio. measures (e.g. RVHR) tends to remove ANS-linked brain signal
- Could be good or bad! Be aware of what is removed, esp. in studies of emotion, self-regulation, conflict assessment
- Data-driven correction highly sensitive to task-coupling; may remove significant signal in complex, high-effort tasks
- Like MPR, can be group- and subject-dependent

Case studies

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Interactions between preprocessing steps

- Preprocessing steps can interact with each other in complex ways
- Focus on specific issue: what is the optimal order to apply preprocessing steps
- Important consideration: do steps alter data in a way that violates assumptions of subsequent steps?

Order of preprocessing steps:
Motion, Physio, Slice-Timing

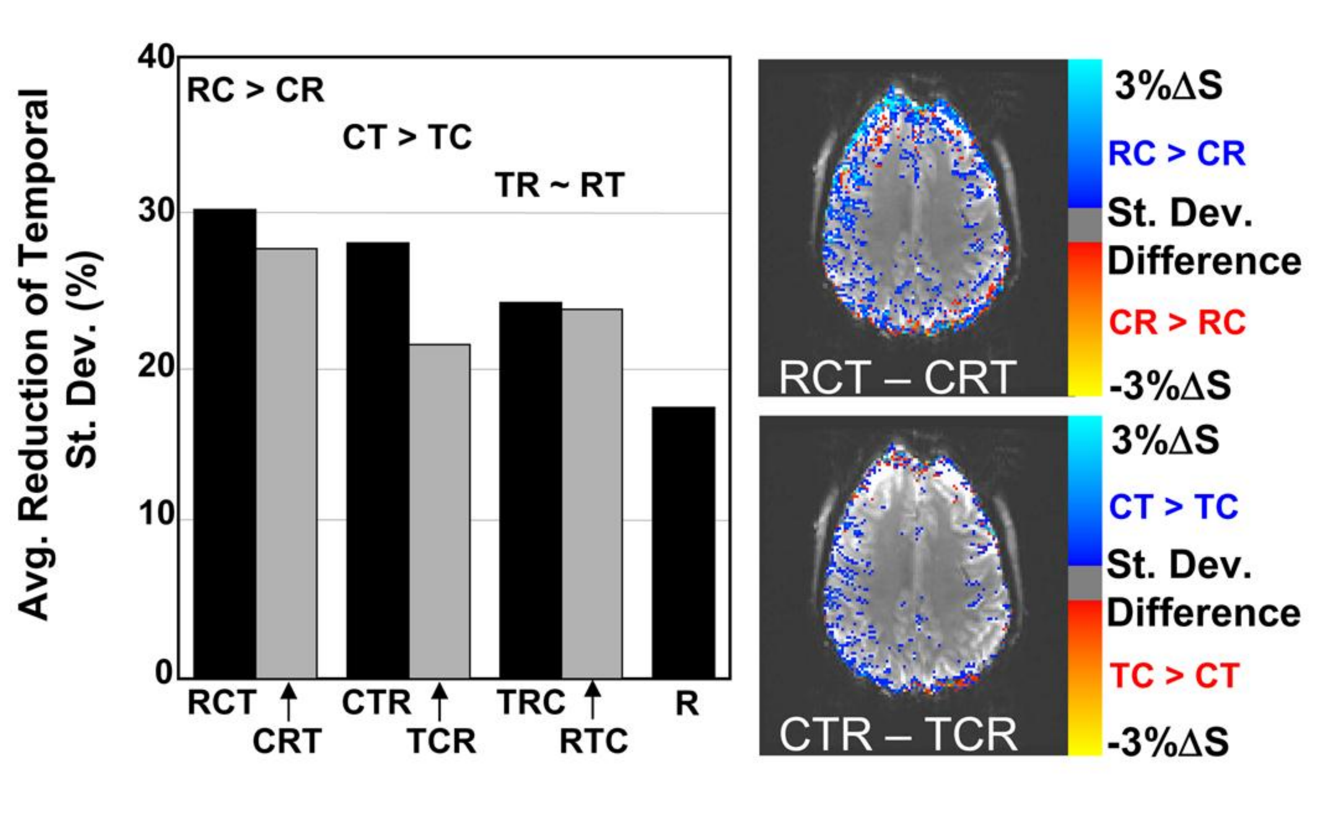
- **Example**: ordering of 3 basic preprocessing steps
  - Motion Correction
  - Physiological Correction
  - Slice-Timing Correction

- What order optimizes model fit?

- Jones et al. (2009) examined for resting state

Order of preprocessing steps:
Motion, Physio, Slice-Timing

R = motion correction
C = physiological correction
T = slice-timing correction



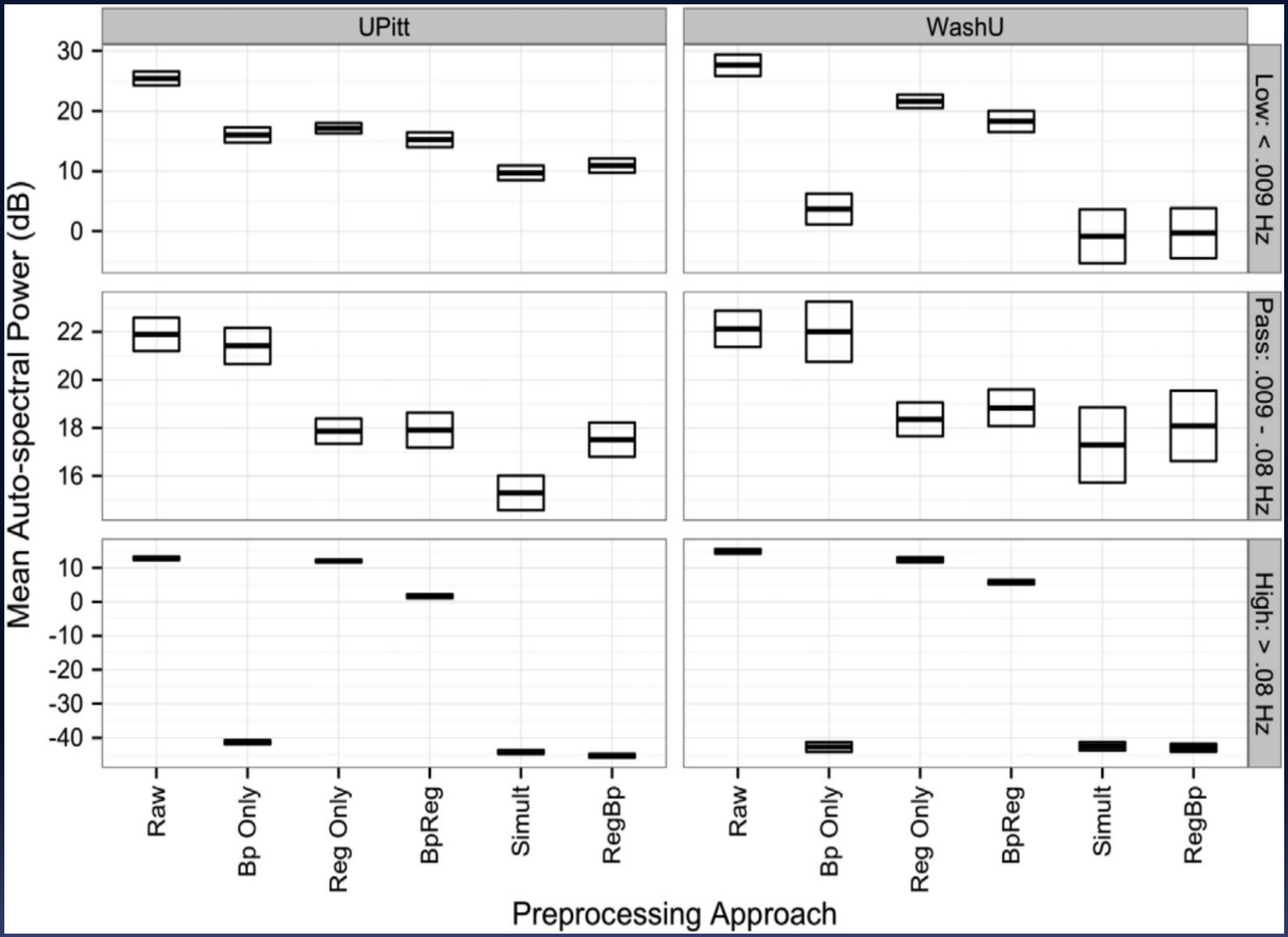
Order of preprocessing steps:
Regression, Band-pass filtering

- **Example**: order of nuisance regression, bandpass filter
  - Regression before band-pass filtering
  - Simultaneous regression+filtering
  - Bandpass filtering before regression

- What order optimizes model fit?

- Hallquist et al. (2013) examined for resting state

Order of preprocessing steps:
Regression, Band-pass filtering



Bp: bandpass
Reg: regress

BpReg: bandpass, regress
Simult: filter data + regressors
RegBp: regress, bandpass

Interactions between preprocessing steps: Summary

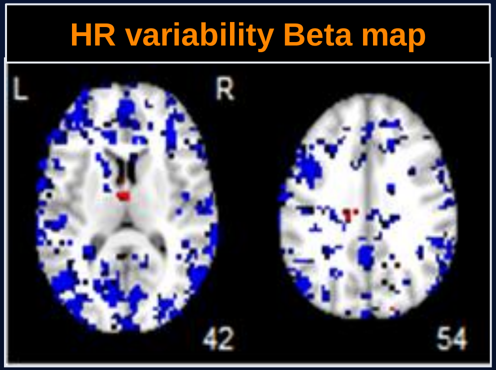
- The order of preprocessing steps can significantly impact analysis results
- **Minimize data variance:** Motion Correction, RETROICOR, Slice-Timing correction
- **Minimize artifacts**: simultaneous filtering of fMRI data and noise regressors *…do not filter before regression!*

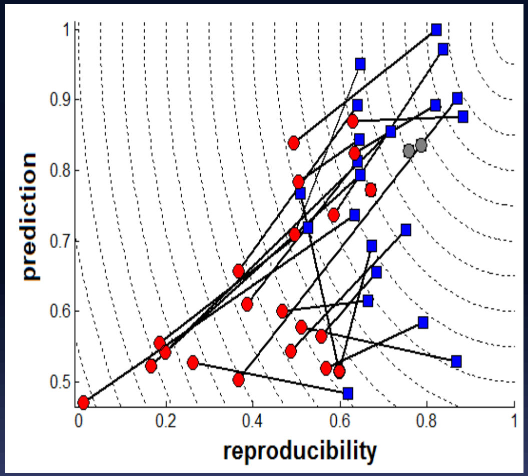
Conclusions

- Effects of preprocessing steps depend on:
  - **Effects of subjects and groups** (young/old, healthy/clinical)
  - **Effects of task design** (block / event / rest)
  - **Interactions with other preprocessing steps**
- Important to be aware of interactions when preprocessing (and comparing) datasets
- *To allow for broad range of subject vs. preprocessing interactions, may need to adjust steps individually*

Recommendations

- Test preprocessing effects on new datasets!
- Examine the discarded "noise" space e.g. GLM residuals (Lund et al., 2006)
- Test impact of preprocessing steps on quality of data by cross-validation (Churchill et al., 2012; Kay et al., 2013)





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References: conclusions and recommendations

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