Wavelet-Based Functional Mixed Models
for the Analysis of Lateralized Readiness Potentials

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Problem Setting: Task Switching Paradigm

- Laboratory analogue of ‘real-life task switching’
- Choice Response Time tasks: 2 computer tasks which both require binary responses (left/right hand)
• Cue signals which task must be performed
• Switch Cost: slower reaction times on task switch trials (compared to repetitions)
• Locus of switch cost: cue or task processing?
• Explicit versus transition cuing:
  – **Explicit**: (Parity/Magnitude): Cue and Task Perfectly Associated
  – **Transition**: (Same/Different): Possibility to Disentangle Cue and Task Switches
Lateralized Readiness Potential

- **EEG**: Electro-encephalogram
  (registration of cortical electric potentials, brain waves)

- **ERP**: Event-related potential
  (experimental psychology)

- **LRP**: Lateralized Readiness Potential
  (neurophysiological measure of motor preparation:
  motor cortex: C3, C4)
LRP = \[ \frac{\text{Mean (C4 - C3)}_{\text{left hand}} + \text{Mean (C3 - C4)}_{\text{right hand}}}{2} \]
Study Design

• Task *switching paradigm* (magnitude vs parity task) + Double *registration* (task indication + task response)

• LRP = outcome of interest

• 2 X 2 X 2 design:
  
  – **transition**: task repetition vs switch (within)
  – **cuing type**: explicit vs transition (between)
  – **indication**: selection vs no selection (between)

• 32 participants: 72 blocks (each 17 trials)
Wavelet-Based Functional Mixed Models

• Wavelets widely applied to EEG analyses:

to characterize time-varying properties of unaveraged EEG signal

• Discrete wavelet transform (DWT) to denoise signal:

transform the signal into the wavelet domain, shrink relatively small coefficients towards zero and use inverse DWT
to project the signal back to the data domain

• Functional Mixed Models: $Y(t) = XB(t) + ZU(t) + E(t)$

$Y(t) = (Y_{1}(t), \ldots, Y_{N}(t))$ vector of observed functions

$B(t) = (B_{1}(t), \ldots, B_{p}(t))$ vector of fixed-effect functions with $N \times p$ design matrix $X$

$U(t) = (U_{1}(t), \ldots, U_{m}(t))$ vector of random-effects functions with $N \times m$ design matrix $Z$

$E(t) = (E_{1}(t), \ldots, E_{N}(t))$ vector of functions representing the residual error process
**Multiplicity issue**

Determine time interval where condition has significant effect.

- pointwise posterior credible bands ⇒ multiple looks

- use of Bayesian False Discovery Rate
  - calculated by summing the posterior samples from the MCMC
  - assuming an effect size of at least \( \delta \)
• joint posterior credible bands
  
  – no unique way to identify joint posterior credible bands
  
  – based here on the pointwise credible intervals derived from the $\alpha/2$ and $1 - \alpha/2$ quantiles of the samples
  
  – next, scale these pointwise intervals with a constant factor until $1 - \alpha$ of all sampled curves are contained in credible band
Results

Model with main effects for cuing type and transition and its interaction.

- no effect of cuing type
- clear divergence between task switches and task repetitions
- no interaction between cuing type and transition
- onset of divergence with FDR depends on *subjective* choice of $\delta$
- performance of *objective* joint posterior band relatively good

$\Rightarrow$ needs further exploration with simulations.
Posterior Mean- Pointwise 90% Credible Band - Joint 90% Credible Band

Bayesian FDR ($\delta = 0.75$: dotted line, $\delta = 1.00$: dashed line, $\delta = 1.25$: solid line) at $\alpha = 10\%$
References


