Use of Wavelet Transformation to Identify Longitudinal Trends of Time-Frequency Components in Visual Learning Paradigm

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Outline

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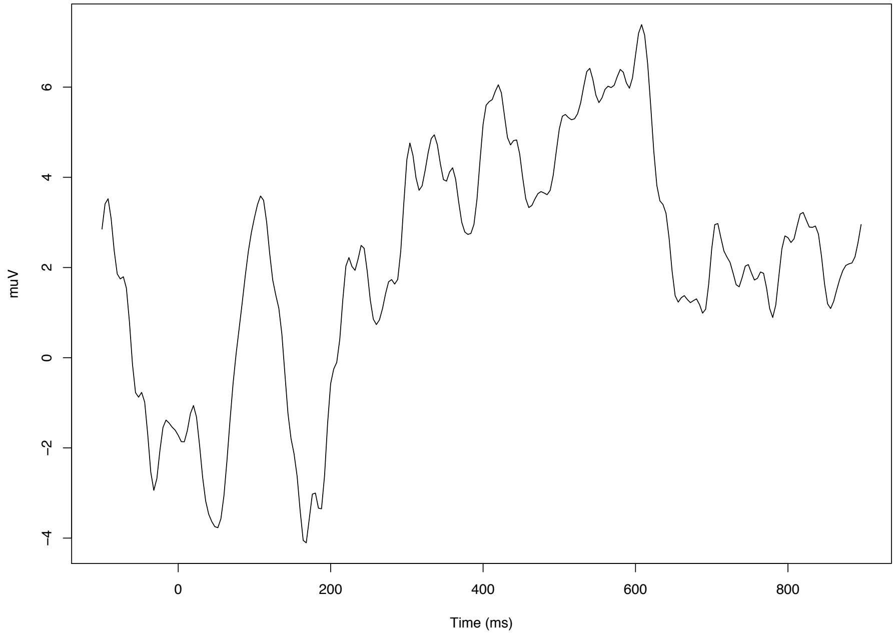
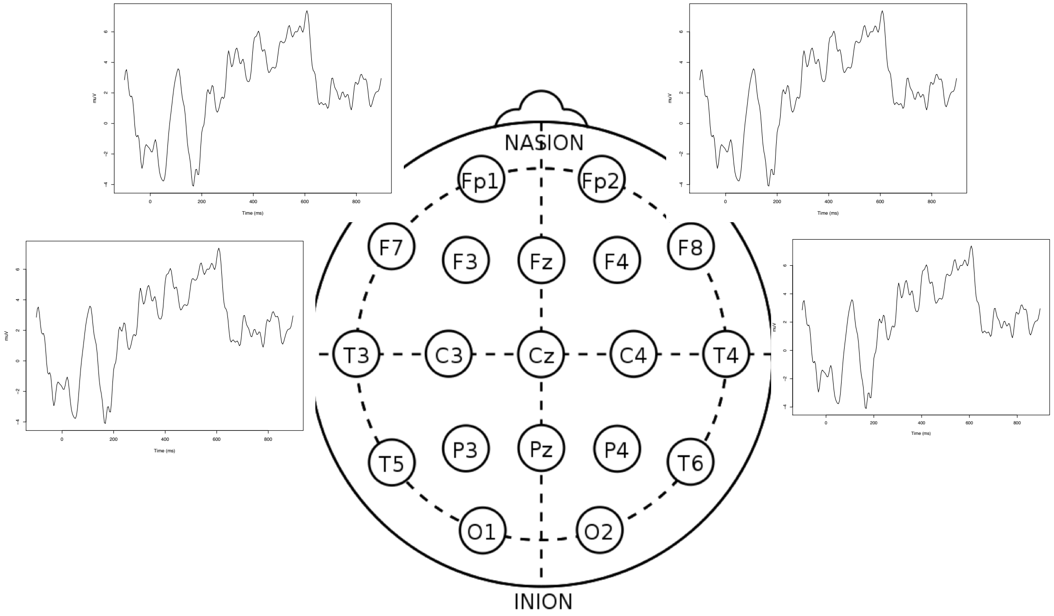
  - Experimental Conditions
  - Previous Works
- Mathematical Introduction
  - Inner Product
  - Wavelet Transformation
- Algorithm
- Results
  - Next Steps

Introduction to Functional Data

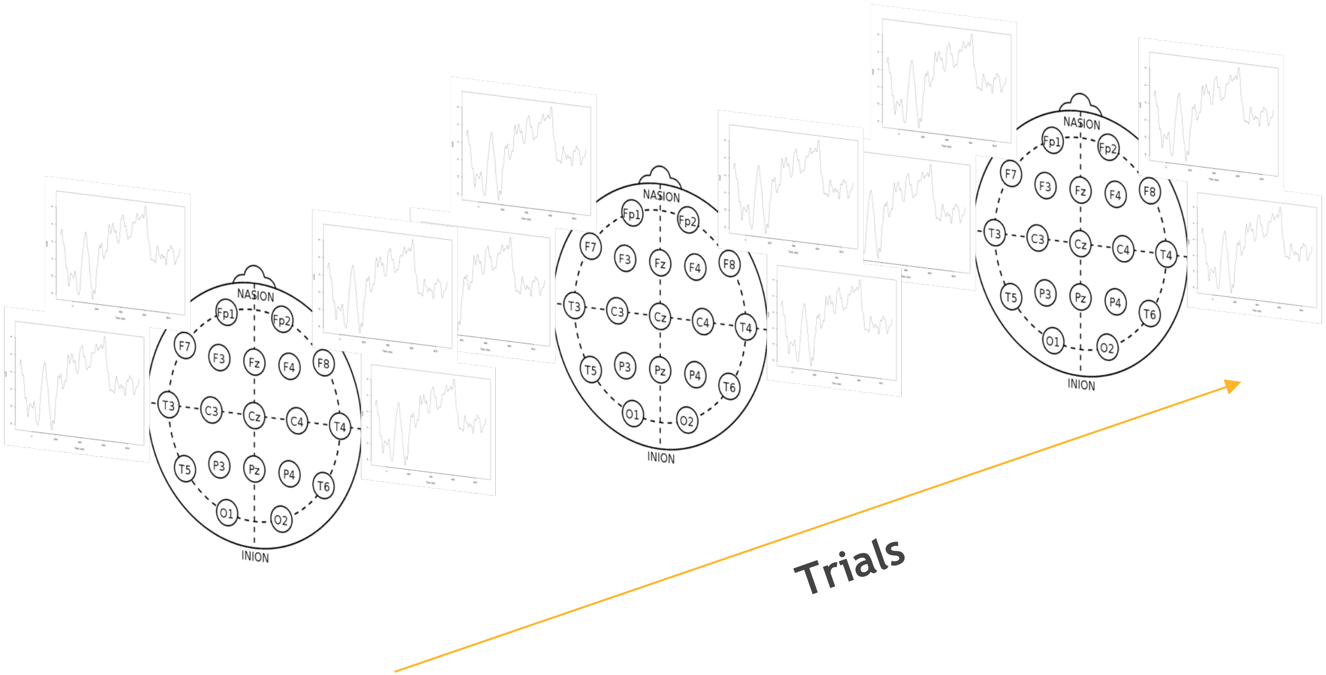
A Single Event Related Potential (ERP)



ERPs Collected Across a Scalp



Repeated Over Trials



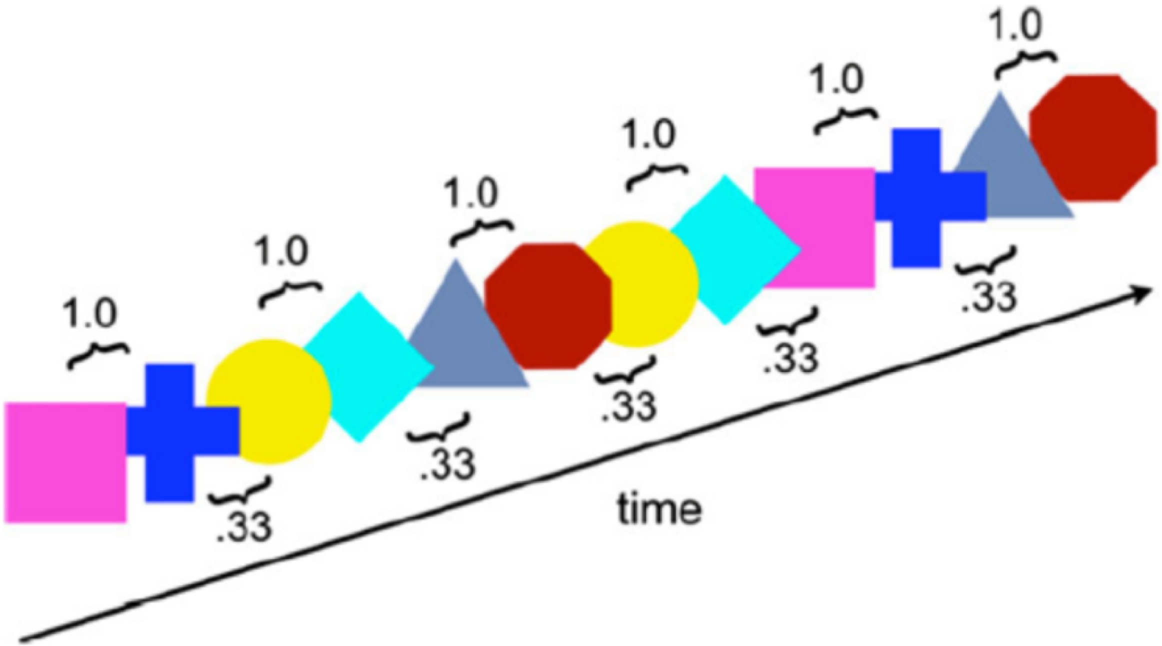
Functional x Spatial x Longitudinal

EEG Data

- HIGH temporal resolution
  - LOW spatial
- Low Signal-to-Noise Ratio (SNR)
  - Average over trials
  - Loss of longitudinal dimension
- Analyzed in Time or Frequency domains

Experimental Conditions

- Dr. Shafali Jeste from UCLA SEMEL Institute
  - Study Implicit Learning
  - 37 Autism Spectrum Disorder (ASD)
  - 34 Typically Developing (TD)
  - Age-matched
- Continuous stream of colored imaged
  - Paired shapes – Expected transition
  - Unpaired shapes – Unexpected transition
  - 120 trials per condition


1.0
1.0
1.0
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1.0
.33
.33
.33
.33
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time

Previous Work

- Time domain window average
    - Boosts SNR
    - Damping of signal
- Kernel smoothing of Fourier Transform
    - Frequency power and coherence
    - Not good for short signals
- Wavelet Transforms
    - Time-Frequency representation
    - Yay!

Wavelet Transformation

Review of Inner Product

The inner product $\langle \cdot\,, \cdot \rangle : V \times V \to F$ for vector space V and field F. It must allows satisfy three condition for all vectors x, y, $z \in V$ and scalars $a \in F$:

(i) Conjugate Symmetry

$$\langle x\,, y\rangle = \overline{\langle x\,, y\rangle}$$

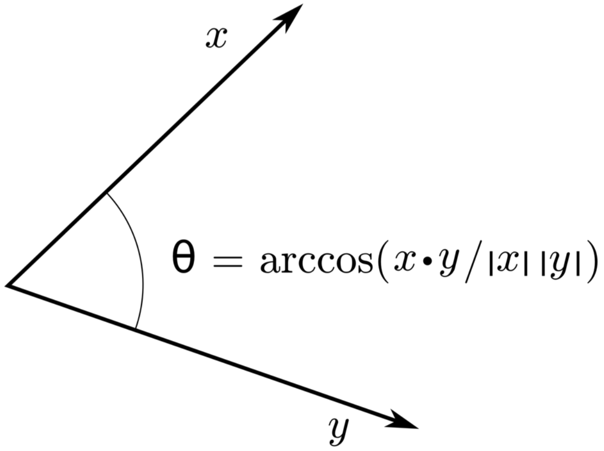
(ii) Linearity in first argument

$$\langle ax\,, y\rangle = a\langle x\,, y\rangle$$

$$\langle x + y\,, z\rangle = \langle x\,, z\rangle + \langle y\,, z\rangle$$

(iii) Positive-definiteness

$$\langle x\,, x\rangle \geq 0 \ \langle x\,, x\rangle = 0 \Leftrightarrow x = 0$$

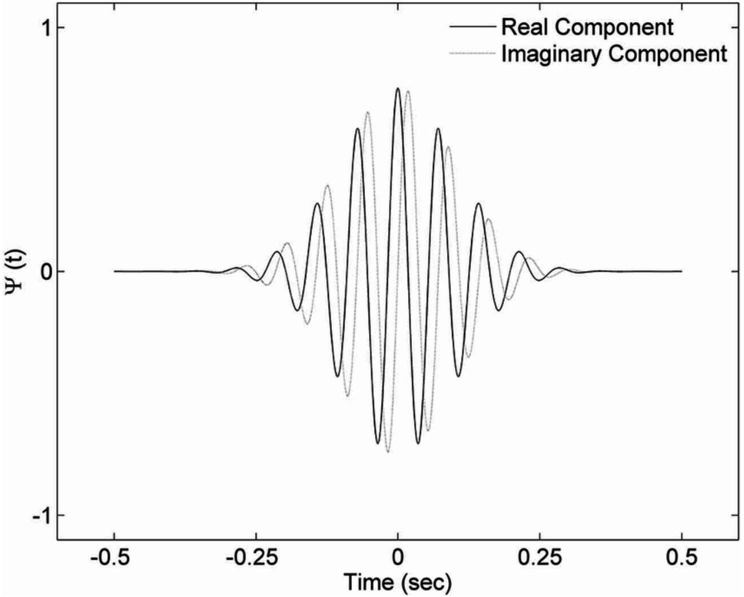


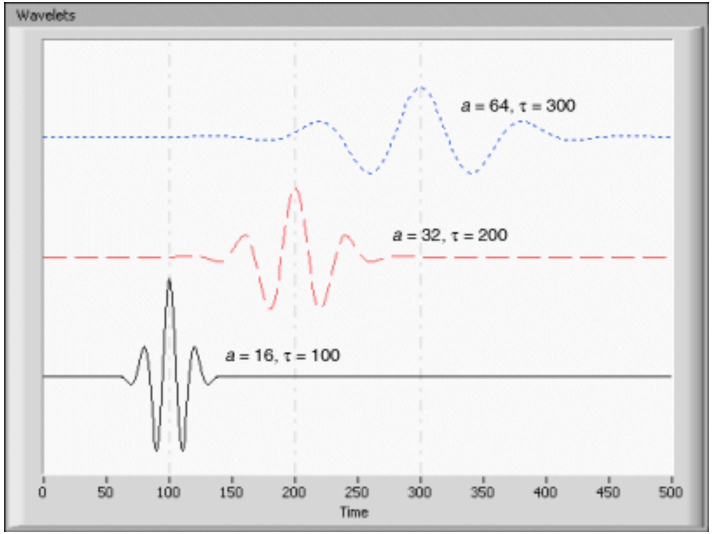
The Wavelet Transformation

Let $x(t)$ be signal we wish to transform. Let $\psi(t)$ be a complex valued Mother Wavelet of our choice. For a given scale parameter $a > 0$ and translation parameter $b \in \mathbb{R}$, the wavelet transformation coefficient at scale a and time b is

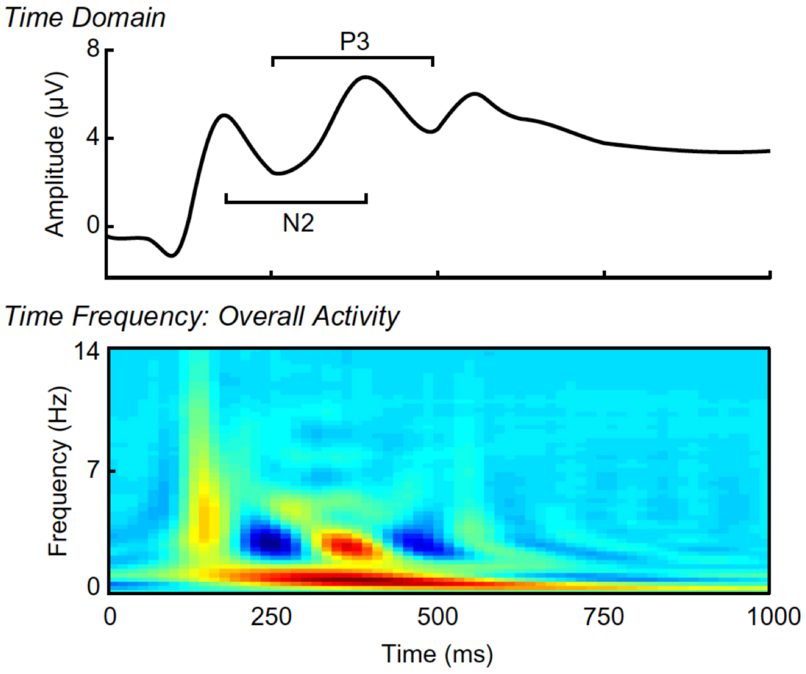
$$W(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\overline{\psi}\left(\tfrac{t-b}{a}\right) dt$$

The Wavelet Transformation





The Wavelet Transformation

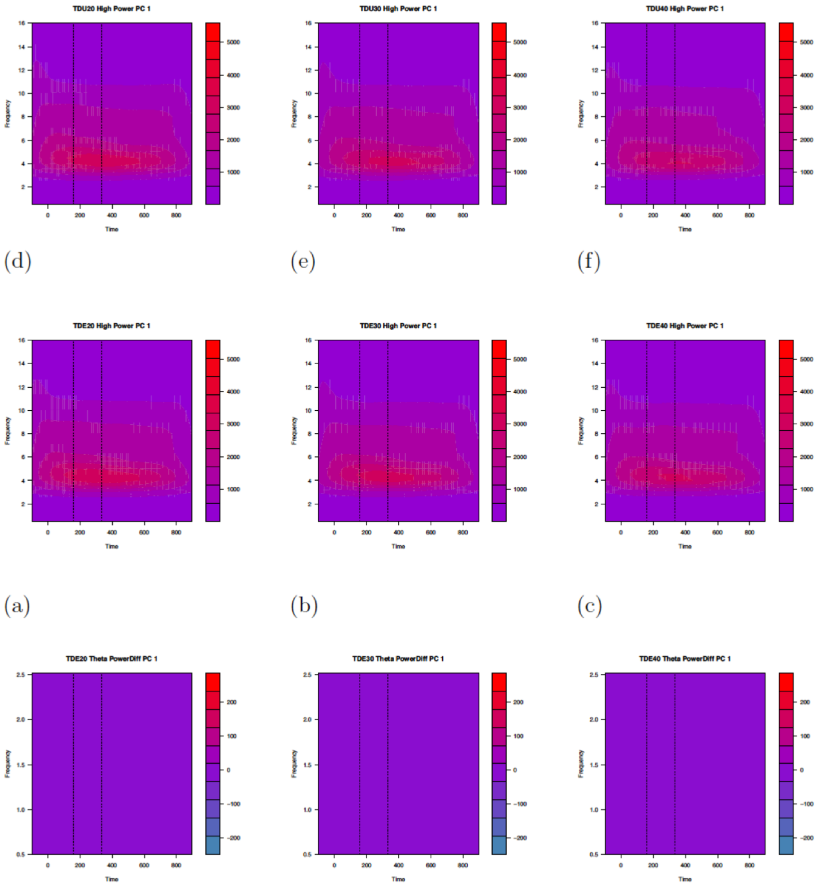


Algorithm

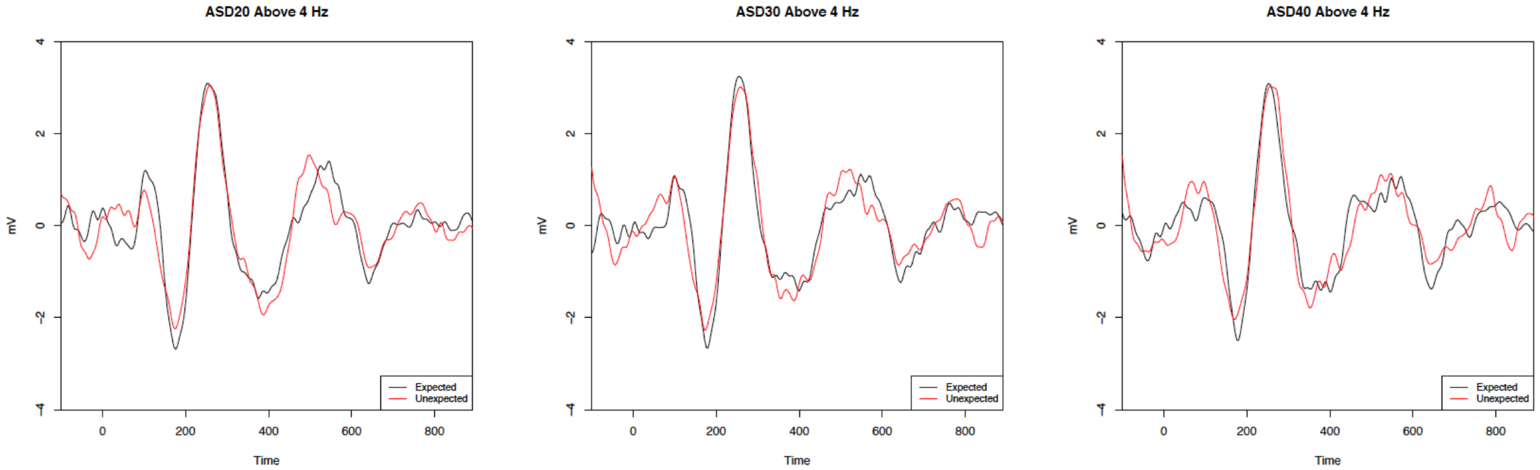
1. Filter signal.
2. Apply Wavelet Transformation chosen time and frequency parameters.
3. Collected vectorized TF surfaces for all subjects and electrodes in a given group, condition, and trial window.
4. Perform PCA and extract principal (column) vector and value.
5. Repeat for each trial window, condition, and group.

Results

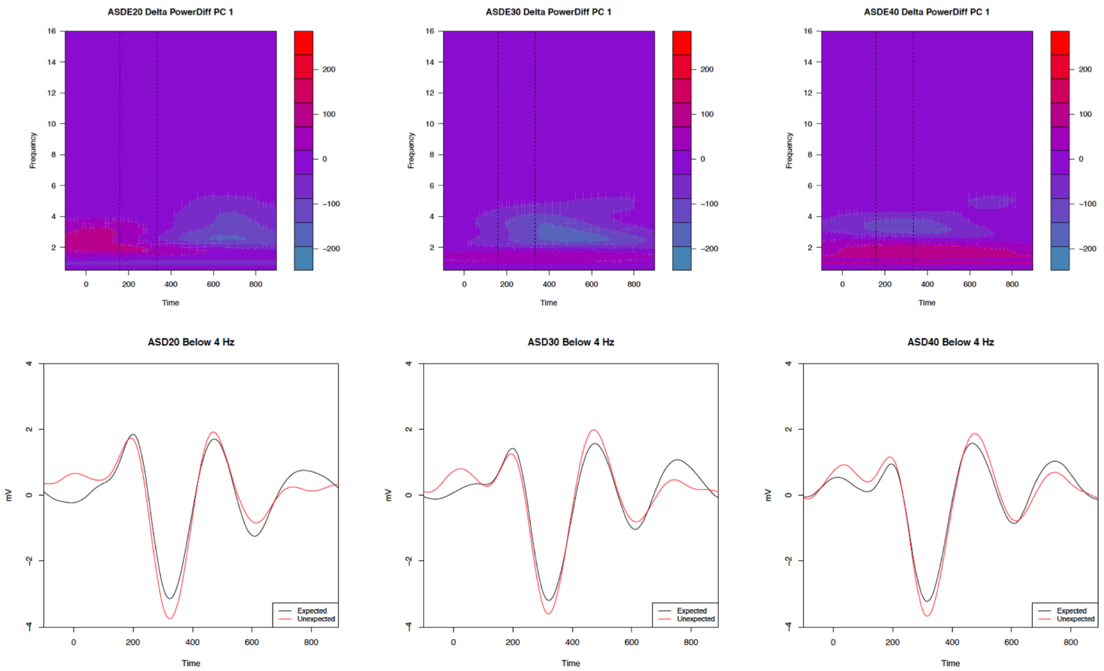
Theta Band: 4Hz - 8Hz



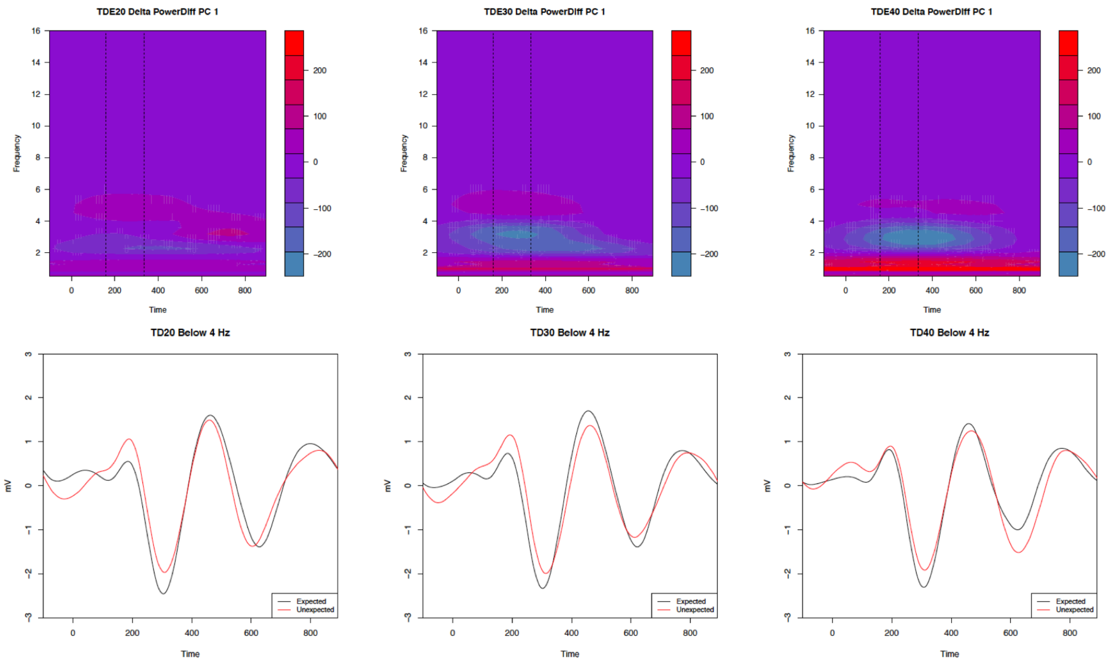
Theta Band: 4Hz - 8Hz



Delta Band: .5Hz – 4Hz (ASD)



Delta Band: .5Hz - 4Hz (TD)



Remarks

- Theta band contributes to shape of N1-P3 response.
- Delta band contributes to the difference in magnitude
  - Associated attention-tasks
- Evolving process over trials
  - Different between ASD and TD

Next Steps

- Examine more trials
- Compare direction of variation
- Make a model!
  - Use principal component and single trial waveforms to form score
  - Add random effects for individual
    - Maybe electrode

Recap

- EEG data is noisy, we need lots of it!
- Wavelet Transformations have the best of both worlds, high time AND frequency resolution.
- We can analyze concurrent temporal frequency learning behavior in kids with autism.
- Lots of colorful graphs

Thanks!

Any questions?

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