Power-Based Connectivity

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Power-based connectivity

Correlating time-frequency power between two electrodes across **time** or **over trials**

Gives you **flexibility** for analysis: 😊

- Test specific hypotheses
- Data-driven exploratory analyses
Many options for looking at connectivity over *time* and *frequency*.

Does not assume connectivity is instantaneous (like phase, last chapter), or at the same frequency.

Hence the flexibility.
Important note

Power-based connectivity is most similar to fMRI connectivity measures that correlate BOLD time series.

Because the correlated fluctuations in activity are relatively slower than phase-based connectivity.

Fox et al, 2005
Bivariate correlation coefficients
Pearson vs Spearman

Pearson correlation coefficient: covariance of two variables, scaled by the variance of each variable.

\[ r = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2 \sum_{i=1}^{n}(Y_i - \bar{Y})^2}} \]

Assumption: Data are normally distributed.
- violate this, and you introduce bias into the correlation coefficient.

Matrix algebra way
\[ r = \frac{xy^T}{\sqrt{(xx^T)(yy^T)}} \]
Use MATLAB functions

corr
or
corrcoef

demo
Spearman correlation

Nonparametric
Uses a rank correlation
• order data from each variable
→ this removed outliers

Pearson vs Spearman correlation:
Only difference is that Spearman rank-transforms the data before applying equation on last slide.
• can be done over time or trials
Two reason to use Spearman

(when doing within subjects power correlations)

1) EEG data are **non-normally distributed**

2) They contain **outliers**

Note: See chap 18 for discussion on why EEG data is non-normally distributed
(hint: $1/f$)
How Pearson correlation can misrepresent a bivariate relationship: Anscombe’s quartet

A bivariate relationship in the data sets causes different outcomes in correlation analysis:

I) **a:** Pearson and Spearman are the same – data normally distributed.

II) **b** and **d:** outliers give you inflated correlation.

III) **c:** outlier gives deflated correlation.
Since EEG data is non-normally distributed and may contain outliers

**Use Spearman correlation**

- provides a less biased estimate of a bivariate relationship in your data.

**Note**: trial-averaged baseline-corrected power is often normally distributed. Use Pearson correlation.

- looking at cross sub correlations between EEG activity and task performance
Final note:

Correlation coefficients have a bounded distribution ( -1 to 1)
They are not drawn from a normal distribution.

Thus, you must normalize them before statistical evaluation.

- Use Fisher z-transform
Finally!
Power correlations over time

Correlating power time series between two electrodes over a period of time.

- Use for task data or resting state
- Can be in the same or different frequency bands

→ Cross frequency coupling

Steps
1) Pick 2 electrodes
2) Compute power time series
3) Compute a correlation coefficient between time-varying power of the 2 elects
Figure 27.4

Time series for 6Hz, trial 10

Power relationship

Rank-power relationship

Pearson R = 0.66621

Spearman Rho = 0.81547
Time series for 6Hz, trial 1

Power relationship

Rank-power relationship
Shows correlations of alpha power (1 second time series) with BOLD responses.

Occipital, superior temporal, inferior frontal, and cingulate cortex show negative correlations, and increased signal in the thalamus and insula

Pearson correlation on bottom bar.
Length of time segment used to compute correlation coefficient is crucial

Too long, transient changes in connectivity might not be detected
Too short, no robust correlation coefficient estimates

Time segment should be
a) at least one cycle of the frequency band
b) task data, least two to four cycles
Power correlations not limited to instantaneous correlations (previous slides)

Cross-correlation analysis

Reveals weather peak connectivity is observed when one time series is temporally shifted relative to another

Computed in frequency domain (efficiency)

\( \text{Xcov with 'coeff' turned on, need to rank-transform your data first (tiedrank)} \)
Cross correlation plot for trial 10

Cross correlation plot for trial 1

Figure 27.5
Power correlations over **trials**

1) **T/f windows prior to analysis**
   → **Hypothesis driven** (pre define windows)

2) **At each time point over trials**
   → **Hypothesis driven** (you select two electrodes and frequency bands), but gives flexibility to assess changes in connectivity over time; can do many frequencies too

3) **“Seed” analysis**
   → **Exploratory**
**T/f windows prior to analysis**

I) Select t/f windows for two electrodes (need not be same length)

II) Extract power from that window for each trial (averaging over all points in window)

III) Compute one correlation coefficient

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Figure 27.6

Figure 4. The topography of the correlation (Spearman) between cue-related alpha modulation and behavioral benefits across each group. (A) Across the typical children, there was significant anticorrelation ($r = -0.61, p < .05$) between alpha power in the occipital electrodes and the difference in reaction time between validly and invalidly cued trials. This is seen in the map as focus of anticorrelation (deeper blue color) over the posterior scalp (bottom of map). (B) No relationship between cue-related alpha modulation and behavioral benefits was observed in the children with attention-deficit/hyperactivity disorder (ADHD).
(A) The parieto-occipital channel (marked with a star) was used as a seed location for the correlation analysis. The correlations between alpha power in the reference electrode and theta power in all the other sensors were calculated on a trial-by-trial basis within subjects and converted to t values then z scores across subjects. For the typically developing children, there was a strong anticorrelation between parieto-occipital alpha and midline frontocentral theta power. No such correlation was observed in the children with attention-deficit/hyperactivity disorder (ADHD). (B) The mean frontal theta and posterior alpha correlations across cue and groups. Error bars represent the standard error of the mean. From Mazaheri et al 2010. Biological Psychiatry
At each time point over trials

Gives you times series of correlation coefficients

Can use same (below) or different frequency bands

Lets you assess changes in connectivity over time

Figure 27.6
“Seed” analysis

More open to exploration

By selecting a “seed” electrode and correlating it with cross-trial power fluctuations in the seed t/f window with cross-trial power fluctuations in all other t/f points at one, some or all electrodes

Gives you a t/f electrode map of correlations between power at t/f point and power in the seed t/f window

Important advantage over phase: does not require connectivity to be simultaneous or same freq band
Correlation over trials from seed fz, 6 Hz and 200-400 ms
Partial correlations

Measure the relationship between two variables while holding a third constant

Two main uses

I) Test hypotheses about networks comprising more than two nodes.
II) Minimize volume conduction artifacts during power correlations

Can be over time or trials

- If power correlation of X & Y is similar to Z & Y, could be due to correlation between X & Z
- So hold Z constant
I) **Down sample**

I) High temporal resolution is needed to extract frequency

II) After frequency info is extracted, and increase in autocorrelation in signal

III) Thus temporal resolutions is greater than temporal precision and you can down sample

IV) Lower freq can be downsampled, not higher

V) T/f methods that increase temporal smoothing

VI) Use code 27.8 to see effects of downsampling on specified freqs

II) **Corr** or **Corrcoef** are slow, just write Spearman correlation equation yourself.

I) Don’t forget to **tiedrank**