Summary of common approaches to EEG data analysis

Planned document updates

* Key references

# EEG outcome measures

* Event-Related Potentials (ERPs): provides neural activity that is both time-locked (i.e. occurring at the same point in time with respect to the stimulus onset over all 20 trials) and phase-locked (i.e. the phase of neural oscillations is consistent with respect to the stimulus onset over trials). ERPs have the advantage of high signal:noise ratio as long as there are sufficient trials over average the data over (20 trials is a bare minimum although likely to be too small when many trials are rejected during cleaning for some patients). However, phase-locking is not a necessary assumption and may mean that useful information (non-phase locked is missed). Also, another disadvantage is that certain frequencies of neural activity (largely low frequency theta/alpha) will be over-represented in ERP analysis.
* Oscillatory power (over time and frequency). These are time-locked (but not phase-locked) neural signals. The analysis allows breaking down the neural activity into multiple frequency bands, thus providing more information, including higher frequencies that are not well represented in the ERP. However, the cost of having more information is that statistical tests will be less powerful due to the multiple comparisons problem. It is therefore wise to focus on a subset of frequencies rather than focussing on the whole frequency spectrum.
* Source activity: In both the cases of ERPs and oscillatory power, the data can be represented either on the scalp surface (2D) or with locations estimated within the brain volume (3D).
* Connectivity: There are a range of connectivity metrics (this list is not exhaustive):
  + Exploratory research benefits from phase-locking metrics (finding oscillatory activity that is synchronised across scalp areas) although there is debate about how closely these metrics reflect actual functional neural connections. Extensions of this might include, for example, graph theory metrics that summarise the connectivity patterns into theoretically interesting statistics.
  + Hypothesis-driven research can benefit from more model-based approaches such as Dynamic Causal Modelling. This approach compares competing models of neural connectivity and results in estimates of how probable these different models are. It provides greater statistical power but requires hypothetical models that are highly plausible based on past literature.

# EEG statistical methods

* Univariate methods requiring data reduction: This is the most common approach historically but is becoming less popular. Neural signals are first reduced to a smaller number of measurements either based on a priori hypotheses or empirical observation of the data (the former is considered more robust). For example, rather than analysing all 64 electrodes, the data can be reduced down to an average of a small number of electrodes of interest over a scalp region of interest, resulting in a single value to analyse rather than 64 values. Alternatively, a more exploratory approach might divide the data into 9 scalp regions and average within those regions; each region can be a level within a factor of an ANOVA. Likewise, data can be reduced over time, focussing on specific latencies of the ERP, for example. The main advantage of data reduction is improving statistical power by reducing the number of comparisons made; however, the approach has been criticised for providing too much researcher degrees-of-freedom (i.e. results are heavily dependent on researcher analysis choices).
* Mass univariate methods: These have become more common in recent years due to improvement in analysis software. They can be considered more “principled” than the above approach in that the whole data can be included (without artificially reducing the data) while correcting for multiple comparisons using methods that take into account non-independence in the EEG data (and that are therefore more sensitive than overly-conservative Bonferroni corrections). Examples include:
  + Fieldtrip cluster-based statistics: these are non-parametric tests applied to all electrodes/time-points of interest. Non-parametric tests do not make assumptions about the distribution of the data (i.e. not required to be normally distributed) but have the disadvantage of providing less complex models (e.g. complex ANOVAs are not possible – tests are restricted to single factors). This can be partially circumvented by conducting subtractions first, e.g. subtracting motor present vs. absent trials, prior to conducting paired tests on painful vs non-painful trials (which approximates an interaction effect). However, this method is currently only available for sensor-level data and not source-level data.
  + SPM sensor and source statistics: SPM conducts parametric statistics, allowing complex ANOVAs, and can be applied to sensor and source data. However, it assumes normality of the residuals of the model (which may not be accurate for some types of data).
* Multivariate methods: The multiple comparisons problem, and the problem of assuming certain data distributions (i.e. normality), can be bypassed using multivariate approaches such as multivariate pattern analysis (MVPA). These analyses look for co-dependent patterns across the data (e.g. over electrodes and time) rather than differences in mean levels of activity. MVPA is particularly sensitive to differences between conditions compared to univariate methods and therefore provides higher statistical power. Such methods are commonly used for classification (i.e. using neural activity to predict class membership, e.g. classifying a patient vs. healthy control, or classifying one condition from another). However, the results are less easy to interpret as they do not necessarily localise the neural activity to specific points in space and time. There are methods that can around this by applying sub-sections of the data at a time to the classification algorithm (e.g. searchlight methods).