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Editorial

Cutting-edge methods for EEG research on cognition

Electroencephalography (EEG) is at the same time the oldest brain imaging technique and one of the methodologically most rapidly expanding tools in cognitive neurosciences. Its exquisite temporal resolution, its ever-growing spatial precision, its ease of use, and its relatively modest price make it a method of choice for cognitive neuroscience labs. In recent years, the explosion of computing power and new developments in acquisition hardware has literally revolutionized our approach to EEG analysis. We have long left examining traces on paper sheets as was done in the early days. Today, we process gigabytes of data on desktop computers to analyze experiments in a way that we could not have thought of only two decades ago. Yet extracting meaning from EEG signals is still not an easy feat. Both beginners and experts may find it difficult to keep an overview of the plethora of analysis methods, let alone to implement them in their own analysis workflows. Furthermore, with new methods and analysis tools come up new challenges that reveal the limitations of previous approaches. It is the purpose of this special issue of the *Journal of Neuroscience Methods* to address both problems. Several papers present state-of-the-art reviews on novel developments in EEG signal analysis, while other papers review best-practices and established methods that have proven useful for studying cognition with EEG. This special issue was initiated at the first edition of the Cutting EEG symposium on cutting-edge EEG methods for the study of cognition, held in Berlin, on February 19th–21st, 2014.

One of the most well-known challenges posed by the EEG signal is its low signal-to-noise ratio. Indeed, this limitation was addressed already long ago and prompted the widely used averaging method of event-related potentials. But it also deeply conditioned the way we construct experiments and the features of the signals we can extract from the EEG. Indeed, the event-related potential can only reveal strictly time-locked signals. This limitation has been acknowledged since the mid-1990s, when researchers made a distinction between evoked and induced oscillatory EEG responses (Tallon-Baudry et al., 1996). Three papers in this special issue present alternative ways to reveal events with variable latencies in the EEG signal.

Delorme and coworkers present an elegant method and visualization technique they call ERPimage (pronounced "Urp-image"). The principle of this method is simply to sort trials based on the known latency of a specific event (e.g. reaction time or eye movement), and then to use a sliding average across neighboring sorted trials to aggregate them where the variable latency event occurred at similar time points. The resulting matrix is displayed in an image with time on the horizontal axis, sorted trials on the vertical axis, and amplitude coded in color. This method is versatile in the sense that, to the extent that one can produce matrices of equal size across participants and conditions, standard statistical methods can straightforwardly be applied to reveal variable latency effects in the EEG signal. This method is available in the open source EEGLAB analysis software.

The second paper by Ouyang and coworkers takes another approach to solve a similar problem. These authors reason that there are three types of events occurring in a typical psychological EEG experiment: events that are strictly time-locked to the stimulus, events that are strictly time-locked to the response, and events that occur at variable latencies between the two others. The authors present the Residue Iteration Decomposition (RIDE) method that uses advanced signal processing to isolate time-locked, and most interestingly, variable latency components. They make a compelling case for their approach by validating it and successfully isolating each type of component using three different datasets. The RIDE toolbox is made available for download (see paper for the hyperlink).

The third paper by Williams and coworkers takes a different approach to isolate different types of single trials. This paper presents a complete pipeline of signal processing to isolate clusters of single trials in order to dissect the cognitive constituents of individual experimental conditions.

A well-known alternative way of dealing with the low signal to noise ratio of the EEG signal is to consider that only certain frequencies are of interest and to use filters to attenuate signals outside this frequency band. Filtering is a straightforward operation used in virtually every EEG experiment that allows removing unwanted frequencies from the signal. But, as ubiquitous as it is, this processing step is not devoid of limitations and pitfalls, and proper filtering is not a trivial operation. Widmann and coworkers provide an in-depth documentation of relevant filtering parameters and of the effects that badly designed filters may have on EEG signal.

The signal to noise ratio of EEG data is often degraded by artifacts such as eye blinks, muscle noise, or technical glitches. The traditional strategy for removing such artifacts has been to reject affected trials altogether. However, artifact rejection may lead to considerable data loss, and the remaining data cannot be guaranteed to be free of sub-threshold artifacts. A popular alternative to artifact rejection is artifact correction, which attempts to remove only the artifactual portion of the signal while keeping the genuine EEG signal. For example, Independent Component Analysis

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is often used to decompose the EEG signal into statistically independent components, some of which typically represent common artifacts such as eye blinks. Removing these components improves the signal to noise ratio of the remaining signal tremendously. But who decides which components to remove and why? While some researchers prefer to make the decision themselves, others prefer a fully automated approach, where a computer algorithm decides based on statistical criteria. Chaumon and coworkers recommend a semi-automatic approach, in which the user makes informed decisions about which components to reject based on a number of statistical measures that are indicative of artifactual components. This approach is implemented in their SASICA toolbox, which is available for download (see paper for the hyperlink).

Localizing the brain sources of the signal recorded at scalp electrodes is a second challenge that receives a lot of attention. Indeed, the problem of estimating the location of several thousands of sources based on a few dozen electrodes has an infinity of solutions. Various methods exist to solve this ill-posed problem and find the most plausible solution. Cottereau and coworkers present a didactic review of their own method, which uses individual functional magnetic resonance imaging localizers to impose constrains on sources of activity. They provide a detailed point-by-point overview of each step required to use their unique method, which allows implementing analyses of EEG signal based on functional regions of interest.

Interesting questions are not only about *where* are the sources of the EEG signal, but also about *what* they represent. The somatosensory high-frequency oscillations (sHFOs) evoked by electric nerve stimulation have been shown to be markers of human cortical population spikes. Previously, their analysis was based on massive averaging of EEG responses. In this special issue, Waterstraat et al. go one step further by optimizing their methods to allow their study at the single-trial level (Python and Matlab code provided).

The massive use of computer software to perform repeated statistical tests over entire datasets allows more in-depth analyses of EEG signals. Rather than performing single statistical tests based on specific a priori hypotheses, it is now possible to extract statistics from every data point in seconds. But a naive use of such approaches leads inevitably to a well-known shortcoming that impacts on the validity of the results. This problem is known as the multiple-comparisons-problem, whereby the mere fact of conducting multiple testing inevitably leads to false positive results. Pernet et al. review several methods correcting for the multiple comparison problem and provide recommendations as to which method and parameters to use in order to best correct for this problem.

Offering an alternative to running multiple tests on each electrode separately, multivariate pattern analysis methods (MVPA) are gaining in popularity in the EEG field. Considering the topographical pattern of activity, rather than each electrode separately, is a powerful method that can reveal differences between conditions at the single-trial level. In this special issue, three articles developed and used variants of these methods for the analysis of EEG signal. Lajnef et al. introduced a specific MVPA pipeline for the automatically classification of sleep stages from EEG activity. Their method, based on decision-tree and support vector machines (SVM), allow above chance prediction of sleep stage, and rivals with the best existing methods. De Lucia and Tzovara analyzed brain responses in comatose patients and classified responses to deviant auditory stimuli above chance level in these patients within 24–48 h of coma onset. These two articles have important implications for fundamental EEG research (in sleep and auditory perception) but also for clinical practice. As with any new method, as promising as it is, the statistical analysis of MVPA results from EEG data can easily be misinterpreted if one is not careful. Combrisson et al. are thus providing important warnings and guidelines, including simulations, on how to compute the “chance” level in classification studies, and how to assess if the obtained classification performance is above this chance level.

EEG is increasingly used to study interactions between brain areas using functional connectivity analyses. However, EEG scalp channels can appear to be connected not only due to a true interaction of different underlying brain areas, but also due to volume conduction from a single brain area. The study by Cohen compares two connectivity methods (spatial filtering in combination with standard connectivity methods and weighted phase lag index) using simulated data in which the degree of connectivity and volume conduction is known. The paper discusses the advantages and disadvantages of both methods and gives recommendations for when to use which approach.

In this special issue, we sought to create a mix of reviews and original contributions that best encompassed the spirit and excitement that the first edition of the Cutting EEG workshop offered. We are now glad to make some of the contributions of this meeting available in greater depth to a wider audience, while waiting for the next editions of this meeting in the years to come (Cutting EEG 2015 takes place 09/29–10/02 in Berlin).

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