Scorepochs: a computer-aided scoring tool for resting-state M/EEG epochs

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Abstract

M/EEG resting-state analysis requires the definition of the epoch length and the criteria to select which epochs to include in the subsequent steps. However, the effects of epoch selection remain scarcely investigated and the procedure used to (visually) inspect, label and remove bad epochs is often not documented thus hindering the reproducibility of the reported results. In this study, we present Scorepochs, a simple and freely available tool for automatic scoring of resting-state M/EEG epochs that aims to provide an objective method to aid M/EEG experts during epoch selection procedure.

Introduction

Task-free resting-state recording from M/EEG (magneto/electroencephalogram) represents one of the most used experimental paradigms to investigate the baseline level of brain activity in healthy subjects and patients (Stam, 2014). However, the resting-state condition is an elusive concept which is influenced by different states of vigilance that are usually out of control from the experimenter (Diaz et al., 2013). Generally, the first steps performed during an M/EEG resting-state analysis consist of (i) segment the raw/filtered EEG traces into a set of non-overlapping epochs and (ii) select a number of artifacts-free epochs to be used during the subsequent steps of the pipeline. These steps require the definition of the epoch length and the criteria to select which epochs to include in the subsequent analysis. The effects of the epoch length have been previously investigated (Fraschini et al., 2016), while the effects of epoch selection, induced by the inter-observer variability and unclear criteria used for this task, remain scarcely investigated. Epoch selection is performed at individual level (independently for each subject) and usually is conducted by one or more experts. Some kind of procedure to detect and mitigate EEG artifacts may be applied before this step. However, the precise procedure used to (visually) inspect, label and remove bad epochs is often not documented (van Diessen et al., 2015), thus hindering the reproducibility of the reported results. Most importantly, especially in the case the selection procedure is performed by different experts, it would be of relevance to assure that homogeneous criteria were used. In this context, most of the studies using resting-state paradigms make some kind of assumptions on stationarity of EEG signal and perform averaging of individual features (extracted at subject-level) to make inferences at group-level. In short, this means that it is assumed a strong within-subject stability of M/EEG features and that these individual characteristics may be consistent within a group[4]. Subjective visual scoring and/or inter-observer variability poses a possible threat to the validity of these assumptions. In this study, we present Scorepochs, a simple and freely available tool for automatic scoring of resting-state M/EEG epochs that aims to provide an objective method to aid M/EEG experts during epoch selection procedure. Our approach, which works at subject-level, provides a score for each epoch within a single M/EEG recording, with the attempt to make this crucial procedure less ambiguous, more objective and reproducible.

Methods

The proposed method is based on a very simple and fast algorithm which takes as input (*i*) a set of M/EEG recordings and (*ii*) the length of the desired epoch. After that, the algorithm provides as output a score for each single M/EEG epoch. A schematic representation of the proposed method is depicted in Figure 1. Furthermore, all the scripts used to perform the analysis are freely available: https://github.com/matteogithub/scorepochs. For each subject, each epoch and each channel, the algorithm computes the power spectral density (PSD) via Welch method into a specific range of frequencies (see Figure 1, panels A and B). At channel-level, a similarity score, computed by using the Spearman correlation coefficient, is evaluated between the PSD extracted from all the epochs, thus providing a correlation matrix with a dimension equals to *number of epochs x number of epochs* (see Figure 1, panel C). A first average is now computed over the rows (/columns) of the symmetric matrix to obtain a *score vector* with a length equals to *number of epochs*, where the entries represent the mean similarity score of the corresponding epoch (see Figure 1, panel D). Computing the *score vector* for each channel and then averaging the *score vectors* across channels it is possible to obtain a final score for each epoch (see Figure 1, panel E). Finally, for each subject, the score can be sorted in descending order allowing to select the suggested epochs to be included in the subsequent steps of the analysis.

We tested our approach on a freely available EEG dataset containing recordings from 109 subjects with a 64 channel system. We decided to define an easily interpretable hypothetical scenario where the interest was to contrast two different baseline conditions, namely eyes-open (EO) and eyes-closed (EC) resting-state. To contrast the two conditions the relative alpha power (computed in the range between 8 and 13 Hz) was the perfect candidate as this property is a very commonly yet effective feature able to detect macroscopic differences between EO and EC conditions. The analysis was performed on 99 out of the 109 subjects since some of them were excluded due to differences in recording parameters or overall poor quality. We used an epoch length of 5 seconds and thus segmented the one-minute available recordings into twelve non-overlapping epochs. For each epoch and each channel we extracted the relative alpha power and the average across channels was successively done for each epoch, thus computing the relative alpha power at global level. To mimic a realistic epoch selection procedure and investigate its possible effect, we decided to select for each subject four of the twelve available epochs, considering 495 different selections, representing all the possible combinations using the same subset of epochs for all the subjects. We then compared the results in terms of magnitude of effect-size obtained contrasting the two conditions (EO vs EC) on a group-level. We computed 495 t-tests where for each test we selected 4 epochs for every subject in sequential order (i.e, for all subjects, for the first test the epochs selected were [1, 2, 3, 4], for the second test the epochs selected were [1, 2, 3, 5], for the third test the epoch selected were [1, 2, 3, 6], …, until for the last test the selected epochs were [9, 10, 11, 12]). We then compared the magnitude of the paired Cohen's d

effect-size obtained using the selection suggested by scorepochs against the distribution of Cohen's d effect-size based on the sequential random selection.

Results

All the results are summarized in Figure 2 which shows the comparison, in terms of Cohen's d effect-size values, between the described sequential random selection and the selection suggested by our approach. In particular, Figure 2, Panel A, depicts the 'effect-size time-course' using this random selection, with the result derived by the application of our method represented by the green dashed line. A decreasing trend in terms of effect-size values can be observed. Figure 2, Panel B, shows the distribution of the effect-size values (independently of the sequential order), where the vertical green dashed line represents the value of effect-size obtained using the epochs suggested by our approach. The Cohen's d value for the scorepochs algorithm is 1.4512 which is around the 75th percentile of the random epoch selection distribution. It is worth noting that the minimum effect-size is bigger than 1, meaning that, as expected, we are in a situation where the difference is largely independent from the epoch selection strategy (i.e. the difference between the two conditions EO and EC is reliably measurable).

Summary

In this study, we proposed an automatic method to aid M/EEG experts during the epoch selection procedure in resting-state analysis. Our method represents an objective approach (i.e., less subjective) to perform epochs selection if compared to the potential arbitrariness introduced by human observers and the lack of clear and shared criteria used to accomplish this crucial task. We showed, in a prototypical scenario of a group comparison between two resting-state conditions (EO vs EC), that the effect-size varied extensively depending on the epochs included in the analysis. In fact, even if it is possible to detect an effect between the two conditions EO and EC almost independently from the selected epochs (since the detection of an effect is highly probable Cohen's d > 1 for every epoch selection), there is a considerable variation on the effect-size depending on the actual selection. Specifically, we showed a decreasing trend (see Figure 2, Panel A) in terms of effect-size with respect to the time in which the selection occured (i.e. selecting epochs at the beginning of the experiment gives higher effect-size compared to the end of the experiment). This could be influenced by different states of vigilance related to tiredness or drowsiness that are reflected in the recorded signals. The magnitude of effect-size obtained using our proposed epoch selection is close to the mean effect-size (which should represent the best estimate of the population effect-size) and more importantly is based on a quantifiable, objective and replicable strategy (i.e. scores computed on PSD). Compared to other semi-automatic procedures for the selection of the 'best artefact-free epochs' suitable for the analysis (e.g. independent component analysis, ICA), our method is completely data-driven and it does not require any intervention or particular skills of the user compared to other selection strategies (e.g. knowledge of stereotypical EEG pattern related to artefact components using ICA). Moreover, scorepochs method, because of the small amount of requirements (i.e. computation of PSD), is not computationally expensive. In no way, the proposed approach aims to replace the work to be performed by experts (alone or using other automatic or semi-automatic methods) during visual inspections of real M/EEG data. Scorepochs guided selection should be complementary to the human expert (or any other selection method).

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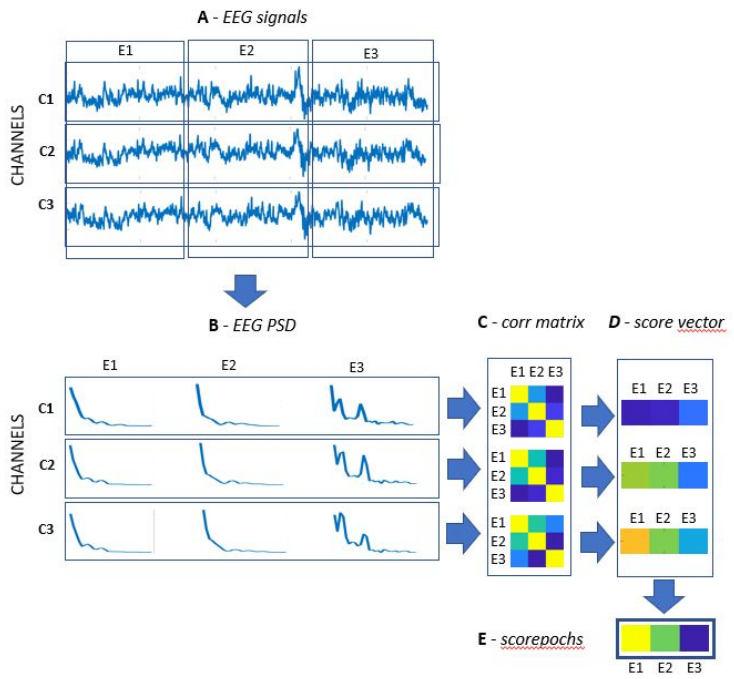

Figure 1. A schematic representation of the algorithm used to compute scorepochs. Panel A: EEG raw signals of three channels with epoching scheme; Panel B: Power spectral density plots for each channel and each epoch; Panel C: correlation matrices for each channel; Panel D: score vector for each channel and for each epoch; Panel E: score for each epoch.

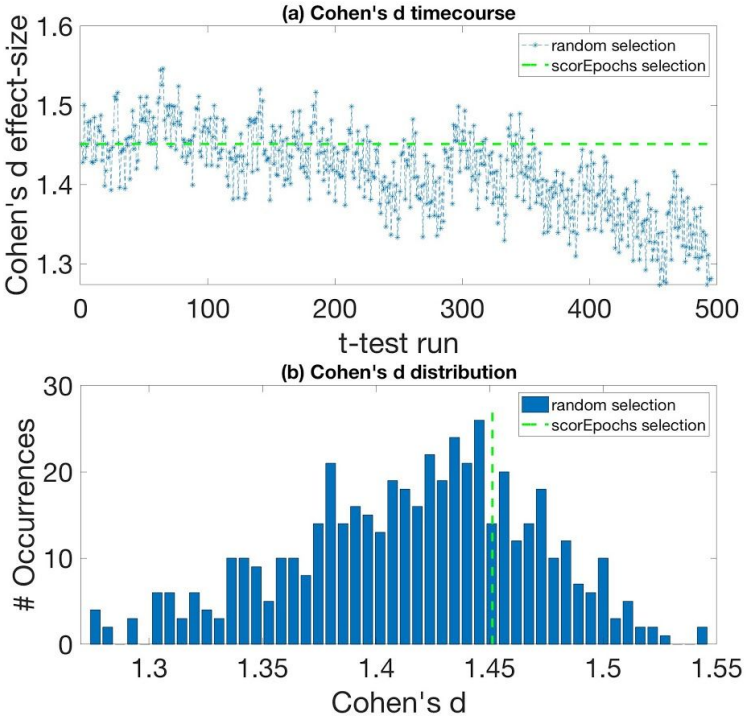

Figure 2. Cohen's d effect-size for random selection and scorepoch selection. (a) shows the 'time course' of the effect-size computed using a sequential random selection. On the y-axis the effect-size values are reported, while the x-axis indicates the t-test with a sequential random selection selection. The green dashed line represents Cohen's d value selecting the epochs using scorepochs. (b) Cohen's d effect-size distribution for random epoch selection and the scorepoch selection. On the x-axis the effect-size values are reported, while the y-axis indicates the occurrences specific value of effect-size. The vertical green dashed line represents Cohen's d value selecting the 4 epochs suggested by scorepochs.