High-pass filters and baseline correction in M/EEG analysis. Commentary on: "How inappropriate high-pass filters can produce artefacts and incorrect conclusions in ERP studies of language and cognition"

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Abstract

Tanner et al. (2015. Psychophysiology, 52(8), 1009. doi: 10.1111/psyp.12437) convincingly demonstrate how a late deflection like the N400 or the P600 is reflected into both earlier and later latencies by the application of high-pass filters with cutoff frequencies higher than 0.1 Hz. It nicely underlines the importance of test-wise application of filters with different parameters to electrophysiological data to identify such unwanted filter effects. In general, we agree with their approach and conclusions, particularly with the notions that the application of a high-pass filter is reasonable if it improves the signal-to-noise ratio (SNR) of the signal of interest, and that low frequency signals may carry important information. However, we disagree in two aspects: First, the test data of Tanner et al. are not optimally suited to demonstrate the benefits of high-pass filtering as they are only minimally contaminated by low frequency noise, and second, the standard baseline correction for particular applications in M/EEG data analysis should be replaced with high-pass filtering—as recommended by Widmann et al. (2015. J Neurosci Methods, 250, 46. doi: 10.1016/ j.jneumeth.2014.08.002).

Keywords

Baseline correction
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MEG

1. Improvement of signal-to-noise ratio vs. filter distortions

The quality of the unfiltered data presented by Tanner et al. (2015) appears to be so good that the difference between DC, 0.01 and 0.1Hz high-pass filtering is (almost) unperceivable in the plots. Therefore, it can easily be shown that the application of higher cutoff frequency filters only introduces unwanted signal distortions, while gaining little. However, the selection of an appropriate cutoff frequency depends on both the properties of the signal of interest and the noise characteristics of the data. Under noisy conditions – as for instance with measurements obtained from children or outside an electromagnetically shielded lab – the usage of a high-pass filter is the better-controlled and more powerful tool than alternatives such as detrending and even baseline correction (see below). The selection of a particular cutoff is a necessary compromise—improvements in SNR may come at the cost of undesired signal changes (filter distortions). Tanner et al. nicely demonstrate how filter distortions can be identified by appropriate means. Thus, our recommendation is to apply filters, which actually improve the signal-to-noise ratio while appropriately and reproducibly controlling for filter distortions rather than avoiding filters altogether (Van Rullen, 2011). We also argue in favor of individually suited rather than generalized filter parameters for all kinds of data or applications. Furthermore, we would like to argue in favor of establishing standards for the identification of filter distortions (high-pass as well as low-pass) and to consider them carefully in the data analysis to avoid biased or incorrect conclusions. Effective approaches to identify filter distortions are the systematic comparison of data filtered with different filter parameters (Tanner et al.,

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2015; Widmann and Schröger, 2012; Widmann et al., 2015) and the systematic analysis of the signal removed from the data by filtering (Widmann et al., 2015). We would like to point out, that high-pass filter cutoff frequencies and the length of analysis time windows should match. As a rule of thumb, an epoch length of one second is matched by a filter cutoff of about 0.16 Hz (time constant 1 s). Lower cutoff frequencies lead to longer filter time constants, and longer epochs should be selected to enable full visibility of the low frequency part of the data.

2. High-pass vs. baseline correction

Tanner et al. (2015) correctly argue that a high-pass filter takes pre-stimulus (condition) differences and reflects an inverted version into the post-stimulus time interval. However, as baseline correction also constitutes a high-pass filter by itself (defined by epoch/baseline duration), this notion also applies to baseline correction and does not constitute an argument against the replacement of baseline correction by high-pass filters. Instead, it underlines the importance of well-controlled experimental designs to prevent systematic condition differences in the pre-stimulus voltage. It is not always possible to avoid any pre-stimulus evoked activity—even in well-controlled designs. For example, in experiments during which stimulation is provided at a fast repetition rate, or even continuously, or in experiments with stimulus expectation or response preparation effects (e.g., CNV, BP, S1-S2 designs), there is no activity-free baseline interval available. Evoked activity from within the baseline interval is subtracted from the complete data and injected as underlying but time-invariant activity in the signal range (Urbach and Kutas, 2006). Applying baseline correction using these contaminated time intervals is only reasonable when the analysis is exclusively based on the condition difference assuming identical activity in the baseline interval. Applying a high-pass filter, however, provides an elegant means to introduce the zero as signal level of reference—without injecting evoked pre-stimulus activity into the analysis time interval given a sufficiently low cutoff frequency (Tanner et al., 2015; Widmann et al., 2015) while suppressing DC offsets and even slow drifts. Furthermore, the high-pass filter is superior to baseline correction as it can be used to test the experimental design: Systematic differences in the pre-stimulus interval point to possible problems in the experimental design assuming that it is not due to filter distortions. These problems need to be identified rather than to be obscured by baseline correction. Finally, combining a high-pass filter with baseline correction might even be dangerous as demonstrated by Tanner et al. (2015). Because evoked effects from the post-stimulus interval might be spread into the pre-stimulus interval due to filtering, the baseline correction would reflect them back onto the post-stimulus interval. It should be noted that even using a well-controlled design without any systematic differences or activity in the baseline range and possibly even using considerably low cutoff frequencies does not prevent this adverse effect of inducing artificial pre-stimulus effects.

In summary, if the data quality is high – and as a consequence, low frequency interferences are minimal – the possible improvement in SNR by applying a high-pass filter is limited. Under these conditions, no high-pass filter or one with a cutoff of 0.1 Hz for a typical analysis (e.g., one-second-epochs) is recommended. However, applications requiring higher cutoff high-pass filters (or low-pass filters) allow valid conclusions if filter distortions are identified and appropriately considered in the analysis. This is hardly possible with baseline correction.

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