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High-pass filters and baseline correction in M/EEG analysis–continued discussion

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1. Low frequency interference

In our commentary (Maess, Schröger, and Widmann, 2016 – short MSW) on Tanner, Morgan-Short, and Luck (2015 – short TMSL) we argued that the application of filters should always be justified by an improvement in signal-to-noise ratio (SNR) of the effect of interest, here the N400 or the P600. The data presented by TMSL reaches a maximum in the SNR for filters with a cutoff of 0.1 Hz (P600) or 0.01 Hz (N400; see Tables 1 and 2 and the Monte Carlo simulations). Apparently, the data were not contaminated by sufficient low frequency interferences to justify a high-pass filter with a cutoff frequency higher than 0.1 Hz. In their reply, Tanner, Norton, Morgan-Short, and Luck (2016 – short TNMSL) argue that their raw data contained strong low frequency noise and they display some raw data and an amplitude spectral density of 10 s time windows. However, the very low frequency interference level demonstrated in Fig. 1 in TNMSL does not provide any information about the relevant low frequency interference at the level of statistical testing. Low frequency interference is suppressed not only by high-pass filtering but also by epoching and baseline correction (implementing a high-pass filter!) and averaging across trials and subjects (suppressing any non-phase locked noise). Therefore, the impact of the different high-pass filters can be evaluated when comparing the means and the variance (here, standard error of the mean, SEM, as shown in TMSL Tables 1 and 2) of the grand-average. Importantly, a high-pass filter may not only attenuate the noise but also the signal, thus, possibly degrade the signal-to-noise ratio. TMSL Table 2, column 300–500 ms (N400) presents almost identical values for the mean condition difference and its SEM in case of unfiltered data (DC) and 0.01 Hz filtering. With 0.1 Hz high-pass and higher both, the mean condition difference and its SEM, are reduced resulting in degraded SNR (mean/SEM; here, t-value). TMSL Table 1, column 500–800 ms (P600) presents a similar picture for the SEM, but the mean condition difference has a maximum for the 0.1 Hz high-pass filter (this is surprising since both procedures – high-pass filtering and grand averaging – should always attenuate and never amplify the signal; however, by removing low-frequency drifts from the signal of both conditions the difference may increase). In summary, in the N400 analysis the 0.01 Hz filter marginally improves SNR; in the P600 analysis the 0.01 Hz and 0.1Hz filters improve the SNR (mainly due to an increase of signal amplitude) while the 0.3Hz filter reduces SNR due to attenuation of the signal. That is, the data in TMSL do not contain sufficient low frequency interference at the level of the statistical test (grand-average) to justify a high-pass filter with a cutoff frequency higher than 0.1Hz. If however, a dataset is contaminated by considerably stronger low frequency interference, then a high-pass filter with a cutoff frequency higher than 0.1 Hz will actually improve the SNR pending the signal is still sufficiently separated in its spectrum. In this case, high-pass filtering might well be justified although great care is needed to identify filter artifacts and signal distortions in order to avoid biased results and wrong conclusions.

2. Identifying filter distortions

In MSW we recommend to actively optimize filter settings in favor of applying a single conservative default setting. This, however, needs guidelines of how to identify filter artifacts and signal distortions (for a discussion see also Widmann, Schröger, and Maess, 2015). We suggested following the procedure as provided by TMSL (testing of different filter parameters). We appreciate the emphasis TNMSL put on simulations to monitor the impact of high-pass filtering on the data. TNMSL further discourage testing of different filter parameters as this "can lead to problems of researcher bias". We disagree. Testing of different filter settings is needed for an optimal separation of signal and noise (not known a priori; see TNMSL for discussion). Furthermore, it is also

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very helpful to identify possible artifactual early effects as discussed in TMSL. Finally, a discussion about scientific integrity can easily be avoided by openly publishing the complete procedure on how the filter parameters were selected.

3. Baseline correction

TMSL rejected our suggestion to replace baseline correction by high-pass filtering in situations where a clean baseline cannot easily be defined due to evoked activity from preceding stimuli (Widmann, Schröger, and Maess, 2015). We are grateful for the demonstration of possible caveats if not performing baseline correction in TNMSL. However, in TNMSL they do not demonstrate or explain how to deal with the situation of pre-stimulus evoked activity (similar across conditions!). The underlying problem affects multi-channel data, because the topography of baseline evoked activity is copied into the post-stimulus data which is described and discussed in detail by Urbach and Kutas (2006). This problem applies to a variety of important and established experimental paradigms including language, fast repetition rates, stimulus expectation, and others. Therefore, we recommend avoiding baseline correction in combination with high-pass filtering. The data may show differences in the baseline interval and researchers should consequently investigate why this is the case (filter distortions, design problems, etc.). If appropriate, baseline correction can be additionally applied at a later stage of analysis (before statistics).

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