Digital filter design for electrophysiological data – a practical approach

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Highlights

- Filtering may introduce significant distortions and bias results
- Filter responses, types, and parameters are introduced and explained
- Implementations in five common analysis packages are evaluated
- Strategies to recognize filter distortions are suggested
- Best practices for digital filter design and use are provided

Abstract

Background: Filtering is a ubiquitous step in the preprocessing of electroencephalographic (EEG) and magnetoencephalographic (MEG) data. Besides the intended effect of the attenuation of signal components considered as noise, filtering can also result in various unintended adverse filter effects (distortions such as smoothing) and filter artifacts.

Method: We give some practical guidelines for the evaluation of filter responses (impulse and frequency response) and the selection of filter types (high-pass/low-pass/band-pass/band-stop; finite/infinite impulse response, FIR/IIR) and filter parameters (cutoff frequencies, filter order and roll-off, ripple, delay and causality) to optimize signal-to-noise ratio and avoid or reduce signal distortions for selected electrophysiological applications.

Results: Various filter implementations in common electrophysiology software packages are introduced and discussed. Resulting filter responses are compared and evaluated.

Conclusion: We present strategies for recognizing common adverse filter effects and filter artifacts and demonstrate them in practical examples. Best practices and recommendations for the selection and reporting of filter parameters, limitations, and alternatives to filtering are discussed.

Keywords

Filtering
Filter distortions
Filter parameters
Preprocessing
Electrophysiology

1. Introduction

Filtering is an almost ubiquitous step in the preprocessing of EEG and MEG data. It lies in the nature of this process itself that filtering might seriously change the appearance of the signals and thereby affect the results obtained. Consequently, one may prefer not to filter at all (e.g., VanRullen, 2011) or to only filter very cautiously (e.g., Acunzo et al., 2012; Luck, 2005). There is an ongoing discussion in the literature (Acunzo et al., 2012; Rousselet, 2012; Widmann and Schröger, 2012; Zoefel and Heil, 2013) on how to avoid suboptimal practices resulting in systematically distorted or even spurious results.

In this paper, we would like to argue in favor of using filters while taking care of unwanted adverse side effects (distortions). Filtering is a very useful and necessary tool for improving the signal-to-noise ratio in electrophysiological data, making many applications and analyses possible in the first place. A poor sig-

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nal-to-noise ratio results in large confidence intervals associated with the estimated parameters, for example, peak amplitudes or onset latencies (see Widmann and Schröger, 2012 for simulations and discussion). Filters improve the signal-to-noise ratio, but also introduce signal distortions, which may lead, for instance, to a systematic underestimation of onset latency (VanRullen, 2011), artificial components (Acunzo et al., 2012), or spurious dependencies of stimulus detectability on pre-stimulus phase (Zoefel and Heil, 2013). Importantly, in many cases these signal distortions are not necessarily a consequence of filtering per se but rather a consequence of poor filter design. We have identified two reasons for the persistence of suboptimal practices: (a) lack of understanding of implications of filter parameters; (b) lack of investigation of the consequences of data filtering. In summary, researchers are often not aware of the signal changes introduced by the application of a filter. As a consequence, filtering is not devoted the effort it would deserve (considering the possible distortions) as it is "just a minor part" of data preprocessing. We strongly recommend selecting the filters and adjusting their parameters specifically to the needs of each application to achieve the required attenuation of noise without biasing the estimated parameters and to avoid the frequent practice of reusing a previously applied filter without careful consideration. Researchers in electrophysiology should investigate the filter's impact on the estimates they would like to report. We would encourage everybody to use filters, but to realize that they are like sharp knives – a very useful tool but to be handled with care.

Here, we aim to formalize the filter parameters relevant for electrophysiological data and to evaluate the filter responses. In order to keep this introduction widely accessible, we narrowed down and simplified the complex general concepts of frequency filtering to the relevant parts for common applications in filter design in electrophysiology, and we avoided formulas where possible. We assume a coarse understanding of the frequency domain representation of signals and the Fourier transform (see, e.g., Smith, 1999 for introduction and Ifeachor and Jervis, 2002 for further reading). In the second part, we demonstrate how to adjust filter parameters in selected implementations in electrophysiology software and highlight possible caveats. Finally, we examine common signal distortions (resulting in the above recommendations) and introduce heuristics how to recognize and deal with filter distortions. In general, we focus on the practical aspects of filter design and filter implementations. See, for example, Luck (2005) or Edgar and colleagues (2005) for a more general and theoretically focused introduction on the filtering of electrophysiological data.

2. Part 1: filter design

Temporal filtering or frequency filtering (in contrast to spatial and other types of filtering) refers to the attenuation of signal components of a particular frequency (band). The common rationale behind filtering in general is to attenuate noise in the recordings, while preserving the signal (of interest). In electrophysiology neither noise nor signal are clearly defined as, e.g., sine-shaped oscillations of isolated frequencies. Typically, there is even an overlap of signal components and noise components in the same frequency band. The temporal filters discussed here cannot separate signal from noise in the same band; they will simply attenuate everything in the targeted band. It is important to realize that changes in the frequency spectrum (the attenuation or delay of spectral components) must cause changes in the temporal signal, as both representations are coupled by the Fourier transform. Care must be therefore taken when selecting and designing the filter, that is, the filter parameters have to be adjusted in order to achieve an improved signal-to-noise ratio to estimate the parameters. However, it is impossible to design filters that do not alter the signal at all. Instead, by selecting the appropriate filter, the signal is altered according to the researcher's goals and thereby increased in its signal-to-noise ratio.

The systematic method to design and investigate filters considers each filter as an element in a two-port network, which is a black box having two inputs and two outputs (also named four-terminal network or quadripole). We do not go into the details here but simply state that this is a powerful concept for the analysis of complex situations in analog electronics or signal processing. One electrode is fed to one input and the reference to the other. The output represents the filtered signal of this electrode against the same reference. This box representation provides us with a standardized way of analyzing filter properties: feeding test signals to the input and evaluating the output. All temporal filters can be investigated this way. A further interesting point of the two-port network model is that more complicated filters such as band-pass filters can be easily constructed as a chain of a low-pass and a high-pass filters or vice versa.

2.1. Filter responses

By convention, filters are tested with a single very sharp pulse as a test signal. The filter response to this input is then the so-called *impulse response*. The *frequency response* is the Fourier transform of the *impulse response* and consists of two parts, namely the *magnitude* and the *phase response*. All these re-

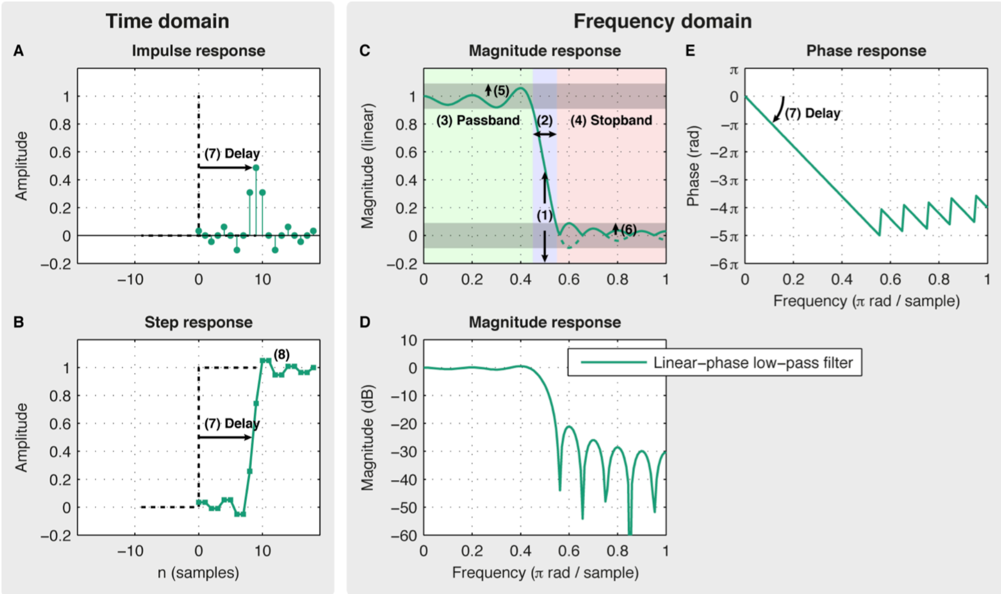

Fig. 1. Time domain (impulse and step; panels A and B) and frequency domain (magnitude and phase; panels C–E) responses of an example filter (order 18 linear-phase low-pass finite impulse response [FIR]). The impulse and step response reflect the filter output of a filtered impulse or step signal (black dashed lines in panels A and B). The cutoff frequency (1) in the center of the transition band (2) separates passband (3) and stopband (4). The deviation from designed passband (one) and stopband magnitude (zero) is described by passband ripple (5) and stopband attenuation (6). Note that the transition bandwidth is defined by passband and stopband ripple. The filter delays (7) the output relative to the input. Signal distortions like smoothing (usually desired) or artifacts like ringing (8; usually undesired) can be evaluated with both time domain responses, the impulse and step responses.

sponses are used to characterize properties of the filter. The impulse and the frequency response describe the transfer function of a filter in the time or frequency domain. That is, they describe the effect of a filter on the signal input resulting in a filtered output. Therefore, it is essential to understand the filter responses for good filter design.

In the time domain, the filter is described by the filter's *impulse response* (see Fig. 1A). Sample number (or time in seconds) is usually plotted along the abscissa relative to the input signal and amplitude is plotted along the ordinate in linear scale. The impulse response reflects the filter output when filtering an impulse (black dashed lines in Fig. 1A). Similar to the impulse response, the *step response* reflects the filter output when filtering a step signal (e.g., a series of zeros followed by a series of ones). Note that DC offset step-like signals occur in electrophysiology at signal discontinuities resulting in DC filter artifacts (often observable at the beginning or end of epochs or at pauses in the recording). As both impulse and step signals have energy across the whole spectrum, they are excellent tools to evaluate possible filter distortions when filtering broadband complex signals.

In the frequency domain, the filter's characteristic is described by the Fourier transform of the impulse response, which gives the magnitude (or amplitude) and the phase responses (see Fig. 1C–E). Frequency is usually plotted along the abscissa in Hertz (from 0 Hz/DC to half the sampling rate/Nyquist frequency) or normalized units (by convention in MATLAB, frequency is normalized to π radians / sample; i.e., one is half the sampling rate). In the *magnitude response*, amplitude is usually plotted along the ordinate in linear or logarithmic scale (dB). The magnitude response reflects the (complex) modulus of the frequency response and can only have zero or positive values (see Fig. 1C). The magnitude response is the frequency domain envelope, which is effectively multiplied with the spectrum of the signal during filtering. Frequency bands in the passband ideally have magnitude values of one, which lets these spectral components pass without changing their amplitudes. Frequency bands in the stopband ideally have zero magnitude values, thereby removing these spectral components in the output. Digital filters usually deviate from these ideal (zero/one) responses depending on other design criteria (e.g., steepness, finite impulse response), i.e., the stopband actually never removes the spectral components completely – it attenuates them by a certain (hopefully large) factor. In the *phase response*, phase is usually plotted along the ordinate in radians or degree. The slope of the unwrapped phase response reflects the delay of the filter output relative to the filter input. Negative phase values reflect delayed spectral components. A filter with a linear phase response in the passband has the same delay for all spectral components, which means that the time domain shape of a signal with spectral components within the filter's passband is not changed by filtering. A nonlinear phase introduces frequency-dependent delays, which will cause changes in the shape of a signal even for spectral components within the filter's passband.

Fig. 1 shows a set of response functions for a linear phase low-pass filter as an example. The time domain responses give a direct impression of how the filter alters the signal (widening or smoothing of sharp transients, ripples around larger signal changes) and they clearly show the delay introduced by the filter The frequency domain responses show details of the filter's attenuation resolved spectrally and aid the evaluation and appropriate adjusting of the filter parameters, such as filter type, cutoff frequencies, roll-off (steepness of the change of attenuation in the transition band), amplitude of ripples in pass- and stop-band, and even the delay as the slope of the phase response.

2.2. Filter type

Low-pass (attenuating high-frequency bands), high-pass (attenuating low-frequency bands), band-pass (attenuating high- and low-frequency bands), and band-stop filters (attenuating specific frequency bands) are implemented in the common electrophysiology software packages. Attenuating high-frequency components with a *low-pass filter* smoothens the filter output (see Fig. 2A and B). Attenuating DC ("direct current") offset and low-frequency components with a *high-pass filter* forces the filter signal to return to zero amplitude[1]. The choice of the cutoff frequency defines how fast the filtered signal converges to zero following signal deflections: the higher the cutoff frequency, the faster the filtered signal converges to zero due to the attenuation of low frequencies. Note that zero-phase filters (see Section 2.6) introduce a symmetric change in the signal around a step, i.e., before and after the step (see, e.g., the green line in Fig. 2G). These types of filter distortions can easily be observed in the step response. The evaluation of the step response intuitively helps one to understand that both low-pass and high-pass filters smear the signal in the time domain. *Band-pass* and *band-stop filters* combine a low-pass and a high-pass filter. In most electrophysiology software implementations, the roll-off characteristics (or transition bandwidth) of the high-pass and low-pass parts have to be identical (with the exception of, e.g., the MATLAB filter design tool). However, steep high-pass filters are frequently needed in applications such as event-related potentials/fields (ERP/Fs) to achieve the intended low cutoff frequencies (Acunzo et al., 2012; Luck, 2005), while on the other hand the low-pass transition could be designed significantly shallower. Shallower filters are widely recommended as they produce less signal distortions and spread them less in the time domain (due to their shorter impulse response; see Section 2.4 below). Thus, a separate successive application of a steep high-pass and a shallow low-pass filter is often preferred over a band-pass filter with steep high-pass *and* low-pass transition. The use of band-stop filters is not recommended in ERP research as they likely produce strong artifacts (see, e.g., Luck, 2005 for examples). In electrophysiology, band-stop filters are almost exclusively used to suppress line (50/60 Hz) or cathode ray tube (CRT) noise and should be replaced by time domain regression-based approaches (Mitra and Bokil, 2007) as, e.g., implemented in the Cleanline EEGLAB plugin (Mullen, 2012). These approaches are superior due to the very high phase stability of line noise.

2.3. Cutoff frequency

The cutoff frequency separates passband and stopband of the filter and always lies in the transition band (see Fig. 1C). This is the value that is most likely to be reported when a filter is applied during the signal processing, but it is not sufficient to characterize the filter. Different definitions of cutoff frequency are used: −3 dB (half-energy) cutoff (common for IIR filters; see Section 2.7 below) and −6 dB (half amplitude) cutoff (common for FIR and two-pass IIR filters). Therefore, cutoff frequencies should always be reported together with the definition used. Optimally, the cutoff frequency should separate signal from noise components in the frequency domain. To avoid unwanted signal distortions, it is essential to select the cutoff frequency so that no spectral component of the signal is attenuated but as much noise as possible is removed. This may render the use of particular filters impossible for certain sections of ERP/F research. Some authors argue against high-pass filtering (or restrict the applicable high-pass cutoff to frequencies as low as <0.1 Hz; in particular if estimating window mean or peak amplitudes; Acunzo et al., 2012; Luck, 2005) or low-pass filtering (in particular if estimating onset latencies; VanRullen, 2011). We certainly want to stress their point – care is needed – but, on the other hand, if the filter applied really increases the signal-to-noise ratio (as it should to motivate its usage) and does *not* systematically bias the to-be-estimated parameter, these values can be determined with greater precision with than without filtering.

[1] This property of high-pass filters allows one to replace baseline correction by high-pass filtering, thereby solving the problem of baseline definition. In many experimental paradigms, systematic pre-stimulus neuro-electric activity (e.g., due to preparation or ongoing speech) cannot be excluded and, thus, no "clean" baseline can be defined. Baseline correction implicitly subtracts the mean distribution in a specified time interval (the "baseline") from the ERP (Urbach and Kutas, 2006).

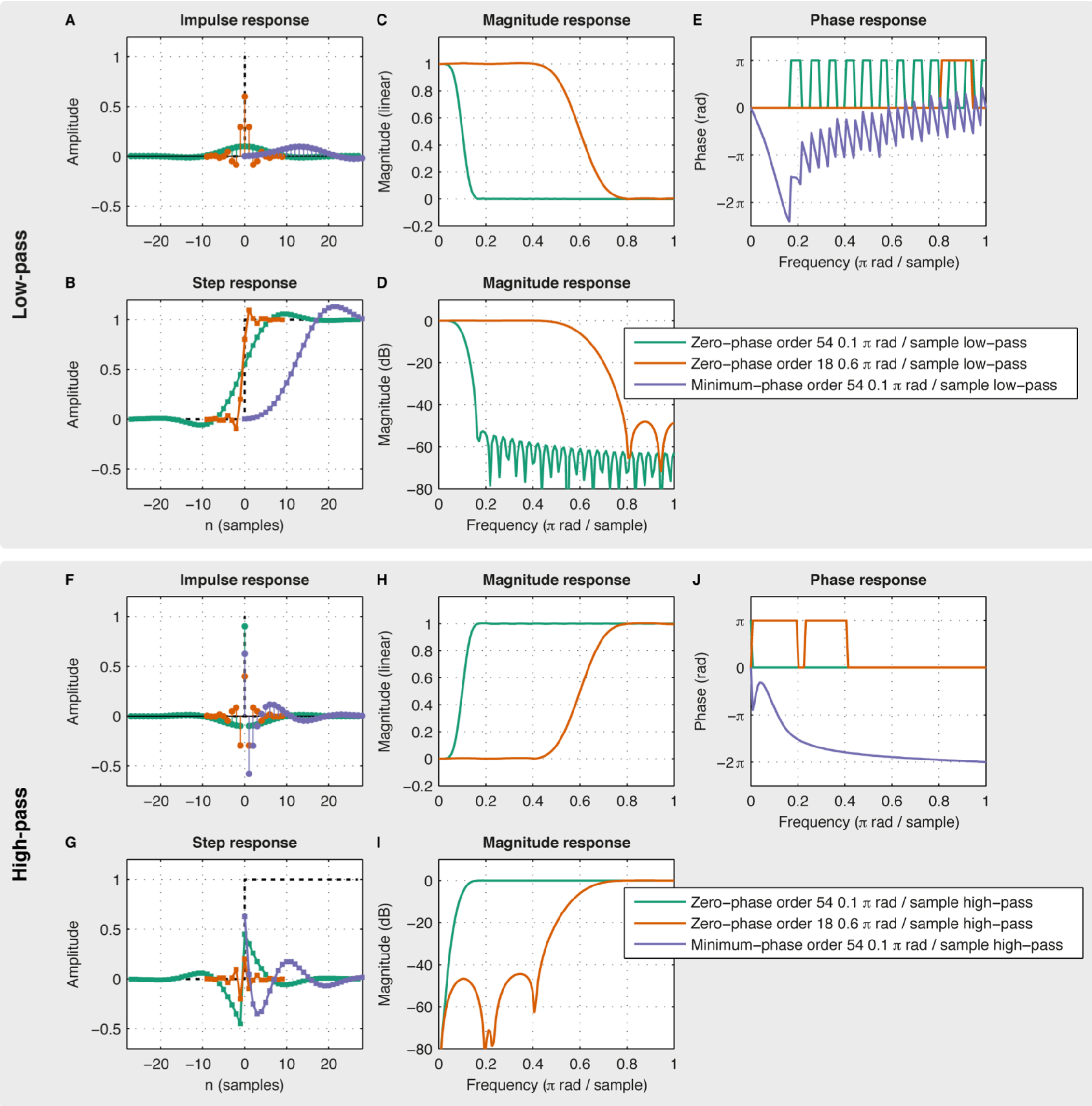

Fig. 2. Example low-pass (panels A–E) and high-pass (panels F–J) filter responses (Hamming windowed sinc FIR). The step responses best demonstrate the prototypical signal distortions, smoothing for the low-pass filter (stronger for lower cutoff frequencies) and the apparent roughing for the high-pass filter (also stronger for lower cutoff frequencies). Filters with longer impulse responses have a steeper roll-off (and a narrower transition band; 0.37 and 0.12 π radians / sample for the order 18 and order 54 filters, respectively), but smear filter distortions and ringing artifacts wider in the time domain. The filter length only has a minor influence on the amplitude of filter ringing artifacts. The π-phase jumps in the phase response of the zero-phase filter reflect stopband ripple ("negative amplitudes" or 180° phase changes) and only occur in the stopband. The low-pass minimum-phase filter introduces a large delay despite "minimum-phase" property. Both minimum-phase filters considerably distort the signal.

2.4. Roll-off, transition bandwidth, and filter order

The transition region between passband and stopband enclosing the cutoff frequency is defined as the transition band. For most FIR filters the −6 dB cutoff frequency is at the center of the transition band. The transition band edges are defined by the magnitude response exceeding the passband and stopband ripple, respectively (see Section 2.5 below and Fig. 1C). The slope of the magnitude response in the transition band is termed roll-off. Narrow transition bands lead to a steep filter roll-off, wide transition bands allow a shallow roll-off. Filters with a steep roll-off can better separate signal and noise components in adjacent frequency bands than filters with a shallow roll-off. The filter roll-off is a function of the filter order (number of filter coefficients/filter length minus one), more specifically the (effective) impulse response duration. "Sharp" filters with narrow transition bands or steep roll-off have longer impulse responses than filters with wide transition bands or shallow roll-off. Sharper and longer filters produce stronger signal distortions and they also produce a wider temporal smearing of distortions and ringing artifacts. Convolution implies that current filter output depends not only on current input but also on past input (causal filters; or past and future input for non-causal filters; see Section 2.6 below) weighted by the impulse response function. That is, the longer the impulse response, the wider the range of input data from which current output is computed. This is commonly interpreted in the sense that precision (spread) in the frequency domain (sharper filter) is inversely related to precision in the time domain (spread; longer impulse responses; Luck, 2005). The filtered signal shows stronger autocorrelation at higher lags up to the length of the impulse response. Thus, shorter filters with wider transition bands are preferable where possible. This is an important argument against the use of band-stop filters and for the careful use of high-pass filters often requiring a very steep roll-off. On the other hand, as the low-frequency noise is typically the strongest source of noise in electrophysiological data, applying high-pass filters very likely results in significant improvements in the signal-to-noise ratio. However, it also results in prominent signal distortions, which have to be accounted for during further analysis (see below).

Ringing filter artifacts, as shown in Fig. 1B (8), occur at sharp step-like signal transients. To avoid DC and ringing artifacts, one should never filter across signal discontinuities and DC offset corrections. Furthermore, the signal must be properly padded at the signal edges for filtering, e.g., by a time and amplitude inverted mirror image (as in MATLAB filtfilt; Gustafsson, 1996) or a DC constant. The required amount of data padding depends on the filter order, which implies that filtering should be preferably done on continuous rather than epoched data, in particular for high filter orders (relative to epoch length) as required for high-pass filters. If critical for a particular purpose, Gaussian or Bessel filters can be used to avoid or reduce ringing artifacts (Luck, 2005; Smith, 1999).

2.5. Passband ripple/stopband attenuation

The practically achieved magnitude response usually deviates from the requested magnitude response, which is one (no attenuation or amplification) in the passband and zero (complete attenuation) in the stopband. This deviation is commonly termed passband ripple in the passband and stopband attenuation in the stopband (see Fig. 1C and D). Passband ripple is reported as maximal passband deviation in linear or logarithmic units. With a passband deviation of, for example, 0.01, the filter output does not amplify or attenuate the signal by more than 1% in the passband (0.086 dB; in MATLAB passband ripple is defined as peak-to-peak ratio: $r_p = 20 \log_{10}((1 + 0.01) / (1 - 0.01)) = 0.174$ dB). Stopband attenuation is reported most commonly in logarithmic units. With a stopband attenuation of −60 dB (or 0.001), the signal is attenuated by a factor of 1000 in the stopband. Passband ripple and stopband attenuation can be well controlled in most filter implementations. However, less passband ripple and stronger stopband attenuation again require longer (effective) impulse responses, thus, values should not be chosen too small. For instance, passband ripple of 0.002–0.001 (0.2%–0.1%) and −54 to −60 dB stopband attenuation are reasonable values for many ERP/F applications. For high amplitude low-frequency noise (near DC), a stopband attenuation of −100 dB or stronger might be required. Due to the very small values, stopband ripple/attenuation is best evaluated in the logarithmically scaled magnitude response (Fig. 1D) while passband ripple is better evaluated in the linearly scaled magnitude response (Fig. 1C).

2.6. Delay

Every (non-trivial) filter necessarily delays the filter output relative to the filter input (see Fig. 1A, B, and E). The most relevant parameter for electrophysiological applications is the group delay, defined as the delay of the envelope of the signal at a particular frequency (computed as the derivative of the phase with respect to frequency). Two classes of filters have to be distinguished. So-called *linear-phase* filters introduce an equal (group) delay at all frequency bands – the slope of the phase response is constant within the passband. Consequently, a signal with all its spectral components in the passband will not change its temporal shape. Linear-phase filters have a perfectly symmetric impulse response (or antisymmetric only changing sign between left and right half). The group delay of linear-phase filters can be easily computed based on the length of the filter's impulse response as $(N - 1) / 2$ (in samples). So-called *non-linear-phase* filters with an asymmetric impulse response introduce different delays in different frequency bands (see Fig. 2 for examples). Thus, non-linear-phase filters distort the temporal shape of spectrally complex or broadband signals (such as ERP components) even if all spectral components are in the passband (and they disturb cross-frequency phase relationships if analyzing phase-phase or phase-amplitude coupling in time-frequency analysis).

The delay of linear-phase filters can be corrected by shifting the filter output back in time, resulting in a *zero-phase* filter having no delay (see Fig. 2). Due to the shift, each sample in the filtered output signal is computed from preceding (past) and following (future) samples of the unfiltered input signal; the filter is therefore classified as non-causal. In practice this means that the signal in the smoothed zero-phase filter output might already deviate from baseline before signal onset in the input, possibly systematically underestimating onset latencies after low-pass filtering (cf. the step responses in Fig. 2B; see Rousselet, 2012; VanRullen, 2011; Widmann and Schröger, 2012 for discussion), introducing non-causally smeared artificial or artificially enhanced components after high-pass filtering (Fig 7D; see Acunzo et al., 2012 for discussion), or smearing post-stimulus oscillations into the pre-stimulus interval leading to spurious interpretations of pre-stimulus phase (Zoefel and Heil, 2013). A causal filter, in contrast, computes the output only on the basis of preceding (past) input samples. The step response of a causal filter does not exhibit signal changes due to the step (for example smoothing or ringing) before the onset of the step in the filter input (blue line in Fig. 2B and 2G). Importantly, zero-phase (non-causal) filters preserve peak latencies, while causal filters necessarily shift the signal in time. If a causal filter is needed, a non-linear *minimum-phase* filter should be considered as it introduces only the minimum possible delay at each frequency for a given magnitude response but distorting broadband or complex signals due to non-linearity (see Fig. 2). Causal high-pass minimum-phase (and other non-linear) filters introduce rather small delays (Fig. 2F and G) while causal low-pass (and band-pass and band-stop) filters introduce larger delays even with minimum-phase property (Fig. 2A and B), which is why they are not recommended in electrophysiology (Rousselet, 2012).

Zero-phase delay can also be achieved with non-linear filters by filtering the filter output a second time in the reverse direction ("two-pass filtering") to compensate for the filter delay (Smith, 1999, p. 331; filtfilt function in MATLAB/Octave). Two-pass forward and reverse filtering results in a non-causal filter with a symmetric impulse response. Two-pass filtering (equivalent to concatenating the same filter twice in the two-port model) doubles the filter order and doubles the length of the (effective) impulse response. Thus, the two-pass filter smears the output wider in the time domain. Two-pass filtering squares the magnitude response, which shifts the −3 dB half-energy and the −6 dB half-amplitude cutoff frequencies, and needs to be reported properly (attenuation at the one-pass −3 dB cutoff is enhanced to −6 dB for IIR and at the one-pass −6 dB cutoff to −12 dB for FIR filters; see Section 2.7 below; Edgar et al., 2005). Two-pass filtering enhances (squares) passband ripple and stopband attenuation. Different software implementations use different strategies to compensate for the doubled filter order and shifted cutoff frequencies. For replicability it is thus important to report cutoff frequencies together with not only their definition but also whether they apply to one-pass or two-pass filtering including possible adjustments of order and cutoff frequency. Importantly, the shapes of the (squared) magnitude response of a two-pass filter and the equivalent one-pass filter of double the filter order (having the same effective impulse response length) can be significantly different in particular in frequency bands near the cutoff frequency. One-pass linear-phase filters (corrected by shifting) can achieve a similar magnitude response shape (in particular steepness at the cutoff frequency but not stopband attenuation) at lower orders than a corresponding two-pass filter. This makes linear-phase one-pass filtering preferable in many applications (see Fig. 4B).

2.7. IIR vs. FIR

Digital filters can be implemented as Infinite Impulse Response (IIR) or Finite Impulse Response filters (FIR). *IIR* filters have asymmetric impulse responses and non-linear phase. The cutoff frequency usually has to be specified and reported as −3 dB cutoff. The impulse response of IIR filters is implemented implicitly in a functional form defined by the filter coefficients and state variables. IIR filters can be instable, that is, accumulated rounding errors in the state variables result in deviating filter responses. IIR filtering should be performed with double precision, and stability of IIR filters should always be checked, in particular when the filter has an extreme cutoff frequency as used, for example, in high-pass filtering of ERP/F data analysis (see Section 2.3). In electrophysiology commonly Butterworth and elliptic IIR filters are applied. Butterworth filters have no passband and stopband ripple and have the shallowest roll-off near the cutoff frequency (the most relevant roll-off region) compared to the other commonly used Chebyshev and elliptic IIR filters (in general IIR filters have a roll-off of −6 dB/octave or −20 dB/decade per order). Elliptic filters have passband and stopband ripple and the steepest roll-off near the cutoff frequency.

FIR filters can have either (anti-)symmetric (linear-phase) or asymmetric impulse responses (non-linear phase). The cutoff frequency is usually specified as −6 dB cutoff. Filtering is implemented as convolution (step-wise multiply-add) of the filter input with the impulse response; impulse response and filter coefficients are identical; hence, the filter length of a FIR filter is the length of the impulse response. In electrophysiology almost exclusively odd length, symmetric (type I) FIR filters are applied (only odd-length FIR filters can be corrected to zero-phase delay by left-shifting as the group delay is an integer number of samples). *Windowed sinc* FIR filters are based on the sinc-function approximating a rectangular magnitude response, thus, sometimes termed "ideal" filters. For finite filter orders, the impulse response has to be windowed by a window function to reduce passband and stopband ripple (equal for windowed sinc filters). The transition bandwidth is a function of filter order (filter length minus one) and window type. The necessary filter order can be estimated based on the normalized transition width per window type (see

Table 1
Properties of selected window types for windowed sinc FIR filters (adapted from Ifeachor and Jervis, 2002, p. 357). Required filter order m for requested transition bandwidth Δf can be computed as m = ΔF / (Δf / f_s). Transition bandwidth Δf provided by a filter order m is computed as $\Delta f = (\Delta F / m) f_s$ (Smith, 1999).

Window type	Beta	Stopband attenuation (dB)	Max. passband deviation	Normalized transition width ΔF
Rectangular		−21	0.0891 (8.91%)	0.9 / m
Hann		−44	0.0063 (0.63%)	3.1 / m
Hamming		−53	0.0022 (0.22%)	3.3 / m
Blackman		−75	0.0002 (0.02%)	5.5 / m
Kaiser	5.65	−60	0.001 (0.1%)	3.6 / m
Kaiser	7.85	−80	0.0001 (0.01%)	5.0 / m

Tab. 1). *Equiripple* FIR filters derived from the Parks-McClellan (or McClellan-Parks; McClellan et al., 1973) algorithm have equal ripples within the respective bands. However, passband and stopband ripples can be adjusted separately. The requested transition bandwidth as well as passband and stopband ripple determine the filter order. Equiripple filters are also termed “optimal” filters as they have the smallest order for given parameters.

Filter orders of IIR and FIR filters cannot be compared due to the recursive implementation of IIR filters. Instead, the resulting impulse response lengths have to be compared. Despite IIR filters often being considered as computationally more efficient, they are recommended only when high throughput and sharp cutoffs are required (Ifeachor and Jervis, 2002, p. 321). In electrophysiology, throughput is only relevant during recording. For offline data analysis, however, throughput and computational time do not matter on modern computer hardware. So, crucially, for sharp cutoffs and when a causal filter is needed an IIR filter should be considered. A causal filter can be preferable in some specific cases. A causal filter only smears effects from earlier towards later latencies. On the other hand, the effective impulse response is also finite for IIR filters due to numerical precision, thus, all relevant properties can also be implemented with FIR filters. Taken together, FIR filters are easier to control, are always stable, have a well-defined passband, can be corrected to zero-phase without additional computations, and can be converted to minimum-phase. We therefore recommend FIR filters for most purposes in electrophysiological data analysis.

3. Part 2: filter implementations in selected electrophysiology software

3.1. EEGLAB 13 (MATLAB toolbox)

The EEGLAB 13 (SVN rev. 10348; Delorme and Makeig, 2004; Delorme et al., 2011) default filter is the *“Basic FIR filter (new)”* implementing zero-phase Hamming-windowed sinc FIR filter on the basis of the firfilt EEGLAB plugin (version 1.6.1 as of writing this manuscript; Widmann, 2006). Importantly, in the Basic FIR filter the passband edges are to be specified rather than the cutoff frequencies. If filter order is not specified, a default for filter order is implemented, providing a transition bandwidth of 25% of the lower passband edge but, where possible, not lower than 2 Hz and otherwise the distance from the passband edge to the critical frequency (DC, Nyquist). The −6 dB cutoff frequency, filter order, and transition bandwidth are reported. We recommend directly using the *“Windowed sinc FIR filter”* implementing additional window types, in particular the efficient Kaiser window family allowing the free adjustment of passband ripple/stopband attenuation. Cutoff frequencies (defined as half amplitude, i.e., −6 dB) and filter order have to be specified. A tool to estimate the required filter order for a specified transition bandwidth and window type is provided. Basic and windowed sinc filter are implemented as one-pass non-causal zero-phase filters optionally convertible to causal non-linear minimum-phase filters (non-zero delay). A zero-phase *“Parks-McClellan (equiripple)”* filter is also provided by the firfilt-plugin distributed with EEGLAB. For this filter, −6 dB cutoff frequencies and transition bandwidth have to be specified. Frequency band weights and filter order can be specified or estimated from the transition bandwidth and passband and stopband ripple (MATLAB Signal Processing Toolbox required). Windowed sinc and Parks-McClellan equiripple filters include a tool to visualize the filter responses. The *“Basic FIR filter (legacy)”* included for backward compatibility is deprecated and should no longer be used (cf., Widmann and Schröger, 2012).

An iirfilt plugin implementing an *elliptic IIR filter* is available for download (version1.0.1; Pozdin et al., 2004). Zero-phase (forward and reverse filtered) and causal non-linear-phase (forward filtered) filters can be applied. As in the default Basic FIR filter, passband edges instead of cutoff frequencies have to be specified. The default transition bandwidth is 1 Hz. User defined values for the transition bandwidth can

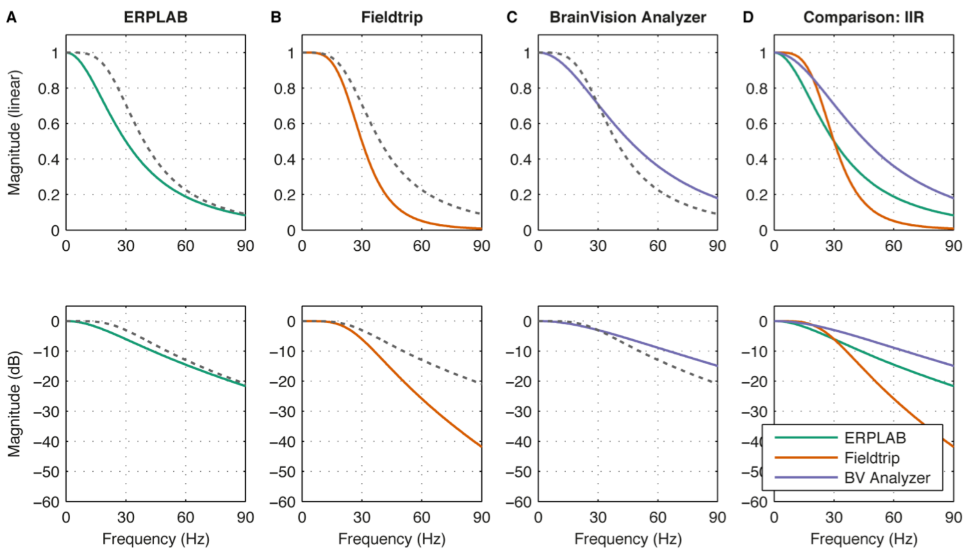

Fig. 3. Magnitude responses of a 30 Hz (sampling frequency f_s = 500 Hz) low-pass 2nd order IIR Butterworth filter as implemented by ERPLAB, Fieldtrip, and BrainVision Analyzer. ERPLAB compensates for two-pass forward and reverse filtering by adjusting filter order, BrainVision Analyzer compensates by adjusting filter order and cutoff frequency of the applied filter, Fieldtrip does not compensate for two-pass filtering (which means cutoff frequencies and order refer to the one-pass filter although typically a two-pass filter is applied instead). For comparison, the magnitude response of a 2nd order IIR Butterworth filter is shown as it would be found in text books (gray dashed lines). Note that the 0–30 Hz frequency band would be considered as passband for a Butterworth filter (Ifeachor and Jervis, 2002, p. 482). The three different implementations result in significantly different magnitude responses (and filter output) despite identical filter parameters (see panel D for direct comparison).

be specified in the user interface. Passband ripple defaults to 0.0025 dB and stopband attenuation to −40 dB (effectively 0.005 dB and −80 dB after two-pass filtering, respectively). Ripple can only be adjusted to user defined values on the command line. Band-pass (and band-stop) filters are implemented as separate high-pass and low-pass filters.

3.2. ERPLAB (EEGLAB plugin)

ERPLAB is an EEGLAB plugin providing its own filter routines (version 4.0.2.3; Lopez-Calderon and Luck, 2014). IIR Butterworth, Hamming-windowed sinc FIR, and Parks-McClellan FIR (notch only) filters are all implemented as two-pass forward and reverse filtered non-causal zero-phase filters. The −6 dB cutoff frequency and the filter order have to be specified for IIR and FIR filters. The minimum required filter order can be estimated. The graphical user interface visualizes magnitude and impulse responses and reports the −3 dB and −6 dB cutoff frequencies resulting after two-pass filtering. To compensate for two-pass filtering, the filter order of the applied filter is adjusted to half the reported order for IIR and FIR filters internally (see Fig. 3A and D). For FIR filters, additionally the cutoff frequency is implicitly adjusted to achieve −6 dB attenuation at the specified cutoff frequency after two-pass filtering (see Fig. 4A). The filter order of the FIR filters is limited to a maximum of 4096 samples (independent of sampling rate) making it impossible to design high-pass (and band-pass) filters with very low cutoff frequencies as often recommended for ERP/F analysis (note that for the corresponding IIR filters, longer effective impulse responses are applied; e.g., 7880 points for a 0.1 Hz high-pass 1st order Butterworth filter at sampling frequency f_s = 500 Hz as estimated by MATLAB impz function, which is doubled in the case of two-pass filtering). Transition bandwidth cannot be specified and is not reported for the FIR filters.

3.3. Fieldtrip (MATLAB toolbox)

The Fieldtrip MATLAB toolbox (SVN rev. 9473; Oostenveld et al., 2011) provides IIR Butterworth, Hamming-windowed sinc FIR and “firls” (MATLAB firls function least-square fitted) FIR filters. The default filter is a Butterworth filter of 6th order (high-pass, low-pass), or 4th order (band-pass, band-stop). The FIR filter’s default filter order is computed as 3 × fix(f_s / f_c) with f_c being the lower cutoff frequency. All filters default to non-causal zero-phase forward and reverse filtering doubling the filter order, squaring the magnitude response, and shifting the cutoff frequencies (see Fig. 3B and D, and 4A). One-pass forward or one-pass reverse filters are available but not corrected for the filter delay. The firls filter is fitted to a rectangular frequency domain function. As the default filter order is too low to approximate a rectangular frequency response, fitting may result in various adverse effects like excessive filter ringing, excessive passband ripple, non-unity DC gain, and others, as demonstrated in the example in Fig. 4A (see also Widmann and Schröger, 2012). We strongly recommend not using the firls option. Filter order and

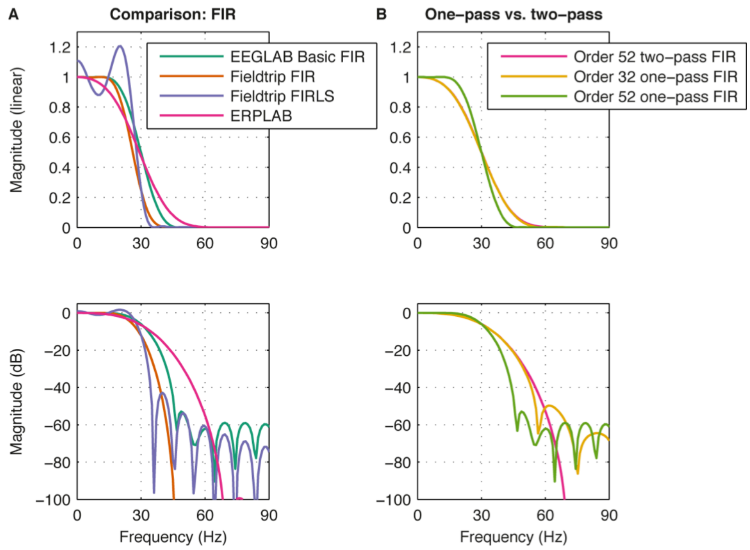

Fig. 4. Magnitude responses of a 30 Hz (f_s=500 Hz) low-pass FIR filter with filter order 52 as implemented by the EEGLAB "Basic FIR filter (new)", the Fieldtrip "fir" filter, the Fieldtrip "firls" filter, and the ERPLAB FIR filter (panel A). Fieldtrip performs two-pass filtering resulting in shifted cutoff frequencies. The "firls" filter shows excessive passband ripple (23%), and non-unity gain at DC. The ERPLAB filter adjusts filter order and cutoff frequency to compensate for two-pass filtering. The resulting −6 dB cutoff frequency of the ERPLAB filter is 29.25 Hz. The three different implementations result in significantly different magnitude responses (and filter output) mainly due to adjustments (not) to compensate for two-pass filtering. Effects of two-pass filtering are shown in panel B. The same roll-off slope (but not the same stopband attenuation) as achieved by the order 52 two-pass FIR filter (an order 26 filter applied forward and reverse as the ERPLAB filter in panel A) can be achieved already by the order 32 one-pass FIR filter (30 Hz Hamming-windowed sinc FIR, f_s=500 Hz). A one-pass filter of equal order (here 52) can achieve a significantly steeper roll-off.

−3 dB (IIR) or −6 dB (FIR) cutoff frequencies after two-pass filtering are not reported; filter responses are not visualized. Transition bandwidth cannot be specified and is not reported for the FIR filters, that is, filter order must be estimated manually (see Tab. 1). At the time of submission of a revised version of this manuscript, the first author ported and integrated the EEGLAB firfilt plugin windowed sinc FIR filters to Fieldtrip. An upcoming version of Fieldtrip will allow control of passband ripple and stopband attenuation, estimation of filter order by transition bandwidth, one-pass zero-phase filtering, and the plotting of the filter responses with the "firws" option.

3.4. BrainVision Analyzer

The BrainVision Analyzer (version 2.0.4.368; filter component version 2.0.4.1057; Brain Products GmbH, Gilching, Germany) provides zero-phase IIR Butterworth filters of order 2, 4, or 8 (−12, −24, or −48 dB/oct roll-off). The −3 dB cutoff frequencies have to be specified. The magnitude response is visualized. Zero-phase is presumably (judging from the filter output) achieved by applying a filter with half the filter order twice, i.e., in forward and reverse direction. The applied cutoff frequency is presumably adjusted to compensate for two-pass filtering and to maintain −3 dB attenuation at the specified cutoff frequency (see Fig. 3C and D). The use of two-pass filtering and the implicit adjustment of cutoff frequency and filter order are undocumented, making it difficult to replicate the filter with other software.

3.5. EEProbe

EEProbe (version 3.3.148; ANT Neuro, Enschede, Netherlands) provides non-causal zero-phase windowed sinc (Hamming, Hann, Blackman, Bartlett, Tukey, and Rectangular windows) and Parks-McClellan ("Remez-Exchange") FIR filters. Both are designed with the xfir-software. Zero-phase is achieved by correcting the delay of the filter output. The −6 dB cutoff frequencies have to be specified. The −3 dB cutoff frequencies are additionally reported. The linearly and the logarithmically scaled magnitude responses and the step response can be displayed. For the windowed sinc FIR filters, the transition bandwidth cannot be specified and is not reported, that is, the required filter order must be estimated manually (see Tab. 1; note that the EEGLAB firfilt plugin can export EEProbe-compatible FIR filter settings). For the Parks-McClellan filters, transition bandwidth, passband ripple, and stopband attenuation can be specified and the necessary filter order can be automatically computed.

3.6. Interim conclusion

The various filter implementations result in considerably different frequency characteristics of the applied filters despite identical or similar filter parameters, i.e., cutoff and order. In particular, two-pass filtering appears to introduce more problems than it solves. For instance, a 30 Hz low-pass realized as 2nd order IIR Butterworth filter will have considerably different magnitude responses if designed and applied by either ERPLAB, Fieldtrip, or BrainVision Analyzer (see Fig. 3A–D; −3 dB cutoff at 19, 23, and 30 Hz; −6 dB cutoff at 30, 30, and 46 Hz, respectively; note that the −3 dB cutoff frequency is frequently defined as passband edge for Butterworth filters if passband deviation is not explicitly defined; this is the case in all implementations tested here; Ifeachor and Jervis, 2002). These different magnitude responses are due to the necessary adjustments in cutoff frequency and filter order to compensate for two-pass filtering, which differ between the different implementations. Two-pass filtering is not necessary and even detrimental to linear-phase FIR filters in many use cases (see Fig. 4A and B). The use of two-pass filtering, the applied adjustments in cutoff frequency, and the resulting filter parameters (−3 dB or −6 dB cutoff, order) after two-pass filtering are not consistently documented and reported. This makes correct reporting of filter parameters and frequency characteristics difficult and seriously undermines the replicability of electrophysiological data analysis. Significantly different results will be obtained by different software packages. We strongly encourage users to examine the effective filter responses and parameters themselves by filtering impulses with their software package and analyzing the filter output. Note that we used this approach to generate Fig. 3 and 4; the MATLAB code is provided in the supplementary materials. Most FIR filter implementations lack support for users to adjust the filter order to reasonable values as tools to report and/or estimate the resulting transition bandwidth are missing. Gaussian FIR filters as recommended by Luck (2005) to avoid filter-ringing artifacts are not implemented in any of the tested software packages.

4. Part 3: recognizing and avoiding filter distortions

The most common signals in electrophysiology are spectrally complex or broadband signals. Band-limiting these signals or attenuating or delaying signal components necessarily results in signal distortions and possibly biased results. As a clarification, filtering always changes the signal – otherwise, what would be the purpose of the filter? Yet often these desired changes in the signal are accompanied by undesired distortions of the signal or filter artifacts. Both types of change in the signal may bias results depending on estimates taken from the filtered signal. The signal-to-noise ratio in unfiltered electrophysiological recordings might, however, be too low for a specific data analysis. Filtering can be a recommendable option in this case – however, the authors should verify that filtering actually improved the signal-to-noise ratio in the data analysis. Furthermore, the variety of signals and applications in electrophysiology is very diverse, hence giving strict and general recommendations for filtering is close to impossible. It is thus important to understand the underlying signal and the effects of filtering to recognize and avoid filter distortions.

We recommend three main measures to recognize and avoid filter distortions: (1) considering the frequency domain structure of signal (and noise) components; (2) using test signals to analyze the effects of different filters and filter parameters; and (3), most importantly, systematically inspecting the difference between filtered and unfiltered signals, that is, the signal components *removed* by filtering, for obvious features.

Gaussian waveforms could be used as simplified test signals for filtering in ERP/F analysis suitable due to their broadband spectrum resembling many ERP/F components in the time and frequency domain. In Fig. 5, a Gaussian test signal is displayed in the time and frequency domain unfiltered as well as filtered by a 20 Hz low-pass (Fig. 5A–C) and a 5 Hz high-pass filter (Fig. 5D–E). The low-pass and high-pass filter will selectively attenuate frequency components of the broadband signal. Attenuating the high-frequency components with the low-pass filter results in earlier signal onset and later offset, reduced peak amplitude, and artificial oscillations with a frequency near the cutoff frequency (see e.g., Luck, 2005 for a more detailed discussion of these oscillations). Similarly, attenuating the low-frequency components with the high-pass filter results in reduced peak amplitude and a low-frequency artificial oscillation forcing the signal to zero amplitude. The differences between unfiltered and filtered data display the signal components that were attenuated by filtering (Fig. 5B and E). The characteristic shape of the differences can be used to recognize signal distortions in more complex signals (see Fig. 6 and 7). Whether or not these distortions are considered relevant depends on the estimated parameters and how they are estimated. Both low-pass and high-pass filtered data show that estimation of peak latencies should not be biased using these filters. Peak amplitudes are biased, if estimated relative to a baseline, but likely unbiased (always check), if estimated as the difference between adjacent neighboring peaks and troughs, thereby accounting for the observable distortion. Onset latencies of low-pass filtered signals are systematically biased

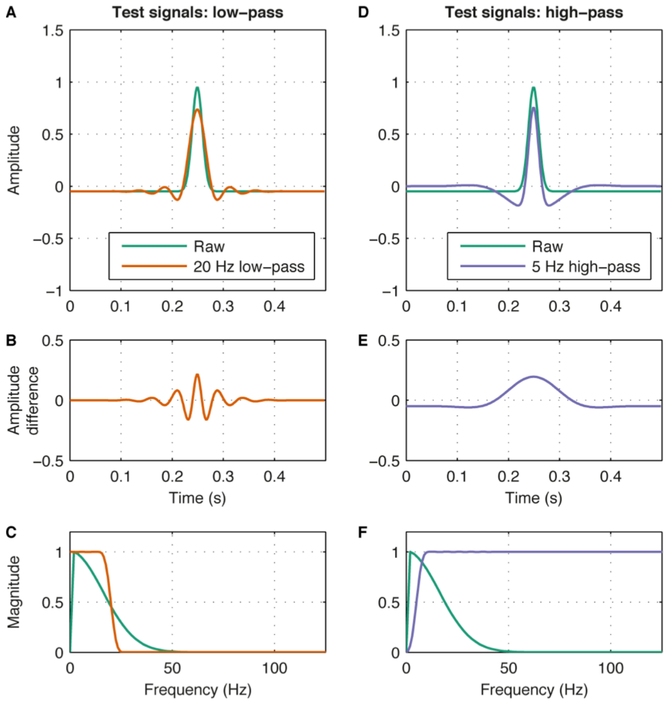

Fig. 5. Typical filter distortions resulting from low-pass (panels A–C; 20 Hz order 166 Hamming windowed sinc FIR) or high-pass filtering (panels D–F; 5 Hz order 166 Hamming windowed sinc FIR) of a Gaussian-shaped test signal (σ = 10 ms; zero mean). The differences between raw and filtered signal (panels B and E) display the signal components attenuated by filtering; they indicate and characterize the typical low-pass and high-pass filter distortions. The spectrum (panels C and F) of the test signal (scaled to arbitrary units) compared to the filters' magnitude responses indicate that the signal is band-limited by filtering.

toward earlier onsets. Proper account for the onset latency bias is difficult as it is a matter of definition when a component starts to significantly differ from baseline. One may consider fitting ERP model signals to the real data and estimating the parameters from the model instead of from the real data.

The characteristic low-pass and high-pass filter distortions derived from the analysis of the test signal aids the recognition of these distortions in real data. In Fig. 6 and 7, we demonstrate this by the example of auditory ERPs with different low-pass and high-pass filters (note that the filter parameters were optimized to demonstrate typical distortions and we would *not* use or recommend these filters for real-world data analysis). The example data originate from an unpublished dataset of an auditory oddball paradigm including frequent standard (352 Hz, 1440 trials) and rare deviant sounds (422 Hz, 180 trials, 300 ms duration, 5 ms rise-and-fall times, 300 ms inter-stimulus interval, 65 dB SPL intensity, task: count deviants; 6 subjects, 500 Hz sampling rate, vertex electrode, nose reference). The unfiltered data show regular P1 and N1 vertex potentials for standards and deviants, and additionally mismatch negativity (MMN; including an enhanced N1 response), N2 and P3 potentials in response to deviants. Filtering the standards with a 15 Hz low-pass filter appears to remove only noise from the data at a first glance. Roughly, it seems as if the filtered signal preserves almost all temporal parameters including onset and peak latencies as well as peak amplitudes. Exploring the difference between raw and filtered data, however, reveals that filtering significantly attenuated the high-frequency P1 peak (see Fig. 6B). Excessive filtering of the data with a 7.5 Hz low-pass filter clearly shows the characteristic distortions demonstrated with the test signal (cf. Fig. 5A), a smoothed signal with earlier signal onsets (cf., VanRullen, 2011), and reduced peak amplitudes. The oscillations in the difference between raw and filtered waveforms, in particular for the deviants, reveal that relevant signal components were attenuated and filtering resulted in significant distortions.

Filtering the data with a 0.75 Hz high-pass filter (Fig. 7) has only minor effects on the standard waveform because this carries only moderate energy at low frequencies. The deviant waveforms, however, show significant distortion with a reduced P3 peak amplitude non-causally carrying over the distortion into preceding components, resulting in artificially enhanced N1/MMN and N2 peak amplitudes (relative to prestimulus baseline but not relative to neighboring peaks and troughs; see, Acunzo et al., 2012 for detailed discussion). The difference between raw and filtered waveforms intuitively demonstrates this non-causal effect (Fig. 7E). Excessive filtering of the data with a 1.5 Hz high-pass filter drastically enhances the distortions. Note that not only peak amplitudes are artificially enhanced but also the topography of the components is distorted, as exemplarily demonstrated on the scalp potential and current density topographies

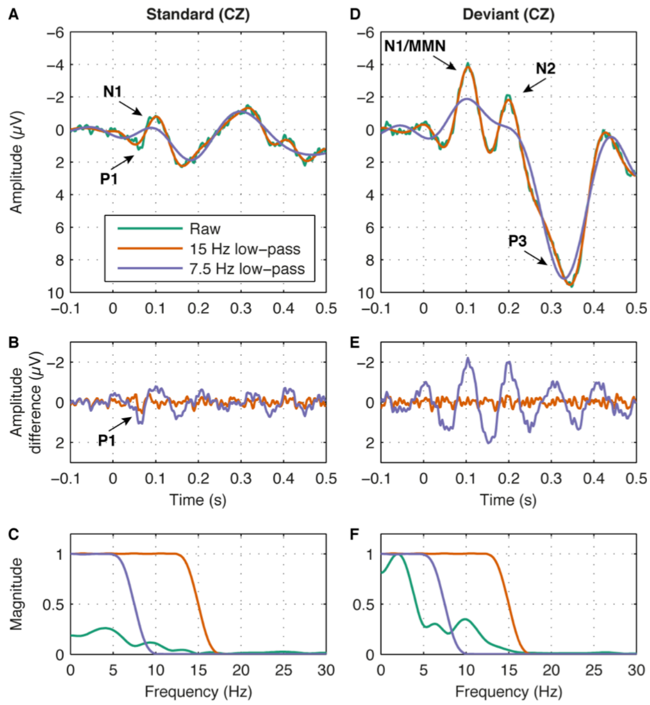

Fig. 6. Low-pass filter distortions in ERP data. Panels A and D: ERPs elicited by standard (panel A) and deviant (panel D) tones with different low-pass filter settings (see text for details; noise in the raw data is attenuated by averaging across trials and participants). Panels B and E: difference between raw and filtered ERPs. Panels C and F: spectrum of the raw ERP (scaled to arbitrary units) compared to the filters' magnitude responses. Note that the 15 Hz low-pass filter (−6 dB cutoff, zero-phase order 330 Hamming-windowed sinc FIR) attenuates the standard's P1 component. The 7.5 Hz low-pass filter (same parameters) smoothens the deviant's N1/MMN and N2 components, resulting in reduced peak amplitudes and earlier component onsets.

of the N2 component (Fig. 7G). The amplitude of the fronto-central current sink-source configuration is attenuated by factor two. The raw minus filtered difference in the N2 time window (Fig. 7E and G, middle column) shows that the N2 component is superimposed by a distinct parietal P3-like topography due to the non-causal filter. Rousselet (2012) suggested causal filtering to avoid the non-causal effects (the non-causal artificial enhancement of the N1 and N2 components is due to attenuating the low-frequency components of the *succeeding* P3 component) of filtering. Rousselet demonstrated that causal filtering is not feasible for low-pass filters due to the introduced (non-linear phase) delay, but might be an option for high-pass filtering. Indeed, causally filtering the example data with a 0.75 Hz minimum-phase converted filter reveals no indication of artificially enhanced N1/MMN and N2 components (rather, peak amplitudes are slightly reduced due to the attenuation of low-frequency components). The raw minus filtered difference shows no P3-like (but rather a P2-like) topography demonstrating that the effects of filtering on the N2 are indeed introduced non-causally and are not due to possibly overlapping P3 activity. Due to the non-linear phase characteristic, the minimum phase filter, however, dramatically distorts the temporal dynamics of the P3 component. Thus, a causal non-linear filter can be employed to separate long- and short-latency components, avoiding non-causal effects, but should be used carefully because it introduces a delay and signal shape distortions.

5. Recommendations and best practices

The low signal-to-noise ratio of EEG and MEG recordings makes filtering an indispensable tool for the analysis of electrophysiological data. However, filtering is also prone to introducing severe distortions into the data, biasing or even invalidating the results (see, e.g., VanRullen, 2011; Acunzo et al., 2012; Zoefel and Heil, 2013 for prominent examples and Luck, 2005 for discussion). Thus, filtering should not be regarded as a default step in data preprocessing automatically and necessarily improving signal quality. Instead we recommend putting significant effort into carefully and appropriately designing digital filters that really improve the signal quality for the specific purpose, and verifying whether this goal has been achieved. Filtering representative test signals and the exploration of the difference between raw and filtered signals are valuable tools to recognize and control the impact of filter distortions on the observed results. Furthermore, complete reporting of the applied filters and their parameters is mandatory to allow for the replication of data analysis.

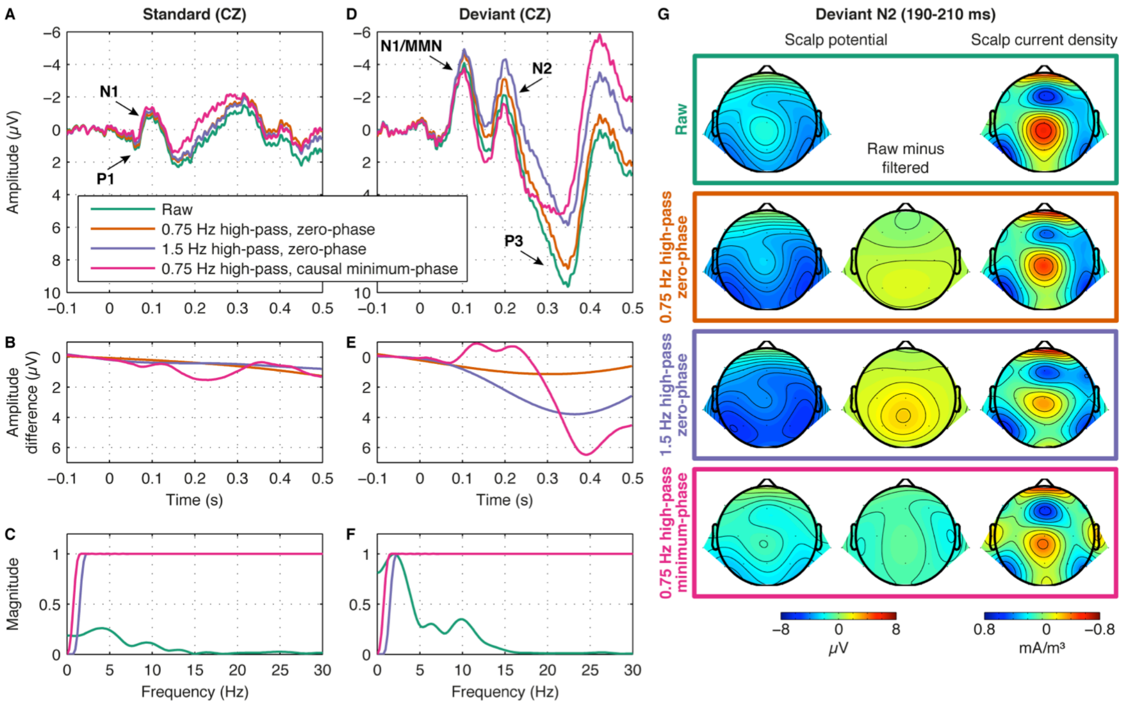

Fig. 7. High-pass filter distortions in ERP data. Panels as in Fig. 6. Note that the 0.75 Hz high-pass filter (−6 dB cutoff, zero-phase order 1100 Hamming-windowed sinc FIR) has only minor effects on the standard ERPs. In the deviant ERPs, it reduces P3 response amplitude and artificially enhances preceding N1/MMN and N2 response amplitude measured relative to the pre-stimulus baseline (but only marginally measured relative to the neighboring peaks and troughs). The 1.5 Hz high-pass filter (same parameters) drastically enhances the distortions. Panel G displays N2 (190–210 ms) scalp potentials, the raw minus filtered scalp potential difference and current density topographies. Note that the high-pass filters may distort not only the temporal dynamics but also component topographies (relative to the pre-stimulus baseline). The causal minimum-phase filter preserves the topography and temporal dynamics of N1/MMN and N2 components but distorts P3 component morphology due to non-linear effects.

Selectively attenuating spectral components of complex or broadband signals necessarily results in distortions of the temporal dynamics of the signal, systematically biasing signal (onset) latencies and signal (peak) amplitudes. Crucially, there exists no generally valid definition as to which spectral components of the unfiltered data constitute wanted signal and which ones constitute unwanted noise. Rather, the definition of signal and noise depends on the estimated parameters and the analysis strategy. It may well be appropriate to use different filters for different parameter estimates or analyses of the same dataset. For many ERP/F applications, in particular unguided, exploratory ERP/F analysis, it is recommended to refrain from high-pass filtering or to apply very low (≤0.1 Hz) cutoff high-pass filters (Acunzo et al., 2012; Luck, 2005). However, high-pass filtering replacing baseline and drift correction can be a valid means to remove strong low-frequency (near DC) interferences, e.g., in ERP/F analysis of ongoing speech. Even higher high-pass cutoff frequencies accepting a minor attenuation of evoked components such as the N400 can be reasonable (see e.g., Maess et al., 2006). In that study, the preprocessing including high-pass filtering made localization of the N400 response possible in the first place. Importantly, peak amplitudes and onset latencies were not reported, because these parameters would have been biased by the filter.

Various practices and recommendations exist for low-pass cutoff frequencies in ERP/F analysis including the suggestion not to apply low-pass filters at all (VanRullen, 2011). Indeed, low-pass filters frequently serve primarily cosmetic purposes as high-frequency noise (except line noise) usually has low energy in electrophysiology recordings (cf. e.g., Widmann et al., 2012, who recorded children's EEG in electrically unshielded rooms at primary schools; 100 Hz low-pass cutoff filtered ERPs only show very moderate noise levels). Furthermore, later steps in data analysis, such as computing mean amplitudes in given time windows, are low-pass filter equivalents. As a rather unspecific recommendation, we suggest applying low-pass filters with cutoff frequencies higher than 40 Hz during ERP analysis, thereby preserving the visible high-frequency components in the ERPs such as the sharp peak of the low latency (P1) component.

In summary, we encourage the careful design of appropriate filters rather than avoiding filtering completely. Short filters with soft roll-off should be preferred. Attenuation must not be stronger than necessary. Separate high-pass and low-pass filters should replace band-pass filters if the roll-off cannot be adjusted separately. Band-stop filters should be avoided where possible and replaced by time domain based measures in the case of line noise. Non-linear (causal) filters should be used when a transfer of information back in time, i.e., from later to earlier components, needs to be excluded. These filters always delay the signal; therefore, all latencies are systematically delayed in time. Usually, zero-phase (non-causal) filters are preferable for many applications in electrophysiology. The side effects of two-pass forward and reverse filtering must be considered. Filters should be applied to the continuous (rather than segmented) data. Filters must not be applied across signal discontinuities. The persistence of signal discontinuity information must be provided throughout preprocessing. Segments have to be processed separately if this information is not provided (as, e.g., with the EEGLAB bdfimport plugin). All parameters set to default values should be checked. Manual setting of all relevant filter parameters is preferred. All filter parameters, including filter type (high-pass, low-pass, band-pass, band-stop, FIR, IIR), cutoff frequency (including definition), filter order (or length), roll-off or transition bandwidth, passband ripple and stopband attenuation, filter delay (zero-phase, linear-phase, non-linear phase) and causality, and direction of computation (one-pass forward/reverse, or two-pass forward and reverse) must be reported. In the case of two-pass filtering it must be specified whether reported cutoff frequencies and filter order apply to the one-pass or the final two-pass filter. Finally, filtering should not replace measures to improve the signal-to-noise ratio during the recording and analysis of electrophysiological data such as proper electrode preparation (e.g., lower impedances; Kappenman and Luck, 2010), care for participants' comfort and compliance (avoid muscle artifact, sweating, etc.), prevention of electromagnetic interference (shielding; remove fans, transformators, cable coils, etc.), a sufficient number of recorded trials for average-based applications; time domain based approaches (mean subtraction, removal of line noise). Unfiltered and filtered data should always be compared and evaluated for the improvement in signal-to-noise ratio as well as distortions biasing the estimated parameters. With these recommendations in mind, we hope the reader is well prepared for filtering electrophysiological data without the pitfalls or myths commonly associated with this analysis step.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jneumeth.2014.08.002.

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