Published in final edited form as:
Neuroimage. 2019 April 01; 189: 763–776. doi:10.1016/j.neuroimage.2019.01.026.

Reducing power line noise in EEG and MEG data via spectrum interpolation

Sabine Leske[1,2,3] and **Sarang S. Dalal**[1,2,4]

[1]Center of Functionally Integrative Neuroscience, Aarhus University, Denmark

[2]Department of Psychology, University of Konstanz, Germany

[3]Department of Psychology, Faculty of Social Sciences, University of Oslo, Norway

[4]Zukunftskolleg, University of Konstanz, Germany

Abstract

Electroencephalographic (EEG) and magnetoencephalographic (MEG) signals can often be exposed to strong power line interference at 50 or 60 Hz. A widely used method to remove line noise is the notch filter, but it comes with the risk of potentially severe signal distortions. Among other approaches, the Discrete Fourier Transform (DFT) filter and CleanLine have been developed as alternatives, but they may fail to remove power line noise of highly fluctuating amplitude. Here we introduce spectrum interpolation as a new method to remove line noise in the EEG and MEG signal. This approach had been developed for electromyographic (EMG) signals, and combines the advantages of a notch filter, while synthetic test signals indicate that it introduces less distortion in the time domain. The effectiveness of this method is compared to CleanLine, the notch (Butterworth) and DFT filter. In order to quantify the performance of these three methods, we used synthetic test signals and simulated power line noise with fluctuating amplitude and abrupt on- and offsets that were added to an MEG dataset free of line noise. In addition, all methods were applied to EEG data with massive power line noise due to acquisition in unshielded settings. We show that spectrum interpolation outperforms the DFT filter and CleanLine, when power line noise is nonstationary. At the same time, spectrum interpolation performs equally well as the notch filter in removing line noise artifacts, but shows less distortions in the time domain in many common situations.

Keywords

power line noise; artifact removal; spectrum interpolation; notch filter; ringing; Gibbs effect

Address correspondence to: Sabine Leske, Department of Psychology, Faculty of Social Sciences, Forskningsveien 3A, University of Oslo, 0373 Oslo, Norway, sabine.leske@psykologi.uio.no.

Conflict of Interest

The authors declare no competing financial interests.

1 Introduction

Among the variety of artifacts affecting the quality or signal to noise ratio of MEG and EEG (MEG/EEG) measurements, the 50 or 60 Hz interference from power lines is probably the most pervasive one. Shielded rooms can help reduce the influence of power line interference on MEG/EEG recordings, but often not completely. Furthermore, the mobility of EEG systems makes them a good candidate for “field” or mobile measurements (Gramann et al., 2014; Makeig et al., 2009), where shielding is usually impractical and proximity to everyday electrical appliances is more likely.

In this context, wireless and dry electrode EEG systems facilitate measurements in natural environments outside the lab, which is also especially desirable in the context of brain-computer interfacing (De Vos et al., 2014; Debener et al., 2012; Gramann et al., 2014; Zander and Jatzev, 2012). This expands opportunities for research, but also increases the exposure of the EEG system to power line noise, since shielding against this interference is impractical in these scenarios.

Similar problems occur in clinical applications of the EEG, including monitoring of sleep disorders and epilepsy, which typically occur in unshielded environments subject to electrical noise from both medical equipment and ordinary infrastructure. Intracranial EEG, often employed prior to neurosurgical resection for epilepsy or brain tumors, can also be subject to line noise.

There are several approaches to remove artifacts stemming from power line noise, with different strengths and weaknesses. The most prevalent method might be to filter the data in the respective frequency band with a notch filter (a bandstop filter with a narrow stopband). This attenuates the power for frequencies in the respective stopband (centered at either 50 or 60 Hz). However, filtering comes with the risk of causing distortions in the passband and in the resulting time domain signal, producing artifacts like ringing (Widmann et al., 2014).

One of the possible causes for ringing artifacts is the Gibbs effect (Smith, 1997), which can be especially pronounced when there are sharp discontinuities in the filter’s frequency response (Fay and Kloppers, 2001). This is especially the case with notch filters, due to the sharp and narrow stopband. Spectrum interpolation results in a smoother Fourier spectrum, which has been shown to reduce the Gibbs phenomenon (Brezinski et al., 2004).

Such signal distortions can be evaluated by examining the time and frequency domain responses of the filter to artificial signals like an impulse or step signal. An ideal frequency domain response would have unity passband and zero stop magnitude. A real-world filter necessarily deviates from this ideal, with potential ripples in the passband and stopband as well as a certain transition bandwidth. The impulse and step responses reveal filter behavior in the time domain, visualizing the amplitude and extent of distortions.

There are several studies reporting severe signal distortions in the temporal domain, such as filter or ringing artifacts and artificial components after the application of filters (Luck, 2005; Widmann et al., 2014). This might cause unwanted effects in the MEG/EEG parameters of interest, e.g., a distortion of the peak amplitude (Acunzo et al., 2012) or even artificial oscillations with a frequency near the cutoff frequency of the filter (Widmann et al., 2014).

A widely used notch filter in this context is the Butterworth filter. This type of filter is an infinite impulse response filter (IIR), causing a delay in the time domain and a nonlinear phase response that can be corrected (zero-phase delay) by reverse filtering, also referred to as two-pass filtering (Widmann et al., 2014). In consequence, signal components in the time domain as, e.g., event-related potentials might be shifted back in time after non-causal low-pass filtering, which hinders the correct estimation of onset latencies or peak amplitudes (Rousselet, 2012; VanRullen, 2011). Low-pass filtering can also cause artificial smearing of oscillations to preceding samples, which might lead to misinterpretations of phase or connectivity effects, as, e.g., spurious prestimulus phase effects (Zoefel and Heil, 2013) or it might cause detrimental effects on Granger causality (Barnett and Seth, 2011; Bigdely-Shamlo et al., 2015).

Even though features of zero-phase filters are often desired in MEG/EEG signal processing, since they do not introduce a delay in the time domain signal, all these filters come at the cost of introducing a symmetric smearing of the signal in the time domain (Widmann et al., 2014). In consequence some authors recommend to avoid notch filters in ERP research in general, due to the high probability of introducing strong artifacts (Luck, 2005; Widmann et al., 2014).

Consequently, other alternatives to reduce line noise artifacts have been developed. One method widely applied (Buch et al., 2012; Fiebelkorn et al., 2013) to MEG/EEG data containing line noise interference is the discrete Fourier transform (DFT) filter, an example of which is implemented in FieldTrip, an open source MEG/EEG analysis toolbox (Oostenveld et al., 2011). The DFT filter is realized by fitting a sine and cosine at interference frequency to the signal. The estimated components are subtracted from the data.

One major advantage over the notch filter is that the DFT filter avoids potential corruption of frequencies away from the powerline frequency. The best performance can be achieved by applying the DFT filter to relatively short segments of data (e.g., 1 s or less), ensuring the closest fit of the estimated components, in case the line noise interference exhibits certain dynamics. This filter approach assumes a constant amplitude of the line noise component. Hence it may fail if the amplitude of the power line noise fluctuates over the input data segment, as is likely to occur with longer trials or continuous data. In consequence, the mean estimated amplitude does not apply to the actual amplitude of the line noise, resulting in additional line noise artifacts after subtraction (for a schematic illustration, see http://www.fieldtriptoolbox.org/faq/why_is_there_a_residual_50hz_line-noise_component_after_applying_a_dft_filter).

In the Fourier domain, fluctuations in the amplitude of line noise interference effectively translates to spreading of the noise component to neighboring frequencies, thereby escaping the DFT filter.

There are also regression-based approaches to remove line noise interference. The CleanLine method uses a sliding window and Slepian multitapers, to transform the data into the frequency domain (Bigdely-Shamlo et al., 2015; Mullen, 2012). Subsequently a regression model is applied to estimate the amplitude and phase of the power line noise to reconstruct the time-domain sinusoid for the respective frequencies, which is afterwards subtracted from the data. Compared to notch filters that often result in distortions around line noise frequencies, CleanLine removes only deterministic line components, while trying to preserve “background” spectral energy. Nevertheless the developers demonstrated how this approach might fail in case of large, non-stationary spectral artifacts (Bigdely-Shamlo et al., 2015).

An alternative approach to remove power line noise – termed spectrum interpolation – has been developed to remove line noise from the electromyogram (Mewett et al., 2004), but has not yet been applied to EEG or MEG data. This method is based on the simple concept of: (I) transforming the time domain signal into the frequency domain via a discrete Fourier transform (DFT), (II) removing the line noise component in the amplitude spectrum by interpolating the curve at interference frequency according to neighboring frequencies, and (III) transforming the data back into the time domain via an inverse discrete Fourier transform (iDFT). The undesired signal distortions in the time and frequency domain mentioned above may be reduced by the application of spectrum interpolation.

The objective of this study was to evaluate and compare the performance of the spectrum interpolation approach to a notch filter, a DFT filter and the CleanLine method, three widely used methods to remove power line interference in EEG and MEG data. The three methods were applied to (I) synthetic test signals, as an impulse, step and a Gaussian-shaped signal, (II) abrupt on- and offsets of power line noise added to line-noise-free real MEG data, (III) simulated power line noise data exhibiting non-stationarities in amplitude and frequency, that was added to line-noise-free real MEG data and (IV) unshielded EEG measurements in a typical home environment, presumably containing non-stationary power line noise components.

Europe PMC Funders Author Manuscripts

2 Material and Methods

Data were simulated and analyzed using FieldTrip, an open source MEG/EEG analysis toolbox (Oostenveld et al., 2011), together with in-house MATLAB (MathWorks, Natick, MA, USA) scripts.

2.1 Experimental Paradigms and Data Simulation

2.1.1 Synthetic Test Signals—The properties of a filter are by convention tested by a sharp impulse and step signal. The unit impulse signal had a length of 2 s, ranging from -1 to 1 s, with a sampling rate of 500 Hz and consisted of zeros with a single element of unit magnitude (value of one) at time point zero, constituting a single sharp pulse (delta function). The same length and sampling rate applies to the step signal created, but the signal consists of zeros for negative time points and of ones for time point zero and the following positive time points.

Gaussian waveforms are suitable test signals to investigate the effects of filtering on ERP/ERF results (Widmann et al., 2014). The Gaussian-shaped test signal had a length of

500 ms with a sampling rate of 500 Hz. The signal was a probability density function of a normal distribution with a standard deviation of 5 ms.

2.1.2 Power Line Noise Simulation and MEG Data—

To quantify the robustness of the methods against non-stationary line noise interference, power line noise with fluctuating amplitude and with abrupt on- and offsets was simulated and added to an MEG dataset that was practically free of line noise.

MEG data: visual evoked fields. The MEG dataset was recorded for a study investigating visual perception and information processing of light flashes. Full-field white flashes were presented to the right eye, while the left eye was occluded. The flashes had a duration of 16.67 ms with an ISI of 2.41 s. The experimental task required no behavioral response. Brain activity was recorded via MEG with a 148-magnetometer whole head MEG (MAGNES 2500 WH, 4D Neuroimaging, San Diego, USA) in a magnetically shielded room. MEG was recorded with a sampling rate of 1017.2 Hz and a 0.1 Hz high pass hardware filter was applied prior to digitization. A sample dataset with a length of 109.2 s of one participant (27 years old, male) was chosen for the current investigation of power line noise artifact removal methods. Global noise, incorporating power line noise, was removed by subtracting external noise recorded via 11 MEG reference channels. These reference channels were multiplied with individually calculated fixed weight factors, before their signal was subtracted from MEG data. Hence the MEG dataset exhibited no discernible power line noise at 50 Hz and its respective harmonics (Figure 2A).

Simulated power line noise with abrupt on-/offsets and with fluctuating amplitude. In order to create abrupt on- and offsets of power line noise, a 50 Hz sinusoid (zero phase) was multiplied with a unity-height rectangular pulse with a width of 4.93 s centered at a signal with a length of 16.4740 s. Six of these rectangular pulse signals were concatenated, multiplied with the 50 Hz sinusoid and added to line-noise-free MEG data of 109.2 s length, such that the resulting line noise segments had a root mean square (RMS) amplitude approximately four times as high as the original line-noise-free MEG data and a width of 4.93 s. The simulated six abrupt on- and offsets of 50 Hz line noise were centered at the epochs that were used later for single trial and ERF analysis in order to reveal possibly detrimental filter effects.

In order to simulate line noise interference with fluctuating amplitude, Gaussian white noise with a length of 109.2 s and a sampling rate of 1017.2 Hz (parameters matched to the real MEG dataset), was filtered with a 0.4 Hz low-pass filter (FIR filter, zero-phase forward and reverse filter). Low-pass filtering included mirror-padding the data to a length of 250 s, to avoid filter edge artifacts. The maximum of the absolute values of the lowpass-filtered white noise signal was added to the signal to ensure only positive values for the amplitude modulation. The resulting filtered white noise signal was multiplied with a 50 Hz sinusoid (zero phase) to create an amplitude-modulated line noise component. The simulated line noise signal was added to the power line-noise-free MEG dataset (described above) such that the resulting signal had a root mean square (RMS) amplitude approximately twice as high as the original MEG signal, yielding a signal-to-noise ratio (SNR) of -6.0 dB.

2.1.3 Slow-Wave-Sleep (SWS) Experimental Paradigm and Procedure—The artifact removal methods were also tested by applying them to an EEG dataset that we recorded for an overnight sleep study. EEG measurements took place in the participants' own homes without the benefit of a shielded EEG booth, so these measurements were subject to line noise interference presumably exhibiting different types of non-stationarities. The all-night EEG recordings (including electrooculogram and electromyogram recordings) were conducted with a portable BrainAmp DC EEG system and a BrainProducts ActiCap electrode system (BrainProducts GmbH, Gilching, Germany). The electrode placement was according to the standard international 10-20 system layout (Schomer and Lopes da Silva, 2011). The ground electrode of the BrainProduct ActiCap electrode system is AFz and the reference electrode is FCz. The electrode impedances were below 20 kΩ, as recommended by the manufacturer (BrainProducts GmbH, Gilching, Germany). This was checked to the extent possible, at the beginning and at the end of the recording in the morning. For online preprocessing hardware filter settings were set to a bandwidth of 0.016 – 1000 Hz, with a sampling rate of 2500 Hz. During the night, a continuous auditory stimulation of condensation-rarefaction clicks of 100 ms length was performed. The stimuli were saved as a lossless WAVE-format file, with an inter-stimulus-interval (ISI) of 500±150 ms. The acoustic stimuli were presented via a battery-powered iPod Nano 2G (Apple Inc., Cupertino, USA) and delivered via in-ear earphones (hf5, Etymotic Research Inc., Elk Grove Village, IL, USA) at a volume level of 40 dB sound pressure level. In order to ensure trigger recording with high temporal precision, the stimulus signal from the playback device was split into two channels. This way simultaneously sound impulses were send to the earphones and to the trigger recording box. Recording sessions lasted between 5.5 and 8.5 hours. For the present analysis, the dataset of one participant (29 years old, male) was used to compare the performance of the different approaches. The signal from electrode TP10 was selected for the respective analysis.

2.2 Signal Processing: Preprocessing and ERP/ERF Analysis

2.2.1 Analysis of MEG Data with Simulated Line Noise—The data was segmented into epochs including the flash stimulus, with a prestimulus and a poststimulus time period of 500 ms, resulting in 40 non-overlapping trials of 1 s length. A baseline correction was performed by demeaning single trials according to the prestimulus period of -200 ms to 0 ms.

2.2.2 Analysis of EEG SWS Data—Slow wave sleep periods were defined as data segments representing deep sleep (stage N3) according to current international guidelines (Iber et al., 2007). These periods were identified by inspecting the time-frequency spectrogram of the whole night's data for extended epochs of <2 Hz activity. These blocks were subsequently further processed via an automatic slow wave detection program (FASST toolbox for MATLAB) (Leclercq et al., 2011). Data segments with a high number of slow wave events were considered to represent stage N3 sleep, and were visually confirmed to fulfill sleep slow wave morphology (Iber et al., 2007). For the dataset used in the present analysis, this resulted in two data segments of 1100 s and 1000 s length.

In order to calculate auditory ERPs, these two long data segments were bandpass-filtered with a Butterworth filter (filter order of 4) between 15-500 Hz for the so-called middle latency response (MLR) component of auditory brain responses (Picton et al., 1974). Then the data was segmented into epochs, with a pre- and poststimulus period of 500 ms relative to the auditory stimulus, resulting in 4197 trials of 1 s length.

2.3 Signal Processing: Power Line Noise Removal

2.3.1 Spectrum Interpolation—If power line noise interference is considered as an additional component – with a peak at 50 Hz – superimposed on the continuous power spectrum curve of MEG/EEG data, it can be removed by interpolating the curve of the power spectrum at the respective frequency samples (Mewett et al., 2004). If this interpolation is calculated in complex Fourier space, the inverse Fourier transformation can be used to retain the time domain signal in which the line noise is now reduced.

The code for spectrum interpolation is made available in FieldTrip, an open source MEG/EEG analysis toolbox (http://fieldtriptoolbox.org ; Oostenveld et al., 2011). We implemented spectrum interpolation in FieldTrip (Oostenveld et al., 2011), involving the following processing steps. First the data is transformed into Fourier space by calculating a DFT. The absolute value of the complex Fourier coefficients is calculated to retain the amplitude. The interpolation of the interference frequencies is realized by calculating the mean of the amplitude of the neighboring frequencies and replacing the amplitude of the line noise Fourier coefficients with the respective value. The number of neighboring frequencies to be included can be determined by the user. After interpolation, the amplitude spectrum is combined with the original phase information via Eulers formula. It is not known a priori how the phases of neighboring frequencies relate to each other, hence phases of the Fourier spectrum were not interpolated, but the original phase information was retained. The interpolated complex Fourier signal is then transformed back into time domain by calculating the inverse DFT. To retain a real-valued signal after the inverse transform, Fourier coefficients were treated as conjugate symmetric, ensuring that the positive and negative frequency components are mirror images of each other (Mewett et al., 2004).

The code for spectrum interpolation can be directly accessed here (https://github.com/fieldtrip/fieldtrip/blob/master/preproc/ft_preproc_dftfilter.m, section Method B: Spectrum Interpolation).

First, a DFT was applied to continuous data segments, resulting in Fourier coefficients with a frequency resolution higher than 0.01 Hz for both datasets (EEG and MEG). Spectrum interpolation can also be applied to short data segments (e.g., epochs). We decided to apply the method to the continuous data in order to ensure high frequency resolution for a precise comparison with the other approaches. It should be noted, however, that there is a risk of spreading distortions wider in the time domain with longer DFT inputs. In any case, the DFT length should fit the periodicity of the frequency of the power line noise in order to avoid leakage, so an integer number of cycles of the line noise fits in the data. Therefore the DFT input length was adjusted accordingly for the MEG and EEG data. The length of the DFT input for the MEG data (mixed with simulated fluctuating power line noise or abrupt on- and offsets) was 108 s, with a sampling rate of 1017.25 Hz. With respect to the EEG dataset (sampling rate of 2500 Hz), the length of the DFT input was 1100 s and 1000 s length for the two data segments. The line noise component was interpolated in the amplitude spectrum by replacing the amplitude of the 50 Hz Fourier coefficient ($\Delta = \pm 2$ Hz) with the mean of the amplitude of the adjacent Fourier coefficients of 48 Hz and 52 Hz ($\Delta = \pm 2$ Hz) for the synthetic test signals and for the MEG dataset mixed with simulated fluctuating line noise. For the analysis of the EEG datasets the amplitude of the 50 Hz Fourier coefficient ($\Delta = \pm 3$ Hz) was replaced with the mean of the amplitude of the adjacent Fourier coefficients of 47 Hz and 53 Hz ($\Delta = \pm 3$ Hz). Since the width of the line noise component was larger for the EEG dataset, as revealed by the power spectrum, the width of the interpolated frequency range was adjusted accordingly to ± 3 Hz. The simulation of abrupt on- and offsets of power line noise (mixed with MEG data) produced the largest width of the power line noise component. Here, a wide range of frequencies around 50 Hz ($\Delta = \pm 12$ Hz) were replaced with the mean of the adjacent Fourier coefficients of 38 Hz and 62 Hz ($\Delta = \pm 12$ Hz). In general, the width of spectrum interpolation can be adjusted to the nature of the line noise interference.

Spectrum interpolation was repeated for the respective harmonics up to 500 Hz for the EEG data, since the ERP analysis incorporated a band signal width up to 500 Hz for the SWS study (see above: Analysis of EEG SWS Data).

2.3.2 Notch Filter—A 4th-order Butterworth notch filter (zero-phase two-pass) was applied to the continuous MEG data segment (mixed with simulated line noise). A stopband of 48-52 Hz (please note that cutoff frequencies are defined for the single-pass case in FieldTrip, accordingly cutoff frequencies are shifted slightly for the two-pass version of the filter, e.g. to 47.58 Hz and 52.24 Hz in this particular case) was used for the synthetic test signals and the MEG data with simulated fluctuating power line noise. For the abrupt on- and offsets of power line noise that had been added to the MEG data a stopband of 38-62 Hz (defined for the single-pass case) was used. The same filter was applied to the continuous EEG data segments (SWS sleep segments of 1100 s and 1000 s length, see Methods section above). Here, the stopband included frequencies between 47-53 Hz (defined for the single-pass case) and the respective harmonics up to 500 Hz ($\Delta = \pm 3$ Hz), in order to account for the nature of the line noise in the EEG dataset (for an explanation see section above).

2.3.3 DFT filter—A DFT filter was applied after data segmentation into trials of 1 s length for the MEG and EEG data. The DFT filter implemented in FieldTrip was used. The line noise removal is realized by fitting a sine and cosine at the respective interference frequency to each data segment. The estimated components are afterwards subtracted from the signal. With respect to the synthetic test signals, the DFT filter was applied for the 50 Hz component. Since power line noise was broadband and to ensure comparability to the other approaches, the DFT filter was not only applied for 50 Hz but also for the neighboring integer frequency values of 48, 49, 51 and 52 Hz for the MEG data mixed with simulated fluctuating line noise. The frequency resolution of the DFT filter is limited by the frequency resolution of the signal, which is 1 Hz for a trial length of 1 s. Therefore, only the neighboring integer values were removed. For the MEG data with added abrupt on- and offsets of line noise, the DFT filter was only applied for the 50 Hz component because this generated the best performance. With respect to the EEG data, the DFT filter was applied for integer frequency values between 47-53 Hz and the respective harmonics up to 500 Hz ($\Delta = \pm 3$ Hz). It is advantageous to apply the DFT filter to relatively short segments of data or trials, since it fails to remove power line noise if it is non-stationary, e.g., line noise that fluctuates in amplitude over time. Therefore, to enable a fair comparison of the different artifact removal methods, the DFT filter was not applied to the long SWS data segments, but as recommended to segmented trials of relatively short duration.

2.3.4 CleanLine—

The CleanLine EEGLAB plugin developed by Mullen (2012) was used to compare a regression-based method to the other approaches. CleanLine transforms the signal into the frequency domain using a sliding window and Slepian tapers. After estimating amplitude and phase for line noise frequencies with a regression model, a time-domain sinusoid is reconstructed and the fitted signal is subtracted from the data. For further details about this method, please refer to Bigdely-Shamlo et al., (2015).

Here, a sliding window of 4 s and a 1 s step size (EEGLAB default) was used for the MEG dataset mixed with fluctuating line noise and a sliding window of 0.3 s and a 0.1 step size was applied for the abrupt on-/offsets of line noise. A sliding window of 1 s and a 0.1 s step size was used for the EEG dataset, because this improved the performance. A taper bandwidth of 4 Hz was used for the MEG data with fluctuating amplitude (centered around 50 Hz), a bandwidth of 24 Hz was used for the abrupt on-/offsets and a taper bandwidth of 6 Hz was used for the EEG data, to achieve comparable results to the other methods (see bandwidths for the other methods above). Default values from the EEGLAB implementation were used for all other parameters.

2.3.5 Evaluation—

Synthetic Test Signals. In order to evaluate the impulse and step response of the different filter approaches and the distortions in the time domain, the mean root mean squared error (RMSE) was calculated between the filtered signal (time domain response) and the synthetic test signals, leaving out time periods with an amplitude of one (time point zero for the impulse and in addition all time points for the step signal that were larger than zero). This was done to evaluate time domain distortions with respect to the signal period that had an amplitude of zero before line noise removal. In order to evaluate the effects of the different approaches on a Gaussian-shaped test signal, the mean RMSE was calculated between the processed signal (after line noise removal) and the original Gaussian-shaped signal.

MEG Data with Simulated Line Noise. The original MEG signal was free of discernible line noise, and therefore represents the "ground truth". The normalized RMSE (nRMSE) between the signal after line noise removal and the original MEG signal was calculated for each single trial and then averaged. In order to normalize the results, the single trial RMSEs were divided by the difference of the maximum and the minimum of the respective original single trials (line-noise-free) they were compared to.

EEG SWS Data. The mean RMSE between the original, notch- or DFT-filtered single trials and the spectrum-interpolated single trials was calculated. Results were not normalized since the ground truth (line-noise-free signal) is unknown.

Europe PMC Funders Author Manuscripts

3 Results

3.1 Synthetic test signal results

Synthetic test signals – as an impulse and step signal – are commonly used to characterize the properties of a filter and can reveal possible distortions in the time domain that might occur due to power line noise removal by the different approaches presented in the current study. For all approaches, frequencies between 48-52 Hz were attenuated (except for the DFT filter, which was only applied to 50 Hz), since this is a commonly used frequency range to reject power line noise artifacts. The unit impulse response of the Butterworth notch filter revealed the most pronounced time domain signal distortions (Figure 1A), with the highest RMSE = 0.0038. It is followed by the DFT filter response that deviates from the original signal with a RMSE = 0.0014. These distortions become apparent as artificial oscillations near line noise frequency (50 Hz) around the impulse (Figure 1A, magnified view), at time points that contained no energy in any frequency band beforehand (zero line of the impulse signal). These distortions are also referred to as ringing artifacts that might occur when only part of a broadband signal is attenuated.

In contrast, spectrum interpolation shows almost no deviations from the original signal, with a RMSE = 8.4631×10^{-18}. These time domain distortions are so small, that they are not even visible in the magnified view (Figure 1A). CleanLine shows the best performance, with no distortions and a RMSE = 0. A statistical test is used to identify significant power line noise frequencies, accordingly there is no attenuation of the energy in the 48-52 Hz frequency band, since the impulse signal did not contain line noise interference.

The same applies to the step signal, which also did not contain power line noise and therefore no frequency component was attenuated by CleanLine, resulting in the best performance with no time-domain distortions and a RMSE = 0 (Figure 1B). The application of the notch filter as well as spectrum interpolation resulted in distortions visible as small artificial oscillations around 50 Hz before and after the step, with a RMSE = 0.0057 for spectrum interpolation and RMSE = 0.0061 for the notch filter. The performance of the DFT filter was considerably better, showing almost no distortions with a RMSE = 7.7039×10^{-16} (Figure 1B).

The Gaussian-shaped signal served as a test signal to compare the different approaches with respect to possibly detrimental effects of line noise removal on the analysis of ERP/ERF components and other measures that might be affected, as phase or connectivity measures. Here spectrum interpolation performs better than the Butterworth notch filter and the DFT filter, showing less distortions with a RMSE = 0.0014 compared to a RMSE = 0.0142 for the notch filter and a RMSE = 0.0103 for the DFT filter (Figure 1C). These time domain distortions become apparent as artificial oscillations near line noise frequency before and after the Gaussian-shaped curve (Figure 1C, magnified view). CleanLine shows the smallest and a neglectable deviation from the original signal, with a RMSE = 2.6795×10^{-9}.

3.2 ERF and single trial results for MEG-Simulated-Noise data

The original MEG data did not show artifacts stemming from power line noise (50 Hz) in the power spectrum of the continuous data segments (Figure 2A). In order to evaluate the performance of the different approaches, simulated power line noise (50 Hz sinusoid) with abrupt on- and offsets was added to the line-noise-free MEG data.

Over the time course there were six sudden on- and offsets of power line noise (width of 4.93 s), centered at the respective epochs, with an RMS amplitude four times as high as the original MEG signal (Figure 2B), which mimics an extreme case of power line noise pulses. The power spectrum of the mixed signal reveals that the abrupt on- and offsets of line noise resulted in a pronounced 50 Hz component incorporating a wide frequency range between 38-62 Hz (Figure 2B). Spectrum interpolation was used to reduce line noise interference by replacing values for all Fourier coefficients between 38-62 Hz by the mean of the neighboring frequencies (26-38 Hz and 62-74 Hz) in the amplitude spectrum (see Method section and Figure 2C for the resulting power spectrum). The same frequency range (38-62 Hz) was used for the two other approaches, as the notch filter and the CleanLine method (see Method section), except for the DFT filter. Here fitting and removing a single 50 Hz sinusoid from each trial resulted in better performance than the removal of all integer values between 38-62 Hz.

The frequency spectra reveal that the application of spectrum interpolation and the notch filter resulted in a reduction of line noise interference (Figure 2C, D and E), whereas CleanLine was not able to reduce line noise to a satisfying extent (see also Bigdely-Shamlo et al. 2015 for demonstrating this issue with large non-stationary power line noise).

Figure 3B shows three example trials for single trial difference curves between the filtered signals and the original clean signal, with a line-noise-free trial, a trial with an abrupt onset of line noise at the center and a trial with line noise over the whole time period. The single trial difference curves reveal that all methods lead to slight signal distortions even in time periods that were free of line noise before filtering except for CleanLine, showing no visible distortions (Figure 3B and C, first sample trial). Especially notch filtering leads to artificial oscillations (around 50 Hz) in these time ranges, but also spectrum interpolation shows these distortions to a slightly lesser extent (Figure 3C, D).

The CleanLine method and the DFT filter show the least (or no) distortions at these time ranges, but both methods perform worse around sudden on- and offsets of line noise. In addition, the difference curves during time periods of line noise reveal substantial residual line noise after the application of the CleanLine method (Figure 3B), but an effective attenuation of line noise with the three other methods. The performance of the filter methods was quantified by calculating the mean nRMSE of all single trial difference curves. There was a mean nRMSE = 0.2450 between the simulated line noise interference with abrupt on- and offsets and the original clean MEG data.

The nRMSE exhibited high variance as revealed by the box plot (Figure 3D). Leaving the few extreme outliers (stemming from the trials with on- and offsets of line noise) aside, the DFT filter shows the best performance, with a mean nRMSE = 0.0439, but with the lowest median (Figure 3D). Spectrum Interpolation performs slightly better than the notch filter, with a mean nRMSE = 0.0201 compared to a mean nRMSE = 0.0221 (Figure 3D).

Europe PMC Funders Author Manuscripts

CleanLine shows the lowest performance, with a mean nRMSE = 0.0454 and with a substantial variance.

The ERFs reveal that the few extreme outlier trials (containing on- and offsets of line noise) of the DFT filtered signal corrupted the averaged ERF (Figure 3A). The same applies to the ERF after the application of CleanLine, though restricted to a time window of approximately 200 ms, revealing an artificially enhanced ERF component. Spectrum Interpolation and the notch filter show the most faithful reproduction of the original ERF (Figure 3A).

For the investigation of the effects of filtering non-stationary power line noise with fluctuating amplitude, simulated line noise (50 Hz) with an amplitude modulation was added to the original MEG data (free of line noise). The power spectrum of the mixed signal shows a strong 50 Hz component, leaking into neighboring frequencies (48-52 Hz) due to the amplitude modulation (Figure 4A). Hence this was the target frequency range to be removed by all approaches. The amplitude of the simulated line noise changed on a fast time scale, randomly between 0 and 0.4 Hz and the RMS amplitude of the simulated line noise signal was scaled to be a factor of 2 of the RMS amplitude of the original MEG signal. The parameters were chosen in a way to simulate a severe case of non-stationary line noise interference, but with a magnitude comparable to what we have observed “in the field” as with our sleep EEG data.

The notch filter and spectrum interpolation substantially reduced line noise, as evident from the frequency spectra (Figure 4B and C). CleanLine was not able to attenuate this non-stationary line noise interference, and introduced seemingly inappropriate components corresponding to integer frequencies (Figure 4D). The frequency spectra also reveal how the signal is slightly changed in the passband frequencies after notch filtering, while it is preserved with spectrum interpolation (Figure 4A, B and C).

The comparison of the single trials after line noise removal reveals substantial residual 50 Hz noise for the DFT-filtered signal and the signal after applying CleanLine, but only small deviations from the original signal for the spectrum-interpolated and notch-filtered signal (see Figure 5B for an example trial). This is visualized by the difference curves between the filtered (DFT filter, notch filter, CleanLine or spectrum interpolation) signal and the original noise free MEG signal for the example trial (Figure 5C).

With respect to the simulated line noise, there was a mean nRMSE = 0.3828 for the single trial differences between the MEG signal mixed with the simulated line noise and the original noise-free MEG signal (Figure 5D). The mean nRMSE between the DFT-filtered signal and the original signal was relatively reduced, but larger (nRMSE = 0.0234) than the nRMSE between the spectrum-interpolated and the original signal (nRMSE = 0.0061). This indicates a higher artifact removal performance of the spectrum interpolation method compared to the DFT filter and a slightly better performance compared to the notch filter (nRMSE = 0.0072).

Compared to all other methods, CleanLine showed the largest deviation from the original signal, with a mean nRMSE = 0.1522. This is also mirrored by the ERF. While performance differences between the DFT filter, the spectrum interpolation and notch filter were not revealed by averaged data, showing almost no differences between the three filter methods, the ERF of the CleanLine-processed data shows residual line noise (Figure 5A).

3.3 ERP results for EEG sleep data

In order to visualize the performance of the different filter methods removing line noise interference, auditory ERPs (in this case the MLR component) were calculated for the SWS periods of one dataset of the EEG sleep study.

The original EEG signal showed high amounts of power line noise artifacts for the 50 Hz component and the respective harmonics, which is visualized in the power spectrum of an example SWS segment (Figure 6A). In addition, the power line noise appears to be non-stationary with amplitude fluctuations. This amplitude modulation of the 50 Hz line noise is mirrored by the broadness of the 50 Hz component, which is not confined to 50 Hz but extends to the neighboring frequencies of 47 Hz and up to 53 Hz. The frequency spectra demonstrate that spectrum interpolation and notch filtering attenuated power in the 50 Hz frequency and in the harmonics up to 500 Hz to a large extent as intended (Figure 6B, C). But applying the CleanLine method results in substantial residual energy in those frequency ranges and additional artificial frequency components (Figure 6D).

The large non-stationary power line noise artifacts of the original data are also visible in the MLR. Here the power line noise in the original MLR has an amplitude of several multiples of the spectrum-interpolated MLR (Figure 7A), with a mean RMSE = 63.8567 μV for the MLR single trial differences between the original noisy and the spectrum-interpolated signal (Figure 7B). CleanLine shows the largest residual line noise interference of all methods, with a mean RMSE = 9.2486 μV compared to spectrum-interpolation. The DFT-filtered MLR also shows large residual line noise artifacts of fluctuating amplitude. Compared to the spectrum-interpolated MLR, there is a mean RMSE = 3.3336 μV for the single trial differences. Again the notch-filtered MLR and spectrum-interpolated MLR show almost no residual line noise left and only small differences between them, with a mean RMSE = 0.5253 μV for the MLR single trial differences between both signals (Figure 7B).

4 Discussion

In the present study, we suggest spectrum interpolation as an alternative approach to remove power line noise artifacts in MEG/EEG data and compare its performance to three other widely used approaches: the notch filter (Butterworth), the DFT filter and CleanLine. Spectrum interpolation had been introduced by Mewett et al. (2004) to remove power line noise in EMG data. Here we applied spectrum interpolation to synthetic test signals, a MEG data set that included simulated abrupt on-/offsets of 50 Hz and nonstationary power line noise of fluctuating amplitude and to EEG data from an overnight sleep study that was subject to substantial power line noise due to unshielded measurement conditions. With respect to the MEG dataset that included non-stationary power line noise and the EEG dataset, spectrum interpolation outperformed the DFT filter (Buch et al., 2012; Fiebelkorn et al., 2013) and the CleanLine method and performed equally well to the notch filter. Compared to notch filtering with a Butterworth filter, spectrum interpolation introduced less signal distortion in the time domain, as indicated by the synthetic test signals used in the current study.

The impulse and step responses of a filter are practical methods to evaluate filter behavior and distortions that might occur when broadband signals are filtered (Widmann et al., 2014). The impulse response revealed the largest undesired distortions in the time domain for the Butterworth notch filter, indicated by artificial oscillations near the notch frequency. Likewise, the DFT filter also resulted in signal distortions of the same nature, but smaller in magnitude. The CleanLine method showed no deviation from the original signal and did not affect the signal at all, since it incorporates a statistical test to identify significant line noise interference, which was not present in the impulse signal. Aside from CleanLine, spectrum interpolation showed the best performance with neglectable deviations from the impulse signal. The step response on the other hand revealed signal distortions in the time domain for both the notch filter and spectrum interpolation. Here CleanLine and the DFT filter performed better than the other approaches, with no or almost no deviations.

The Gaussian-shaped signal served to test the potentially detrimental effects of line noise removal on the analysis of ERP/ERF signals. Again, it revealed the strongest signal distortions for the notch filter, followed by the DFT filter. CleanLine, which again almost did not affect the signal, showed the best performance with almost no deviations from the original test signal. Aside from CleanLine, spectrum interpolation performed considerably better than the other approaches, with only slight signal distortions in the time domain, visible as very small artificial oscillations near the line noise frequency.

These time domain signal distortions are also referred to as ringing artifacts, and can occur if only part of the frequency range of a broadband signal is attenuated. Since all synthetic test signals had a broadband spectrum, ringing artifacts occurred in all approaches presented here, except for CleanLine, which had no impact on the impulse or step signal.

The simulated power line noise allowed us to measure and compare the effectiveness of the different approaches to remove non-stationary power line noise (with fluctuating amplitude and with abrupt on-/offsets), since it was added to MEG data practically free of line noise, which therefore represented the “ground truth” that is otherwise missing in experimental datasets. Spectrum interpolation effectively removed the simulated power line noise (both for abrupt on-/offsets and fluctuating line noise), resulting in a smaller nRMSE (compared to the line-noise-free MEG dataset) than the signal processed with CleanLine, which showed residual power line noise artifacts that was clearly visible in single trials and in the ERF. For the MEG data that incorporated simulated line noise with fluctuating amplitude, spectrum interpolation in addition outperformed the DFT filter, which was not able to remove line noise interference completely.

Likewise, spectrum interpolation performed considerably better than the DFT filter and CleanLine with respect to the EEG sleep data, that was subject to large line noise artifacts. The results of the application of the DFT filter and CleanLine to the EEG data revealed that residual line noise artifacts might also be clearly evident in the ERP. The developers of

Europe PMC Funders Author Manuscripts

CleanLine have already demonstrated the respective difficulties this regression based method might encounter with large non-stationary spectral artifacts (Bigdely-Shamlo et al., 2015).

The reason for the failure of the DFT filter is the non-stationary nature of the power line noise, fluctuating in amplitude (at 50 Hz in the current study). This amplitude modulation of the 50 Hz sinusoid resulted in a 50 Hz component with a width of 4 Hz in the frequency domain, spreading the artifact into the neighboring frequencies.

Since the DFT filter is realized by fitting a sine and cosine (here at 50 Hz) at the respective interference frequency to each data segment, the width of the frequencies removed cannot be controlled directly, but only indirectly via the width of the time window of the trial, which in turn determines the frequency resolution of the DFT. In addition the estimated amplitude of the power line noise is a mean across time. This is only feasible if the amplitude of the power line noise is stable over time. If the amplitude fluctuates, the subtraction is not removing the artifact but can even add artifacts in this frequency range. Even though the DFT filter was applied in addition to the neighboring frequencies (48-52 Hz) to account for the amplitude modulation and respective width of the line noise component, the DFT filter was not able to attenuate power line noise to a sufficient extent. The failure of the DFT filter to remove a non-stationary power line noise artifact has already been described and therefore advised to be used with caution by the developers of FieldTrip: http://www.fieldtriptoolbox.org/faq/why_is_there_a_residual_50hz_line-noise_component_after_applying_a_dft_filter

The performance of the notch filter (Butterworth) was comparable to the spectrum interpolation approach and removed power line noise equally well in the MEG and EEG datasets. There was almost no difference in RMSE between both approaches, except for the simulated amplitude modulated line noise and the abrupt on-/offsets of line noise added to MEG data. In both cases spectrum interpolation had slightly less deviations from the original signal, but this difference was very small and not as clear as the comparison to the other approaches.

However, the application of a notch filter might cause unintended adverse filter effects that seriously change the signal and affect results (Widmann and Schröger, 2012; Widmann et al., 2014). The resulting signal distortions can affect MEG/EEG features of interest as, e.g., ERPs or phase and connectivity measures and therefore might lead to spurious effects (Acunzo et al., 2012; Luck, 2005; Rousselet, 2012; VanRullen, 2011; Widmann et al., 2014). The severity of the signal distortions after filtering depend on the signal properties and on the filter types and settings, which can – if carefully selected – minimize unwanted side effects of filtering (Widmann and Schröger, 2012; Widmann et al., 2014). However notch filters are very likely to induce strong filter artifacts, therefore many guidelines recommend completely avoiding notch filters in ERP research (Luck, 2005; Widmann and Schröger, 2012; Widmann et al., 2014). Since the precision of the filter in the frequency domain is inversely related to the precision in the time domain, a sharp notch filter (high frequency resolution) results in signal distortions and wider temporal smearing (low temporal resolution) of distortions in the time domain (Widmann et al., 2014).

These signal distortions might include ringing artifacts, which become evident as artificial oscillations in the filtered signal or oscillations that are smeared back in time, which could lead to false interpretations of the results (Acunzo et al., 2012; Rousselet, 2012; VanRullen, 2011; Widmann et al., 2014). In the current study, the removal of power line noise from synthetic test signals also revealed this type of signal distortions, which were especially pronounced for the Butterworth notch filter.

Here we demonstrate that spectrum interpolation might be a preferable alternative to the DFT filter and the CleanLine method in case the power line noise exhibits severe non-stationarities, as e.g., large fluctuations in amplitude over time. In this case, it is as effective as a Butterworth notch filter in removing the artifact, but likely introduces less distortion in the time domain.

Limitations of the current study are related to the application of the four methods to the EEG datasets, since the “ground truth” of a clean signal without power line noise was unknown here. Hence the RMSE compared to a noise free signal cannot be computed and the evaluation of the performance of the different approaches is limited to the visualization of the ERPs and the computation of the RMSE is restricted to a relative comparison of the notch- and DFT-filtered signal to the spectrum-interpolated signal. The quantification of the superior performance of spectrum interpolation over the DFT filter was only possible by applying it to artificially simulated power line noise added to line-noise-free MEG data.

The relevance of time domain signal distortions (demonstrated here for synthetic test signals) might differ strongly between studies, depending on the measures of interest and many other parameters. Therefore it should be evaluated individually to what extent the time domain signal distortions presented here are of relevance for the different types of analysis (as, e.g., ERP/ERF or phase and connectivity measures). For the current study, we applied the Butterworth filter that is commonly applied when sharp cutoffs in the frequency response are required, but other filter types might show less signal distortions in the time domain than the Butterworth filter. Therefore the demonstrated superior performance of spectrum interpolation with respect to time domain signal distortions is limited to the comparison with the Butterworth filter.

A further limitation of the study is that the application of CleanLine involves the complex interplay of many parameters that can be adjusted by the user. We attempted to select parameters that improved performance as much as possible, but it may be the case that different parameters could have yielded better performance. Since the developers already demonstrated that one shortcoming of CleanLine is that it might fail with large non-stationary artifacts, we believe that there is no substantial improvement possible with this specific type of high amplitude power line noise (Bigdely-Shamlo et al., 2015).

By visualizing ERPs of real EEG data, we were able to demonstrate cases where the application of CleanLine and the DFT filter clearly fails to remove power line noise, while spectrum interpolation is capable of removing this artifact and performs as well as a notch filter. At the same time the synthetic test signals revealed that undesired filter distortions as they occur with a notch filter are reduced with spectrum interpolation, considering the

Europe PMC Funders Author Manuscripts

impulse signal and the Gaussian-shaped test signal. Since the Gaussian-shaped test signal mimics the ERP/ERF components occurring in almost all neurophysiological signals it is especially notable that spectrum interpolation performs better than the Butterworth notch filter. A further advantage of spectrum interpolation over notch filtering is that it does not affect frequencies in the passband, preserving spectral energy of frequencies outside the stopband.

However, CleanLine showed the best performance with respect to signal distortions in the time domain in synthetic test signals. In many cases time domain regression-based methods as, e.g., CleanLine might be preferable over a notch filter or spectrum interpolation, since they only remove deterministic line components, inducing almost no time domain signal distortions (Bigdely-Shamlo et al., 2015; Widmann et al., 2014). Since CleanLine incorporates a sliding window estimation, it also allows for non-stationarities in the phase and amplitude of the line noise component to a certain extent (Bigdely-Shamlo et al., 2015). But if non-stationarities are especially strong, as, e.g., with amplitude fluctuations of line noise as large as in the presented EEG and MEG data, CleanLine may fail to remove line noise interference. In these scenarios, the line noise removal of spectrum interpolation is superior to the CleanLine approach and the DFT filter, while the risk of signal distortions in the time domain seems to be relatively reduced in comparison to a notch filter. The artifact removal approach should be carefully selected in each case according to the measures of interest and the nature of the power line noise.

The code for the spectrum interpolation approach introduced here has been made available in FieldTrip, an open source MEG/EEG analysis toolbox (http://fieldtriptoolbox.org; Oostenveld et al., 2011).

5 Conclusions

Power line noise is a pervasive artifact in MEG and EEG data that cannot always be satisfactorily reduced by shielding the recording environment. Typical filter approaches to remove this type of artifact come at the risk of introducing ringing or other signal distortions that can lead to spurious effects or may not be effective for longer data segments. In addition, some of these approaches, such as the DFT filter and the CleanLine method, are not capable of removing non-stationary line noise interference of high magnitude. Here we demonstrate how spectrum interpolation can be used as an alternative approach to also effectively reduce non-stationary power line noise in MEG and EEG data, while undesired signal distortions in the time domain are reduced compared to the Butterworth notch and the DFT filter.

Acknowledgments

The authors gratefully acknowledge Jonathan L. Lilje for acquisition and pre-processing of the EEG datasets, as well as Mathis Kaiser and Michael Morgenroth for acquisition of the MEG dataset. This work was supported by the European Research Council (Starting Grant 640448 to SSD) and the Zukunftskolleg of the University of Konstanz.

Abbreviations

MLR	Middle Latency Response

SWS	Slow Wave Sleep
nRMSE	normalized root mean squared error

References

Acunzo DJ, MacKenzie G, van Rossum MCW. Systematic biases in early ERP and ERF components as a result of high-pass filtering. J Neurosci Methods. 2012; 209:212–218. DOI: 10.1016/j.jneumeth.2012.06.011 [PubMed: 22743800]

Barnett L, Seth AK. Behaviour of Granger causality under filtering: Theoretical invariance and practical application. J Neurosci Methods. 2011; 201:404–419. DOI: 10.1016/j.jneumeth.2011.08.010 [PubMed: 21864571]

Bigdely-Shamlo N, Mullen T, Kothe C, Su K-M, Robbins KA. The PREP pipeline: standardized preprocessing for large-scale EEG analysis. Front Neuroinform. 2015; 9:1–20. DOI: 10.3389/fninf.2015.00016 [PubMed: 25750622]

Brezinski C. Extrapolation algorithms for filtering series of functions, and treating the Gibbs phenomenon. Numer Algorithms. 2004; 36:309–329. DOI: 10.1007/s11075-004-2843-6

Buch ER, Modir Shanechi A, Fourkas AD, Weber C, Birbaumer N, Cohen LG. Parietofrontal integrity determines neural modulation associated with grasping imagery after stroke. Brain. 2012; 135:596–614. DOI: 10.1093/brain/awr331 [PubMed: 22232595]

De Vos M, Kroesen M, Emkes R, Debener S. P300 speller BCI with a mobile EEG system: comparison to a traditional amplifier. J Neural Eng. 2014; 11:036008.doi: 10.1088/1741-2560/11/3/036008 [PubMed: 24763067]

Debener S, Minow F, Emkes R, Gandras K, de Vos M. How about taking a low-cost, small, and wireless EEG for a walk? Psychophysiology. 2012; 49:1617–1621. DOI: 10.1111/j.1469-8986.2012.01471.x [PubMed: 23013047]

Fay TH, Kloppers PH. The Gibbs' phenomenon. Int J Math Educ. 2001; 32:73–89. DOI: 10.1080/00207390150207077

Fiebelkorn IC, Snyder AC, Mercier MR, Butler JS, Molholm S, Foxe JJ. Cortical cross-frequency coupling predicts perceptual outcomes. Neuroimage. 2013; 69:126–137. DOI: 10.1016/j.neuroimage.2012.11.021 [PubMed: 23186917]

Gramann K, Ferris DP, Gwin J, Makeig S. Imaging natural cognition in action. Int J Psychophysiol. 2014; 91:22–29. DOI: 10.1016/j.ijpsycho.2013.09.003 [PubMed: 24076470]

Iber, C, Ancoli-Israel, S, Chesson, A, Quan, S. The AASM Manual for the Scoring of Sleep and Associated Events: Rules, Terminology and Technical Specifications. 1st ed. American Academy of Sleep Medicine; Westchester, IL: 2007.

Leclercq Y, Schrouff J, Noirhomme Q, Maquet P, Phillips C. fMRI Artefact Rejection and Sleep Scoring Toolbox. Comput Intell Neurosci. 2011; 2011:1–11. DOI: 10.1155/2011/598206 [PubMed: 21837235]

Luck, SJ. An introduction to the event-related potential technique. MA: Cambridge: MIT Press; 2005.

Makeig S, Gramann K, Jung TP, Sejnowski TJ, Poizner H. Linking brain, mind and behavior. Int J Psychophysiol. 2009; 73:95–100. DOI: 10.1016/j.ijpsycho.2008.11.008 [PubMed: 19414039]

Mewett DT, Reynolds KJ, Nazeran H. Reducing power line interference in digitised electromyogram recordings by spectrum interpolation. Med Biol Eng Comput. 2004; 42:524–531. DOI: 10.1007/BF02350994 [PubMed: 15320462]

Mullen, T; NTRC. CleanLine. 2012. Tool/Resource Info [WWW Document]. URL https://www.nitrc.org/projects/cleanline/

Oostenveld R, Fries P, Maris E, Schoffelen J-M. FieldTrip: Open source software for advanced analysis of MEG, EEG, and invasive electrophysiological data. Comput Intell Neurosci. 2011; 2011doi: 10.1155/2011/156869

Picton TW, Hillyard SA, Krausz HI, Galambos R. Human auditory evoked potentials. I: Evaluation of components. Electroencephalogr Clin Neurophysiol. 1974; 36:179–190. DOI: 10.1016/0013-4694(74)90155-2 [PubMed: 4129630]

Europe PMC Funders Author Manuscripts

Rousselet GA. Does filtering preclude us from studying ERP time-courses? Front Psychol. 2012; 3:1–9. DOI: 10.3389/fpsyg.2012.00131 [PubMed: 22279440]

Schomer, DL, Lopes da Silva, FH. Niedermeyer's Electroencephalography: basic principles, clinical applications, and related fields. Lippincott Williams & Wilkins; Philadelphia: 2011.

Smith, SW. The Scientist and Engineer's Guide to Digital Signal Processing. California Technical Publishing San Diego; CA, USA, San Diego: 1997. ©1997

VanRullen R. Four Common Conceptual Fallacies in Mapping the Time Course of Recognition. Front Psychol. 2011; 2doi: 10.3389/fpsyg.2011.00365

Widmann A, Schröger E. Filter Effects and Filter Artifacts in the Analysis of Electrophysiological Data. Front Psychol. 2012; 3:1–5. DOI: 10.3389/fpsyg.2012.00233 [PubMed: 22279440]

Widmann A, Schröger E, Maess B. Digital filter design for electrophysiological data – a practical approach. J Neurosci Methods. 2014; 250:34–46. DOI: 10.1016/j.jneumeth.2014.08.002 [PubMed: 25128257]

Zander TO, Jatzev S. Context-aware brain-computer interfaces: exploring the information space of user, technical system and environment. J Neural Eng. 2012; 9:016003.doi: 10.1088/1741-2560/9/1/016003 [PubMed: 22156069]

Zoefel B, Heil P. Detection of near-threshold sounds is independent of eeg phase in common frequency bands. Front Psychol. 2013; 4:1–17. DOI: 10.3389/fpsyg.2013.00262 [PubMed: 23382719]

Europe PMC Funders Author Manuscripts

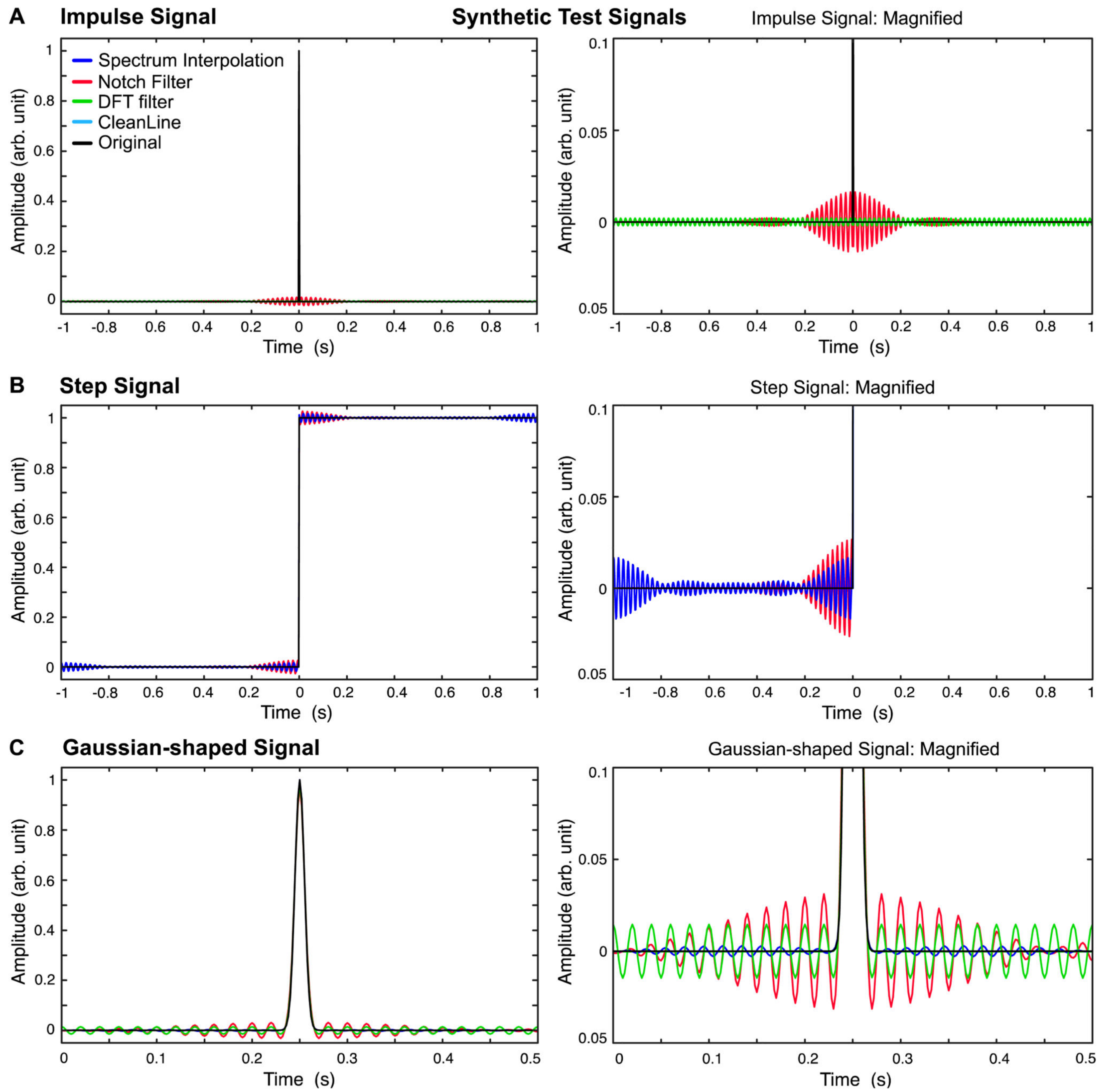

Figure 1.

The synthetic test signals that were used to compare signal distortions in the time domain incorporated A) a unit impulse signal, B) a unit step signal and C) a Gaussian-shaped curve to mimic the ERP/F case (magnified views on the right). The original signal is shown in black, the spectrum interpolated (48-52 Hz) signal in blue, the DFT filter (50 Hz) in green, the notch filtered (48-52 Hz) signal in red and the signal after the application of CleanLine (48-52 Hz) in light blue. The impulse and the Gaussian-shaped signals reveal the largest signal distortions for the notch filter (Butterworth), followed by the DFT filter, while spectrum interpolation shows the smallest distortions apart form CleanLine. Please note that CleanLine did not affect the signal in case of the impulse and step signal (and showed almost no effect in case of the Gaussian-shaped signal) and therefore shows no difference to the original test signal.

Europe PMC Funders Author Manuscripts

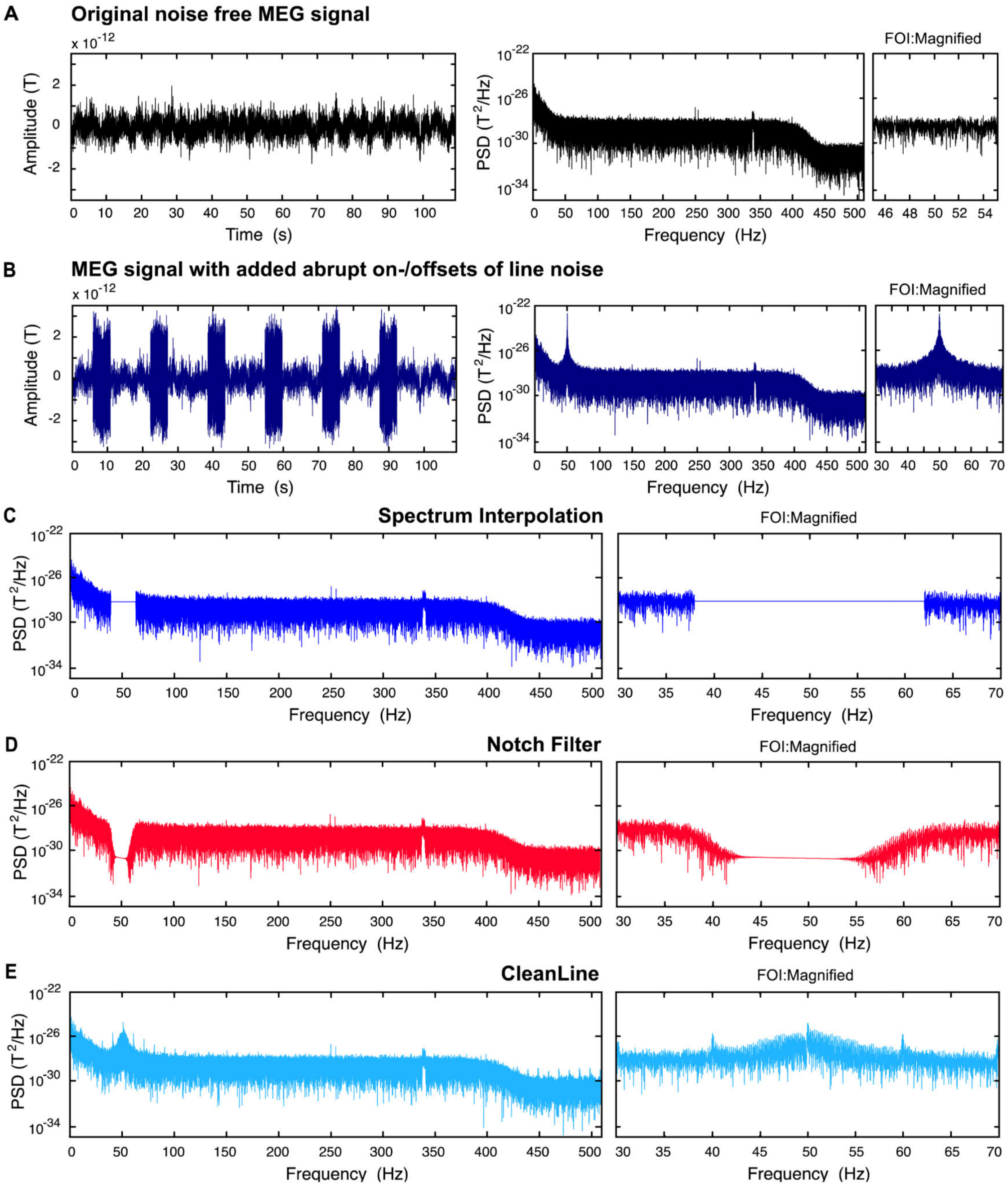

Figure 2.

Original MEG signal and MEG signal with added simulated abrupt on- and offsets of line noise interference. A) Example time series of the line-noise-free original MEG raw data and the respective power spectral density (PSD, Log scale). The frequencies of interest (FOI) around line noise interference are shown in a magnified view on the right. B) Time series of the simulated line noise with abrupt on- and offsets added to the original noise free MEG signal are shown and the respective power spectrum, with a magnified view of the FOI (right panel). C) PSD of the signal after the application of spectrum interpolation (blue) D) a notch filter (Butterworth, red) and E) the regression based method CleanLine (light blue) reveal that spectrum interpolation and the notch filter attenuate power line noise to a sufficient extent, while CleanLine does not. All magnified views of the FOI are shown on the right side.

Europe PMC Funders Author Manuscripts

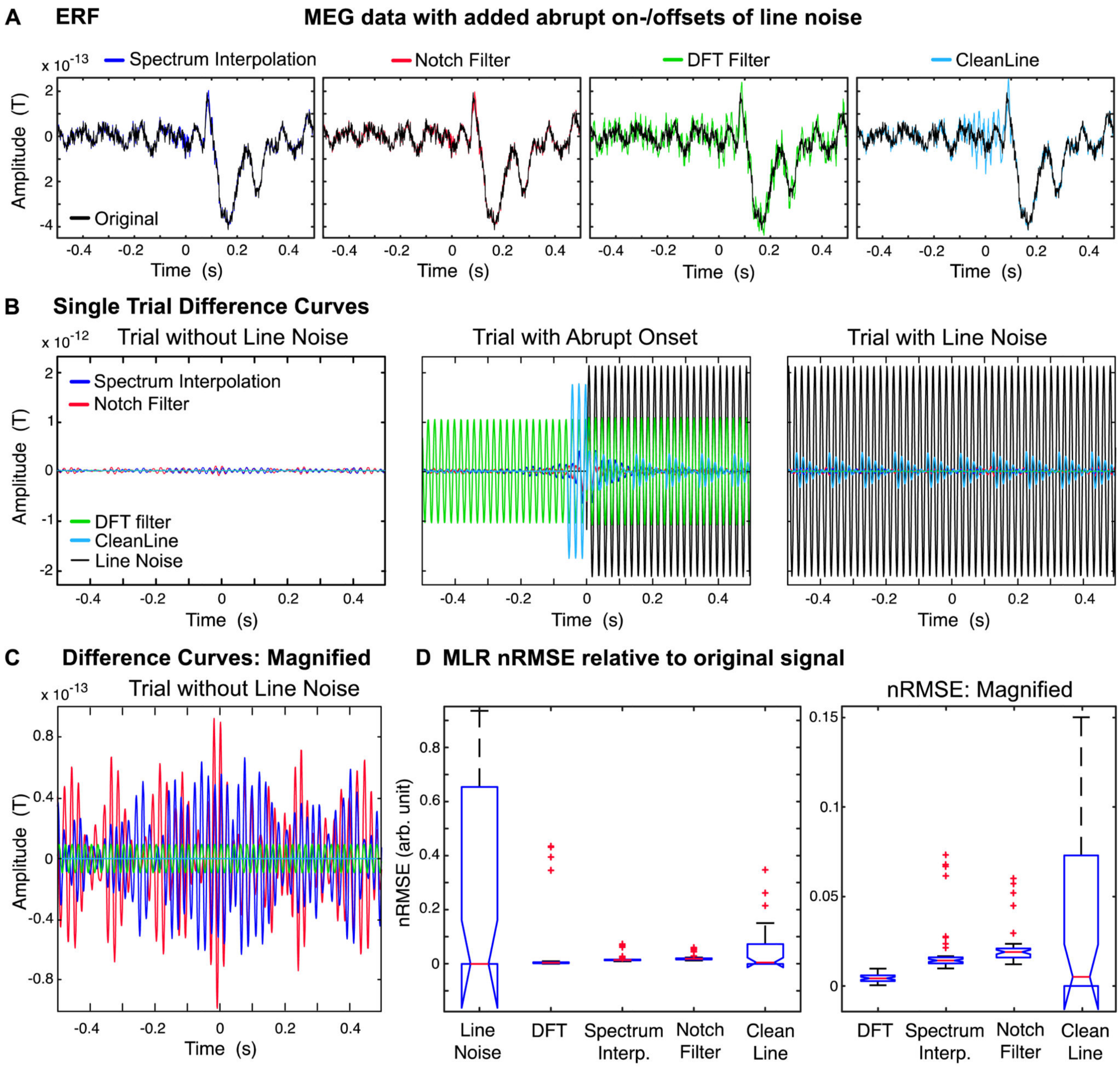

Figure 3.

MEG signal with added simulated abrupt on- and offsets of line noise interference. A) ERF (here the MLR) after the application of spectrum interpolation (blue, first panel), the notch filter (red, second panel), the DFT filter (green, third panel), CleanLine (light blue, fourth panel) and for the original noise-free MEG signal (black, all panels). There is residual line noise for the DFT filter and CleanLine. B) Single trial difference curves (relative to the original MEG signal) after the application of all four methods reveal signal distortions in the time domain with different magnitude. CleanLine shows the largest deviation from the original signal during time segments of line noise and around the abrupt onset, while C) the notch filter and spectrum interpolation show larger deviations during line-noise-free time segments (magnified view of the first trial). D) The boxplot of the nRMSE relative to the original data reveals that over all single trials of the MLR component CleanLine shows the largest signal distortion, followed by the notch filter (Butterworth), spectrum interpolation and the DFT filter. The magnified view of the boxplot is shown on the right.

Europe PMC Funders Author Manuscripts

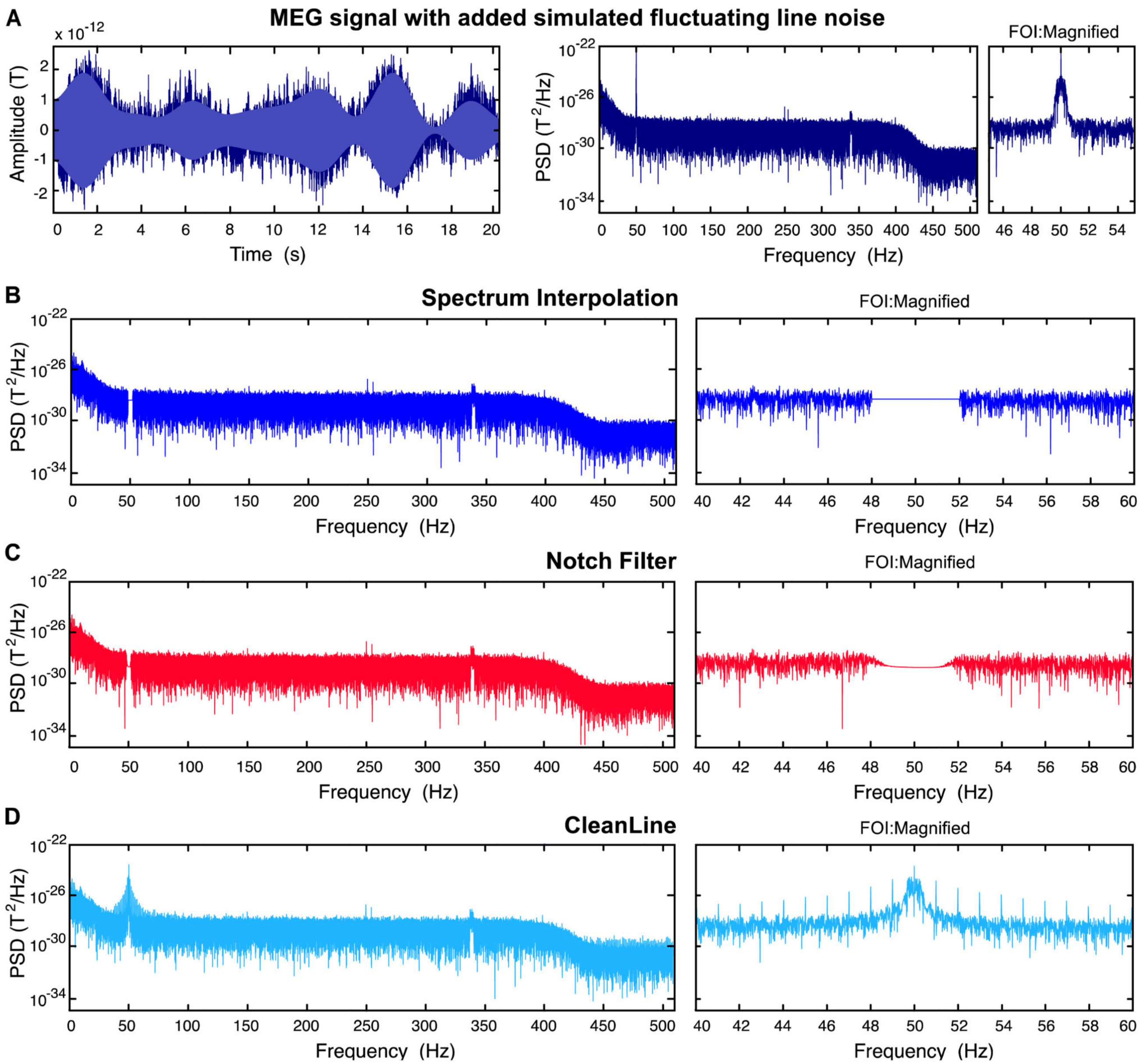

Figure 4.

MEG signal with added simulated fluctuating line noise interference. A) Example time series (20 s length) of the simulated amplitude modulated line noise signal (amplitude modulation in a lighter blue) mixed with the original MEG signal (mixed signal in dark blue) and the respective power spectrum (PSD, Log scale, right panel). The magnified view of the FOI is shown on the right. B) PSD (Log scale) after the application of spectrum interpolation (blue), C) the notch filter (red) and D) after the application of CleanLine (light blue) reveal that spectrum interpolation and notch filtering attenuate line noise interference, while CleanLine is not able to attenuate it to a sufficient extent. All magnified views of the FOI are shown on the right.

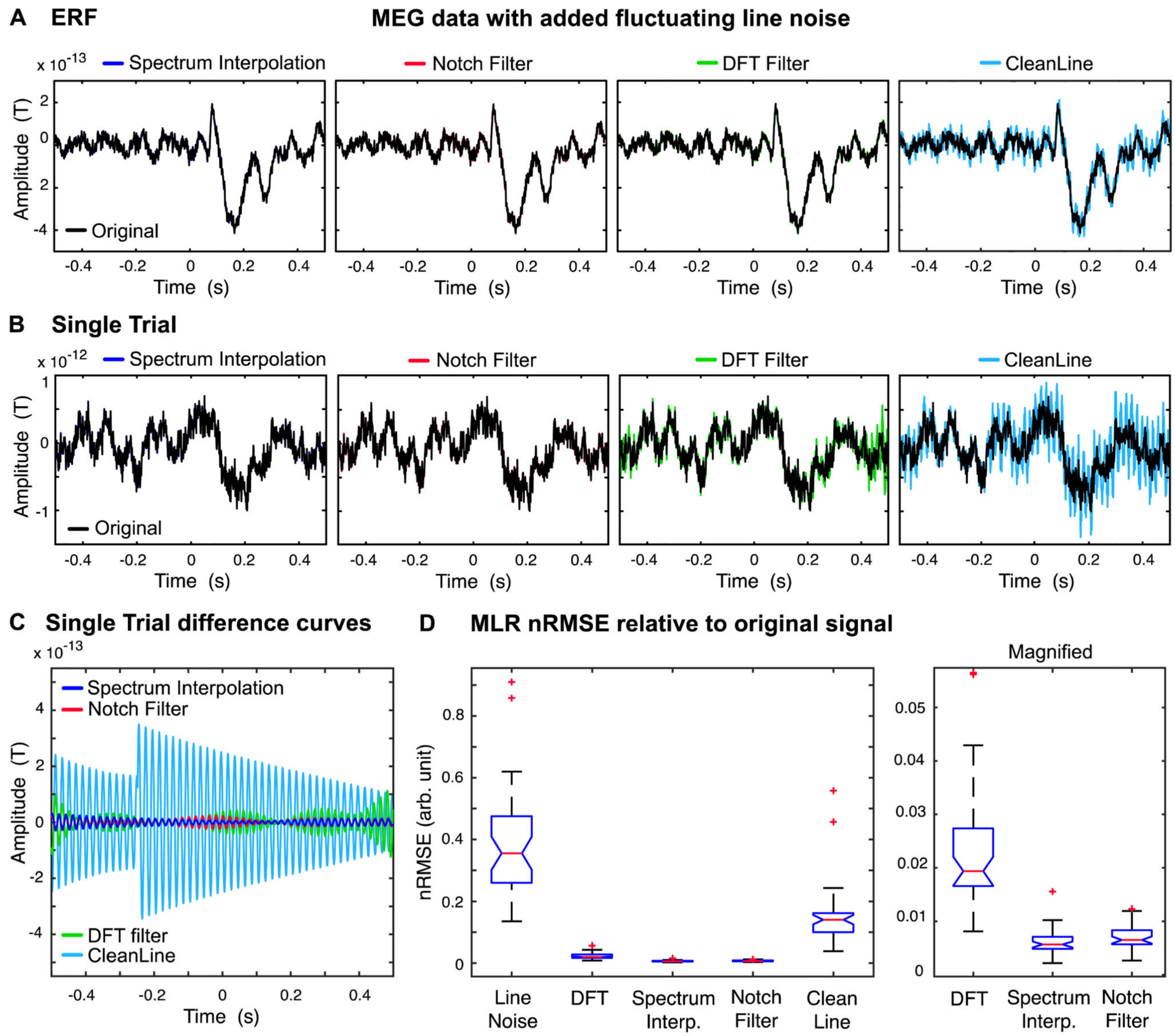

Figure 5.

MEG signal with added simulated fluctuating line noise interference. A) The ERFs (here the MLR) after the application of spectrum interpolation (blue, first panel), the notch filter (red, second panel), the DFT filter (green, third panel), CleanLine (light blue, fourth panel) and for the original noise-free MEG signal (black, all panels) reveal residual line noise interference after the application of CleanLine. B) An example trial reveals also substantial residual line noise after DFT filtering (in addition to CleanLine), only visible on a single trial level. C) The single trial difference curves (relative to the original MEG signal) for the same trial show the signal distortions in the time domain more clearly. D) The boxplot of the nRMSE (arbitrary units) relative to the original data reveals that over all single trials of the MLR component, CleanLine shows the largest signal distortion followed by the DFT filter.

Spectrum interpolation shows a slightly better performance than the notch filter (Butterworth). The magnified view of the boxplot is shown on the right.

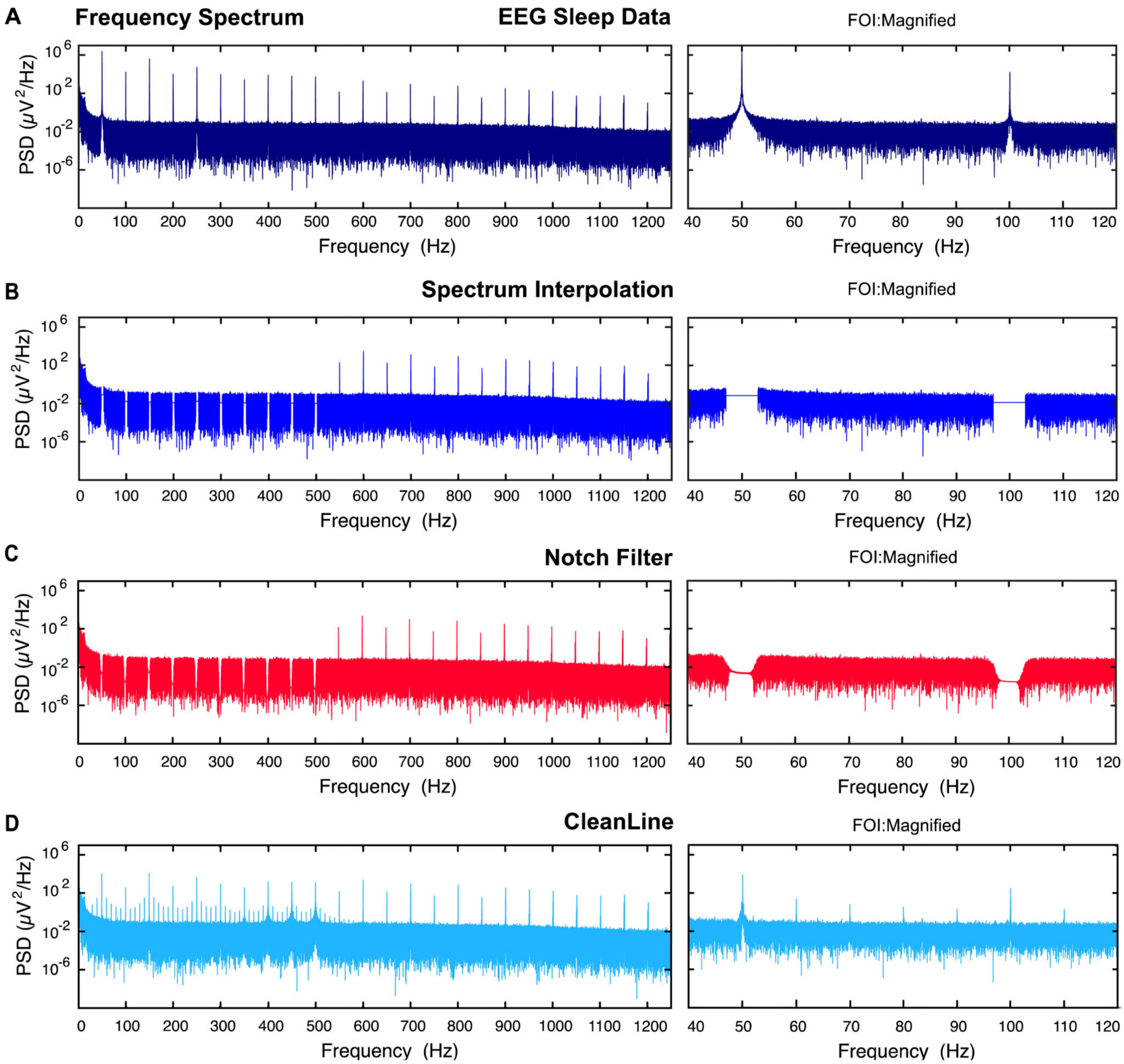

Figure 6.

Example segment for EEG sleep data with massive power line noise due to acquisition in unshielded settings. A) The power spectra (PSD, Log scale) of the original EEG signal (dark blue) and B) after the application of spectrum interpolation (blue), C) a notch filter (red) and D) the regression based method CleanLine (light blue) reveal that spectrum interpolation and the notch filter attenuate power line noise to a sufficient extent. CleanLine does not attenuate the line noise interference sufficiently while even adding artificial components in the frequency domain. All magnified views of the FOI are shown on the right side.

Europe PMC Funders Author Manuscripts

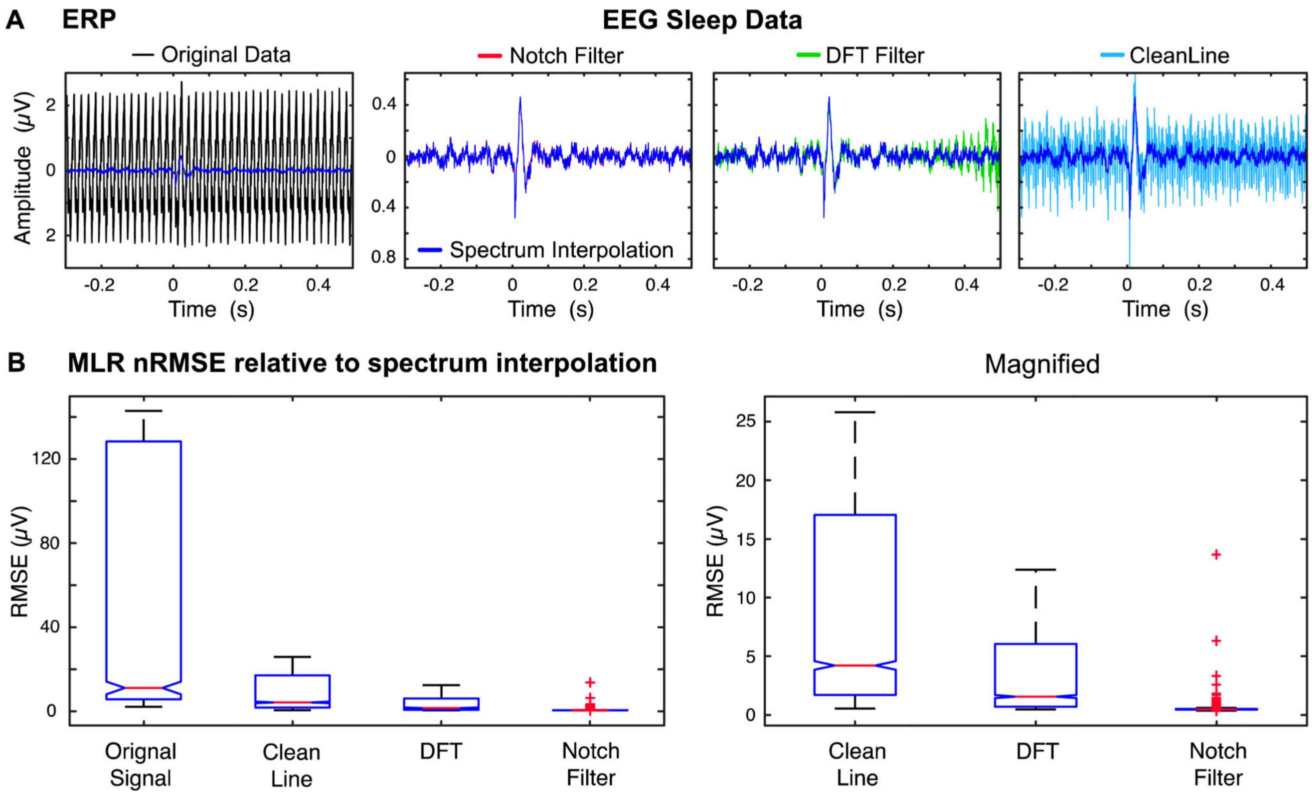

Figure 7.
Example segment for EEG sleep data with massive power line noise due to acquisition in unshielded settings. A) The ERFs of the original noisy EEG signal (black), after the application of the notch filter (red, second panel), the DFT filter (green, third panel), CleanLine (light blue, fourth panel) and for the spectrum interpolated signal (blue, all panels) reveal residual line noise interference after the application of the DFT filter and CleanLine. B) The boxplot of the RMSE relative to the spectrum interpolated data reveals that over all single trials CleanLine shows the lowest performance, followed by the DFT filter. The notch filter (Butterworth) and spectrum interpolation show the best performance, with almost no differences. The magnified view of the boxplot is shown on the right.