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A novel method for removal of deep brain stimulation artifact from electroencephalography

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HIGHLIGHTS

- DBS causes artifacts in EEG that preclude meaningful brain activity from being quantified.
- We modeled the DBS stimulation artifact as a series of narrow band components.
- We illustrated a technique for removing the stimulation artifact from EEG using matched filters.
- The technique was validated using synthetic DBS artifacts superimposed on EEG data.
- The technique successfully removed DBS artifacts for typical stimulation and recording setups.

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ABSTRACT

Background: Deep brain stimulation (DBS) has treatment efficacy in neurological and psychiatric disorders such as Parkinson's disease and major depression. Electroencephalography (EEG) is a versatile neurophysiological tool that can be used to better understand DBS treatment mechanisms. DBS causes artifacts in EEG recordings that preclude meaningful neurophysiological activity from being quantified during stimulation.

New method: In this study, we modeled the DBS stimulation artifact and illustrated a technique for removing the artifact using matched filters. The approach was validated using a synthetically generated DBS artifact superimposed on EEG data. Mean squared error (MSE) between the recovered signal and the artifact-free signal was used to quantify the effectiveness of the approach.

Results: The DBS artifact was characterized by a series of narrow band components at the harmonic frequencies of DBS stimulation. The filtering approach successfully removed the DBS artifact with MSE value being less than 2% of base signal power for the typical stimulation and recording setups. General guidelines on how to setup DBS EEG studies and configure the subsequent artifact removal process are described.

Comparison with previous method: To avoid stimulus artifacts, a number of EEG studies with DBS subjects have resorted to turning the stimulator off during recording, while other studies have used low pass filters to remove artifacts and look at frequencies well below 50 Hz.

Conclusions: This study establishes a method through which DBS artifact in EEG recordings can be reliably eliminated, thereby preserving a meaningful neurophysiological signal through which to better understand DBS treatment mechanisms.

1. Introduction

Deep brain stimulation (DBS) is becoming an effective treatment option for medication resistant neurological and psychiatric disorders. It is an approved treatment for late stage Parkinson's disease (Deuschl et al., 2006) and has shown therapeutic efficacy for treatment resistant depression (Holtzheimer et al., 2012; Kennedy et al.,

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2011). While clinical studies have established the efficacy of DBS, its treatment mechanisms are not yet understood. Electroencephalography (EEG) is a versatile neurophysiological tool that can be used to better understand DBS treatment mechanisms. However, DBS stimulation creates large amplitude artifact in the recorded EEG. To avoid this artifact, some clinical studies have resorted to turning the stimulator off during recording (Broadway et al., 2012; Kuhn et al., 2008), which is an approach that cannot assess the direct neurophysiological effects of DBS.

For removing DBS artifacts from EEG signals recorded with the DBS stimulator ON, several studies have applied filters online or offline with a low pass cutoff below the frequency of stimulation. For example, in one study, EEG data was recorded from subjects with their DBS stimulators set at frequencies ranging from 100 Hz to 185 Hz. To remove the artifacts, a 0.5–100 Hz bandpass filter was applied online during recording and a 50 Hz low pass filter was applied offline (Cavanagh et al., 2011). In another study, EEG data was recorded with DBS stimulators set at 130 Hz, 160 Hz or 185 Hz. No online bandpass filter was described, but a 50 Hz low pass filter was applied offline (Swann et al., 2011). In both cases, the assumption was that the artifact components generated by the DBS was entirely located in the high frequency range above the low pass filter cut off. As will be discussed in this paper, this assumption does not hold for all DBS stimulation setup and signal acquisition parameters. In fact, some DBS studies have reported artifact components in the recorded EEG below the frequency of stimulation, which is likely due to aliasing (Allen et al., 2010; Jech et al., 2006). Aliasing can occur if an appropriate low pass filter is not applied prior to data acquisition (Oppenheim and Schafer, 1999). Assuming that these studies did apply a low pass filter before sampling, the results suggest that the filters were not sufficient to remove artifact components prior to sampling.

Online low pass filters provided by many EEG systems are not configured to remove artifacts with narrow band components several times in amplitude higher than the background EEG. This is the challenge when dealing with EEG recordings with active DBS stimulation. Therefore, even if low pass filtering is adequate for examining neuronal activity in the theta or beta frequency range of previous studies, a more generalized artifact rejection approach would be necessary, especially for studies that are interested in brain oscillations up to 80 Hz or more. Successful attempts to extract DBS artifiacts have been done in magnetoencephalography studies looking at the effect of active DBS stimulation in Parkinson's patients (Airaksinen et al., 2011; Park et al., 2009).

In this study, we aimed to fully characterize the DBS stimulation artifact and develop a better method to remove it while preserving the underlying neurophysiological signal. Since DBS stimulation is periodic with a set frequency, the artifact waveform can be well approximated by a set of sinusoidal components located at predicted frequencies (Oppenheim and Schafer, 1999). Moreover, by knowing the signal acquisition parameters used in a study, the frequency of aliased components for the artifact can also be predicted. With our understanding of the DBS artifact waveform, we propose using the method of the matched filter to remove the narrow band components, which would not affect the underlying base signal that spans a broad frequency range. To evaluate the filtering approach, synthetic stimulator ON data with a known base signal is used. This can be done by adding a simulated DBS artifact to an existing EEG recording. After filtering the synthetic ON data, the recovered signal can then be compared with the original base signal to quantify the difference. To establish the general utility of the approach, simulation tests were run with DBS artifacts simulated in two different ways: (1) synthetically reconstructing the DBS artifact using a series of additive sinusoidal components at frequencies observed experimentally; (2) using the actual mathematical equation which describes the DBS pulse generated by the stimulator and filtering this signal. The precise methodology will be described later. These simulated artifacts were added to real EEG signals obtained from both a resting condition as well as a task condition to form the base signals used to evaluate our artifact removal algorithm.

2. Materials and methods

2.1. DBS artifact characterization

Given that DBS treatment involves repetitive stimulation, the artifact signal can be well approximated by a set of sinusoidal components. The frequencies of the sinusoidal components or natural harmonics (f_{harmonic}) are integer multiples of the stimulation frequency (f_{stim}) (see Eq. (1)). For example, if the stimulation is at 130 Hz, then sinusoidal components would be expected at 130 Hz, 260 Hz, 390 Hz, etc. (see Fig. 1).

$$f_{\text{harmonic}} = nf_{\text{stim}}, \quad n = 1, 2, 3, \ldots \tag{1}$$

In addition to the natural harmonics, frequencies of possible aliased artifacts in an EEG recording can be determined when given the sampling frequency (F_s). Frequencies of the aliased artifacts can be calculated by first taking integer multiples of the sampling frequency (F_s), then adding or subtracting integer multiples of the stimulation frequency (f_{stim}), and finally checking which of the resulting frequencies fall within the captured signal bandwidth from 0 to $F_s/2$ (see Eq. (2)). For example, if the stimulation frequency is set at 130 Hz and the data is sampled at 1000 Hz, then aliased components would be expected at 480, 350, 220, 90, 40, 170, 300, and 430, which are calculated from the first integer multiple of F_s. Likewise, aliased components at 440, 310, 180, 50, 80, 210, 340,

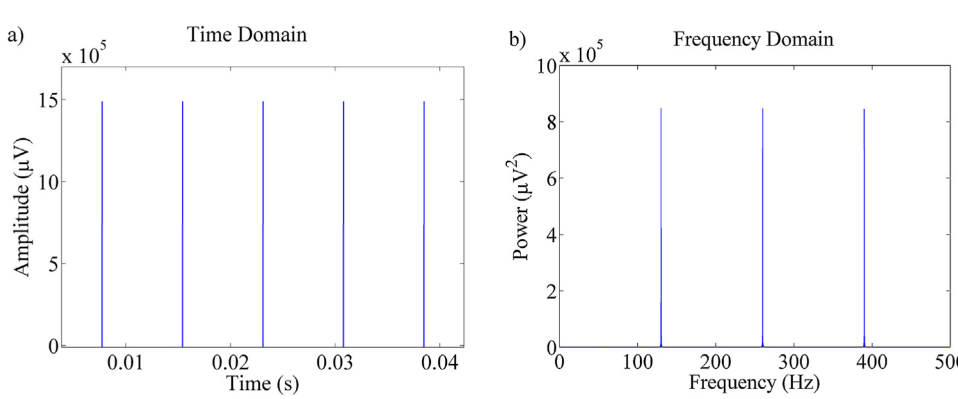

Fig. 1. Ideal DBS signal with frequency set at 130 Hz frequency, 1.5 V amplitude, and 60 μs square wave pulses plotted in (a) time domain, and (b) frequency domain.

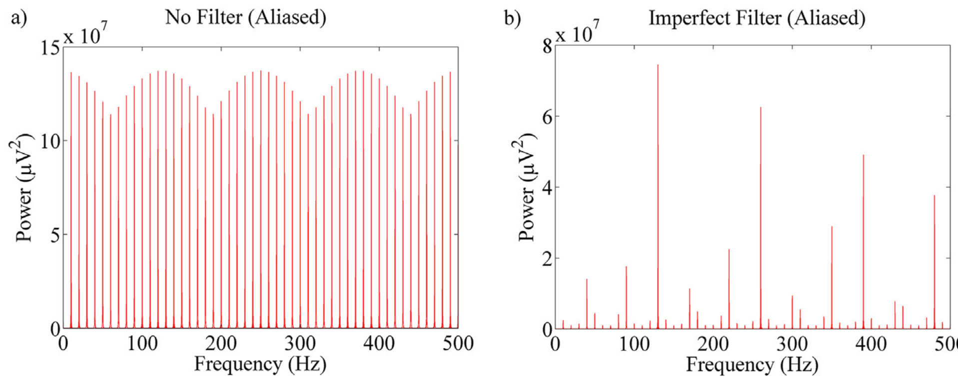

Fig. 2. Ideal DBS 130 Hz signal sampled at 1000 Hz (a) with no filter and (b) with a 500 Hz low pass filter (1st order Butterworth).

and 470 would be expected from harmonics of the second integer multiple of F_s.

$$f_{alias} = |mF_s - nf_{stim}| \quad \text{if } |mF_s - nf_{stim}| \le F_s/2 \quad m = 1, 2, 3, \ldots n = 1, 2, 3, \ldots \tag{2}$$

The contaminating effect of the aliased components depend on its original amplitude and the effectiveness of the anti-aliasing filter applied before sampling. In theory, there should be no aliased artifacts if an ideal low pass filter with cutoff at $F_s/2$ is applied prior to sampling. However, real filters can only suppress the harmonic components partially, with the level of attenuation increased for higher frequency components. If harmonic components above $F_s/2$ are not sufficiently suppressed to be considered negligible, then aliased components can still appear when the signal is sampled, albeit with a smaller amplitude than the case without a filter (see Fig. 2). For further explanations of aliasing, please refer to supplementary Fig. S1 and the fourth chapter of *Discrete-Time Signal Processing* (Oppenheim and Schafer, 1999).

Supplementary Fig. S1 related to this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jneumeth.2014.09.002.

2.2. Filtering approach

DBS artifact components are sinusoidal and can be expressed in the form of Eq. (3) in a recorded EEG.

$$F(k) = A * \sin\left[2\pi f\left(\frac{k + \Delta k}{F_s}\right)\right] \tag{3}$$

A, signal amplitude; f, artifact frequency; F_s, sampling rate; k, time in terms of samples; Δk, time shift in terms of samples.

One way to remove a pure sinusoidal component is to apply a notch filter centered at the frequency of the sinusoid. A notch filter will attenuate signals, but depending on the strength of the unwanted component, can lead to insufficient attenuation in certain cases and overcorrection in other cases. Moreover, real notch filters have a spectral spread which leads to suppression of surrounding frequencies as well.

In comparison, matched filters offer a more refined approach whereby the amplitude and phase of any sinusoidal component at a predicted frequency is first estimated empirically and then subtracted out (Kay, 1993; Turin, 1960). It is effective when the artifacts to be removed are linearly additive and uncorrelated with the underlying signal, which is true for DBS artifacts. Moreover, it requires that the artifact remain constant in amplitude and phase over the period of subtraction. In this study, a matched filter is applied by calculating the cross-correlation between an EEG signal and a sinusoidal artifact component template in the form of Eq. (3). While the artifact components will appear at frequencies that can be calculated from the stimulation frequency and the sampling rate, it is often better to determine the precise frequency $\hat{f}$ by cross-correlating the EEG signal to a series of sinusoidal waveforms within a narrow range of frequencies around the expected component frequency f. The frequency with the highest cross-correlation value ($corr_{\max}$) gives the frequency of the artifact component with highest precision. To find the highest cross-correlation value between the raw EEG signal and a template waveform, cross-correlation values at indices between $L - \left\lceil \frac{1}{2}\frac{F_s}{f} \right\rceil$ and $L + \left\lceil \frac{1}{2}\frac{F_s}{f} \right\rceil$ are examined. L is the length of the signal and also the middle point of the cross-correlation indices, while F_s/f is the number of samples per cycle for the template waveform. The ceiling function $\lceil\,\rceil$ is applied to ensure that the index for the search is an integer. This procedure can be repeated to get a higher precision for the matched artifact frequency $\hat{f}$ by searching through frequencies that differ by smaller intervals. In this exploration, the procedure was repeated twice to obtain a precision of 0.01 Hz.

The cross-correlation procedure also allows us to find the amplitude (A) and time shift in terms of samples (Δk). The amplitude of the artifact is proportional to the maximum correlation value ($corr_{\max}$) and can be calculated based on Eq. (4), assuming that the template waveform is a sinusoid:

$$A = 2 * \frac{corr_{\max}}{L} \tag{4}$$

The time shift Δk is derived from the relative location ($ibest$) of the maximum cross-correlation value at the optimal frequency $\hat{f}$ (see Eq. (5)).

$$\Delta k = \left\lceil \frac{1}{2}\frac{F_s}{\hat{f}} \right\rceil - ibest + 1 \tag{5}$$

A positive Δk represents a time advance of the template waveform relative to the raw EEG signal. Once the frequency, amplitude, and time shift of the artifact component are determined, we subtract it from the raw EEG signal. A critical assumption to this approach is that the artifact component is stationary during the recording period, which is 4096 ms (duration of data epoch) in this study.

2.3. Verification with synthetic data

To evaluate the filtering approach, synthetic DBS ON data with a known base signal was used. This can be done by adding a simulated DBS artifact to an existing EEG recording. After applying the filters to the synthetic DBS ON data, the recovered signal can be compared with the original base signal to quantify the difference. In this study, the difference was quantified by the mean squared error percentage

(MSE%), which was calculated by taking the mean squared error between the original and recovered base signal and then dividing it by the average power of the original signal (see Eq. (6)).

$$\begin{aligned} \mathrm{SE} &= \sum_{i=1}^{n} (X_{\mathrm{recovered}} - X_{\mathrm{original}})^2 \\ \mathrm{MSE\%} &= \frac{\mathrm{SE}}{\sum_{i=1}^{n} (X_{\mathrm{original}})^2} \end{aligned} \tag{6}$$

One of the key factors that affect the ability of filters to separate useful signals from noise (or artifact) is the signal to noise ratio (SNR) which is calculated from the ratio of signal power to noise power (see Eq. (7)). In this case, the signal refers to the base signal and the noise refers to the DBS artifact.

$$\mathrm{SNR} = \frac{\mathrm{Power}_{\mathrm{Base\ signal}}}{\mathrm{Power}_{\mathrm{DBS\ artifact}}} \tag{7}$$

The variation of MSE% as a function of SNR is useful for predicting the effectiveness of artifact rejection under different experimental conditions.

2.4. Description of test dataset

The EEG recordings obtained from a study examining the effects of DBS stimulation for patients with major depressive disorder were used. The recordings were collected using a 64-channel Synamp2 amplifier system (Neuroscan) with 1000 Hz sampling rate and an online bandpass filter of 0.3–200 Hz. Subjects were tested with the DBS stimulator ON and OFF, during which they were either at rest with eyes closed or performing n-back working memory tasks (Barr et al., 2009). Data from five different subjects were used, which included resting EEG data and 3-back EEG data. The DBS stimulation frequency for all subjects was set at 130 Hz, while other stimulator parameters were optimized individually.

2.5. Description of simulation tests

2.5.1. Simulation with empirically determined DBS artifact

To demonstrate the approach, it is necessary to test with a simulated DBS ON signal that closely matches the actual recorded signal. To achieve this, DBS OFF recording from the dataset was used as the base signal, while the simulated DBS artifact was created with frequency components extracted directly from the Fourier transform of the corresponding DBS ON data (i.e. same subject, task, and recording electrode). The frequencies of the sinusoidal artifact components were calculated from Eqs. (1) and (2) using the various stimulation and recording parameters. Moreover, to minimize the difference in power between the simulated ON data and the associated actual ON data, a scalar multiplier for the artifact components

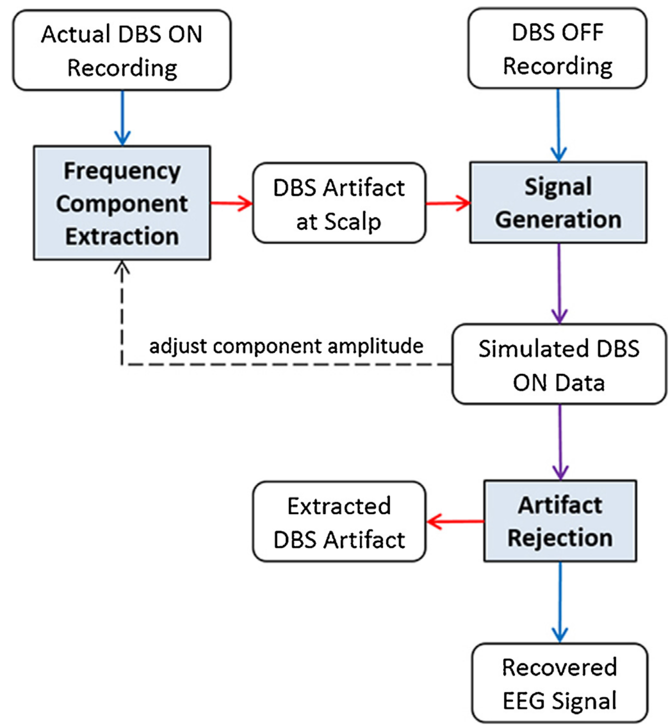

Fig. 3. A flow chart illustrating the simulation process for testing with synthetic data created with empirically derived DBS artifact.

was adjusted for each instance of the simulated signal. Fig. 3 shows the simulation process for testing with the empirically determined DBS pulse. Fig. 4 shows an example comparing the simulated ON data with the actual ON data.

2.5.2. Simulation with theoretically modeled DBS artifact

In the last section, the DBS artifact was determined empirically from a DBS ON recording. This approach to artifact generation is limited however to one particular set of setup parameters. To test the effectiveness of the algorithm over a wider range of DBS parameters, we will need to simulate DBS ON data without the need of a real DBS ON signal. This can be achieved by finding a transfer function that can take in the DBS stimulation parameters and produce the expected response due to the DBS artifact.

In this study, the transfer function was approximated by a series of filters that simulate stages that the DBS signal undergoes before reaching the scalp, which include volume conduction through the head, analog filtering, initial high frequency sampling, and user specified digital filtering and resampling. The filters associated

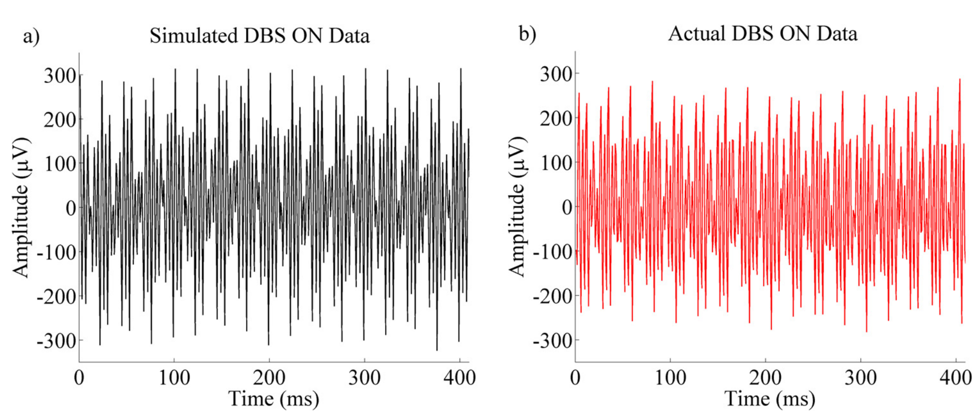

Fig. 4. Comparing (a) simulated DBS ON data to (b) actual DBS ON data.

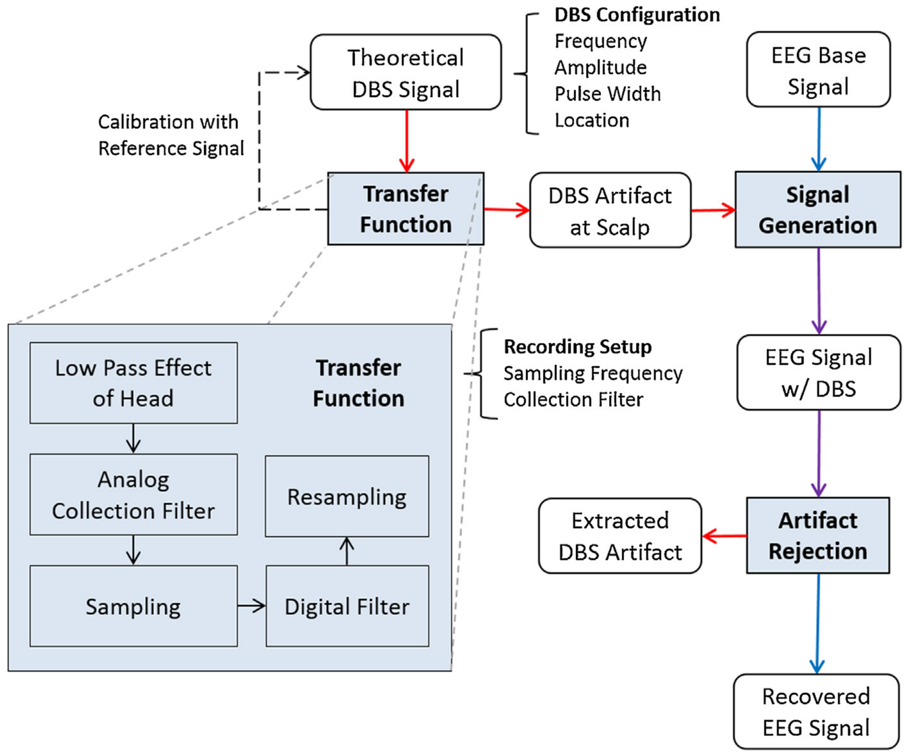

Fig. 5. A flow chart illustrating the simulation process for testing with synthetic data created with DBS artifact predicted by general transfer function.

with the recording of the signal can be fixed based on the manufacture specifications (i.e. analog filtering, initial high frequency sampling) and experimental setup (i.e. user specified digital filtering and resampling). The volume conduction through the head is approximated by a low pass filter based on physiology (Nunez and Srinivasan, 2006). For the remaining additional, unspecified signal attenuation, filters were applied to a simulated ON reference signal with corresponding real DBS ON data and an amplitude parameter was adjusted empirically so that the output signal of the transfer function had matching power as the measured signal. This parameter is then used to calibrate the amplitude. Fig. 5 shows the simulation process for testing with the generalized test setup.

3. Results

Tests were carried out using DBS artifacts created by the two methods described earlier: (1) determined empirically from real EEG data recorded during DBS stimulation, (2) modeled from different combinations of stimulation and signal acquisition parameters.

3.1. Empirically determined DBS artifact

Results from this approach show that the filtering appears to work with the chosen test case. As observed in Fig. 6, the original and recovered signal almost completely overlaps in the time domain and frequency domain. The overall MSE% (fraction of total signal power, see Eq. (7)) was $0.61 \pm 0.55\%$ for all the test cases combined, while the values for individual subject conditions were mostly 1% or less (see Table 1).

Based on the topoplot of the average SNR and MSE% values for all subjects and trials (Fig. 7), the filtering approach works better when the SNR is higher, which is expected. When the MSE% values for the individual trials are plotted against their corresponding SNR values, there is an inverse correlation between the MSE% values and SNR values (see Fig. 8). There is no significant difference between

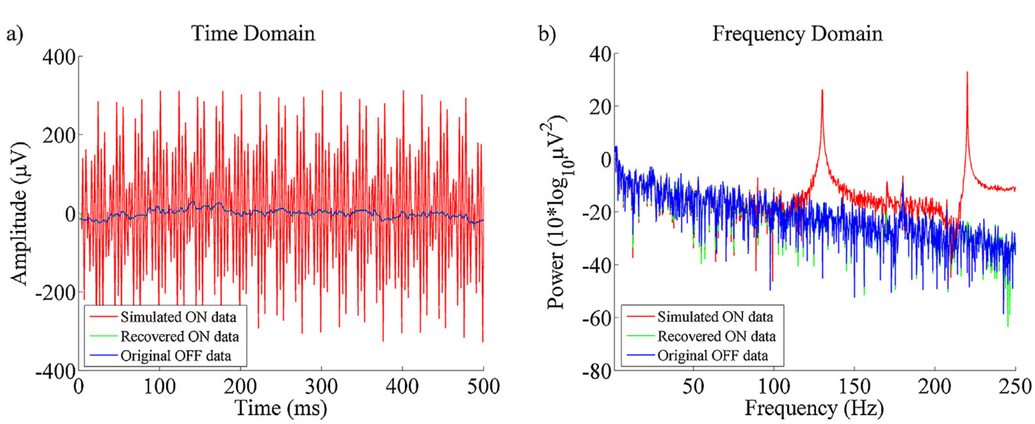

Fig. 6. Sample plot showing the simulated DBS ON data along with the original and recovered base signal in (a) time domain and (b) frequency domain.

Table 1
Performance of filtering approach for test dataset.

Subject	Average SNR		Average MSE%	
	Rest	Task	Rest	Task
1	0.04 ± 0.09	0.04 ± 0.08	0.26 ± 0.13	0.35 ± 0.14
2	0.29 ± 0.87	3.25 ± 16.15	0.40 ± 0.12	0.50 ± 0.21
3	1.10 ± 8.17	0.31 ± 1.53	0.80 ± 0.36	0.61 ± 0.37
4	0.49 ± 1.47	0.69 ± 2.18	0.75 ± 0.42	0.62 ± 0.26
5	0.39 ± 2.82	1.01 ± 4.36	1.08 ± 0.62	0.87 ± 0.65
Overall	0.46 ± 4.37	1.06 ± 8.51	0.66 ± 0.58	0.59 ± 0.54
	0.86 ± 7.40		0.61 ± 0.55	

the effectiveness of the filtering approach for the resting and task related data.

3.2. Synthetically generated DBS artifact

Simulations with synthetically generated DBS artifacts showed that the filtering approach works for a wide range of setup parameters. Parameter values tested are included in Table 2. The choice of values for each parameter is not exhaustive, but does span the range of clinical values.

The test was done exhaustively by varying the parameters one at a time from their 'standard' values of 130 Hz stimulation frequency, 60 us pulse width, 1000 Hz sampling frequency, and 200 Hz collection filter. The analog collection filter and initial sampling rate was chosen based on specifications from the Neuroscan SynAmps 2 system. The volume conduction of the head was modeled by a low pass filter with the cut-off frequency set at the typical upper limit of reliable EEG signals (Cacioppo and Berntson, 2007) (see Table 3). Simulation with the 'standard' values produced a MSE% of 1.32% with an SNR of 0.027.

3.2.1. Effect of stimulation frequency (Table 4a)

Increasing the stimulation frequency slightly increased the SNR. This is likely due to the fact that the main signal peak is more attenuated by the low pass filters used in the transfer function. The MSE% did not deviate much from the average, with the variation coming from the strength of the original signal at the frequencies that the filter was applied. When the power of the original signal is high at the frequency of an artifact component (e.g. 10 Hz aliased harmonic for 165 Hz stimulation), then the filter can cause overcorrection, thereby introducing a small error. A simple way to overcome this is to apply the same filters to all the comparison datasets, thereby avoiding any potential bias arising from the filtering process.

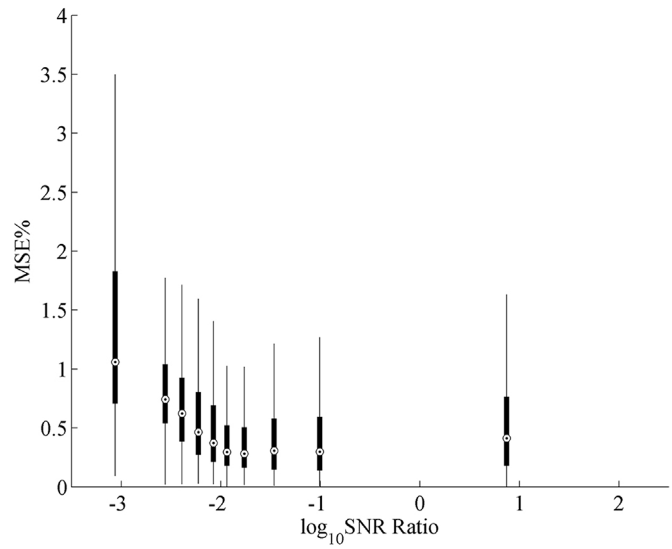

Fig. 8. Box plots showing the MSE% versus SNR values for all conditions sorted into 10 bins with equal number of points. Each box plot is horizontally centered over the range of SNR values included in its bin. The whiskers extend over the range of MSE% values that include 99.3% of the data points in each bin.

Table 2
Variable setup parameters for simulation with theoretical DBS.

Test parameters	Values
Stimulation frequency (Hz)	130–185 by increment of 5
Stimulation pulse width (μs)	60–90 by increment of 10
Sampling frequency (Hz)	1000, 2000, 5000, 10,000
Sampling filter (Hz)	50, 100, 200

Table 3
Fixed setup parameters for the transfer function.

Setup parameters	Specifications
Analog collection filter	Band-pass, 0.5–3500 Hz
Sampling rate	10,000 Hz
Low pass effect of head	Low-pass, 100 Hz

3.2.2. Effect of pulse width (Table 4b)

Increasing the pulse width decreases the SNR. This is expected because a wider pulse width for the artifact translates to a higher power for the DBS artifact. The MSE% stayed constant with fluctuations associated with differences in the SNR value.

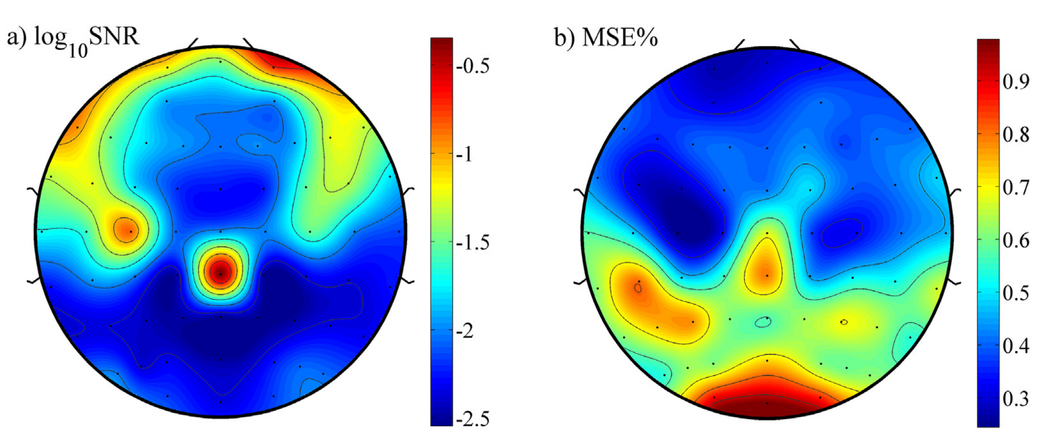

Fig. 7. Topoplots showing (a) SNR and (b) MSE% values averaged across all subjects and trials. While the MSE% is still low for the posterior electrodes, the relative increase in error is due to the decreased SNR ratio.

Table 4
Effect of varying simulation parameters on the performance of filtering approach.

(a) Stimulation frequency

Value (Hz)	SNR	MSE%
130	0.0272	1.318
135	0.0275	0.969
140	0.0277	1.988
145	0.0283	3.388
150	0.0285	1.812
155	0.0294	0.925
160	0.0291	4.483
165	0.0308	1.538
170	0.0317	1.619
175	0.0324	2.105
180	0.0337	2.495
185	0.0350	1.145
Average	0.0301	1.982

(b) Pulse width

Value (μs)	SNR	MSE%
60	0.0272	1.318
70	0.0200	1.428
80	0.0153	1.549
90	0.0121	1.638
Average	0.0187	1.483

(c) Sampling frequency

Value (Hz)	SNR	MSE%
1000	0.0272	1.318
2000	0.0272	1.470
5000	0.0272	1.256
10,000	0.0272	1.742
Average	0.0329	1.447

(d) Sampling filter

Value (Hz)	SNR	MSE%
50	1.1582	2.040
100	0.0968	1.887
200	0.0272	1.318
Average	0.4274	1.748

3.2.3. Effect of sampling frequency (Table 4c)

Given the same base signal, changing the sampling rate did not affect the SNR value. Increasing the sampling rate (i.e. >1000 Hz) for the same setup resulted in no aliased components and therefore only the natural harmonic components were considered for artifact removal. The MSE% values were less than 2% for all conditions.

3.2.4. Effect of sampling filter (Table 4d)

Decreasing the frequency of the sampling filter reduced the SNR. This is expected because the high frequency portion of the DBS ON signal is dominated by DBS artifact components, which are more affected by the low pass filter if the cut-off is set to a lower frequency. The resulting MSE% was 2% or less.

3.2.5. Sample test case

For a sample test case (185 Hz stimulation, 70 us pulse width, 2000 Hz sampling frequency, 100 Hz collection filer), the MSE% was calculated to be 1.540% with SNR of 0.192.

3.3. Comparison with low pass filtering approach

Previous studies have applied low pass filters to avoid DBS artifacts (Cavanagh et al., 2011; Swann et al., 2011). Applying 50 Hz low pass filter to a simulated test signal resulted in a MSE% of 2.240%. When matched filters were applied to the same signal before low pass filtering, the resulting MSE% was 0.802%, which is more than a factor two improvement.

3.4. Optimized approach

While matched filters are more effective at removing DBS artifact components than notched filters, the two can be used in tandem in the case of large amplitude frequency components. Using a sample test case, it was found that only applying notch filters to predicted frequency components resulted in a MSE% of 6.01%, only applying matched filters resulted in a MSE% of 4.01%, and applying both resulted in a MSE% of 1.32%.

4. Discussion

In this study, it was shown that the DBS artifact in scalp EEG recordings can be well approximated by a summation of sinusoids. These artifact components can include both natural harmonics (i.e. multiples of the stimulation frequency) and aliased harmonics. The aliased harmonics can have frequencies well below the frequency of stimulation, thereby making offline low pass filtering inadequate in certain cases. To overcome this problem, we showed that the frequencies of both the natural and aliased harmonics can be predicted when given the DBS stimulation frequency and EEG recording sampling rate. Given the frequencies of the artifacts, matched filter was introduced as a way to remove the unwanted components.

We verified the filtering approach using synthetic DBS ON data generated in two different ways: (1) DBS artifacts empirically determined from a real case study with EEG recorded during DBS stimulation, (2) DBS artifact generated synthetically using a transfer function. Testing with the first way proved that the filtering approach works for real datasets regardless of the subject, electrode, or task condition. Testing with the second way showed the effectiveness of the filtering approach for a wide range of setup parameters, which justified the approach for most EEG studies involving DBS stimulation. In both cases, the filtering approach successfully removed the DBS artifact with MSE value being less than 2% of base signal power. When compared against the application of low pass filtering or notch filtering, the current approach produced significant lower error.

For future studies that intend to apply this method for DBS artifact removal, it is suggested that the researcher run simulation tests with the chosen setup parameters to determine how to optimize the filtering approach. Likewise, they could also run simulation tests with different EEG recording parameters to determine which setup would minimize the amount of recorded artifacts. A general advice for preventing aliased artifacts, especially for EEG systems that cannot apply sharp online low pass filters, is to record the EEG signal at a very high sampling rate (e.g. 20 kHz or system maximum for a 130 Hz signal) that allows most of the higher powered harmonics to be captured without distortion. Once the data has been recorded at the high sampling rate, more effective low pass filters can be applied digitally offline before the signal is resampled to a lower sampling rate (e.g. 1000 Hz). Of course, if the recording has to be done at a set frequency or is limited by the hardware capabilities of the EEG system, then the frequencies of the aliased artifacts can be calculated and removed based on the method presented in this paper.

In summary, this study established a method through which DBS artifact in EEG recordings can be reliably eliminated, thereby preserving a meaningful neurophysiological signal through which to better understand DBS treatment mechanisms.

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