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# DBS Artifact Suppression using a Time-Frequency Domain Filter*

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*Abstract*— **Electroencephalogram (EEG) is a useful tool for brain research. However, during Deep-Brain Stimulation (DBS), there are large artifacts that obscure the physiological EEG signals. In this paper, we aim at suppressing the DBS artifacts by means of a time-frequency-domain filter. As a pre-processing step, Empirical-Mode Decomposition (EMD) is applied to detrend the raw data. The detrended signals are then filtered iteratively until, by visual inspection, the quality is good enough for interpretation. The proposed algorithm is demonstrated by an application to a clinical DBS-EEG data set in resting state and in finger-tapping condition. Moreover, a comparison with a Low-Pass filter (LPF) is provided, by visual inspection and by a quantitative measure.**

## I. INTRODUCTION

Patients suffering from Parkinson's disease can be treated by a therapy called Deep-Brain Stimulation (DBS), which improves, on average, the parkinsonian motor symptoms by 55% [1]. In order to investigate the effects of using DBS, neuroimaging techniques such as positron-emission tomography (PET) have been used. However, they do not have the temporal resolution required to explore the movement-related cortical activities. Therefore, high temporal-resolution techniques are needed, such as EEG [2]. The problem with EEG is that the DBS produces a high-amplitude artifact that obscures the physiological EEG signals.

Many methods have been used to suppress the DBS artifacts [2–5]. For example, Kühn et al. [3] proposed to switch off the stimulation for a few seconds in order to record the true EEG signals. However, it might also be necessary to analyze the signals when the stimulation is ON. Therefore, a filtering technique is needed to suppress the DBS artifact.

The DBS artifact consists of strong spectral peaks at the stimulator frequency and its harmonics. The stimulation peak may overlap certain physiological frequency bands, such as $\beta$ ($13-30$ Hz) and $\gamma$ ($40-90$ Hz), which could contain valuable information. Therefore, the information in those frequency bands should not be distorted by the filtering [2]. As a straightforward solution, low-pass and notch filters have been used [5]. However, if the stimulation peaks overlap many frequency bins, these filters are not appropriate.

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In the present work, we propose a filter that employs both domains (time and frequency) to remove the DBS artifact and to keep the physiological signal. The filtering algorithm, as used in this paper, is based on the one proposed in [6], and it is called here time-frequency-domain filter (TFDF).

To test the performance of this filter, we have used a real EEG data set from a Parkinsonian patient treated with DBS. The data correspond to segments in resting state and in finger-tapping conditions.The filtered outputs are compared with data segments in the same conditions, but recorded when the stimulation is OFF. Moreover, low-pass filters (LPF) have been applied to the artifactual data, and their output is compared with the result of the proposed filter, by visual inspection and by a quantitative measure.

Due to the fact that the employed EEG signals present a very strong trend behavior, a pre-processing step has been performed. For this purpose, the Empirical-Mode Decomposition (EMD) is employed. EMD is a novel technique proposed by Huang et al. [7], which is generally used for denoising and detrending. The EMD decomposes a signal into different components (called Intrinsic-Mode Functions, IMFs) plus one residual which might correspond to the trend.

In section II, the algorithm employed in this work is described. The results are presented in section III. A conclusion is given in section IV.

## II. ALGORITHM DESCRIPTION

### A. Pre-processing step: Detrending

As stated above, the DBS signals show a strong trend behavior. The technique used in this work for detrending is the EMD.

The EMD [7] decomposes an arbitrary input signal $x(t)$ into a set of $N$ IMFs ($IMF_i(t)$) plus a residue ($r_N(t)$), which can be either a constant, a monotonic slope, i.e., a trend, or a curve having only one extremum. Hence, the input signal can be expressed as follows:

$$x(t) = \sum_{i=1}^{N} IMF_i(t) + r_N(t). \quad (1)$$

An IMF is any function that has the same number of extrema and zero crossings, with the mean value of the upper and lower envelopes, defined by all local maxima and minima, being zero at any point. The procedure to extract single IMFs from a given data set is called sifting process. The sifting process employs the distances between consecutive extrema to determine the characteristic time scale of an oscillatory mode. Thus, the first IMF will contain the signal components with the highest frequencies, while the last IMF (or residue) extracts the lowest frequency. Therefore, in order to detrend the signals, the residue is removed and the remaining IMFs are added to reconstruct the signals.

To stop the sifting process, two stoppage criteria are used. The first one tests the relative discrepancy between two consecutive sifting steps. It is called sum of differences, SD, which has to be smaller than a preassigned threshold, $T_{SD}$. In this work, we choose $T_{SD} = 0.1$. The second stoppage criterion is defined as the number of consecutive siftings when the number of zero-crossings and extrema are equal or differ at most by one. It is called the S-number, which in the present work is equal to 10.

The EMD algorithm has been implemented in MATLAB based on the explanation given in [7], using the two criteria mentioned above to stop the sifting process.

### B. Filter Design

The algorithm used in this paper is a modified version of the one given in [6]. In the following, a brief explanation is given. For further details, refer to [6].

We start with the assumption that the measured signal $x(t)$ consists of a superposition of the physiological signal $s(t)$ and the DBS artifacts $d(t)$:

$$x(t) = s(t) + d(t). \tag{2}$$

The DBS artifacts are not only pure spectral lines at specific frequencies; rather, through broadening, they leak into many neighboring bins. Therefore, if a frequency-domain filter is designed, it might fail because it would suppress only the power at specific frequencies, but not at the neighboring bins. For that reason, the filtering is performed in time domain:

$$\hat{s}(t) = x(t) - \sum_n c_n \sin(2\pi f_n t + \varphi_n), \tag{3}$$

where $\hat{s}(t)$ is an estimation of the physiological signal, $n$ loops over the DBS spurious peaks in the power spectrum of $x(t)$, and $c_n$, $f_n$, and $\varphi_n$ correspond to the amplitude, frequency, and phase of the *n-th* peak, respectively. In order to be successful in the suppression, optimal estimates of the three mentioned parameters have to be found for each peak.

Two objective functions, which have to be minimized by using the Levenberg-Marquardt algorithm [8], are used to find the optimal estimates for $c_n, f_n$ and $\varphi_n$. The first one is given by

$$F_1(c_n, f_n, \varphi_n) = \sum_t \left|\left(x(t) - c_n \sin(2\pi f_n t + \varphi_n)\right)\right|. \tag{4}$$

The second choice is:

$$F_2(c_n, f_n, \varphi_n) = |\tilde{\xi}(k)|^2 \ , \tag{5}$$

where $k$ represents each bin to be filtered, and $\tilde{\xi}(k)$ is the discrete Fourier transform of

$$\xi(t) = x(t) - c_n \sin(2\pi f_n t + \varphi_n) \ . \tag{6}$$

In practice, we are taking not only the power in bin $k$, but a sum of the powers over a set of a few neighboring bins.

In order to apply the functions, the original signal is segmented, and the power spectrum is computed per segment. To find the first estimates by using $F_1$, initial values for the amplitude, frequency, and phase are required: The square-root of the spectral power of the bin containing the peak to be filtered will be the initial value of the amplitude. The frequencies are initialized with the nominal stimulator frequency, and the phases are set to 0. The parameter estimation is performed independently for each segment.

Once a set of initial estimates are obtained by using $F_1$, they can be iteratively improved using $F_2$, considering the time series

$$x_{n,j}(t) = \hat{s}_j(t) + c_{n,j} \sin(2\pi f_{n,j} t + \varphi_{n,j}), \tag{7}$$

where $j$ stands for the iteration number, $n$ denotes the bins to be filtered, and $\hat{s}_j(t)$ is given by

$$\hat{s}_j(t) = x(t) - \sum_n c_{n,j} \sin(2\pi f_{n,j} t + \varphi_{n,j}). \tag{8}$$

In every iteration, an improved filtered time series is created. After three iterations, there are no further improvements. That means that the estimates are optimal, and hence, the filtered signal can be obtained.

At this point, we know the filtered signal and, hence, also the amplitudes and phases of all bins, except of those which were filtered. The power in those bins should be zero. However, it is expected that the physiological EEG signal has non-zero power in these bins. In order to retrieve the power in the filtered bins, an averaging over neighboring bins is performed. The phases are then recovered in the frequency domain by transforming (2) using the Fourier transform:

$$\tilde{x}(f) = \tilde{s}(f) + \tilde{d}(f) = a_s(f)e^{j\phi_s(f)} + a_d(f)e^{j\phi_d(f)}, \tag{9}$$

where $\tilde{x}(f)$, $\tilde{s}(f)$, and $\tilde{d}(f)$ are the spectral representations of $x(t)$, $s(t)$, and $d(t)$, respectively. As can be seen in this equation, the measured signal is composed by a complex addition, where not only the amplitudes ($a_s(f)$ and $a_d(f)$), but also the phases ($\phi_s(f)$ and $\phi_p(f)$) are taken into account. At this point, $\tilde{x}(f)$ and $\tilde{d}(f)$ are known. To get the phases, a complex subtraction is carried out. In this manner, an estimation of $\tilde{s}(f)$, i.e. of $a_s(f)$ and $\phi_s(f)$ is obtained. With these values, an approximate phase reconstruction is possible; also another amplitude estimate $a_s(f)$ results, which provides an alternative to the estimate obtained by averaging over neighboring bins.

### C. Quantitative Measure

The low-pass and the time-frequency-domain filters are compared not only by visual inspection, but also by a quantitative measure. It is expected that, after filtering, the power spectrum of the artifactual segment ($Pow\_DBS_{\text{on}}$) is very similar to the power spectrum of the signal segment when the stimulator is OFF ($Pow\_DBS_{\text{off}}$). In order to measure the efficiency of the artifact suppression, the following ratio $R$ is computed:

$$R(p) = mean_\mu \left( \left| 10 \cdot log\left( \frac{Pow\_DBS_{\text{off}}(p,\mu)}{Pow\_DBS_{\text{on}}(p,\mu)} \right) \right| \right), \tag{10}$$

where $p$ denotes the channel number and $\mu$ denotes the frequency; $mean_\mu$ corresponds to the arithmetic mean over all frequencies. In order to obtain the average power spectrum $Pow\_DBS_{\text{off}}$, each signal has been divided into frames of 1s length, the power spectrum was computed per frame, and then an average was performed over all frames. The same procedure holds for $Pow\_DBS_{\text{on}}$.

In the best case, $R$ should be close to zero if the artifact has been suppressed. The ratio is computed for the signals before and after each filtering technique.

In the next section, the performance of the TFD filtering is demonstrated by a real EEG example.

## III. RESULTS

Real DBS-EEG data segments in resting and finger-tapping conditions were used to test the performance of the TFDF. The results were compared with segments in resting state and finger-tapping conditions when the DBS was OFF.

The data have been recorded using a 256-EEG electrode system. The sampling frequency is 1 kHz and the stimulator frequency is 180 Hz. The length of the signals used here is 30s. The filter has been applied to 35 EEG electrode signals; the results for 6 of them are presented numerically below, but graphical results of only one electrode are shown in this work. The six analyzed signals are: F5, F6, C3, C4, O1 and O2. They were selected as representatives for the frontal, central and occipital brain regions. All power spectra were estimated by averaging over the DFT of a set of segments of 1s length.

As a preprocessing step, the EMD is applied to each signal. In all the cases, the last IMF has been considered as the residue, i.e., as a trend. Therefore, it has been removed in order to create detrended signals. The detrending has made easier the recognition of the frequencies to be filtered.

The detrended signals have then been filtered with the TFDF: First, the components of 180 and 360 Hz (the stimulator frequency and its harmonic, respectively) were filtered. Afterwards, additional filtering iterations are needed to eliminate undesired components that are identified just after the elimination of the main artifactual peaks. The frequencies to be filtered in each iteration were selected by visual inspection of the power spectrum. After four iterations, all the peaks were removed and the filtered signal was obtained. To compare these results, a Butterworth LPF, with a cutoff frequency of 100 Hz and with an order of 10, has also been applied to the detrended signals.

Since the finger-tapping was carried out with the right hand, we selected the electrode signal C3 to be analyzed. In Fig. 1a, 300ms of this signal is shown. This signal corresponds to the resting-state case, with the stimulator ON. Figure 1b presents the outputs of the LPF (dashed-circle line) and the TFDF (continuous line). As can be seen, in the original signal it is not possible to see any EEG activity, while after filtering brain activity is observed. In the time domain, the output of both filters is very similar, where the LPF removes some "fine structure".

Figure 2a shows the average power spectrum of the DBS-contaminated signal before filtering (continuous line) and the average power spectrum of the signal when the stimulator was OFF (dotted line). The latter served as a reference, i.e., as a *clean* signal. It is expected that the power spectrum of the filtered signal is very similar to that of the signal when the stimulator is OFF. As observed in this figure, the DBS artifact creates two strong peaks at the stimulator frequency

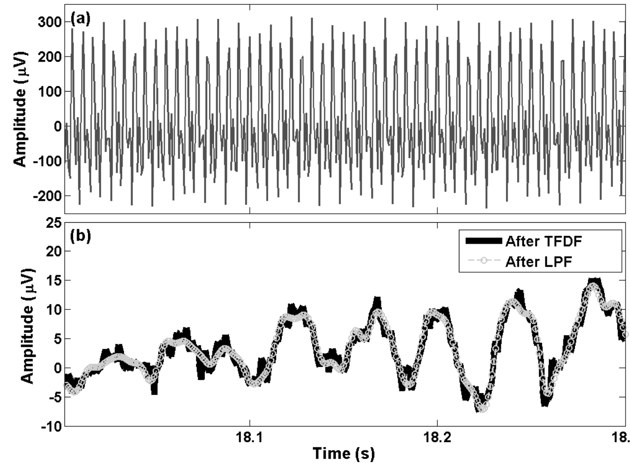


Fig. 1. (a) A segment of 300ms out of 30s of the original time signal C3 when the DBS is ON. (b) Same signal as in (a) after TFDF (continuous line), and after LPF (dashed-circle line). Note the different amplitude scales of (a) and (b).

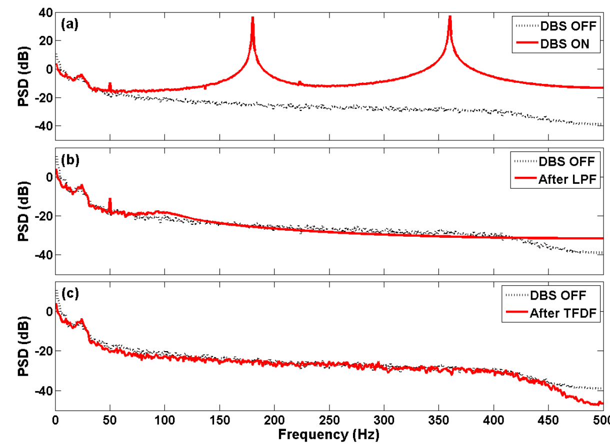


Fig. 2. Power spectrum of signal C3 in resting state. Dotted line: (a-c) Signal when stimulator is OFF. Continuous line: (a) DBS signal when stimulation is ON; (b) after LPF; (c) after TFDF.

and its harmonic. Peaks at 50 Hz and 223 Hz are also visible. However, as mentioned above, the first two frequencies to be filtered are those of the DBS artifact. Figures 2b and 2c plot the power spectrum of the signals after a LPF and after using the TFDF, respectively (continuous line). The spectrum of the signal when the stimulator was OFF (dotted line) is also shown. As can be observed in Fig. 2b, after a LPF the 50 Hz artifact is still present, while for the TFDF (Fig. 2c) a good suppression not only of the DBS artifact, but also of the 50 Hz artifact has been achieved. It can be recognized that, after filtering, the peaks in the $\alpha$ and $\beta$ bands are still preserved.

In Fig. 3, the power spectra before and after filtering (continuous line), and the spectrum of the signal when the stimulator is OFF (dotted line), for the finger-tapping condition, are shown. As can be seen in Fig. 3a, the power spectrum of the artifactual signal presents two strong peaks at the stimulator frequency and its harmonic. After applying a LPF, not only the DBS-artifact was suppressed, but also presumably physiological information is lost, as can be seen in Fig. 3b. It can also be observed that the 50 Hz artifact is still present. On the other hand, after the application of the

TABLE I

COMPARISON OF RATIOS AMONG THE ORIGINAL SIGNAL ($R_O$), LOW-PASS FILTER ($R_{\text{LPF}}$) AND TFD FILTER ($R_{\text{TFDF}}$).

| | Resting state | | | Finger tapping | | |
|---|---|---|---|---|---|---|
| Electrode | $R_O[dB]$ | $R_{\text{LPF}}[dB]$ | $R_{\text{TFDF}}[dB]$ | $R_O[dB]$ | $R_{\text{LPF}}[dB]$ | $R_{\text{TFDF}}[dB]$ |
| F5 | 10.80 | 2.63 | 1.41 | 10.55 | 4.21 | 1.01 |
| F6 | 9.97 | 4.53 | 1.68 | 9.87 | 3.66 | 1.38 |
| C3 | 9.95 | 2.43 | 1.69 | 10.23 | 4.05 | 1.28 |
| C4 | 10.39 | 2.31 | 1.25 | 10.30 | 2.36 | 1.36 |
| O1 | 12.04 | 3.53 | 1.30 | 12.74 | 3.37 | 1.64 |
| O2 | 11.21 | 3.57 | 1.11 | 12.68 | 3.90 | 3.00 |

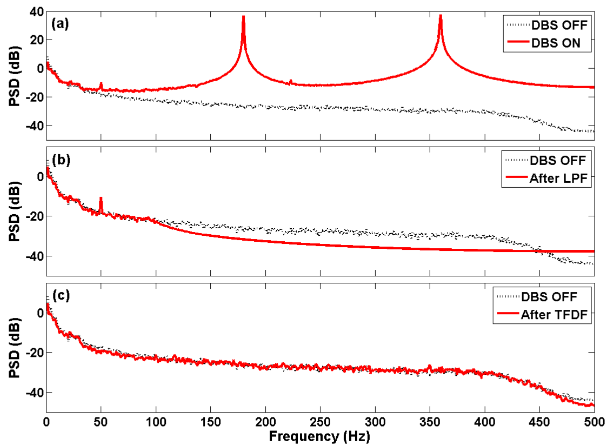


Fig. 3. Power spectrum of signal C3 in finger-tapping condition. Dotted line: (a-c) Signal when stimulator is OFF. Continuous line: (a) DBS signal when stimulation is ON; (b) after LPF; (c) after TFDF.

TFDF, both the DBS artifact and the power-supply artifact were suppressed. The power spectrum of the filtered signal is very similar to the reference. A small peak in the $\theta$ region is also observed, which is due to the finger-tapping task.

In Table I, the quantitative measures are shown. At first, the ratio between the signal when the stimulation is OFF and the DBS signal when the stimulation is ON is computed ($R_O$). Then, the ratio is obtained after each filtering technique. It is expected that this ratio should be closer to zero, which would mean that the artifacts are suppressed.

As observed in the table, after both LPF ($R_{\text{LPF}}$) and TFDF ($R_{\text{TFDF}}$), the signals are improved. However, using a TFDF, the ratio is smaller, indicating that the artifacts are better suppressed. This result holds for both situations: resting state and finger tapping.

## IV. CONCLUSION

In this paper, a novel approach for removing DBS artifacts has been introduced. The suppression was achieved by means of a time-frequency-domain filter: The strong peaks present at the stimulator frequency and its harmonic were removed in time domain, while the phases were reconstructed in the frequency domain.

The TFDF was successfully applied to real DBS-EEG data from three patients, but only the results of one of them has been shown in this work.

As a pre-processing step, the signals have been detrended. For that purpose, the EMD was applied. After detrending, the frequencies to be filtered at each stage were better observed.

Two cases were analyzed, namely the resting state and the finger-tapping condition. The detrended signals have been filtered not only with the TFDF, but also with a Butterworth LPF. A comparison between these two methods has been performed graphically and quantitatively. As a reference, a signal segment when the stimulator was switched OFF has been used. According to the results, for both the resting state and the finger-tapping data, the TFDF and the LPF improved the signals. However, the LPF can be just tuned with a cutoff frequency, while the TFDF has a higher flexibility for eliminating undesired spectral lines.

The initial values for the frequencies have been set manually. Further research will focus on their automatic detection and correction. Moreover, data from other patients should be corrected in order to analyze the behavior of the power in the $\beta$ band.

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