

Introducing SPECTER 2.0 - an Enhanced Version of the Tensor Based Eye Blink Removal Algorithm

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Abstract. *SPECTER (the Signal sPECTrum Tensor decomposition and Eye blink Removal) is a novel algorithm designed to detect and eliminate eye blink-related artifacts from electroencephalogram (EEG) recordings. Our previous study [1] demonstrated its superior performance compared to established regression-based methods or independent component analysis, especially in situations where these approaches failed to accurately detect eye blinks or introduced spurious oscillations into the signal. In this study, we introduce SPECTER 2.0, an improved version that addresses the limitations of the original algorithm, and we demonstrate its improved performance on a real EEG dataset affected by eye blinks.*

Keywords: *Eye Blink Removal, Electroencephalogram (EEG), Tensor Decomposition*

1. Introduction

Human electroencephalogram (EEG) provides valuable insights into brain activity. However, raw EEG signals can be contaminated by various artifacts, which may arise from factors such as eye blinks, muscle movements, electrical resistance between the skin and electrodes, and nearby electronic devices. These non-EEG sources can significantly impact data analysis. Therefore, the removal of these artifacts is a crucial preprocessing step for EEG data.

In our previous study [1], we introduced a tensor-based eye-blink removal algorithm called SPECTER. A key advantage of SPECTER is that it does not require information from an electrooculogram, unlike regression-based eye-blink removal methods. Moreover, SPECTER avoids the problem of spectrum overestimation, a known limitation of artifact correction using independent component analysis [2].

Despite its strengths, the preliminary version of SPECTER had several drawbacks, primarily related to a slight time shift and the opposite sign problem. This study aims to address these issues with SPECTER 2.0, an improved version of the original algorithm, and demonstrate its performance on the same set of real EEG data used in [1].

2. A brief overview of the original SPECTER algorithm

The SPECTER algorithm is described in detail in [1], so we provide only a brief overview. First, consider an EEG signal recorded by J electrodes at a sampling rate of S_f Hz. The initial step involves dividing the EEG signal from each electrode into overlapping time windows of length W . Within each time window, the EEG signal is convolved with the Hanning window, and the Fast Fourier Transform is applied to compute its amplitude spectrum. Then, the $\log_{10}$ -transformed spectral values are concatenated into a three-dimensional tensor $\underline{X} \in \mathbb{R}^{I \times J \times K}$, where I represents the number of time windows, J is the number of electrodes, and K denotes the number of considered frequencies.

In the second step, tensor $\underline{X}$ is decomposed using the CANDECOMP/PARAFAC (CP) method [3]. Artifact-related components are identified through an automatic selection criterion, followed by manual inspection if necessary, and are subtracted from $\underline{X}$ [1]. The cleaned tensor

is then transformed into a nonnegative form using the element-wise 10^X function. Finally, the clean EEG signal is reconstructed by the spectrum-to-signal transformation [4].

3. SPECTER 2.0

Due to the effects of windowing and convolution with the Hanning window, the original SPECTER version struggled to accurately reconstruct the first and last $\frac{S_f}{2}W$ time points of the EEG signal. Additionally, the reconstructed signal sometimes exhibited slight time shifts either to the left or right compared to the original EEG signal (Fig. 1, red). To mitigate these timing discrepancies, we applied the dynamic time warping (DTW) algorithm [5] between the original and reconstructed EEG signals in [1]. However, DTW can be time-consuming, and the length of the input time series limits its effectiveness.

The second issue arises from missing information regarding the phase spectrum of the cleaned EEG, which causes discrepancies in the signs of the values between the original and reconstructed signal. In [1], we proposed a heuristic based on the Spearman correlation coefficient ρ between the original and reconstructed signals over short, non-overlapping time intervals. If $\rho < 0$ or other criteria were met, the reconstructed signal in that interval was multiplied by -1 .

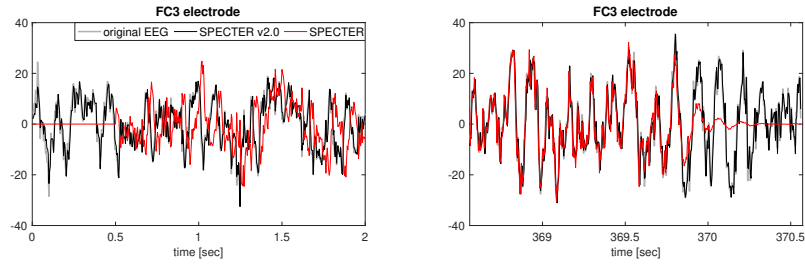


Fig. 1: An example of the EEG signal (grey) from the FC3 electrode, showing the first (left) and last two seconds (right), along with its versions reconstructed by SPECTER (red) and SPECTER 2.0 (black).

To address both issues, we propose the following modifications in SPECTER 2.0:

- Before applying SPECTER 2.0, we extend the EEG signal by adding constant segments of length $\frac{S_f}{2}W$ to both the beginning and the end of the original signal for each electrode. These segments are equal to the initial and final values of the EEG, respectively. After reconstructing the signal, we trimmed the added segments to ensure that the cleaned EEG signal matched the length of the original one. Nevertheless, the option to apply DTW remains available in SPECTER 2.0.
- In the spectrum-to-signal transformation step, the unknown phase spectrum of the cleaned EEG was replaced by the phase spectrum of the original EEG. We hypothesize that, during non-artifact intervals, the phase spectra of both the original and reconstructed signals should overlap. As will be described in Section 5, this adjustment significantly improved the issue of opposite signs. The heuristic introduced in [1] can still be applied to correct any remaining intervals with opposite sign values.

4. Data

To demonstrate the advantages of SPECTER 2.0 over the original version, we focused on the same eye-blink corrupted OSF dataset used in [1]. This dataset includes EEG signal from 19 electrodes¹ collected from 40 subjects divided into four groups (studies). Additionally, the EEG

¹Fp1 (or AF3), F3, F7, C3, T7, P3, P7, O1, Pz, Fp2 (or AF4), Fz, F4, F8, Cz, C4, T8, P4, P8, and O2

signal for each subject consists of eight-second segments labeled as either “eye blink” or “non-blink.” The sampling frequency was 100 Hz (for study 04) or 200 Hz (for studies 01-03). In both versions of SPECTER, we applied 0.5-second time windows with 400 ms of overlap.

5. Results

In the initial step, the reconstructed EEG signal was divided into 100 ms time intervals. We examined the ratio of these intervals that exhibited the opposite sign problem for each electrode separately. For the EEG signal reconstructed using the original version of SPECTER, approximately half of the time intervals for each subject and electrode required a sign change (see Fig. 2, red). In contrast, with SPECTER 2.0, the average ratio of time intervals needing a sign change decreased to between 0.10 and 0.19 for all electrodes (see Fig. 2, black).

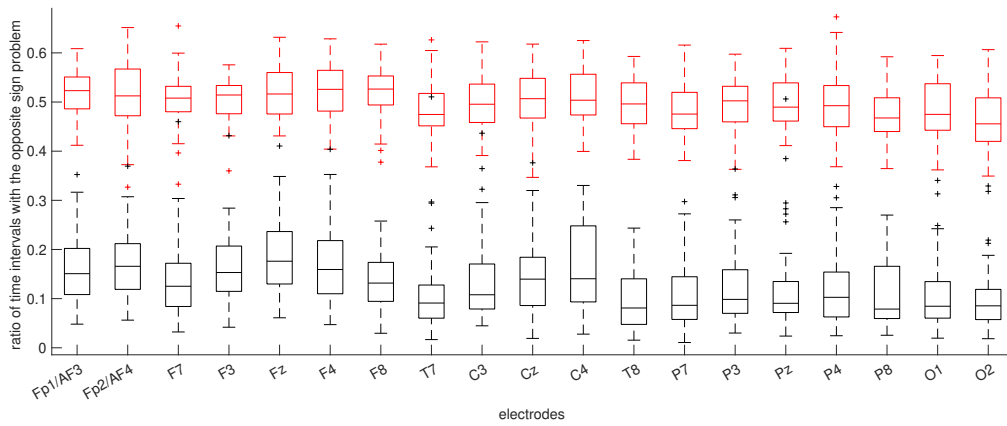


Fig. 2: The ratio of time intervals with the opposite sign problem after signal reconstruction with SPECTER (red) and SPECTER 2.0 (black) in 40 subjects from the OSF dataset.

In the second step, we focused on the slight time shift problem. The reconstructed and original EEG signal were time-aligned by DTW for each non-blink time segment. Then, the Euclidean distance D_{dtw} between the warping and the real time was computed. Given the modifications made, we anticipated that the warping time would be closer to the actual time in SPECTER 2.0 compared to the original version of the method. To test this expectation, we applied the non-parametric Wilcoxon signed-rank test to assess the following hypothesis:

$$H_0 : D_{dtw}^{SPECTER} \leq D_{dtw}^{SPECTER_2.0} \quad \text{vs.} \quad H_1 : D_{dtw}^{SPECTER} > D_{dtw}^{SPECTER_2.0}$$

The test was conducted for each electrode individually. We rejected the null hypothesis for all 19 electrodes, as the p-values were approximately $\approx 10^{-17}$, which were well below the Bonferroni-corrected threshold of $\frac{0.05}{19} = 0.0026$.

Furthermore, we computed the Spearman correlation coefficient between the original EEG signal and its reconstructed version over non-blink intervals. Similarly to the findings in [1], we hypothesized that the signals would overlap on these intervals. The results for 19 subjects are illustrated in Fig. 3. Without the DTW correction for slight time shifts, SPECTER 2.0 achieved higher correlations than the original SPECTER (Fig. 3, dotted lines). Moreover, SPECTER 2.0 without DTW produced results comparable to SPECTER with DTW for several subjects, including Subjects 2 and 3 from study 01 and Subject 5 from study 02 (Fig. 3), is consistent with the significantly lower distance between the original and warping time in SPECTER 2.0.

When applying the DTW correction, SPECTER 2.0 generated a reconstructed EEG signal that was more similar to the original signal. This conclusion was supported by higher or comparable correlation values relative to the previous version of SPECTER (Fig. 3, solid lines).

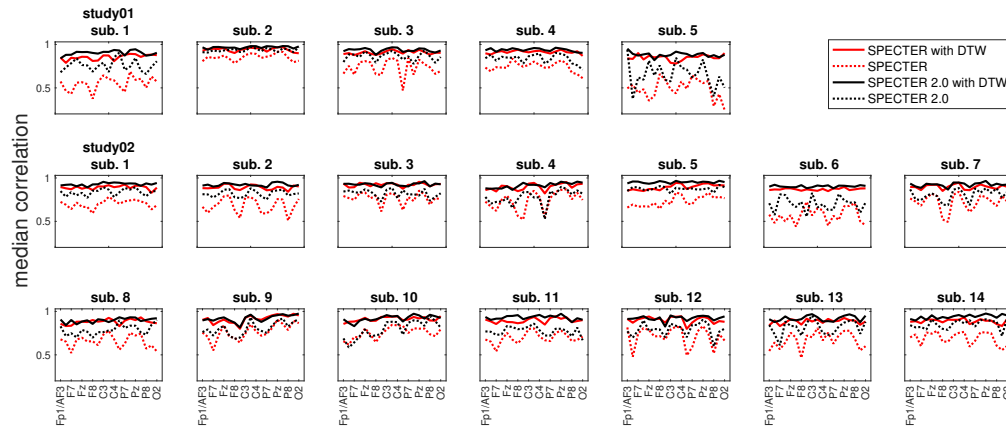


Fig. 3: The median Spearman correlation coefficient between the original EEG signal and its versions reconstructed by SPECTER (red) and SPECTER 2.0 (black) over the non-blink epochs. In both cases, correlations were computed without (dotted line) or with (solid line) the DTW correction for the slight time shift problem. Only labels for each second electrode are depicted on the x-axis.

6. Conclusion

In this study, we introduced an enhanced version of the eye-blink removal algorithm known as SPECTER. The modifications we made significantly reduced the proportion of time intervals containing opposite sign values. Additionally, SPECTER 2.0 produced EEG signals with a lower incidence of slight time shifts. This improvement was evident in two ways: the warping time was closer to the real time compared to the original SPECTER version, and there were comparable correlations between the original EEG signal and the reconstructed signals from both SPECTER 2.0 without DTW and the original SPECTER followed by DTW. This held true across multiple subjects. Nevertheless, in the future, we plan to evaluate the performance of SPECTER 2.0 on EEG signals affected by other types of artifacts, in addition to eye blinks.

Acknowledgements

Funded by the EU NextGenerationEU through the Recovery and Resilience Plan for Slovakia under the project No. 09I03-03-V04-00205 (Z.R.) and project No. 09I03-03-V04-00443 (R.R.).

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