Dean&Francis
ISSN 2959-6157

Ocular Artifacts Removal in EEG Signal Based on Discrete Wavelet Transform and Savitzky-Golay Filter

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Abstract:

Electroencephalography (EEG) is a critical tool in neuroscience and clinical diagnostics, offering valuable insights into brain activity. However, EEG signals are often contaminated by ocular artifacts, which can significantly distort the data, leading to potential misinterpretations. This study introduces a novel method for removing ocular artifacts from EEG signals using a combination of Discrete Wavelet Transform (DWT) and Savitzky-Golay (SG) filter. The proposed method effectively separates the EEG signal into multiple subbands using DWT, followed by the application of the SG filter to the contaminated subbands to remove artifacts while preserving the integrity of the original EEG signal. The performance of the proposed method is evaluated using a publicly available EEG dataset. Two performance metrics (signal-to-noise ratio improvement, and percentage reduction of correlation coefficient) are used to test the DWT-SG method. The results show superior artifact removal capabilities and lower computational complexity compared to traditional methods. The results demonstrate that the DWT-SG approach has an average SNRI and η values of 10.367 dB and 25.26%.

Keywords: Ocular artifacts, Electroencephalography, Discrete wavelet transform, Savitzky-Golay filter.

1. Introduction

Electroencephalography (EEG) is essential in neuroscience and clinical diagnostics for monitoring and analyzing brain activity, as it helps us understand brain disorders and neurological conditions [1]. However, due to the use of electrodes located on the scalp for EEG signal acquisition, the electrical signals generated in the brain are partially blocked by the skull, resulting in relatively low amplitude and frequency of EEG signals. In clinical medicine, EEG can help doctors evaluate the development of diseases such as epilepsy. In the intensive care unit, EEG monitoring can provide doctors with information on the state of the patient's brain, helping them adjust treatment plans in a timely manner based on the patient's con-

ISSN 2959-6157

dition. In the above scenarios, if the collected EEG signals are not properly processed, the invalid information contained therein is likely to cause misdiagnosis of the patient. The noise or artifacts present in EEG signals push us to search for efficient and effective methods to remove them.

This study will focus on methods for removing artifacts. The artifacts in EEG signals can generally be classified into physiological and non-physiological sources based on their sources. For research on physiological artifact removal, because artifacts caused by large-scale body movements can generally render the collected EEG signals unusable, it is usually focused on dealing with artifacts from eye movements, neck muscle movements, and heart movements. Non-physiological artifacts, particularly interference from power lines, can cause a peak in the EEG signal spectrum at 50Hz or 60Hz, depending on the country and region where the signal was collected. EEG signals often get mixed up with these artifacts, making it hard to extract meaningful features. These unwanted artifacts can hide true neural signals, affecting the accuracy and reliability of EEG analysis. For example, the electromyographic signals generated by neck muscle movements can produce high-frequency components in EEG signals. Meanwhile, blinking and other eye movements mainly affect the electrodes in the frontal lobe. These movements cause voltage changes much bigger than brain waves. Therefore, careful filtering is required to keep the EEG data accurate [2]. Therefore, removing these artifacts is a crucial step in EEG preprocessing to ensure high-quality and interpretable data. This field in EEG signal processing has been extensively studied and various methods have been developed to handle different types of artifacts.

To better understand the context of this paper proposed method, it's worth examining the evolution of ocular artifact processing techniques. In the early development of this field, researchers tended to use traditional processing methods, such as regression analysis [3]. This method is more complex in data collection, as it requires electrodes to be placed around the eyes to capture electrical signals from the eyes (EOG) while collecting EEG signals. However, this method has obvious drawbacks. Without a reference EOG signal, artifact removal becomes challenging. Additionally, the EOG signal may contain some brain activity. Consequently, removing artifacts inevitably leads to the loss of some EEG signals [4]. Therefore, subsequent research has shifted towards using multi-scale analysis techniques such as discrete wavelet transform (DWT) and multivariate variational mode decomposition (MVMD), as well as blind source separation (BSS) such as independent component analysis (ICA) and principal component analysis (PCA) [5-7]. In recent years, researchers have started using hybrid methods such as DWT-ICA and MVMD-PCA to address the challenges posed by ocular artifacts [5] [8]. However, these methods, which combine BSS, generally have high computational resource requirements and are difficult to achieve real-time signal processing.

The Savitzky-Golay (SG) filter is a smoothing method that fits adjacent data points to a low-order polynomial within a moving window, using the least squares method [9]. Some recent researches have looked into using the SG filter for ocular artifacts removal, showing that it can reduce noise while keeping the signal intact [10]. Although SG filters require less computation compared to BSS, they need constant adjustment of window size and filter order to achieve better filtering performance. This process can be time-consuming for researchers. DWT can decompose the original signal into a series of wavelets, and by applying SG filtering to specific wavelets, it can achieve good results in removing ocular artifacts. The challenge is not just removing these artifacts but doing so without distorting the original EEG signals. This paper proposes a novel ocular artifact removal technique that combines the multi-resolution analysis capabilities of DWT with the signal preservation properties of SG filters, aiming to achieve effective artifact removal while maintaining the integrity of the underlying EEG signals.

This paper is structured as follows: Section 1 introduces the topic and reviews relevant literature. Section 2 outlines the principles and experimental setup, detailing the theory and design methodology behind the SG filter implementation. The experimental results and analysis of the designed filters are demonstrated in Section 3. Limitations and future directions are discussed in Section 4, and the work is concluded in Section 5.

2. Materials and Methods

2.1 EEG Datasets

This study used a publicly available dataset, which can be obtained from the following link: https://osf.io/2qgrd/ [11]. This dataset contains EEG recordings from 50 healthy participants, using 64 electrodes to record EEG signals. The electrode placement follows the international 10-10 system, with the reference electrode located at the right mastoid and the grounding electrode being AFz. This dataset also includes horizontal and vertical EOG collected by six electrodes: two placed at the outer canthi of each eye for horizontal EOG, and two above and below one eye for vertical EOG. The EEG and EOG data were resampled at 200 Hz. Power line interference was removed using notch filters with cutoff frequencies of 49 and 51 Hz. Additionally, a 0.4 Hz high pass filter was applied [12].

2.2 Decomposition using Discrete Wavelet Transform

This study use DWT to decompose the EEG signal $y = [y(n)]_{n=1}^{N}$ with a sampling rate of 200 Hz into multiple frequency subbands. Based on the sampling frequency characteristics of the selected dataset, this study chose to decompose it into 5 levels and selected db4 as the mother wavelet. In this operation, the original signal is subjected to multi-level decomposition, which is equivalent to passing the EEG signal through multiple low-pass filters and high pass filters, ultimately producing a series of approximation coefficients $A_J(m)$ and detail coefficients $D_j(m)$. The former represents the low-frequency part of the signal, while the latter represents the high-frequency part. For the signal y, the approximation band wavelet coefficients vector AJ $= [A_J(m)]_{m=1}^{N_A}$ is given as,

$$A_J(m) = \sum_{n=1}^{N} y(n)\left[2^{-\frac{J}{2}}\varphi\left(2^{-J}n - m\right)\right] \tag{1}$$

and j^th^ detailed subband wavelet coefficients vector D_j $= [D_j(m)]_{m=1}^{N_D}$ can be evaluated as,

$$D_j(m) = \sum_{n=1}^{N} y(n)\left[2^{-\frac{j}{2}}\psi\left(2^{-j}n - m\right)\right] \tag{2}$$

where N is the length of the EEG signal and j = 1, 2, …, 5 [4]. The φ and ψ represent the scaling function and the wavelet function respectively. The approximate subband signal and j^{th} detailed subband signal constructed using A_J and D_j are given by

$$y_A(n) = \sum_{m=-\infty}^{\infty} A_J(m)\left[2^{-\frac{J}{2}}\varphi(2^{-J}n - m)\right] \tag{3}$$

$$y_{D_j}(n) = \sum_{m=-\infty}^{\infty} D_j(m)\left[2^{-\frac{j}{2}}\psi(2^{-j}n - m)\right] \tag{4}$$

For $y_A(n)$ and $y_{D_j}(n)$, the size of m depends on the length of the approximation band wavelet coefficients vector and jth detailed subband wavelet coefficients vector, which means $m = 1, 2, \ldots, N_A$ and $m = 1, 2, \ldots, N_D$, respectively.

This study calculated the power spectral density (PSD) of EEG signals contaminated by ocular artifacts and reference signals. The results show that the contaminated parts are mainly in the low-frequency range of the EEG signals. Specifically, these artifacts primarily affect the reconstructed approximate subband signals and the first few detailed subband signals. This will result in higher frequency amplitude values of the contaminated signals in the low-frequency range, as shown in Fig. 1(a) and (b). In addition, Fig. 1(c)–(h) shows the PSD plots of the approximate sub-band signals and the first to fifth detailed sub-band signals, with a total frequency range of 0-100 Hz. In Fig. 1(c) and (d), the waveform of the contaminated EEG signal clearly does not overlap with the reference signal, indicating that ocular artifacts mainly occur in the approximate sub-band and the first detailed subband, with a frequency range from 0 to 6.25 Hz.

ISSN 2959-6157

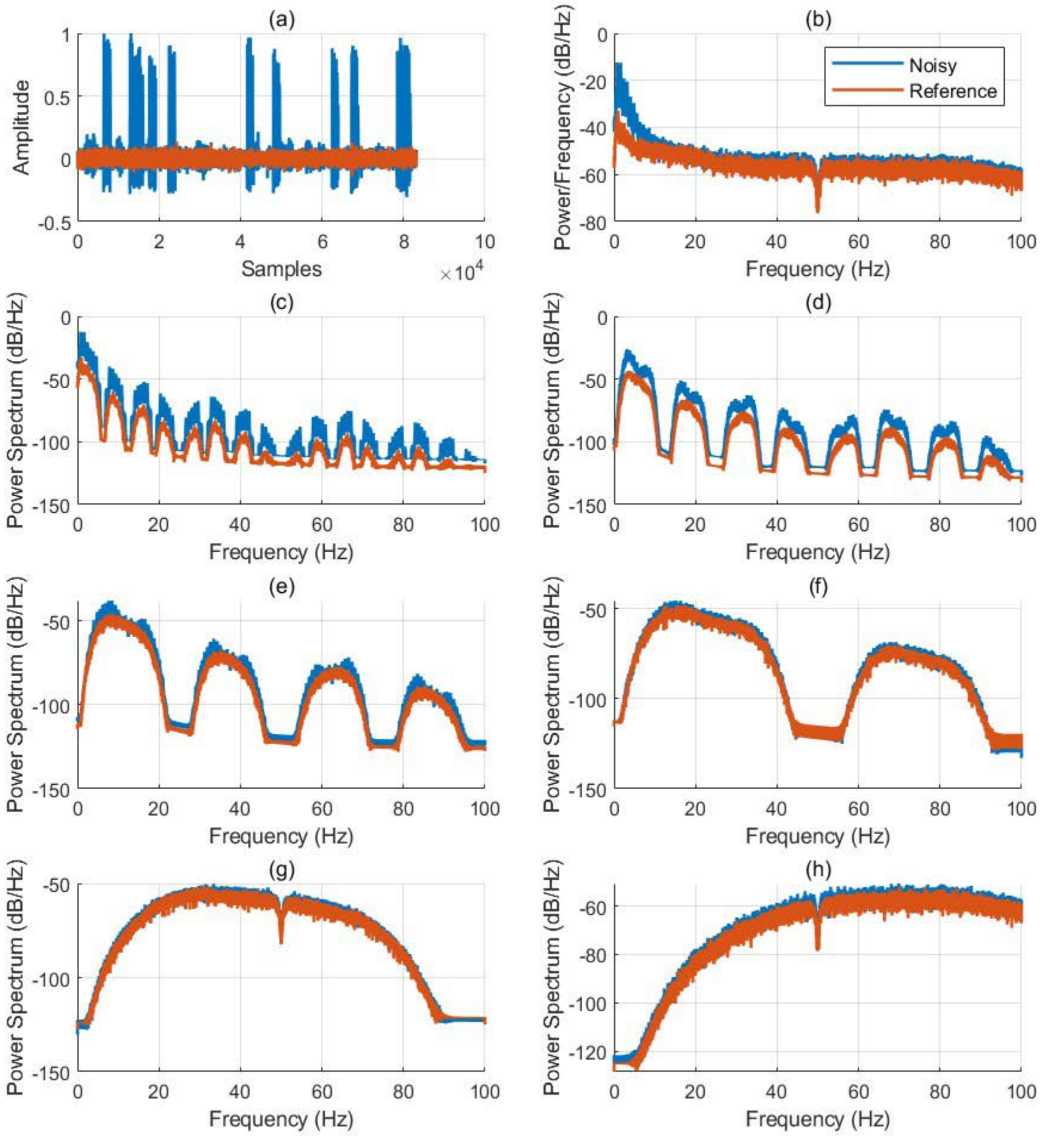

Fig. 1 (a) Ocular artifact contaminated EEG signal (blue) and reference signal (orange). (b) Power spectral density (PSD) of artifact contaminated EEG signal and reference signal. (c) PSD plots for the approximation subband signal. (d) PSD plots for the first detailed subband signals. (e) PSD plots for the second detailed subband signals. (f) PSD plots for the third detailed subband signals. (g) PSD plots for the fourth detailed subband signals. (h) PSD plots for the fifth detailed subband signals (Photo/Picture credit: Original).

2.3 SG filer

The SG filter can filter out noise while maintaining the main characteristics of the signal. Given this property, This study decided to apply SG filters to the subbands contaminated by eye artifacts in this study. Specifically, This study focused on the approximate subband signal and the first detailed subband signal. For a set of data points with a length of N, assuming a window size of $N = 2k + 1$, the fitted p-order polynomial is

$$y = a_0 + a_1 x + a_2 x^2 + \ldots + a_p x^p \tag{5}$$

where $a_0, \dots a_p$ are polynomial coefficients fitted at each data point. By minimizing the squared error between the data points and the fitting polynomial, the optimal polynomial coefficients can be obtained. For the SG filter, minimize its cost function within a window of length N

$$C_p = \sum_{i=-k}^{k} \left(\sum_{z=0}^{p} a_z i^z - x_i \right)^2 \quad (6)$$

where a_z is the zth polynomial coefficients [13]. After the EEG signal is processed by the SG filter, its output is

$$y_{OUT}^{SG}(z) = \sum_{i=-k}^{k} h_i x_{z-i} \quad (7)$$

Here, the h_i is the impulse response of the SG filter. From the above, it can also be seen that the filtering process of SG filter also convolves the signal.

2.4 Performance metrics

This study will use two performance metrics to evaluate the proposed method for removing ocular artifacts. The first item is the improvement of signal-to-noise ratio (SNRI), which can be calculated by the following formula:

$$SNRI = SNR_{OUT} - SNR_{IN} \quad (8)$$

and SNR_{IN} represents the SNR of the EEG signal at the port of input, and SNR_{OUT} represents the SNR of the output signal after artifact removal [14]. The mathematical expressions of the two are as follows

$$SNR_{IN} = 10 \times log\left(\frac{\| y_R \|_2^2}{\| y_{IN} \|_2^2} \right), SNR_{OUT} = 10 \times log\left(\frac{\| y_R \|_2^2}{\| y_{OUT} \|_2^2} \right) \quad (9)$$

Here, y_R is the reference signal, y_{IN} is the artifact contaminated EEG signal, and y_{OUT} is the filtered signal [4]. The second performance metric is the percentage reduction in the correlation coefficient (η), and it can be evaluated by

$$\eta = \left[\frac{1-\rho_{OUT}}{1-\rho_{IN}} \right] \times 100 \quad (10)$$

where $\rho_{IN} = \rho(y_R, y_{IN})$ and $\rho_{OUT} = \rho(y_R, y_{OUT})$ are the correlation coefficients of contaminated EEG signal evaluated before and after processing [14].

3. Results and discussion

Table 1. Values of SNRI and η for channel data using the proposed approach

Channel Data	SNRI (dB)	η (%)
P1_Channel 1	15.033	9.290
P1_Channel 4	8.925	8.860
P1_Channel 5	7.806	4.008
P1_Channel 6	7.968	8.435
P1_Channel 34	11.857	7.949
P1_Channel 35	11.374	10.803
P1_Channel 37	8.839	6.171
P2_Channel 1	12.357	39.732
P2_Channel 34	10.215	55.802
P2_Channel 35	10.788	53.612
P2_Channel 37	8.877	73.194

ISSN 2959-6157

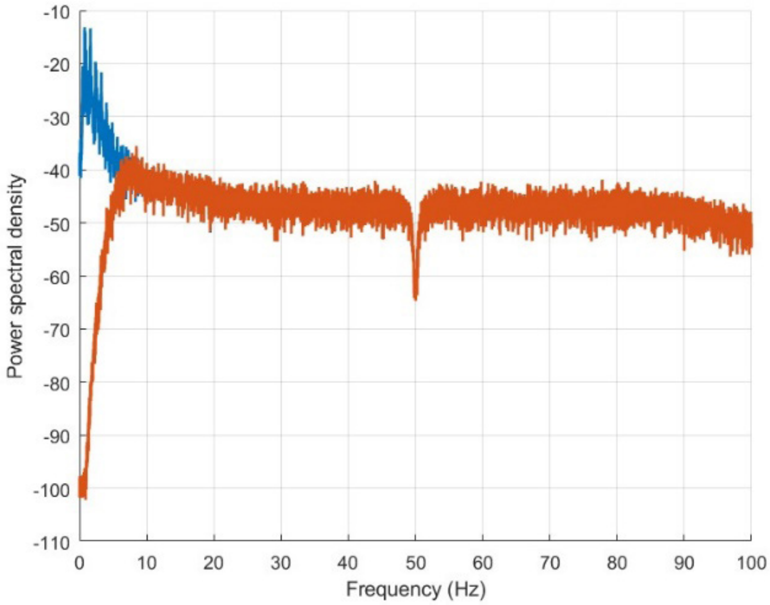

Fig. 2 PSD plots of artifact contaminated EEG signal (blue) and filtered signal (orange) (Photo/Picture credit: Original).

By calculating the SNRI and η of the data before and after filtering, the results shown in Table 1 can be obtained. In terms of channel selection, this study chose multiple electrodes located in the frontal lobes that were contaminated by ocular artifacts. The results in Table 1 show that the hybrid method consisting of DWT and SG filter (DWT-SG) has a good effect on removing ocular artifacts. Compared to other traditional filtering methods such as median filtering and Gaussian filtering, the method proposed in this paper has higher SNRI and lower η. This performance indicates that the SG filter can effectively remove artifacts while preserving the fundamental characteristics of the EEG signal, likely due to its polynomial fitting approach which adapts well to local signal variations. Fig. 2 demonstrates that the DWT-SG method effectively removes artifacts from the low-frequency part of contaminated EEG signals. Notably, the Power Spectral Density (PSD) of the filtered signal in the low-frequency range shows a 40 dB average reduction in artifact-related power compared to the original signal. In addition, the DWT-SG method demonstrates lower computational complexity compared to hybrid methods using blind source separation. For instance, this paper method requires only 6% of the computational resources needed by ICA-based methods, making it significantly advantageous for deployment on mobile platforms with limited processing power. At the same time, this method also has good prospects in application scenarios that require lower latency.

4. Conclusion

This article proposes a novel hybrid method, DWT-SG, for removing ocular artifacts from EEG signals. This paper approach first decomposes the original EEG signal into approximate and detailed subband signals through multi-resolution analysis. Subsequently, this study apply SG filters to the contaminated subband signals. This combination of techniques allows for effective ocular artifact removal while preserving the essential characteristics of the EEG data. This study used a publicly available dataset when evaluating this method. The results show that compared to traditional methods, this method has better performance in removing ocular artifacts and lower computational complexity.

Due to the advantage of computational complexity, this hybrid method has lower latency when processing continuous EEG data. Therefore, this study hope to use the DWT-SG method in EEG data processing on mobile platforms with lower computing power, or in clinical data monitoring scenarios that require low latency in the future. Afterwards, this study will continue to improve the DWT-SG method in order to achieve better results in removing ocular artifacts. For SG filters, better filtering performance can be achieved by finding more suitable parameter sets or adding modules that automatically tune parameters for different signals. Secondly, the current DWT-SG method cannot automatically select contaminated sub-band signals, and further optimization can be carried out in this regard.

References

[1] Sawangjai P, Hompoonsup S, Leelaarporn P, Kongwudhikunakorn S, Wilaiprasitporn T. Consumer grade EEG measuring sensors as research tools: A review. IEEE Sensors Journal, 2020, 20(8): 3996-4024.

[2] Croft RJ, Barry RJ. Removal of ocular artifact from the EEG: a review. Clinical Neurophysiology, 2000, 30(1).

[3] Kenemans JL, Molenaar PC, Verbaten MN, Slangen JL. Removal of the ocular artifact from the EEG: A comparison of time and frequency domain methods with simulated and real data. Psychophysiology, 1991, 28: 114-121.

[4] Gajbhiye P, Tripathy RK, Bhattacharyya A, Pachori RB. Novel approaches for the removal of motion artifact from EEG recordings. IEEE Sensors Journal, 2019, 19(22): 10600-10608.

[5] Vempati R, Sharma LD. EOG Eye Blink Artifact Removal using Multivariate Variational Mode Decomposition and PCA. Proceedings of the 2022 IEEE 6th Conference on Information and Communication Technology (CICT), Gwalior, India, 2022, 1-5.

[6] Jung TP, Makeig S, Humphries C, et al. Removing electroencephalographic artifacts by blind source separation. Psychophysiology, 2000, 37(2): 163-178.

[7] Jiang X, Bian GB, Tian Z. Removal of Artifacts from EEG Signals: A Review. Sensors, 2019, 19(5): 987.

[8] Erkan E, Erkan Y. Ocular Artifact Removal Method Based on the Wavelet and ICA Transform. Chaos Theory and Applications, 2023, 5(2): 111-117.

[9] Savitzky A, Golay MJE. Smoothing and Differentiation of Data by Simplified Least Squares Procedures. Analytical Chemistry, 1964, 36(8).

[10] Rahman FA, Othman M. Real Time Eye Blink Artifacts Removal in Electroencephalogram Using Savitzky-Golay Referenced Adaptive Filtering. Proceedings of the International Conference for Innovation in Biomedical Engineering and Life Sciences, 2016, 68-71.

[11] Kobler RJ, Sburlea AI, Lopes-Dias C, Schwarz A, Mondini V, Müller-Putz GR. EEG eye artifact dataset. 2020.

[12] Kobler RJ, Sburlea AI, Lopes-Dias C, Schwarz A, Hirata M, Müller-Putz GR. Corneo-retinal-dipole and eyelid-related eye artifacts can be corrected offline and online in electroencephalographic and magnetoencephalographic signals. Neuroimage, 2020, 218.

[13] Sadeghi M, Behnia F, Amiri R. Window selection of the Savitzky–Golay filters for signal recovery from noisy measurements. IEEE Transactions on Instrumentation and Measurement, 2020, 69(8): 5418-5427.

[14] Sweeney KT, McLoone SF, Ward TE. The use of ensemble empirical mode decomposition with canonical correlation analysis as a novel artifact removal technique. IEEE Transactions on Biomedical Engineering, 2013, 60(1): 97-105.