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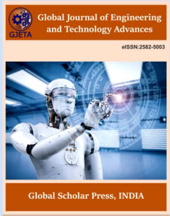

(REVIEW ARTICLE)

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A review for filtering techniques of the Electrooculography (EOG) signals

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Abstract

Electrooculography (EOG) is a non-invasive method employed for the measurement of the electrical potential produced by ocular movements. EOG signals frequently encounter contamination from diverse forms of interference, thereby impeding precise analysis and interpretation. In order to address these obstacles, numerous filtering methodologies have been devised to ameliorate the quality of EOG signals. The objective of this paper is to examine the filtering techniques commonly employed for EOG signals, elucidating their respective benefits and limitations.

Keywords: Electrooculography; EOG; De-noising; Independent Component Analysis; Wavelet Transform

1. Introduction

The electrical voltage produced by eye movements is measured using an approach that is not invasive called electrooculography (EOG) [1–3]. It is an important area of focus in the field of electrical and computer engineering due to its wide range of applications. EOG signals are useful in several fields, including interaction between humans and computers, biomedical engineering, and neurophysiology [4–7]. They provide insightful information about eye movements. This academic introduction aims to explore the fundamentals of EOG signals and highlight their applications in electrical and computer engineering. The corneo-retinal potential generates EOG signals through polarization variations between the cornea and retina. Electrodes placed around the eyes, typically in a bipolar configuration, capture these signals. The electrodes detect voltage changes resulting from eye movements like saccades, blinks, and smooth pursuit [8, 9]. EOG signals have been extensively utilized in electrical and computer engineering, particularly in the area of human-computer interaction. EOG-based interfaces enable individuals, especially those with motor disabilities, to control devices using eye movements. This technology facilitates interaction with computers, assistive devices, and even robotic systems. Biomedical engineering also benefits from EOG signal applications. EOG aids in diagnosing and monitoring ocular disorders such as nystagmus, strabismus, and amblyopia. Analyzing EOG signal characteristics provides clinicians with insights into ocular system functionality and the detection of abnormalities. Additionally, EOG signals have been employed in neurophysiology research to study cognitive processes and brain activity. By examining eye movements and their corresponding EOG signals, researchers gain insights into attention, perception, and decision-making processes, contributing to the advancement of models and theories on human cognition [10]. In the realm of electrical and computer engineering, EOG signals present both challenges and opportunities. Signal processing techniques, including filtering, artifact removal, and feature extraction, are crucial for extracting meaningful information from EOG signals. EOG signals can be reliably classified and interpreted using sophisticated machine learning algorithms, such as neural networks and pattern recognition methods. Additionally, combining EOG signals with other modalities like electromyography (EMG) and electroencephalography (EEG) creates

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additional opportunities for study and application. The integration of these signals enables the creation of cutting-edge human-machine interfaces and offers a more thorough understanding of human behavior [11–13].

2. Various Types of Noise in EOG Signal

In this section, we will explore the typical forms of interference encountered in EOG signals. Baseline Drift: Baseline drift refers to the gradual, slow changes in the EOG signal's baseline over time. It can be caused by electrode movement, variations in skin impedance, or environmental factors. Baseline drift can obscure the underlying EOG signal and hinder the accurate detection of eye movement-related information [14]. Power line Interference: Power line interference, also known as mains hum, arises from the coupling of the EOG electrodes with the electrical power supply network. It presents as periodic noise at the powerline frequency (typically 50 or 60 Hz) and its harmonics. Power-line interference can corrupt the EOG signal and make it challenging to extract meaningful eye movement information [15]. Muscle Artifacts: Muscle artifacts occur due to the contraction or relaxation of facial muscles surrounding the eyes. These artifacts can contaminate the EOG signal and introduce unwanted noise. Muscle artifacts are particularly noticeable during eye blinks or strong eye movements, and they can obscure the desired eye movement-related information [16]. Electrode Noise: Electrode noise refers to the noise introduced by the EOG electrodes themselves. It can stem from inadequate electrode-skin contact, electrode polarization, or impedance mismatch. Electrode noise can degrade the signal quality and introduce additional noise components that interfere with the analysis of the EOG signal [17, 18]. Environmental Noise: Environmental noise sources, such as electromagnetic interference (EMI) from nearby electronic devices, can corrupt the EOG signal. EMI can introduce high-frequency noise or spurious signals that overlap with the desired EOG signal, making it difficult to extract accurate eye movement information [19].

3. EOG Filtering Approaches

Electrooculography (EOG) signals find extensive application in diverse fields, including eye movement analysis and human-computer interaction. The accuracy and dependability of the analysis might be significantly impacted by the noise that frequently taints these signals. Therefore, it is essential to provide effective filtering methods to reduce the negative impacts of noise in EOG signals. Following is a summary of the importance of filtering methods for EOG signals [20, 21]:

- Enhancement of signal quality: EOG signals are susceptible to noise from various sources, such as electrical interference, muscle artifacts, and environmental factors. Filtering techniques play a critical role in reducing or eliminating these noise components, thereby improving the quality and fidelity of the EOG signals.
- Facilitation of accurate analysis and interpretation: Noise in EOG signals can distort the underlying eye movement patterns, making it challenging to accurately analyze and interpret the data. By applying suitable filtering techniques, unwanted noise can be attenuated, enabling more reliable analysis and interpretation of the EOG signals.
- Augmentation of diagnostic capabilities: EOG signals are employed in clinical settings for diagnosing eye-related disorders and abnormalities. However, the presence of noise can impede the accurate detection and characterization of these conditions. Filtering techniques can aid in improving diagnostic capabilities by reducing noise and enhancing the visibility of relevant features in the EOG signals.
- Enhancement of EOG-based system performance: EOG signals are utilized in various applications, such as gaze tracking systems and assistive technologies. The presence of noise can degrade the performance of these systems, leading to inaccurate results or unreliable user interactions. Effective filtering techniques can significantly enhance the robustness and accuracy of EOG-based systems.

3.1. Low-Pass Filtering

Low-pass filtering is a widely utilized method in EOG signal processing. It diminishes high-frequency noise and artifacts while preserving the low-frequency elements of the signal. The benefits of low-pass filtering encompass [22-24]:

3.1.1. Advantages

- Effective elimination of high-frequency noise and artifacts.
- Preservation of low-frequency components that are pertinent to eye movement analysis.
- Enhancement of the signal-to-noise ratio (SNR) for subsequent processing.

3.1.2. Drawbacks

- Potential loss of high-frequency information, which may hold relevance in specific applications.
- Introduction of phase distortion, resulting in a time delay in the filtered signal.
- Challenges in selecting an appropriate cut-off frequency to strike a balance between noise removal and signal preservation.

3.2. High-Pass Filtering

High-pass filtering is utilized to eliminate low-frequency drift and baseline wander from EOG signals, facilitating the isolation of components associated with rapid eye movements. The benefits of employing high-pass filtering include [25, 26]:

3.2.1. Advantages

- Enhancement of eye movement-related components' clarity by eliminating low-frequency drift and baseline wander.
- Improved temporal resolution for the detection of rapid eye movements.
- Reduction of power line interference.

3.2.2. Drawbacks

- Potential loss of valuable information contained in low-frequency components.
- Introduction of phase distortion, similar to low-pass filtering.
- Difficulty in selecting an appropriate cut-off frequency to strike a balance between noise removal and signal preservation.

3.3. Band-Pass Filtering

Band-pass filtering combines the benefits of low-pass and high-pass filtering techniques, enabling the isolation of specific frequency bands that are relevant to the analysis of eye movements. The advantages of band-pass filtering encompass the selective elimination of noise and artifacts beyond the desired frequency range, improved preservation of frequency components of interest, and enhanced signal-to-noise ratio for subsequent analysis [27, 28]. However, there are certain drawbacks associated with band-pass filtering, including the potential loss of frequency components outside the chosen range, which may contain valuable information, the introduction of phase distortion similar to low-pass and high-pass filtering, and the challenge of selecting appropriate cut-off frequencies to strike a balance between noise removal and signal preservation.

3.4. Adaptive Filtering

Adaptive filtering techniques aim to dynamically estimate and eliminate noise components from the EOG signal. These approaches employ adaptive algorithms to continuously update the coefficients of the filter based on the input signal. The benefits of adaptive filtering encompass the following advantages [29, 30]:

3.4.1. Advantages

- Capability to adapt to varying characteristics of noise, rendering it suitable for real-time applications.
- Effective elimination of non-stationary noise sources, such as eye blinks and saccades.
- Preservation of signal features by adaptively adjusting the coefficients of the filter.

3.4.2. Drawbacks

- Considerable computational complexity, particularly for intricate adaptive algorithms.
- Sensitivity to initial conditions and parameter settings, necessitating meticulous tuning.
- Limited performance in the presence of highly non-linear noise sources.

3.5. Wavelet Transform

Wavelet transform-based filtering methods have become increasingly popular in the processing of EOG signals, primarily due to their capability to capture both temporal and spectral information. The benefits associated with wavelet transform filtering are as follows [31-33]:

3.5.1. Advantages

- Multiresolution analysis enables simultaneous examination of various frequency components.
- Improved noise elimination while preserving crucial signal characteristics.
- Flexibility in the selection of wavelet functions and decomposition levels to achieve optimal filtering.

3.5.2. Drawbacks

- Complexity in determining appropriate wavelet functions and decomposition parameters.
- Balancing the trade-off between noise reduction and potential signal distortion necessitates meticulous parameter adjustment.
- Greater computational demands compared to simpler filtering techniques.

3.6. Independent Component Analysis (ICA)

ICA is a widely utilized technique in signal processing applications for filtering electrooculography (EOG) signals. The advantages and drawbacks of employing ICA for EOG signal processing are as follows [34, 35]:

3.6.1. Advantages

- Signal source separation: ICA effectively separates mixed signals into independent components, enabling the isolation of EOG signals from other sources of noise or interference.
- Blind source separation: ICA does not necessitate prior knowledge about the characteristics of the EOG signal or the noise sources, making it suitable for scenarios where the signal sources are unknown or complex.
- Non-invasive approach: EOG signals can be captured using non-invasive electrodes positioned around the eyes, making ICA a convenient and practical method for EOG signal processing.

3.6.2. Drawbacks

- Assumption of statistical independence: ICA assumes that the independent components are statistically independent, which may not always hold true in real-world situations. Deviation from this assumption can result in inaccurate separation of the EOG signal.
- Sensitivity to noise: The performance of ICA can be influenced by the presence of noise in the signal. If the noise is highly correlated with the EOG signal, accurately separating them can be challenging.
- Computational complexity: Implementing ICA algorithms can be computationally demanding, particularly for large datasets or real-time applications. This may restrict its practicality in certain scenarios.

3.7. Kalman Filter

The Kalman filter is a widely utilized technique in signal processing applications for the purpose of filtering electrooculography (EOG) signals. The following are the advantages and drawbacks associated with using the Kalman filter for EOG signal processing [36, 37]:

3.7.1. Advantages

- State estimation: The Kalman filter combines measurements with a dynamic system model to provide an optimal estimation of the true EOG signal. It is capable of effectively estimating the underlying EOG signal even in the presence of noise or missing data.
- Adaptability: The Kalman filter can adapt to changes in the characteristics of the EOG signal over time. It continuously updates its estimates based on new measurements, making it suitable for dynamic EOG signal processing scenarios.
- Real-time processing: The Kalman filter is computationally efficient and can be implemented in real-time applications, enabling immediate feedback or control based on the filtered EOG signal.

3.7.2. Drawbacks

- Model assumptions: The performance of the Kalman filter relies on accurate knowledge of the system dynamics and noise characteristics. If the model assumptions are violated or the noise characteristics are not well-known, the filter's performance may degrade.
- Complexity of implementation: Implementing the Kalman filter requires a thorough understanding of the underlying system dynamics and noise characteristics. It may involve complex mathematical calculations and can be challenging to implement correctly.

- Sensitivity to model errors: If the dynamic model used in the Kalman filter does not accurately represent the EOG signal dynamics, the filter's performance may be compromised. Model errors can lead to inaccurate estimates and filtering results.

3.8. Moving Average Filter

The moving average filter is a widely utilized technique for the filtration of EOG signals. Presented below are the advantages and drawbacks associated with the application of a moving average filter for EOG signal filtering [38, 39]:

3.8.1. Advantages

- Simplicity: The moving average filter is characterized by its straightforward implementation and comprehensibility, rendering it accessible to users with varying levels of expertise.
- Smoothing effect: It effectively diminishes high-frequency noise and fluctuations in the EOG signal, resulting in a more even output.
- Real-time processing: Due to its simplicity and low computational requirements, the moving average filter can be employed in real-time applications.

3.8.2. Drawbacks

- Signal distortion: The utilization of a moving average filter can introduce signal distortion, particularly when applied to rapidly changing EOG signals or signals with abrupt transitions. This may lead to a delay or blurring effect in the filtered signal.
- Attenuation of high-frequency components: The moving average filter tends to attenuate high-frequency components of the EOG signal, potentially resulting in the loss of crucial information.
- Window length selection: The selection of an appropriate window length for the moving average filter is critical. A shorter window may not effectively eliminate noise, while a longer window can introduce a significant delay in the filtered signal.

3.9. Butterworth Filter

The Butterworth filter is a widely utilized technique for processing EOG signals. Here, we present the advantages and drawbacks associated with using the Butterworth filter for EOG signal filtering [40, 41]:

3.9.1. Advantages

- Smooth frequency response: The Butterworth filter exhibits a smooth frequency response, effectively eliminating unwanted noise or interference while preserving the desired EOG signal components.
- Easy implementation: Implementing and comprehending Butterworth filters is relatively straightforward compared to other filter types. They possess a simple design and can be easily adjusted to meet specific filtering requirements.
- Minimal distortion: Butterworth filters maintain a flat passband and minimal distortion within the passband region, ensuring that the filtered EOG signal closely resembles the original.

3.9.2. Drawbacks

- Non-linear phase response: Butterworth filters introduce a non-linear phase response, resulting in different delays for various frequency components of the EOG signal. This can introduce phase distortions in the filtered signal.
- Limited stopband attenuation: In comparison to other filter types, Butterworth filters may exhibit limited stopband attenuation. Consequently, they may not effectively attenuate certain types of noise or interference in the stopband region.
- Trade-off between sharpness and passband ripple: Adjusting the Butterworth filter's sharpness (order) can impact the passband ripple. Higher-order filters offer sharper roll-off but may introduce more passband ripple, while lower-order filters exhibit less ripple but a slower roll-off.

3.10. Machine learning and deep learning Filters

Machine learning and deep learning algorithms have gained increasing popularity in signal processing applications for the purpose of filtering EOG signals. In this regard, it is important to consider the advantages and drawbacks associated with the utilization of these algorithms [42-45]:

3.10.1. Advantages

- Adaptive filtering: Machine learning and deep learning algorithms possess the capability to adaptively learn and adjust their filtering parameters based on the specific characteristics of the EOG signal. This adaptability enables effective noise reduction and removal of artifacts.
- Nonlinear filtering capabilities: These algorithms are capable of capturing intricate relationships and nonlinear patterns present in the EOG signal. Consequently, they offer more accurate filtering compared to traditional linear filtering techniques.
- Feature extraction: Machine learning and deep learning algorithms can automatically extract pertinent features from the EOG signal. These extracted features can be valuable for subsequent analysis or classification tasks.

3.10.2. Drawbacks

- Data requirements: Optimal performance of machine learning and deep learning algorithms typically necessitates a substantial amount of labeled training data. The process of acquiring and labeling such data for EOG signals can be time-consuming and resource-intensive.
- Computational complexity: Training and applying machine learning and deep learning models can be computationally demanding, particularly when dealing with large datasets or real-time applications. This may limit their practicality in certain scenarios.
- Interpretability: Some deep learning models, such as deep neural networks, are often regarded as black-box models. Consequently, comprehending the filtering process and understanding the underlying reasons for their decisions can be challenging.

4. Conclusions

In conclusion, the selection of a filtering technique for EOG signal processing is contingent upon the specific requirements of the application, the characteristics of the signal and noise sources, and the available computational resources. Further research and development in this area are imperative to explore advanced filtering techniques and optimize their efficacy for EOG signal analysis. Future endeavors in reviewing filtering methods for EOG signals can focus on several key areas to enhance comprehension and application of these methods.

Future works

Potential academic future work directions include:

- Comparative analysis: Conduct a comprehensive comparative analysis of various filtering methods for EOG signals, such as ICA, adaptive filtering, wavelet-based methods, and others. Evaluate their performance in terms of signal quality improvement, noise reduction, computational efficiency, and robustness to different noise sources.
- Optimization of filtering parameters: Investigate the impact of different parameter settings on the performance of filtering methods. Explore optimization techniques, such as machine learning algorithms or metaheuristic algorithms, to automatically determine optimal parameter values for each filtering method.
- Real-time implementation: Develop real-time implementations of filtering methods for EOG signals, considering challenges associated with low-latency requirements and limited computational resources. Evaluate the performance and feasibility of these methods in real-time applications, such as eye-tracking systems or human-computer interfaces.
- Noise modeling and simulation: Enhance understanding of noise characteristics in EOG signals by developing realistic noise models and simulators. This can aid in evaluating and benchmarking filtering methods, as well as provide insights into limitations and challenges associated with EOG signal processing.
- Combination of multiple filtering techniques: Investigate potential benefits of combining multiple filtering techniques, such as ICA with adaptive filtering or wavelet-based methods. Explore fusion strategies and evaluate performance improvement achieved by these hybrid approaches.
- Validation on diverse datasets: Validate performance of filtering methods on diverse datasets, including different age groups, eye movement patterns, and pathological conditions. This can help assess generalizability and robustness of filtering methods across various EOG signal scenarios.
- Application-specific evaluation: Evaluate performance of filtering methods in specific applications heavily reliant on EOG signals, such as sleep monitoring, driver fatigue detection, or neuro-rehabilitation. Assess effectiveness of filtering methods in improving accuracy and reliability of these applications

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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