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Research Article

Artifact Removal in Physiological Signals Using Singular Value Decomposition

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Abstract Physiological signals are collected from the human body using electrodes and are evaluated manually by medical professionals. The process of analyzing the data is time-consuming, especially when dealing with physiological signals that require long-term recording, such as electroencephalography, and interpretations may vary from expert to expert. To eliminate these disadvantages, automatic diagnosis systems are being designed. However, for these systems to perform highly accurate classifications, the signals they evaluate must be clean and free of artifacts. Currently, electroencephalography signals used in the automatic detection and evaluation of sleep disorders are frequently corrupted by ocular artifacts and electromyographic noise. This significantly reduces the classification accuracy of automatic sleep assessment systems. This study aims to eliminate the negative effects of artifacts originating from electrooculography on sleep electroencephalography signals. The artifact elimination process was performed using the singular value decomposition method. This method has been found to be highly effective for online sleep staging systems due to its speed, its ability to preserve the main signal, and its effective artifact elimination capability.

Keywords: Artifact, Artifact Elimination, EOG, Sleep EEG, Singular Value Decomposition.

1. INTRODUCTION

Structurally, humans have a highly complex organization. Numerous systems work in conjunction to sustain life, and a malfunction in one or more of these systems affects the others as well. Identifying and correcting these malfunctions, which are defined as diseases, is crucial for the continuity and quality of life. To detect diseases, measurements are sometimes taken directly from patients using electrodes and transducers, while at other times, various samples taken from the human body are analyzed in a laboratory. This study focuses on physiological signals that are vital for diagnosis and can be acquired and processed quickly from the patient.

As a fundamental physiological state, sleep is critical for systemic restoration. It underpins key processes including cellular repair, neurochemical regulation, and cognitive consolidation, which are prerequisites for optimal daytime functioning. Fundamentally, sleep is characterized by a periodic, reversible state of reduced consciousness and responsiveness. A key feature that distinguishes it from unconscious states is the preserved ability to react to salient environmental stimuli [1, 2]. Human sleep is a cyclical process composed of distinct, periodic stages. The classification and analysis of these stages have long been guided by the standardized framework established in A Manual of Standardized Terminology, Techniques and Scoring System for Sleep Stages of Human Subjects, commonly known as the Rechtschaffen and Kales (R&K) manual. Published in 1968 by a consortium of twelve researchers, this work became the cornerstone of sleep science for decades [3]. According to this report, the sleep architecture of a healthy individual is categorized into two primary states: Non-Rapid Eye Movement (NREM) sleep and Rapid Eye Movement (REM) sleep. NREM sleep comprises three distinct stages, designated as N1, N2, and N3.

A significant milestone was reached in 2007 when researchers at the American Academy of Sleep Medicine (AASM), under the direction of Dr. Iber Conrad, released a comprehensive manual. This work provided a standardized framework for the scoring of sleep and all associated events [4]. The sleep scoring guide was revised in 2012 and 2014, culminating in a final version that introduced updated scoring criteria. A key structural modification in this update was the removal of NREM Stage 4; it is now scored as part of Stage 3 [5, 6].

The sleep staging process is typically performed in three steps.

a. For the purpose of standardized scoring, sleep stages are segmented into 30-second intervals termed epochs.

b. Following the criteria specified in the scoring manual, each epoch is analyzed and assigned a corresponding sleep stage.

c. In cases where two stages co-occur within a single epoch, the epoch is assigned the identifier of the stage that accounts for more than 50% of its duration.

The architecture of nocturnal sleep in a typical adult is characterized by the following distribution: Stage 1 (2-5%), Stage 2 (45-55%), Stage 3 (20-25%), and REM sleep (20-25%) [7].

Automatic sleep staging systems leverage algorithms and signal processing techniques to perform all steps of sleep scoring without human intervention. The primary objective is to convert a traditionally labor-intensive and lengthy process into one that yields standardized results rapidly and with high reproducibility.

Electroencephalography (EEG) is commonly employed as a supporting tool for diagnosing neurological conditions [8]. Automated sleep staging systems rely predominantly on sleep EEG signals. The efficacy of spectral processing applied to these signals is contingent upon their purity. This necessity arises from the characteristic low amplitude of EEG signals, which makes them highly susceptible to contamination by artifacts that often possess higher energy content.

Common artifacts in sleep EEG recordings encompass those arising from muscle activity during arousal, rapid eye movements, sweating which can lead to poor electrode contact and general body movements [9]. Among these artifacts, those originating from EOG are particularly problematic because their spectral properties often overlap with those of slow-wave sleep activity. This overlap can cause Stage 3 sleep to be misclassified.

The presence of EOG artifacts, which are concurrently recorded with EEG, can distort the EEG signals and compromise the performance of automated sleep staging algorithms. Consequently, the effective filtering of these artifacts is essential for reliable sleep analysis.

Although several methods have been proposed for removing EOG artifacts from clinical EEG signals [10-14], their application to, or development for, sleep EEG data remains limited.

1.2. Current Methodologies for Artifact Detection in Sleep EEG Data

The presence of artifacts in biomedical signals has long been a critical issue that necessitates effective solutions. In response, a substantial body of research has focused on developing methods to eliminate diverse types of artifacts from EEG data. Mariani et al. [15] removed artifacts from sleep EEG signals using their average power densities and compared the performance with a commercial automated artifact removal system. They reported that their method achieved the highest accuracy of 96.8%–99.4% during NREM sleep. Rozario et al. [16] reported an accuracy of 94.7% during NREM sleep and 95.8% during REM sleep in their study, which leveraged differences in spectral power density between artifact-free and artifact-contaminated EEG signals. According to Somervail et al. [17], they developed an add-on based on the Artifact Subspace Reconstruction (ASR) method to reduce classification time, which could be integrated with the EEGLAB program. Erdoğan et al. [18] investigated noise reduction in ECG signals using the Empirical Mode Decomposition method. Their study successfully achieved an automatic classification of hypertension with 99.99% accuracy by employing Support Vector Machines (SVM). Davut [19] developed a hybrid method for artifact removal in real-time signals, which significantly increased the convergence speed while reducing the mean square error (MSE). This led to an overall superior performance compared to traditional methods.

The existing literature in this domain includes key reviews by Mannan et al. [20], who synthesized the findings of previous studies, and by Jiang et al. [21], who provided a comparative analysis of different artifact types and the techniques used to eliminate them. Following the development of an automatic artifact removal tool for multi-channel EEG by Cox et al. [22], Ujma et al. [23] conducted a comparative analysis of manual and automatic methods, evaluating their performance based on power spectral density (PSD) estimates. These methods have also been proposed for use in semi-automatic systems. However, a significant limitation is their dependence on a skilled operator [24-26].

This study aims to develop a fast, user-independent, and online-suitable artifact removal system for EEG that preserves the integrity of the neural signal. For this purpose, the Singular Value Decomposition (SVD) method was utilized to remove EOG artifacts from sleep EEG recordings.

2. MATERIALS

2.1. Collection of Data

For this study, polysomnography (PSG) recordings were sourced from the PhysioNet [27] and DREAMS [28] databases. The data, which included one EEG channel and two electrooculography (EOG) channels from patient records, had the following characteristics:

I. EEG, sampling frequency 128 Hz

II. EOGR-L (Right and Left eye EOG channel), sampling frequency 128 Hz.

As shown in Figure 1, these signals were recorded via electrodes placed on the scalp and around the ocular region.

2.2. Pre-Signal Processing

The EEG and EOG signals were initially converted from the device's proprietary format to the standardized EDF format. Subsequently, the specific EEG, EOGR, and EOGL channels were isolated from the multichannel dataset using specialized

software. These isolated signals were then converted into a format compatible with MATLAB for analysis, thereby completing the data preparation phase.

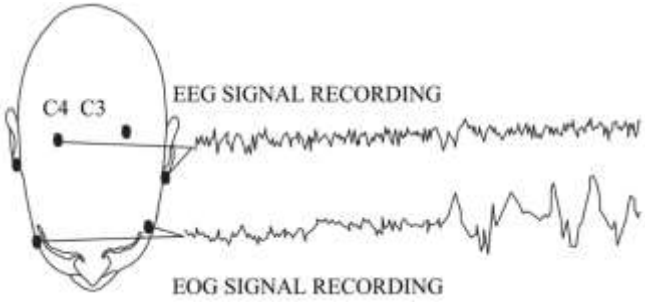


Figure 1. Placement of EEG and EOG electrodes for sleep monitoring and sample signal traces [3].

All data obtained from the databases were initially filtered using a 6th-order Butterworth IIR filter with a passband of 0.3–35 Hz. This bandpass filtering was applied to remove frequencies outside this range, as they hold limited clinical utility for routine scalp recordings. Following filtration, the data were segmented into consecutive 30-second epochs for subsequent evaluation. A representative 30-second sleep EEG epoch containing EOG artifacts is presented in Figure 2.

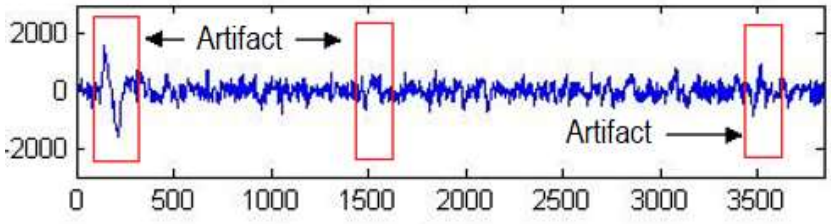


Figure 2. EOG-contaminated EEG epoch

This study aimed to eliminate artifacts from EEG signals, such as the one illustrated in Figure 2. A representative example of these artifacts can be seen in the simultaneous EOG recordings presented in Figure 3, where three distinct artifact regions are clearly marked in both the right (EOGR) and left (EOGL) channels.

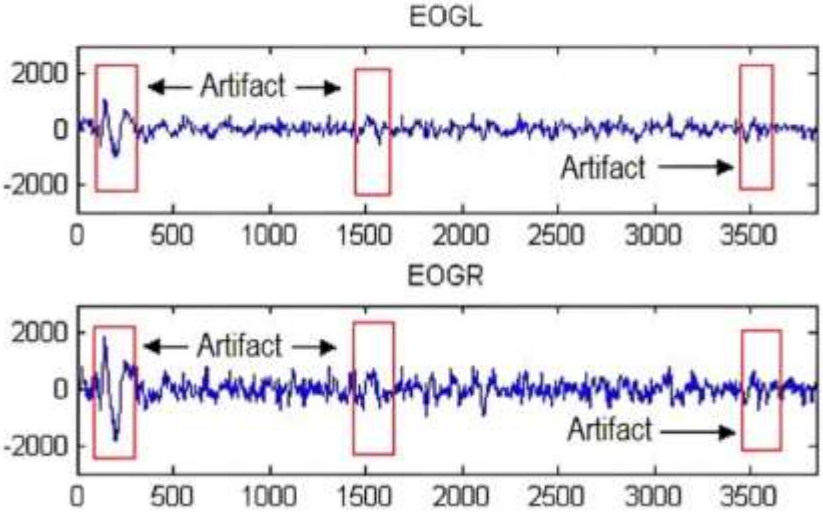


Figure 3. A segment of a 30-s EOGR-L signal exhibiting artifacts.

2.3. Single Value Decomposition

In data science and numerical computation, the SVD is one of the most fundamental tools, despite its origins in the 1870s. The SVD is a factorization of a real or complex matrix. It represents a real matrix of dimensions mxn. Matrix X can be factorized via SVD, a process which partitions it into three distinct matrices [27]. This factorization is represented by Equation (1).

$$X = USV^T \quad (1)$$

In this notation, U and VT are orthogonal matrices of dimensions mxn and nxn. The matrix S symbolizes a diagonal matrix of dimensions nxn. The elements outside the diagonal of this matrix S are zero. The diagonal elements are called the singular values of the matrix X. If the rank of the matrix X is expressed by r, then the value S=diag(σ1, σ2,…, σn) satisfies the equality σ1 ≥ σ2 ≥ … ≥ σr ≥ σr + 1 = σr + 2…= σn=0 [28]. In fact, this diagonal matrix consists of singular values, and the singular values of the given data matrix contain information about the noise level in the data. Therefore, the rank of a matrix is a fundamental property in signal processing.

3. METHOD

In this study, EEG signals contaminated with EOG artifacts were processed using the SVD method for artifact elimination. SVD was preferred for processing large datasets, particularly those collected by long-term signal monitoring devices such as polysomnography, due to its ability to provide more reliable and faster results while preserving meaningful information.

The corresponding block diagram of the proposed system is depicted in Figure 4.

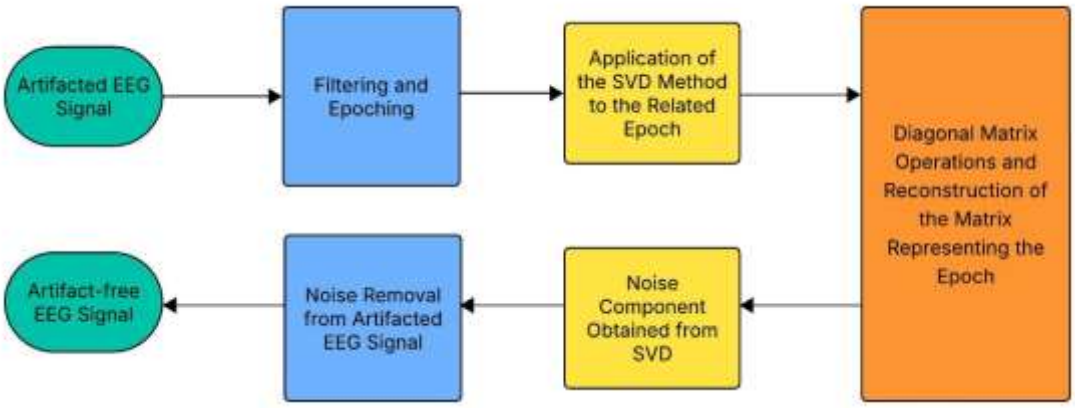


Figure 4. Block Diagram for the Elimination of EOG Artifacts via SVD

As illustrated in the block diagram, the EEG data were loaded and initially filtered within the MATLAB environment. The entire signal was subsequently segmented into epochs to isolate sections that had been identified as containing artifacts by a sleep specialist. These artifact-laden epochs were selected based on the specialist's labels. SVD was then applied to each selected epoch using MATLAB. The resulting matrices were processed to yield the X-matrix, which represents the noise component, specifically the EOG artifact. Finally, the clean EEG signal was derived by subtracting the EOG artifact signal (the X-matrix) from the original contaminated signal. The resulting cleaned signal is presented in Figure 5.

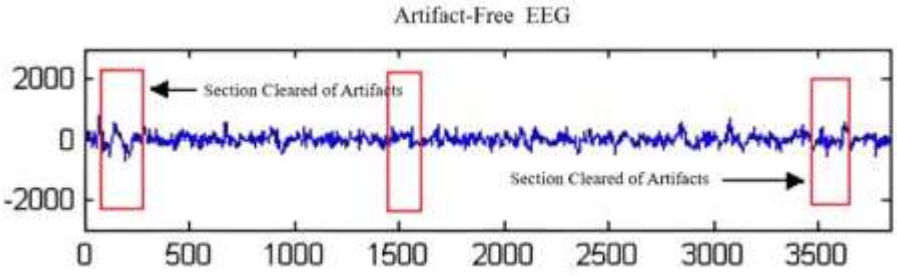


Figure 5. A 30-second epoch of an EEG signal free from EOG artifacts.

The changes in amplitude and frequency caused by an anomaly in the EOG signal are presented in Figures 6 and 7. As shown in Figure 8, the artifact from the EOG signal, caused by an abnormal condition, introduces spurious low-frequency components into the EEG signal. This contamination alters the characteristic features of the EEG signal for that specific sleep stage.

Following the application of the SVD method for artifact removal, Figure 9 presents the resultant clean signal.

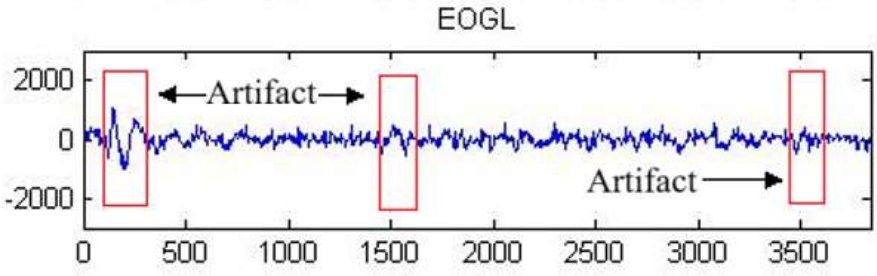


Figure 6. EOGL signal with artifacts

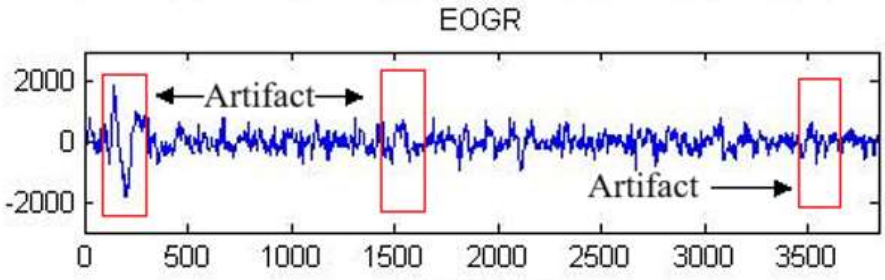


Figure 7. EEG signal with artifacts

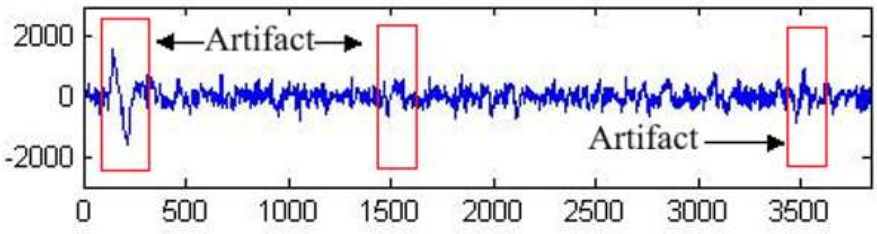


Figure 8. EEG signal with artifacts

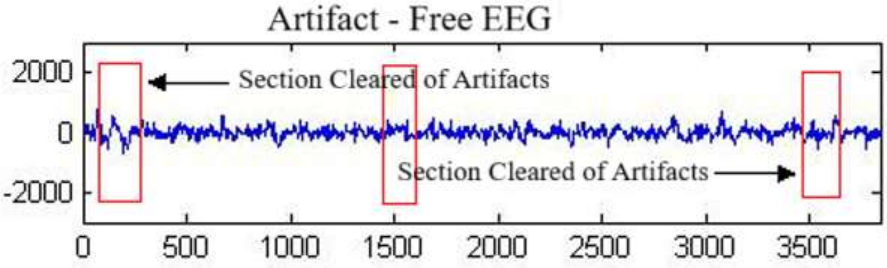


Figure 9. Artifact-Free EEG signal

4. CONCLUSION

This study developed a model for the removal of EOG artifacts from EEG signals. The data utilized were EEG and EOG recordings obtained via PSG from patients in sleep laboratories. During acquisition, EOG signals are susceptible to artifacts, which subsequently propagate to and corrupt the concurrent EEG data. By altering the morphological characteristics of the affected signal epochs, these artifacts can lead to misclassification by automated sleep staging systems, thereby compromising the reliability of such systems.

In this study, SVD was applied to the EEG signals to identify components originating from EOG artifacts. These components were then removed from the raw signal, yielding a clean EEG signal. To identify the artifactual components in the EEG data, the raw data matrix was decomposed into its factors. The diagonal matrix, which is one of these factors, was then isolated for further analysis. To simulate the effect of artifacts, selected diagonal elements of the diagonal matrix were set to zero, which resulted in

a corrupted output signal. The final step was to remove the artifact-containing signal from the raw EEG, producing a clean signal as shown in Figure 9.

This paper presents the initial findings of a broader study that employs expert systems to classify artifact-contaminated and artifact-free EEG data-preprocessed using the SVD method-into sleep stages, with the aim of comparing their performance.

Ethics Statement

The data underlying this article are available in PhysioNet and The DREAMS databases. Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. Written informed consent for participation was not required for this study in accordance with the national legislation and the institutional requirements.

Competing Interests

The authors declare that they have no conflict of interest.

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