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A Neural Learning-Based Approach for EOG Artifact Removal from EEG

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I. Introduction

One of the most prominent modalities to record brain activation is electroencephalogram (EEG) signals, which primarily records scalp voltages indicating the superposition of many neural activities and contributing to different tasks [1]. However, these signals are prone to contamination from various disruptions, specifically the electrooculogram (EOG) artifacts caused by eye movements. The most effective approach to mitigate EOG artifacts involves recording EOG signals simultaneously with EEG and employing blind source separation techniques (BSS), such as independent component analysis (ICA). Nevertheless, EOG recordings, particularly in pre-recorded datasets, are not always available. The object of this study is to present a novel methodology that combines a long short-term memory (LSTM)-based neural network with ICA to address the challenge of EOG artifact removal from contaminated EEG signals. Our approach aims to accomplish two primary objectives: 1) estimate the horizontal and vertical EOG signals from the contaminated EEG data, and 2) employ ICA to eliminate the estimated EOG signals from the EEG, thereby producing an artifact-free EEG signal.

II. Materials and Methods

This paper introduces two different approaches: a single-channel approach and a multi-channel approach. Each approach consists of two stages: an offline stage and an online stage. In the offline stage, a deep LSTM network is trained to learn the underlying time series, sequences, and features in both contaminated EEG signals and EOG recordings. In the online stage, the estimated EOGs are treated as external EOG channels and are combined with other EEG recording electrodes. Subsequently, ICA is applied to extract both clean and artifactual sources. Finally, the artifactual sources are removed during back projection, resulting in a cleaned recording. The estimated EOG recordings are also provided as part of the outputs.

We utilized a semi-simulated EEG/EOG dataset[1] consisting of 54 recordings from 27 healthy subjects (age: 27.17 ± 5.2) each consisting of 30 seconds of closed eyes without any eye movements to capture clean and pure EEG signals. The signals were sampled at a frequency of 200 Hz and filtered using a bandpass filter (0.5 to 40 Hz). In parallel, EOG recordings were acquired from the same subjects and during the same time duration. These EOG signals were then filtered using a 0.5 to 5 Hz bandpass filter and added to the pure EEG signals. Finally, signals are normalized by applying a zero mean unit variance normalization to both the EEG and EOG channels. Additionally, the means and standard deviations of the signals are stored in vectors for reconstruction purposes after network training.

[1]https://data.mendeley.com/datasets/wb6yvr725d/1

III. Results

To evaluate the performance of our proposed method, we employed mean squared error (MSE), mean absolute error (MAE), and mean error (MA). We also compared the performance of our approach with two state-of-the-art deep learning-based methods, which demonstrated the superior performance of our proposed methodology as shown in Table 1.

Table 1: Comparison of the proposed method with the existing similar literature in terms of α subband MAE in PSD (Mean $\pm$ STD).

Method	MSE	MAE	ME
SAE-RLS [2]	0.15	0.39	**0**
DLN-SAE [1]	0.08	0.29	0.01
Proposed method	**0.05**	**0.16**	0.02

IV. DISCUSSION

In this paper, we introduced an LSTM-ICA methodology for effectively removing EOG artifacts from EEG recordings in the absence of external EOG recordings. The proposed approach was evaluated using a dataset that included both contaminated and non-contaminated EEG recordings. Our methodology demonstrated superior performance compared to existing deep learning-based approaches, emphasizing the potential of combining ICA and LSTM in future EEG studies. It would also be worth noting that our proposed methodology in its current form still needs the ICA, as a non-linear source separation method, which can be replaced with end-to-end deep neural network approaches in future studies.

References

1. B. Yang, K. Duan, C. Fan, C. Hu, and J. Wang, "Automatic ocular artifacts removal in eeg using deep learning," *Biomedical Signal Processing and Control*, vol. 43, pp. 148–158, 2018.
2. B. Yang, K. Duan, and T. Zhang, "Removal of eog artifacts from eeg using a cascade of sparse autoencoder and recursive least squares adaptive filter," *Neurocomputing*, vol. 214, pp. 1053–1060, 2016.