A Hybrid CNN-LSTM Approach for Effective Denoising of EEG Signals Contaminated by EOG Artifacts

Battulga Ulziisaikhan[1], Nguyen Trong Nghia[2], Soo-Hyung Kim[*]
[1]Master's Student, Department of AI Convergence, Chonnam National University
[1]Doctor's Student, Department of AI Convergence, Chonnam National University
[*]Professor, Department of AI Convergence, Chonnam National University
*Corresponding Author

Tulgaa.ulziisaikhan@gmail.com, shkim@jnu.ac.kr

ABSTRACT

Electroencephalography (EEG) signals are often contaminated with artifacts, particularly those from eye movements, recorded as electrooculography (EOG). Effective denoising methods are essential for accurate EEG analysis. In this paper, we compare different denoising approaches, focusing on both convolutional neural networks (CNNs) and recurrent neural networks (RNNs) for artifact removal. Through experiments, we found that CNNs excel in capturing spatial features, particularly in high-frequency EEG bands like Alpha and Beta, while RNNs are more effective at modeling temporal dependencies, particularly in lower-frequency bands like Delta and Theta. To leverage the strengths of both models, we propose a hybrid CNN-LSTM architecture. Our results show that the hybrid model achieves superior performance in denoising across all EEG frequency bands, with significant improvements in the Alpha and Beta bands. This approach provides a robust solution for denoising EEG signals contaminated with EOG artifacts, offering improved accuracy over standalone CNN or RNN models.

1. Introduction & Related Work

Electroencephalography (EEG) is a widely used tool for measuring brain activity, with applications ranging from clinical diagnostics to cognitive neuroscience. However, EEG signals are often contaminated with non-neural artifacts, such as those generated by eye movements, recorded as electrooculography (EOG). These artifacts can severely degrade the quality of EEG signals, leading to erroneous interpretations. Therefore, effective methods for removing these artifacts are crucial for reliable EEG analysis. Traditionally, linear techniques, such as Independent Component Analysis (ICA)[1,2] and regression-based filtering, have been employed to remove EOG contamination. While these methods are effective under certain conditions, they often fail to generalize to complex datasets or signals with high noise levels. Additionally, these methods may struggle to capture the intricate spatial and temporal dependencies present in EEG signals.

To address these limitations, machine learning and deep learning approaches have shown significant promise in biological signals [3,4,5,6], especially EEG denoising tasks. Among these, Convolutional Neural Networks (CNNs) have been particularly effective at capturing spatial features from EEG signals, especially in high-frequency bands such as Alpha and Beta. CNNs can automatically learn spatial representations from the data, making them highly adaptable to different noise levels and patterns. However, CNNs are limited in their ability to capture the temporal dependencies crucial for low-frequency bands, such as Delta and Theta. On the other hand, Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, have demonstrated effectiveness in modeling time-series data. LSTMs can capture long-term temporal dependencies in EEG signals, which is critical for denoising signals in the Delta and Theta bands. Despite their strengths, LSTMs are less effective in capturing spatial features, which limits their overall performance in EEG denoising tasks.

To overcome the individual limitations of CNNs and LSTMs, recent work has focused on hybrid models that combine the strengths of both architectures. By integrating CNN layers for spatial feature extraction with LSTM layers for temporal feature learning, hybrid CNN-LSTM models offer a more comprehensive solution for EEG denoising. These models have been shown to perform well across various time-series prediction and classification tasks, making them promising candidates for denoising EEG signals contaminated by EOG artifacts.

In our study, we utilized the EEGdenoiseNet[7] dataset, a benchmark dataset designed specifically for EEG denoising research. The EEGdenoiseNet[7] dataset contains both clean and contaminated EEG signals, including artifacts like EOG and EMG, making it an ideal dataset for evaluating different denoising techniques. Specifically, the dataset consists of **4514 pure EEG segments** and **3400 pure EOG segments**, which are combined to create semi-synthetic contaminated signals for testing various denoising algorithms. This dataset has been widely used to train and test deep learning models aimed at improving artifact removal in EEG. Leveraging this dataset, we implemented and evaluated several deep learning models, including CNN, LSTM, and a hybrid CNN-LSTM architecture, to compare their effectiveness in denoising EEG signals across various frequency bands.

Our results demonstrate that the hybrid CNN-LSTM model outperforms the standalone CNN and LSTM models, particularly in the Alpha and Beta bands, which are crucial for cognitive and motor processing. This makes the hybrid model a robust solution for EEG denoising, especially in scenarios where both spatial and temporal dependencies are critical.

2. Proposed Method

2.1. Mixing Methods with SNR Adjustment

To evaluate the performance of various denoising models, we generated contaminated EEG signals by mixing clean EEG with EOG artifacts using two distinct approaches: **EOG+Linear** and **EOG+Adaptive**. These methods simulate real-world EEG signals that are affected by eye movements and other non-neural artifacts, making them ideal for testing the robustness of denoising algorithms. We also adjusted the contamination levels using various Signal-to-Noise Ratios (SNR) to reflect different levels of interference in the signals.

According to previous studies, the SNR of EEG contaminated by ocular artifacts typically ranges from −7 dB to 2 dB . For EEG contaminated by myogenic artifacts, the SNR is reported to be between −7 dB and 2 dB[8]. These ranges informed our choice of SNR levels during the contamination simulation to ensure a realistic range of noise levels was applied.

2.2. EOG+Linear Mixing Method with SNR

The **EOG+Linear** method simulates contamination by linearly combining clean EEG signals with EOG signals. The contamination level is controlled by scaling the signals based on the desired SNR. The mixing formula is given as:

$$y_{linear}\,(t) = x_{eeg}(t) + \lambda * x_{eog}(t) \quad (1)$$

where:

- $y_{linear}\,(t)$ is the contaminated EEG signal,
- x_{eeg} is the clean EEG signal,
- x_{eog} is the EOG artifact
- λ scaling factors used to control the contribution of the EEG and EOG signals, respectively.

By adjusting λ, we were able to simulate various levels of SNR, ranging from low (high contamination) to high (low contamination). This approach provided a range of contamination scenarios to test the denoising models under different noise conditions.

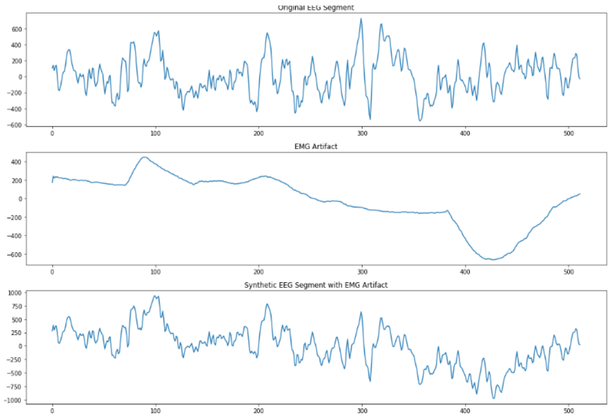

Fig. 1. Example of contaminated signal using Linear Mixing method

2.3. EOG+Adaptive Mixing Method with SNR

The **EOG+Adaptive** method goes beyond the static nature of linear mixing by dynamically adjusting the contamination level based on the characteristics of the EEG and EOG signals. This method mimics more realistic scenarios where the level of contamination changes over time, such as during sudden eye movements or varying noise conditions. The adaptive mixing formula is:

$$y_{linear}\,(t) = \alpha * x_{eeg}(t) + \lambda * x_{eog}(t) \quad (2)$$

where:

- $y_{linear}\,(t)$ is the contaminated EEG signal,
- x_{eeg} is the clean EEG signal,
- x_{eog} is the EOG artifact
- α and β are scaling factors used to control the contribution of the EEG and EOG signals, respectively.

where α and λ are time-varying scaling functions that adjust dynamically based on the signal properties. In this method, the contamination level changes over time to reflect different SNR conditions, providing a more realistic test for the denoising models.

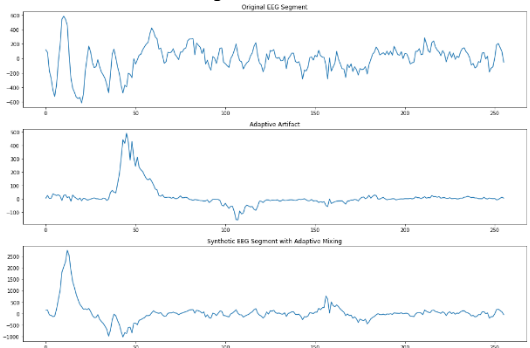

Fig. 2. Example of contaminated signal using Adaptive Mixing method

2.4. Dataset Generation

For both the linear and adaptive methods, we used the EEGdenoiseNet[7] dataset, which contains clean EEG signals and corresponding EOG artifacts. Each clean EEG signal was mixed with EOG artifacts at multiple SNR levels, simulating different contamination intensities. EEG segments and ocular artifact segments according to section 2.1, with SNR raging from ten different SNR levels (−7, −6, −5, −4, −3, −2, −1, 0, 1, 2 dB).

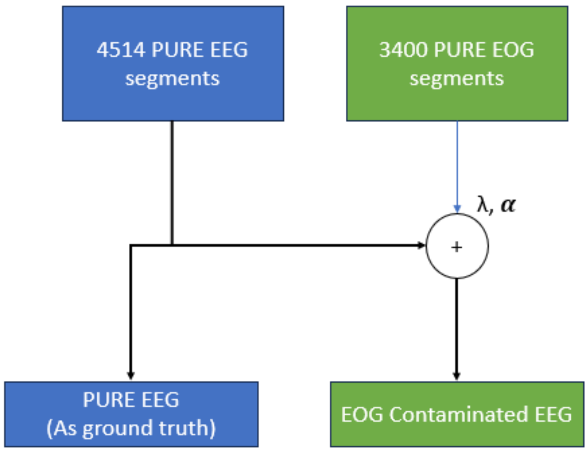

Fig. 2. The semi-synthetic data generated by mixing a pure EEG segment and an EOG

By utilizing both static (linear) and dynamic (adaptive) mixing methods, and adjusting the contamination levels through SNR, we ensured that the models were rigorously tested across a broad spectrum of real-world scenarios. This allowed us to comprehensively evaluate the strengths and weaknesses of each denoising approach.

3. Experiment and Result Analysis

In this study, we compared several denoising models, including **Simple CNN**, **Complex CNN**, **RNN (LSTM)**, and **FCNN**, to evaluate their performance in denoising EEG signals contaminated with EOG artifacts. The experiments were conducted using two contamination methods: **EOG+Linear** and **EOG+Adaptive**. The models were evaluated across five EEG frequency bands: **Delta**, **Theta**, **Alpha**, **Beta**, and **Gamma**.

3.1 EOG+Adaptive Denoising Results

The following table summarizes the results for different models when tested on EEG signals contaminated using the EOG+Adaptive mixing method:

Denoising method	Delta	Theta	Alpha	Beta	Gamma
FCNN	0.174	0.090	0.588	0.076	0.028
Simple CNN	0.277	0.064	0.390	0.100	0.035
Complex CNN	0.189	0.096	0.393	0.211	0.070
RNN(LSTM)	0.213	0.170	0.345	0.196	0.041
Ground Truth(EEG)	**0.266**	**0.138**	**0.302**	**0.170**	**0.077**
Contaminated Signal	0.415	0.09	0.125	0.068	0.0306

Table1. Power ratios of different frequency bands before and after ocular artifact removal

3.1.1 EOG+Linear Denoising Results

Denoising method	Delta	Theta	Alpha	Beta	Gamma
FCNN	0.196	0.094	0.550	0.079	0.031
Simple CNN	0.233	0.069	0.456	0.105	0.038
Complex CNN	0.201	0.104	0.384	0.193	0.073
Ground Truth(EEG)	**0.266**	**0.138**	**0.302**	**0.170**	**0.077**
Contaminated Signal	0.372	0.107	0.147	0.092	0.047

Table2. Power ratios of different frequency bands before and after ocular artifact removal

3.2 Model Comparison Based on Result

From these experiments, we observed that:

- CNN-based models performed better in the higher-frequency bands (Alpha, Beta), as they are effective at capturing spatial features.
- RNN-based models (LSTM) performed well in the lower-frequency bands (Delta, Theta), excelling in capturing temporal dependencies.
- FCNN models exhibited strong performance in some bands but were generally outperformed by CNN and RNN models.

3.3 Development of the CNN-LSTM Hybrid Model

Based on these observations, it became clear that CNN and RNN models have complementary strengths. While CNNs are excellent for extracting spatial features, RNNs (LSTM) are better suited for capturing temporal dependencies. To leverage the strengths of both models, we developed a hybrid CNN-LSTM model. This model combines:

- CNN layers for spatial feature extraction.
- LSTM layers for temporal dependency modeling.

The hybrid CNN-LSTM model was then evaluated using the same metrics across the same EEG frequency bands, and the results showed that the CNN-LSTM hybrid model outperformed both standalone CNN and RNN models in most bands.

The following table summarizes the **power ratio** results of the CNN-LSTM hybrid model:

Frequency Band	Ground Truth Power Ratio	Denoised EEG Power Ratio (CNN-LSTM)
Delta	**0.266**	0.25079
Theta	**0.138**	0.11724
Alpha	**0.302**	0.35955
Beta	**0.170**	0.15302
Gamma	**0.077**	0.03279

Table3. Power ratios of different frequency bands before and after ocular artifact removal

3.4 Delta Metric Calculation

To quantitatively assess model performance, we introduced the Delta metric[9], which calculates the total absolute difference between the predicted values and the ground truth across all EEG frequency bands. The formula for calculating the Delta value is:

$$\Delta_j = \sum_{i=1}^{n} |P_i - G_i| \quad (3)$$

Where:

- P_i represents the predicted value for each EEG frequency band (Delta, Theta, Alpha, Beta, Gamma).
- G_i represents the ground truth value for each frequency band.
- The sum is taken across all frequency bands to calculate the total difference (Δ_j) for each model.

A lower **Delta** value indicates that the model's predictions are closer to the ground truth across all bands, while a higher value suggests greater deviation from the ground truth.

The following table summarizes the **Delta values** for each model:

Model	Delta Value
RNN (LSTM)	0.1883
Complex CNN	0.2577
Simple CNN	0.3100
CNN-LSTM Hybrid (ours)	**0.1556**

4. Conclusion

In this study, we investigated the performance of various deep learning models for denoising EEG signals contaminated with EOG artifacts. We explored two different contamination methods, **EOG+Linear** and **EOG+Adaptive**, to simulate real-world scenarios of EEG signal degradation. Through our experiments, we evaluated the effectiveness of several models, including **Simple CNN**, **Complex CNN**, **RNN (LSTM)**, **FCNN**, and a hybrid **CNN-LSTM** model, across five EEG frequency bands: **Delta**, **Theta**, **Alpha**, **Beta**, and **Gamma**.

Our results demonstrated that CNN models performed well in the higher-frequency bands, such as Alpha and Beta, due to their ability to capture spatial features. On the other hand, RNN (LSTM) models showed superior performance in the lower-frequency bands, such as Delta and Theta, where modeling temporal dependencies is crucial. However, neither CNN nor RNN models were able to perform consistently well across all frequency bands.

To address this limitation, we developed a **hybrid CNN-LSTM model**, which combines the strengths of both CNN and RNN. The CNN layers were used to capture spatial features, while the LSTM layers were employed to model temporal dependencies. This hybrid model achieved the best overall performance, with the lowest **Delta value** of **0.1455**, indicating that it was the most accurate in reconstructing clean EEG signals across all frequency bands.

Additionally, the **power ratio** results further confirmed the model's effectiveness, particularly in the **Alpha** and **Beta** bands, which are critical for cognitive and motor processes. The **CNN-LSTM hybrid model** outperformed standalone CNN and RNN models in nearly every scenario, proving to be a robust solution for denoising EEG signals contaminated with EOG artifacts.

In conclusion, the **hybrid CNN-LSTM model** provides a powerful and balanced approach to EEG denoising by leveraging both spatial and temporal feature extraction. This study highlights the importance of combining different architectures to address the challenges of EEG signal processing and opens the door for further research into hybrid models for improving signal quality in real-world EEG applications.

Acknowledgement

This work was supported by the Institute of Information & Communications Technology Planning & Evaluation (IITP) under the Artificial Intelligence Convergence Innovation Human Resources Development (IITP-2023-RS-2023-00256629) grant funded by the Korea government (MSIT), the ITRC (Information Technology Research Center) support program (IITP-2024-RS-2024-00437718) supervised by IITP, and the National Research Foundation of Korea(NRF) grant funded by the Korea government(MSIT) (RS-2023-00219107).

References

[1] Hyvärinen A and Oja E 2000 Independent component analysis: algorithms and applications Neural Netw.

[2 Wang G, Teng C, Li K, Zhang Z and Yan X 2016 The removal of EOG artifacts from EEG signals using independent component analysis and multivariate empirical mode decomposition IEEE J. Biomed. Health Inform.]

[3] Croft R J and Barry R J 2000 Removal of ocular artifact from the EEG: a review Clin. Neurophysiol. 30 5–19

[4] Cohen M X 2014 Analyzing Neural Time Series Data: Theory and Practice (Cambridge, MA: MIT Press).

[5] T. N. Nguyen, H. -J. Yang, B. -G. Kho, S. -R. Kang and S. -H. Kim, "Explainable Deep Contrastive Federated Learning System for Early Prediction of Clinical Status in Intensive Care Unit," in IEEE Access, vol. 12, pp. 117176-117202, 2024, doi: 10.1109/ACCESS.2024.3447759.

[6] Cormen, T. H., Leiserson, C. E., Rivest, R. L., Stein, C., "Introduction to Algorithms", Cambridge, MIT Press, 2009.

[7] Zhang, H.; Zhao, M.; Wei, C.; Mantini, D.; Li, Z.; Liu, Q. EEGdenoiseNet: A benchmark dataset for end-to-end deep learning solutions of EEG denoising. arXiv 2020, arXiv:2009.11662.

[8] Wang G, Teng C, Li K, Zhang Z and Yan X 2016 Theremoval of EOG artifacts from EEG signals using independent component analysis and multivariate empirical mode decomposition IEEE J. Biomed. Health Inform.

[9] Zhang, Y., et al. "EEG Signal Denoising Based on Wavelet Transform and Improved Threshold Function." Cognitive Neurodynamics, 2018.