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Removal of Ocular and Myogenic Artifacts from EEG Signal Using Deep-Learning Method

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Abstract. Electroencephalography (EEG) provides concepts and techniques for researching brain activity and human behavior by directly measuring electrical signals in the cerebral cortex. The actual EEG signal will, however, have noise as a result of the acquisition process, which will reduce the application effect. Therefore, one of the key issues in growing the EEG application field is how to efficiently eliminate noise from EEG signals. Although deep learning techniques have outperformed conventional techniques in noise reduction tasks like speech and picture, research on its use in EEG signal noise reduction is still lacking. To achieve dual-domain suppression of the two main EEG signal types (ocular and myogenic artifacts), this research suggests a CNN-BiGRU-AT network. After measuring and comparing several perspectives and evaluation indicators, it performs better in terms of noise reduction than the traditional deep learning network architecture, such as CNN or RNN network.

Keywords: EEG noise reduction, deep learning, Ocular and Myogenic Artifacts.

1. Introduction

EEG is a technology that uses appropriately placed electrodes to record electrical activity in the brain from the scalp of the human head. The use of EEG signal processing has become more popular in recent years, for example, in the medical field, EEG is utilized in epilepsy treatment, sleep research, disease prevention, etc., and in the field of brain-computer interface (BCI), EEG is a significant means to gather brain signals [1]. However, the EEG signal itself has the characteristics of being weak and being subject to noise interference. The noise of EEG signal has influence on its application effect, so it is necessary to find an excellent noise reduction algorithm.

The two main types of noise in EEG signals are ocular artefacts and myogenic artefacts [2]. For ocular artefacts, the horizontal and vertical electrooculography (EOG) appears as a sudden overall jump in the time domain waveform (see Fig.1(a)) because of the subject's eye movement or blinking. For myogenic artefacts, facial surface electromyography (EMG) is the main source of them, which

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appears as an explosive chaotic waveform (see Fig.1(c)) because of the subject's facial muscle movements.

In the past, various methods have been developed for denoising EEG signals, such as a comparative analysis implemented by Salis et al [3]. was performed on empirical mode decomposition, discrete wavelet transform, and Kalman filtering techniques, to eliminate EOG artifacts of varying magnitudes from EEG signals. Recently, current studies are becoming more focused on the use of deep learning algorithms to improve the denoising performance. Eoin Brophy proposed a method using Generative Adversarial Networks to denoise EEG signals [4].H Zhang et al applied different neural networks to study the noise reduction of EOG and EMG [5].H Zhang's result showed Convolutional Neural Networks (CNN) played a better performance in EOG denoising and Recurrent Neural Network (RNN) played better in EMG denoising.

However, the above studies are all aimed at reducing one of the two main types of noise. Based on Zhang's results, we hope to combine the above characteristics of CNN and RNN to achieve noise reduction of EEG signals containing these two types of noise. Therefore, we propose a network by using the model combining CNN, bidirectional Gate Recurrent Unit (BiGRU) and attention mechanism (CNN-BiGRU-AT) to denoise EEG signals with EOG and EMG noise. In the field of EEG for epilepsy detection, CNN-BiGRU has been utilized [6]. In order to improve reconstruction accuracy in critical portions, we integrated this model with optimization techniques for attention. In this study, we will compare CNN-BiGRU-AT's performance and application in denoising EEG signals with CNN and RNN techniques for denoising both types of noise.

2. Methodology

2.1. Dataset preparation

In this study, we employ EEGdenoiseNet, a publicly available benchmark dataset that includes 3400 EOG, 5598 EMG, and 4514 clean EEG data, specifically tailored for developing and evaluating deep neural network architectures in electrophysiological signal purification. All of them are acquired from publicly available data repositories and preprocessed into non-overlapping 2-second data. In Zhang's research, they have re-sampled EEG and EOG signals to 256Hz, and EMG signals to 512Hz. For a better fusion signal, we resampled EMG signals to 256Hz, so every signal has 512 sample points.

We employed EEGdenoiseNet to generate simulated contaminated EEG signals. Synthetically contaminated EEG signals may be constructed through linear combination of pristine EEG with EOG and EMG artifacts following the methodology outlined in Equation 1:

$$y = x + \omega_1 \cdot \alpha + \omega_2 \cdot \beta \tag{1}$$

where y denotes the simulated contaminated EEG signal, x denotes the clean EEG signal, α denotes EOG signal and ω_1 denotes EOG's contribution to y, β denotes EMG signal and ω_2 denotes EMG's contribution to y. ω_i is related to signal-to-noise ratio (SNR), which we adjusted in experiment to change ω_i.

Based on the afore mentioned methodology and formula, we can systematically generate simulated contaminated EEG signals contaminated with artifacts at specified SNRs for EOG and EMG signal (as illustrated in Fig.1). The simulated contaminated EEG and corresponding clean EEG signal were utilized for model training.

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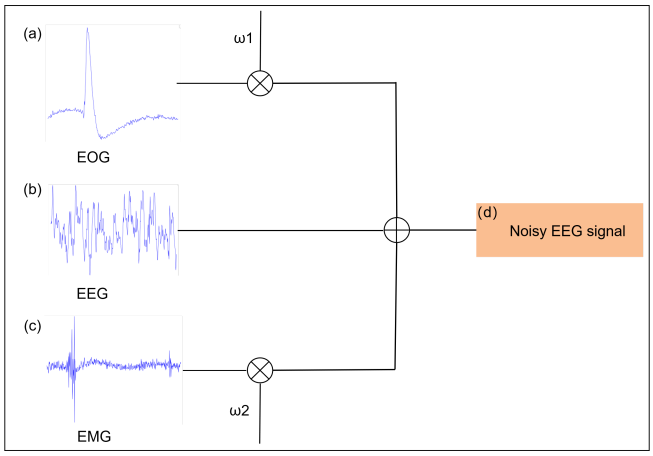

Figure 1: The pipeline of contaminated EEG signals, (a)an EOG signal, (b)an EEG signal, (c)an EMG signal, (d)after combining EEG with EOG and EMG linely, the contaminated EEG signal is generated

2.2. Model

We utilized two standard CNN and RNN models in this experiment to assess the performance of CNN-BiGRU-AT after merging the features of CNN and RNN networks to handle noise. For the specific network structure, please refer to Kur1su-m/Removal-of-Ocular-and-Myogenic-Artifacts-from-EEG-Signal-Using-Deep-Learning-Method. The CNN and RNN networks' architectures in this experiment were directly adapted from H Zhang's published study. The RNN network makes use of LSTM gate, whereas the CNN network employs a basic convolutional kernel.

In the CNN-BIGRU-AT model, we employ a convolutional layer-based encoder to extract local features step by step using three-layer convolution, followed by normalization procedures to compress spatial information. The bidirectional GRU layer then records the timing data and sharpens the focus on the important time points by utilizing the self-attention method. The length is then gradually deconvoluted using the decoder to preserve additional low-frequency information. The whole neural network structure is shown in the Fig.2.

2.3. Performance evaluation

To intuitively identify and comprehend the performance variations of the networks, we begin by identifying the worst and best noise reduction outcomes that correspond to each model using the test set data.

Then, to quantitatively evaluate the denoising performance, we will use two metrics: Relative Root Mean Square Error (RRMSE) in temporal/spectral domains and correlation coefficient (CC), which provide robust comparisons across models. According to previous research by Gang Wang et al [7], the SNR for both ocular artifacts and myogenic artifacts we chosen in this work is ranging from -7dB to 2dB. So in order to make the result more representative, the SNR of the two noises will be a random number from -7dB to 2dB when performing this indicator.

Given the importance of frequency components in EEG analysis, we performed spectral evaluations by quantitatively comparing denoised and original signals' frequency content to assess frequency retention. We further analyzed network performance under varying noise SNR conditions. These indicators enabled comprehensive assessment of CNN-BiGRU-AT's noise reduction capabilities.

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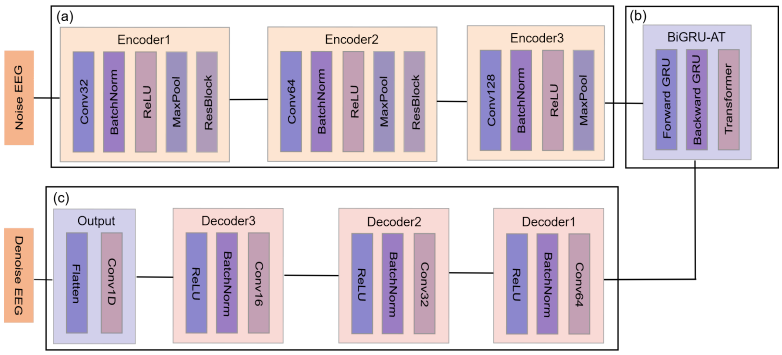


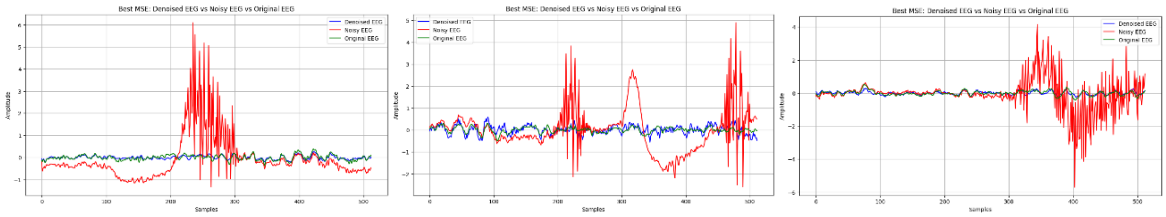
Figure 2: The structure of CNN-BiGRU-AT, (a)Encoder part based on CNN (b)BiGRU part optimized by attention method (c)output part using Decoder to restore signal

3. Result

The best and worst results of the respective test sets of each network are shown in Fig. 3. The findings demonstrate that our models perform exceptionally well at denoising EEG signals with high EOG signal fluctuation, pulse and frequency change. However, when the high-frequency components completely interfere with the EEG signal, the noise reduction effect is not satisfactory.

Tables 1 and 2 clearly show that CNN-BiGRU-AT has the highest CC and the lowest RRMSE in both domains, while CNN has the lowest. This demonstrates how well our model performs in the EEG denoising task.

The results of Power ratios across distinct spectral ranges preceding and subsequent to network networks are shown in Table 3. The original power spectrum of the three models is approximately the same. After denoising, we find that at the relatively mid-range frequency band like Theta and Beta, CNN-BiGRU-AT performed best, while in other bands, it didn't have the best retention performance, especially in the highest band Gamma and the lowest band Delta.Similarly, we can see that RNN also shows similar characteristics, because the characteristic of RNN network is to increase the connection of signal timing, while EOG and EMG noise is more high frequency than EEG signals, so RNN network damages the high frequency information in the original signal. In addition, CNN-BiGRU-AT uses a bidirectional GRU block, so the response to abnormal frequencies is more intense, resulting in a loss of high and low frequencies and and an increase in mid-frequency.



(a)best of CNN-BiGRU-A (b)best of CNN (c)best of RNN

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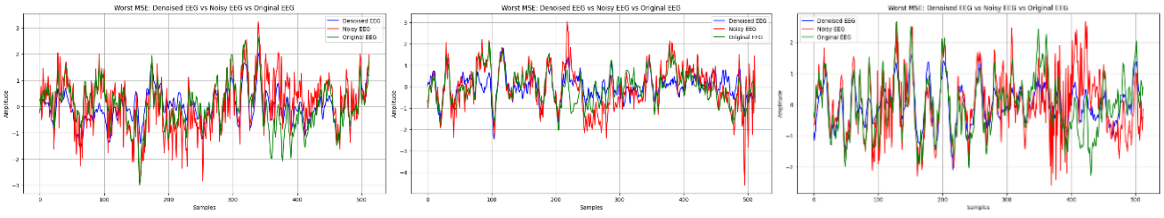

(d) worst of CNN-BiGRU-AT (e)worst of CNN (f)worst of RNN

Figure 3: The best and worst result of each network, red line indicates the noisy EEG, green line indicates the original EEG, blue line indicates the denoised EEG

Table 1: RRMSE and CC in temporal domain of different models

Model	$RRMSE_{temporal}$	$CC_{temporal}$
CNN	1.229	0.646
RNN	0.915	0.707
CNN-BiGRU-AT	0.850	0.733

Table 2: RRMSE and CC in spectral domain of different models

Model	$RRMSE_{spectral}$	$CC_{spectral}$
CNN	1.224	0.831
RNN	0.910	0.858
CNN-BiGRU-AT	0.893	0.866

Table 3: Power ratios across distinct spectral ranges preceding and subsequent to networks

Model	Delta	Theta	Alpha	Beta	Gamma
CNN	0.224	0.134	0.307	0.212	0.099
RNN	0.234	0.141	0.408	0.159	0.036
CNN-BiGRU-AT	0.194	0.149	0.445	0.176	0.023
Ground truth	0.264	0.145	0.326	0.176	0.071

Fig.6 shows the performance of these three models in the case of different SNR. The SNR for both ocular artifacts and myogenic artifacts we chosen here is also ranging from -7dB to 2dB. From Fig.6, we can see CNN-BiGRU-AT shows a better performance in all of the SNRs, and the RNN comes second. In the case of high SNR level, the three networks are similar in noise reduction performance, on the contrary, in the case of low SNR level, CNN-BiGRU-AT shows significantly better performance than the other two.

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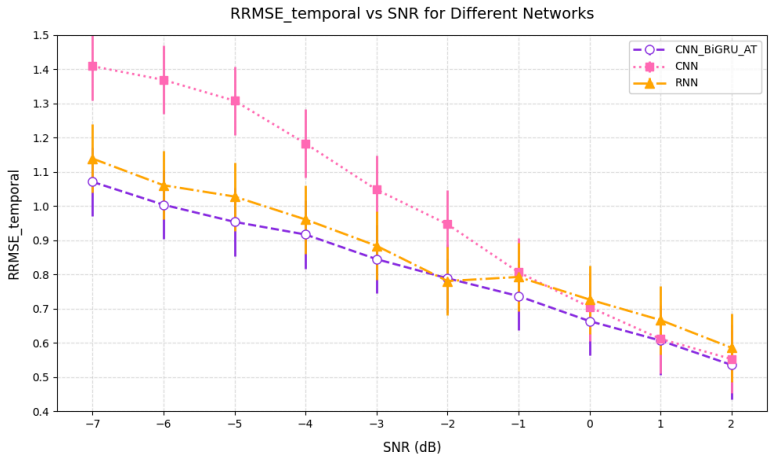

Figure 4: The RRMSE in temporal domain of models under different SNR, CNN-BiGRU-AT shows the best performance of three models

4. Discussion

Comparative Analysis of Denoising Methods. Overall, the study provides a new way to denoise EEG signal by a deep-learning method using CNN-BiGRU-AT model. It turned out to be a better performance in restoring the original EEG signal using the model than conventional CNN, RNN models, closer to the feature of the original EEG signal, and retains excellent performance at diverse SNRs.

Suppression of Joint Noises. In general, the framework provides an attempt for denoising joint EOG and EMG noises concurrently. These two universal nonlinear noises are integrated to restore the real scenario. Method of CNN-BiGRU-AT, in the end, performed well in suppressing both EOG and EMG. The simulation is close to reality under the combined noise environment.

Broader Implications. Originally, we noticed CNN-BiGRU-AT structure from sentiment analysis and emotion prediction cases, its cross-domain application of EEG denoising highlights the potential of deep learning methods in the BCI. The scope of this contribution was to introduce a CNN-BiGRU-AT method. Compared to conventional techniques, the potential might enhance EEG data and signal processing.

Limitations of Model Training. While there are important discoveries revealed by our studies, there are also limitations. As the CNN-BiGRU-AT model has several structural issues that need to be optimized, it requires an enormous amount of time to complete a training progress. One important future direction of optimization is to adjust and simplify the code structure. One possible way is to tweak the convolutional layer and make sure LSTM added to the RNN layer. Besides, the attention mechanism has insufficient sensitivity to local features. These modifications will improve the performance, which will promote real-time applications in future medical and bioengineering industry [8].

5. Conclusion

The research proposes a hybrid CNN-BiGRU-AT method for joint suppression of EOG and EMG noises in EEG signals. The model shows better performance over conventional deep learning methods (CNN, RNN) in reconstructing original EEG signal while maintaining its feature. After analyzing the performance in various SNRs in the simulation, the CNN-BiGRU-AT method shows great potential for future application in signal denoising compared with traditional ways.

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Future optimizations will focus on tweaking the network structure and processing noises that close to real scenario. Other noise reduction tasks, especially those involving complex artifacts in random situations, could be readily adapted to the framework's modular architecture.

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The authors wish to clarify the individual contributions to this work: Chen Qian and Xiangyu Wen contributed equally to this work as first authors. Yichen Mao and Kangcheng Zou contributed equally to this work as second authors.

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References

[1] Li, Bohao, Tianshuo Cheng, and Zexuan Guo. "A review of EEG acquisition, processing and application." Journal of Physics: Conference Series. Vol. 1907. No. 1. IOP Publishing, 2021.

[2] Fatourechi, Mehrdad, et al. "EMG and EOG artifacts in brain computer interface systems: A survey." Clinical neurophysiology 118.3 (2007): 480-494.

[3] Salis, Christos I., et al. "Denoising simulated EEG signals: A comparative study of EMD, wavelet transform and Kalman filter." 13th IEEE International Conference on BioInformatics and BioEngineering. IEEE, 2013.

[4] Brophy, Eoin, et al. "Denoising EEG signals for real-world BCI applications using GANs." Frontiers in Neuroergonomics 2 (2022): 805573.

[5] Zhang, Haoming, et al. "EEGdenoiseNet: a benchmark dataset for deep learning solutions of EEG denoising." Journal of Neural Engineering 18.5 (2021): 056057.

[6] De, Sagnik, et al. "A Fusion of CNN and Grey Wolf Optimization-Enhanced BiGRU for Epileptic Seizure Recognition Using EEG Signals." 2023 3rd International Conference on Mobile Networks and Wireless Communications (ICMNWC). IEEE, 2023.

[7] Gang Wang, Chaolin Teng, Kuo Li, Zhonglin Zhang, and Xiangguo Yan. The removal of eog artifacts from eeg signals using independent component analysis and multivariate empirical mode decomposition. IEEE Journal of Biomedical & Health Informatics, 20(5): 1301–1308, 2016.

[8] Wang, Bin, Fei Deng, and Peifan Jiang. "EEGDiR: Electroencephalogram denoising network for temporal information storage and global modeling through Retentive Network." Computers in Biology and Medicine 177 (2024): 108626.