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Scientific Forum

Physics-informed attention temporal convolutional network for EEG-based motor imagery classification

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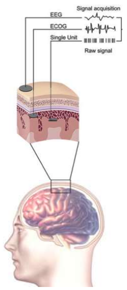
Introduction

- The brain-computer interface (BCI) is an emerging technology that has the potential to transform the world, with a wide range of applications ranging from medical applications to human augmentation. MI-EEG signal has been used in many BCI applications to assist disabled people and to augment human capabilities.

- EEG is a non-invasive, low cost, low risk, and portable method that records the electrical activities of the brain. Motor imagery (MI) is the activity of thinking about moving a human body part without physically moving it.



- Recognizing human intention from EEG signal is challenging due to the low SNR ratio and various sources of artifacts, the recorded EEG signal is only ~ 5% of the actual brain signal.

Aims

The goal is to develop a high-performance attention-based deep learning model to classify EEG-based MI brain signals, which outperform state-of-the-art models.

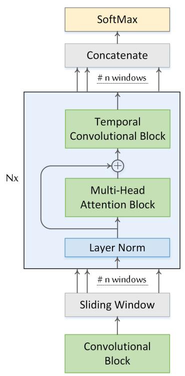
Proposed Method

The proposed model consists of three main blocks:

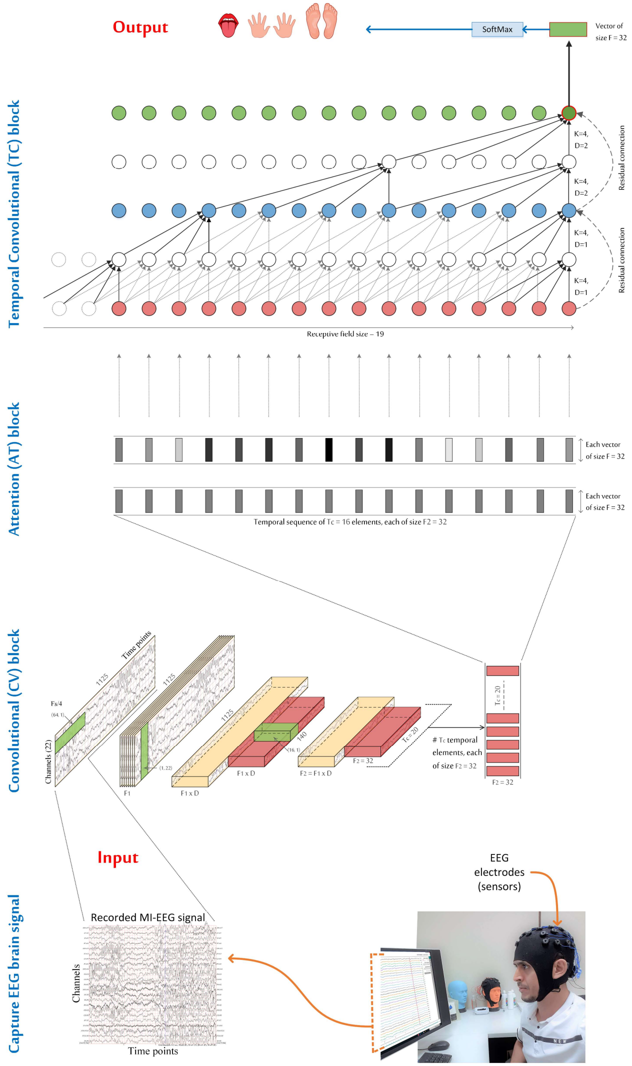
Convolutional (CV) block: encodes low-level spatio-temporal information within the MI-EEG signal into a sequence of high-level temporal representations through three convolutional layers.

Attention (AT) block: highlights the most important information in the temporal sequence using a multi-head self-attention (MSA).

Temporal convolutional (TC) block: extracts high-level temporal features from the highlighted information using a temporal convolutional layer



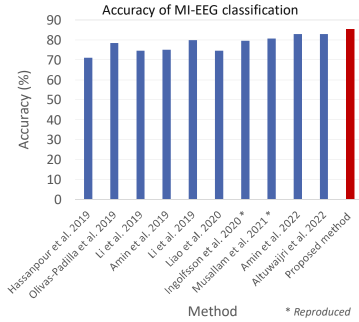
The proposed model also utilizes the convolutional-based sliding window to augment MI data and boost the performance of MI classification efficiently.



Visualization of the components of the proposed ATCNet model. ATCNet consists of three main blocks: the convolutional (CV) block, the multi-head self-attention (AT) block, and the temporal convolutional (TC) block.

Results

- The proposed ATCNet model achieves an overall accuracy of 85.38% and a κ-score of 0.81, using the challenging and benchmark BCI Competition IV-2a dataset, which outperforms the state-of-the-art techniques by at least 2.51%.
- Ablation analysis showed that each block adds its contribution: the AT block increased the overall accuracy by 1.54% and SW by 2.28%. The addition of the TC block also increased accuracy by 1.04% compared to using the CV block only.



Ablation analysis: contribution of each block in the ATCNet model. AT: attention, SW: sliding window, TC: temporal convolution.

Removed block	Accuracy %	κ-score
None (ATCNet)	85.38	0.805
AT	83.84	0.784
SW	83.10	0.775
SW + AT	82.75	0.770
TC	79.44	0.726
SW + TC	80.48	0.740
AT + TC	82.60	0.768
SW + AT + TC	81.71	0.756

Conclusions

- This study proposed a novel attention-based temporal convolutional network (ATCNet) for EEG-based motor imagery classification that outperformed state-of-the-art techniques in MI-EEG classification using the BCI-2a dataset with an accuracy of 85.4% and 71% for the subject-dependent and subject-independent modes, respectively. These high results came with a relatively small number of parameters (115.2K), which makes ATCNet applicable to limited devices.
- The ablation analysis showed that each block in the ATCNet model made a significant contribution to the performance of the ATCNet model.
- The proposed model demonstrated a powerful ability to extract MI features from a raw EEG signal without pre-processing using a limited-size and challenging dataset.

Future work

- The proposed model can be further improved by using attention mechanisms in several domains, i.e., temporal, spectral, and spatial domains.
- The proposed model can also be refined using preprocessing methods to remove artifacts and deep generative models to increase the size of the dataset.

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Code shared on GitHub: https://github.com/Altaheri/EEG-ATCNet

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