 DOI: 10.3217/978-3-85125-962-9-160

EEG-SimpleConv, an efficient and fast architecture for Motor Imagery EEG classification

Ghaith Bouallegue[1], Yassine El Ouahidi, Bastien Pasdeloup, Nicolas Farrugia, Vincent Gripon , Giulia Lioi
IMT Atlantique, Lab-STICC, France

Recent studies in EEG decoding have shown that deep learning methods have good classification performances, without the need for *ad hoc* preprocessing techniques and feature engineering steps in the design of Brain-Computer Interface (BCI) classifiers. Nevertheless, deep-learning methods in motor imagery (MI) tasks stagnate in offering high accuracies, suffer in some cases from biased evaluation of model performance, and are usually tested on single datasets. This limitation can be associated with the fact that the proposed models fail to generalize to different EEG recording systems and setups. In addition, the rationale behind specific architectural or optimization choices is often unclear and scarcely validated.

We propose EEG-SimpleConv, a straightforward convolutional neural network with a regular architecture. We evaluate its performances on three EEG MI datasets (BCI IV-2a[1], Physionet MI[2], and Cho 17[3]) and compare it to recent deep learning models (EEGNetv4[4] ,TIDNet[5], EEG-ITNet[6]). We test different optimization techniques such as Mixup, Euclidean Alignment (EA), and batch normalization on the test set statistics, and evaluate their impact on classification performances with an ablation study. EEG-SimpleConv shows up to 6% improvement in accuracy in different scenarios and datasets compared to the other models. In fact, this model shows a trade off of high number of parameters that enables better learning, and a low inference time which explains how fast the proposed model is. We have also made Our code freely accessible at `https://github.com/GhBlg/EEG-Benchmarking`.

Keywords : Electroencephalography (EEG), Brain-computer interface (BCI), Motor Imagery (MI), Deep learning (DL), EEG Classification

References

[1] M. Tangermann, K.-R. Müller, A. Aertsen, N. Birbaumer, C. Braun, C. Brunner, R. Leeb, C. Mehring, K. Miller, G. Mueller-Putz, G. Nolte, G. Pfurtscheller, H. Preissl, G. Schalk, A. Schlögl, C. Vidaurre, S. Waldert, and B. Blankertz, "Review of the bci competition iv," *Frontiers in Neuroscience*, vol. 6, 2012. [Online]. Available: https://www.frontiersin.org/articles/10.3389/fnins.2012.00055

[2] A. L. Goldberger, L. A. N. Amaral, L. Glass, J. M. Hausdorff, P. C. Ivanov, R. G. Mark, J. E. Mietus, G. B. Moody, C.-K. Peng, and H. E. Stanley, "Physiobank, physiotoolkit, and physionet: components of a new research resource for complex physiologic signals." *Circulation*, vol. 101 23, pp. E215–20, 2000.

[3] H. Cho, M. Ahn, S. Ahn, M. Kwon, and S. C. Jun, "EEG datasets for motor imagery brain–computer interface," *GigaScience*, vol. 6, no. 7, 05 2017, gix034. [Online]. Available: https://doi.org/10.1093/gigascience/gix034

[4] V. J. Lawhern, A. J. Solon, N. R. Waytowich, S. M. Gordon, C. P. Hung, and B. J. Lance, "Eegnet: a compact convolutional neural network for eeg-based brain–computer interfaces," *Journal of Neural Engineering*, vol. 15, no. 5, p. 056013, jul 2018. [Online]. Available: https://dx.doi.org/10.1088/1741-2552/aace8c

[5] D. Kostas and F. Rudzicz, "Thinker invariance: Enabling deep neural networks for bci across more people," *Journal of neural engineering*, vol. 17, 09 2020.

[6] A. Salami, J. Andreu-Perez, and H. Gillmeister, "EEG-ITNet: An explainable inception temporal convolutional network for motor imagery classification," *IEEE Access*, vol. 10, pp. 36 672–36 685, 2022. [Online]. Available: https://doi.org/10.1109%2Faccess.2022.3161489

Table 1: model performances across datasets (standard deviation).

		EEGNet	TIDNet	EEG-ITNet	EEG-SimpleConv
Datasets	BCI IV-2a	70.31 (8.09)	63.52 (6.38)	69.83 (7.58)	**76.26 (7.73)**
	Physionet MI	65.94 (2.94)	58.94 (2.37)	65.73 (3.14)	**69.27 (2.09)**
	Cho 2017	70.88 (6.37)	67.35 (4.91)	71.18 (5.57)	**77.93 (3.96)**

Published by Verlag der Technischen Universität Graz