An end-to-end deep convolutional pipeline for BCI classification task

Aras Dargazany [‡],
[‡]Corresponding Author, arasdar@uri.edu

***Abstract*—Brain-computer interface (BCI) conventional classification pipeline is composed of local feature extraction for filtering and denoising purposes (e.g. spatial Laplacian and Morlet Wavelet), global feature extraction (e.g. PCA and ICA), and machine learning approaches for classification. An end-to-end deep learning (DL) pipeline for the entire BCI classification task can avoid fixed local filtering and denoising, manual local feature extraction, manual data analysis, and different classification approaches. This end-to-end DL approach is also capable of adapting and scaling to a bigger datasets as more data become available via more experimental data collection. If the entire BCI classification pipeline can be replaced with one end-to-end DL pipeline, then we can conclude that the pre-processing steps for filtering/denoising in BCI classification task is not really necessary.**

I. Introduction

Deep learning [1]–[3] was introduced as an approach to learn deep neural network architecture using vanilla backprop [4]. Extremely deep networks (end-to-end pipelines) learning reached unprecedented depth for layers of representation with residual and highway networks [5], [6]. Hierarchical convolutional neural network have been biologically inspired and investigated [7]–[10].

Cecotti et al. (in 2008 [11]) applied convolutional neural networks (CNN) to BCI for the first time (as far as I can see in the BCI literature) which is a pioneering work in terms of applying DL to BCI applications. He applied CNN with embedded Fourier transform for EEG classification. In 2011 [12], he again applied CNN for P300 BCI experimental data for detection purposes. In another work and roughly the same year [13], he applied CNN in time-frequency domain for offline classification of steady state event-related potentials (ERP) for recognizing evoked potential responses classes. Recently (in 2017 [12]), he discussed the power and the impact of CNN architecture in ERP detection.

Trakoolwilaiwan et al. (in 2017 [14]) applied CNN to fNIRs data for move/ rest BCI classification task for automating feature extraction and classification modules in conventional pipeline of BCI classification (figure 1). They used a preprocessing step (wavelet and multi resolution filters) for denoising the data and then applied a deep CNN for classification. The reported classification accuracy using CNN is better than SVN and vanilla ANN although the reported online processing time is much worse.

This work [14] inspired/ motivated our work in terms of replacing the pre-processing step with an end-to-end DL pipeline for a fully automated local feature extraction, global feature extraction, and classification in BCI classification task (figure 1).

Our proposed end-to-end CNN approach (DL pipeline) for BCI classification task is illustrated in this figure 2.

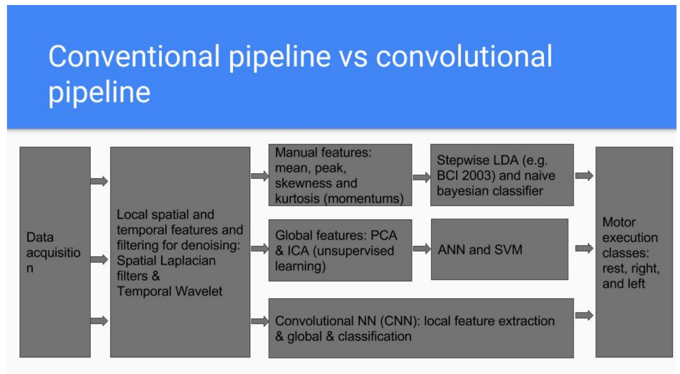

Fig. 1. The convolutional pipeline (CNN) vs the conventional one (BCI) including different required modules [14]. The inspiration behind our work for replacing the preprocessing step with the convolutional pipeline (deep CNN).

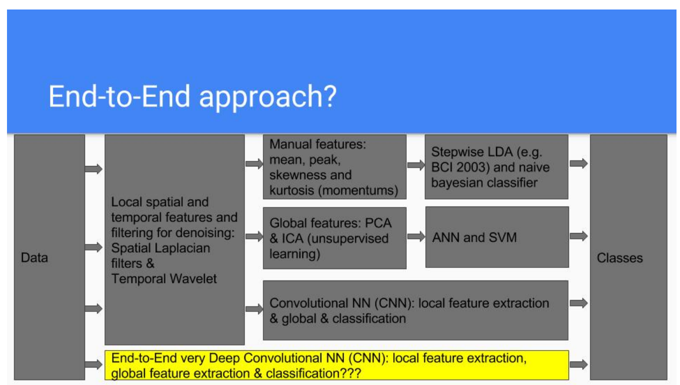

Fig. 2. Our proposed end-to-end deep CNN compared to the proposed CNN in [14], traditional BCI classification pipeline.

References

[1] Y. LeCun, B. Boser, J. S. Denker, D. Henderson, R. E. Howard, W. Hubbard, and L. D. Jackel, “Backpropagation applied to handwritten zip code recognition,” *Neural computation*, vol. 1, no. 4, pp. 541–551, 1989.
[2] Y. LeCun, Y. Bengio, and G. Hinton, “Deep learning,” *Nature*, vol. 521, no. 7553, pp. 436–444, 2015.
[3] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “Imagenet classification with deep convolutional neural networks,” in *Advances in neural information processing systems*, 2012, pp. 1097–1105.

[4] D. E. Rumelhart, G. E. Hinton, and R. J. Williams, "Learning internal representations by error propagation," CALIFORNIA UNIV SAN DIEGO LA JOLLA INST FOR, Tech. Rep., 1985.

[5] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2016, pp. 770–778.

[6] R. K. Srivastava, K. Greff, and J. Schmidhuber, "Highway networks," *arXiv preprint arXiv:1505.00387*, 2015.

[7] D. H. Hubel and T. N. Wiesel, "Receptive fields of single neurones in the cat's striate cortex," *The Journal of physiology*, vol. 148, no. 3, pp. 574–591, 1959.

[8] K. Fukushima, "Neocognitron: A hierarchical neural network capable of visual pattern recognition," *Neural networks*, vol. 1, no. 2, pp. 119–130, 1988.

[9] ——, "Cognitron: A self-organizing multilayered neural network," *Biological cybernetics*, vol. 20, no. 3-4, pp. 121–136, 1975.

[10] D. L. Yamins and J. J. DiCarlo, "Using goal-driven deep learning models to understand sensory cortex," *Nature neuroscience*, vol. 19, no. 3, pp. 356–365, 2016.

[11] H. Cecotti and A. Graeser, "Convolutional neural network with embedded fourier transform for eeg classification," in *Pattern Recognition, 2008. ICPR 2008. 19th International Conference on*. IEEE, 2008, pp. 1–4.

[12] H. Cecotti, "Convolutional neural networks for event-related potential detection: impact of the architecture," in *Engineering in Medicine and Biology Society (EMBC), 2017 39th Annual International Conference of the IEEE*. IEEE, 2017, pp. 2031–2034.

[13] ——, "A time–frequency convolutional neural network for the offline classification of steady-state visual evoked potential responses," *Pattern Recognition Letters*, vol. 32, no. 8, pp. 1145–1153, 2011.

[14] T. Trakoolwilaiwan, B. Behboodi, J. Lee, K. Kim, and J.-W. Choi, "Convolutional neural network for high-accuracy functional near-infrared spectroscopy in a brain–computer interface: three-class classification of rest, right-, and left-hand motor execution," *Neurophotonics*, vol. 5, no. 1, p. 011008, 2017.