

Investigating Self-Supervised Learning for EEG Processing

Victor Delvigne^{1,2}, Hazem Wannous²

¹ ISIA Lab, Faculty of Engineering, *University of Mons*, Belgium

² IMT Nord Europe, *CRISTAL UMR CNRS 9189*, France

Electroencephalogram (EEG) signals processing has been of growing interest for some years now. This motivation is translated by the apparition of various works investigating symptoms assessment, help in diagnosis or brain-computer interfaces. One of the big challenges to overcome in this context is the reduction of signals dimension to make them easier to be processed.

Although several works have focused on dimension reduction [3], the two most considered approaches present drawbacks: 1). Handcrafted feature extraction methods are difficult to generalise, did not consider all the properties of EEG signals simultaneously (i.e. temporal, spectral and spatial properties) and seem simplistic compared to existing Deep Learning (DL) methods employed in other fields. 2). DL-based networks extracting features are hardly (if at all) generalizable from one paradigm to another, are not applicable for datasets with smaller sizes and did not use huge available corpus of EEG due to their poor/weak labels.

In this work, the use of a novel DL-based approach to automatically extract feature vectors has been investigated. Concretely, the recent advances in Self-Supervised Learning (SSL) and their encouraging results in many fields have been a motivation to consider this learning approach. With the latter, the learning paradigm is reformulated: the goal is not to find the best model able to make classification from a given modality but to ensure that it can process it correctly.

In this context, three SSL tasks have been investigated, each of them considering an aspect of EEG properties:

- Temporal Jigsaw: inspired by the jigsaw puzzle [4] consisting to replace image patches in the correct location. The task has been adapted to suit EEG by dividing the signal into windows and replacing them in the correct order.
- Spectral attraction: contrastive function [2] applied on the EEG signal and its spectral representation. The task aims at teaching the network the relationship between EEG signals and their spectral properties.
- Spatial attraction: contrastive function [2] aiming to teach the network the spatial or electrodes-wise relationship in EEG signals.

The above-listed tasks (i.e. pretext task) have been applied to the TUEEG corpus [5]. Then, a classification task (i.e. downstream task) was proceeded on BCI-IV EEG [1] to evaluate the knowledge acquired during the pretext task.

For this purpose, different policies have been considered to investigate the advances of pretext tasks prior to downstream tasks. The latter corresponds to measuring the cross-validation accuracy with various settings: without the pretext task, with each task separately and with all tasks simultaneously. The analyses show that solving pretext tasks provides better results that corroborates the fact that the network learns abilities during the pretext task to better classify during the downstream task.

References

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