 DOI: 10.3217/978-3-85125-962-9-82

Neural network transfer learning with fast calibration for mental imagery decoding

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Introduction: A typical decoding challenge faced with brain-computer interfaces (BCI) is the small dataset size compared to other domains of machine learning like computer vision or natural language processing. A possibility to tackle this lack of training data is through transfer learning, but this is non-trivial because of the non-stationary of EEG signals. Consequently, explicit calibration phases at the start of BCI sessions are usually required.
In this study, we show how a deep neural network can be used in the context of motor imagery transfer learning, while still allowing for a session-specific calibration phase and without a computationally expensive model fine-tuning.

Methods, Materials and Results: We introduce a simple domain adaptation technique. It first learns an embedding (i.e., abstract vectorial representation) across subjects to deliver a generalized data representation. It then feeds the embeddings into subject-specific or session-specific simple classifiers. The embedding functions were obtained by training EEGNet [1] using a leave-one-subject-out (LOSO) protocol, and the embedding vectors were classified by the logistic regression algorithm. We conducted offline experiments on multiple motor imagery datasets from the MOABB library [2]. Our pipeline was compared to two baseline approaches: EEGNet without subject-specific calibration and the standard Filter-Bank Common Spacial Patern (FBCSP) [3] pipeline in a within-subject training.

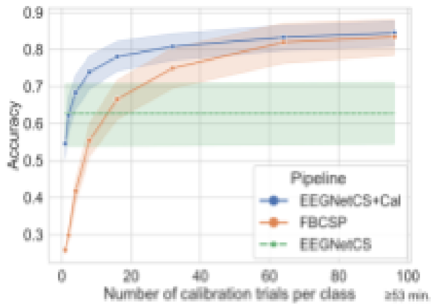

Figure 1. *Classification accuracy of the different pipelines on the High Gamma Dataset [4].*

Discussion: We observed that the representations learned by the embedding functions were non-stationary across subjects, justifying the need for an additional subject-specific calibration. We also observed that the subject-specific calibration improved the score. Finally, our data suggest, that building upon embeddings requires fewer individual calibration data than the FBCSP baseline to reach satisfactory scores.

Significance: Our method allows to use deep learning and all its recent advances for EEG decoding while still having a session-specific calibration in a reasonable time.

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 Article ID: 144463