Embedding neurophysiological signals

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INTRODUCTION

Problem Setting

Neurophysiological time-series recordings of brain activity like the electroencephalogram (EEG) or local field potentials can be decoded by machine learning models in order to either control an application, e.g., for communication or rehabilitation after stroke, or to passively monitor the ongoing brain state of the subject, e.g., in a demanding work environment.

Challanges in BCI

A typical decoding challenge faced by a brain-computer interface (BCI) is the **small dataset size** compared to other domains of machine learning like computer vision or natural language processing. The possibilities to tackle classification or regression problems in BCI are to either train a regular model on the available small training data sets or through transfer learning, which utilizes data from other sessions, subjects, or even datasets to train a model. Transfer learning is non-trivial because of the non-stationary of EEG signals between subjects but also within subjects. This variability calls for explicit calibration phases at the start of every session, before BCI applications can be used online.

Approach

In this study, we present arguments to BCI researchers to encourage the use of **embeddings for EEG decoding**. In particular, we introduce a simple domain adaptation technique involving both deep learning (when learning the embeddings from the source data) and classical machine learning (for fast calibration on the target data). This technique allows us to learn embeddings across subjects, which deliver a generalized data representation. These can then be fed into subject-specific classifiers in order to minimize their need for calibration data.

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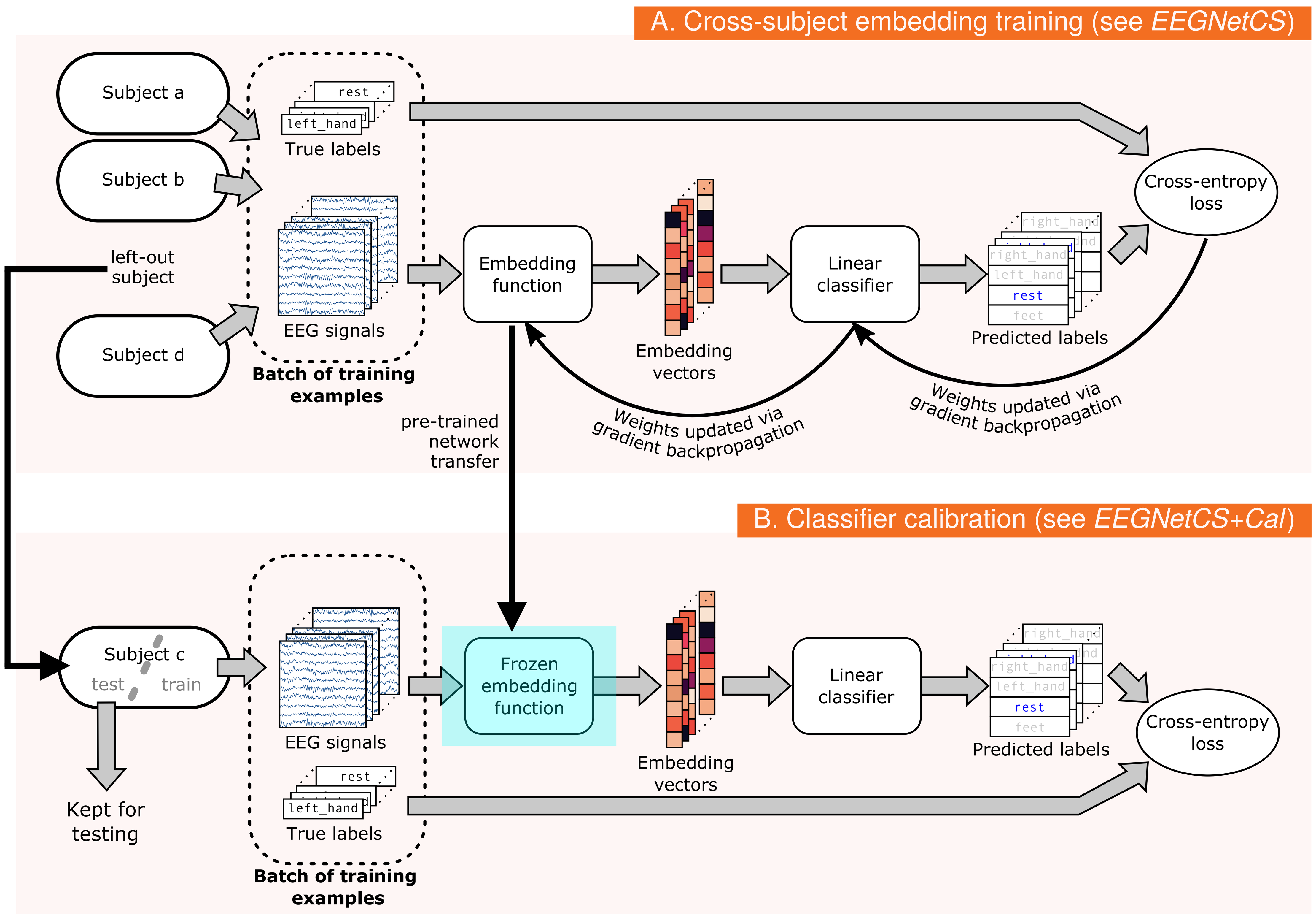
MATERIALS AND METHODS



Pipelines:

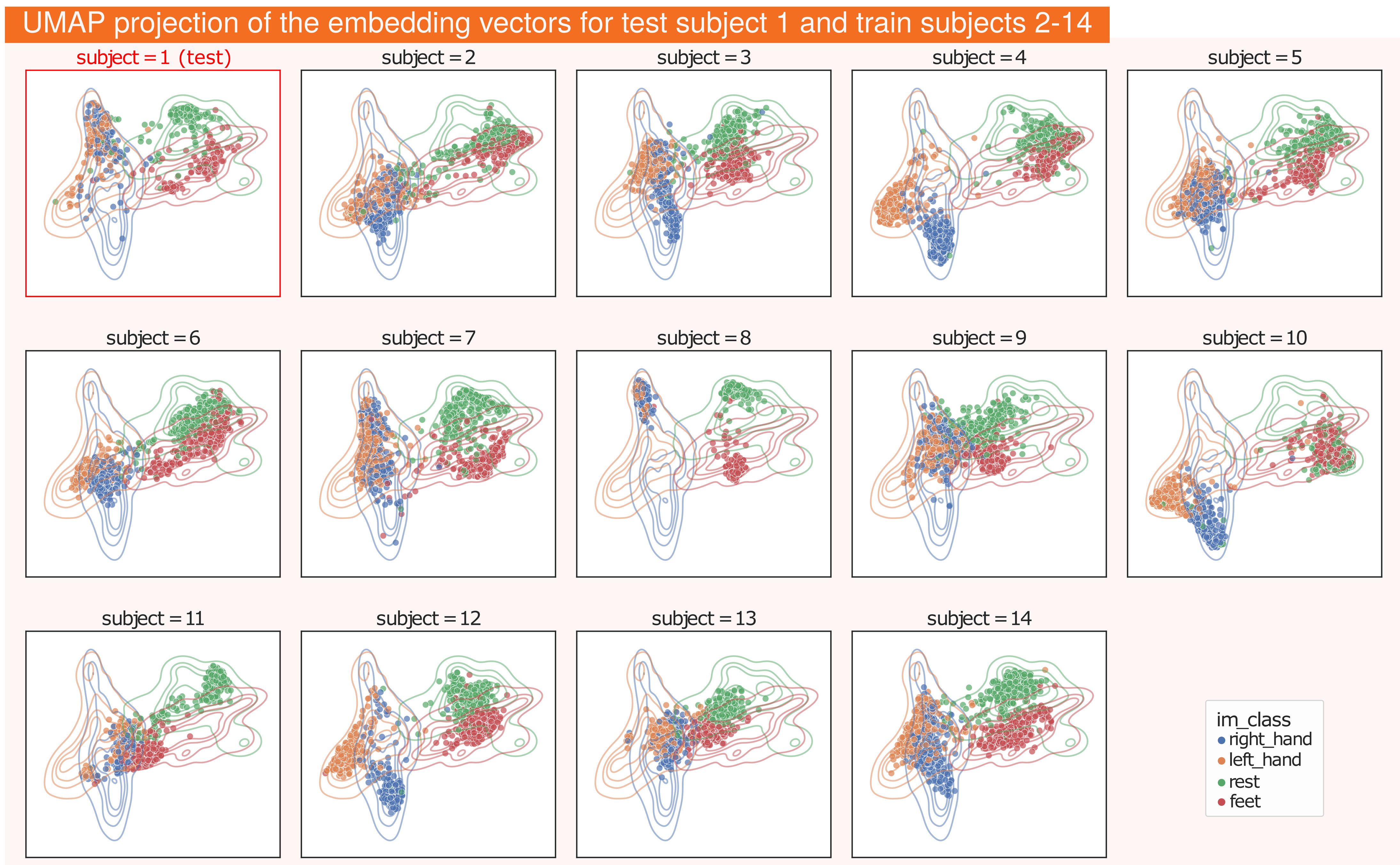
- *EEGNetCS* (EEGNet Cross-Subject) is a pipeline trained in a leave-one-subject-out manner using a classification loss and has the original EEGNet architecture [**1**]. See diagram **A**.
- *EEGNetCS+Cal* (EEGNet Cross-Subject + Calibration) uses a pre-trained and frozen embedding function from the *EEGNetCS* pipeline to extract a representation and a linear layer calibrated on data from the test subject for classification. See diagram **B**.
- *FBCSP*: is the standard classification pipeline [**3**] and is trained on data of the test subject only.

Dataset: High gamma dataset [**2**].

- EEG recordings (44 channels at 128 Hz)
- 14 subjects, each executing 1000 trials of 4 s duration
- Balanced classes (250 each): **left** hand movement, **right** hand movement, **feet** movement and **resting**.
- One example is a 512×44 matrix.

RESULTS

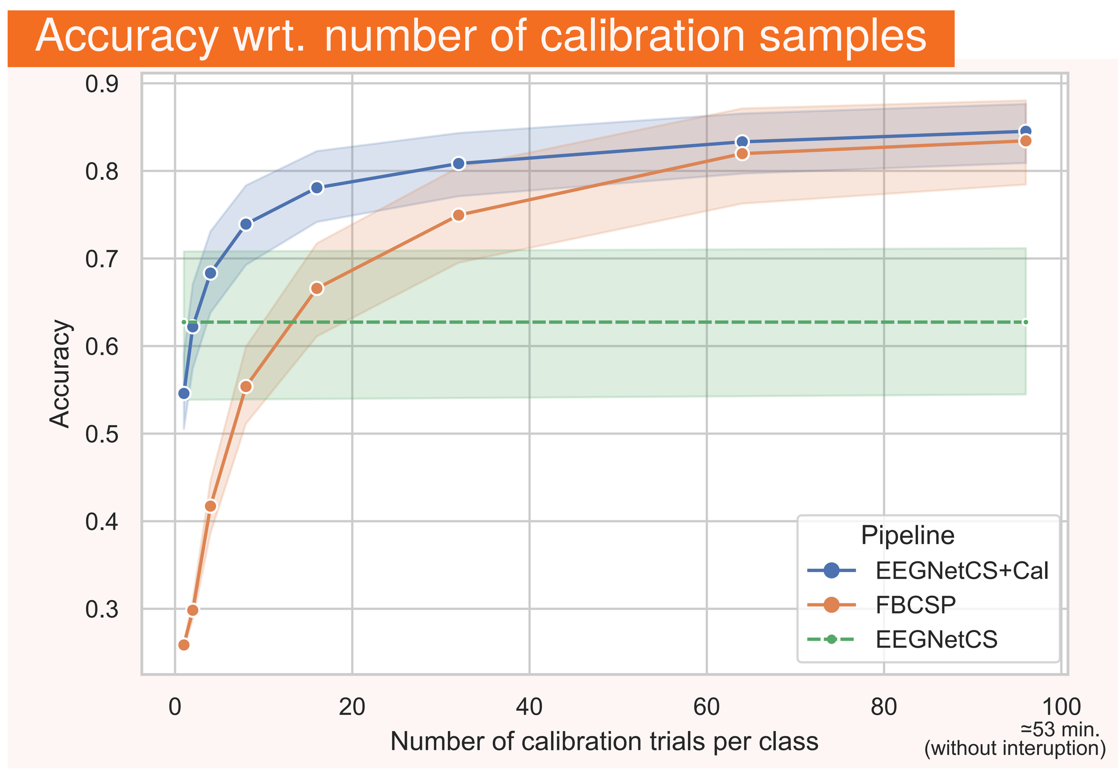
UMAP projection of the embedding vectors for test subject 1 and train subjects 2-14



Classification accuracies when using all calibration samples

Subject	1	2	3	4	5	6	7	8	9	10	11	12	13	14	mean	std
EEGNetCS	0.86	0.73	0.61	0.45	0.74	0.81	0.76	0.31	0.51	0.53	0.41	0.74	0.52	0.79	0.63	0.17
EEGNetCS+Cal	0.93	0.86	0.87	0.91	0.89	0.87	0.88	0.88	0.78	0.80	0.75	0.95	0.82	0.89	0.86	0.058
FBCSP	0.89	0.80	0.95	0.95	0.91	0.93	0.73	0.91	0.74	0.85	0.81	0.92	0.90	0.95	0.87	0.078

Accuracy wrt. number of calibration samples



OBSERVATIONS

1. The UMAP projection shows a good generalisation of the embedding to the test subject (i.e. subject 1).
2. The right-hand/left-hand and rest/feet class pairs are harder to separate than the other pairs.
3. Within-class embedding distribution is subject-dependent (cf. UMAP projection). Therefore, subject-specific calibration is relevant.
4. The pipelines with subject-specific calibration outperform the cross-subject one (as expected).
5. The individually-calibrated pipelines reach the same score when trained using all the trials (c.f. table),
6. But EEGNetCS+Cal can be trained with fewer calibration data than the FBCSP baseline (c.f. line plot).

DISCUSSION

With this study, we presented some of the advantages of using deep learning-based embeddings for EEG signals. Most importantly: (1) They **can be pre-trained** on related data (e.g., from other sessions or subjects). (2) They can be **calibrated quickly on novel data**.

In this work, embeddings are trained on labelled data using a classification loss. Labelled BCI data is rare compared to other fields like computer vision or language processing. The key to finding EEG representations suited to be used as pre-training in multiple BCI paradigms might lie in the use of prior knowledge about the recordings (i.e. patient files, questionnaires, expert knowledge ...) or in self-supervised learning that does not require labelled data.

References [**1**] Vernon J Lawhern et al. (2018), *Journal of Neural Engineering* EEGnet: a compact convolutional neural network for EEG-based brain-computer interfaces. [**2**] Schirrmeister R. T. et al. (2017), *Human brain mapping*, Deep learning with convolutional neural networks for EEG decoding and visualization. [**3**] Chin Z. Y. et al. (2009), *Annu Int Conf IEEE Eng Med Biol Soc*, Multi-class filter bank common spatial pattern for four-class motor imagery BCI.

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