Shallow convolutional neural network with rank-1 Fourier domain weights for brain signal classification

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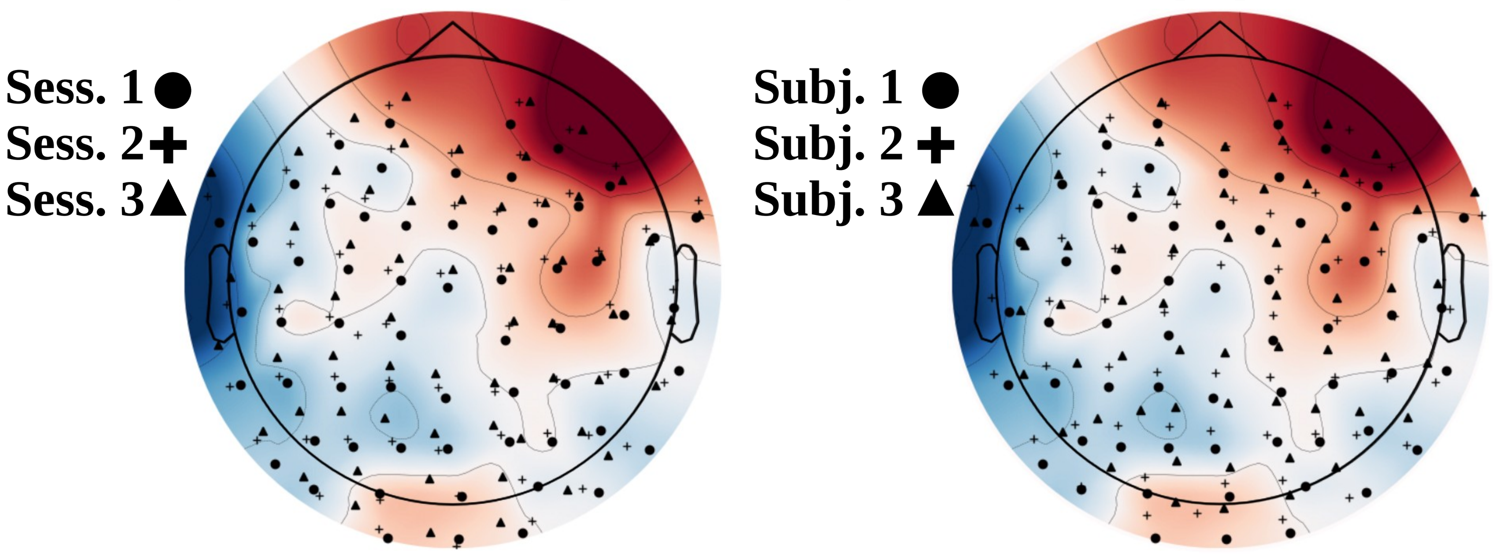
Abstract: Magnetic field strength and electric potential recorded scalp (or in its proximity) by magneto- and electro-encephalography (M/EEG) devices are direct measures of the brain activities. M/EEG devices are broadly used in brain-computer interfaces (BCI), evaluation of multiple neurological diseases, cognitive science, analysis of dynamic brain networks, etc. Active and passive BCI applications, as well as characterization of certain neurological disorders such as epilepsy, require employment of M/EEG signal classifiers. Under the assumptions that a multivariate M/EEG signal can be represented as sum of the rank-1 multivariate signals corresponding to the individual brain activities and noise and that the relevant brain waveforms are of transient and recurrent nature, we propose a shallow convolutional neural network (CNN) classifier. Proposed model contains rank-1 trainable spatial and temporal weights, regularized by the representation in the Fourier domain. The model is evaluated on the problems of active and passive BCI.

1 M/EEG signals

EEG	MEG
Portable	In shielded room
Low prices	Expensive
Active and passive BCI	BCI for rehabilitation
High temporal resolution	
Low spatial resolution	
High inter-session and inter-subject variablity	
Low signal to noise ratio	

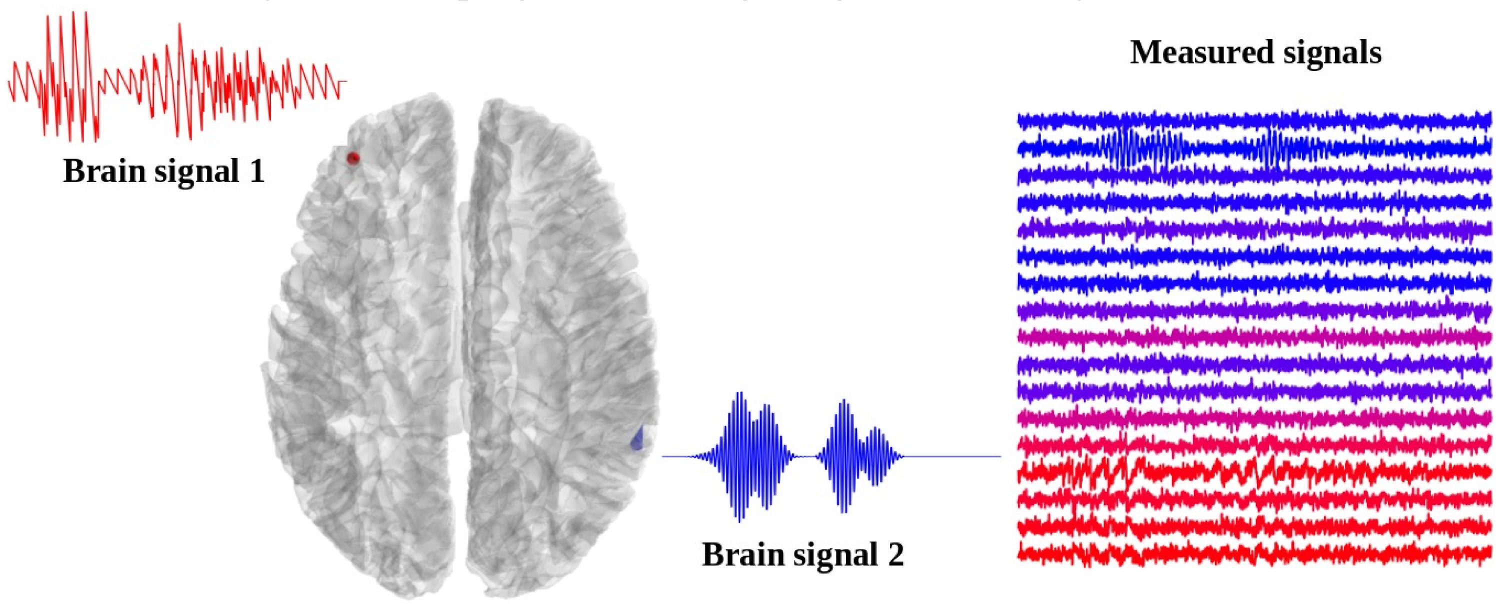
High inter-session and inter-subject variability

(subject alertness, sensor positions, head geometries, cortex properties)



Low signal to noise ratio

(measuring device imperfections, artifacts from other organs, ambient noise)



Images created with ***MNE-toolbox*** **[1]**

2 Shallow CNN classifier with rank-1 Fourier domain weights

Given an M/EEG signal $X\in\mathbb{R}^{C\times T}$, where C and T are the number of sensors and time instants, the following assumptions are made:

1) X can be modeled as a **sum of rank-1 signals** associated to individual sources and noise [2, 3] as

$$X=\sum_{k=1}^{K}\boldsymbol{u}_k\boldsymbol{x}_k^T+N.$$

K is the number of sources. $\boldsymbol{u}_k\in\mathbb{R}^C$ is topographic map. $\boldsymbol{x}_k\in\mathbb{R}^T$ is source signal. $N\in\mathbb{R}^{C\times T}$ is noise.

2) Given a **recurrent and transient nature** of the brain waveforms [3, 4], a source signal $\boldsymbol{k}$ can be represented as $\boldsymbol{x}_k=\boldsymbol{v}_k*\boldsymbol{z}_k$. $\boldsymbol{v}_k\in\mathbb{R}^{\tau}$ is brain waveform. $\boldsymbol{z}_k\in\mathbb{R}^{T+\tau-1}$ is a sparse vector of activations.

3) A head can be modeled as a sphere [5], thus $\boldsymbol{u}_k$ can be represented in terms of **spherical harmonics (SH)** as $\boldsymbol{u}_k=Y\hat{\boldsymbol{u}}_k$. $\hat{\boldsymbol{u}}_k\in\mathbb{R}^{N_L}$ contains SH coefficients and $Y\in\mathbb{R}^{C\times N_L}$ contains N_L SH basis elements. Thus

$$\tilde{X}\approx\sum_{k=1}^{K}\hat{\boldsymbol{u}}_k[\boldsymbol{v}_k*\boldsymbol{z}_k]^T,\ \tilde{X}=Y_{inv}X.\ Y_{inv}\text{ is pseudo-inverse of }Y[6].$$

4) Waveforms can be expressed in terms of **discrete cosine (DC) basis** as $\boldsymbol{v}_k=C\hat{\boldsymbol{v}}_k$. $\hat{\boldsymbol{v}}_k\in\mathbb{R}^F$ contains DC coefficients. $C\in\mathbb{R}^{\tau\times F}$ contains DC basis. F is the number of DC basis elements. Thus

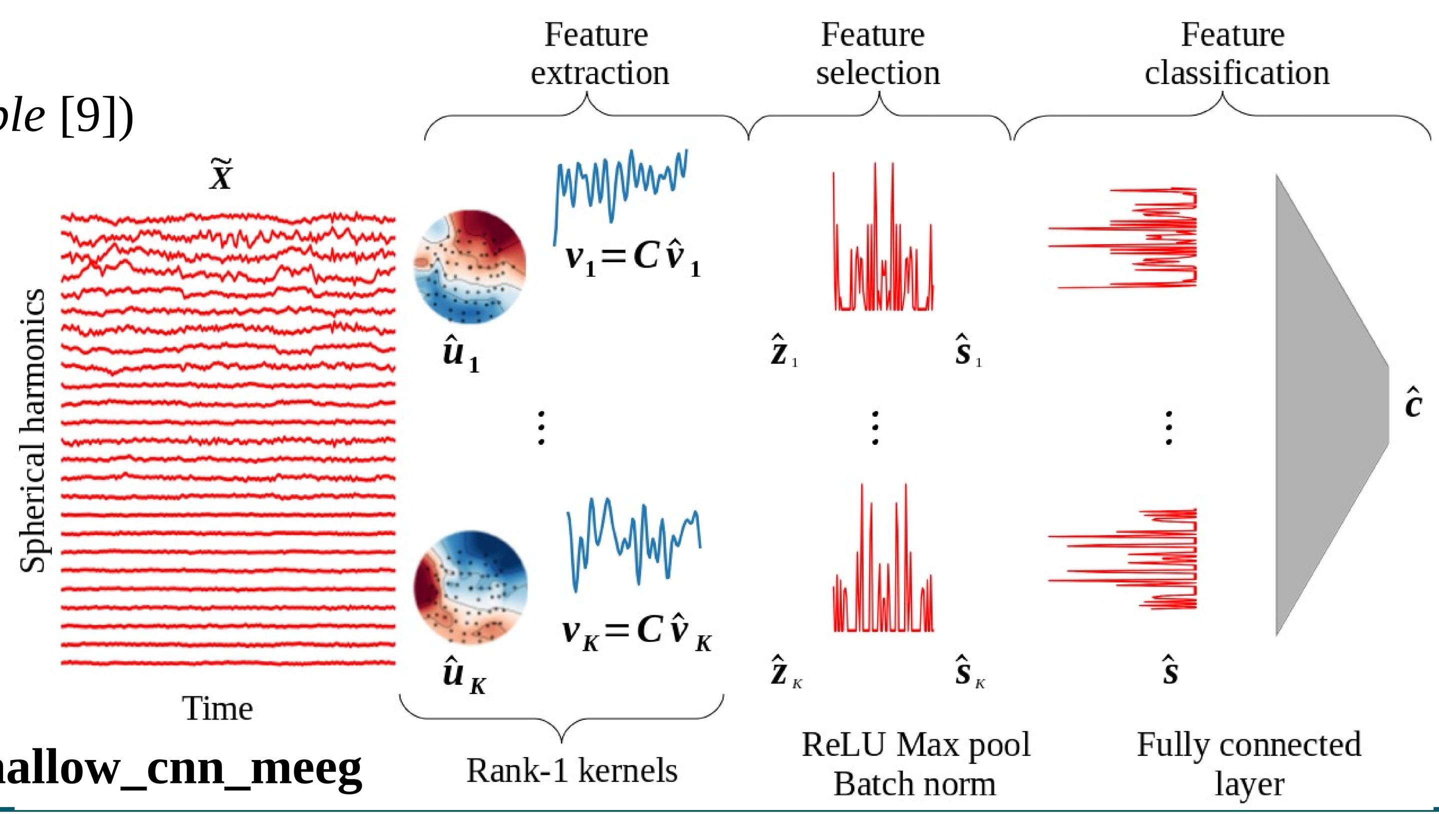
$$\tilde{X}\approx\sum_{k=1}^{K}\hat{\boldsymbol{u}}_k[[C\hat{\boldsymbol{v}}_k]*\boldsymbol{z}_k]^T$$

Model characteristics

Feature extraction:
- correlation with rank-1 kernels (special case of *depthwise* [10] which is special case of *separable* [9])
- Fourier domain kernels

Feature selection:
- ReLU (thresholding)
- max-pooling
- batch-normalization

Feature classification:
- a single fully connected layer



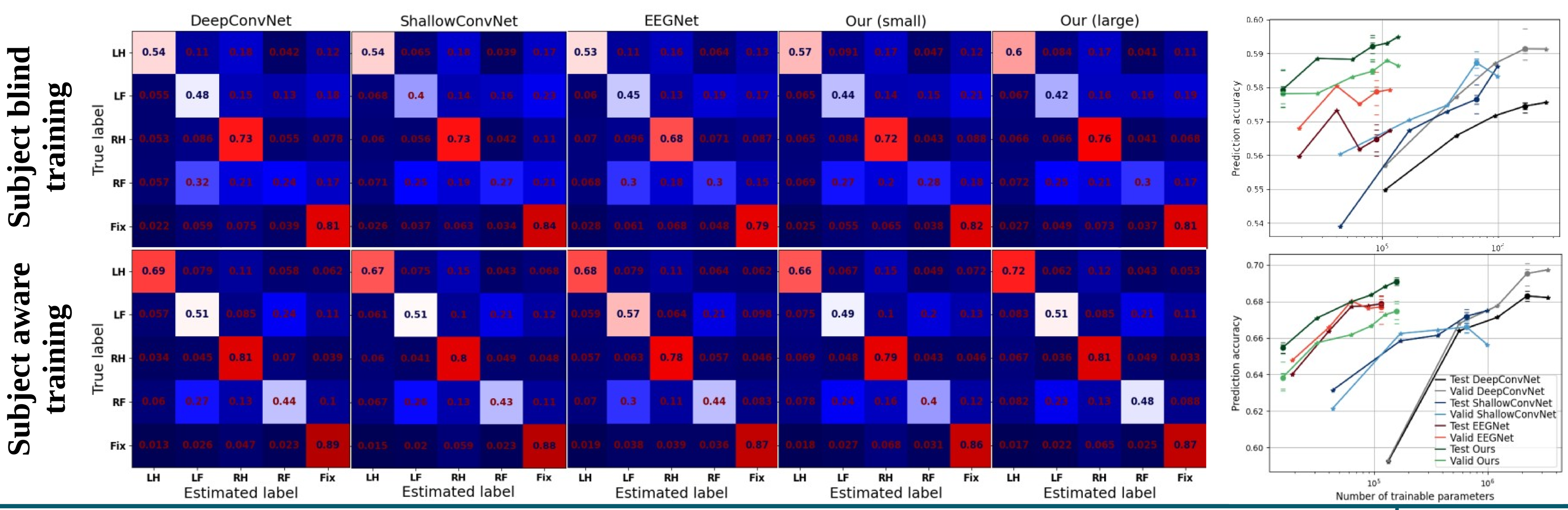
https://gitlab.inria.fr/ssedlar/shallow_cnn_meeg

3 Experiments and results

- **Human Connectome Project (HCP) MEG motor task data** [7] classification:….. **5 classes**: Left Hand (**LH**), Left Foot (**LF**), Right Hand (**RH**), Right Foot (**RF**), fixation (**fix**).
- **Mental Workload EEG data** [8] classification: …………………………………… **3 classes**: easy mental task (**Easy**), medium mental task (**Med**), difficult mental task (**Diff**).
- **Subject blind (SB) setup: ………………………** subjects in train and validation subsets do not exist in the test subset.
- **Subject aware (SA) setup: ……………………..** sessions in train and validation subsets do not exist in the test subset.
- **Models compared:** ***DeepConvNet*** **[9],** ***ShallowConvNet*** **[9],** ***EEGNet*** **[10],** ***Ours*** **[11]**

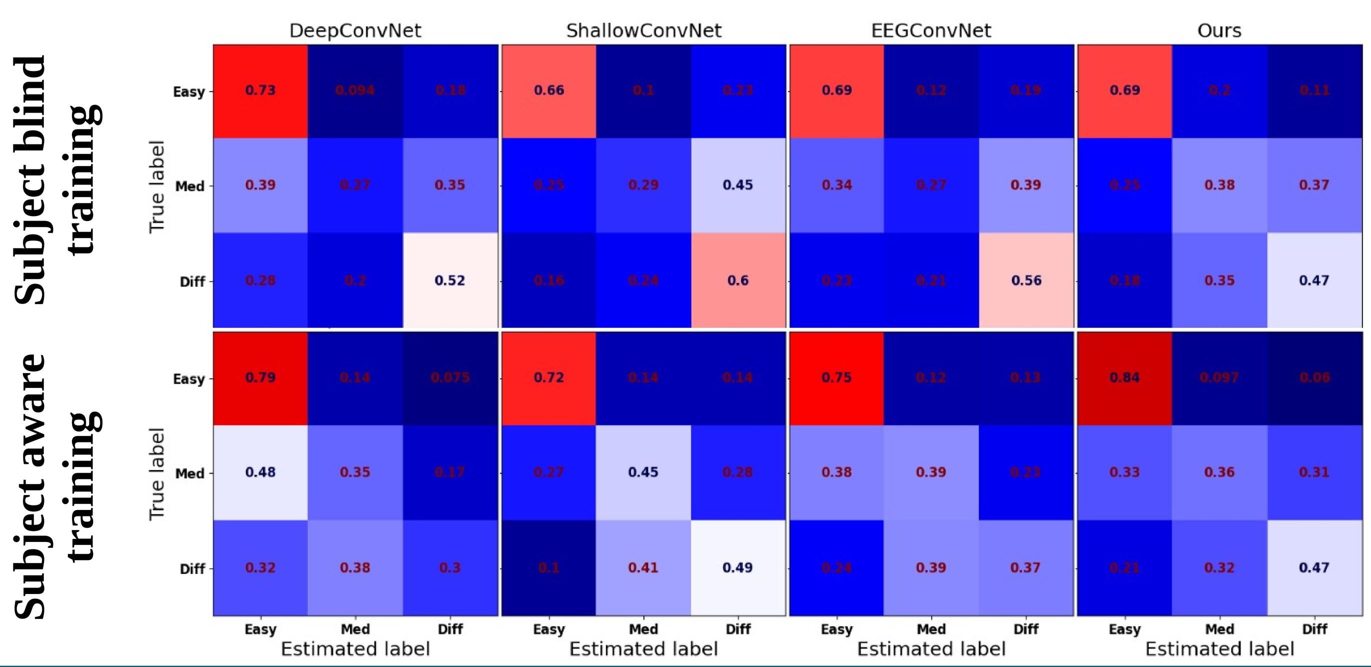
MEG motor task

	DeepConvNet	ShallowConvNet	EEGNet	Our (small)	Our (large)
SB (acc.)	0.575	0.576	0.565	0.579	**0.592**
SA (acc.)	0.683	0.673	0.679	0.655	**0.691**
SB (params.)	1708305	652005	88901	**13755**	82505
SA (params.)	2223555	652755	116245	**15755**	157505



EEG mental workload

	DeepConvNet	ShallowConvNet	EEGNet	Our
SB (acc.)	0.505	**0.520**	0.506	0.514
SA (acc.)	0.479	0.552	0.504	**0.557**
SB (params.)	4823403	161003	**14851**	36003
SA (params.)	1889903	44253	**16163**	41003



4 Conclusions

In this work we have proposed a compact shallow CNN with rank-1 trainable parameters regularized by representation in the Fourier domain.

The experiments conducted on the MEG and EEG active and passive BCI problems showed that our model achieves comparable or higher classification accuracy then the state-of-the-art CNN models while preserving a low number of trainable parameters.

5 References:

[1] Gramfort, A. et al, *Frontiers in neuroscience*, 2013 **[2]** Hari, R., & Puce, A. *Oxford University Press*, 2017 **[3]** Dupré La Tour, T. et al, *Advances in NIPS*, 2018 **[4]** Van Ede, F. et al, *Trends in neurosciences*, 2018 **[5]** Vatta F. et al, *Computational intelligence and neuroscience*, 2010 **[6]** Descoteaux, M. et al, *Magnetic Resonance in Medicine*, 2007 **[7]** Van Essen, D. C. et al, *Neuroimage*, 2013 **[8]** Hinss, M. F. et al, *Conference on NER*, 2021 **[9]** Schirrmeister, R. T. et al, *Human brain mapping*, 2017 **[10]** Lawhern, V. J. et al, *Journal of neural engineering*, 2018 **[11]** Sedlar, S. et al, *Neuroergonomics conference*, 2021

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