Semi-Supervised Contrastive Learning for Generalizable Motor Imagery EEG Classification

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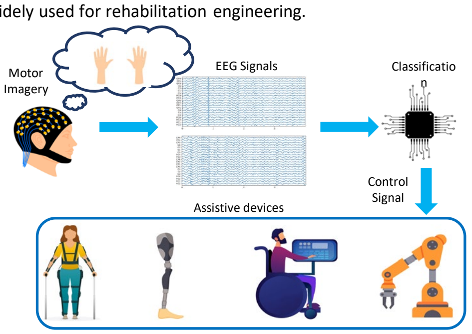
Introduction

Motor Imagery (MI) based EEG systems

Allow users to control external devices by mental execution by non-invasive EEG recordings.
Widely used for rehabilitation engineering.



Challenges

- The evoked potential of the brain activities is weak and noisy
- Expensive and difficult to label data accurately.
- High inter-session variation and inter-subject variation.

Objective

- To develop a semi-supervised framework with a combination of self-supervised contrastive learning [1] and adversarial training.
- Learn transformation invariant features without any labels and diminish the feature distribution of different subjects/sessions.
- Supervised learning on the partial labelled data to force the model to learn task-relevant features.

Method

The framework consists of: data augmentation T, an encoder E, a task classifier C, a domain discriminator D, and a projector P.

Data augmentation

Apply two sets of augmentations to the input EEG signals x yielding $T_1(x_i)$ and $T_2(x_j)$

Contrastive Learning

The Encoder E produces latent representations h_i = E($T_1(x_i)$) and h_j=E($T_2(x_j)$)
The Projector P projects latent representation h_i and h_j to a lower dimension $z_i = P(h_i)$ and $z_j = P(h_j)$. E and P minimises the contrastive loss $L_{contrast}(z_i, z_j)$.

Supervised Learning

The latent representation of labelled data, $h_{i,j} \epsilon L$ are used to train the supervised classifier C and calculate a cross-entropy loss $L_{MI}(h_{i,j} \in L)$

Adversarial Training

The domain discriminator D is trained to predict the identities of the domains based on latent vectors h by minimising the lost L_{dis}
The encoder E is encouraged to confuse the discriminator D by minimising L_{enc} .

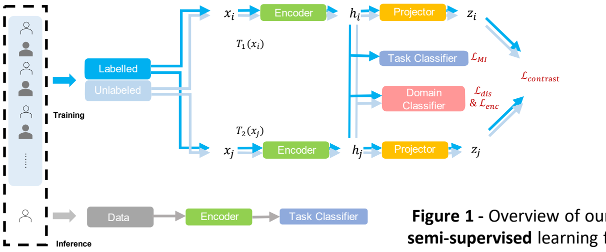


Figure 1 - Overview of our proposed **semi-supervised** learning framework.

Experiment Settings

- Dataset: BCI IV2A [2] MI-EEG, binary classification (left hand and right hand)
- Encoder backbones: EEGNet-8,2 [3] and DeepConvNet [4]
- Validation method: Leave-One-Session-Out (LOSO) + 10-fold cross-validation

Quantitative Results

Models	10%	20%	50%	100%
FBCSP	54.7%	58.8%	62.2%	64.8%
EEGNet	60.7%	68.0%	71.4%	75.8%
DeepConvNet	56.2%	65.4%	76.5%	**80.9%**
Semi-EEGNet	66.6%	71.5%	75.3%	75.6%
Semi-DeepConvNet	**67.6%**	**74.3%**	**77.4%**	79.4%

Table 1 - Classification accuracy of different methods with different ratios of labels in the training.

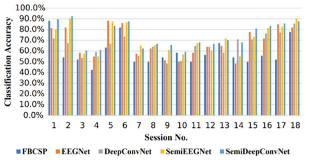


Figure 2 – LOSO classification results of different methods with 20% labels.

Ablation study

evaluate the effectiveness of augmentation, contrastive learning and adversarial training

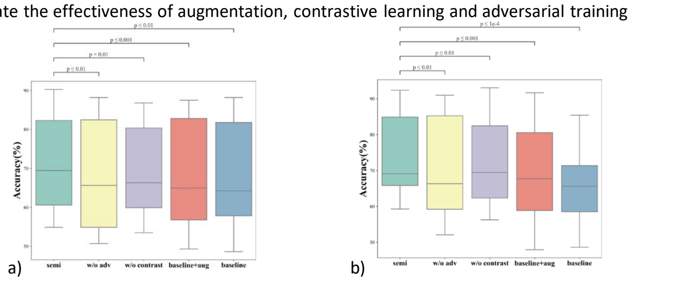


Figure 3 - Impact of different framework components (adv: adversarial loss, contrast: contrastive loss, aug: augmentation) removed, with 20% labels. (a) EEGNet; (b) DeepConvNet

Discussion

- Developed domain independent, end-to-end semi-supervised learning framework for classifying MI EEG signals with limited labels.
- Our method outperforms the baseline methods when there are limited labels.
- Our work opened new possibilities for using deep neural networks for real-world applications without the need for tedious calibration processes.

Future Plan

Develop a Generative model capable of generating new meaningful data to facilitate training whilst force the Encoder to learn domain invariant MI features through the training process of the Generative model.

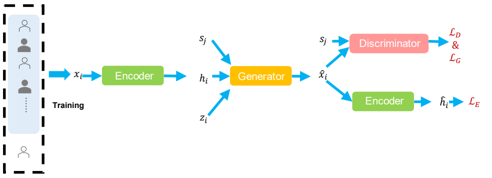


Figure 4 – Subject disentangled GAN framework (s: a random subject/session vector produced by an embedding model, z: a noise vector sampled from the normal distribution)

References

[1] T. Chen, et al., "A simple framework for contrastive learning of visual representations," in *Int. Conf Mach Learn. Proc Mach Learn Res.*, 2020, pp. 1597–1607.
[2] M. Tangermann, et al., 2012. Review of the BCI competition IV. *Front. Neurosci.*, 6, p.55.
[3] V. J. Lawhern, et al., "Eegnet: a compact convolutional neural network for eeg-based brain–computer interfaces," *J. Neural Eng.*, vol. 15, no. 5, p.056013, 2018.
[4] R. T. Schirrmeister, et al., "Deep learning with convolutional neural networks for eeg decoding and visualization," *Hum. Brain Mapp.*, vol. 38, no. 11, pp. 5391–5420, 2017.

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