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# Minimal calibration MI-BCIs via inter-subject transfer learning with optimal transport

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*Introduction:* The prolonged calibration phases required to record user-specific electroencephalography (EEG) data for training decoding models constitute a significant barrier to the practical implementation of motor imagery-based brain-computer interfaces (MI-BCIs). When deep learning (DL) models are used to decode brain data, these calibration times might need to be extended even further. A potential solution to this issue is leveraging available EEG data from other subjects to train the model. However, the inherent high inter-subject variability of EEG signals requires effective adaptation methods to enable transfer learning across subjects. Here, we use a supervised version of the Backward Optimal Transport for Domain Adaptation (BOTDA) [1] approach to align the DL features of the target subject with the feature distribution of the training set derived from other users.

*Material, Methods and Results:* Experiments were conducted using three right vs. left hand MI publicly available EEG datasets: Lee2019_MI [2] (training dataset), and Cho2017 [3] and Dreyer2023 [4] (testing datasets). EEG data from only three channels (C3, C4, and Cz) were employed. The EEGNet [5] was used as the DL model. It was trained with the full Lee2019_MI dataset with the default AdamW optimizer and the cross-entropy loss for 500 epochs. The learning rate was set to 0.001. For each target subject from the testing datasets, the 10 first trials of each MI class were kept as adaptation/fine tuning data, while the remaining trials constituted the testing data. In our approach, the full model trained from the Lee2019_MI dataset was kept frozen at the evaluation stage. The representations preceding the classification block were used as DL features, with adaptation applied at this level. Our approach was compared with two reference methods: (a) trained model without adaptation, (b) trained model fully fine-tuned for 100 epochs using subject-specific adaptation data. The mean classification accuracies across all testing subjects were: $0.88 \pm 0.13$ for DL+BOTDA, $0.61 \pm 0.11$ for the no-adaptation DL reference, and $0.62 \pm 0.12$ for the fine-tuning method.

*Discussion:* The results presented highlight the effectiveness of DL+BOTDA in overcoming the challenges of high inter-subject variability in EEG data for MI-BCIs. By applying adaptation at the feature level, a substantial improvement in performance was achieved with the proposed method, outperforming the no-adaptation baseline and the fine-tuning approach. It is important to note that although fine-tuning is a widely used method to adapt pre-trained models to subject-specific characteristics, it does not perform well with limited target subject data, reinforcing the advantage of the BOTDA method in this scenario.

*Significance:* Reducing subject-specific calibration data to only 20 trials could enhance and empower the usability and practicability of MI-BCIs, especially in motor rehabilitation scenarios.

*References:*

[1] Peterson, V., Nieto, N., Wyser, D., Lambercy, O., Gassert, R., Milone, D. H., & Spies, R. D. Transfer learning based on optimal transport for motor imagery brain-computer interfaces. In *IEEE Transactions on Biomedical Engineering*, 69(2), 807-817, 2021.
[2] Lee M H, Kwon O Y, Kim Y J, Kim H K, Lee Y E, Williamson J, Fazli S, Lee S W. EEG dataset and OpenBMI toolbox for three BCI paradigms: An investigation into BCI illiteracy. In *GigaScience*, *8*(5), giz002, 2019.
[3] Cho, H., Ahn, M., Ahn, S., Kwon, M., & Jun, S. C. EEG datasets for motor imagery brain–computer interface. In *GigaScience*, 6(7), gix034, 2017.
[4] Dreyer, P., Roc, A., Pillette, L., Rimbert, S., & Lotte, F. (2023). A large EEG database with users' profile information for motor imagery brain-computer interface research. In *Scientific Data*, 10(1), 580, 2023.
[5] Lawhern, V. J., Solon, A. J., Waytowich, N. R., Gordon, S. M., Hung, C. P., & Lance, B. J. EEGNet: a compact convolutional neural network for EEG-based brain–computer interfaces.In *Journal of Neural Engineering*, 15(5), 056013, 2018.





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