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Beyond Single Datasets: Transfer Learning for iBCI Decoding

E. Mo Nipshagen[1,3]*, Yağmur Güçlütürk[1], Pieter L. Kubben[3], Marcel van Gerven [1], Julia Berezutskaya[2]

[1]*Donders Centre for Cognition, Department of Social Sciences, Radboud University, Nijmegen, Netherlands;*
[2]*Brain Center, Department of Neurology and Neurosurgery, University Medical Center Utrecht, Utrecht, Netherlands;*
[3]*Department of Neurosurgery, School of Mental Health and Neurosciences, Maastricht University, Maastricht, Netherlands*

* E-mail: mo.nipshagen@ru.nl

Introduction: Implanted brain-computer-interfaces (iBCIs) using (high-density, HD) electrocorticography (ECoG) grids have successfully been used to help individuals with severe motor paralysis interact with their environment via synthesising speech or translating their movement intent into functional outputs. Due to differences in grid placement and interindividual variability, these high-performing systems usually need to be trained from scratch to be tailored to each user, which requires large amounts of labelled data. Acquiring that labelled data takes a lot of time and effort from iBCI users. In this work, we aim to create a model that can leverage unlabelled neural data, pooled from several HD ECoG participants and datasets. If successful, such a model can be used to reduce iBCI training time for new users (and tasks), create meaningful neural representations, and improve closed-loop, continuous iBCI decoding.

Material and Methods: One approach to transfer learning and dealing with ECoG grid placement variability was demonstrated with HT-Net [1], which classified neural data as either rest or task-related activity. Beyond pooling different datasets, we expand on their work in several ways: 1) We filter and reconstruct the data in 3 individual frequency bands to capture the movement-relevant high-frequency parts of activity. 2) We build three model variations, all based on the auto-encoder structure to compress and reconstruct neural data: a) linear, b) recurrent and c) convolutional recurrent models. 3) We define a denser set of common sources aligned with HD grid spacing in sensorimotor regions following the Human Connectome Atlas.

Our dataset consists of two finger movement experiments, totalling two hours across 14 able-bodied participants, who were being monitored for medication-resistant epilepsy and had 64- to 128-channel HD ECoG grids implanted. The models are trained on time-domain data sampled at 250 Hz, fed into the model in 500-ms windows, and band-passed into 0-12, 12-24, and 24-125 Hz bands. Our models consist of an encoder, which extracts spatiotemporal features and compresses the 500-ms window into a bottleneck representation, and a decoder, which mirrors the architecture of the encoder and reconstructs the three frequency bands from the bottleneck. The models are optimised by reducing the mean-squared error between reconstruction and input signal for each band. The model performance is assessed on unseen data: 1) in-participant: the models are trained on one run of the task and are tested on an unseen run; 2) across-participants: trained on multiple participants (from one or several datasets), tested on an unseen participant.

Results: The convolutional recurrent model outperformed the linear and recurrent models by a significant margin in baseline tests, for both in-participant (correlation of reconstruction: 0.543, compared to 0.221 & 0.238 for the linear and recurrent models respectively, $p < 0.0001$) and across-participants evaluation (0.576, vs 0.338 & 0.526, $p < 0.0001$). Adding the projection matrix (ECoG channels to common sources), and bandpass filters to the model yielded further improvement for in-participant reconstruction (0.628 correlation on test set).

Conclusion: We are introducing a novel approach for transfer learning in iBCI development, combining data across several datasets to learn motor-relevant neural dynamics that are applicable to unseen participants. Our study showcases a potential avenue to lower the hurdle of training iBCI devices for new users. In further evaluation, we will assess the performance of this method for fine-tuning to an individual participant, explore what dynamics & features the model extracts from the data, and employ it to decode motor intent when applied in a closed-loop setting.

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References: [1] S. M. Peterson, Z. Steine-Hanson, N. Davis, R. P. N. Rao, and B. W. Brunton. Generalized neural decoders for transfer learning across participants and recording modalities. In *Journal of Neural Engineering, vol. 18, no. 2. IOP Publishing, p. 026014*, 2021

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