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Transfer Learning Promotes Acquisition of Individual BCI Skills

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Introduction: Motor imagery (MI) is a commonly used modality for controlling non-invasive brain-computer interfaces (BCIs). However, non-invasive MI-BCIs typically require tedious calibration sessions for collecting neurophysiological data to build personalized decoders. In this work we propose two inter-subject transfer learning frameworks based on Riemannian geometry-based real-time incremental domain adaptation [1]. Subjects relied on such a machine learning technique to follow a longitudinal, mutual learning training program [2], which has proven to be crucial for acquiring BCI skills to operate complex devices [3]. We show that naïve subjects acquired personalized MI-BCI skills using a decoder built with data of a single expert subject, thus removing the need of subject-specific calibration sessions.

Material, Methods, and Results: Eighteen (18) subjects were randomly split in two groups, each training over 5 online sessions with one of the two frameworks a) Generic Recentering (GR) which applies unsupervised adaptation, b) Personally Adjusted Recentering (PAR) which extends GR with a supervised re-calibration using a limited number of samples at the start of a session. In each online session, subjects used their MI-BCI to control two devices: a bar (continuous feedback) and a car racing game (discrete feedback) [4]. Both groups showed a significantly increasing trend in Command Delivery during the bar task (GR, Fig 1A: r^2=0.6795, p=0.002; PAR, Fig 1B: r^2=0.7854, p=0.00002) over the 5 online sessions. Race Completion Time values in the car racing task exhibited a significantly negative trend across sessions for both frameworks (GR, Fig 1C: r^2=0.7620, $p<10^{-5}$; PAR, Fig 1D: r^2=0.8606, $p<10^{-5}$). Along with improved BCI performance, we also observed a statistically significant increasing trend in separability of EEG control features, assessed by Feature Distinctiveness (FD) [5], in both groups (GR: bar, r^2=0.70, p=0.001, car racing: r^2=0.8549, p=0.0076; PAR: bar, r^2=0.7145, p=0.0019, car racing, r^2=0.6135, p=0.013). Initial EEG control features of an expert subject evolved and became subject specific (Fig 1E, F, G).

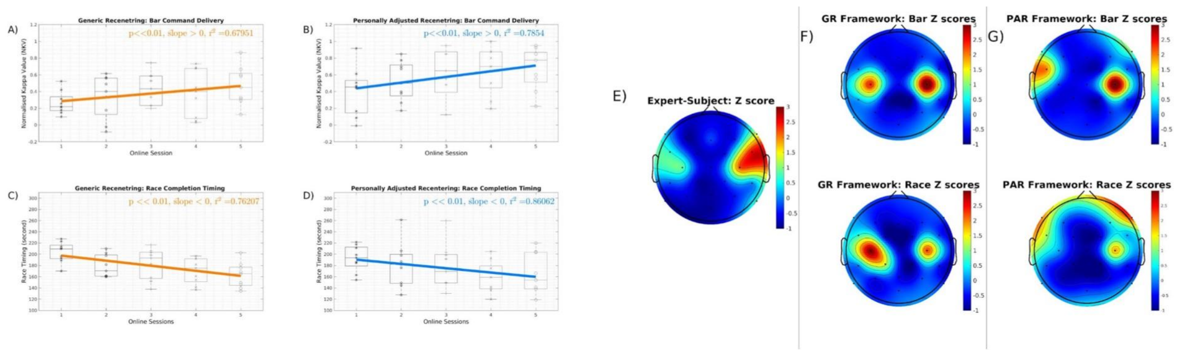

Figure 1. BCI Skill Acquisition. *MI Performance for: A) Generic Recentering (GR) Bar task and B) Personally-Adjusted Recentering (PAR) Bar task. Race timing for: C) GR and D) PAR. Electrode Contribution Z-score Maps for E) initial Expert Subject, F) GR group, and G) PAR group averaged across subjects in the race and bar tasks during the last two online sessions.*

Discussion: The improvement in task-oriented performance and increasing feature discriminability over multiple sessions demonstrate that our inter-subject transfer learning frameworks promote the acquisition of BCI skills in naïve subjects. Contrary to the popular belief that personalization or supervised tuning of decoders would lead to better BCI performance, subjects in the GR and PAR groups reached statistically similar performance in both tasks.

Significance: Our study opens new avenues for real-time calibration-free BCI and mutual learning training. Our frameworks could become relevant for patients with severe motor deficits who cannot modulate their EEG to provide good calibration data.

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