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A Case Study in BCI Skill Learning: Preliminary Results from a Longitudinal BCI-Power Mobility Study

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Introduction: Brain-computer interfaces (BCIs) are well-positioned to increase independence and participation for people with disabilities. BCIs have enabled children with quadriplegic cerebral palsy (QCP) to experience independent movement through access to power mobility devices (PMDs) [1]. However, both BCI and PMD control are skills that must be developed over time [2], [3]. BCi-Move, a multi-centre, longitudinal case study, was designed to investigate whether dedicated training can help children with QCP learn to use BCI to reach personal mobility goals. Learning of BCI-PMD skills can be characterized in many forms; one way is by identifying whether users can gradually produce more distinct and stable brain patterns, which could lead to more accurate BCI control [4].

Methods & Results: For BCi-Move, children with QCP (n=30 across 4 sites) will participate in a 12-week BCI-power mobility training program. Study recruitment and data collection are ongoing, but here we present results for the first participant. A cap-style Emotiv Flex headset with 14 saline-based electrodes was used for the hardware, and each training session started with 12 runs of motor imagery (MI) calibration. Results for 2 commands ("push" for forward, and "neutral" for no movement) are presented. To explore MI learning, 2 user skill metrics were quantified and compared with classification accuracy. These metrics are class distinctiveness, a measure of how distinct classes are from one another, and class stability, a measure of much variation there is in each class [4]. For signal processing, EEG signals (sampled at 128Hz) were filtered between 8-30Hz and epoched (2s segments). Covariance matrices were estimated for each epoch and used to calculate class distinctiveness and stability. The Riemannian minimum distance to the mean (RMDM) algorithm was used for classification. Class distinctiveness was observed to increase on average over the training sessions, stability of the 'push' class was observed to decrease, and no trend was observed for stability of the 'neutral' class. Significant variability was seen across sessions for all metrics. Classification accuracy was strongly positively correlated with class distinctiveness, and more weakly correlated with stability.

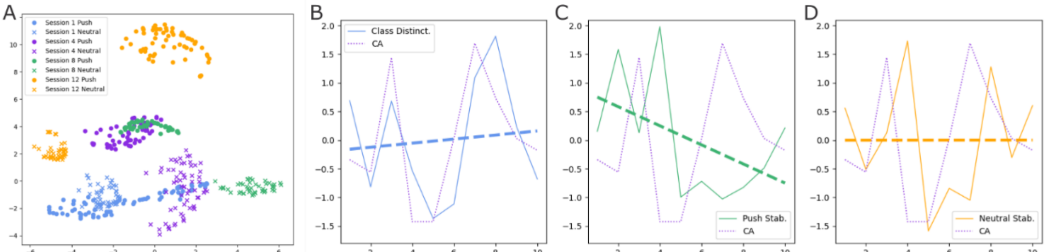

Figure 1: A) t-SNE visualization of the covariance matrices for each class (push = dots, neutral = x's) for 4 of the training sessions - session 1 (blue), 4 (purple), 8 (green) and 12 (orange). B)-D) Z-scores of class distinctiveness, push stability, neutral stability, respectively across all sessions. Metric trends are indicated with the bold hashed line. Z-scores of classification accuracy are also plotted in purple (dotted line) on each.

Discussion & Significance: Across the 12 training sessions, class distinctiveness increased on average, indicating the participant was gradually learning to produce more distinct brain patterns. However, the stability of each class did not appear to increase over time. Psychological factors, including mood, fatigue and motivation may have impacted learning on different sessions days, contributing to the observed variability. In addition, the participant was not provided with feedback based on these metrics during calibration; rather, visual feedback was based on classification accuracy. Incorporating user skill metrics as feedback during training could be more meaningful and help users produce more distinct and stable brain patterns, thus leading to increased learning and better BCI performance. Here we have demonstrated a preliminary exploration of BCI user skill learning across longitudinal BCI-PMD training for a child with QCP. A deeper understanding of how BCI skills are learned can help us design better BCI systems and support end-users in reliable, long-term use of BCI.

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