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Riemannian Transfer Learning for Pediatric Brain-Computer Interfaces (BCI)

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Introduction: Brain-computer interfaces (BCI) can provide a method for children with severe neurological disabilities to achieve their right to self-expression and life participation [1]. Pediatric users typically have less success in the calibration of BCI systems compared to adults because typical BCI calibration is not engaging for them. For this reason, children have much to gain from transfer learning methods which use previously collected source data to reduce or eliminate the required calibration. Riemannian geometry (RG) methods for transfer learning have been successful in adult populations [2, 3] but have not been examined in children. This work investigates the performance of existing RG transfer learning methods when applied to pediatric data.

Materials, Methods, and Results: Left/right hand motor imagery (MI) data was collected from 24 typically developing children (ages 6-16, median 10, 19 were female). The collected EEG data consisted of 18 intervals for each hand, each interval containing 6 epochs of 2s, totaling 320s. For each subject, "target data" describes that individual subject's session data, while "source data" describes the cumulative data from all other subjects. Different methods for Riemannian transfer learning were tested with 5-80% of the target data to simulate shorter calibration durations. Direct (DCT), Recentering (RCT), and Riemannian Procrustes Analysis (RPA) methods were explored [3]. Calibration using only target data served as a control. All methods used the same Riemannian distance to mean (MDM) base classifier [4]. The trends shown in Fig. 1. indicate that RCT is an effective method for calibration durations from 0-100s (~30%), while RPA performs at or slightly above calibration in terms of accuracy for durations >200s (~60%).

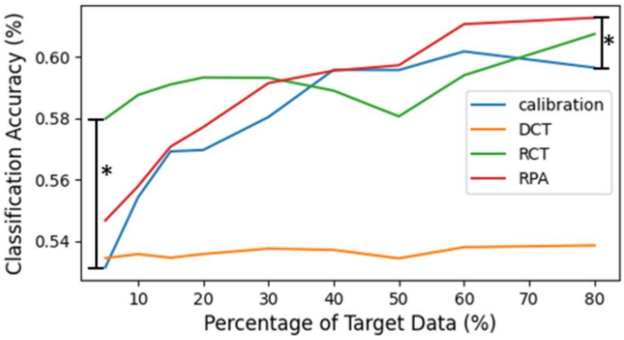

Figure 1. Mean classification accuracy with different amounts of target data. Calibration only uses target data. Direct (DCT) uses only source data. Recentering (RCT) and Riemannian Procrustes Analysis (RPA) use both source and target data. * - indicates $p < 0.05$ based on related t-test.

Discussion: This evidence suggests that Riemannian methods for transfer learning can offer better accuracy with both short (RCT) and long (RPA) calibration durations. This suggests transfer learning is a suitable choice for improving pediatric BCI when source data is available. The classification accuracy shown, although improved, is lower than commonly reported in adult studies. Further work should determine if transfer learning can help optimize pediatric BCI performance.

Significance: This work demonstrates that Riemannian transfer learning methods can improve accuracy and reduce the required calibration duration for pediatric users of motor imagery brain-computer interfaces.

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