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Improving the performance of non-invasive Brain-Computer interfaces between sessions utilizing Riemannian Procrustes Analysis: Comparison of Deep and Transfer Learning models.

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Introduction: Although brain-computer interfaces (BCIs) show great promise for assisting people in need, BCIs still remain within the laboratory setting due to low classification performance of first-time users and long calibration times required to train algorithms [1]. Brain activity is detected by extracting the relevant brain activity of the participant and then identifying and learning the relevant features by using a machine learning (ML) pipeline [2]. Over the years, deep learning (DL) methods [3] and transfer learning (TL) approaches across participants have been suggested to reduce or even eliminate the long calibration sessions usually required from a participant to control a BCI [4]. Our objective is to compare the performance of DL models and a ML classifier utilizing TL trained across participant's sessions with the purpose of reducing the need for calibration in offline analysis.

Materials and Method: 17 participants were recorded with EEG (32 electrodes) in two sessions. In each session visual feedback was provided to the user while they performed two mental tasks: motor imagery, mental subtractions, with 50 trials per task. Then in an offline analysis two DL models were compared against an ML classifier utilizing Riemannian Procrustes Analysis (RPA) [4] to generalize extracted features across sessions.

Results: Our results suggest that the combination of our best-performing classifier with RPA significantly increases the performance of the system between sessions, within participants.

Discussion: In this study we provide further evidence that matching the statistical distribution of the extracted features between-sessions for each participant could lead to increased performance of the ML pipeline.

Significance: The utilization of TL provides direct evidence on the reduction of the duration of calibration phases and consequently bring the technologies of BCIs a step closer to a more realistic setting and widespread usage.

References

[1] Vidaurre, C., & Blankertz, B. (2010). Towards a cure for BCI illiteracy. Brain Topography, 23(2), 194–198. https://doi.org/10.1007/s10548-009-0121-6

[2] Chang S. Nam, Anton Nijholt, F. L. (eds. . (2018). Brain-Computer Interfaces Handbook_ Technological and Theoretical Advances. Appl. Phys. A, 73(January), 788.

[3] Schirrmeister, R. T., Springenberg, J. T., Fiederer, L. D. J., Glasstetter, M., Eggensperger, K., Tangermann, M., Hutter, F., Burgard, W., & Ball, T. (2017). Deep learning with convolutional neural networks for EEG decoding and visualization. Human Brain Mapping, 38(11), 5391–5420. https://doi.org/10.1002/hbm.23730

[4] Luiz, P., Rodrigues, C., Jutten, C., Congedo, M. (2019). Riemannian Procrustes Analysis : Transfer Learning for Brain-Computer Interfaces To cite this version : HAL Id : hal-01971856 Riemannian Procrustes Analysis : Transfer Learning for Brain-Computer Interfaces.