DOI: 10.3217/978-3-85125-962-9-65

Riemannian vs. Linear P300 classification for a tactile Brain-Computer-Interface in an end-user single-case study

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Introduction: By creating an output directly derived from brain activity, Brain-Computer Interfaces (BCIs) allow people in a Locked-In-State (LIS) to interact with their environment. As classification optimization remains one of the main challenges of the domain, signal classification algorithms have been investigated regarding their suitability for application in the field of BCI. However, since most studies were performed with healthy participants, results may not be fully translatable to impaired potential end-users. Therefore, we aimed to investigate classifier performance on a dataset obtained from a potential end-user in the Locked-in State (LIS).

Material, Methods and Results: A patient in the LIS participated in a total of 17 sessions of a six-class tactile BCI training in his own home [2]. The obtained data were used to test four classifiers, in four calibration modes, to investigate their overall performance, their inter-session transferability and resilience against less training data. Shrinkage Linear Discriminant Analysis (shrinkLDA) and Riemannian Geometry Classifiers (RGCs, i.e., Minimum Distance to Mean (MDM) and MDM with a preceding Fisher Geodesic Discriminant Analysis (FGMDM)) were compared to a Stepwise Linear Discriminant Analysis (SWLDA), which was used during online classification.

In all sessions, the patient elicited a P300 with mean amplitudes of 1.9 µV at Cz (SD=1.7) in the window of interest 350-600ms after stimulus onset (see Fig. 1a). High variances in amplitudes and classification accuracies were observed between sessions and the different classification algorithms. No classifier was able to increase the accuracy significantly compared to the SWDLA used for online feedback in any calibration condition (see Fig. 1b for session-wise calibration (based on 180 target epochs)).

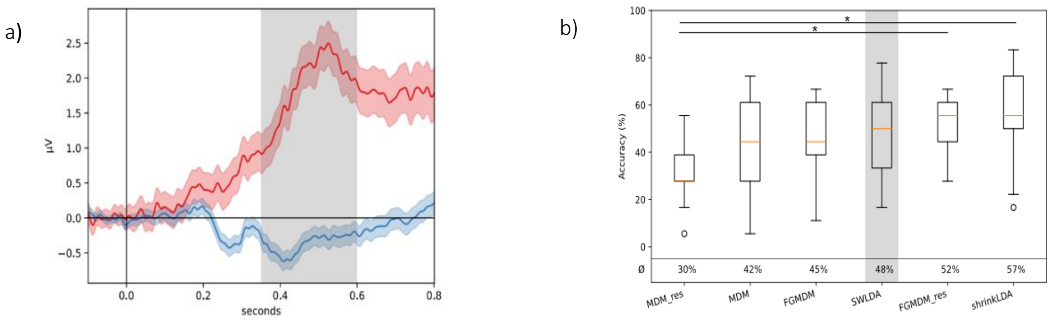

Fig. 1 a) Average P300 amplitude at Cz across all sessions. Red: Target, Blue: Non-Targets, Shaded areas indicate the 95% confidence interval, Grey: window of interest (350-600ms after stimulus onset). b) Boxplots of the accuracy for the implemented classifiers in one of the four calibration conditions (session-wise calibration (based on 180 target epochs)).

Discussion: Although, at least descriptively, the SWLDA appeared to be outperformed in certain conditions, no algorithm was able to perform consistently above the usability criterion level (≥ 70% accuracy) [3] across all sessions in any of the calibration modes, highlighting the urgent need for improvement in this domain. Further, classifier performances did not show clear consistencies in their ranking, and no single classifier always outperformed the others.

Significance*:* These results underline the importance of classification-algorithm selection and a considerable potential for improvement in the overall classification process. More emphasis should be put on research directed toward the classification of data obtained in actual use-cases, in non-laboratory conditions, particularly involving potential end-users with neurodegenerative disease.

Acknowledgements: This project was funded by the Lotte Schopper-Stiftung c/o Rummelsberger Dienste für Menschen mit Behinderung gGmbH - Schwarzenbruck, Landkreis Nürnberger Land, Mittelfranken, Germany

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