## Investigating inter-participant performance variability in mental imagery EEG-BCIs: Descriptive methods to analyze inter- and intra-trial signal variation

Nicolas Ivanov<sup>1,2\*</sup>, Tom Chau<sup>1,2</sup>

<sup>1</sup>Institute of Biomedical Engineering, University of Toronto, Toronto, ON, Canada;
<sup>2</sup>Bloorview Research Institute, Holland Bloorview Kids Rehabilitation Hospital, Toronto, ON, Canada;
\*150 Kilgour Rd, Toronto, ON, Canada, M4G 1R8. E-mail: nicolas.ivanov@mail.utoronto.ca

*Introduction:* Vast literature has reported high inter- and intra-individual variation in electroencephalography (EEG) signals [1]. However, few methods exist to assess and describe EEG signal variability. Here, we present methods to assess EEG variability for mental imagery BCIs. The methods yield insight into different aspects of signal variation, specifically (i) inter-individual, (ii) inter-task, (iii) inter-

trial, and (iv) intra-trial variation. These methods are part of broader work developing descriptive user-performance assessments to improve user training and personalization of BCI design.

Material, Methods and Results: A novel representation of the time evolution of EEG signals was developed. Task trials were segmented into shorter 2 second temporal windows and represented in a feature space derived from unsupervised K-means clustering of trial covariance matrices [2]. Using this representation, temporal signal trajectories through the feature space were constructed as shown in Fig. 1A. Two metrics were defined to assess user performance based on these trajectories: (1) InterTaskDiff, based on time-varying distances between the mean trajectories of different tasks, and (2) InterTrialVar, which measured the inter-trial variation along the different feature dimensions of the observed temporal trajectories. Analysis of three-class BCI data from 14 adolescents revealed both metrics correlated significantly with classification results (Fig. 1B). Further analysis of intra-trial trajectories suggested the existence characteristic taskand user-specific temporal dynamics.



Figure 1: (A) Example of intra-trial temporal trajectories for a single user. Rows and columns represent different feature space dimensions and tasks, respectively. Horizontal axes represent temporal segment windows and vertical axes represent positions along feature space dimensions. Bold lines indicate the mean trajectories; points connected by thin lines are individual trial observations. (B) Classifier-based discernibility metric (RWCA: run-wise classification accuracy [3]) vs. InterTaskDiff (left) and InterTrialVar (right). Dashed lines indicate lines of best fit; r values are pearson correlation coefficients.

*Conclusion:* Our analysis demonstrated significant associations between the proposed metrics and the machine discernibility of EEG-BCI data. Moreover, the methods provide opportunity for more nuanced descriptions of intra- and inter-trial EEG data variation for mental imagery BCIs. Further work will investigate whether participant-specific characteristics revealed by this analysis could be used to improve user training feedback or select user-optimal classification algorithms and hyperparameters.

Acknowledgments and Disclosures: This work has been supported by NSERC CGS-D, Ontario Graduate, and a Kimel Family Pediatric Rehabilitation Scholarships.

## References:

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