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Supporting the user learning process in MI-BCI based on backward adaptation and neurofeedback

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Introduction: To effectively command a motor imagery brain computer interface (MI-BCI), several sessions of practice are typically required. While the user learns how to control the BCI, the decoding algorithm should adapt to the brain signal changes that occur with learning. In electroencephalography (EEG) based BCIs for motor rehabilitation, such changes exacerbate due to multiple session usage. To support the user learning process, it is essential to assess and provide real-time feedback on their self-modulation skills. Moreover, such feedback should be clear and meaningful from the MI task viewpoint [1]. Here we present supportive backward adaptation (SBA), a method that allows across-sessions data adaptation while online assessing MI modulation proficiency. SBA is based on the backward optimal transport for domain adaptation method [2]. By means of SBA, a MI videogame for motor rehabilitation is designed with the aim of building co-adaptive BCIs to improve both the user learning process and the system decoding accuracy.

Material, Methods and Results: First, we assessed whether SBA is a reliable tool to measure MI-BCI skills in real-time. Real [3] and simulated [4] MI vs. rest EEG data were used. Data always comprised two sessions from two different days. Common spatial patterns (CSP) in combination with the linear discriminant analysis defined the decoding model. Training used data from the first session, while data from the second session was used for testing. SBA was applied at the CSP feature space level. The instructed cue information was used to guide the backward adaptation. The algorithmic support, i.e. the effort exerted by the model in performing the adaptation, was used as a measure of online MI modulation skill. Riemannian distinctiveness metrics [5] were used as gold-standard indices to assess users' BCI skills. Results showed that SBA algorithmic support is significantly correlated with the simulated MI capability as well as to Riemannian distinctiveness metrics. Then, we designed a videogame for MI-BCI in motor rehabilitation that uses SBA algorithmic support index to inform in real-time the BCI user on how well the instructed task was performed. Such feedback is presented as an energy bar. Feedback also comprises an avatar hand movement together with an audible tone indicating the predicted mental state. To encourage users, the goal of the game is to catch coins and maximize a score, which depends on the algorithmic support value. Pilot subjects claimed high agency and felt feedback was transparent.

Conclusion: SBA not only facilitates across-sessions adaptation but also measures in real-time the quality of the provided EEG patterns with respect to the indicated mental task. The design of meaningful feedback based on SBA algorithmic support has the potential to enhance users' MI-BCI control capabilities. Future plans involve the development of a longitudinal MI-BCI study to evaluate whether the neurofeedback based on the SBA algorithmic support metric fosters engagement, master MI skills, and ultimately, improve clinical outcomes in motor rehabilitation.

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