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Co-adaptive BCI based on supervised domain adaptation: results in motor imagery simulated data

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Introduction: Brain-computer interfaces (BCIs) can be thought of as a two-learners system, in which the user learns how to control the computer and, simultaneously, the computer learns how to decode the user's brain activity [1]. When used across several sessions, as in motor imagery (MI) BCIs for rehabilitation, the recorded EEG signals contain high variability. Machine learning systems used to decode brain activity should then adapt to those signal changes and help the user in the development of stable EEG patterns. In this line of work, a backward formulation of optimal transport for domain adaptation (BOTDA) was proposed in [2] to avoid recalibration in cross-session MI-BCIs. Although BOTDA showed promising results in a supervised sample-wise scenario, it remains to be elucidated whether the success of the adaptation depends on the subject's ability to perform the MI task or on the adaptive capabilities of the model. Here we hypothesize that supervised adaptation based on BOTDA is successful only when: **H1)** the EEG patterns provided by the user corresponds to the mental task to be performed and **H2)** the calibration data, used to train the decoding model, is discriminative enough from the decoding system viewpoint.

Material, Methods and Results: Considering MI-BCIs for motor rehabilitation, realistic MI vs. Rest EEG data was generated based on a custom implementation that extends [3]. MI alpha desynchronization (aka ERD) was simulated in the left hemisphere for MI. "Rest" corresponded to no-ERD. We used the first session (S1) to train the model (calibration data) and the following session (S2) was used as testing data. For each session, 100 trials of each class were simulated. As a decoding algorithm, a common spatial pattern and a linear discriminant analysis were used, as in [4]. To prove H1 we simulated S1 as the ideal case, i.e the ratio between ERD and baseline amplitudes (%ERD) was set to 50 for all trials belonging to the MI class (0% of failed MI trials). Results show that BOTDA can provide almost perfect classification accuracy (ACC) regardless of the %ERD in S2 (e.g. ACC=0.97 with BOTDA, ACC=0.51 without BOTDA for a S2 with %ERD=10). Experiments varying the percentage of failed MI trials, but with high %ERD, indicated that BOTDA could not help with failed trials (e.g. ACC=0.76 with BOTDA, ACC=0.76 without BOTDA for a S2 with %ERD=45 and 50% of failed MI trials). To validate H2 we trained the decoding model with data from sessions with different %ERD values. We found that when the simulated calibration data did not contain discriminable ERD patterns (%ERD<20, calibration ACC<0.7), the test ACC always yielded by-chance levels.

Discussion: Results on these simulations show that BOTDA can be a valuable tool for building co-adaptive MI-BCI systems, in which calibration data must meet a minimum accuracy of 70% and users need to present some %ERD reflecting correct responses to the indicated mental tasks.

Significance: Supervised adaptation based on BOTDA can help the user during the learning process of commanding a MI-BCI.

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