 DOI: 10.3217/978-3-85125-467-9-159

Transfer Learning with Large-Scale Data in Brain-Computer Interfaces

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Introduction: Brain-computer Interfaces (BCIs) have been developed for translating specific patterns of brain activities into comprehensible commands to control computers or external devices. To deal with individual differences in human electroencephalogram (EEG), BCIs often require a significant amount of training data to build and calibrate a reliable model for each individual. This user-specific training/calibration is not only labor intensive and time consuming, but also hinders the applications of BCIs in real life [1]. To alleviate this problem, transfer learning (TL) has been employed to leverage existing data from other sessions or subjects to build a BCI for a new user with limited calibration data [2, 3]. However, the TL approaches still require representative training data under each of conditions to be classified, which might be problematic when the data of one or more conditions are difficult or expensive to obtain. This study proposed a novel TL framework that could leverage large-scale existing data from other subjects and a very limited amount of calibration data from the test subject. This study also demonstrated the efficacy of this method through a BCI that detected lapses during driving.

Material, Methods and Results: For each new target (test) subject, the proposed TL approach fused a set of existing classification models built upon other source subjects' data into a new model for the subject. The weights of the source models were optimized according to 1) the generalizability of each source model to other source subjects, and 2) the similarity between the subject's calibration data (first 10 trials of the experiment) and data from other subjects. The TL framework was evaluated on a large-scale dataset of a lane-keeping driving task (46 sessions from 28 subjects) within a realistic driving simulator, in which subjects were asked to quickly respond to lane-departure events by steering the car back to the cruising position. The duration from the onset of a lane-departure event to the onset of subject response was defined as reaction time (RT) [4, 5]. In this study, the BCI is developed to classify alert (with RTs <1.5 times of the 5th percentile RT) and lapse trials (with RTs >2.5 times of the alert RT). Figure 1 shows the performance of the TL approach in terms of required calibration data and accuracy of detection, compared to that using within-subject cross-session classification. TL marginally outperformed the within-subject approach (87.62±7.32% vs. 84.55±9.12%, p=0.24 assessed by paired t-test) across 11 target subjects who had multiple sessions. Most importantly, TL required much fewer calibration data than the within-subject approach (1.51±0.23 vs. 85.97±22.57 min, $p<10^{-17}$).

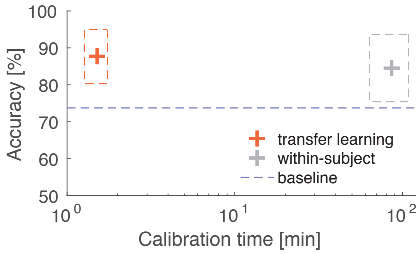

Figure 1. *The proposed TL framework achieved marginly better accuracy of lapse detection (red cross) than the within-subject cross-session prediction (gray cross). The results were obtained from 11 target subjects who had multiple sessions. The TL approach required significantly fewer calibration data than the within-suject approach. Blue dashed line indicates the average blind classification baseline (73.75%) across the 11 target subjects.*

Discussion: Current within-subject and TL approaches both require training data under all study conditions from each individual [2, 3]. These approaches may not be feasible for the detection of lapses because a subject might remain alert across the entire pilot session, resulting in very limited amount of data under the lapse state, making the approaches impossible to build an effective BCI. Thus, it is imperative to develop a novel TL approach that does not rely on the availability of individual's pilot data yet accounts for inter-subject variability.

Significance: With the help of large-scale existing data, the proposed TL approach outperformed the within-subject approach while considerably reducing the required calibration data for the target subject (only ~1.5 min of data from each individual as opposed to ~90 min of a pilot session used in the within-subject approach). The TL approach can enable and facilitate numerous real-world applications (not limited to lapse detection) of BCIs.

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