Exploring Novel Machine Learning Techniques for Brain Computer Interface (BCI) Applications

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Abstract

Existing research on brain-computer interfaces (BCIs) often relies on data from general or non-specific user groups. In contrast, our study examines the impact of transfer learning and domain adaptation on the P300-based speller specifically for users with amyotrophic lateral sclerosis (ALS). We analyzed data from both individuals with ALS and those without (non-ALS) to assess how these techniques can reduce calibration times while maintaining performance. We evaluated model performance on stopping times using a dynamic stopping language model (DSLM) and character accuracy. This approach allowed us to determine the effectiveness of employing non-ALS data for pre-training and fine-tuning machine learning models. Our findings suggest potential improvements in calibration efficiency and accuracy for individuals with ALS through the use of non-ALS data.

Introduction

Amyotrophic lateral sclerosis (ALS) is a neurological disease that causes the deterioration of motor neurons, resulting in severe muscle atrophy, making communication challenging for affected individuals. The P300 speller, a type of brain-computer interface (BCI), enables users to communicate by detecting event-related potentials embedded in electroencephalogram (EEG) signals elicited during character row or column flashes (Farwell and Donchin 1988).

Conventionally, the BCI machine learning model requires extensive calibration on individual subject's data. To mitigate the extensive data requirements and tedious process of BCI calibration, transfer learning has been explored for P300 spellers. Challenges with BCI transfer learning include lack of ALS data, inter-user variability and cross-domain differences between the general population of non-ALS individuals and target BCI end-user populations, such as individuals with ALS. Our study aims to leverage a larger database and both ALS and non-ALS domains towards the transfer learning process.

Methodology

To address the calibration challenges and improve model adaptability, we implement transfer learning techniques. Specifically, pre-train (PT) EEGNet (Lawhern et. al. 2018) on a dataset consisting of either non-ALS or non-target ALS subjects then freeze the initial layers and fine-tune (FT) on target ALS subject's data. In addition we train traditional models and use subject-specific data as our baseline levels of comparisons.

Data. The data for this study is sourced from the bigP3BCI dataset provided by the Duke University Applied Machine Learning Laboratory, which includes EEG recordings from both ALS and non-ALS participants. We focus on the checkerboard (CB) paradigm and utilize data from electrodes Fz, Cz, P3, Pz, P4, PO7, PO8, and Oz.

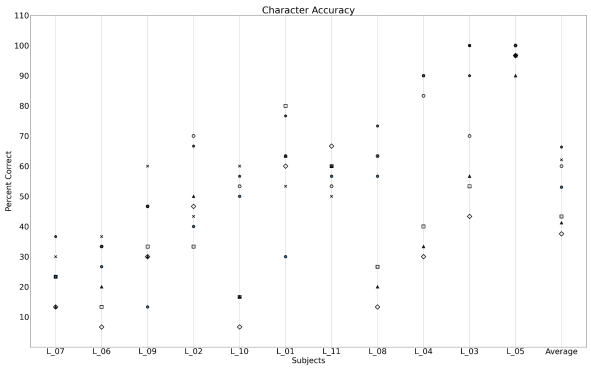
Our data consisted of three different categories: subject-specific, data specifically from the target ALS subjects, cross-domain, data exclusively from non-ALS subjects, and within-domain, data from ALS subjects excluding the target ALS subjects.

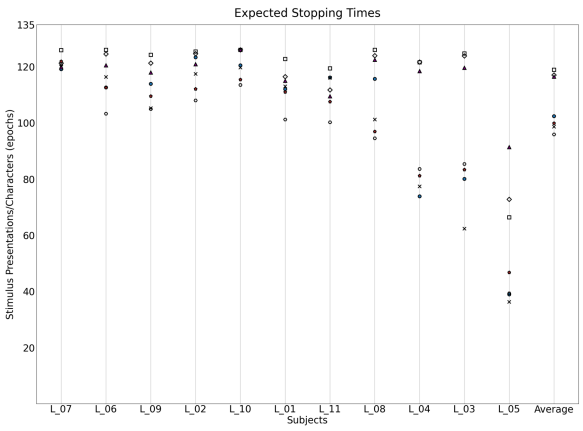
Models. This study utilizes EEGNet, a convolutional neural network designed for EEG-BCIs, to enhance the performance and reduce calibration time of the P300 speller for individuals with ALS. EEGNet's architecture comprises two main blocks: the first block applies 2D Convolutional filters of size (1, 64) followed by depthwise convolution to reduce the number of trainable parameters,

while the second block employs separable convolutions of size (1, 16) to process 500ms of EEG data sampled at 32Hz.

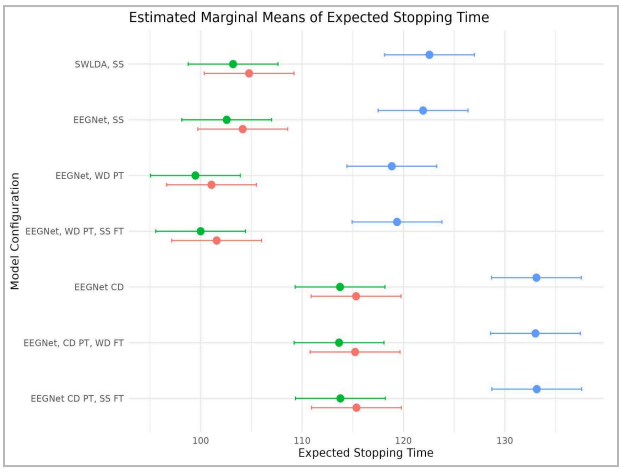
Additionally this study utilized a Stepwise Linear Discriminant Analysis (SWLDA) model as our baseline prior to implementing EEGNet. SWLDA enhances traditional LDA by incorporating a stepwise feature selection process to iteratively select the most relevant features. The produced weights were utilized in different stopping criteria. Under Static Stopping (SS), the stopping rule is fixed for a number of iterations (126 epochs). In Dynamic Stopping (DS), the stopping rule is based on a confidence threshold or probability (alpha = 0.9) (Throckmorton et. al. 2013). Under Dynamic Stopping with Language Model (DSLM), stopping rule is based on a confidence threshold or probability and includes a bigram language model for simple predictive capabilities (Mainsah et. al. 2014).

Results









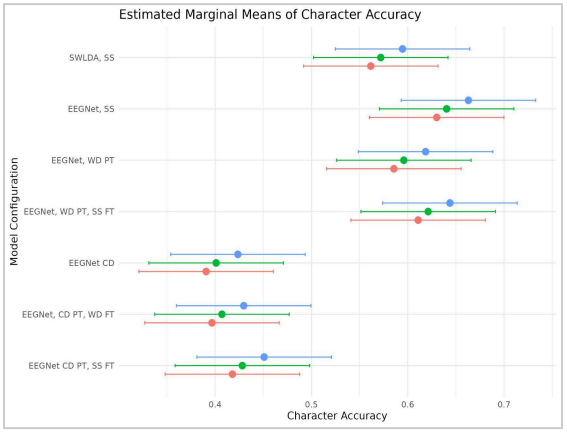




Figure 1: Character Accuracy (DSLM)
Figure 2: Expected Stopping Times (DSLM)
Figure 3: Estimated Marginal Means of Expected Stopping Time
Figure 4: Estimated Marginal Means of Character Accuracy

Statistical Analysis. A linear mixed-effects model was employed in this study; random effects in our model pertain to individual subjects while the fixed effects represent the different treatment groups, specifically the combination of model types and stopping mechanisms. We find statistically significant differences at $p < 0.001$ for stopping times with any instances of within-domain data and every stopping criterion. For character accuracy, stopping criteria showed no significance while the model combination with within-domain demonstrated significance at $p < 0.001$ and the subject specific EEGNet at $p < 0.05$. P values were compared to the baselines: SWLDA and static stopping.

To further explore the differences between treatment groups, post-hoc pairwise comparisons were conducted using estimated marginal means. These comparisons were performed with a confidence level of 0.95. As depicted in Figure 3 and 4, there is a statistically significant decline in character accuracy and an increase in stopping times when cross-domain pre-training and/or fine-tuning are applied. This suggests that while these techniques may have some benefits, they also introduce challenges that warrant further investigation.

Discussion

As expected, Dynamic stopping reduces BCI spelling times across all conditions, with the Dynamic stopping with a language model having comparable stopping times to traditional dynamic stopping. Moreover, generic EEGNet models trained on non-ALS data performed poorly relative to models trained on subject specific data, as shown with cross domain transfer learning having the lowest character accuracy across all stopping criteria, highlighting the limitations of cross-domain transfer learning. However, generic EEGNet models trained on ALS data performed comparably or better than models trained on subject-specific data. Clearly, leveraging within-domain data improves performance and could reduce BCI calibration time through transfer learning. Future work can be done to improve the transfer learning process with enhanced feature preprocessing techniques (Rivet et. al. 2009) and minimizing within-domain variabilities using both GAN transfer and domain adaptation (Wan et. al. 2020).

Conclusion

Overall, generic deep learning models can achieve comparable performance as user-specific models, which minimize calibration time. Our results show that transfer learning for training generic models is more effective with data from the target BCI end-user population, highlighting a need for more publicly available end-user datasets. Without these end-user datasets, there will continue to be a bias resulting in better performance for general users.

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