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Using Generic Models to Improve Tactile ERP-BCI Performance of Low Aptitude Users

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Abstract. Tactile ERP-BCIs may provide unique advantages over visual and auditory BCIs but often suffer from lower user performances. Herein we thus, evaluated the use of generic models for increasing BCI performance of low performing subjects. Such models create a generalized classifier from a pool of calibration sessions. Data of N = 15 healthy participants was used to evaluate different generic models. Preliminary results display the potential of generic models for increasing the performance of those users who do not achieve sufficient accuracy from their own calibration run. Further research will be required to evaluate the effectiveness of different generic models in an online setting with larger sample size.

Keywords: Brain Computer Interface (BCI), event-related potentials (ERP), Generic model, tactile ERP-BCI

1. Introduction

ERP-BCIs offer a high amount of control without the need for long-lasting training sessions. Tactile stimulation allows users to retain visual and auditory senses for non-BCI tasks and can easily be hidden underneath the cloths to reduce visibility of the system. Tactile stimulation was found to be a viable modality for ERP-BCIs [Brouwer and van Erp, 2010]. Although it may yield unique advantages in terms of user-friendliness it was found to achieve lower performance compared to visual or auditory stimulation [Aloise et al., 2007]. It has been shown for the visual modality that some users can use generic model classifiers instead of personalized classifiers to achieve acceptable performances [Jing et al., 2012]. Such models incorporate data from a pool of participants to create a generalized classifier independent from participants' own data. Herein, we evaluated the potential of generic models in tactile ERP-BCIs for increasing accuracy of low performing participants.

2. Material and Methods

N = 15 healthy participants (12 female, mean age 22.5 years, SD = 3.2) participated in the study. Tactile stimulation was applied to participants' left leg, right leg, belly and neck with 4 pairs of vibrate transducers (C2 tactors; Engineering Acoustic Inc., USA; stimulus duration: 220 ms; inter-stimulus interval: 400 ms). EEG signals were recorded from 16 passive Ag/AgCl electrodes and amplified using a g.USBamp amplifier (g.tec Engineering GmbH, Austria). Two data sets per person were included into this offline analysis, i.e. one calibration run and one run for testing of classifier performance. The reported accuracies are based on classification of 48 single sequences.

Offline classification was performed in MATLAB 2010b (The Mathworks Inc., USA) using stepwise linear discriminant analysis. Participants who achieved performances below the required level for communication of 70% [Kübler et al., 2001] were regarded as low performance participants (N = 6). For each participant four different classifiers were generated:

1. *Base model:* Base performances were gained using only participants' own calibration data for classification.
2. *Generic model:* A generic model was computed based on data from the full sample except for the participant on which the model was tested, i.e. the model was different for each participant but comprised data from the remaining N = 14 participants.
3. *Optimized generic model:* Additionally, we created an 'optimized' generic model using only the calibration data of the N = 8 participants who achieved more than 70% performance with their reference classifier. To maintain generic property of the model for those high performance participants, we created classifiers excluding their own calibration data from the optimized model.
4. *Mixed model:* Finally for each participant we created a mixed classifier using the weights from the *generic model* classifier and the participant's personal classifier (*base model*).

3. Results

Different classifiers were used to calculate offline performances for the 6 low performance participants (see Fig. 1a). The three of them who performed worst with their own model (P2, P3 and P15) could achieve higher performances using the optimized generic model classifier. Importantly, optimized generic models boosted

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performance of P3 by 65% and of P15 by 36% of the performance achieved with their own model. However, not all low performers could benefit from generic models. One participant achieved almost the same level of performance and the remainder displayed decreased performances (P8: -4%, P5: -20%; P6: -12% of performance with their own models).

Additionally offline performances were also calculated for the 9 high performance participants. ERPs of some participants well matched the features underlying the generic model, while others displayed great difference. For example participant 1 scored the best performance using the optimized generic model, due to broad similarities between spatio-temporal features (Fig. 1b). On the other hand, participant 9 achieved the lowest performance as his individual pattern did not match the generic model. Our results thus suggest that different models may be needed to account for inter-individual differences.

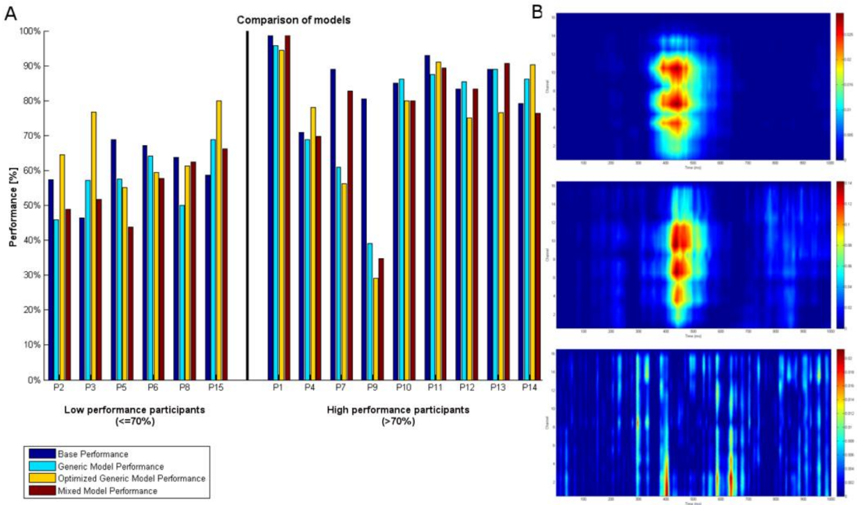

Figure 1. (A) *Average single trial performance, using 4 different classifiers. (B) Determination coefficients for data from generic model (top) vs. data from exemplary participants 1 (middle) and 9 (bottom). Channels are shown on the y-, time on the x-axis and R^2-values are color coded. Please note that color scales are different.*

4. Discussion

Preliminary results show that some low performance users can achieve higher performance using a generic model classifier and particularly display the potential of the optimized model. Some low performance users, however, do not improve using a generic model. Notably for 7 users (4 high performer, 3 low performer) the standard model achieved the highest performance. From data of high performers it can be seen that not all users may display EEG patterns in line with the generic model, e.g. in P9 generic model classifiers did reduce the performance drastically. Despite using features that strongly differed from the generic model, he achieved high performance using his own classifier. Therefore our generic classifier is not generic for all tested participants. Additional participant data is required to evaluate whether there might be different generic models which could account for users not compatible to this generic model. Additional data may also further contribute to a better generalization of the generic model. Furthermore, use of generic models for tactile ERP-BCIs has to proof its validity in an online setting. Finally generic model classifier should be evaluated with the end-user population, to see wether generic models can compensate for lower signal to noise ratios commonly found in end-user data. However, our results are promising in that three participants, who achieved only low performances using their personal classifiers, could benefit strongly from using an optimized generic model classifier.

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