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Skipping BCI calibration: fundamental investigations on Restricted Boltzmann Machines

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Introduction: Operating a brain-computer interface (BCI) that decodes spontaneous electroencephalogram (EEG) rhythms is a skill that users have to learn [1,2]. Feedback is essential for skill learning. EEG is typically recorded from users prior to BCI use and used to train pattern recognition models (calibration). During online operation, the model output is commonly presented as feedback. We aim at developing BCIs that do not require calibration. To this end we study between-user model transfer and online co-adaptation. The former allows providing feedback from the start and the latter enables user-specific finetuning of model parameters to enhance performance. The aim of this offline study is to evaluate the usefulness of the Restricted Boltzmann Machine (RBM) model as a generative classification framework [3] for the above mentioned purposes.

Material, Methods and Results: Dataset 2a from BCI competition IV [4] was used (N=9 healthy users; 2 days; 4 motor imagery classes). Only left hand and feet trials were included in this offline single-trial analysis (72 trials per class per day). Six logarithmic band power [2] features (8-15 Hz, 16-30 Hz; Laplacian channels C3, Cz and C4; 2s estimation window) were extracted and adaptively normalized [1] before training.
Leave-one-user out cross-validation was applied to evaluate between-user model transfer. Recordings of N-1 users were used to train the RBM via contrastive divergence learning [5]. It was then applied to the Nth user's data of day two. The first row of table 1 summarizes mean accuracies achieved. User-specific finetuning was assessed by adapting the model to the held out user's recordings of day one via backprop-learning − see row two. Row three summarizes results for a conventional user-specific shrinkage regularized linear discriminant analysis (sLDA) classifier, which was trained on the Nth user's data of day one and applied on day two.
The RBM performed significantly above chance level for 8 out of 9 users with an average accuracy of 73% in the between-user scenario (sLDA was also evaluated for between-user transfer yielding slightly lower but not significantly different accuracies). After finetuning to the user the mean performance increased by 9% to 82%.

trainings-set	**model**	**accuracy per user [%]**									**overall accuracy [%]**
		1	2	3	4	5	6	7	8	9	
other-users	RBM	91	59	81	69	57	69	82	61	89	**73±13**
day 1	RBM	92	81	89	72	56	82	95	77	94	**82±13**
day 1	sLDA	94	79	89	72	52	79	95	77	95	**81±14**

Table 1. Average classification accuracies for the held out user's 2nd day and mean and standard-deviation across all users. The 95% confidence interval for chance level is [-0.42,0.58].

Discussion: As expected, there was no significant difference between the sLDA classifier and the RBM for log-bandpower features. However, we demonstrated that the RBM model is capable of extracting information, which is inherently stored in the model parameters, from a mixture of users. Unlike sLDA, learning can be seamlessly continued on a single trial basis for a new user. Moreover, since the initial model performs above chance level for many users one can directly start with co-adaptive feedback training.

Significance: The results presented indicate that our RBM based approach is suitable for providing feedback from the start and can be adapted on a single-trial basis. We are currently working on an online implementation.

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