Adaptive hybrid Brain-Computer Interaction: Ask a Trainer for Assistance!

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***Abstract*— In applying mental imagery brain-computer interfaces (BCIs) to end users, training is a key part for novice users to get control. In general learning situations, it is an established concept that a trainer assists a trainee to improve his/her aptitude in certain skills. In this work, we want to evaluate whether we can apply this concept in the context of event-related desynchronization (ERD) based, adaptive, hybrid BCIs. Hence, in a first session we merged the features of a high aptitude BCI user, a trainer, and a novice user, the trainee, in a closed-loop BCI feedback task and automatically adapted the classifier over time. In a second session the trainees operated the system unassisted. Twelve healthy participants ran through this protocol. Along with the trainer, the trainees achieved a very high overall peak accuracy of 95.3 %. In the second session, where users operated the BCI unassisted, they still achieved a high overall peak accuracy of 83.6 %. Ten of twelve first time BCI users successfully achieved significantly better than chance accuracy. Concluding, we can say that this trainer-trainee approach is very promising. Future research should investigate, whether this approach is superior to conventional training approaches. This trainer-trainee concept could have potential for future application of BCIs to end users.**

I. INTRODUCTION

Users of event-related desynchronization (ERD) based brain-computer interface (BCI) systems [4] often need a lot of training. Especially, this was reported in end users, e.g., in patients with spinal cord injury [17] or with cerebral palsy [13]. Just recently, we could show that the use of adaptive classifiers increases BCI performance in a relatively short amount of time [5].

Usually when someone wants to learn new skills, a trainer or teacher is ready to assist. An everyday example would be learning to drive a car. Much more interaction between a trainer, a device and the trainee for example takes place when this person wants to learn how to fly a helicopter. Here, a trainer assists the young pilot using all the handles and levers, until the trainee is able to master flying the helicopter.

A hybrid BCI allows a user to use several input signals with at least one BCI channel to control a certain device or application [16], [11]. Besides classical BCI approaches hybrid BCIs gained more and more importance over the last years. Individuals with severe motor impairment can benefit from such a system as it allows for longer/better control of the device [19]. Various types of hybrid BCIs have been reported and are applied for the control of neuroprostheses, wheelchairs and spelling systems [8], [9]. In general a hybrid BCI can integrate different types of input signals (biosignals, assistive devices,...). However using two or more brain signals at the same time also constitutes a hybrid BCI.

Recent publications showed a hybrid BCI system operated by two different users [3]. The authors describe a multi user game scenario. In detail, two users are provided with a BCI system that combines the users' signals at the level of decision making. Both users are about to play a soccer game by imagining right and left hand movements.

Based on these ideas and other previous work, we want to use an adaptive hybrid BCI system in a trainer-trainee situation. A trainer assists a trainee to attain control with a BCI system. In a first session, brain patterns of a trainer and a trainee were merged into one classifier. Hence, the trainee was assisted by the trainer to experience BCI usage. In a second session, the trainee got full control over the adaptive BCI.

II. METHODS

A. Participants

Twelve healthy BCI novice volunteers, "trainees", (age 19 - 29 years, mean 22.5±2.8 SD, 6 female) and a BCI experienced user, "trainer", participated in this study. All were right handed. None of the participants had known diseases; they had normal or corrected to normal vision and were paid for their participation. At the beginning, all volunteers were informed about the aim of the study and they gave written consent to participate. The experiment was approved by the local ethics committee.

B. EEG recording

During the first session, we recorded EEG with two biosignal amplifiers (g.USBamp, Guger Technologies, Graz Austria). We attached 26 active electrodes (g.LADYbird, Guger Technologies, Graz Austria), half of them to the trainee and the other half to the trainer. The electrode arrangement was identical for trainee and trainer: Three Laplacian derivations centered at the international 10-20 system positions C3, Cz and C4, respectively. We attached the reference electrode at the left ear lobe and the ground electrode at position AFz. The first amplifier was connected with the trainee's electrodes and the second amplifier was connected with the trainer's electrodes (Figure 1). The Amplifiers recorded the data at a sample rate of 256 Hz. We used a band filter between 0.5 and 100 Hz and a notch filter at 50 Hz. All

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the settings were identical in the second session, except that we recorded only the trainee's EEG.

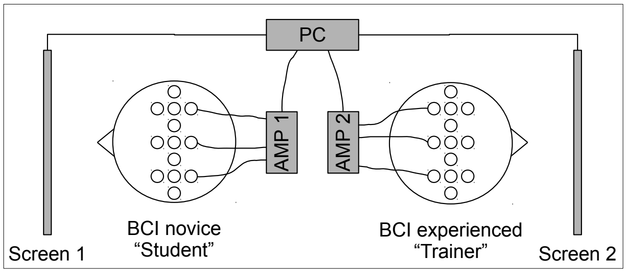

Fig. 1. Schematic representation of the experimental setup.

C. Experimental paradigm

In a cue-guided, two-class Graz-BCI motor imagery paradigm ([18], see Figure 2), the EEG signals from both users were recorded simultaneously, merged and translated into visual online feedback. This feedback was provided to both, trainer and trainee. Figure 1 shows a schematic depiction of the setup, with the two users sitting back to back each looking at the same visual feedback as generated online. In this trainer-trainee situation, four runs containing 20 trials per class were performed. After this training, trainees performed four runs unassisted.

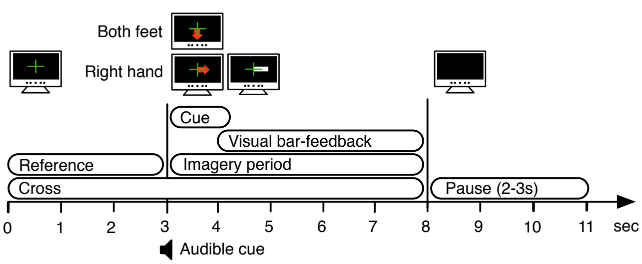

Fig. 2. Overview of the cue-guided motor imagery paradigm. For the reference period, the participants were instructed to visually fixate the cross and otherwise do nothing. Two types of visual cues, "arrow down" and "arrow right", appeared in random order. Both the BCI trainer and BCI trainee were instructed to imagine sustained kinaesthetic plantar extension of both feet for the cue-type "arrow down" and to imagine sustained kinaesthetic palmar grasp of the right hand for the cue-type "arrow right" for the whole imagery period. After less than five minutes, the system auto-calibrated and provided visual feedback, proportional to the LDA distance in form of a white-colored bar for correct activity as in [5] and [1].

D. Adaptive BCI online calibration

An auto-calibration and online adaptation system was used and worked as follows: The co-adaptive ERD BCI first (1) collected ten artifact-free trials for every one of the two classes without providing feedback. Then, (2) it automatically calibrated by training a linear discriminant classifier (LDA, [2]) based on logarithmic band-power features from both users and from then provided visual feedback online. From then on, the co-adaptive ERD BCI (3) retrained the underlying LDA classifier, whenever five new artifact-free trials per class were available.

The automatic online calibration step was identical to our previous work [5]. The following procedure was carried out separately for both users. Every calibration step always operated on all data collected thus far. The algorithm first extracted logarithmic band-power features (averaging over one second) in the frequency bands 10 to 13 Hz and 16 to 24 Hz [14] from every one of the three Laplacian derivations at C3, Cz and C4. From these six features, the system then selected the single feature that scored the highest separability according to the Fisher criterion [2] in the time window between second 4 to 8 relative to trial onset.

The system then trained an LDA classifier based on both of the users' single selected features. The best time-segment to set-up the LDA was selected in a leave-one-out cross-validation (LooCV): First, the system split the time-window from second 4 to 8 relative to trial onset into eight adjacent 0.5 s time-windows and performed LooCV for every one of them. In every LooCV step, the system trained an LDA classifier for the feature values of the two conditions for the current 0.5 s time segment of all trials in the training fold and applied the resulting classifier model to all time-samples in the current test-trial. The time-segment that scored the overall highest median accuracy between second 4 and 8 relative to trial onset across all test-trials was selected to finally train the LDA classifier that was from then on used online.

For the evaluation of the trainee in the second session, signal processing was identical, however, only his/her best feature was used for the LDA.

E. Outlier rejection

The system regularly performed trial based outlier rejection to use only artifact-free trials for online recalibration [5]. The approach worked iteratively: First (1) the algorithm computed the mean logarithmic band-power both across time (window second 4 to 8 relative to trial onset) and trials separately for every condition and for every one of the six features. Then the algorithm (2) removed exactly one trial. Specifically, the trial that had its logarithmic band-power average over time for one feature lay farthest outside three times the standard deviation for this feature and condition. If no more trials had feature values outside the threshold the algorithm stopped. Otherwise the algorithm continued to reanalyze the reduced data set according to step (1).

F. Evaluation and statistical comparison

Peak, mean and median classification accuracies were calculated from the window between second 4 and 8 relative to trial onset of the last 30 trials per class. A rank sum test (Wilcoxon rank sum test) was performed to assess differences in the classification accuracies between trainees together with trainer and trainees alone. The visualization of the ERD patterns was performed according to [6].

III. RESULTS

Classification results are shown in Table I. In the first session, trainees with trainers achieved on average 95.3 %

(peak), 88.8 % (median) and 87.2 ± 6.8 % (mean ± SD). In the second session, trainees were using the system unassisted. They reached an average classification accuracy of 83.6 % (peak), 71.5 % (median) and 69.7 ± 8.5% (mean ± SD), respectively. Using a Wilcoxon rank sum test, it could be shown that trainees performed significantly ($p < 0.01$) better together with a trainer than alone. Figure 3 presents the peak classification accuracy with and without trainer support. Figure 4 depicts the median classification results with and without trainer support. Figure 5 shows the trainer's ERD maps for the different classes. Investigating the features used, it could be seen that the features of the trainer were stable over all 10 sessions (see the clear focused ERD maps, Figure 5).

TABLE I

BINARY CLASSIFICATION ACCURACIES OF THE FIRST SESSION (TRAINER & TRAINEE) AND THE SECOND SESSION (TRAINEE ONLY). LAST 30 TRIAL PER CLASS USED FOR EVALUATION.

ID	Trainer & Trainee - Session 1				Trainee alone - Session 2			
	peak	median	mean	SD	peak	median	mean	SD
P1	100	96.7	93.9	6.8	88.3	80.0	76.5	9.6
P2	88.3	76.7	76.7	6.5	61.7	50.0	48.0	5.9
P3	100	95.0	93.4	7.7	98.3	85.0	82.2	11.3
P4	86.7	76.7	75.8	5.5	83.3	65.0	64.5	9.4
P5	100	98.3	93.7	10.9	96.7	86.7	82.5	11.0
P6	98.3	91.7	87.9	9.3	91.7	81.7	74.7	14.3
P7	100	93.3	92.2	6.7	80.0	68.3	66.9	6.0
P8	100	98.3	96.9	5.3	91.7	81.7	81.2	6.4
P9	85.0	75.0	75.7	5.2	85.0	60.0	62.0	8.9
P10	86.7	75.3	73.4	6.0	65.0	56.7	56.5	4.9
P11	98.3	93.3	92.0	5.9	93.3	81.7	81.3	9.1
P12	100	96.7	94.9	5.9	68.3	61.7	60.2	4.9
aver.	95.3	88.8	87.2	6.8	83.6	71.5	69.7	8.5
median	99.2	93.3	92.1	6.2	86.7	74.2	70.8	9.0

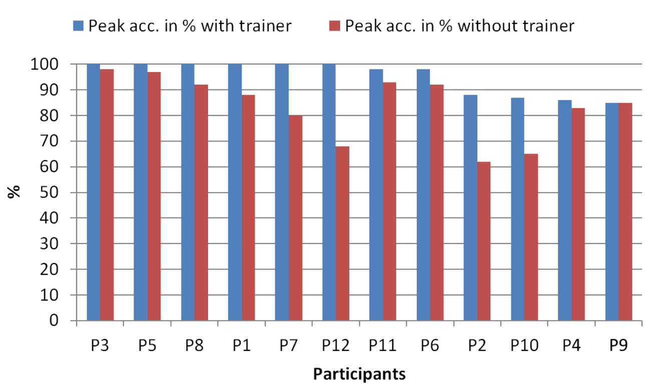

Fig. 3. Peak classification accuracies during the feedback period with and without trainer support.

IV. DISCUSSION

In this work, we demonstrated for the first time a successful implementation of an adaptive, hybrid BCI system in a trainer-trainee setup. Like in real life, when people learn to use or operate a new device or machine, a trainer was equipped with a BCI system too, to assist the trainee with his stable and distinct brain patterns during motor imagery. Final median accuracy of the trainer-trainee system were just below 90 % with a peak accuracy of about 95 %. Trainees, using the system for the first time without a trainer reached a median accuracy of 71 %, peaks at 83 %. Although this result was significantly lower than with the trainer it is still in the range where simple communication can be performed (see [15]). It is of interest that four of the trainees achieved medium performance also with the trainer (P2, P4, P9 and P10), and poor performance without the trainer (average of the median about 58 %). Interestingly, one participant (P12) had 100 % accuracy with the trainer but only 60 % alone.

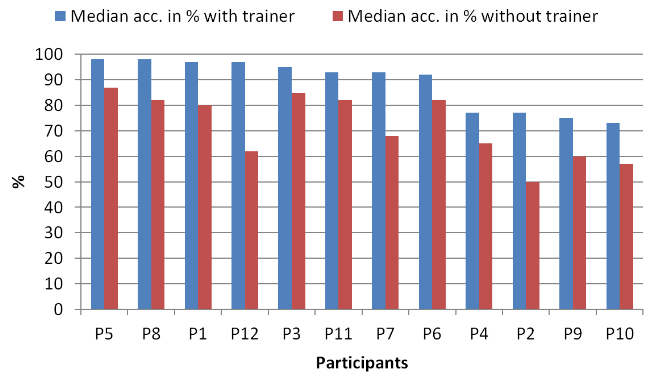

Fig. 4. Median classification accuracies during the feedback period with and without trainer support.

Exploring the data from a physiological perspective, we found no notable changes in the patterns of brain activity during motor imagery for the trainer over all sessions. Figure 5 shows an average over all ERD maps for the trainer. For the trainees however we found differences. While the four trainees described above, seemed to have strong patterns, but not discriminable ones, it seems that participant P12 had a very weak pattern, which was not chosen by the trainer-trainee setup. A more detailed analysis would be necessary to investigate the direct influence to the classification result. Additionally, two of the trainees (P2, P10) performed not better than chance (66.1 %; p=0.01, [12]). We found the performance after the trainer session to be very high compared to state of the art systems. When comparing our results with other studies, we found that even compared to systems that use common spatial patterns and a higher number of electrodes, our performances are in a similar range ([7]; 80 participants, mean feedback accuracy 74 %).

From a psychological perspective, we subjectively observed participants to be highly motivated and focused on the task. Generally, we received very good feedback from the users on this new approach. Our next steps will be to evaluate the exact impact of trainer guidance on the trainee's performance. We are interested whether closed-loop training with a trainer can reinforce the activity patterns of the trainee to induce a lasting improvement in class discriminability. One idea would be to consider other, possibly non-linear mechanisms to fuse the features of trainer and trainee.

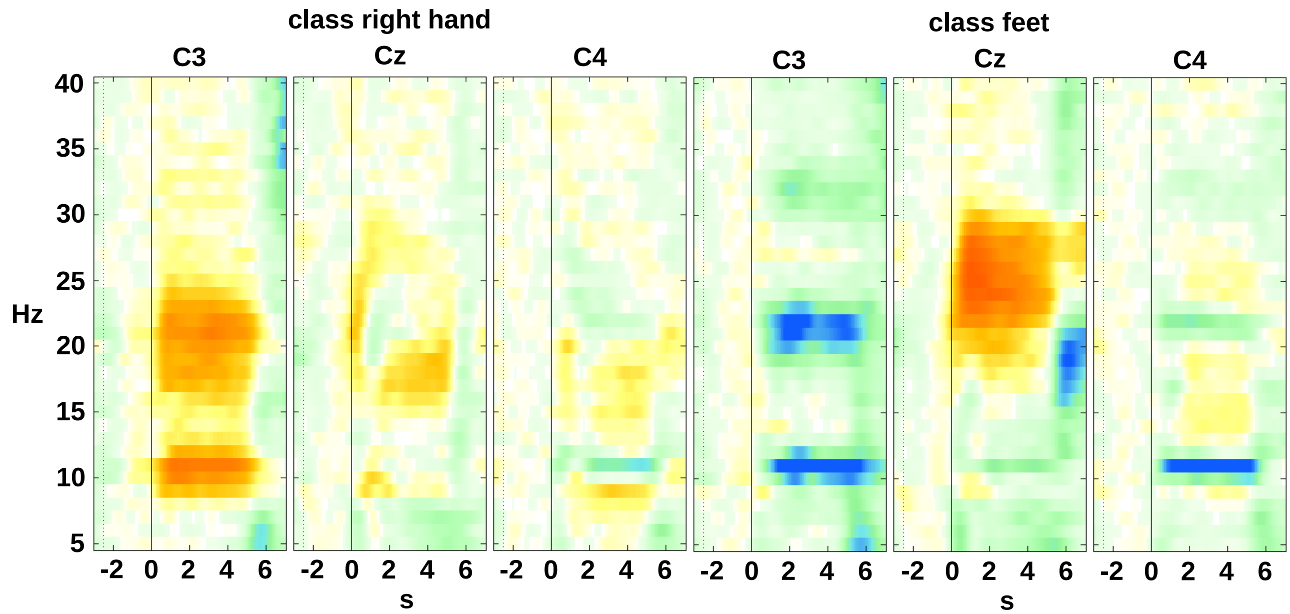

Fig. 5. ERD maps of the trainer. Average over all sessions (680 trials). Red patches indicate ERD and blue patches indicate event-related synchronization (ERS).

Another approach would be to investigate whether gradually reducing the influence of the trainer's features over time could help to improve the trainee's performance.

V. CONCLUSION

Concluding, we can say that this trainer-trainee approach is very promising. It should be further investigated, whether this approach is superior to the conventional training approach. Still the main idea is appealing, starting a training with an end user in need as long as it is required. This could also be performed in a telemonitoring setup [10].

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