Brain-Computer Interface adaptation for an end user to compete in the Cybathlon

Andreas Schwarz, David Steyrl and Gernot R. Müller-Putz
Institute of Neural Engineering, Graz, University of Technology
Stremayrgasse 16 IV, 8010 Graz, Austria
Email:gernot.mueller@tugraz.at

***Abstract*—Non-invasive brain-computer interfaces (BCI) aim to assist severely motor impaired persons in their daily life routine, however only a few BCIs have made it out of the laboratory. To foster further development, the Cybathlon, an international multi-discipline tournament, has been founded. One of the disciplines is the BCI-Race, where end users control avatars in a virtual race game by their thoughts. The game supports 4 different commands which accelerate the avatar and increase the chance to win. So far, no gold standard procedure has been established on how to enable, train and individualize multi-class BCI control for users. In this work, we present a 4-stage procedure to closely tailor a multi-class BCI to an end user who will participate in the Cybathlon. In stage I, we test for basic BCI-capability, in stage II we evaluate the most suitable mental tasks for the user and in stage III, we test user compliance while perceiving feedback. Finally in stage IV, the user is playing the competition game. Our procedure provides a promising way to guide users from first contact with BCI technology to actually play a videogame by thoughts. We demonstrate the feasibility of our procedure at the pilot of the GRAZ-BCI racing team MIRAGE91. We believe that an evidence based procedure, maybe similar to the one presented in this work, is a necessity to introduce BCI technology in the daily life of potential end users.**

I. Introduction

Non-invasive brain-computer interfaces (BCI) enable its users to interact with their environment by means of changes in brain activity, captured for example by the electroencephalogram (EEG) [1]. BCI control strategies rely either on focused attention to external stimuli [2] or on specific mental tasks [3], [4]. One application of BCIs aim to enable severely motor impaired persons to control a computer and consequently assistive devices [5], [6]. So far, only a few BCIs [7] have made it out of the lab for use on daily life basis. Reasons are: (i) handling, (ii) robustness (iii) and reliability of BCI system. Case studies indicate that reliable BCI use can be trained [3], [6]. However, according to these studies, training may take weeks or months. To foster future (competitive) development, the Eidgenössische Technische Hochschule Zürich (ETH Zürich) organizes a novel competition - the Cybathlon [8]. It is a tournament for people with severe motor impairments using assistive prototype devices to compete against each other in various disciplines. The competition is designed for teams. Participating teams consist of an end user, termed the pilot, and a number of undergraduate/graduate students, named the tech-team. One of the disciplines is the BCI-Race, where users have to control avatars in a virtual race game against up to 3 other pilots (see figure 1) by means of mental task based BCIs. Controlling the game by means of a BCI is a challenging task. The avatar in the game is constantly moving along the race track. Three different action fields are placed on the race track which can be triggered by a correct control command. Once correctly triggered, the avatar of the pilot receives a speed boost. If the wrong control command is triggered, the pilot is penalized by slowing his avatar down for a certain time. The game supports four different commands, which increase the speed of the avatar. To be competitive, all 4 commands need to be reliably controlled by the pilot. In the competition, the user has to complete several qualification runs and a final race.

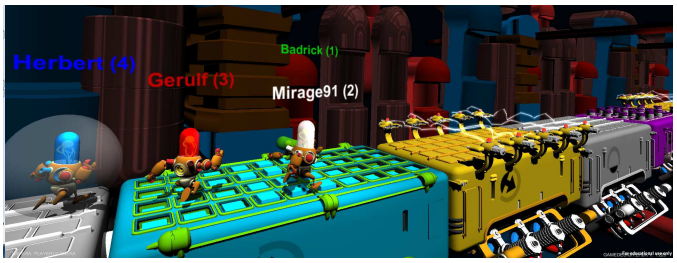

Fig. 1. **Brainrunners, the game of the BCI competition.** The game is played in a competitive manner: Up to four people compete against each other. The racetrack consists of different action fields (colored blocks) and no action fields (grey). When triggering the right command on an action block, a speed boost is enabled. False positive commands are penalized.

There are studies which already attempted robust BCI-multiclass control for games [5], [9]. In particular, Scherer et al. [10] showed the feasibility of a multi-class BCI system where the user was able to navigate through a virtual environment. In a follow up study [11], they applied the same principle for controlling the popular multiplayer game World of Warcraft. Both studies present results which indicate that the Cybathlon challenge lies within possible realms. However, no gold standard procedure to enable users control of multi-class BCI has been established. In the following, we describe our multi-stage procedure for individualizing and adapting BCI technology to a severely motor impaired user. We share our experience and demonstrate the feasibility of each stage by means of the designated pilot of the GRAZ-BCI racing team MIRAGE 91. The team will compete in the Cybathlon

978-1-5090-1897-0/16/$31.00 ©2016 IEEE

tournament in October 2016.

II. Methods

To achieve reliable BCI control, it is essential to closely tailor the BCI to the user. In this work, we report on our experience with a procedure based on findings of Müller-Putz et al. [12], [13] and Friedrich et al. [4], but also incorporate personal experiences and ideas. The procedure consists of 4 consecutive stages (see fig 2):

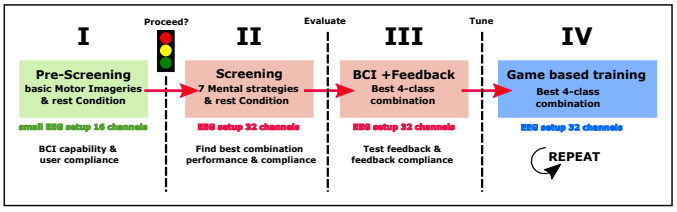

Fig. 2. **4 Stage training procedure:** In pre-screening (stage I) the BCI aptitude of the user is evaluated and a Go/NoGo for further training is decided. In stage II, screening, the best 4-class combination out of a pool of mental strategies is evaluated. Stage III tests user compliance for receiving feedback. Based on all collected data, a closely tailored BCI is implemented. In stage IV the user starts training with the competition game.

In stage I, we perform a pre-screening to test whether the user is able to produce different brain patterns. This also implies that the user is able to concentrate and is compliant with the designated tasks. Results of the first stage indicate whether continuing with this user is reasonable or not. Stage II incorporates a general screening of several mental tasks. Friedrich et al. [4] tested several different mental tasks for inducing changes in the EEG and found that the optimal task is dependent on users. The main goal of this stage is not only to find the most effective 4 mental tasks combination, but also a combination the user is willing to train. In stage III, the user receives feedback based on performed mental tasks for the first time. This stage is implemented primarily to evaluate the findings from stage II and to determine compliance of the user to feedback. Based on the results of stage III, close tailoring of the BCI is done. Modern machine-learning methods [14], [15], which are adapted to the individual brain patterns found and evaluated in stages I to III, are implemented. In stage IV, we already incorporate BCI training using the actual virtual race game which is eventually used in the competition. From this point, the user only trains with the game in short intervals.

A. Pilot

The designated pilot of the GRAZ BCI racing team MIRAGE91 is a 36 year old male. In 2014, he was diagnosed with an incomplete locked-in syndrome resulting from thrombosis of the basilar vein which resulted in an extended stroke of the brainstem and cerebellum (right side). At hospital admission, the patient was almost completely paralyzed with little motor residua of the upper extremity. During treatment, the motor abilities increased to a point where he is able to operate an electric wheelchair using a joystick as assistive device. Currently, the user is vigilant and fully aware of his environment.

B. Stage I: Pre-screening

At the beginning, we performed a pre-screening. The goal was to evaluate whether the user is able to understand and to perform the requested tasks, and if the tasks trigger unwanted side effects, like spasms or discomfort for the user. Furthermore, we wanted to identify whether the user is able to produce distinguishable brain patterns. Pre-screening was done in two sessions on two different days.

1) Methods: For both sessions EEG was recorded using a biosignal amplifier equipped with 16 active electrodes (g.tec OG, Austria). Sample rate was 512 Hz and bandpass filter was set to 0.1 - 100 Hz (8th order butterworth filter). A notch filter was applied (50 Hz). We covered C3, Cz and C4 with five electrodes each in an equidistant manner (2.5cm) so that for each position a single orthogonal (Laplacian) derivation was possible. The remaining electrode was placed at position AFz (see fig 3). All signals were referenced to a clip on the right ear lobe and the ground electrode was placed frontal.

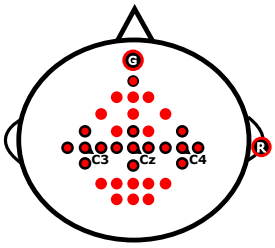

Fig. 3. **Electrode layout:** For pre-screening, only the 16 black-outlined electrodes were used. The consecutive stages used all plotted electrodes)

We used the cue-guided 3 class GRAZ-BCI paradigm which is further described here [16](see fig 4). In the first session, we focussed on standard MI tasks, namely the imagination of movement (motor imagery, MI) of the left hand, right hand and both feet. We recorded 40 trials per class in 4 consecutive runs. In the second session we changed our paradigm to two MI classes, namely MI of right hand and both feet but incorporated a separate rest class where the user was asked to perform no action at all. We recorded 50 trials per class in 5 consecutive runs.

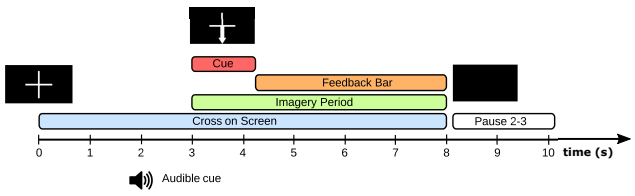

Fig. 4. **GRAZ-BCI Paradigm:** At second 0 a cross appears on the screen followed by an auditory cue at second 2 to get the attention of the user. At second 3 the cue is presented followed by a five second imagery period. Depending on the cue, the user performed the designated task over the whole imagery period.

Each analysis step was preceded by statistical outlier rejection (amplitude threshold, kurtosis, probability) in order to exclude artefact contaminated trials as described in [17]. Time-frequency maps were calculated using Laplacian derivations

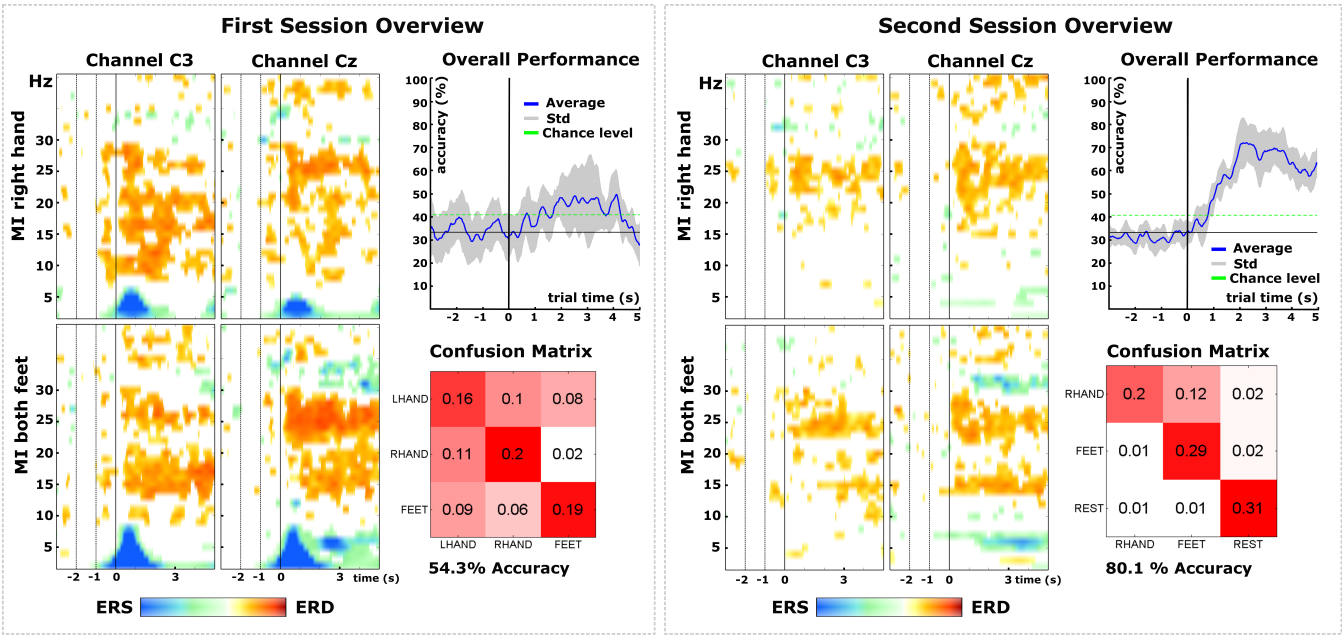

Fig. 5. **Pre-screening results:** ERD/ERS maps calculated for each session for right hand and boot feet ME. Top right each, shows the cross-validation accuracy. Bottom left each, shows the confusion matrix for second 1 to 5.

from channels C3, Cz and C4. Data was bandpass filtered between 2 and 40 Hz and segmented 3 seconds before to 5 seconds after presentation of the visual cue. Event-related (de)synchronization (ERD/ERS) analysis [18] was performed with respect to a specific reference interval (-2 to -1 second before the visual cue). Statistical significance of the the ERD/ERS data was determined by applying a t-percentile bootstrap algorithm with a significance level of alpha = 0.05. We also performed a cross-validation analysis of the recorded data to determine class discriminability. We bandpass filtered the data from 6 to 35 Hz using a 4th order zero-phase butterworth filter.

We applied 10 times 5 fold cross validation to the following steps:

1) Three separate common spatial patterns filters [19] were trained using (training) trial data from one second to four seconds after the visual cue. Filters were calculated so that every possible class combination (class 1 vs. 2, 1 vs. 3, 2. vs. 3) was reflected. We took the first two and the last two CSP projections and calculated 12 bandpower features. Subsequently we applied the logarithm to the band power features.
2) An analytic shrinkage regularized linear discriminant analysis (sLDA) classifier [20] was trained on band-power features located 2.5 s after the visual cue.
3) CSP filter and sLDA model were applied to the data for performance evaluation.

We calculated the confusion matrix over the feedback period from second 4 to second 8: If the majority of the class prediction was correct, the trial was valued as correct. In this manner, all trials were evaluated.

2) Results: Figure 5 summarizes the results from pre-screening session 1 and session 2.

3) Discussion: Results show distinguishable brain patterns as can be seen in figure 5 (left each). Patterns lead to classification performances which both lay over chance level, which is also confirmed by the confusion matrix (figure 4, right each). Setting and experiment did not lead to any unwanted effects like spasms or discomfort to the user, moreover, he was vigilant and concentrated in both sessions. However, in the first session, the user was quite nervous due to the novelty of the situation. As can be seen in the ERD/ERS maps of that session (figure 5, left), EOG artefacts are present right after the presentation of the cue. When comparing to the second session, the user was far more focussed on the task and managed to suppress eye movements. Based on these results we decided to proceed further in the training process and the user became the official pilot for the team.

C. Stage II: Screening

The goal for screening was to find a suitable combination of 4 different classes which on the one hand promised high classification performance and on the other hand was in compliance with the user.

1) Methods: Since screening incorporated not only motor imagery tasks, we extended our EEG-setup to 32 active electrodes positioned in an equidistant manner as displayed in figure 3. For the actual screening we chose 7 different mental strategies and a rest condition to be performed which were also used in [4]:

- **MI of right hand movement (HAND):** repetitive squeezing a training ball
- **MI of both feet movement (FEET):** planar flexion/extension of both feet

- **Word association (WORD):** generating as many words as possible with a presented letter
- **Mental subtraction (SUB):** repeated subtraction from a given number
- **Auditory Imagery (AUDI):** Imagination of singing a song/jingle
- **Spatial Navigation (SPATNAV):** Imagine navigation through your own apartment
- **Mental rotation (ROT):** Imagine rotating a 3 dimensional object
- **Rest(REST):** Relax, but be focussed on the cross on the screen.

We displayed white icons as cue onsets in the center of the screen. In this manner we recorded 45 trials per class (TPC) over 9 consecutive runs.

We calculated ERD/ERS maps for each class in the same way as already described in pre-screening. Since we wanted to find the 4-class combination with the highest performance, we performed for each possible 4-class (70 in total) an analysis to determine class discriminability. Again we bandpass filtered the data from 6 to 35 Hz using a 4th order zero-phase butterworth filter and used a 10 times 5 fold cross validation technique to avoid overfitting. We trained CSP filters on (training) trial data from one second to three seconds after the visual cue on every possible class combination (class 1 vs. 2, 1 vs. 3, 1 vs. 4, 2 vs. 3, 2 vs. 4, 3 vs. 4). We took the first two and the last two CSP projections and calculated 24 bandpower features. Additionally we took the logarithm of the band power features. Thereafter, a sLDA classifier was trained on bandpower features located 2.5 seconds after the visual cue.

2) Results: Table I shows peak and median accuracies of the best five combinations. Figure 6 gives a detailed overview of performance calculated offline over all trials.

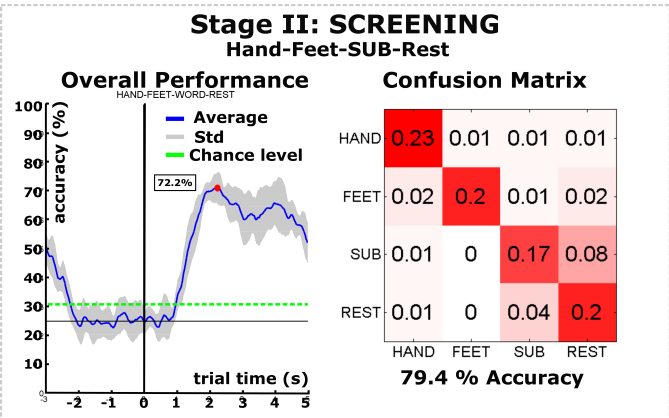

Fig. 6. **Overall performance of the mental strategy combination.** The left plot shows the overall classification performance over all trials. Peak performance is at 72.2.% (left, red dot). The confusion matrix was calculated over the feedback period from second 1 to second 5: If the majority of the class prediction was correct, the trial was valued as correct. In this manner all trials were evaluated.

3) Discussion: We found distinguishable mental tasks. Offline testing of all mental task combinations showed that HAND-FEET-SUB-REST results in highest classification performance. In the best 5 combinations tested (out of 70) both MI classes are always present. This is in line with the findings of Friedrich et al [4], where motor tasks were present at least once in each best-class combination of all their study participants (n=8). The confusion matrix shows high accuracy and low false positive/negative activations. Apart from the technical performance measures, the user is also comfortable with the combination and agreed on it for further training.

TABLE I
SCREENING RESULTS (BEST 5 OUT OF 70): THE COMBINATION OF THE TASKS HAND-FEET-SUBTRACTION-REST WORKED BEST FOR THE USER, NOT ONLY IN PEAK ACCURACY, BUT ALSO IN MEDIAN ACCURACY OVER THE FEEDBACK PERIOD FROM SECOND 4 TO SECOND 8.

Combination	Peak accuracy (%)	Median (4-8s) (%)
Hand-Feet-Subtraction-Rest	75.6	66.1
Hand-Feet-Word-Rest	72.2	63.3
Hand-Feet-Spatial-Rest	68.4	56.1
Hand-Feet-Rotation-Rest	68.9	56.1
Hand-Feet-Subtraction-SpatNav	67.8	60.0

D. Stage III: First Feedback

BCI use commonly incorporates feedback. We created a 4 class BCI, using the class combination identified in the previous stage to test user compliance for perceiving feedback.

1) Methods: We applied configurations for amplifier and electrode setup from the previous screening session. We chose the most suitable combination (HAND-FEET-SUB-REST) from the screening and used these classes for the feedback session. The representative icons which are shown in the paradigm are already color-coded with respect to the action fields of the virtual race (grey (REST), yellow (SUB), blue (HAND) and pink (FEET)). We provided a bar for presenting feedback to the user. The length of the bar was controlled by the amount of correct classifications during the last second.

We recorded 50 trials per class using the described paradigm. Thereafter, we performed statistical outlier rejection (amplitude threshold, kurtosis, probability) on the data to exclude artefact contaminated trials [17]. Six separate CSP filters were trained using (training) trial data from one second to four seconds after the visual cue. Filters were calculated so that every possible class combination was reflected. We took the first two and the last two CSP projections and calculated 24 bandpower features. Additionally we took the logarithm of the band power features. A (sLDA) classifier was trained on bandpower features located at 2.5, 3.5 and 4.5 seconds after the visual cue. CSP filters and sLDA model were now used for online classification and providing feedback to the user. In this manner, we recorded an additional 40 trials per class.

2) Results: Figure 7 shows the overall performance of the stage 3 experiment.

3) Discussion: In this experiment, the user received feedback for the first time. Performance was above chance level and peaked at 63.1% for online feedback and 68.4% for trial based evaluation. In comparison to offline performance, online

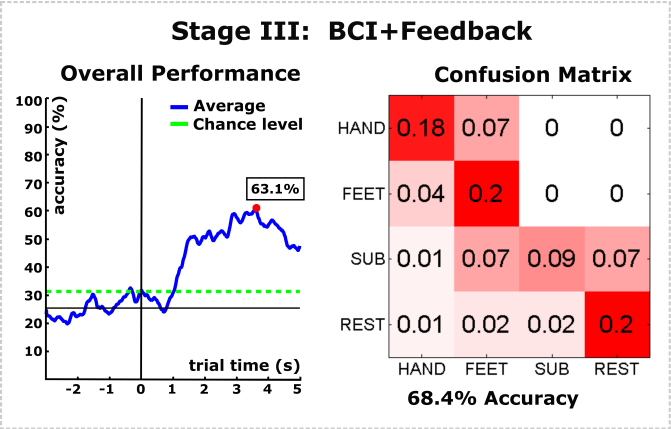

Fig. 7. **Overall performance of the mental strategy combination.** The left plot shows the classification performance of the trials with feedback. Peak performance is at 63.1.% (left, red dot). The confusion matrix was calculated over the feedback period from second 1 to second 5.

results were lower, however the user was fond of receiving feedback and was eager to continue BCI use. Overall user compliance was high. He was focussed on the tasks, avoided eye movements (blinks) and swallowing as much as possible.

E. Stage IV: BCI Game

The feedback experiment was conducted in a cue-based way, with abstract and simplified feedback. Games however, cause distractions which can influence BCI performance negatively. Therefore, we switched over to the actual game to allow our pilot to accustom to the game.

1) Methods: The experiment consisted of two parts. First, collecting training trials and second, playing the game. In training mode, the game sends triggers over UDP to mark game events, like entering new action fields. The pilot was instructed to start with his mental imagery as soon as the avatar enters a new action field. Due to these markers, we were able to assign periods of mental imagery to EEG. These EEG periods were used to train the algorithms of the BCI. In detail, EEG of second 1 to second 3 after a new action field marker was cut out and used to train CSP filters. Classifier training was performed with data at second 3. The BCI itself contained the following signal processing steps: (i) band pass filtering, 2 bands: 8-16Hz and 16-30Hz to separate alpha and beta band activity. (ii) CSP filtering with one separate CSP filter per band and per binary task combination, resulting in 12 CSP filters (6 possible binary combinations of the four mental imageries and 2 frequency bands). Four CSP channels per CSP filter were selected: 2 related to the highest eigenvalues and 2 related to the lowest eigenvalues, resulting in 48 CSP channels in total. (iii) Squaring, logarithm calculation, and subsequent averaging over a sliding window of one second was performed in the next stage. (iv) 48 logarithmic bandpower values were fed to a multi class sLDA classifier which calculated class probabilities. (v) Smoothed class probabilities were compared to thresholds. If a class probability exceeded the threshold, a command was sent to the game. (vi) The game reaction was the feedback to the pilot. For training data collection, we recorded 50 TPC in 5 consecutive training runs (10 TPC each) where the user only performed the mental tasks, but no actions were triggered. Detailed explanation of this procedure is depicted in figure 9. Thereafter, BCI models were calculated and the user performed 4 regular runs including the full spectrum of control options.

2) Results: Figure 8 shows the performance results of 4 runs where the user played the game.

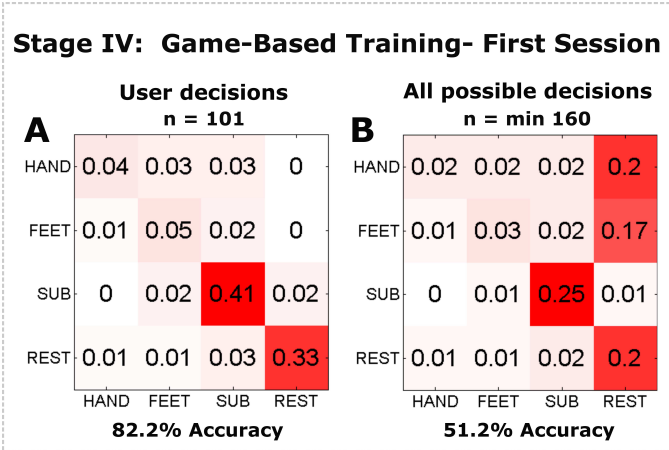

Fig. 8. **First results of the game based training: (A)** User-decision based confusion matrix. In 4 runs, the user triggered an action 101 times. **(B)** Confusion matrix of all possible decisions.

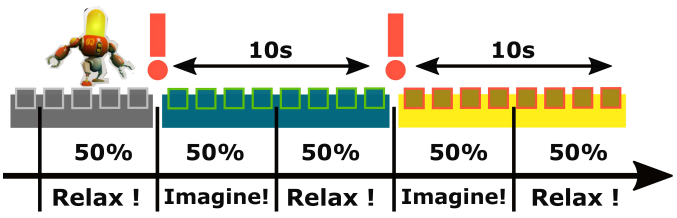

Fig. 9. **Brainrunners training paradigm:** For data collection the user was instructed to perform the mental task on the first half of the action field and relax on the second half. In this manner the user performed 5 seconds of the designated mental task and had 5 seconds until the next mental task.

We performed analysis of the runs where the user was actually playing the game. **(A)** At first we investigated all the user triggered events in a confusion matrix. Whenever the user triggered the corrected event on the respective action field, we valued it as a true positive. If the user did not trigger an event on a non-action field (grey fields), we also counted it as a true positive. In this analysis we did not include action fields where the user did not trigger an action but merely ran over. **(B)** In a second analysis we also included fields where the user should have triggered action fields but did not trigger them.

3) Discussion: In this experiment, the user played the Brainrunners game for the first time. 82.2% of all triggered commands were correct but there is room for improvement:

the user only triggered around 60% of all possible action fields. It was hard for the user to trigger HAND and FEET action fields, however he robustly triggered SUB fields and was able to generate a stable REST condition. Figure 8 shows the corresponding confusion matrices. User compliance was high. He was focussed on the task and tried to avoid producing artefacts of any kind.

III. Conclusion & Outlook

In this work, we presented our multi-stage procedure for individualizing and adapting BCI technology to a severely motor impaired user. Single stages of our procedure have resemblance to or are based on already published procedures [12], [13], [6], [4]. Nevertheless our procedure provides a promising way to guide users from first contact with BCI technology to actually play a videogame by thoughts. When aiming for BCI control, one has to be certain that the user understands instructions. The results of our first stage indicate that the pilot is not only able to understand the instructions but was also able to create distinct ERD/ERS patterns for different mental tasks. Patterns were more pronounced and performance was also higher in the second session of pre-screening. Therefore we favour to perform more than one pre-screening session before deciding to continue training. Past works show [4] that mental task combinations perform differently for each user. We started screening eight different mental tasks and found that classification performance varied widely for different task combinations. From our experience, users can be distracted by received feedback. Results from stage III suggest that the user was able to maintain the mental task while receiving feedback, although his performance was lower than in offline analysis. The transition from an abstract BCI-paradigm to a game-based paradigm is complex. Active game environments provide multimodal visual and auditory distractions, which change brain patterns and therefore influence BCI performance negatively. Nevertheless, we are confident that once the user gets more familiar with the game and establishes a training routine, these distractions will take less influence. In the upcoming weeks and months we will repeat game-based training in short intervals. We hope that our procedure enables the pilot of the GRAZ-BCI racing team MIRAGE91 to successfully participate in the Cybathlon. In conclusion, we believe that an evidence based procedure, maybe similiar to the one presented in this work, is a necessity to introduce BCI technology in the daily life of potential end users.

Acknowledgment

This project was partly supported by: VAMED, City of Graz, Graz University of Technology, Institue of Neural Engineering, Swietelsky Tunnelbau GmbH, and the Horizon 2020 Project MoreGrasp (No. 643955). The GRAZ-BCI racing team MIRAGE91: Maria Höller, Karina Statthaler, Marvin Bigga, Johannes Steininger, Dominik Narnhofer, Lydia Lindner, Lea Hehenberger, Julia Brandstetter, Markus 'Pikachu' Adamek, Bernhard Frohner and Reinmar Kobler.

References

[1] J. R. Wolpaw, N. Birbaumer, and D. J. M. et al., "Brain-computer interfaces for communication and control," *Clinical Neurophysiology*, vol. 113, pp. 767–791, 2002.

[2] S. Halder, A. Pinegger, I. Käthner, S. Wriessnegger, and e. a. J. Faller, J.B.P., "Brain-controlled applications using dynamic p300 speller matrices," *Artificial Intelligence in Medicine*, vol. 63, no. 1, pp. 7–17, 2015.

[3] G. Pfurtscheller, C. Guger, and G. M. et al., "Brain oscillations control hand orthosis in a tetraplegic," *Neuroscience Letters*, vol. 292, pp. 211–214, 2000.

[4] E. Friedrich, C. Neuper, and R. Scherer, "Whatever works: A systematic user-centered training protocol to optimize brain-computer interfacing individually," *PLOS ONE*, vol. 8, no. 9, 2013.

[5] JR.Millan, R. Rupp, G. Müller-Putz, R. Murray-Smith, G. Claudio, M. Tangermann, C. Vidaurre, F. Cincotti, A. Kübler, R. Leeb, C. Neuper, K. Müller, and D. Mattia, "Combining brain-computer interfaces and assistive technologies: State-of-the-art and challenges," *Frontiers in Neuroscience*, vol. 4, no. 161, 2010.

[6] M. Rohm, M. Schneiders, C. Müller, A., V. Kaiser, G. R. Müller-Putz, and R. Rupp, "Hybrid brain-computer interfaces and hybrid neuroprostheses for restoration of upper limb functions in individuals with high-level spinal cord injury," *Artificial Intelligence in Medicine*, vol. 59, no. 2, pp. 133 – 142, 2013.

[7] E. Holz, L. Brotel, T. Kaufmann, and A. Kübler, "Long-term independent brain-computer interface home use improves quality of life of a patient in the locked-in state: A case study," *Archives of physical medicine and rehabilitation*, vol. 96, no. 3, pp. 16–26, 2015.

[8] R. Riener and R. Kundert. (2016, April) Cybathlon championship for athletes with disabilities. Website. ETH Zürich, Professur f. Sensomotorische Syst. Tannenstrasse 1,8092 Zürich,Switzerland. [Online]. Available: http://www.cybathlon.ethz.ch/

[9] R. Scherer, M. Billinger, and J. W. et al., "Thought-based row-column scanning communication board for individuals with cerebral palsy," *Annals of Physical and Rehabilitation Medicine*, 2014.

[10] R. Scherer, F. Lee, and A. S. et al., "Toward self-paced brain-computer communication: navigation through virtual worlds," *IEEE Transactions on Biomedical Engineering*, vol. 55, pp. 675–682, 2008.

[11] R. Scherer, J. Faller, D. Balderas, E. Friedrich, M. Pröll, B. Allison, and G. Müller-Putz, *Brain-Computer interfacing: more than the sum of its parts*, ser. Soft Computing - A Fusion of Foundations, Methodologies and Applications. Springer, 2013, vol. 17, no. 2.

[12] G. Müller-Putz, R. Scherer, G. Pfurtscheller, and R. Rupp, "Eeg-based neuroprosthesis control: A step towards clinical practice,," *Neuroscience Letters*, vol. 382, no. 1-2, 1-8, pp. 169–174, 2005.

[13] G. Müller-Putz, R. Scherer, and G. P. et al., "Temporal coding of brain patterns for direct limb control in humans," *Frontiers in Neuroscience*, vol. 4, no. 34, 2010.

[14] A. Schwarz, R. Scherer, D. Steyrl, J. Faller, and G. Müller-Putz, "A co-adaptive sensory motor rhythms brain-computer interface based on common spatial patterns and random forest," in *Engineering in Medicine and Biology Society (EMBC), 2015 37th Annual International Conference of the IEEE*, Aug 2015, pp. 1049–1052.

[15] D. Steyrl, R. Scherer, and J. F. et al., "Random forests in non-invasive sensorimotor rhythm brain-computer interface: A practical and convenient non-linear classifier," *Biomedical engineering*, 2015.

[16] G. Pfurtscheller and C. Neuper, "Motor imagery and direct brain-computer communication," *Proceedings of the IEEE*, vol. 89, pp. 1123–1134, 2001.

[17] J. Faller, C. Vidaurre, and T. S.-E. et al., "Autocalibration and recurrent adaptation: Towards a plug and play online ERD-BCI," *IEEE Transactions on Neural Systems Rehabilitation Engineering*, vol. 20, no. 3, pp. 313–319, May 2012.

[18] B. Graimann, J. Huggins, S. Levine, and G. Pfurtscheller, "Visualization of significant erd/ers patterns in multichannel eeg and ecog data," *Clinical Neurophysiology*, vol. 113, no. 1, pp. 43–47, 2002.

[19] H. Ramoser, J. Müller-Gerking, and G. Pfurtscheller, "Optimal spatial filtering of single trial EEG during imagined hand movement," *IEEE Transactions on Rehabilitation Engineering*, vol. 8, pp. 441–446, 2000.

[20] B. Blankertz, S. Lemm, M. Treder, S. Haufe, and K. Müller, "Single-trial analysis and classification of erp components - a tutorial," *Neuroimage*, vol. 56, no. 11, pp. 814–825, 2011.