Data Set Description: Autocalibration and recurrent adaptation: Towards a plug and play online ERD-BCI

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1 Original paper

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The data was recorded at the Institute for Knowledge Discovery, Graz University of Technology, Graz, Austria.

2 Abstract of the original paper

System calibration and user training are essential for operating motor imagery based brain-computer interface (BCI) systems. These steps are often unintuitive and tedious for the user, and do not necessarily lead to a satisfactory level of control. We present an Adaptive BCI framework that provides feedback after only minutes of autocalibration in a two-class BCI setup. During operation, the system recurrently reselects only one out of six predefined logarithmic band-power features (10 to 13 and 16 to 24 Hz from Laplacian derivations over C3, Cz and C4), specifically, the feature that exhibits maximum discriminability. The system then retrains a linear discriminant analysis classifier on all available data and updates the online paradigm with the new model. Every retraining step is preceded by an online outlier rejection. Operating the system requires no engineering knowledge other than connecting the user and starting the system. In a supporting study, ten out of twelve novice users reached a criterion level of above 70 % accuracy in one to three sessions (10 to 80 min online time) of training, with a median accuracy of 80.2 ± 11.3 % in the last session. We consider the presented system a positive first step towards fully autocalibrating motor imagery BCIs.

3 Materials and Methods

3.1 Data acquisition

We acquired the EEG from three Laplacian derivations ([3]), 3.5 cm (center-to-center) around the electrode positions (according to International 10-20 System of Electrode Placement) C3 (FC3, C5, CP3 and C1), Cz (FCz, C1, CPz and C2) and C4 (FC4, C2, CP4 and C6). The acquisition hardware was a g.GAMMAsys active electrode system along with a g.USBamp amplifier (g.tec, Guger Technologies OEG, Graz, Austria). The system sampled at 512 Hz, with a bandpass filter between 0.5 and 100 Hz and a notch filter at 50 Hz. The order of the channels in the data is FC3, FCz, FC4, C5, C3, C1, Cz, C2, C4, C6, CP3, CPz, CP4.

3.2 Structure of the data file

The data is stored in ".mat" files. These can be loaded with Matlab (Mathworks, Natick, MA, USA). Every file stores the data collected for one subject in one day (recording session). The structure data in every file holds five variables: X, is the EEG signal in μV in a matrix (datapoints $\times$ channels) of double values. The array y, holds the true labels for every trial according to the visual cues that were displayed in the paradigm during the recording. Label 1 indicates hand movement imagery, while label 2 indicates movement imagery of both feet. The array trial, indicates the position in datapoints where every trial starts. fs, is the sampling rate and classes indicates that class 1 (label 1) was right hand movement imagery and class 2 (label 2) was movement imagery of both feet.

3.3 Online BCI system

The BCI system was based on a synchronous, two-class Graz BCI training paradigm ([2]), that used LDA classification on one from six logarithmic band-power features to provide feedback. In each run, the system randomly presented 20 trials for each of the two conditions (sustained hand or feet movement imagery). Figure 1 explains the trial structure.

We extended the online BCI system to trialwise send EEG data to a standalone Matlab Optimization Instance and receive classifier-model updates online in return (see Figure 2). The Matlab Optimization Instance was running on the same machine. All communication was carried out in the trial pauses using a custom socket protocol on top of TCP/IP. In the first run of each session, the system started without giving feedback. The Optimization Instance gathered a small set of trials (10 trials per class) for initial training, and then sent the first set of classifier weights to the online BCI system. The Optimization Instance then sent weight updates at the start of every new run and whenever it had 5 new trials per class to retrain the classifier during a run.

The online BCI system only provided correct visual feedback, based on the classifier output to the user. The length of the white colored feedback bar in the

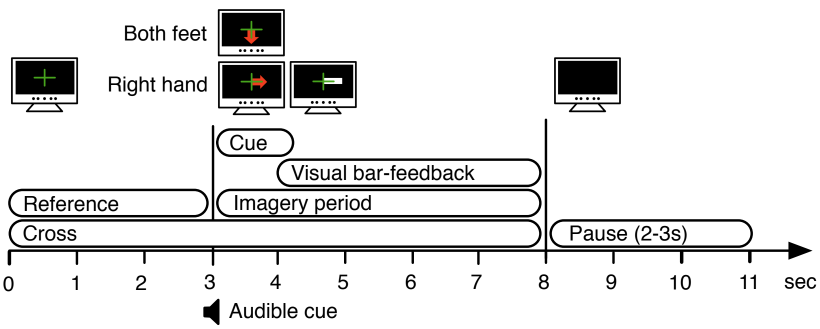

Figure 1: Trial structure within the synchronous training paradigm. The task for the user was to perform sustained right hand versus both feet movement imagery starting from the cue (second 3) to the end of the cross period (second 8). A trial started with 3 s of reference period, followed by a brisk audible cue and a visual cue (arrow right for right hand, arrow down for both feet) from second 3 to 4.25. The activity period, where the users received feedback, lasted from second 4 to 8. There was a random 2 to 3 s pause between the trials.

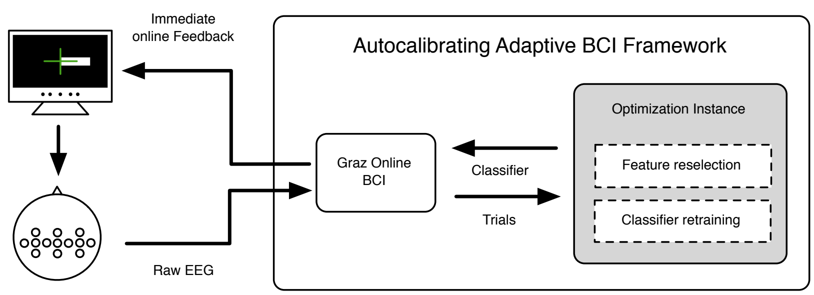

Figure 2: Architecture Overview Diagram for the Adaptive BCI framework.

direction of the cue-arrow, was mapped directly from the current distance from the LDA hyperplane. We chose to only display correct feedback to motivate the participants as much as possible ([1]).

3.4 Participants and task

Twelve able-bodied, BCI-novice volunteers (seven male, five female, age 24.8 ± 3.0 years) participated in our BCI-study. We decided to conduct at least two sessions for each participant to capture inter-session variance. Based on ([4]), we use a criterion level of 70 % accuracy as the threshold for successful BCI operation. One additional session was recorded for participants who did not reach the criterion level in two sessions, to see whether there would be learning or training effects. We performed a third measurement for S09 since he/she showed strong improvement from session 1 to 2 and was only slightly above the threshold in session 2. The participants performed five runs of 40 trials (i.e. 200 trials) in each session. The pure measurement-time per session was 38 min, however including briefing, montage (10 min) and pauses, 1 session lasted around 90 minutes. All subjects were right handed and had normal or corrected to normal vision. None of the volunteers suffered from neurological or psychological disorders or had been using medication which could have adversely affected the measurement. The measurements for each participant were carried out on different days within a time frame of 5 days. The volunteers were compensated with 7.5 Euro per hour. The experimenter thoroughly informed the volunteers beforehand about the nature of the experiment and the specifics of the tasks. All participants gave written, informed consent.

The task was to relax and to perform sustained, kinesthetic movement imagery ([5]) during the complete activity period of the presented trials (see Figure 1). For condition 1 (arrow right), the task was to imagine a palmar grip with the right hand (CLASS LABEL 1 in the data). The task for condition 2 (arrow down) was to imagine a plantar extension of both feet (CLASS LABEL 2 in the data). For the reference period, we instructed the subjects to relax with eyes open. The participants were seated in a comfortable chair, 60 cm away from the computer monitor that displayed the paradigm. Their arms were rested on the table before them. The experimenter sat slightly to the left, behind the participant and monitored that the subject adhered to the task. The experimenter informally interviewed the participants in the pauses how they liked the training and whether they preferred the brief offline or online training phase.

4 Contact

Please contact Dr. Reinhold Scherer (reini.scherer@gmail.com) or Josef Faller (josef.faller@gmx.at) for any questions you may have.

References

[1] A. Barbero and M. Grosse-Wentrup. Biased feebdack in brain-computer interfaces. *Journal of Neuroengineering and Rehabilitation*, 7:1–4, 2010.

[2] C. Guger, A. Schlögl, C. Neuper, D. Walterspacher, T. Strein, and G. Pfurtscheller. Rapid prototyping of an EEG-based brain-computer interface (BCI). *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 9:49–58, 2001.

[3] B. Hjorth. An on-line transformation of EEG scalp potentials into orthogonal source derivations. *Electroencephalography and Clinical Neurophysiology*, 39:526–530, 1975.

[4] A. Kübler, F. Nijboer, J. Mellinger, T. M. Vaughan, H. Pawelzik, G. Schalk, D. J. McFarland, N. Birbaumer, and J. R. Wolpaw. Patients with ALS can use sensorimotor rhythms to operate a braincomputer interface. *Neurology*, 64:1775–1777, 2005.

[5] C. Neuper, R. Scherer, M. Reiner, and G. Pfurtscheller. Imagery of motor actions: differential effects of kinesthetic versus visual-motor mode of imagery on single-trial EEG. *Brain Research Cognitive Brain Research*, 25:668–677, 2005.