Subject-oriented training for motor imagery brain-computer interfaces*

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***Abstract*— Successful operation of motor imagery (MI)-based brain-computer interfaces (BCI) requires mutual adaptation between the human subject and the BCI. Traditional training methods, as well as more recent ones based on co-adaptation, have mainly focused on the machine-learning aspects of BCI training. This work presents a novel co-adaptive training protocol shifting the focus on subject-related performances and the optimal accommodation of the interactions between the two learning agents of the BCI loop. Preliminary results with 8 able-bodied individuals demonstrate that the proposed method has been able to bring 3 naive users into control of a MI BCI within a few runs and to improve the BCI performances of 3 experienced BCI users by an average of 0.36 bits/sec.**

I. INTRODUCTION

Motor imagery (MI)-based brain-computer interface (BCI) systems have been established as a promising solution for restoring communication and control abilities of disabled people [12]. Successful, self-paced control of brain-actuated devices prerequisites a mutual learning process between the BCI and the human subject [7], [9]. In the conventional, mutual learning approach, the BCI modules are first trained to optimally decode a subject's mental intentions (machine learning calibration [4]). Subsequently, the subject learns to optimally modulate his/her brain activity through feedback training (subject learning, [1], [7]). Recent efforts have focused on co-adaptive methods, considerably minimizing the required training time (e.g., [11]).

Both conventional and co-adaptive mutual learning methods are characterized by the failure to bring a non-negligible percentage of prospective users into control of an MI BCI [2], [5], [11]. Additionally, both approaches have, so far, only explicitly targeted the machine-related challenges of mutual learning and mainly those concerning classifier adaptation. Hence, there is still considerable room for refinement of training protocols, by shifting the focus from the adaptation of the BCI modules to that of subject-related factors [8], as well as to the optimal control of the two parallel learning processes in BCI training [3].

This work proposes a novel training protocol, introducing interventions on multiple levels of the state-of-the-art training paradigms along these lines. Our preliminary results, acquired in online experiments with 8 able-bodied users, demonstrate the effectiveness of the proposed approach in bringing very quickly naive users into control of an MI BCI as well as in improving the performances of experienced MI BCI subjects.

II. NOVEL FEATURES AND MOTIVATIONS

The main goal of the implemented training method is to promote modulable EEG brain patterns, in other words, strong ERD/ERS [10] activations during MI that can be easily distinguishable from the "'resting" state. This is achieved by explicit modeling of the Intentional Non-Control (INC, "rest") feature distributions and by the requirement of producing MI feature values at the tails of these distributions through appropriate thresholding in order to identify optimal features and get positive feedback rewards. On top of that, the separability of brain patterns is naturally enhanced by enforcing non-overlapping modulable feature sets for two distinct MI tasks through an online feature selection scheme. Increased modulability and separability are thus expected to improve both Intentional Control (IC) performances (accuracy, rejection) and INC performances (false positive rate).

A second series of interventions regards the coupling of (i) an instructed exploration of mental tasks and strategies [6] in immediate online feedback training and subsequent exploitation of those strategies shown to be optimal, with (ii) the aforementioned online feature selection, to capture the inevitable changes of brain patterns. Hence, the automatic, online task selection and machine calibration can be hoped to reduce the overall training time compared to conventional training. Optimal accommodation of the machine- and subject-learning processes is also attempted through explicit treatment of the plasticity/stability dilemma: feature selection is performed both in short-term, as long as no stable features exist, thus immediately rewarding a favourable MI strategy with minimum delay before it is abandoned, and solely in long-term, as soon as stable features have been identified, in order to promote stability.

Last but not least, the protocol follows a game-like design (pacman), targeting increased engagement by the user, as well as an incremental learning approach towards progressive and adaptive training [8].

III. METHODS

A. Experimental apparatus and participants

During the experiment, subjects are comfortably seated about 1 m away from a monitor displaying the protocol's graphical user interface (GUI). 16 active Electroencephalography (EEG) channels over the sensorimotor cortex are recorded (Fz, FC3, FC1, FCz, FC2, FC4, C3, C1, Cz, C2, C4, CP3, CP1, CPz, CP2, CP4, reference on earlobe)

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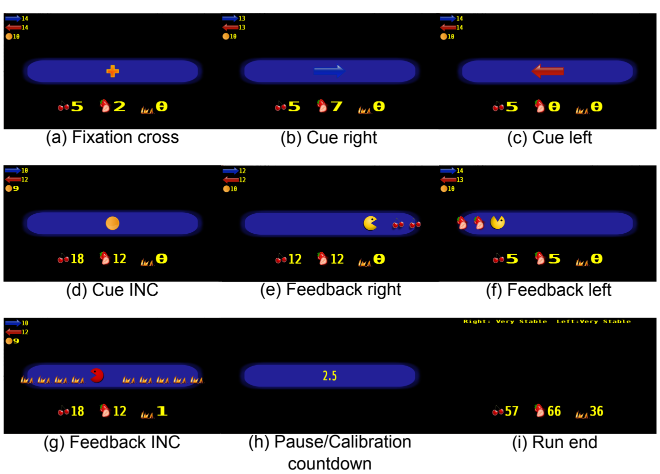
with a gUSBamp system (gTec medical engineering GmbH, Schiedlberg, Austria) at 512 Hz.

The experiment takes place in 1-2 BCI sessions lasting approximately one hour and consists of 3 stages of increasing difficulty (incremental learning): At Stage-1, the subject learns a 1-class BCI (30 trials/run), exploring optimal mental strategies to drive pacman right. Once stable features are found, the subject proceeds with Stage-2, where 30 class-2 trials/run are executed with exploratory efforts on a second MI task. As soon as a second, stable (and discriminant from the first class, thus the increased difficulty) brain pattern has been found, the subject can proceed with Stage-3 runs, where 10 INC trials are added, along with 15 trials/IC class. The protocol terminates with three Stage-3 runs (even if the stability criteria are not met).

Eight able-bodied users have participated in the study (7 male and 1 female, 27.4±5.7 of age), among which 4 expert users (S1-S4), three naive users (S6-S8) and one user (S5) who failed with the conventional training approach described in [7]. The color coding for the subject categories is the same used subsequently in the presented figures.

B. Protocol GUI and trial structure

The training protocol is a 2-class BCI version of pacman (game-like design). Fig. 1 illustrates the protocol's GUI and trial structure. A trial starts with a fixation cross (5 sec), followed by a cue (2 sec, right/left arrow for IC MI class-1/2, respectively, and a yellow circle for INC trials). 5 positive rewards (cherries/strawberries for class-1/2 on the respective side of the feedback bar) or 10 negative rewards ("fires", on either side) are then arranged and the user either employs some MI task to collect them (IC) or "idles" to avoid negative rewards (INC). The trial ends either when all available rewards have been collected (minimum 2.5 sec), or when a trial time-out of 15 sec occurs. A 3-5 sec countdown marks the inter-trial interval.



(a) Fixation cross (b) Cue right (c) Cue left
(d) Cue INC (e) Feedback right (f) Feedback left
(g) Feedback INC (h) Pause/Calibration countdown (i) Run end

Fig. 1. Pacman training protocol GUI and trial structure.

C. Preprocessing, feature extraction and online feature selection

Signal pre-processing involves band-pass filtering (0.1-100 Hz) and cross-neighbour Laplacian spatial filtering. Feature extraction is implemented at a rate of 2 Hz (1 sec-long windows with 50% overlapping), where the Power Spectral Density (PSD) is extracted for all 16 Laplacian channels between 8 and 30 Hz with a resolution of 2 Hz (12 frequency bands in total).

The online feature selection scheme is based on modeling the ERD/ERS phenomena as absolute normalized deviations r_t^i (z-score of the i-th feature at time t) of individual feature values x_t^i from the individual feature distributions f_k^i during INC ("rest"): $r_t^i = |x_t^i - \mu_k^i|/s_k^i$; the latter is represented by univariate normal distributions $f_k^i \sim \mathcal{N}(\mu_k^i, \sigma_k^i), \sigma_k^i = (s^2)_k^i$, where the mean μ_k^i and standard deviation s_k^i of each feature are estimated on the latest 2 min of data, extracted during an initial 60 sec calibration (eyes-open) and updated with the fixation period of each trial.

The fitness of each individual feature is evaluated based on the frequency of ERD/ERS activations measured within a certain amount of recent past. These frequencies are calculated separately for the first (right) and second (left) class, in two different timescales; short-term (last 7.5 sec) and long-term (last 2 min). Four 192-dimensional feature maps $\mathbf{V_l^j}$, where l ={short,long} and j ={left,right} are kept in memory and updated with each incoming sample of the respective class (thus implementing a supervised feature selection adaptation scheme). The value $[V_l^j]_t^i$ for feature i at time t is calculated as the frequency of r_t^i threshold crossings, where the "activation" threshold is fixed to 1.5.

Based on the current maps $[V_l^j]_t^i$ a final feature selection for both classes is derived with a rule-based approach. Starting with the first class maps, in case any of the values of the long-term map exceeds an activation frequency threshold of $t_a^{long} = 0.4$, feature selection for this class is performed based only on this (long-term and thus "stable") map, selecting up to 3 features. In case no "stable" feature emerges, selection is performed on the short-term map with a higher activation frequency requirement of $t_a^{short} = 0.6$. The selection procedure proceeds identically for the second class, with the extra requirement of rejecting any features which demonstrate activation frequency over $t_b = 0.2$ for the first class. Therefore, the online feature selection framework provides a minimum of 0 (pacman stays still) and a maximum of 6 features.

D. Classification

The classification framework is based on a multiple-detection scheme quantified through Mahalanobis Distance (MD) and founded on the preceding feature selection. MD-based activations A_j^t are computed separately for each class j at time t based on the 1-3 features currently selected for each class. Pacman moves one step right when $A_{right}^t \geq 1.5$ and $A_{left}^t \leq 1.3$, and left when the reverse holds. Otherwise, or when no feature is selected for any of the two classes, pacman stays still at time t (rejected sample).

IV. RESULTS

The protocol evaluation is based on comparisons of the hereby derived performances to high/low baselines achieved with the conventional protocol described in [7], in a large study involving 37 able-bodied and 21 end-users. For each examined metric, the associated values in all runs by all subjects are pooled together, and a low baseline is defined as the value corresponding to the 25%-percentile, while the high one to the 75%-percentile. All users reached Stage-3, apart from S7 (unstable class-2) and S5 (both classes unstable).

A. IC and INC performances

Fig. 2a shows the single-sample accuracy achieved by all subjects on their latest three, Stage-3 runs, derived with a Linear Discriminant Analysis (LDA) classifier, which is trained offline in the first run and applied on the subsequent two runs. Simulated performances are chosen for comparability with the conventional training study. It is illustrated that all trained users (S1-S4) exceed the high baseline, as well as their own previous performances (with conventional training, not shown) by an average of 10.5%. Most importantly, naive users are shown to operate above the low baseline and close to the high one, with only S5 failing this goal. This showcases that naive users can be successfully trained within a few runs of direct feedback training, thanks to the features of the proposed protocol.

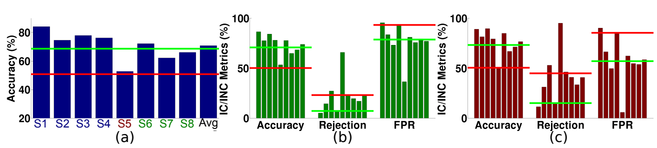


Fig. 2. IC and INC performances. (a) Accuracy without rejection. (b) Accuracy, Rejection and False Positive Rate for rejection threshold $t_c = 0.6$ and (c) $t_c = 0.7$. Green horizontal lines denote the high baseline and red the low ones for the respective metrics.

When probabilistic sample rejection is introduced (Fig. 2b-c, see [7]), all users (except, again, S5), operate well above the low baseline for accuracy and False Positive Rate (FPR), and only rejection is shown to be slightly compromised. Regarding expert users (S1-S4), for both probabilistic sample rejection thresholds ($t_c = 0.6/0.7$) the average Information Transfer Rate (ITR) increases from 0.19 bits/sec to 0.55 bits/sec, while the average FPR remains unaffected for $t_c = 0.6$ and reduces from 86.3% (conventional training) to 73% (pacman training) for $t_c = 0.7$. These results indicate that the learned/refined brain patterns lead to extremely improved IC and moderately ameliorated INC control using standard methods (binary classification, probabilistic rejection), which should be attributed to higher levels of modulability and separability "tought" by the proposed method.

B. Modulability and separability

The latter claim is substantiated by Fig. 3, which presents a combined index $CI = (MI_1 + MI_2 + SI)/3$ as the average of class-1/2 modulabilities, $MI_{1,2}$, and separability, SI, in Stage 3 runs. MI and SI are Kullback-Leibler divergences $D_{KL}(f_A||f_B) = \frac{1}{2}\left(tr(\Sigma_B^{-1}\Sigma_A) + (\mu_{\mathbf{A}} - \mu_{\mathbf{B}})^T\Sigma_A^{-1}(\mu_{\mathbf{A}} - \mu_{\mathbf{B}}) - D - \ln\frac{|\Sigma_B|}{|\Sigma_A|}\right)$ between the multivariate normal brain pattern distributions $f_{A,B} \sim \mathcal{N}(\mu_{\mathbf{A},\mathbf{B}}, \Sigma_{A,B})$ either of the two MI tasks (separability), or MI task-1/2 and "rest" (class-1/2 modulability). The dsitributions $f_{A,B}$ are constructed within each run using the 6 most separable (as evaluated by Fisher Score) features between the implicated tasks. All subjects, but S5, perform close or above the high baseline, for at least one of the Stage 3 runs shown (and close to that for the rest), demonstrating that even naive users were able to find a good compromise between modulability and separability, gaining control over the BCI game.

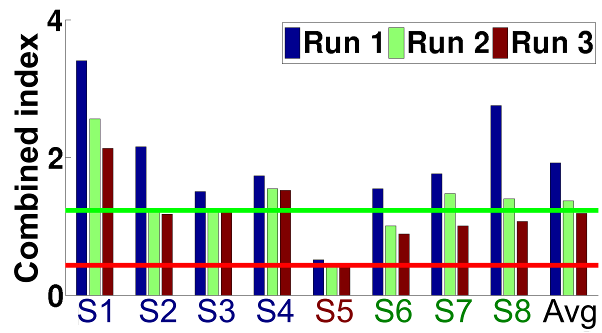


Fig. 3. Combined modulability and separability index.

C. Online feature selection fitness

The online feature selection module is hereby designed to have a dual role of selecting both the most modulable and most separable features. Its success in these complementary (but, also, antagonistic) aspects is evaluated separately below.

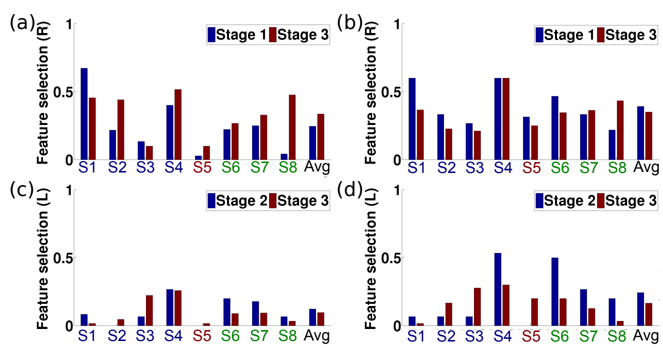


Fig. 4. Feature selection fitness against modulability. Selection of most modulable features with (a) a strict criterion and (b) a tolerant criterion for the first class. Equivalently, in (c) and (d) for the second class.

Feature selection fitness is evaluated as the average set-overlapping index $FS = |S \cap B|/min(|S|,|B|) \in [0,1]$, where S the selected feature set and B the set of the 6 most modulable or separable (see below) features, on consecutive 10-trial chunks of data in a run, then averaged within all runs for a given training stage. Since feature selection is computed on two time-scales, two metrics are extracted, a "strict" and a "tolerant" one: For the strict metric, only selected features derived from the "stable" maps are accounted for in S, while for the "tolerant" metric, feature contributions from the short-term maps are included.

Fig. 4 evaluates the ability of the proposed method to pick the most modulable features for both classes. It is thus shown that, for class-1 (right), all subjects but S3 and S5 are rewarded through the feature selection mechanism for producing modulable class-1 patterns (Fig. 4a). It is easy to see that for most subjects this index improves from Stage 1 to Stage 3 runs, reflecting that the initial exploration of mental strategies has eventually converged to optimal, stable strategies, which the online feature selection scheme is able to identify. Using the tolerant index (Fig. 4b), the situation is further improved. The comparison of these figures provides evidence on the successful accommodation of the stability/plasticity dilemma regarding modulability: Features selected on the short-run (exploration) are largely sustained on the long-run (exploitation). On the downside, feature selection fitness regarding modulability is considerably decreased for the second class for all subjects but S3 and S4. Fig. 4c-d reveal the fact that for most subjects selection of modulable second-class features is compromised already in the short-run, while it also fails to transfer in the long-term selection.

Evaluating feature selection fitness with respect to separability (Fig. 5) showcases the existence of a modulability/separability trade-off with respect to feature selection, as, with the strict criterion, enough separable features are selected for all subjects (better than the low baseline, which, for this metric, has been almost 0), but no subject, even among the experienced ones, manages to reach or exceed the high baseline. The situation is improved regarding the tolerant criterion. Yet, the fact that no big differences occur between the two criteria for most subjects (exceptions, S5 and S6), shows that subjects have been mostly stable in producing certain separable features, and the feature selection module successful enough in picking most of those.

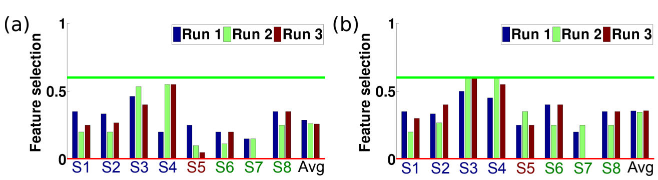


Fig. 5. Feature selection fitness against separability. Selection of most separable features with (a) a strict criterion and (b) a tolerant criterion.

V. DISCUSSION

The most important outcome of this study has been the demonstration of the possibility to enable MI training of naive users and further improve performances of trained users within a few runs and avoiding offline BCI calibration in a completely automatic manner. The proposed protocol is shown to achieve the goals of increased separability and modulability over conventional training for most subjects, a fact also reflected in the improved IC and INC performances. A decreasing trend of the combined index across runs for most subjects could be attributed either to fatigue, or to a need of adapting the task difficulty to the subject's performance. Furthermore, the feature selection scheme is shown to balance well the trade-off of selecting features that are both adequately modulable and separable. Additionally, the introduction of a double-buffer adaptation approach, in combination with the provided instructions, allows users to discover optimal mental tasks as soon as they have been adopted and sustain them after those are shown to be stable, by selecting features on short- and long-term scales, as needed. The latter, as well as the fact the both subject- and machine-related metrics are shown to simultaneously improve, justify an optimal accommodation of the interactions between the two learning agents.

The main limitations are, first, the fact that the only user who failed to achieve good performance with conventional training has failed to improve with respect to the subject-related or high-level factors also with the proposed method, and, second, that the difficulty in producing a second highly modulable MI pattern does not seem to be alleviated. Yet, these effects could be also attributed to the short training period applied. Future work entails testing with more BCI sessions and a large numbers of users failing with traditional training approaches, as well as algorithmic modifications to automatically adjust the task difficulty within a run so as to further exploit the incremental learning concept.

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