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The effect of distinct mental strategies on classification performance for brain–computer interfaces

Elisabeth V.C. Friedrich [a,b,*], Reinhold Scherer [b], Christa Neuper [a,b]

[a] Department of Psychology, University of Graz, Universitätsplatz 2/III, 8010 Graz, Austria
[b] Institute for Knowledge Discovery, Graz University of Technology, Krenngasse 37/IV, 8010 Graz, Austria

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A B S T R A C T

Motor imagery is the task most commonly used to induce changes in electroencephalographic (EEG) signals for mental imagery-based brain computer interfacing (BCI). In this study, we investigated EEG patterns that were induced by seven different mental tasks (i.e. mental rotation, word association, auditory imagery, mental subtraction, spatial navigation, imagery of familiar faces and motor imagery) and evaluated the binary classification performance. The aim was to provide a broad range of reliable and user-appropriate tasks to make individual optimization of BCI control strategies possible. Nine users participated in four sessions of multi-channel EEG recordings. Mental tasks resulting most frequently in good binary classification performance include mental subtraction, word association, motor imagery and mental rotation. Our results indicate that a combination of 'brain-teasers' – tasks that require problem specific mental work (e.g. mental subtraction, word association) – and dynamic imagery tasks (e.g. motor imagery) result in highly distinguishable brain patterns that lead to an increased performance.

1. Introduction

A brain–computer interface (BCI) translates the electrophysiological signals of the brain into an output that reflects the user's intent and thus provides a non-muscular channel for communication and control (Birbaumer et al., 1999; Millán et al., 2004; Pfurtscheller et al., 2005; Wolpaw et al., 2002). A BCI cannot only be beneficial to people with severe motor disabilities, but BCI technology also becomes more and more interesting for non-medical use (Nijholt et al., 2009; Venthur et al., 2010; Zander and Kothe, 2011). There are different approaches to improve the performance of BCIs. Most studies focused on signal processing and classification aspects. However, BCI performance can also be improved by optimizing the user's control strategies and determining user-appropriate mental tasks for control (Curran and Stokes, 2003). This study aimed to explore a broad range of mental tasks and to investigate which pair of tasks can be reliably implemented for BCI control so people can choose among them according to their preferences.

BCI control can be realized by recording the changes in the rhythmic activity of the brain's electrophysiological signals (event-related (de) synchronization, ERD/S, Neuper and Pfurtscheller, 2001; Pfurtscheller and Aranibar, 1977; Pfurtscheller and Lopes da Silva, 1999) by scalp-recorded electroencephalography (EEG). ERD/S can be generated intentionally (Pfurtscheller and Neuper, 1997) which makes them suitable for BCI use. In most studies, users were asked – at least in the early stage of training – to imagine moving a specific part of their body in order to achieve BCI control by frequency band modulation (e.g. Kübler et al., 2005; McFarland et al., 2010; Müller et al., 2008; Pfurtscheller and Neuper, 2001; Royer et al., 2010). Motor imagery activates primary sensorimotor areas and (de)synchronizes oscillatory components in specific frequency bands and thus is a valuable strategy for learning to control a BCI (e.g. Halder et al., 2011; McFarland et al., 2000; Neuper and Pfurtscheller, 1999; Neuper et al., 2005; Pfurtscheller and Neuper, 1997, 2001). Several studies demonstrated that motor disabled individuals are also able to control a BCI by motor imagery (Kübler et al., 2005; Neuper et al., 2003; Pfurtscheller et al., 2000).

In contrast, it is also known that about 20% of all people who want to learn to control a BCI, are not able to attain effective control (Allison and Neuper, 2010; Blankertz et al., 2010). Besides failures due to methodical issues, it is possible that concentration, emotional states, fatigue, distraction, motivation and intentions affect the ability to gain and maintain voluntary control (Curran and Stokes, 2003; Kleih et al., 2010). Furthermore, user acceptance, training of the user, instructions and used mental strategies have a great impact on performance. For every person, different mental strategies might be more or less appropriate. Thus, motor imagery might not be the best choice for every user. Especially for individuals with an impairment of certain brain areas, a choice between different mental tasks

* Corresponding author at: Department of Psychology, Neuropsychology, University of Graz, Universitätsplatz 2/III, 8010 Graz, Austria. Tel.: +43 316 380 8493; fax: +43 316 380 9808.
E-mail addresses: elisabeth.friedrich@uni-graz.at (E.V.C. Friedrich), reinhold.scherer@tugraz.at (R. Scherer), christa.neuper@uni-graz.at (C. Neuper).

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for BCI control is valuable. For example, if a person suffered a stroke in the motor area, a mental subtraction task could be used rather than a motor imagery task for BCI control. Furthermore, selective motor imagery defects in patients with locked-in syndrome in contrast to other mental tasks were reported (Conson et al., 2008). As the best strategy to modulate brain activity for users – disabled or able-bodied – might be highly individually specific, a broader range of reliable BCI control strategies and also user's evaluation of the different tasks in order to evaluate user acceptance is crucial (Allison et al., 2010; Curran and Stokes, 2003; Curran et al., 2003; Millán et al., 2002; Neuper et al., 2005; Pfurtscheller et al., 2000).

Millán et al. (2004) and Galán et al. (2008) already implemented asynchronous BCI protocols in which participants successfully controlled a wheelchair, a robot or a virtual keyboard over several sessions with three mental strategies of their choice out of the following: relaxation, left and right hand (or arm) motor imagery, cube rotation, subtraction and word association. This approach emphasized the importance of individual control strategies for BCIs. Roberts and Penny (2000) used a mental subtraction task together with a motor imagery task to control a cursor on a computer screen. Besides these online experiments, studies using offline classification of different mental tasks exist (e.g. Obermaier et al., 2001). Keirn and Aunon (1990) discriminated offline between five mental tasks and did not find significant differences between them. They suggested investigating other mental tasks as well and focusing on individual differences. Curran et al. (2003) compared auditory imagery of a familiar tune and spatial navigation imagery in a familiar environment to left and right hand motor imagery. The results showed that not only classification accuracy of the auditory and spatial imagery was best, but also that user's evaluation indicated that the two non-motor tasks were easier to perform and needed less concentration. Cabrera and Dremstrup (2008) implemented a BCI with an auditory imagery and a spatial navigation imagery task and confirmed these findings. De Kruif et al. (2007) designed a BCI which was completely controlled by auditory imagination: The classification discriminated between accented versus non accented tones within an imagined rhythm. Dyson et al. (2010) examined relevant electrode positions for various mental tasks. Of course, there are many more possible mental tasks that have not been used for BCI control yet. A strategy that might be very easy and enjoyable for the user could be the imagery of familiar faces (Başar, et al., 2006; Özgören et al., 2005), for example. In the present study we extended the above mentioned work and examined a broad range of mental tasks in one controlled study over more sessions and not only in respect of classification accuracy but also of user's evaluation and neurophysiologic correlates of the tasks.

We chose tasks from different domains such as mental rotation (i.e. figural), word association (i.e. verbal), auditory imagery of a melody (i.e. musical), mental subtraction (i.e. arithmetic), spatial navigation through a familiar environment (i.e. spatial), imagery of familiar faces (i.e. social) and motor imagery of the right hand (i.e. motor). According to the literature, these tasks can be expected to elicit different brain activation patterns. Motor imagery of the right hand should lead to ERD over the left central cortex (Neuper et al., 2005). The word association task was reported to activate the left frontal area and the anterior cingulate gyrus (Petersen et al., 1988). Mental calculation is a rather complex process and can involve frontal as well as parietal processes (Chochon et al., 1999; Burbaud et al., 2000). There is controversial literature if mental rotation tasks activate rather the left or right parietal area (e.g. Alivisatos and Petrides, 1997; Papanicolaou et al., 1987; Roberts and Bell, 2003). Spatial navigation tasks are generally considered a right hemispheric task (e.g. Cutmore et al., 2000; Kolb and Wishaw, 1996). For auditory imagery tasks, a cortical activation of the primary auditory cortex is suggested (Kraemer et al., 2005; Zatorre and Halpern, 2005). The main center for imagery of familiar faces was localized in the fusiform gyrus and prefrontal regions (e.g. Boly et al., 2007; Haynes and Rees, 2006; Klopp et al., 1999).

Based on the mentioned literature, we hypothesized that our chosen seven mental tasks demonstrate different ERD/S patterns and can be classified successfully over several sessions. We chose to compare each task with each other in order to be able to group the tasks into categories and to find suggestions which of these categories are worth implementing for future BCI applications. Therefore, we pursued three research questions: First, we aimed to investigate which pairs of these seven mental tasks can be classified most accurately and reliably over sessions. Second, we wanted to underlie and explain the classification results with neurophysiologic correlates of the mental tasks as to ERD/S. Third, we evaluated which tasks were considered user-friendly concerning the quality of imagery, task ease and enjoyment.

2. Methods

2.1. Participants

This study included 11 female volunteers who were initially naïve to the tasks. All were right-handed, between 20 and 32 years old, and without any diagnosed disability. Each participant gave informed consent to the study which was approved by the ethical review board of the University of Graz. Each volunteer participated in four sessions on different days over a period of 2 weeks. Due to movement artifacts in the EEG recordings, two participants had to be excluded from further analyses. Thus, all results are based on 9 participants.

2.2. Task

Details on the experimental paradigm are summarized in Fig. 1. Users were asked to perform the indicated mental task for 7 s while staying relaxed and motionless. The mental tasks occurred in randomized order and included:

- (1) Mental rotation (ROT): visualize a 3-dimensional L-shaped figure to rotate in the 3-dimensional space;
- (2) Word association (WORD): generate as many words as possible that begin with the presented letter in your mother tongue (e.g. B = bank, bold, buy, etc.);
- (3) Auditory imagery (AUD): imagine listening to a familiar tune without articulating the words but rather focusing only on the melody;
- (4) Mental subtraction (SUB): perform successive elementary subtractions by a presented fixed number (e.g. 105–6 = 99, 99–6 = 93, etc.);
- (5) Spatial navigation (NAV): imagine navigating through a familiar house or flat from room to room, focusing on orientation rather than on movement;
- (6) Imagery of familiar faces (FACE): imagine the face of the best female friend;
- (7) Motor imagery of the right hand (MOTOR): imagine repetitive self-paced movements of the own right hand in the form of squeezing a ball without any actual movement.

In all trials of every session, participants were asked to imagine the same house or flat to navigate through, the same face and the same tune. In the AUD task, four users chose children songs, two users imagined jazz songs, two users imagined a classical music piece and one participant chose the melody of a Christmas song. The subtractions for the SUB task and the initial letters for the WORD task changed randomly between trials. As the number of letters in the alphabet is limited, users were asked to always think of new words in case of repetition of letters.

Before users were asked to perform all described tasks mentally (imagery runs), they completed an overt exercise run. In this exercise run, participants actually had to physically carry out the seven tasks instead of imagining them (i.e. actually rotate a 3-dimensional L-shaped figure made of paper; speak out the words loud, hum a melody, solve subtractions, describe navigating through the house, look at a photograph of the best friend and squeeze a ball with the right hand). The purpose of the exercise run was to familiarize the participants with

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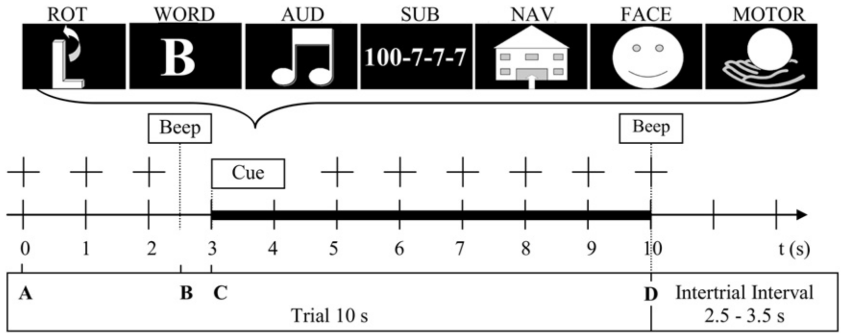

Fig. 1. Experimental paradigm. (A) At t = 0 s, a fixation cross was presented on the screen (baseline). (B) At t = 2.5 s, a beep was played. (C) At t = 3 s, one out of seven symbols was randomly presented for 1.25 s in the middle of the screen. In case of the word association or mental subtraction tasks, an initial letter or specific subtraction, respectively, was presented. Users were asked to perform the indicated task for 7 s (imagery period highlighted with a bold black line). (D) At t = 10 s, a second beep indicated the end of the trial, and the screen remained blank for 2.5–3.5 s before the next trial started.

the different tasks and to ensure that they performed them according to the instructions. Furthermore, the frequency of how often the users performed the subtasks in a trial (e.g. how many subtractions were solved per trial) were collected with self-reports in order to provide more insight in what participants were doing during the imagery periods.

2.3. Procedure, EEG recordings and evaluation of tasks

After the instruction, participants underwent a 1-h EEG measurement. The EEG was recorded from 30 Ag/AgCl sintered scalp electrodes: AFz, F7, F3, Fz, F4, F8, FC3, FCz, FC4, T3, C3, Cz, C4, T4, CP3, CPz, CP4, P7, P5, P3, P1, Pz, P2, P4, P6, P8, PO3, PO4, O1, and O2. Additionally, electrooculography (EOG) was recorded from the outer canthus of the left eye and from above the nasion. Each electrode was referenced to the left and grounded at the right mastoid. The data was filtered (0.5–100 Hz; 50 Hz notch filter), amplified and digitized (256 Hz). Each session started with a 6-min exercise run followed by five 9-min imagery runs with short breaks in-between.

After the EEG recordings, the users rated each mental tasks on a 5 point scale regarding the following three aspects: the quality of their imagery (1 = 'no image at all, you only 'know' you are thinking of the object' and 5 = 'perfectly clear and as vivid as normal vision'), the task ease (1 = 'very exhausting and full concentration needed' and 5 = 'very relaxing and possible to perform also during major distractions such as activated television, visit of friends or in the traffic') and the enjoyment (1 = 'no fun at all and very frustrating' and 5 = 'a lot of fun and not frustrating at all'). The whole session (including the instruction, EEG montage, self-reports and the 1-h EEG recordings with breaks in-between) lasted 2 h.

2.4. Classification

EEG signals were visually inspected and trials contaminated with muscle or eye movement activity were removed. Two participants had to be excluded from the study due to excessive muscle artifact. For the nine remaining participants, a minimum of 25 out of the 30 trials per task and session remained.

Fisher's linear discriminant analysis (LDA, Duda et al., 2001) was used to classify combinations of pairs of mental tasks. The method of common spatial pattern (CSP, e.g. Blankertz et al., 2007; Müller-Gerking et al., 1999; Ramoser et al., 2000) was used to compute most discriminative features for classification. Two different offline analyses were performed: First, the performance of mental tasks within a session was tested (i.e. single-session classification). Each session was analyzed independently to rank the discriminability of the imagery pairs and evaluate the performance variability between sessions. Second, a classification between sessions was performed. The classifier was trained on sessions 1 and 2 and then evaluated on unseen data from sessions 3 and 4 which should simulate a real-time BCI experiment in which the classifier was trained from data from the screenings and then applied in the next sessions for online control. Therefore, we train and evaluate the classifier only in a causal way and call this classification between sessions 'simulation'.

First, the classification within sessions (i.e. single-session classification) is explained: The EEG was band pass filtered in the range of 8–30 Hz. To characterize the discriminatory power as function of time the imagery period of trials (3–9.5 s after trial onset) was subdivided into thirteen 1-s data segments with 0.5 s overlap (Müller-Gerking et al., 2000; Scherer et al., 2008). For each time segment and imagery pair, CSPs and LDA were computed by using a 10-times 10-fold cross-validation statistic. Ten-fold cross-validation means that the dataset was divided into 10 segments: Nine segments were used to compute CSP and train LDA and the remaining segment (test dataset) was used to test the performance. In this way 10 different performance estimates were computed. This procedure was repeated 10-times, i.e., ten random permutations of the data pool were computed. As result we obtain 100 performance evaluations. The overall performance estimate was the mean of the 100 evaluations. Since the numbers of trials per task were uneven due to artifact screening, Cohen's kappa (κ) coefficient was computed instead of the classification accuracy (Cohen, 1960; Pfurtscheller et al., 2006; Schlögl et al., 2005, 2007). Kappa is computed from the confusion matrix H that defines the relationship between the known 'true' task label and the label predicted by the classifier. From H, we can derive the classification accuracy ACC

$$\mathrm{ACC} = p_0 = \frac{\sum_i H_{ii}}{N} \tag{1}$$

and the chance expected agreement

$$p_e = \frac{\sum_i n_{oi} \times n_{io}}{N \times N} \tag{2}$$

where $N = \sum_i \sum_i H_{ii}$ is the total number of samples, H_{ii} is the elements of the confusion matrix H on the main diagonal, and n_{oi} and n_{io} are the sums of each column and each row, respectively. Then the estimate of the kappa coefficient κ is

$$\kappa = \frac{p_0 - p_e}{1 - p_e} \tag{3}$$

and its standard error se (κ) is obtained by

$$se(\kappa) = \frac{\sqrt{p_o + p_e^2 - \sum_i [n_{oi} \times n_{io} \times (n_{oi} \times n_{io})] / N^3}}{(1 - p_e)\sqrt{N}} \tag{4}$$

(Schlögl et al.; 2005).

Kappa ranges from 1 (perfect match) over 0 (chance level) to negative numbers. Kappa values were significant above chance level if all values contained in the 95%-confidence interval were above 0 ($\kappa \pm 1.96 * se(\kappa) > 0$). A $\kappa > 0.4$ is considered a moderate/fair to good agreement (Fleiss, 1981; Landis and Koch, 1977) and equals an accuracy >70% given that the same number of trials for each class is available. An accuracy of 70% is considered necessary for meaningful communication with a 2-class BCI (Nijboer et al., 2008; Perelmouter and Birbaumer, 2000).

Second, the classification between sessions (i.e. simulation) is explained: To evaluate whether CSP and LDA models can be transferred between sessions (transfer from offline to online BCI), model parameters were estimated from the first two sessions (50–60 trials) and used to classify the data of sessions 3 and 4. CSP and LDA parameters were computed and cross-validated according to the above scheme from data of sessions 1 and 2. The CSP and LDA trained from the segment with the highest κ was selected and applied without any adaptation on the unseen data of sessions 3 and 4. Classification was computed every 0.5 s.

2.5. ERD/S analyses and statistics

The artifact-free EEG (see first paragraph in Section 2.4.) was re-referenced according to the common average reference method (CAR, McFarland et al., 1997). ERD/S (i.e. percentage power decrease/increase in relation to a reference interval) was calculated with a method referred to as inter-trial variance (Kalcher and Pfurtscheller, 1995) that removes the evoked activity. The ERD/S values of the imagery period were calculated relative to the baseline between seconds 1 and 2 after trial onset for the following four frequency bands: lower alpha (7–10 Hz), upper alpha (10–13 Hz), lower beta (13–20 Hz) and upper beta (20–30 Hz).

For statistical comparisons (repeated-measurement ANOVAs), Gaussianity was approved (except of 2 variables in the evaluation of tasks) and Greenhouse–Geisser Epsilon was taken. The post-hoc tests were conducted with the Newman–Keuls test ($p<0.05$).

3. Results

3.1. Single-session classification of mental tasks

In Fig. 2, the imagery pairs were arranged with descending mean classification results. In the first columns, the mean kappa values, averaged over participants and sessions, at the best classification time point between 3 and 9.5 s after trial onset were summarized (Fig. 2A). There was no difference in the kappa values between sessions ($\kappa = 0.55$–0.56, S.E. = 0.03–0.04). WORD and SUB were always included in the first third of the 21 pairs (i.e. combinations with highest mean kappa; $\kappa = 0.6$–0.7, S.E. = 0.02–0.03) and never in the last third (i.e. combinations with lowest mean kappa; $\kappa = 0.41$–0.53, S.E. = 0.02–0.03). Besides in combination with WORD and SUB, FACE always was included in combinations with lowest mean kappa values. On an individual basis, we plotted for every user and session the kappa values at the best time point in Fig. 2B. The participants were arranged with descending mean classification results. Besides user D, all reached a $\kappa > 0.7$ with the peak at $\kappa = 0.94$ (equals accuracies over ≈95%) at their individually best imagery pair stable over at least 3 sessions. Six users reached a $\kappa > 0.4$ in all imagery pairs of the first third of task combinations with the highest kappa values at least in 3 sessions.

Fig. 3 shows that the reported maximal kappa values at the best time point are not the only time segment in which classification was possible. Kappa was at chance level before the cue at t = 3 s and then increased rapidly and remained high throughout the trial with a slight descend toward the end of the trial.

3.2. Simulation of classification

The classifier was computed and trained only with data from sessions 1 and 2 and then evaluated on the unseen data from sessions 3 and 4 (i.e. simulation, see Section 2.4). The combinations ROT/WORD, ROT/AUD, ROT/SUB, ROT/MOTOR, WORD/SUB, WORD/MOTOR and SUB/MOTOR reached mean classification results of $\kappa > 0.4$ in the simulation which equals accuracies >70%. As can be seen in Fig. 4, individuals showed a high variability in these combinations. Six users reached kappa values over 0.7 peaking at 0.92 (≈85%– >95% accuracy) in some of these imagery pairs and additionally in WORD/FACE, WORD/NAV and AUD/NAV.

3.3. ERD/S patterns

Differences between the tasks were reflected in their ERD/S patterns. To underpin these results, we computed repeated-measurement ANOVAs separately for each frequency band (7–10 Hz, 10–13 Hz, 13–20 Hz and 20–30 Hz). The independent variables were the sessions, the mental tasks and the regions of interest. For the regions of interest, we

A) Mean kappa values

Tasks	$\kappa \pm$ S.E.	$t^{\kappa}_{max} \pm$S.E.
SUB/MOTOR	0.70±0.02	5.6±0.2
WORD/MOTOR	0.65±0.03	5.9±0.2
AUD/SUB	0.65±0.03	6.3±0.3
ROT/SUB	0.63±0.02	6.8±0.2
SUB/FACE	0.62±0.02	6.2±0.3
WORD/NAV	0.60±0.03	6.6±0.2
ROT/WORD	0.60±0.02	6.6±0.2
NAV/MOTOR	0.59±0.03	6.4±0.2
WORD/SUB	0.59±0.03	6.6±0.2
AUD/NAV	0.57±0.03	6.6±0.3
SUB/NAV	0.57±0.02	6.1±0.3
ROT/MOTOR	0.56±0.03	5.7±0.2
WORD/FACE	0.54±0.03	6.6±0.3
WORD/AUD	0.53±0.03	6.2±0.3
AUD/MOTOR	0.53±0.03	5.7±0.2
FACE/MOTOR	0.52±0.03	5.6±0.1
ROT/AUD	0.51±0.03	6.1±0.2
ROT/NAV	0.48±0.03	6.4±0.2
NAV/FACE	0.45±0.03	6.5±0.2
ROT/FACE	0.44±0.02	6.1±0.2
AUD/FACE	0.41±0.03	6.2±0.3

B) Individual kappa values

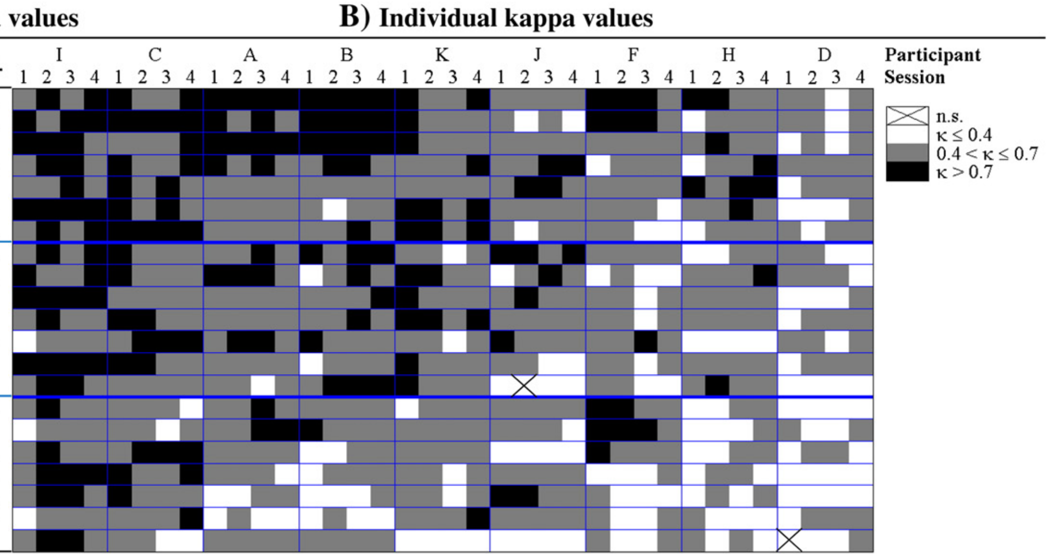

Fig. 2. Single-session classification. In the first column, the imagery pairs are arranged with descending mean kappa values. (A) The mean kappa values (κ), averaged over sessions and participants, and the corresponding best classification time points in s (t^{κ}_{max}) between 3 and 9.5 s after trial onset are indicated with standard errors (S.E.). (B) Individual kappa values at the best time point are plotted for every participant (I–D) and session (1–4). The participants are arranged with descending mean kappa values.

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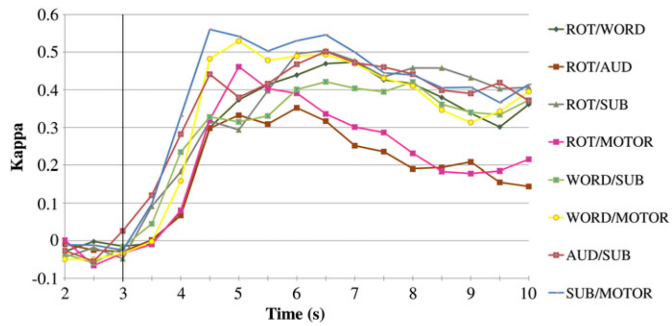

Fig. 3. Mean time course of relevant combinations of tasks. Kappa values are averaged over sessions and participants and plotted as a function of time.

clustered the activation from electrodes in the following 8 regions: left frontal (F7, F3, FC3), right frontal (F4, F8, FC4), left central (C3, CP3), right central (C4, CP4), left parieto-temporal (P7, P5), left parieto-occipital (P3, P1, PO3), right parieto-occipital (P2, P4, PO4) and right parieto-temporal (P6, P8). We focused on the main effect sessions and mental tasks and on the interactions mental tasks × regions of interest (Table 1).

First, we computed the ANOVAs with the absolute power values of the baseline (1–2 s after trial onset) as dependent variable and the sessions, mental tasks and regions of interest as independent variables (see Table 1.1). No differences in the absolute power values of the baseline between sessions or mental tasks and no interactions were found in any of the frequency bands. Thus, a comparison of the ERD/S values of the different mental tasks in the imagery period is justified.

Second, we computed ANOVAs with the ERD/S values of the imagery period as dependent variable and the sessions, mental tasks and regions of interest as the independent variables (see Table 1.2). Therefore, we divided the imagery period in four 1.5-s intervals from 3.5 to 9.5 s after trial onset and computed the ANOVAs separately for each time interval in order to represent temporal changes in activation of the different mental tasks. No differences between sessions or interaction between sessions and mental tasks were found in none of the frequency bands or time segments. However, there were significant differences between the mental tasks as well as interactions with regions of interest in the beta bands (see Table 1.2 and Fig. 5): First, there was a significant difference between mental tasks and a significant interaction between tasks and regions of interest in the lower beta range (13–20 Hz) in the time period of 3.5–5 s (see Table 1.2 (A) and Fig. 5A). Both results indicated that the WORD, ROT and SUB tasks showed generally more ERD than the AUD, NAV and MOTOR tasks. In contrast, FACE showed most

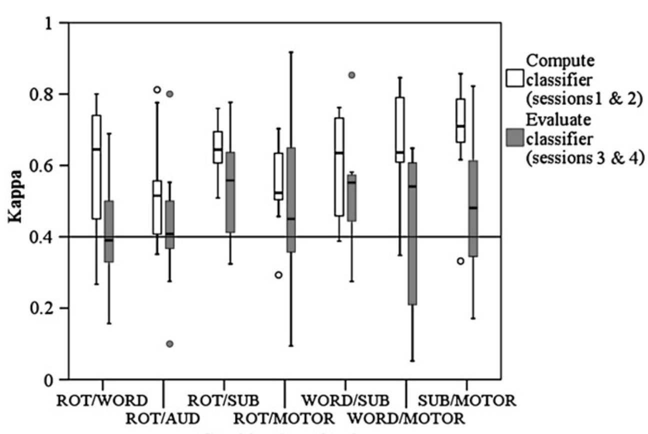

Fig. 4. Simulation of classification. Boxplot of the kappa classification values for computing the classifier based on data from sessions 1 and 2 (white) and evaluating the classifier on the distinct data set for sessions 3 and 4 (gray). Only the combinations of tasks with $\kappa > 0.4$ in the simulation are shown.

significant differences in the regions of interest to SUB and NAV. Second, the main effect of mental tasks was still significant in the lower beta band in the following time period (5–6.5 s after trial onset) showing significant synchronization (i.e. ERS) of the SUB task in comparison to the ROT, FACE and MOTOR tasks (see Table 1.2 (B) and Fig. 5B). Third, a significant interaction between mental tasks and regions of interest in the same time period (5–6.5 s) in the upper beta band (20–30 Hz) showed that SUB showed more ERS than WORD in parietal regions and more ERS than MOTOR in central regions (see Table 1.2 (C) and Fig. 5C). MOTOR showed more ERD than AUD left central and more ERD than NAV right central. At the right parieto-temporal region, SUB and NAV had more ERS than all other tasks (except of NAV was not more synchronized than ROT).

3.4. Self-reports and evaluation of tasks

Users stated in the self-reports that they imagined per 7-s imagery period of a trial on average 7 complete rotation of the figure around its axis (S.E. = 2.5), 5 words (S.E. = 0.5), 1 verse of the tune (S.E. = 0.2), 4 subtractions (S.E. = 0.5), navigation through 1 room (S.E. = 0.2), 4 aspects of the familiar face (S.E. = 0.5) and 5 hand contractions (S.E. = 0.5).

Concerning the evaluation of tasks in respect of the quality of imagery, task ease and enjoyment, no significant differences between sessions or mental tasks were found. The tasks were rated on average as performed with 'a rather clear and vivid imagery' (quality of imagery: MN = 4.1, S.E. = 0.1), as 'rather fun and hardly frustrating' (enjoyment: MN = 3.8, S.E. = 0.1) and between 'not relaxing nor exhausting' and 'rather relaxing and possible to do this task also during small distractions like background noise' (ease: MN = 3.5, S.E. = 0.2) (see Fig. 6). The WORD task (MN = 4.07, S.E. = 0.1) was rated best, whereas, the SUB task (MN = 3.3, S.E. = 0.2) was rated worst over all three aspects. The low ratings of the SUB task in enjoyment and ease increased over the sessions, whereas evaluation rather decreased in the FACE task. However, Fig. 6 shows that there was a high variability in the task evaluation between users.

4. Discussion

The mental tasks investigated in the present study achieved mean accuracies comparable to the standard task left versus right hand motor imagery (e.g. Neuper et al., 2009) and thus can be considered appropriate for BCI control. The high variability between participants in classification performance and in task evaluation suggested that an individual choice between several task combinations could enhance BCI acceptance, user-friendliness and performance. However, the only way to confirm the efficacy of our task combinations is to run real-time feedback experiments, which is a high priority for future research.

Before comparing our study to the literature, we have to keep in mind that all studies used different methods for classification. Furthermore, we have to compare accuracies as most studies report

Table 1

Statistical analyses of brain patterns. Repeated-measurement ANOVAs were computed separately for time intervals and frequency bands. The dependent variable is indicated as 'DV'. The independent variables (IV) included the sessions, mental tasks and regions of interest. The table only shows the most relevant comparisons, i.e. the main effects 'sessions' and 'mental tasks' and the interaction (IV × IV) 'mental tasks × regions of interest'. (1.1) ANOVAs were computed with the absolute power values of the baseline as DV. No significant differences were found in any frequency band. (1.2) ANOVAs were computed with the ERD/S values of the imagery period as DV. The table only shows the ANOVAs that revealed a significant result. (A) There was a significant difference between mental tasks and a significant interaction between tasks and regions of interest in the lower beta band (13–20 Hz) in the time period of 3.5–5 s after trial onset. The tasks ROT, WORD and SUB showed more ERD (i.e. '>') than AUD, NAV and MOTOR. (B) In the following time period (5–6.5 s), the main effect of mental tasks was still significant in the lower beta band showing significant synchronization (i.e. ERS, '<') of the SUB task in comparison to the ROT, FACE and MOTOR tasks. (C) There was a significant interaction between tasks and regions of interest in the upper beta band (20–30 Hz) in the same time period.

	Time	Frequency band	DV	IV	IV	IVxIV
1.1	Baseline		Absolute Power	Sessions	Tasks	Tasks x Region s of interest
	1–2s	Lower alpha		n.s.	n.s.	n.s.
	1–2s	Upper alpha		n.s.	n.s.	n.s.
	1–2s	Lower beta		n.s.	n.s.	n.s.
	1–2s	Upper beta		n.s.	n.s.	n.s.
1.2	Imagery period		ERD/S Values	Sessions	Tasks	Tasks x Regions of interest
(A)	3.5–5s	Lower beta		n.s.	$F_{2.8, 22.5}$=3.8, p<.05 ROT, WORD, SUB > AUD, NAV, MOTOR	$F_{5.9, 47.4}$=2.9, p<.05
(B)	5–6.5s	Lower beta		n.s.	$F_{2.7, 21.6}$=3.9, p<.05 SUB < ROT FACE MOTOR	n.s.
(C)	5–6.5s	Upper beta		n.s.	n.s.	$F_{5.0, 40.3}$=2.6, p<.05 SUB < WORD parietal regions MOTOR central regions MOTOR > AUD left central NAV right central SUB, NAV < all tasks right parieto-temporal

accuracy instead of kappa values. However, kappa values make the interpretation of the results easier if the number of trials is not identical in all tasks and sessions (Schlögl et al., 2007). The classification stayed stable across the four sessions and showed a characteristic slope within trials: Kappa was at chance level before the cue and then showed a steep rise from the baseline to the maximum and a slow decay until the end of a trial (Scherer et al., 2008). We used a 10-times 10-fold cross-validation statistic to compute the kappa values for individual time segments. The use of an inner cross-validation would allow an even better estimation of the true discriminative power and thus of the best classifier, as the method intrinsically compares multiple classifiers (Varma and Simon, 2006). According to our practical experience, however, the selected 10-times 10-fold cross-validation procedure achieves a good generalization and is less computationally demanding. The selected approach furthermore allows a direct comparison of the kappa and the ERD/S values over time. The ERD/S patterns confirmed the classification results, as the patterns were most distinguishable in the beta bands (13–20 Hz, 20–30 Hz) shortly after cue onset. Both classification and ERD/S results indicated that the mental tasks can be clustered in categories according to the actions the tasks require from the users. In the following paragraphs, we will discuss the tasks and categories in more detail and make suggestions which task categories might be most promising to use for online control.

The WORD and SUB tasks require problem specific mental work and therefore can be described as 'brain-teasers'. They were included in most of the best imagery pairs in terms of classification (see Figs. 2 and 4; Sections 3.1 and 3.2) and showed similar ERD/S patterns (see Fig. 5; Section 3.3.). WORD showed a left hemispheric activation which is in line with findings from literature (Indefrey and Levelt, 2004). The rather left hemispheric activation in the SUB task indicated that participants might have used a linguistic strategy to solve the mental calculations (Chochon et al., 1999; Burbaud et al., 2000). Also working memory processes might have been involved in these tasks (Delazer et al., 2003; Kondo et al., 2004). For online control, brain-teasers could impose additional work load on the user and might impair BCI control. However, Galán et al. (2008) showed that users were able to control a wheelchair with 3 mental tasks including a word association task and Roberts and Penny (2000) showed cursor movement by means of a mental subtraction task. Furthermore, users in this study indicated that they could imagine using the WORD task under small distractions (see Section 3.4). For the SUB task, the ease-scale showed an increasing trend over sessions which indicates that practice might reduce the workload also in the SUB task. As this was only a hypothetical question of the ease-scale, the suitability of brain-teasers has still to be evaluated in real-world applications.

The ROT task required a dynamic visualization of an object (i.e. dynamic visual imagery) and therefore, did probably not imply the same kind of mental work as brain-teasers. However, the ROT task showed very similar ERD/S patterns as the brain-teasers and was included in most of the best imagery pairs in the simulation classification (see Fig. 4; Section 3.2). Anderson and Sijercic (1996) also reported an overlap between a visual counting task – which would fall in the same category as the ROT task – and an arithmetic as well as a verbal task. Besides verbalization, also visualization could be a common feature of these tasks (Curran and Stokes, 2003). In the study of Anderson and Sijercic (1996) a mental rotation task was also included. However, users had to study different complex figures before imagining rotating them which made the task more complex than our ROT task in which users always imagined the same 3-dimensional L-shaped figure. The rather left than right hemispheric activation found in this study in the ROT task could also be explained by the study of Roberts and Bell (2003) who suggested that information processing resources from the right hemisphere might not be required if the mental rotation task is very easy and familiar. However, this finding was related to sex differences and stated for men. In this study, we aimed to keep the group homogeneous in respect of sex, age and handedness to be able to compare the ERD/S patterns over the whole group.

The AUD, NAV and MOTOR tasks required dynamic imageries involving one-self (i.e. dynamic first-person imagery). Neuper et al.

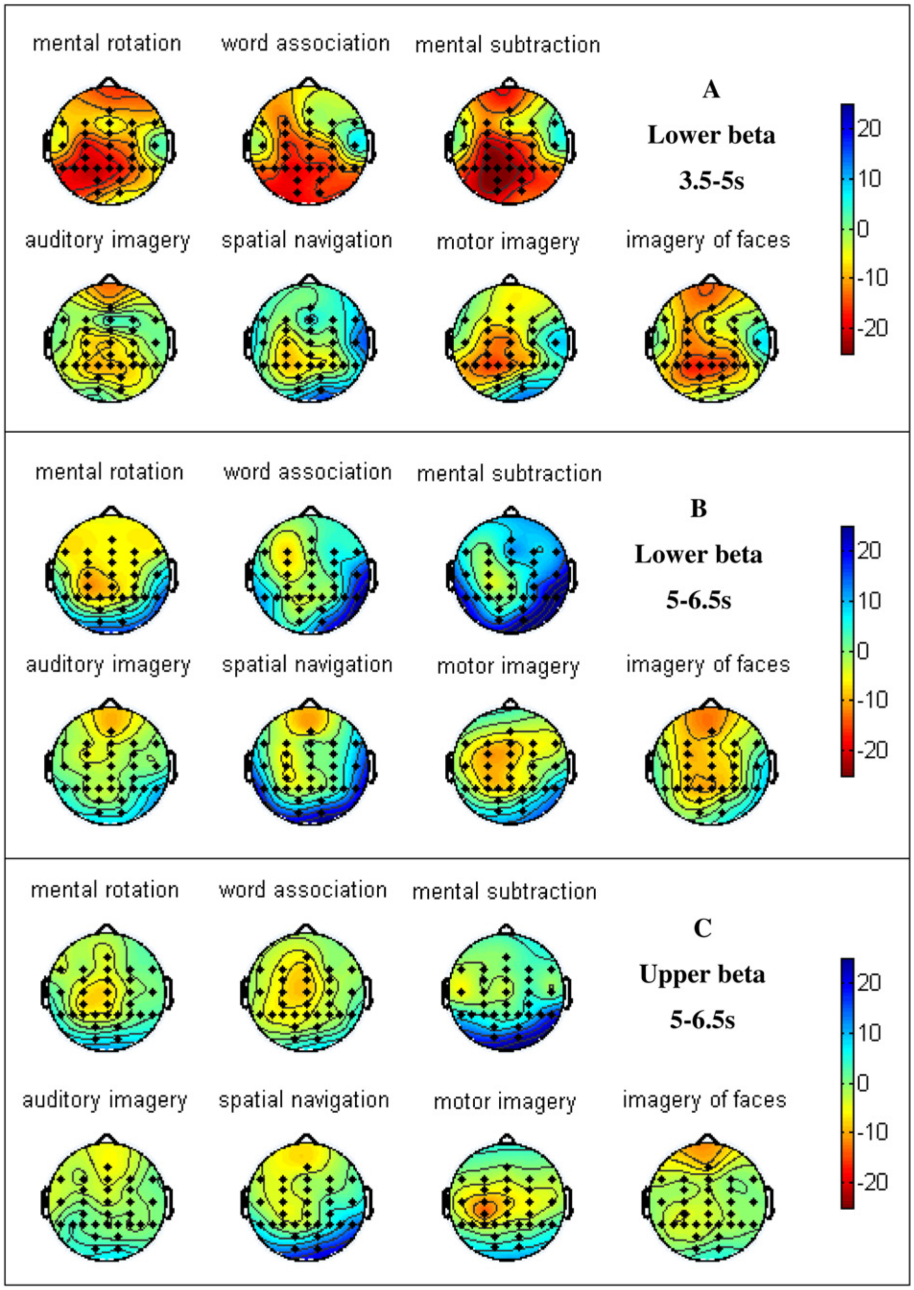

Fig. 5. ERD/S patterns averaged over users for the mental tasks. ERD (i.e. negative values) is indicated in red and ERS (positive values) is indicated in blue. The black dots represent the electrode positions. (A) ROT, WORD and SUB showed more ERD than AUD, NAV and MOTOR in the lower beta band (13–20 Hz) in the time period of 3.5–5 s after trial onset (cue at t = 3 s). (B) SUB synchronized most (i.e. ERS) and ROT, MOTOR and FACE showed ERD in the lower beta at t = 5–6.5 s. (C) SUB, AUD and NAV showed ERS and ROT, WORD and MOTOR displayed ERD in the upper beta band (20–30 Hz) at t = 5–6.5 s. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

(2005) already showed that there are differences in classification and ERD/S patterns between visual imagery of movements and motor imagery including one-self. The MOTOR task in this study reached high classification results when combined with the WORD, SUB or ROT task (see Figs. 2 and 4). This is in accordance with Millán et al. (2004) and Galán et al. (2008) who demonstrated good online control with these task combinations. Curran et al. (2003) compared the first-person imagery tasks among each other and found that the pair wise classification of spatial navigation and auditory imagery was superior to any other combination with motor imagery. Furthermore, they reported that users rated the non-motor tasks easier than the motor tasks. In the presented study, there was no such trend in terms of accuracy. In our ease-scale, NAV and AUD were as well rated descriptively least demanding, but the MOTOR task was not rated more difficult than non-motor tasks in general. In the study of De Kruif et al. (2007), 2 of 4 participants gained control, and the best accuracy was 73% in one session. They used different accented tones in auditory imagery, while we used tasks from very different domains (e.g. spatial, motor, etc.) which seem to be better for classification. The ERD/S patterns of the dynamic first-person imagery tasks revealed similarities (see Fig. 5). The MOTOR task of the right hand showed an ERD focused over left central/parietal regions (Neuper et al., 2005; Yuan et al., 2010). The prominent left hemispheric activation was also found in the other tasks. Besides the already mentioned verbalization, this left hemispheric bias could be explained as well by involved motor components. For example, Zatorre and Halpern (2005) stated that – at least in musicians – auditory imagery is linked to motor imagery. Also in tasks like NAV which is generally considered a right hemispheric task (e.g.

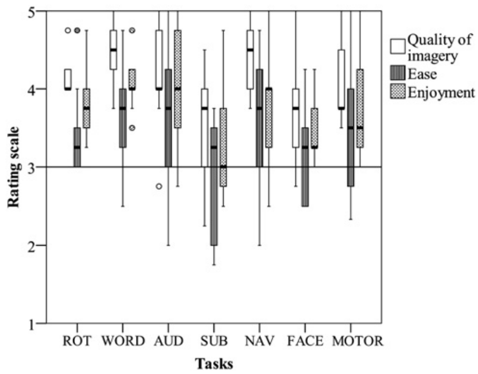

Fig. 6. Evaluation of tasks. All tasks were rated in three aspects concerning the quality of imagery (white; 1 = 'no image at all, you only 'know' you are thinking of the object' and 5 = 'perfectly clear and as vivid as normal vision'), the ease (striped; 1 = 'very exhausting and full concentration needed' and 5 = 'very relaxing and possible to perform also under major distractions such as activated television, visit of friends or in the traffic') and the enjoyment (dotted; 1 = 'no fun at all and very frustrating' and 5 = 'a lot of fun and not frustrating at all'). The boxplot shows that most ratings were in the positive range above the midline (3 = 'neither–nor').

Cutmore et al., 2000), rather left hemispheric activation was found. The left hemispheric activation in the NAV task could also be explained by gaining a more intellectual comprehension of the spatial relationship and generating mental images according to descriptions (Kosslyn et al., 1995). In contrast, the generation of mental images by precise locations in space is represented in the right hemisphere (Kosslyn et al., 1995). Like in NAV – which involves many brain structures such as hippocampus, parietal and premotor regions (Owen et al., 2006) – all mental tasks involve various parts of the brain depending on the specific strategy and exact processes involved. As the engaged regions also communicate with one another constantly, it makes it difficult in general to isolate one or two regions which are activated during a certain mental task (Holländer et al., 1997). In this study, we tried to ensure that all persons were performing the tasks in the same manner and continuously with careful instructions and supervised exercise runs.

The FACE task required a static visualization (i.e. static imagery) and showed different activation than the dynamic tasks (see Fig. 5) which is in accordance with Pfurtscheller et al. (2007) who also reported differences between dynamic and static imagery tasks. FACE did only show good classification performance when combined with brain-teasers and showed a decreasing trend in quality of imagery, task ease and enjoyment (see Section 3.4). FACE might also not be the optimal task for EEG measurement as fMRI or PET studies localized the main center for faces in the fusiform gyrus when watching or imagining familiar faces (e.g. Boly et al., 2007; Haynes and Rees, 2006).

To conclude, this study aimed to provide user-appropriate task combinations that can be reliably implemented for BCI control. Therefore, we investigated mental rotation, word association, auditory imagery, mental subtraction, spatial navigation, imagery of familiar faces and motor imagery tasks in respect of (1) pair wise classification, (2) ERD/S patterns and (3) users' task evaluation. All of our tasks can be voluntary produced, were rather clear and vivid to imagine and enjoyable. The ERD/S patterns demonstrated that the beta bands (13–20 Hz, 20–30 Hz) could discriminate significantly between the mental tasks within 3.5–6.5 s after trial onset (cue at $t = 3$ s) and were stable across the four sessions on different days within 2 weeks. Also task classification stayed stable across the four sessions and showed a characteristic slope with the maximum classification accuracy shortly after the cue onset of a trial. The tasks word association, mental subtraction, mental rotation and motor imagery resulted most frequently in good classification performance. Both, classification results and ERD/S patterns indicated that a reliable and stable BCI implementation of these tasks is possible. On individual basis, kappa of specific combination of mental tasks reached over 0.9 ($\approx$>95% accuracy) in single-session and simulation classification. This suggests that individually chosen control strategies from the investigated range of mental tasks might improve performance substantially. Of course, the only way to confirm the efficacy of our task combinations is to run real-time feedback experiments, which is a high priority for future research. Furthermore, these results still have to be evaluated with disabled individuals. Depending on the specific impairment, disabled individuals might show differences in their task classification, ERD/S patterns as well as evaluation of tasks. However, our study was an important step toward demonstrating that there are good alternatives to motor imagery, which might be especially beneficial for severely motor impaired individuals. Our results suggest that the use of brain-teasers — tasks that require problem specific mental work (e.g. mental subtraction, word association) - and a combination of brain-teasers and dynamic imagery-tasks (e.g. motor imagery) represents a promising choice for future online BCI implementations.

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