DOI:10.3217/978-3-85125-260-6-139

Individual Selection of Mental Tasks and Frequency Bands Boosts Performance in a 4-Class Brain-Computer Interface

E.V.C. Friedrich[1,2], R. Scherer[3], J.A. Pineda[2], C. Neuper[1,3]

[1]University of Graz, Austria; [2]University of California, San Diego; [3]Graz University of Technology, Austria

Correspondence: E.V.C. Friedrich, Department of Cognitive Science, University of California, San Diego, 9500 Gilman Drive, La Jolla, CA 92093-0515, USA. E-mail: efriedrich@ucsd.edu

Abstract. This study aimed at optimizing a 4-class brain-computer interface (BCI) individually in order to achieve high on-line performances for all users within few sessions. Eight able-bodied individuals participated in 10 sessions over 5 weeks. In the first screening session, users performed seven different mental tasks (i.e. mental rotation, word association, auditory imagery, mental subtraction, spatial navigation, motor imagery of the left hand and motor imagery of both feet) while multi-channel EEG was recorded. Out of these seven mental tasks, the best 4-class combination as well as the most discriminative frequency range was selected for each user independently and used for online control. All users achieved mean online accuracies between 58-93% in single-sessions in the present 4-class BCI. This protocol is highly individual adjustable and thus can increase the percentage of users who gain and maintain BCI control. A high priority for future work is to examine this BCI protocol with severely disabled users.

Keywords: BCI, 4-class BCI, EEG, Mental tasks, Event-related (de)synchronization (ERD/S), Individual adjustments, Disabled users

1. Introduction

One way to control a brain-computer interface (BCI) involves recording the changes in the rhythmic activity of the brain's electrophysiological signals through electroencephalography (EEG). Motor imagery is mostly used as control strategy. Additionally, the use of non-motor tasks can lead to good BCI performance e.g. [Curran et al., 2003; Millán et al., 2004]. However, studies including able-bodied as well as disabled individuals revealed huge individual differences in best task combinations for all mental tasks [Friedrich et al., 2011; Friedrich et al., 2012]. Therefore, the present cue-guided experimental protocol was designed to make an individual selection of control strategies and frequency range possible. These individual optimizations should increase performance within few sessions.

2. Material and Methods

This study included 8 able-bodied participants (3 male, aged between 20-36 years, right-handed) who were initially naïve to the use of a BCI. Each volunteer participated in one screening session (i.e. session 1; 42 trials per task) and then in 9 feedback sessions (i.e. sessions 2-10; 60 trials per task and session) over a period of 4-6 weeks.

Participants performed the following seven mental tasks in the screening while multi-channel EEG was recorded: Mental rotation (ROT), word association (WORD), auditory imagery (AUD), mental subtraction (SUB), spatial navigation (NAV), motor imagery of the left hand (HAND) and motor imagery of both feet (FEET). Out of these seven mental tasks, the 4-class combination and frequency range with the highest offline accuracy was selected for online control. The data was classified by means of common spatial patterns (CSP) and Fisher's linear discriminant analysis (LDA) and optimized individually concerning the number and time of classifier adaptation. Continuous online feedback and discrete feedback was provided to the users.

3. Results

The results showed that the selected task combinations and frequency bands differed between the users (Table 1). However, for every user one motor imagery task (hand or feet or both) and one brain-teaser task (word association or mental subtraction but never both) was selected. The mental rotation task was also included in the majority of task combinations. The results showed that the most promising combination of tasks in a 4-class BCI were (1) one motor imagery task, (2) one brain-teaser task, (3) a mental rotation task, and (4) one more dynamic imagery task (auditory imagery, spatial navigation or another motor imagery task). As can be seen in Table 1, the lower border of the frequency range was in the alpha band between 8-10 Hz in the screening and between 8-11 Hz in the updates for all users. The upper border was not as narrow and varied in the beta range between 13 to 30 Hz between users. The mean online performance showed a linear increase over sessions in 6 users and a stable performance in 2 users. From session 5 on, all users performed better than chance in every session ($p \geq 0.25 \pm 0.055$). All users managed to control all 4-classes above chance and achieved mean accuracies between 58-93% in single-sessions (Table 1). User C achieved accuracies > 80% in all single classes with a mean performance of 93%.

Table 1. *Selected tasks, frequency range and online performance per user. The first columns indicate which task combination was selected for BCI control. For the selected task combination, the frequency range between 8-30 Hz with the highest offline accuracy was used for the calculation of the classifier (Screening). After some feedback sessions, the frequency band optimization and the classifier were recalculated (Update1). For 3 users, the update was made another time (Update2). The peak performance is indicated in the last columns with the highest online accuracy and in which session it was achieved.*

User	Task combinations							Frequency range [Hz]			Online Performance	
	ROT	WORD	AUD	SUB	NAV	HAND	FEET	Screening	Update1	Update2	Accuracy	Session
A	x	x				x	x	8-30	11-26	-	80 %	10
B	x		x	x		x		9-17	8-15	-	58 %	10
C	x	x				x	x	8-19	10-25	-	93 %	7
D		x	x		x	x		9-26	9-14	9-15	73 %	9
E	x		x	x		x		9-15	8-16	-	66 %	10
F	x	x			x		x	8-30	8-13	-	64 %	6
G			x	x	x	x		8-20	11-23	10-25	75 %	9
H	x			x	x	x		10-30	9-20	11-30	85 %	6

4. Discussion

BCI performance was substantially improved by individual optimization of task combinations, frequency range and classifier adaptation in comparison to previous 4-class online studies with different mental tasks [Friedrich et al., in press]. Comparing our results to motor imagery-based BCIs, performance was comparably high e.g. [Wolpaw and McFarland, 2004]. In the present BCI protocol, all users performed above chance. Thus, the probability that everyone could gain and maintain BCI control was increased by the selection of user appropriate control strategies and adjustments. The results confirmed that the best BCI control strategies are highly individual, e.g. [Millán et al., 2004]. However, a pre-selection of reliable and robust control strategies from which the users can select is important, as a screening with many mental tasks is time consuming and exhausting for participants. A high priority for future work is to examine this BCI protocol with severely disabled users. Not only motor impaired users but also individuals with neurodevelopmental disorders, such as autism spectrum disorder, may benefit substantially from a BCI that can be adjusted individually. To that end, we have begun exploring the use of EEG-based BCI as well as other physiological signals (e.g. EMG, ECG) to train children on the autism spectrum to improve their social skills.

Acknowledgements

This work was supported by a fellowship provided by the MAX KADE Foundation to the Department of Cognitive Science, University of California San Diego and co-funded by the EU, in the GALA Network of Excellence, 258169.

References

Curran E, Sykaceck P, Stokes M, Roberts SJ, Penny W, Johnsrude I, Owen AM. Cognitive tasks for driving a brain–computer interfacing system: a pilot study. *IEEE Trans Neural Syst Rehabil Eng*, 12:48-54, 2003.

Friedrich EVC, Scherer R, Faller J, Neuper C. Do user-related factors of motor impaired and able-bodied participants correlate with classification accuracy? In *Proceedings of the 5th International Brain-Computer Interface Conference*, 156-159, 2011.

Friedrich EVC, Scherer R, Neuper C. The effect of distinct mental strategies on classification performance for brain-computer interfaces. *Int J Psychophysiol*, 84:86-94, 2012.

Friedrich EVC, Scherer R, Neuper C. Long-term evaluation of a 4-class imagery-based brain-computer interface. *Clin Neurophysiol*, in press.

Millán JdR, Renkens F, Mouriño J, Gerstner W. Brain-actuated interaction. *Artif Intell*, 159:241-259, 2004.

Wolpaw JR, McFarland DJ. Control of a two-dimensional movement signal by a non-invasive brain-computer interface. *Proc Natl Acad Sci USA*, 101:17849-17854, 2004.