Abstract

Neuroergonomic design of Brain-Computer Interface (BCI) experiments can be realized as a data driven optimization of stimuli. The goal of this process is to increase the number and information content of class-discriminant features of the EEG for the BCI task at hand. While existing electrophysiological literature indicated the influence of confounding variables on e.g. P300 latency and amplitude by group studies and grand average statistics, the BCI performance can be boosted by a large amount when optimized stimuli are explored and designed for individual users and then used in single-trials. The potential of this design principle is shown in an offline analysis for the example of a visual ($n = 8$) and an auditory ($n = 5$) ERP study with healthy subjects, where the optimization of stimulus parameters leads to both a decrease in classification errors and an increase in speed.

1 Introduction

Brain-Computer Interfaces (BCI) are still a very difficult approach to controlling computers, with many people in target user groups unable to learn to use them at all. The ratio of people who cannot use BCI depends on the BCI technology applied, but common problems are caused by the slow and inherently uncertain control of BCI applications due to the low signal-to-noise ratio of the commonly used signals of the electroencephalogram (EEG). There is no proprioceptive feedback, what feedback there is is delayed and the interaction principles and mental tasks in BCI are often unnatural.

The transfer of BCI systems out of the research lab and into the real world will only succeed if the usability of BCI systems can be increased. To bridge the gap, this paper underlines the necessity to follow neuroergonomic design principles in order to optimize BCI stimuli. Ideally, the full process of optimizing a BCI paradigm includes (a) investigations in neuroscience (to understand the covariates of human stimulus perception in BCI paradigms), (b) the modelling of these covariates in order to create improved stimulus methods, and (c) the design of BCI interaction paradigms that exploit the stimulus advantages but respect the restrictions imposed by slow and uncertain control. Steps (a) and (b) can be addressed by data-driven approaches. Step (c) requires careful application of human-computer design which takes these constraints into account (e.g. [2]) in a way that is appropriate for the specific target users.

Basic research in the field of electrophysiology revealed early the sensitivity of EEG phenomena to many covariates. Some examples are the influence of the task difficulty or the target-to-target distance on ERP, pitch and amplitude on auditory ERP, age on the lateralization of sensory motor rhythms (see e.g. [3, 4]).

For a number of reasons, it is difficult to transfer these results to the field of BCI. First, the prevailing scientific methods were group studies and evaluation by grand average statistics. In contrast, single trial analysis and performance optimization for individual subjects are the
predominant methods in BCI research. Second, these studies often concentrate on a single aspect like the latency or amplitude of the P300 component. In contrast, for BCI the amount of class discriminant information (between target and non-target stimuli) is of importance and it is typically distributed over several ERP components. Third, the varied range of the investigated confounds in older studies is partially out of the practical range for BCI. However, this basic research is stimulating for the field of BCI by providing entry points to conduct specialized studies.

Following neuroergonomic design principles, interesting new experimental paradigms have recently been created for BCI. On the area of visual ERP paradigms the adjacency problem and repetition blindness have been mitigated by optimized stimulation codes [5, 6] that modify the sequence and layout of highlighting patterns. The crowding effect (which limits the usability if gaze control is restricted) has been tackled by centered presentation of stimuli [7]. In the very recent field of auditory BCIs, spatial encoding has been introduced by [8, 9] to improve the discriminability of tones.

This contribution would like to emphasize the importance of sophisticated and individual stimulus design by presenting two brief examples of successful neuroergonomic optimization for BCI. For an auditory ERP paradigm, a thorough screening from relatively long to extremely short stimulus offset asynchrony (SOA) intervals is investigated. For a visual ERP paradigm, the effects of a variety of basic visual transformations are compared. In both cases, changes in BCI performance upon variation in the stimuli were tracked.

2 Methods

To examine the influence of stimulation parameters onto ERP paradigms, results from two studies are examined.

Auditory Oddball Study: In a two-tone auditory oddball paradigm, the influence of SOA (50, 75, 125, 175, 225, 275, 400 and 1000 ms) is investigated. Five healthy volunteers (three male, all non-smokers) participated in a single session of this offline study. A simple two-tone auditory oddball paradigm with counting task was implemented, with 83% of non-target tones. In eight block-randomized conditions the SOA steps were compared. For each condition and subject, 1296 epochs (216 targets and 1080 non-targets) were available. EEG was recorded from 61 wet Ag/AgCl electrodes placed at symmetrical positions. The band-pass filtered data (0.5 Hz to 40 Hz) was epoched between -150 ms and 1000 ms relative to each stimulus onset. Binary classification of target and non-target epochs was performed using a (linear) Fisher Discriminant Analysis (FDA) with shrinkage regularization. The mean potentials in hand-selected intervals (based on $r^2$ values) of epochs were taken as features. The binary classification error was estimated by $[5 \times 5]$ cross-validation.

Photobrowser: In a (6 × 6) matrix layout of 36 photos, six different visual highlighting effects for rows and columns are compared:

- Brightness increase: Photos were increased to high brightness and back.
- Inversion: Photos were stepwise inverted to a color negative and back.
- Masking: Photos were overlaid with a grid of high contrast lines (B&W, magenta).
- Rotation: Photos were rotated clock-wise by 10 degrees and back.
- Scaling: Photos were scaled to 110% size and back.
- Combination: Photos underwent a combination of the above effects (excluding Inversion).

The duration of each effect was 100 ms with 100 ms pause between two highlighting events (SOA of 200 ms). Taking the discretization by the screen update rate of 60 Hz into consideration, an effect was present during 5 to 7 frames. Eight healthy volunteers (three male, all non-smokers) participated in a single session of this offline study. A visual oddball paradigm with counting task was implemented, with 83% non-targets. The six conditions were presented in a block-randomized order. For each condition, 1800 epochs (300 targets and 1500 non-targets) were available. EEG signals were recorded and processed as described above.
Figure 1: A: N2 and P3 for two visual stimulation conditions (one subject). The top row shows ERP traces of electrodes O2 and Cz for Inversion and Masking. Two middle rows: ERP maps for targets and non-targets. Lower row: spatial distribution of class-discriminant information. B and C: Estimated class-wise balanced classification loss. B: Binary loss (single epochs for single subjects and grand average (GA)) and simulated GA loss for 15 s trial duration for auditory SOA conditions \((n = 5)\). C: Binary loss for visual highlighting conditions \((n = 8)\).

3 Results

The class discriminant information contained in the EEG epoch of a single stimulus remains the major factor for a quick BCI. For this reason the loss derived from the binary classification task of target vs. non-target epochs is used in the following. In addition, an analysis of ERP location and time structure illustrates the influence of a neuroergonomic stimulus design.

An analysis for both studies reveals that the majority of subjects shows typical ERP components. For short SOA values however, early components (P1, N2) dominate the target and non-target ERP responses. Later components (e.g. P3a and P3b) are decreased in amplitude by recurring strong N2 of following stimuli. Even slight changes of the SOA can lead to a complete elimination of class-discriminant late ERP components. This explains the non-monotonic changes of the binary loss for successive SOA values in Figure 1 B for some subjects. For different stimulation conditions, drastic changes of ERP components within each subject were observed. To illustrate this, the ERPs of conditions Inversion and Masking are compared in Figure 1 A.

Judging by the binary loss estimated by cross validation, the optimal design of stimulation parameters has the potential to improve the individual performance for both study designs. The left plot in Figure 1 C shows that for the Photobrowser study the grand average classification loss based on single epochs can be reduced by ~50% compared to the standard visual highlighting effect in the form of a brightness increase. The improvement is strongest for the rather complex combination effect (reduction of loss from 0.16 to 0.085), but even the simple masking effect improves the performance by nearly 40% (to ~0.1). If optimized individually, only slightly stronger classification gains are possible. Figure 1 A compares the effect of a brightness highlighting and a mask highlighting. The plot in Figure 1 B shows that a reduction of SOA intervals from 1000 ms to 175 ms or even 125 ms results in minor increases of the grand average binary loss for the auditory oddball paradigm. At first glance, these results seem to favor long SOA values. However, shorter SOA values strongly improve the transmitted information per time (e.g. in terms of simulated loss over 15 s trial duration), especially if BCI applications have a reduced overhead in terms of inter-trial pauses or time needed for result feedback. In this light, the short SOA conditions...
SOA\textsubscript{75}, SOA\textsubscript{125} and SOA\textsubscript{175} are to be preferred on average. Condition SOA\textsubscript{50} shows a strongly increased binary loss on the grand average, such that it is not competitive despite even shorter trial durations. Please note the individual sensitivity even for neighboring SOA steps.

4 Discussion

The data driven optimization of BCI stimuli according to neuroergonomic principles leads to more class-discriminative ERP responses of the EEG. As interpretable models of the underlying functions of perception and focused attention do not come “for free” from these data driven methods, it is difficult to describe the exact causes of the resulting performance improvements.

The improvements were exemplified in an auditory and a visual ERP study not only for the grand average of subjects, but - even more emphatically - when optimizing the stimuli for individuals. In particular, performance improvements were largest in a visual ERP paradigm for a novel visual masking effect that outperforms the predominantly used highlighting methods (rotation, scaling and change of brightness). For an auditory ERP paradigm, short SOA values of 75 to 175 ms showed best results, but the best SOA for an individual is relatively sensitive to fine-tuning. While one of the stimulus types could even be optimized across subjects (visual highlighting effect), the other (SOA) should clearly be selected individually for users.

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References


