Exploring the impact of stimulus transparency in ERP-BCI under RSVP

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ABSTRACT

Rapid serial visual presentation (RSVP) is currently one of the most suitable paradigms for implementing a visual brain–computer interface based on event-related potentials (ERP-BCI) for patients with limited ocular motility. This paradigm presents stimuli centered in the user's field of vision, which may hinder the patient from attending to other elements on the screen. A potential solution to this could be the use of semi-transparent stimuli, allowing both the stimulus and the background to be perceived. Therefore, the objective of this study is to evaluate the impact of stimulus transparency on ERP-BCI performance under the RSVP paradigm. Five participants tested the ERP-BCI under RSVP using three different stimulus transparencies with alpha channels set to 255 (C1), 85 (C2), and 28 (C3). The results showed the following average BCI classification accuracies: C1, 70%; C2, 74.67%; and C3, 60.67%. Although the analyses did not reveal significant differences, the results suggest that the transparency level should be carefully manipulated to maintain a balance between stimulus transparency and performance, with C2 even exhibiting the highest accuracy among the conditions. This finding should be considered by future ERP-BCI proposals aimed at users who need gaze-independent systems.

Keywords: brain-computer interface (BCI), event-related potential (ERP), rapid serial visual presentation (RSVP), stimulus, transparency

INTRODUCTION

Brain-computer interfaces (BCIs) act as assistive technology, enabling users to interact solely through brain signals (Wolpaw et al., 2002). The overarching goal of assistive technology, including BCIs, is to facilitate user interaction with the environment (Karikari and Koshechkin, 2023). Conditions like amyotrophic lateral sclerosis (ALS) can make traditional assistive technologies ineffective due to compromised muscular and ocular control (Aust et al., 2024). In severe motor limitations, BCIs offer a promising alternative, initially bypassing the need for muscular control.

BCIs can utilize various input brain signals, with electroencephalographic (EEG) signals like sensorimotor rhythms (SMRs) and event-related potentials (ERPs) widely used for their portability and cost-effectiveness (Ramadan and Vasilakos, 2017). ERPs, especially, are effective in controlling applications without requiring ocular mobility, making them suitable for severe muscular impairment (Lees et al., 2018; Xu et al., 2021). Visual ERP-based BCIs, particularly in the rapid serial visual presentation (RSVP) paradigm, prove valuable for users lacking control over their eye movements (Acqualagna and Blankertz, 2013).

In RSVP, visual stimuli are sequentially presented in the same spatial location, requiring the user to attend to a specific stimulus. The goal of an ERP-BCI is to distinguish between brain signals associated with attended (target) and non-attended (non-target) stimuli, typically focusing on the P300 component occurring 300–600 ms after stimulus presentation (Kalra et al., 2023). Visual ERP-BCI performance is affected by factors like stimulus type, duration, size, and spatial distribution impact their performance (Chen et al., 2016; Lees et al., 2020; Fernández-Rodríguez et al., 2022; Won et al., 2018).

Transparency of the stimulus, an unexplored factor in ERP-BCIs, could have a significant impact on performance. According to Li et al. (Li et al., 2014), increasing the luminosity of the stimulus (letters over a black background) may enhance the effectiveness of ERP-BCIs. However, this study was conducted using a matrix-based paradigm and may not necessarily be applicable to RSVP (Fernández-Rodríguez et al., 2021). However, although manipulating the stimulus luminosity on a black background has a similar effect to manipulating its transparency, it is not exactly the same when dealing with more complex backgrounds. Thus, it would be necessary to test the effect of stimulus transparency under RSVP and backgrounds more complex than a monochromatic black background.

Some previous ERP-BCI works–not based on RSVP–have integrated stimuli to be selected within the user's field of vision through augmented reality techniques (Iturrate et al., 2009; Zhong et al., 2020). Augmented reality enables users to control the interface while remaining attentive to their surroundings. However, for users with limited motor capabilities, expressing their intent to use the interface becomes challenging (i.e., discriminating between when they want to use the interface and when they do not). In such cases, stimuli must be presented continuously in their field of vision. This situation may result in the user being unable to attend to their visual surroundings if they do not wish to control the interface, as the persistent interface stimuli can be disruptive. A potential solution could involve implementing semi-transparent stimuli, aiming to strike a balance between facilitating effective ERP-BCI usage (when the user wants to select a command from the interface) and maintaining awareness of the environment (when the user does not want to select any commands and wishes to attend to the surroundings).

In summary, this study investigates how stimulus transparency influences the performance of a visual ERP-BCI under RSVP. The findings not only enhance system performance but also have practical implications for users with motor limitations, enabling better control of the interface while remaining aware of their surroundings in everyday use.

MATERIALS AND METHODS

Participants

The study involved five French-speaking students with normal or corrected-to-normal vision from the École Nationale Supérieure de Cognitique de Bordeaux. The participants had no prior experience with BCI systems, were of legal age, and approved by the Ethics Committee of the University of Malaga in line with Helsinki Declaration standards. Self-reports confirmed no history of neurological or psychiatric issues, and participants were not on regular medication. Written consent was obtained from all participants.

Data Acquisition and Signal Processing

EEG data were recorded at a 256 Hz sample rate using electrode positions Fz, Cz, Pz, Oz, P3, P4, PO7, and PO8, following the 10/10 international system. All channels were referenced to the right earlobe and grounded to position FPz. Signals were amplified by a 16-channel g.USBamp amplifier from g.Tec, Guger Technologies, Austria. A band-pass filter within the range of 0.1–60 Hz was applied. The BCI software tool utilized for displaying the graphical interface and data collection was BCI2000 (3.6 R5711.1) (Schalk et al., 2004). A stepwise linear discriminant analysis of the data was conducted to determine classifier weights and calculate accuracy using the P300Classifier tool in BCI2000.

Experimental Conditions

Three conditions were investigated based on the transparency of visual stimuli in the ERP-BCI under RSVP. Each condition involved presenting a background video with pictograms appearing at varying transparency levels. Due to BCI2000 limitations in modifying the display, the Processing software synchronized with BCI2000 was used to present stimuli in each condition (Reas and Fry, 2006). Processing, coded in Java, received the temporal instant of the target stimulus from BCI2000 via a UDP port. The alpha channel controlled the transparency level of pictograms in Processing, set to 255, 85, and 28 units (figure 1A). Given the absence of prior studies on the effects of stimulus transparency, conducting a preliminary investigation using three subjectively selected transparency levels was deemed appropriate. These levels comprised a fully opaque condition (alpha channel 255, C1), a barely perceptible condition (alpha channel 28, C3), and an intermediate condition facilitating both background visibility and stimulus discrimination (alpha channel 85, C2). One of the primary objectives of this study is to preliminary assess how the chosen stimulus transparency levels influences users' ability to perceive the stimuli and their performance in controlling an ERP-BCI under RSVP conditions.

The pictograms utilized in this study were carefully sourced from the "Centro Aragonés para la Comunicación Aumentativa y Alternativa" (ARASAAC) database (`https://arasaac.org`). These pictograms were specifically selected due to their relevance to potential user messages or applications in alternative and augmentative communication (AAC) (Elsahar et al., 2019). Each experimental condition featured a set of 10 distinct pictograms, chosen to represent a range of commonly used symbols in AAC, within the Rapid Serial Visual Presentation (RSVP) paradigm (see Figure 1B). This selection process aimed to ensure that the stimuli used in the study were both meaningful and applicable to individuals who rely on AAC systems for communication. These stimuli were consistently presented at the screen center, with a diameter of 864 pixels (screen resolution equal to 1920 $\times$ 1080 pixels), for 187.5 ms, with 93.75 ms of interstimulus interval (ISI), resulting in a stimulus-onset asynchrony (SOA) of 281.25 ms. The distance between the user's eyes and the screen was approximately 60 cm.

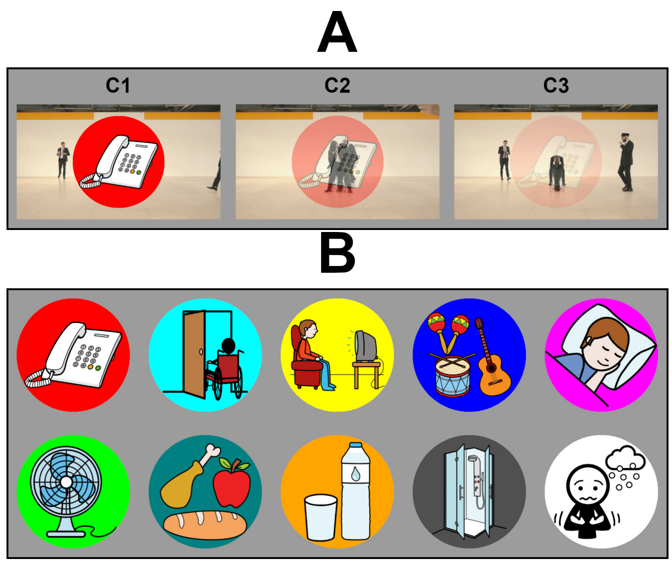

Figure 1. **(A)** Screenshot that showcases the visual representation of a pictogram under three distinct conditions (varying in the alpha channel intensity of the pictogram: C1, 255 units; C2, 85 units; and C3, 28 units). The backdrop includes videoclip 2 (Ok Go - The One Moment). **(B)** All stimuli used in the study, encompassing both the pictogram and colored circle.

Procedure

When each participant arrived at the laboratory, the test was explained to them, they signed the informed consent form, and the instrumentation was prepared. The experiment took place in a single session. The aim of the BCI task was to obtain the accuracy of the system with each stimulus transparency to establish a comparison between them, and there was no online feedback in which the user actually controlled the interface. An intra-subject (also known as repeated measures) design was used, meaning that all users tested all three conditions.

The user was asked to focus his/her attention on one of the indicated pictograms (i.e., the target stimulus) while one of the video clips played in the background. The objective was for the BCI system to discriminate between the ERP signal associated with the target stimulus and the non-target ones. The user did not receive online feedback since it was an exclusively offline BCI task, and their performance was calculated once the session had ended. The process of selecting a pictogram in the interface was referred to as a trial and involved the action of choosing a target pictogram from the 10 possible options shown in the interface (figure 2). During a trial, each pictogram was presented five times. The presentation of each pictogram available on the interface corresponded to a sequence, and thus, a trial was composed of five sequences. The order of presentation of the pictogram in each sequence was random, without replacement. The user was asked to mentally count the number of presentations of the target pictogram to ensure that his/her attention was focused on the task. Before starting each trial, there was a pause of

3000 ms. At the beginning of this pause, the pictogram to be attended to in the next trial was indicated by the message ”Focus on”, and the target pictogram was shown simultaneously at the same time and position (2500 ms). At the end of the trial—after all sequences had finished—there was another pause of 1468.75 ms during which an image was presented to remind the participant to press the space bar in case they had counted the five appearances of the target pictogram. The duration of a single trial was 13968.75 ms: 50 stimulus presentations (5 sequences × 10 pictograms) of 187.5 ms and 49 inter-stimulus intervals (ISI) of 93.75 ms. A run was also defined as the set of trials from when the application was started by the experimenter until it was automatically stopped. In the present experiment, each run consisted of 10 selections (trials), in which 10 pictograms were focused on. The order of pictogram selection was always the same, as depicted in figure 1B in row-mayor order. For each condition, 3 runs were carried out one after another (30 selections per condition, 3 runs × 10 trials). The order of the conditions was also counterbalanced—i.e., evenly distributed—across participants to prevent any unwanted effects such as learning or fatigue, and all conditions were equally distributed.

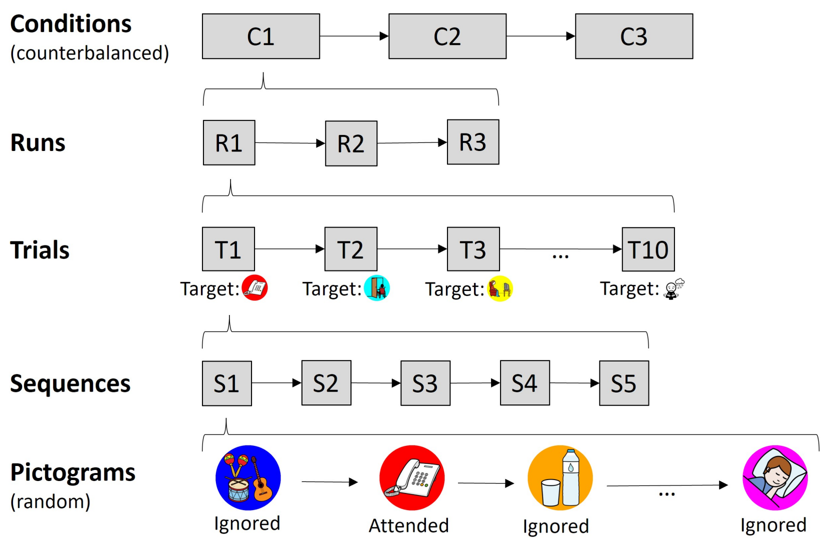

Figure 2. Experimental procedure followed by the participants. The order of the conditions (C1, C2 and C3) was counterbalanced between different participants. Likewise, the order of presentation of the stimuli in each sequence was random, without replacement.

Evaluation

To investigate the impact of the stimulus transparency factor, two variables were measured: perceived stimuli and BCI accuracy. On one hand, to assess users' effectiveness in perceiving stimuli at each transparency level, they were required to press the space bar at the end of each trial to indicate that they had indeed observed all five presentations of the target stimulus. The total number of trials per condition (C1, C2 and C3) is 30; thus, this measure represents the percentage of trials in which the user correctly perceived all desired stimuli. On the other hand, the BCI classification accuracy represents the number of accurately predicted selections divided by the total number of predicted selections. It was obtained by applying a three-fold cross-validation method to evaluate performance across different conditions. This variable was compared across the various conditions (C1, C2 and C3) for each of the sequences (from 1 to 5).

RESULTS AND DISCUSSION

The percentage of detected target stimuli for each condition was as follows: C1, 92.67±7.04%; C2, 93.33±9.76%; and C3, 82.67±17.92%. The Friedman analysis did not reveal significant differences between the conditions (χ^2 (2) = 2.333, p = 0.311). Therefore, it cannot be asserted that there is a significant impact of transparency level on stimulus detection. However, in figure 3A, it can be observed that condition C3 shows a lower percentage of detected stimuli compared to C1 and C2. Additionally, it is interesting that the values for C1 and C2 are so close to each other; this could indicate that despite the lower transparency level of C2, stimuli are perceived similarly to those in C1, which were completely opaque. Regarding BCI accuracy, the results obtained were above the chance threshold (1 out of 10 stimuli, 10%) from the first sequence, reaching at least 60% accuracy at most in all conditions (figure 3B). Specifically, the maximum accuracy levels obtained (all in the fifth sequence) were as follows: C1, 70±26.56%; C2, 74.67±20.9%; and C3, 60.67±29.38%. The Friedman test did not show the existence of significant differences between any of the conditions in any of the sequences (sequence 1, χ^2 (2) = 0.778, p = 0.678; sequence 2, χ^2 (2) = 2.8, p = 0.247; sequence 3, χ^2 (2) = 3.6, p = 0.165; sequence 4, χ^2 (2) = 3.6, p = 0.165; and sequence 5, χ^2 (2) = 2, p = 0.368). It cannot, therefore, be stated that accuracy is affected by stimulus transparency. Nevertheless, similar to the percentage of detected target stimuli, a consistent trend of condition C3 to exhibit lower performance compared to C1 and C2–more than 10% lower–is observed in each of the sequences.

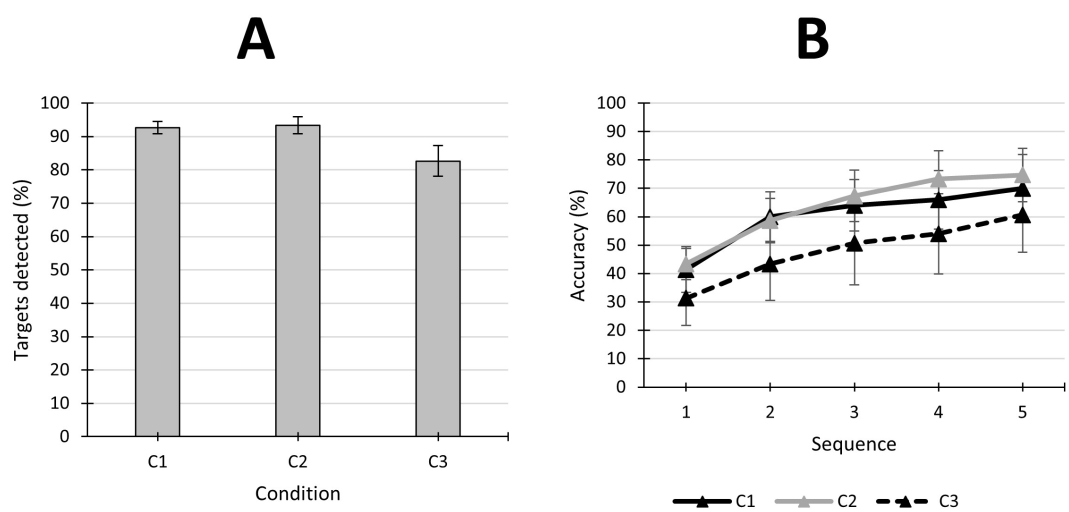

Figure 3. **(A)** Percentage of detected target stimuli (mean ± standard error) during the use of each condition with different alpha channel level to manipulate the transparency of the pictograms: C1, 255 points; C2, 85 points; and C3, 28 points. **(B)** Brain-computer interface (BCI) classification accuracy (mean ± standard error) of the different conditions as a function of the number of sequences used.

The potential decrease in BCI accuracy noted in our study corresponds with findings reported by Li et al. (2014), illustrating how lower luminosity levels can adversely affect performance. Their research highlighted that decreased luminosity of stimuli led to a heightened perception of the black background. However, it's crucial to approach this correlation with caution as the observed effect may not universally apply across different experimental paradigms. Nevertheless, the outcomes of both studies suggest that higher contrast between the stimulus and the background may yield better results for the BCI system. Moreover, our study's overall findings may imply that the background video effect could hinder BCI performance. This hypothesis finds support in prior studies indicating superior performance, with accuracy rates averaging approximately 80% to 90%, when utilizing the RSVP paradigm with either a black or white background (e.g., Fernández-Rodríguez et al. (Fernández-Rodríguez et al., 2022), and Ron-Angevin et al. (Ron-Angevin et al., 2021)). These observations underscore the significance of considering background characteristics in BCI investigations and emphasize the need for further exploration to optimize background conditions for enhanced BCI accuracy and usability.

CONCLUSIONS

This study aimed to preliminarily evaluate the effect of stimulus transparency on an ERP-BCI under RSVP. Although the analyses did not show significant differences, there is a trend in condition C3 (higher transparency level) to exhibit both a lower percentage of detected target stimuli and poorer accuracy in classifying the stimuli detected by the BCI. However, condition C2, with an intermediate transparency level, could potentially allow users to attend to their surroundings behind the presented stimuli without being as intrusive as opaque stimuli and without negatively impacting BCI performance (although not statistically significant, its performance is even superior to C1).

Given the preliminary nature of this study, these results should be further explored by future research. Here are some proposed modifications for subsequent studies. Firstly, it would be appropriate to measure the level of discomfort or comfort with stimuli when the user intends to focus on the background rather than the BCI stimuli. Secondly, it is recommended to expand the experimental sample for more reliable results. Additionally, testing this study on the target population of these interfaces, patients with severe motor impairments, would be beneficial. Despite the limitations, this study underscores the value of preliminary investigations as an initial step in exploring novel research topics. This study lays the groundwork for subsequent, more robust experiments, allowing for the refinement of hypotheses and methodologies. This iterative approach contributes to the advancement of scientific knowledge and the establishment of more reliable conclusions over time.

In summary, this work suggests that stimulus transparency could be a factor influencing BCI system usability. However, an intermediate transparency level may not degrade system performance while allowing for proper observation of the background behind the interface. This preliminary study may be valuable for future efforts aiming to provide a BCI system that enables more integrated control with the patient's environment. In any case, it is recommended to further this research with the aforementioned improvements to assess the impact of stimulus transparency levels in an ERP-BCI under RSVP.

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