

Interacting Effects of Command Set Size and Temporal Parameters in Brain-Computer Interface Based on the RSVP Paradigm

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Abstract—Rapid Serial Visual Presentation (RSVP) is a promising paradigm for gaze-independent Event-Related Potential (ERP) Brain-Computer Interfaces (BCIs), particularly in accessibility-oriented applications, although performance strongly depends on interface configuration and stimulation parameters. This study examines the combined effects of command set size, Stimulus Onset Asynchrony (SOA), and number of stimulation sequences on system performance and task execution. Fourteen participants took part in an offline RSVP-based ERP-BCI experiment evaluating six interface configurations. Conditions are denoted as $Cn-s-q$, where n indicates the number of available commands, s the SOA in milliseconds, and q the number of stimulation sequences (i.e., repetitions of the full stimulus set). Specifically, the 6 conditions tested were denoted as C2-188-32, C4-188-16, C8-188-08, C2-375-16, C4-375-08, and C8-375-04. The total selection time was kept constant at 12 s. Performance was assessed using classification accuracy and pictograms per minute, and complemented by subjective ratings reflecting how easily participants were able to perform the target-counting task required to operate the interface. The results reveal clear trade-offs between temporal parameters and command set size, with configurations C2-375-16 and C4-188-16 achieving the highest overall performance. Moreover, conditions with longer SOAs were consistently associated with easier execution of the counting task, independently of the number of commands. These findings support conservative RSVP-based ERP-BCI designs in which command set size and temporal configuration are jointly tuned to achieve reliable control while maintaining feasible task execution.

Keywords—Brain-Computer Interface (BCI); Event-Related Potential (ERP); Rapid Serial Visual Presentation (RSVP).

I. INTRODUCTION

Brain-Computer Interfaces (BCIs) have emerged as a promising assistive technology by enabling direct communication and control pathways between neural activity and external devices without relying on muscular output [1]. This capability is particularly relevant in accessibility-oriented contexts, where BCIs can provide alternative interaction channels for individuals with severe motor impairments.

Among the different BCI approaches, systems based on Event-Related Potentials (ERPs), especially those exploiting the P300 component, have been widely investigated due to their non-invasive nature, robustness, and relatively short training requirements [2].

Traditional ERP-BCIs have commonly relied on matrix-based visual paradigms, such as the classical row-column speller [3]. However, these paradigms impose substantial visual and oculomotor demands, which may limit their usability for users with gaze control deficits [4]. In response to these limitations, the Rapid Serial Visual Presentation (RSVP) paradigm has been proposed as an alternative visual stimulation approach. In RSVP-based BCIs, stimuli are presented sequentially at a single spatial location, thereby reducing the need for eye movements and minimizing spatial attention requirements [5]. These characteristics make RSVP particularly suitable for accessibility-oriented applications, where robustness across heterogeneous user capabilities is a critical design goal.

Despite these advantages, the performance of RSVP-based ERP-BCIs is strongly influenced by the configuration of the user interface and stimulation parameters. Previous studies have shown that factors such as stimulus presentation rate, the Stimulus Onset Asynchrony (SOA, i.e., the time interval between the onset of two consecutive stimuli), the number of repetitions or stimulation sequences per target, and target probability substantially affect ERP amplitude, classification accuracy, and overall system efficiency [5]–[8].

RSVP-based studies have shown that excessively fast presentation rates can degrade ERP separability, whereas slower rates reduce interaction efficiency [9]. Increasing the number of stimulation sequences (i.e., number of repetition of each stimulus) can improve classification accuracy at the cost of longer selection times [7][8].

Another key design dimension in accessible BCI systems

is the number of available commands. While expanding the command set increases system expressiveness and functional flexibility, it also reduces target probability and may negatively impact ERP detectability and overall performance [10]. At the same time, given the well-established inverse relationship between target probability and ERP amplitude [6], an excessively small command set combined with very rapid stimulus presentation may also be suboptimal, as it can alter the temporal dynamics of target detection and reduce system efficiency due to temporal overlap and refractory effects [9]. Therefore, understanding the trade-offs between command set size, temporal parameters, and interaction time is essential for designing interfaces that can be adapted to individual user needs and capabilities.

From an accessibility perspective, it is important to acknowledge that BCI performance in real end-user populations remains limited. In particular, achieving reliable and sustained BCI control continues to be a major challenge in users in a Complete Locked-In State (CLIS), who represent one of the primary target populations for assistive BCI technologies [11], [12]. These limitations highlight the gap that still exists between laboratory-based demonstrations with healthy participants and practical, everyday use in severely impaired users. Consequently, a conservative and user-centered design approach is warranted. Rather than prioritizing high expressiveness or large command sets, interface designs should focus on simplicity, robustness, and cognitive manageability. In this context, interfaces relying on a small number of commands—even as few as two—may represent a pragmatic and meaningful starting point, particularly when the goal is to ensure reliable interaction under demanding attentional and physiological constraints.

In this work, we present an experimental study that systematically evaluates different RSVP-based ERP-BCI interface configurations by jointly varying three core parameters: the number of available commands, the SOA, and the number of stimulation sequences used for decision making. By analyzing objective performance metrics together with subjective ratings of task execution difficulty during the target counting task, this study aims to provide empirical evidence to support informed, accessibility-oriented interface design choices.

II. METHODS

A. Participants

Fourteen French-speaking students (mean age 21.00 ± 1.11 years; 7 females and 7 males) with normal or corrected-to-normal vision participated in the study. All participants were of legal age and reported no prior experience with BCI systems. Self-reports confirmed the absence of neurological or psychiatric conditions, and none of the participants were taking regular medication at the time of the experiment. Written informed consent was obtained from all participants prior to data collection.

B. Data Acquisition and Signal Processing

EEG data were recorded at a sampling rate of 256 Hz using eight electrode positions (Fz, Cz, Pz, Oz, P3, P4, PO7, and PO8) according to the international 10–10 system. All channels were referenced to the right earlobe and grounded at FPz. Signals were amplified using a 16-channel g.USBamp amplifier (g.tec Medical Engineering GmbH, Austria) and band-pass filtered between 0.1 and 60 Hz.

Data acquisition and stimulus presentation were implemented using BCI2000 (version 3.6, R5711.1) [13]. Offline artifact correction was performed using the artifact subspace reconstruction (ASR) algorithm with default EEGLAB (version 2025.0.0) parameters [14], combined with a Riemannian distance-based approach [15]. Feature extraction and classification were carried out using the *P300Classifier* tool in BCI2000, employing Stepwise Linear Discriminant Analysis (SWLDA). Classification performance was evaluated using a 16-fold cross-validation procedure to ensure generalizability.

C. Experimental Conditions

Six experimental conditions were defined by systematically varying three interface parameters: the number of available commands, the SOA, and the number of stimulation sequences (Table I). The number of commands was set to 2, 4, or 8 pictograms, and the SOA was set to either 187.5 ms or 375 ms. The stimulus duration was fixed at 100 ms across all conditions; therefore, variations in SOA were implemented by modifying the Inter-Stimulus Interval (ISI, i.e., is the temporal interval between the offset of one stimulus to the onset of another). These parameters resulted in different Target-to-Target Intervals (TTIs) across conditions. TTI denotes the mean time between successive presentations of the target stimulus. The number of stimulation sequences was adjusted across conditions such that it decreased as the number of commands increased. This design ensured that the total selection time per trial was constant (12 s) for all conditions, allowing direct comparisons of performance and perceived task execution across interface configurations.

The pictograms used in this study were obtained from the ARASAAC database [16] and were selected for their relevance in Augmentative and Alternative Communication (AAC) contexts (Figure 1). Stimuli were presented sequentially at the center of the computer screen, using a single fixed spatial location. Each pictogram was displayed with a diameter of 10.5 cm. The viewing distance between the participant and the display was approximately 60 cm.

D. Procedure

The experiment was conducted in a single session using a within-subject (repeated-measures) design. Upon arrival, participants received standardized instructions, provided informed consent, and were prepared for EEG recording. No online feedback was provided during the experiment, and participants did not interact with the system in real time.

TABLE I. EXPERIMENTAL CONDITIONS USED IN THE RSVP-BASED ERP-BCI STUDY.

Condition	Number of stimuli	Stimulus onset asynchrony (ms)	Target-to-target interval (ms)	Sequences
C2-188-32	2	187.5	375	32
C2-375-16	2	375	750	16
C4-188-16	4	187.5	750	16
C4-375-08	4	375	1500	8
C8-188-08	8	187.5	1500	8
C8-375-04	8	375	3000	4

Note: Target-to-target interval values correspond to mean intervals, as the presentation order of stimuli within each sequence was randomized, resulting in local variability in the temporal spacing between successive target occurrences.

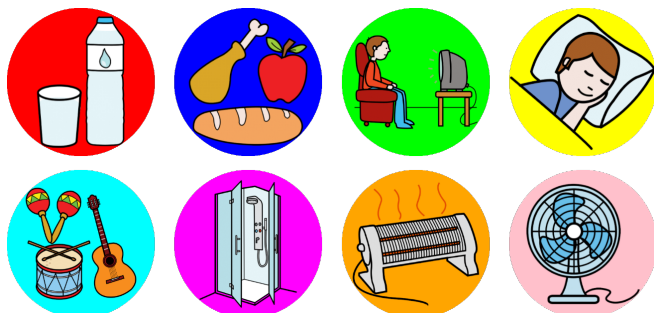


Figure 1. Pictograms used as visual stimuli in the RSVP-based ERP-BCI.

Each trial consisted of attending to a target pictogram while ignoring non-target stimuli. Participants were instructed to mentally count the number of times the target pictogram appeared in order to maintain attentional focus. A trial was defined as the selection of one pictogram from the available set, whereas a sequence consisted of a complete presentation of all pictograms in the set; therefore, each sequence included one presentation of the target stimulus. The order of pictograms within each sequence was randomized without replacement.

Each trial comprised a fixed number of stimulation sequences depending on the experimental condition, resulting in a constant trial duration of 12 s across all conditions. A 3000 ms pause preceded and followed each trial. A run consisted of eight consecutive trials (T1-T8), and each experimental condition included two runs (R1 and R2, 16 trials per condition). Before each condition, a short training run (R0) consisting of two trials was administered to familiarize participants with the stimulus presentation and timing of that configuration. These training trials used exactly the same temporal parameters as the experimental trials but were not included in the computation of classifier parameters or performance metrics. The order of conditions was counter-balanced across participants to minimize learning effects and fatigue (Figure 2 shows the experimental procedure for the particular case of the condition C2-375-16).

E. Evaluation and Statistical Analysis

Objective BCI performance was quantified using classification accuracy (%), defined as the proportion of correctly

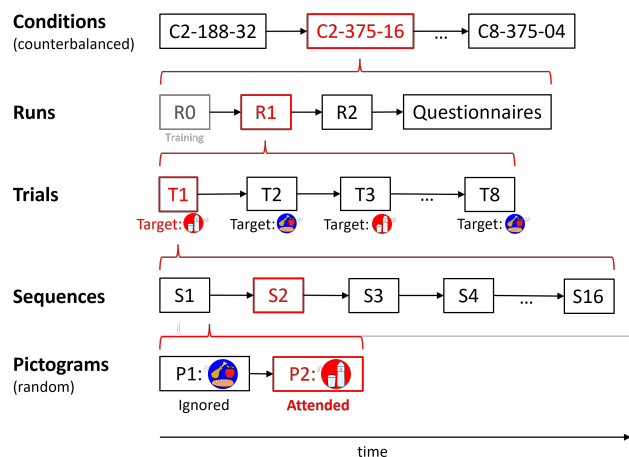


Figure 2. Experimental procedure followed by the participants.

classified target selections. Accuracy values were computed at fixed temporal intervals of 375 ms throughout the trial. This interval corresponds to the sequence duration of the fastest condition and represents the greatest common divisor of the sequence durations across all experimental configurations, thereby allowing accuracy to be tracked at equivalent temporal points across conditions. For example, the duration of a single sequence was 375 ms for C2-188-32, 1500 ms for C4-375-08, and 3000 ms for C8-375-04. However, given the number of experimental conditions and the large number of time points obtained per trial, performing a full inferential statistical analysis on the time-resolved accuracy curves would have resulted in an excessive number of multiple comparisons. For this reason, accuracy time courses were not subjected to inferential statistical testing. Instead, overall system efficiency was summarized using Pictograms Per Minute (PPM), a metric that jointly captures classification accuracy and selection speed.

PPM values were computed at each temporal update throughout the trial for every participant and experimental condition. For each participant and condition, the maximum PPM achieved over the course of the trial was then extracted and used as a summary performance measure. This procedure yields a single, representative efficiency value per participant and condition, reflecting the best achievable trade-

off between speed and accuracy under each interface configuration, and enabling direct statistical comparisons across conditions. The selection time, denoted as T , was defined as the total duration required to complete a trial, including stimulus presentation and inter-trial pauses. Specifically, T was computed as the product of the SOA, the number of stimuli per sequence, and the number of sequences, plus a 3 s pause preceding the trial and a 3 s pause following the trial. For each participant and condition, the maximum PPM achieved during the trial was computed according to (1). This approach provides a compact and interpretable performance metric while avoiding the methodological and statistical issues associated with multiple time-resolved comparisons. Although maximum PPM provides a compact summary of performance, it reflects peak performance rather than typical performance across the full trial. Therefore, it should be interpreted as an estimate of best achievable efficiency rather than sustained performance.

$$PPM = \begin{cases} \frac{(2P-1)}{T} & P > 0.5 \\ 0 & P \leq 0.5 \end{cases} \quad (1)$$

In addition, a subjective preference rating was collected at the end of each condition using a three-point Likert scale. Participants were asked to provide a single overall rating reflecting how the task was experienced, specifically how fluently they were able to attend to and mentally count the target pictogram throughout the trial. A rating of 1 indicated a frustrating and unpleasant task execution, characterized by difficulties in maintaining the count; a rating of 2 indicated a satisfactory execution despite occasional difficulties or frustration; and a rating of 3 indicated a smooth task execution, with no perceived difficulty or frustration while counting the target stimuli.

Non-parametric Friedman tests were applied for overall comparisons across conditions, followed by Wilcoxon signed-rank tests for pairwise comparisons. Effect sizes were reported using Kendall's W for Friedman tests and r for Wilcoxon tests. To control for multiple comparisons, the Benjamini–Hochberg procedure was applied to maintain the false discovery rate [17].

III. RESULTS AND DISCUSSION

This section reports and discusses the results obtained across experimental conditions. The analysis jointly considers objective performance metrics and subjective evaluations in order to examine how variations in the number of commands, SOA, and number of stimulation sequences influence both system efficiency and perceived task execution in the RSVP-based ERP-BCI.

A. Performance

The classification accuracy over time for each condition is shown in Figure 3. Classification accuracy evaluated at the end of each trial—after completion of all stimulation

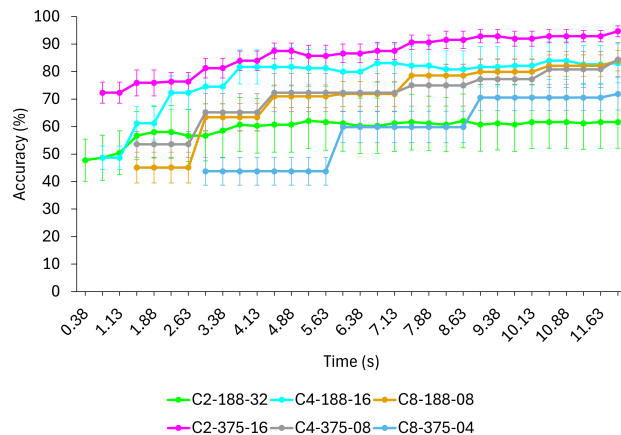


Figure 3. Classification accuracy (% , mean \pm standard error) as a function of elapsed time for each experimental condition in the RSVP-based ERP-BCI.

sequences and a fixed selection time of 12 s—varied substantially across interface configurations. Under this final-trial criterion, mean accuracies ranged from 61.61% for C2-188-32 to 94.64% for C2-375-16, with intermediate values observed for C4-188-16 (83.04%), C8-188-08 (83.94%), C4-375-08 (84.38%), and C8-375-04 (71.88%). These results indicate that the tested interface configurations did not perform equivalently in enabling reliable identification of the user's intended pictogram.

To capture overall interaction efficiency, performance was further quantified using the maximum PPM, which integrates speed and classification accuracy. A significant effect of interface configuration on maximum PPM was observed ($p < 0.001$, Kendall's $W = 0.409$), indicating a moderate-to-strong effect size. As shown in Figure 4, condition C2-375-16 yielded significantly higher maximum PPM values than configurations combining larger command sets and/or shorter SOAs, including C4-375-08 ($p = 0.009$, $r = 0.480$), C8-188-08 ($p = 0.005$, $r = 0.639$), and C8-375-04 ($p = 0.008$, $r = 0.765$). Similarly, C4-188-16 outperformed both eight-command configurations, namely C8-188-08 ($p = 0.044$, $r = 0.343$) and C8-375-04 ($p = 0.010$, $r = 0.587$). Among the eight-command conditions, C8-375-04 showed significantly lower performance than both C4-375-08 ($p = 0.019$, $r = 0.417$) and C8-188-08 ($p = 0.010$, $r = 0.430$).

Taken together, accuracy evolution and maximum PPM results do not point to a single parameter as the dominant determinant of performance. Instead, performance emerges from a trade-off between command set size, temporal configuration, and number of stimulation sequences. Notably, the two best-performing conditions (C4-188-16 and C2-375-16) differ markedly in both SOA and number of commands, yet share a similar TTI of approximately 750 ms. Conditions with intermediate TTIs (C4-375-08 and C8-188-

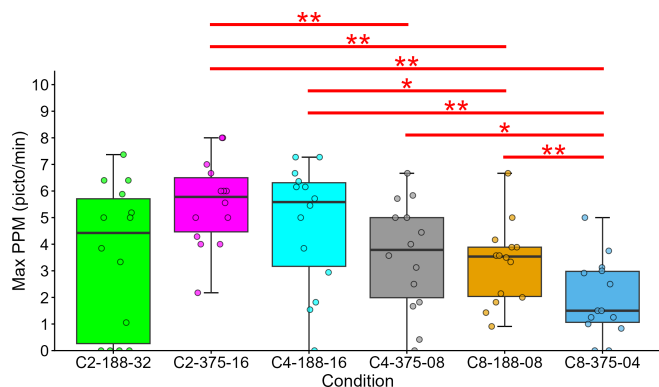


Figure 4. Distribution of the maximum pictograms per minute (PPM) across experimental conditions in the RSVP-based ERP-BCI. Red lines indicate statistically significant pairwise differences (* $p < 0.05$, ** $p < 0.01$).

08, around 1500 ms) yielded intermediate performance. In contrast, configurations with extreme TTIs were associated with less stable outcomes. In particular, although C2-188-32 did not yield the lowest median performance, it showed the highest inter-individual variability, with several participants achieving zero maximum PPM values, indicating unreliable control under excessively rapid stimulation (TTI ≈ 375 ms). Similarly, overly slow stimulation combined with a small number of sequences (C8-375-04, TTI ≈ 3000 ms) resulted in reduced overall performance.

Importantly, as indicated, C2-188-32 included cases in which maximum PPM values were equal to zero. In these cases, the classifier could not be reliably computed by the *P300Classifier* tool, suggesting that the combination of very short TTI and high stimulation rate may exceed both user attentional capacity and the robustness of the classification approach. While this effect may partly reflect user-related difficulties in task execution, it also motivates future work exploring more sophisticated signal processing and classification methods for extreme temporal configurations.

Overall, these findings are consistent with previous RSVP-based BCI studies highlighting the critical role of target probability and temporal spacing in ERP detectability [5]–[7]. The present results further confirm that RSVP-BCI performance arises from the interaction between temporal and structural design choices rather than from any single parameter in isolation.

B. Perceived Task Execution

Subjective evaluations of task execution were analyzed to complement the objective performance results. After each condition, participants rated the perceived fluency and difficulty of the counting task using a three-point scale, reflecting how easily and comfortably they were able to carry out the required attentional task. The obtained results of the subjective evaluations are shown in Figure 5.

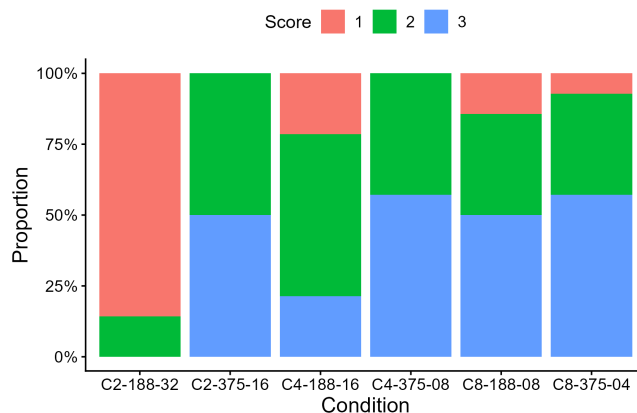


Figure 5. Percentage of users selecting each rating for perceived task execution across experimental conditions in the RSVP-based ERP-BCI (1: *frustrating and unpleasant task execution*; 2: *satisfactory task execution despite some difficulty or frustration*; 3: *smooth task execution with no frustration or perceived difficulty*).

A significant effect of experimental condition on perceived task execution was observed ($p < 0.001$, Kendall's $W = 0.472$). Post-hoc analyses showed that condition C2-188-32 was rated significantly worse than all other configurations, including C2-375-16 ($p = 0.006$, $r = 0.845$), C4-188-16 ($p = 0.021$, $r = 0.641$), C4-375-08 ($p = 0.006$, $r = 0.854$), C8-188-08 ($p = 0.007$, $r = 0.727$), and C8-375-04 ($p = 0.007$, $r = 0.795$). This result indicates that the combination of a minimal command set with very rapid stimulation and a short TTI led to a significantly more difficult and frustrating task execution.

Notably, C2-188-32 was also the condition in which several participants failed to achieve adequate BCI control. In these cases, classification accuracy did not exceed chance level (50%), resulting in maximum PPM values equal to zero according to the adopted performance criterion. The co-occurrence of poor subjective ratings and unstable objective performance suggests that excessively rapid stimulation can exceed users' attentional processing capabilities, thereby compromising both task execution and system reliability, as previously noted in RSVP-based BCI paradigms [7][8].

In contrast, configurations with longer SOAs and reduced or intermediate command set sizes (e.g., C2-375-16, C4-375-08, and C8-375-04) were more frequently rated as easier to perform the target pictogram counting task. These conditions appear to support more stable task execution, even when objective performance did not reach its maximum, indicating that perceived ease of task execution does not necessarily scale linearly with accuracy or information throughput.

IV. CONCLUSION AND FUTURE WORK

This study examined how key interface parameters shape the performance and task execution of an RSVP-based ERP-BCI, with a particular emphasis on accessibility-oriented design. By jointly manipulating command set size (2, 4 or 8),

SOA, and number of stimulation sequences while keeping total selection time constant, the results provide empirical evidence of the trade-offs governing RSVP-BCI interaction.

Among the tested configurations, C2-375-16 and C4-188-16 achieved the most favorable balance between performance and feasibility of task execution. Although these conditions differ in both command set size (2 and 4 stimuli) and SOA (375 ms and 187.5 ms), they share a comparable TTI (approximately 750 ms), suggesting that temporal spacing between successive target presentations plays a critical role in enabling reliable control.

Overall, the findings show that RSVP-BCI performance does not depend on any single parameter in isolation, but rather emerges from the interaction between structural and temporal design choices. From an accessibility perspective, this supports conservative interface designs that prioritize robustness and manageable task demands over maximal expressiveness. In addition, it is important to acknowledge the well-known gap between offline evaluation and real-time (online) BCI performance, where factors such as user adaptation, feedback, and non-stationarities may affect system reliability. Future work will explore adaptive parameter optimization and multimodal ERP-based BCIs combining visual RSVP with auditory and/or tactile stimulation, with the aim of improving robustness and usability for users with the most severe motor impairments, as well as validation in online and clinical settings.

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