

Fast-Calibrated c-VEP BCI with Comfort-Optimized Stimulation for Robust Control on Screen and Immersive VR Using Semi-Dry EEG

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ABSTRACT: Code-modulated visual evoked potentials (c-VEPs) are fast and reliable control signals for reactive brain-computer interfaces (rBCIs), but real-world use is often constrained by visually intrusive flicker and the need for wet EEG. We present a usability-oriented c-VEP rBCI that combines visually comfortable, low-salience textured stimulation, low-rate coding with asynchronous evidence accumulation to allow flexible decision times, and a semi-dry EEG setup to improve wearability while maintaining signal quality. We evaluated the system in two settings: a PC condition consisting of an 11-class keypad typing task on a standard computer screen, and a VR condition consisting of a simple shell game. Despite using only 33 s of calibration data, we achieved 100% accuracy in both conditions. Mean decoding time was approximately 4.3 s in the PC condition and 5.4 s in the VR condition, consistent with additional head motion and rendering constraints in VR. Participants also reported high visual comfort, low visual fatigue, and minimal peripheral distraction from the flicker, supporting the usability of the proposed stimulation. Overall, these results demonstrate fast-calibrated, robust, and visually comfortable c-VEP control that generalizes from conventional displays to immersive VR with a practical semi-dry EEG configuration.

INTRODUCTION

Code-modulated Visual Evoked Potentials (c-VEPs) are attracting increasing interest in the reactive brain-computer interface (rBCI) community because pseudo-random stimulation supports rapid code identification and can substantially reduce calibration compared with conventional steady-state visual evoked potentials (SSVEP) approaches [1, 2]. Despite this potential, most c-VEP rBCIs remain largely confined to controlled laboratory settings. Translation to practical use is still limited by user-centered constraints, notably dependence on wet EEG instrumentation and visually salient flicker that can induce foveal discomfort and distract in peripheral vision [3]. To improve practicality while preserving decoding reliability, we build on the Burst-code c-VEP paradigm,

which concentrates stimulation into brief, aperiodic flashes delivered at a low rate (approximately 3 flashes per second). By time-locking stimulus energy into brief two-frame flashes and spacing bursts sufficiently apart (around 300 ms with added jitter), burst stimulation yields roughly double the evoked-response amplitude compared with conventional faster m-sequence-based stimulation [4]. This provides an important step toward higher signal-to-noise ratio (SNR) outside lab-grade conditions. Burst coding also simplifies calibration to a binary discrimination (flash “1” vs. no-flash “0”) and dramatically reduces calibration time (e.g., 40 s in [5]). Online, decoding correlates a stream of flash probabilities with predefined Burst codes and commits only when accumulated evidence becomes consistent, enabling flexible (asynchronous) decision times while remaining robust to transient errors.

In parallel, to reduce visual load and peripheral distraction while amplifying neural responses, we adopted and adapted subtle, near-imperceptible oriented texture stimulation originally introduced in [6], in place of conventional high-contrast flicker. We hereafter refer to these textures as Stimuli for Augmented Response (StAR). StAR is designed to recruit early visual pathways, from contrast-sensitive retinal ganglion cells to orientation-selective cortical populations, while remaining perceptually unobtrusive. In our prior work, StAR produced substantially larger evoked responses (up to 3×) while remaining perceptually unobtrusive [3]. By combining stronger cortical drive with lower visual salience, textured stimulation supports accurate single-trial detection and minimizes distraction when multiple targets are presented simultaneously. When paired with Burst coding, this approach achieved high performance with low channel-count EEG using eight dry electrodes, reaching 93.6% accuracy in a five-class task and 93.3% mean accuracy in an 11-class keypad task [5]. We refer to this combination of textured stimulation and Burst coding as the StAR-Burst paradigm. Participants also reported improved comfort, describing the textured stimulation as far less noticeable in peripheral vision than conventional high-contrast flicker [3].

A complementary route to further improve SNR and ro-

bustness to motion is the use of semi-dry electrodes. While dry systems can shorten setup time and reduce preparation burden, they may compromise comfort, increase sensitivity to motion-related artifacts, and yield less stable signal quality in some users. Semi-dry EEG electrodes—typically based on saline- or hydrogel-assisted contact—offer a practical compromise by preserving rapid application while achieving electrode–skin impedances and signal quality closer to wet EEG, with reduced cleanup and improved wearability [7–9].

Beyond electrode and stimulus usability, there is growing interest in integrating BCIs into immersive virtual environments. Several studies report that BCI performance in VR can be comparable to, or sometimes better than, conventional screen-based setups across multiple paradigms, including P300 [10, 11], SSVEP [12, 13] and motor imagery [14]. In contrast, c-VEP has received comparatively little attention in VR despite its relevance for reactive interaction. To date, the closest demonstration is a mixed-reality c-VEP speller evaluated in an HMD under largely static viewing conditions, where a 2D interface is overlaid on a controlled passthrough background and participants remain seated to limit motion artifacts [15]. This work constitutes an important first step toward HMD-based c-VEP interaction by addressing display optics and timing constraints.

In the present study, we extend this emerging line of work by considering a more embodied VR scenario. Specifically, our stimuli are rendered as an overlay onto 3D objects and remain stable in the participant’s egocentric view (i.e., updated with head motion), while the task itself requires head movements to select targets. This setting introduces additional challenges for c-VEP decoding, including viewpoint changes, and motion-induced artifacts. Moreover, our prior evaluations of the StAR–Burst paradigm were conducted in largely static, screen-based settings with limited body motion [3]. Here, we therefore test whether fast-calibrated c-VEP decoding with comfort-optimized stimulation can remain reliable under the constraints of immersive interaction.

The objectives of this study are therefore twofold: (i) to replicate the 11-class keypad StAR–Burst benchmark in a controlled setting using semi-dry EEG to quantify potential gains in signal quality and accuracy; and (ii) to implement and evaluate the same decoding principles in a simple VR “shell game” task, explicitly testing robustness under realistic head movements while maintaining usability and visual comfort, again using semi-dry EEG.

MATERIAL AND METHOD

Participants: The study was conducted with 12 healthy participants (2 women, mean age = 32 ± 8 years), primarily staff and students at ISAE-Supaero. The research received ethical approval from the University of Toulouse (CER approval number 2025_1012) and complied with the Declaration of Helsinki. Participants provided written informed consent prior to the experiment. Exclusion

criteria included neurological disorders or psychoactive medication use at the time of the study. All participants had normal or corrected-to-normal vision.

Common Setup: For both the PC (Keypad) and VR (shell-game) tasks, each target was assigned a unique Burst code [4]. Codes consisted of binary sequences with low mutual correlation, and were additionally constrained to limit ERP overlap by enforcing a minimum inter-flash interval of 300 ms plus a jitter between consecutive “1” events within a code.

Instead of conventional high-contrast flicker (e.g., alternating colors) or pattern-reversal checkerboards, which can induce visual discomfort, we used texture-based stimuli composed of small, randomly oriented Ricker wavelet patches (see [3]). Stimuli were presented with a moderate modulation depth of 70%, reducing luminance fluctuations to improve visual comfort while preserving classification performance [4, 16]. This design builds on prior work showing that such textured stimulation can maintain high accuracy—including with low channel-count, non-wet EEG setups—while improving subjective comfort [3]. EEG was recorded using an 8-channel semi-dry system (MBrainTrain) at 500 Hz. Electrodes were placed over occipital and parieto-occipital regions (PO7, O1, Oz, O2, PO8, PO3, POz, PO4) to capture visually evoked potentials (VEPs).

Keypad PC-based BCI:

The PC BCI interface consisted of an 11-class keypad inspired by traditional mobile-phone keypad layouts, with selectable keys for digits 0–9 and the ‘#’ character. Participants were instructed to type predefined four-character sequences by overtly attending to the desired key. The current target sequence was displayed in the bottom-left corner of the screen. After each selection, the chosen key was highlighted in green if correct or red if incorrect, providing immediate performance feedback (click here to see the video showcasing the PC condition). Stimuli were presented on a 24.5” LCD monitor (Iiyama Gold Phoenix G-Master GB2590HSU-B1; 1920×1080; 400cd/m²) at a refresh rate of 60 Hz. The interface also provided *pre-decision visual feedback*: the currently leading candidate was progressively enlarged as the decoder’s confidence increased. This cue externalized the evolving decision state before commitment and, consistent with our prior findings, is expected to improve the user’s perceived sense of control [5].

Shell-game VR BCI:

The VR task was implemented in Unreal Engine¹ using Blueprints to control game logic, animate objects, and transmit flash onsets to the decoding pipeline via LabStreamingLayer (LSL). To reduce unnecessary stimulation and improve ecological validity, stimulation was automatically suspended for objects outside the participant’s current field of view (i.e., outside the view frustum or fully occluded). Although not essential for the present three-target task, this mechanism is intended to support future scenarios with more potential targets than avail-

¹<https://www.unrealengine.com>

able codes by temporarily deactivating hidden items and reallocating their codes to visible targets.

Participants performed a simplified shell game. Three cubes (“cups”) were aligned horizontally in front of the participant, and a sphere (the “ball”) was briefly revealed before being hidden under one cube. The three cubes then followed randomized shuffling trajectories and stopped. During the selection phase, the textured stimulus was rendered as a dynamic material mapped onto each moving cube (i.e., the texture remained locked to the object as the viewpoint changed with head motion) and flashed according to the cube’s assigned Burst code. Once the BCI reached a decision, the ball location was revealed and the selected cube turned green if correct and red otherwise (click here to see the video showcasing the VR condition).

The task was performed using a Meta Quest 3 headset fitted with the Elite head strap. This configuration ensured stable headset placement while maintaining clearance over occipital and parieto-occipital electrodes to limit pressure on the sensors and preserve comfort. The scene geometry was set such that the lateral cubes required head rotation to inspect, ensuring that participants actively moved their head to track targets during the task. *Experimental protocol:* Figure 1 shows a graphical representation of the experimental protocol. Participants were seated comfortably and provided written informed consent prior to the experiment. Then the EEG was set up on their scalp and signal was checked.

For the PC-based keypad experiment, each session began with a passive calibration phase used to train the classification pipeline to detect VEP responses to flash events. Participants fixated a central circle while Burst flickers were presented in five blocks, each comprising three code presentations (2.2 s per presentation). Including cueing and rest periods, calibration lasted 40 s in total and yielded 33 s of usable calibration data. Participants then completed an online typing task using the BCI keypad interface that consists of two sets of five 4-number sequences with a pause between the two sets (a total of 40 targets).

After this experimental condition, participants provided subjective ratings using three 10-point visual semantic differential scales assessing peripheral distraction, visual comfort, and visual fatigue. Furthermore, the participants were also asked to provide rating for a CVS questionnaire, to make sure that the task does not induce adverse effects on participants’ vision.

Participants next performed the VR experiment. It starts with a calibration phase where participants had to focus on a single cube on which the stimuli texture is overlaid and flickered with a random burst code. The 43 s calibration phase consists of 5 blocks composed of 3 repetitions of a 2.2 s code and a 2 s pause after, generating 33 s of usable calibration data. Then, participants completed 10 trials of the “shell game”, trying to guess under which cube the ball was hidden, by focusing on the cube they believed the ball was under.

Finally, as for the previous condition, participants were required to provide the subjective rating to the same questionnaires, visual comfort and CVS-Q.

Decoding Pipeline Implementation:

The online BCI decoding pipeline for the PC and VR conditions were the same and developed in *Timeflux* [17], an open-source Python framework for real-time acquisition, processing, and classification of time-series data. The user interface was implemented as a web application (HTML/CSS/JavaScript) running in a standard browser and connected to the *Timeflux* processing graph for the keypad and in Unreal Engine for the VR. Signal processing and classification were implemented in Python using *imblearn-learn* and *pyriemann*. The overall software architecture follows our previous implementation [3], with minor adaptations to support the present PC and VR configurations.

EEG streams were linked to *Timeflux* via Lab-StreamingLayer (LSL), then preprocessed using an IIR band-pass filter (1–25 Hz) and a band-stop filter (48–52 Hz) to attenuate slow drifts and high-frequency noise. The filtered signal was segmented into 300 ms epochs, time-locked to the display refresh cycle. Epoch timestamps were additionally shifted to compensate for an estimated 80 ms end-to-end latency in stimulus delivery and acquisition.

For each epoch, spatial information was summarized by estimating a covariance matrix across channels [18]. Prior to covariance estimation, stimulus-locked activity was enhanced and dimensionality reduced using xDAWN spatial filtering [19], retaining four spatial filters. Feature extraction was implemented with *pyriemann* (*XdawnCovariances*), which computes Riemannian “super-epochs” by concatenating each spatially filtered epoch with the corresponding average evoked response. The resulting covariance matrices were mapped to the tangent space of the Riemannian manifold using the mean covariance as the reference point. Tangent-space features were then downsampled and classified with a linear discriminant analysis (LDA) model, yielding an epoch-wise probability that a burst-evoked response was present. Because the classifier operates at ~60 Hz, a single evoked response can be detected over multiple consecutive frames. To prevent duplicate detections, probabilities were binarized (threshold = 0.5) and a truncation rule was applied: for any run of consecutive detections, only the first frame was retained.

Calibration was performed to train a binary classifier to discriminate stimulus-locked epochs elicited by a flash (1”) versus a no-flash event (0”). The calibration session lasted 43 s and yielded 33 s of usable EEG after excluding non-stationary segments. EEG was segmented into stimulus-locked epochs; epochs following flash onsets were labeled as class 1, whereas epochs following no-flash events were labeled as class 0. During online operation, the trained classifier produced, for each incoming epoch, a probability of class 1 (flash) versus class 0 (no-flash). Multi-class selection was then achieved by

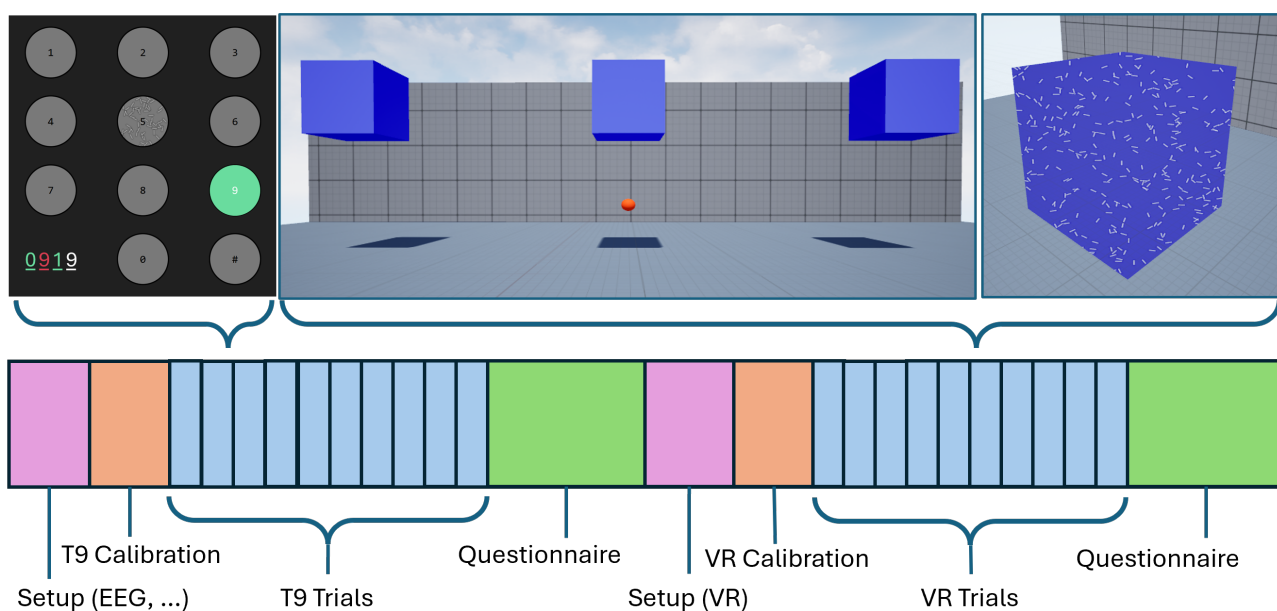


Figure 1: The top row shows the visual setup for each condition: the keypad experiment on the left, with the target sequence displayed in the lower-left corner; the VR experiment in the middle, featuring the three cubes and the ball; and, on the right, an example of a cube overlaid with our textured stimuli. Videos demonstrating the BCI in the PC condition are available here: [PC condition video](#), and in the VR condition here: [VR condition video](#).

code reconstruction: the recent stream of flash probabilities was continuously matched to each target's predefined Burst code. At each video frame, we computed the correlation between the probability stream and each class-specific code, and selected the best-matching candidate. To convert these continuously updated correlations into a robust decision with flexible timing, we used a consecutive-winner strategy with a momentum-decay dynamic [20]. The leading candidate accumulated momentum with an increment that increased as it remained in the lead, while all other candidates decayed by the same increment (bounded by a minimum floor). A decision was emitted when any class exceeded a predefined momentum threshold (see [5, 20] for implementation details).

BCI Metrics: Objective metrics included typing accuracy and decoding time. After each typing task, participants completed a short subjective questionnaire composed of three 10-point semantic differential scales, yielding two questionnaires per participant. The scales assessed perceived visual comfort and visual fatigue, as well as peripheral transparency (i.e., how distractive neighbouring flickers were in peripheral vision).

RESULTS

In both environments, online control reached 100% accuracy. In the screen-based keypad task, mean decoding time was 4.4 s (SD = 2.3 s), whereas in the VR shell-game task it increased to 5.4 s (SD = 0.9 s; Fig. 3). A one-tailed paired t-test indicated a significant increase in decoding time in VR compared with the PC condition ($t = -1.334$, $p = 0.05$, Cohen's $d = -0.536$). Figure 2 shows the ERPs evoked by the flashes during the calibration phase.

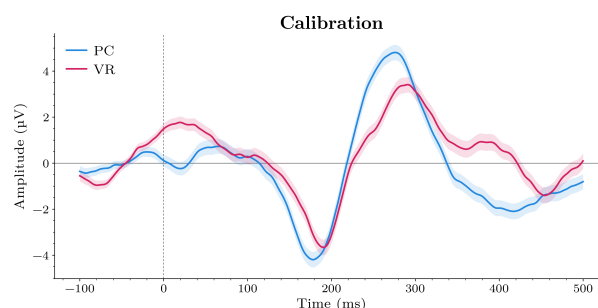


Figure 2: Mean evoked responses to flashes during calibration in the PC (blue) and VR (red) conditions. Shaded regions indicate the standard error.

Subjective ratings remained consistently favorable across conditions. On the PC task, participants reported high comfort (8.2/10, SD = 2.0), good peripheral transparency (7.1/10, SD = 2.5), and low mental fatigue (7.2/10, SD = 3.5). In VR, ratings were slightly lower but comparable (comfort 7.8/10, SD = 1.5; transparency 6.5/10, SD = 2.4; fatigue 6.8/10, SD = 3.4). Paired comparisons did not reveal significant differences between conditions for comfort ($t = 0.95$, $p = 0.18$, $d = 0.27$), mental fatigue ($t = 0.80$, $p = 0.22$, $d = 0.23$), or peripheral distraction ($t = 1.64$, $p = 0.076$, $d = 0.53$).

DISCUSSION

The present study had two objectives: first, to replicate our screen-based 11-class keypad c-VEP benchmark with a *semi-dry* EEG setup in order to quantify potential gains in robustness and performance; and second, to assess whether the same decoding principles generalize to an *immersive VR* task involving embodied interaction (shell

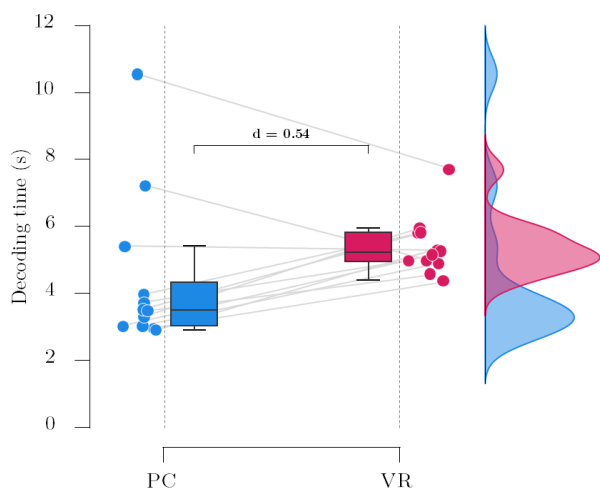


Figure 3: Mean decoding time in s for the PC (blue) and VR (red) experiment.

game) and concomitant motion-related artifacts.

Objective performance and impact of semi-dry EEG: Across both environments, online control reached 100% accuracy after only 33s of calibration data, demonstrating that reliable c-VEP control is achievable with a practical, fast-to-deploy semi-dry EEG configuration. In the screen-based keypad task, this performance exceeds our previous results obtained with a closely matched paradigm using *dry* electrodes (93.3% mean accuracy in [5]). A likely contributor is the higher and more stable signal quality provided by semi-dry contact. Specifically, semi-dry recordings showed larger stimulus-locked deflections (approximately $-4.2\mu\text{V}$ followed by $+4.8\mu\text{V}$) compared with the dry system (about $-3\mu\text{V}$ followed by $+1\mu\text{V}$ in [3]), increasing the discriminability of the elementary flash/no-flash (0/1) responses. This improvement is particularly consequential for the present decoding strategy: because class decisions are reconstructed by matching the inferred 0/1 stream to Burst codes, even modest gains in single-epoch 0/1 classification can propagate into higher reliability in multi-class code identification.

In the immersive VR shell-game task, the system likewise achieved 100% accuracy, supporting the feasibility of visually comfortable c-VEP control in an HMD. However, mean decoding time were statistically increased relative to the screen-based keypad task (5.4 s vs. 4.3 s), despite the VR task involving only three possible targets. This slower decision-making suggests that the effective evidence accumulation rate was reduced in VR. Two factors likely contributed. First, the amplitude of the evoked responses appeared smaller in VR than on the monitor (see figure 2), which reduces the reliability of the 0/1 stream and therefore requires longer accumulation to reach decision thresholds. Second, the headset may have introduced additional constraints on EEG acquisition: pressure from the HMD straps and repeated left–right head movements during target tracking can perturb electrode contact and increase motion-related artifacts affecting on-

line Burst code reconstruction. These integration challenges are consistent with broader observations in VR–EEG systems, where mechanical constraints and motion can impact signal quality and electrode placement [21]. Future work should therefore prioritize tighter mechanical integration of the HMD and EEG (e.g., sensor placement and cabling compatible with the headset strap geometry), as well as motion-aware artifact mitigation during decoding.

Subjective comfort, transparency, and VR-specific factors:

Subjective ratings were overall consistent with our earlier reports that textured, low-salience stimulation improves perceived comfort and reduces peripheral distraction compared with conventional high-contrast flicker [3, 5]. Although mean ratings tended to be slightly lower in VR than on the monitor, paired statistical comparisons did not reveal significant differences between conditions for comfort, mental fatigue, or peripheral transparency. This pattern suggests that the proposed stimulation remains well tolerated when transferred from a standard display to an HMD. At the same time, the small numerical trend toward lower ratings in VR remains plausible given that near-eye displays can impose additional oculomotor and visual demands, which have been associated with digital eye strain and discomfort in VR [22, 23]. Together, these findings indicate that comfort-optimized stimulation generalizes well to immersive VR, while leaving room for further refinements of rendering parameters (e.g., luminance, contrast, texture amplitude depth) and headset fit for longer sessions.

Limitations and future directions: This study has several limitations. First, the sample size was modest; we are currently extending recruitment to confirm the present findings in a larger cohort. Second, although online accuracy was perfect in both conditions, decoding in VR was slower than on the monitor, indicating that responsiveness can still be improved. Promising directions include adaptive decision thresholds driven by real-time signal quality, explicit monitoring and attenuation of motion/EMG artifacts, and improved mechanical integration of semi-dry electrodes with the HMD to minimize pressure-induced contact changes and motion-related impedance fluctuations [21]. Finally, our evidence-accumulation decoder—which correlates a stream of flash probabilities with predefined Burst codes and commits only after sufficient consistent evidence has accumulated—likely contributes to the high accuracy observed here and may also enable *idle-state gating*. When the user is not attending to any target, the incoming evidence should be dominated by “0”-like responses, yielding weak code correlations that remain below the decision threshold. However, this capability must be explicitly demonstrated and quantified. A key next step is therefore to introduce non-control (rest) periods and measure false activation rates, time-to-activation, and overall stability under realistic use conditions.

CONCLUSION

We demonstrated a fast-calibrated (33 s), visually comfortable c-VEP rBCI that achieved 100% online accuracy on a screen-based 11-class keypad task and in an immersive VR shell-game task using a practical *semi-dry* EEG system. Compared with our earlier dry-electrode implementation, semi-dry acquisition likely increased evoked-response amplitude, yielding more reliable code reconstruction leading to 100% accuracy. While VR control remained perfectly accurate, decisions were slower, consistent with motion/headset-induced constraints. Overall, these findings support the feasibility of moving comfort-optimized c-VEP interaction beyond laboratory conditions and into immersive VR, while highlighting the importance of improved EEG-HMD integration for faster, more robust embodied interaction.

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