An event-related potential BCI speller using a wearable, single-channel EEG headset with electrodes on the forehead

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Abstract. We evaluate the feasibility of controlling an event-related potential (ERP) matrix speller using a comercially available, wearable, EEG headset with single-channel electrodes placed on the forehead in a headband configuration. Despite the suboptimal recording location for detecting typical visual ERP components, we conducted experiments with 11 right-handed healthy. Time-domain analysis revealed significant differences between attended and non-attended conditions in 6 participants, as determined by cluster-based permutation testing. A separate decoding analysis using linear discriminant analysis identified above-chance single-trial accuracy in a different subset of 6 participants. The highest decoding accuracy reached 52.5% with 12 repetitions, below the 80% usability threshold. These results show that limited ERP-based communication is possible using forehead single-channel EEG, although current performance is insufficient for practical use. We outline signal processing and interface improvements that could enhance the utility of low-cost, wearable ERP-based BCIs.

Keywords: BCI speller · Wearable BCI · Single-channel EEG · Event-related potentials

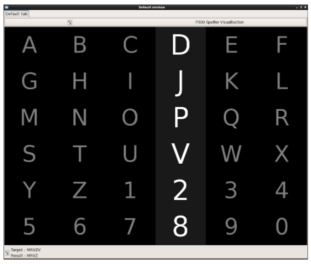
1 Introduction

Brain-computer interfaces (BCIs) enable direct communication between the brain and external devices. BCIs leverage electroencephalography (EEG) signals to interpret neural activity and translate it into actionable outputs [8]. These interfaces are relevant in healthcare, serving as assistive technology for individuals with severe motor disabilities to communicate and interact with their environment. Originally proposed by Farwell and Donchin [4], the event-related potential (ERP) matrix speller (for review, see [11]) relies on visual stimulation that elicits (among others) the P300 ERP component – a positive-going wave that occurs approximately 300 milliseconds after the onset of an attended stimulus. This speller paradigm presents a matrix of characters that are intensified row- and column-wise in an alternating manner, allowing users to select characters by focusing on one of them. The ERP speller has been extensively studied for its potential to enable communication in individuals with ALS, locked-in syndrome, and other neuromuscular disorders and provides an alternative to another commonly used BCI paradigm: steady-state visually evoked potentials (SSVEP) [3].

To adopt BCI speller technology in clinical and at-home applications, *wearable* EEG systems [1] are currently favored due to their practicality and portability. The push for ubiquitous wearable EEG systems in healthcare has led to the development of *single-channel* EEG systems [6]. These systems are affordable, easy to set up, comfortable, and can be designed for aesthetic appeal. However, their ability to record neural EEG signals is mainly limited to analyses of brain rhythms, such as monitoring sleep stages, emotions, stress, or concentration, or for clinical diagnostics. Although there are some examples of SSVEP-based spellers using single-channel EEG [9], it remains unclear whether these devices can support typical ERP-based BCI applications, such as the well-known P300 matrix speller. Most single-channel wearable systems suffer from several limitations: 1. electrode placement on the forehead is suboptimal for detecting ERP components originating from occipital, parietal, and central regions; 2. lateral bipolar referencing suppresses the laterally symmetric components of the evoked response; 3. spatial filtering cannot be applied for decoding; 4. low-cost wireless devices often lack consistent and high sampling rates with low jitter, which are required for accurate time- and phase-locked analyses and decoding.

This study evaluates whether these limitations can be overcome by testing the feasibility of using a single-channel EEG device to control a visual ERP matrix speller. By exploring the capabilities and limitations of such devices in BCI applications, we aim to support the development of accessible, affordable and user-friendly communication tools for individuals with severe motor impairments.

(a) The BrainLink Pro single-channel EEG headset.



(b) The OpenVibe ERP matrix BCI stimulation interface.

Fig. 1: Recording and stimulation setup.

2 Materials and Methods

2.1 Stimulation and signal recording

To evaluate the feasibility of a single-channel ERP matrix speller, we recorded a dataset using the BrainLink Pro (Macrotellect, China) device shown in fig. 1a. This single-channel system uses bipolar referencing and is positioned on the forehead, with recording electrodes at Fp1 and Fp2 and a ground electrode on the left earlobe. The headset connects via Bluetooth 4.0 and operates according to the producer at a sample rate of 512 Hz.z. Since precise timing is critical, we empirically established the effective sampling rate as variable with a mean of 513.84 Hz and developed an application to stream the data to LabStreamingLayer (LSL) [5]. The code is available online[3].

Using the LSL connection, BCI stimulation and signal acquisition were performed with the P300 matrix speller example[4] from the OpenVibe software (v3.6.0) [12]. The stimulation interface is shown in fig. 1b. Each session involved 40 character selections, each prompted by flashing all rows and columns in pseudorandom order, 12 times per selection, with an inter-stimulus interval of 0.3 s. We recorded data from 11 neurologically healthy participants (5 male, 6 female), all right-handed, with a mean laterality index of 92.71±11.70 as determined by the Edinburgh Handedness Inventory [10]. Ages ranged from 22 to 31 (mean 26.27±2.73). All participants provided informed consent under a protocol prior approved by the Ethics Commission of the University Hospitals Leuven (S62547).

2.2 Signal preprocessing and decoding

EEG preprocessing was implemented using MNE-Python (v1.7.1). The code is available online[5]. Signals were bandpass filtered between 1–16 Hz using a fourth-order Butterworth filter. To reduce eye and head movement artifacts, we applied winsorization by clipping the lower and upper 5% of the distribution. For time-domain analysis, the signal was segmented into epochs from 0.2 s before to 1.5 s after stimulus onset for time-domain analysis, and from 0.2 s to 1.2 s post-stimulus for decoding. These epochs were downsampled to 32 Hz through decimation. For the time-domain analyses, baseline correction was performed using the 0.2 s pre-stimulus interval.

Target decoding was performed offline using a linear discriminant analysis classifier with Toeplitz-shrinkage covariance regularization [13,14]. We used 10-fold cross-validation, training on 36 and testing on 4 selections per fold. For each number of repetitions, decoding accuracy was calculated based on target selections made by the row- and column-wise maximum of classification scores of averaged test trials per target over the corresponding number of repetitions.

3 Results

3.1 Time domain analysis

Figure 2 shows the per-subject contrasts between attended and non-attended ERPs. Significant components were identified via temporal cluster-based permutation testing with 1000 permutations, cluster-forming threshold $\alpha = 0.001$, and Bonferroni-corrected acceptance threshold $\alpha = 0.05$. Significant clusters were found in 6 out of 11 subjects. No consistent pattern was observed across subjects, though subjects A09 and A10 exhibited a large negative component between 0.8–1.0 s, visible in the grand average.

[3] `https://github.com/arnevdk/brainlink-lsl`
[4] `https://openvibe.inria.fr/openvibe-p300-speller/`
[5] `https://github.com/arnevdk/brainlink-p300`

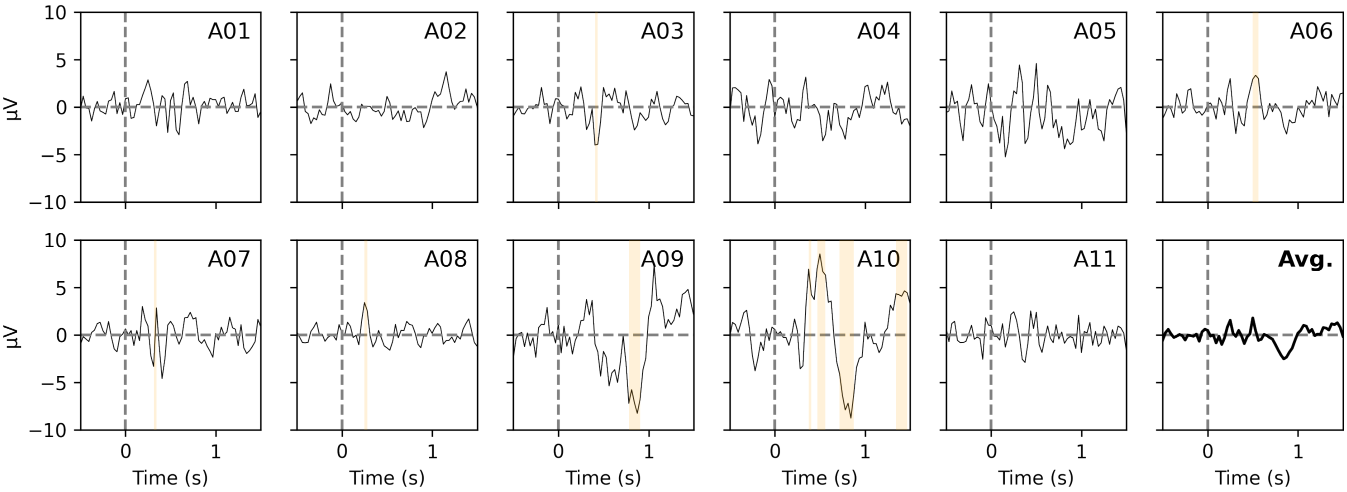


Fig. 2: Event-related potential contrasts with significant components identified by cluster-based permutation testing and grand-average contrast.

3.2 Decoding analysis

Table A.1 reports cross-validated decoding accuracy. First, single-trial accuracy was tested against the chance level of $1/36 = 2.8\%$ using a one-sided Wilcoxon signed-rank test ($\alpha = 0.05$) with Benjamini-Hochberg correction. Six out of eleven subjects significantly exceeded chance. Next, decoding accuracy was evaluated across varying repetition counts. Except for A02 and A04, accuracy increased with more repetitions. Subject A10 reached the highest accuracy of 52.5% at 12 repetitions, below the 80% usability threshold [2].

4 Conclusions

In this study, a subset of participants achieved distinguishable evoked responses in the time domain and decoding results using a single-channel ERP speller. However, performance remains below practical usability, with all subjects failing to exceed the 80% accuracy threshold and requiring substantial training data. This is consistent with hardware limitations discussed above. Other possibly confounding factors include large eye and muscle artifacts, which could be mitigated using single-channel artifact rejection methods such as Singular Spectrum Analysis combined with Independent Component Analysis or others [7]. We also cannot rule out that some participants may have synchronized movements or blinks with the attended stimulation.

Despite these limitations, our results suggest pathways to improvement in single-channel ERP speller performance, which should later be validated on-line and with larger sample sizes. Language modeling and interface design may enhance usability. Decoding could also benefit from embedding the data using time-frequency transforms, Empirical Mode Decomposition, Singular Spectrum Analysis, or time-delay embeddings to compensate for the lack of spatial resolution. Future work should investigate the expression of paradigm-related ERPs recorded with bipolar forehead setups and their variability across subjects, and investigate alternative stimulation paradigms that enhance the signal-to-noise ratio. If performance can be improved, single-channel wearable BCI headsets may support broader adoption of ERP-based communication tools.

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# Repetitions	1	2	3	4	5	6	7	8	9	10	11	12	Single trial
Subject													
A01	7.5	12.5	10.0	7.5	17.5	15.0	12.5	10.0	7.5	7.5	12.5	12.5	**6.7**
A02	5.0	2.5	5.0	7.5	7.5	2.5	2.5	0.0	7.5	5.0	0.0	0.0	3.7
A03	7.5	2.5	12.5	5.0	7.5	12.5	10.0	7.5	7.5	10.0	12.5	15.0	4.6
A04	2.5	0.0	0.0	2.5	5.0	5.0	0.0	5.0	5.0	0.0	2.5	2.5	2.5
A05	5.0	7.5	15.0	20.0	15.0	22.5	25.0	20.0	17.5	12.5	25.0	17.5	4.2
A06	10.0	10.0	7.5	5.0	7.5	10.0	17.5	22.5	12.5	17.5	20.0	15.0	**5.6**
A07	2.5	7.5	12.5	17.5	15.0	22.5	22.5	25.0	27.5	22.5	20.0	30.0	**5.2**
A08	0.0	5.0	0.0	2.5	12.5	10.0	7.5	10.0	7.5	7.5	10.0	7.5	5.2
A09	10.0	7.5	10.0	7.5	7.5	7.5	12.5	22.5	12.5	17.5	20.0	22.5	**10.0**
A10	5.0	15.0	15.0	20.0	25.0	27.5	32.5	35.0	45.0	40.0	50.0	52.5	**9.4**
A11	2.5	7.5	10.0	10.0	7.5	7.5	5.0	10.0	7.5	15.0	20.0	20.0	**5.0**
Average	5.2	7.0	8.9	9.5	11.6	13.0	13.4	15.2	14.3	14.1	17.5	17.7	5.6

Table A.1: Cross-validated row/column selection decoding accuracy (%) for single-trial decoding and when using a varying amount of repetitions. Six subjects indicated in bold significantly outperformed chance level (2.8%) in single-trial performance, but the highest accuracies still falls short of the accepted 80% threshold.