An event-related potential BCI speller using a wearable, single-channel, EEG headset with frontal electrodes
Evaluating feasability in 11 healthy controls

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1 Introduction

Communication brain-computer interfaces (BCIs) are systems that enable direct communication between the brain and external devices. BCIs leverage electroencephalography (EEG) signals to interpret neural activity and translate it into actionable outputs [5]. These interfaces have potential in healthcare, as assistive technology for individuals with severe motor disabilities to communicate and interact with their environment.

The event-related potential (ERP) matrix speller [8] relies on visual stimulation that elicits, among others, the P3 ERP component, a positive-going wave that occurs approximately 300 milliseconds after an attended stimulus. This speller paradigm presents a matrix of characters on a screen which are intensified in rows or columns in an alternating manner, and users select characters by focusing on one of them. The ERP speller has been extensively researched for its effectiveness in enabling communication for individuals with ALS, locked-in syndrome and other neuromuscular disabilities. It offers an alternative to another common visual BCI paradigm, Steady-State Visually Evoked Potentials (SSVEP)

To adopt BCI speller technology in consumer products intended for clinical and at-home use, *wearable* EEG [1] are currently considered due to their practicality and portability. When also accounting for cost-effectiveness and ease-of-use, the quest for ubiquitous wearable EEG systems for various healthcare applications has resulted in the development *single-channel* EEG systems [3]. Next to their affordable price range, designs recording from the forehead are easy to set up, comfortable to wear and can even be aesthetically appealing. It has been established that these recording devices can measure and distinguish the activity of different facial muscles, such as frowning and jaw-clenching. Their capability in measuring EEG signals with neural origins is currently mostly limited to applications involving the analysis of brain wave rhythms, such as monitoring sleep stages, emotions, stress, or concentration, or clinical diagnosis.

While examples implementing an SSVEP spelling paradigm using single-channel EEG exist crafted [6], it remains an open question how useful these devices are in typical BCI applications, such as the widely studied P300 matrix speller. Most single-channel wearable devices suffer from serious drawbacks that hamper ERP BCI development: 1. frontal electrode positioning is suboptimal to measure relevant ERP components originating in the occipital, parietal and central regions; 2. lateralized bipolar referencing further eliminates the symmetric part of the evoked response, which comprises most of the signal; 3. no spatial filtering can be leveraged in decoding; 4. finally, affordable wearables often do not provide the consistent and high sampling rate with low jitter to effectively perform time- and phase locked analyses.

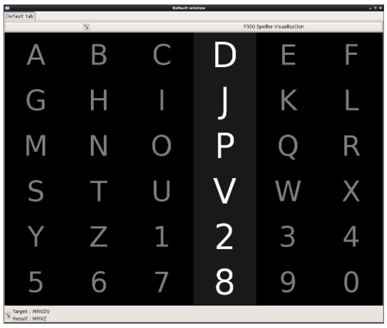
This study investigates whether these challenges can be overcome by testing the capability of a single-channel EEG device toà controlling an ERP matrix speller. By exploring the capabilities and limitations of these devices in BCI applications, we aim to contribute to the development of accessible and user-friendly communication tools for individuals with severe motor impairments.

2 Materials and Methods

2.1 Stimulation and signal recording

To investigate 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 with bipolar reference was positioned on the forehead with two recording electrodes located at Fp1 and Fp2 and the ground clip placed on the left earlobe.

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



(b) The OpenVibe ERP matrix BCI stimulation interface.

Fig. 1: Recording and stimulation setup.

The BrainLink Pro headset connects via Bluetooth (v4.0) and advertises a sample rate of 512 Hz. Since precise timing is important, we established the effective sampling rate as 513.48 Hz through experimentation, and designed an application to connect the device to LabStreamingLayer (LSL) [2]. The code to determine the effective sampling rate of the BrainLink Pro and to connect it to LSL is openly available on-line[3].

Through the LSL connection, BCI stimulation and recording was performed using the P300 matrix speller example[4] and the acquisition server provided by the OpenVibe software (v3.6.0) [9]. The stimulation interface was laid out as show in fig. 1b. In each experimental session, 40 character selections were stimulated by flashing all rows and columns in pseudorandom order, 12 times for each selection, with an inter-stimulus interval of 0.3 s.

The procedure above was performed on 11 participants with no known neurological condition, of which 5 male and 6 female, all right handed, with mean laterality index 92.71±11.70 determined by the Edinburgh Handedness. Only right handed subjects were included, to partially control for potential laterality effects. Inventory [7]. Ages ranged from 22 to 31 with mean age 26.27±2.73). A total of 28741.7 seconds of data was recorded over all scans. All participants provided their informed consent prior to the experiment, under a protocol approved by the Ethics Commission of the University Hospitals Leuven (S62547).

2.2 Signal preprocessing and decoding

EEG signal processing was implemented using the MNE python package (v1.7.1). The code used for analyses and preprocessing is openly accessible on-line[5]. The recorded EEG was first band-pass filtered between 1 Hz and 16 Hz using a fourth-order Butterworth filter. Next, the sections of the recording corresponding to stimulation were winsorized by clipping the lower 5% and upper 5% of the data distribution to their corresponding percentiles, to limit the effect of eye and movement artifacts. Finally, the signal was cut into epochs for further analysis, ranging from 0.2 s before to 1.5 s after stimulus onset for the time domain analysis performed below, and ranging from 0.2 s after to 1.2 s after stimulus onset for the decoding analysis and decimated to a sampling frequency of 32 Hz. Epochs for the time domain analysis were baseline corrected using the period from 0.2 s before stimulus onset to the stimulus onset as baseline interval.

Target selection decoding was performed off-line using a Linear Discriminant Analysis classifier with Toeplitz-shrinkage covariance matrix regularization [10,11]. Decoding accuracy was estimated using 10-fold cross-validation, with each fold including 36 selections as training data and 4 selections as test data. Accuracy per number of repetitions per evaluation fold was calculated by training the classifier on all epochs contained in the training dataset, and choosing per test row or column selection the option with the highest classifier score, obtained by feeding the average per option over the respective number of repetitions to the trained classifier.

3 Results

3.1 Time domain analysis

describe cluster test Figure 2 shows the contrasts between the average attended and non-attended ERP per subject. Components that significantly vary between the two conditions were identified using per-subject temporal cluster-based permutation testing using 1000 permutations, $\alpha = 0.001$ for cluster forming and $\alpha = 0.05$ with Bonferroni correction over the amount of subjects for cluster acceptance. Significant clusters were retained in 6 out of 11 subjects. No clear, consistent evoked component pattern is present over all subjects. Only subjects A09 and A10 show a large negative component between 0.8 s and 1 s, which is reflected in the average.

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

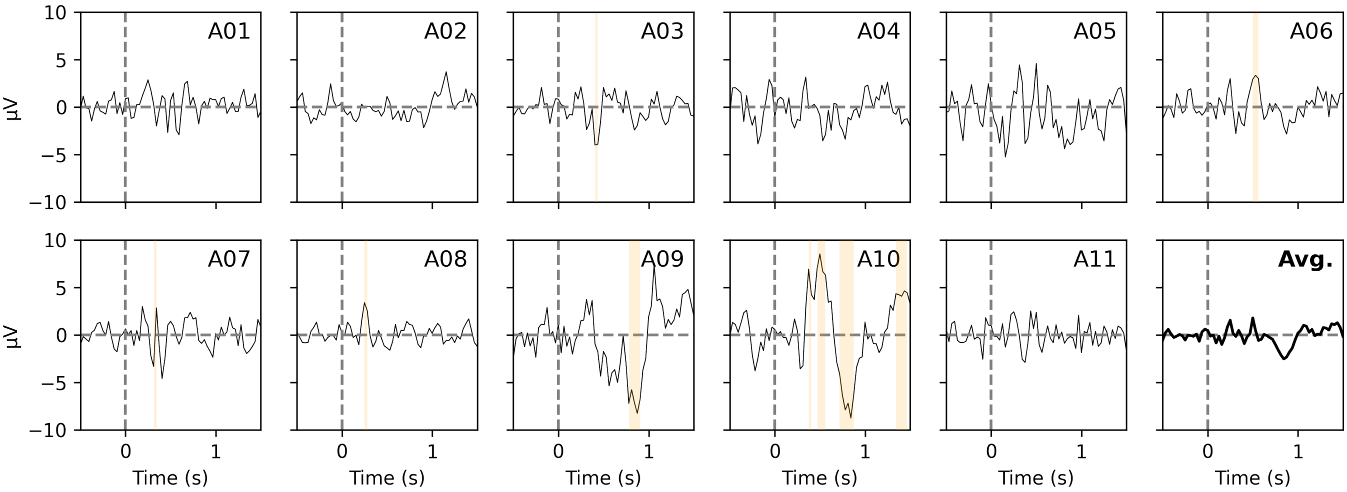


Fig. 2: Event-related potential contrasts with significant components identified by cluster-based permutation testing and grand-average contrast.

3.2 Decoding analysis

Table 1 lists BCI performance cross-validated decoding accuracy for the evaluated subjects. We first estimated single-trial decoding accuracy without separately investigating repetitions, in order to establish for which subjects this single-trial performance exceeded the target selection chance level of $1/(6 * 6) = 2.8\%$. Single-trial accuracies were compared against this chance level using a one-sample, one-sided Wilcoxon signed-rank test with $\alpha = 0.05$, corrected for multiple comparisons using Benjamini-Hochberg's false discovery rate correction procedure. This test revealed that single-trial accuracy for 6 of the 11 participants significantly outperformed chance level.

Next, accuracy results were established when averaging over a varying amount of repetitions. Except for A02 and A04, performance of all subjects generally increased with the number of repetitions. Here, it can be noted that subject A10 achieved the highest accuracy of 52.5% using 12 repetitions, which still falls short of the 80 % standard generally accepted as a BCI target selection usability threshold.

4 Conclusions

For some of the subjects included in this study, the proposed single-channel ERP BCI speller can distinguish attended from non-attended trials, as evidenced by the categorical difference in the evoked response in the time domain and the decoding performance results. However, in its current form, the application might not be practically feasible since all subjects below the usability threshold and the current approach requires a relatively large amount of training data. Indeed, this is to be expected given the severe limitations posed by the hardware as mentioned above. We believe the proposed approach is currently limited by the presence of large eye and muscle artifacts, which could be mitigated by single-channel artifact rejection methods such as Singular Spectrum Analysis combined with Independent Component analysis or other methods [4]. We also cannot fully exclude the possibility that some subjects synchronized movements or eye blinks synchronized to the attended target stimulation, which could contribute to difference between attended and non-attended targets. Despite this limitations, these results open a window to improving the performance of single-channel ERP spellers and to validating their performance on-line and in with larger sample sizes; Predictive language modeling and interface modifications can transform current low target selection accuracies in more usable applications. Decoding itself could potentially be improved after embedding the single-channel data in the using a time-frequency transform, Empirical Mode Decomposition, Singular Spectrum Analysis or time-delay embedding to cope with the lack of spatial information. Future research should also be directed towards the origin of the ERP components measurable with frontal, bipolar EEG relevant for the decoding task and their inter-subject variations. If these changes can be incorporated to improve performance, we believe the appeal of single-channel, wearable BCI headsets can lead to a higher rate of adoption of ERP-based BCI spellers.

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A Per subject decoding results

# 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 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.