Towards gaze-independent c-VEP BCI: A pilot study

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INTRODUCTION

Background

A code-modulated visual evoked potential (c-VEP) is brain activity recorded by EEG, triggered by rapid visual stimulation using a pseudo-random sequence of flashes[1]. Thanks to the rapid and optimized nature of the its stimulus protocol, c-VEP-based BCIs are currently among **the fastest non-invasive BCIs** for communication and control[1].

Challenge

A limitation of standard visual BCI spellers is the requirement of the users' eyes to shift their gaze towards a target symbol. Because **BCI control is fully dependent on eye movements**, this poses a major challenge and quickly renders the BCI uncontrollable for people who have lost voluntary control of their eye movements, such as people living with late-stage amyotrophic lateral sclerosis (ALS).

Approach

To address this challenge, we evaluated **a c-VEP BCI that relies on spatial attention rather than eye movements**. In this preliminary work, stimuli were presented sequentially, to assess whether the c-VEP can be decoded from the far periphery, before testing the more complex parallel stimulation case, where stimuli would be presented simultaneously, which is necessary for BCI control. If successful, this study provides the first steps to a gaze-independent c-VEP BCI.

EXPERIMENT

Recording

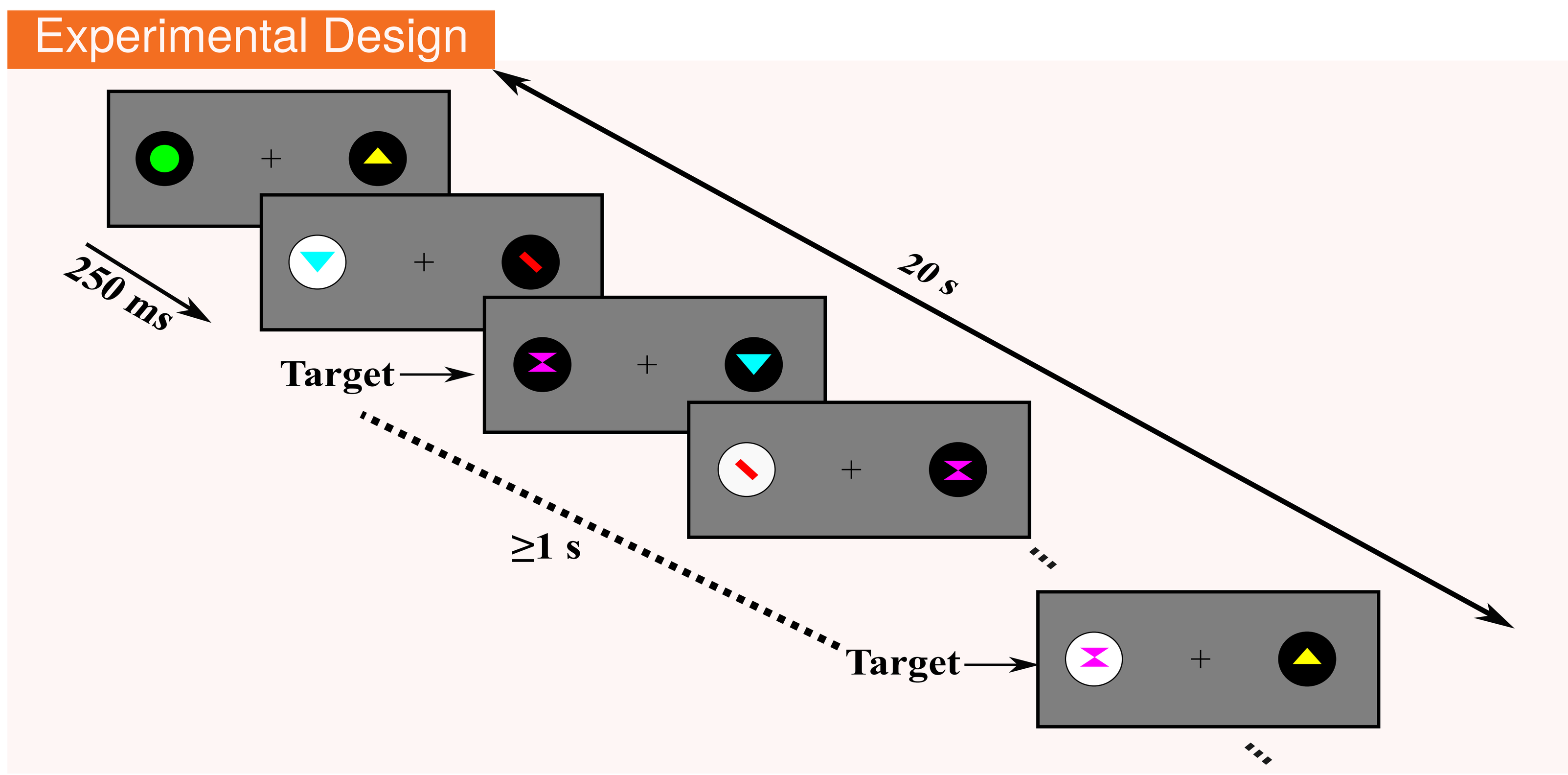
We recorded 64-channel EEG from 5 participants at 512 Hz. Preprocessing involved a 50 Hz notch filter and a bandpass filter from 1 to 40 Hz.

Stimulus presentation

A 2-class BCI was presented with two circles at each side of a fixation cross:

- The background alternated black and white following two modulated Gold codes at 60 Hz[2].
- The foreground displayed one of six shape stimuli changing every 250 ms.
- Participants attended one circle and counted the number of magenta hourglasses.

Experimental Design



Procedure

Participants did 4 covert runs (without eye movements but spatial attention) and 1 overt run (with eye movements). Each run presented 20, 10 for each class, 20-second trials in random order.

ANALYSIS

Classification

Reconvolution canonical correlation analysis (CCA) is a hybrid method decoding-encoding model[2–3], learning a spatial filter $\mathbf{w} \in \mathbb{R}^C$ for multichannel single-trial EEG data $\mathbf{X} \in \mathbb{R}^{C \times T}$ with C channels and T samples, and a temporal response $\mathbf{r} \in \mathbb{M}$ to be combined with a structure matrix $\mathbf{M} \in \mathbb{R}^{M \times T}$ describing event onsets, durations M and overlap.

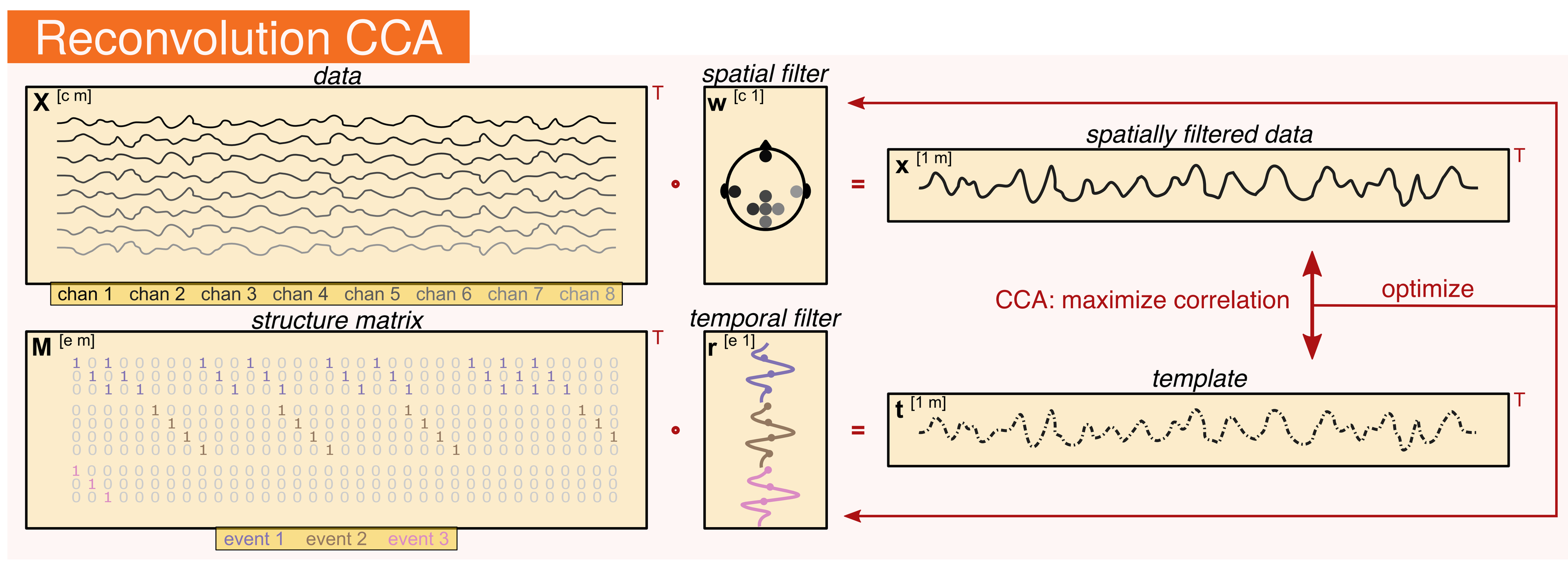
The CCA model is fit on training data by optimizing the correlation ρ:

$$\arg\max_{\mathbf{w},\mathbf{r}} \rho(\mathbf{w}^\top \mathbf{X}, \mathbf{r}^\top \mathbf{M}_i) \tag{1}$$

Determining the attended target symbol $\hat{y}$ is then performed by maximizing the correlation ρ:

$$\hat{y} = \arg\max_{i} \rho(\mathbf{w}^\top \mathbf{X}, \mathbf{r}^\top \mathbf{M}_i) \tag{2}$$

Reconvolution CCA



Code for this reconvolution CCA is available at: `https://github.com/thijor/pyntbci`.

Evaluation

We performed a 5-fold chronological cross-validation to evaluate model performance under the overt and covert conditions.

RESULTS

Hyper-parameter Optimization

Given the potential for distinct transient responses between conditions, we assessed the grand average classification accuracy across transient response lengths spanning from 0.1 to 0.9 s. In the covert condition, mean accuracy fluctuated from 0.55 to 0.99 across participants, whereas in the overt condition, mean accuracy remained consistently at 1.0 for all participants across all transient response lengths. The accuracy in the covert condition was highest at a transient response length of 300 ms. Hence, for subsequent analysis, we used a transient response length of 300 ms.

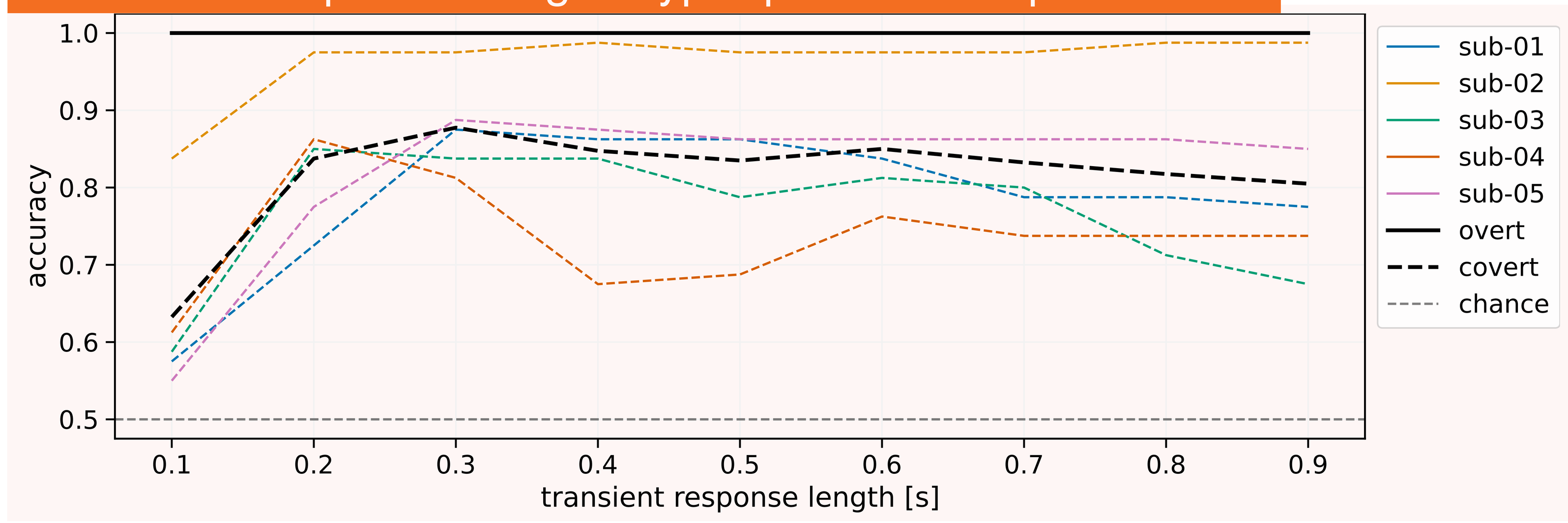
Decoding accuracy

	S1	S2	S3	S4	S5	Avg
Overt	1.00	1.00	1.00	1.00	1.00	1.00
Covert	0.88	0.98	0.84	0.81	0.89	0.88

Classification accuracy

As expected, the overt condition (1.00) consistently outperformed the covert condition (0.88). Importantly, participants consistently reached higher than 0.80 classification performance in the covert condition, showing the feasibility of c-VEP classification with peripheral vision.

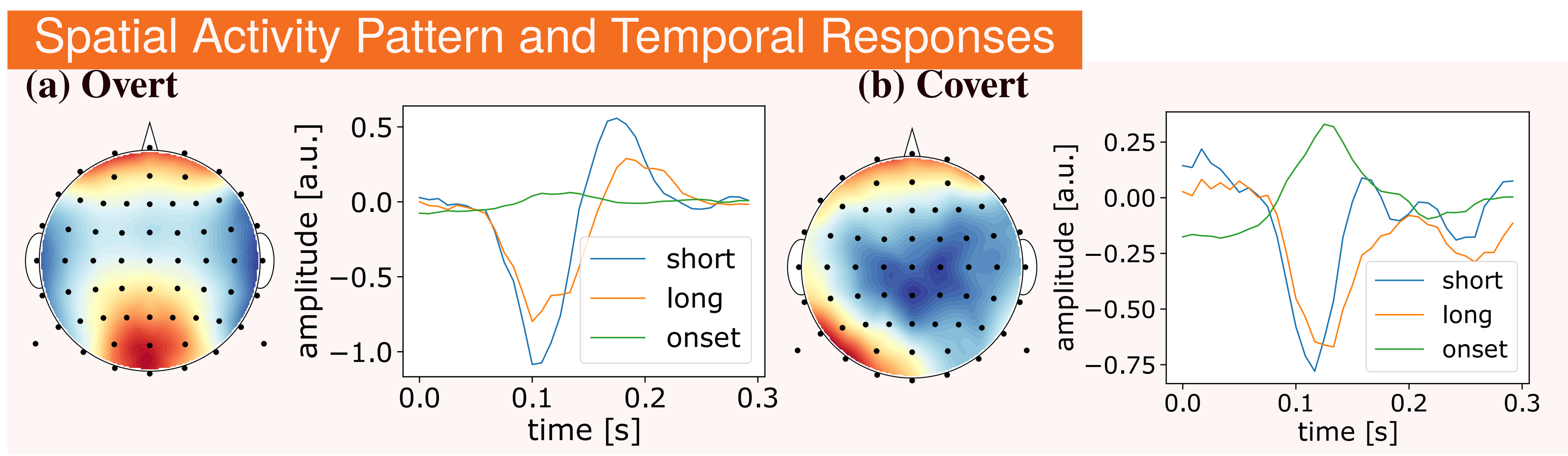
Transient Response Length Hyper-parameter Optimization



Response characteristics

The figure below shows the spatial activity pattern and temporal response of an individual participant for both conditions. We observed similar response characteristics, with subtle indications of spatial lateralization and a subtle temporal delay for the covert as compared to the overt condition.

Spatial Activity Pattern and Temporal Responses



DISCUSSION

Peripheral c-VEP can be decoded

This study shows that **code-modulated stimuli presented in the periphery can be reliably decoded** from the EEG with a grand average accuracy of 88 %. This opens many new avenues for attention monitoring using the c-VEP.

Realizing gaze-independence

This study shows the **feasibility and high performance of a novel gaze-independent c-VEP BCI**. Using peripheral stimulation and covert attention, we eliminated the requirement of eye movements. This is an essential improvement for c-VEP BCIs that are to be used by people that have lost voluntary control over their eye movements, like people living with late stage ALS.

OPEN QUESTIONS

Towards parallel stimulation

This c-VEP protocol employed sequential stimulation, where only the stimulus on the attended side alternated its background based on the pseudo-random noise-code. In practical online usage of the BCI, **simultaneous stimulation of both sides is necessary**. While this study offers valuable fundamental insights into the feasibility of gaze-independent c-VEP BCI, it is imperative to acknowledge this limitation.

Towards hybrid BCI

The design of the study allows the **use of additional measures of brain activity to improve classification performance**. Specifically, the shape stimuli may evoke additional P300 responses, and increased oscillations in the alpha band is expected following covert spatial attention. Both these neural markers of attention can be exploited aside the c-VEP improved target identification.

REFERENCES

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[3] Thielen et al. (2021) *J Neural Eng* doi:10.1088/1741-2552/abecef

[4] Egan et al. (2017) *J Neural Eng* doi:10.1088/1741-2552/aa6bb2

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