

Toward a gaze-independent brain-computer interface using the code-modulated visual evoked potentials

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INTRODUCTION

Background

Brain-computer interfaces (BCIs) enable users to communicate or control devices by translating brain signals into commands, bypassing the motor system. The code-modulated visual evoked potential (c-VEP) BCI is one of world's fastest non-invasive BCI systems^[1].

The Problem

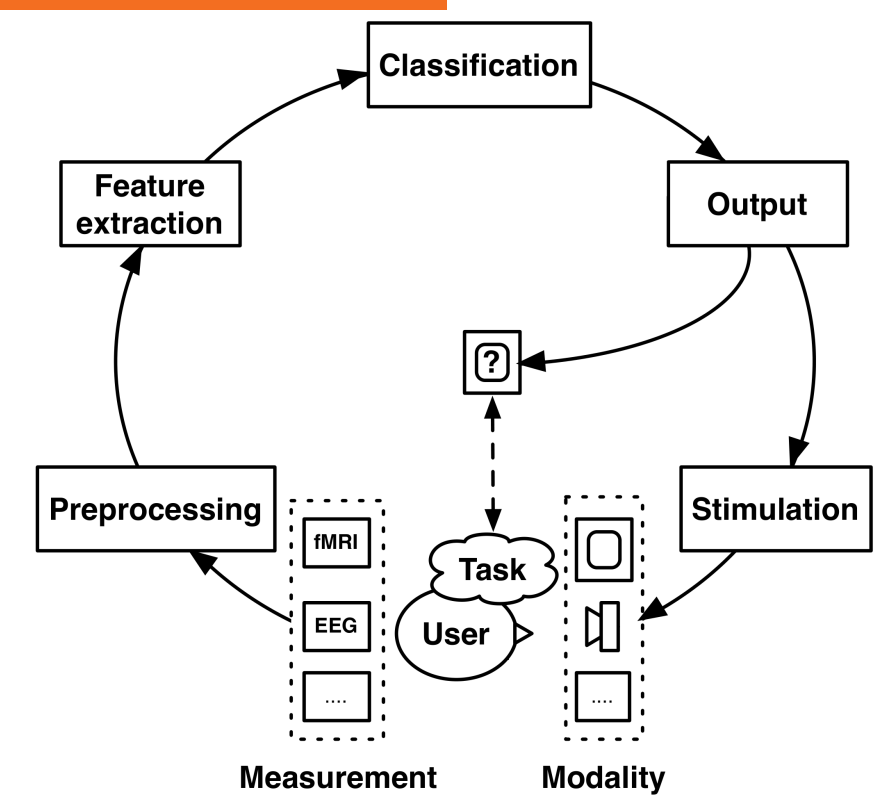
Most BCIs are gaze-dependent: They require users to move their eyes to a target location. This excludes users with impaired oculomotor function.

This study

We present the first demonstration of a gaze-independent c-VEP BCI. We evaluated three parallel, simultaneous well-known gaze-dependent (overt) BCI paradigms, here in a gaze-independent (covert) way:

- **P300 ERP** – the response to an infrequent target
- **Alpha** – the lateralisation of alpha (10 Hz) bandpower
- **c-VEP** – the response to pseudo-random visual stimulation

BCI Cycle



Adapted from [2]

Covert vs Overt

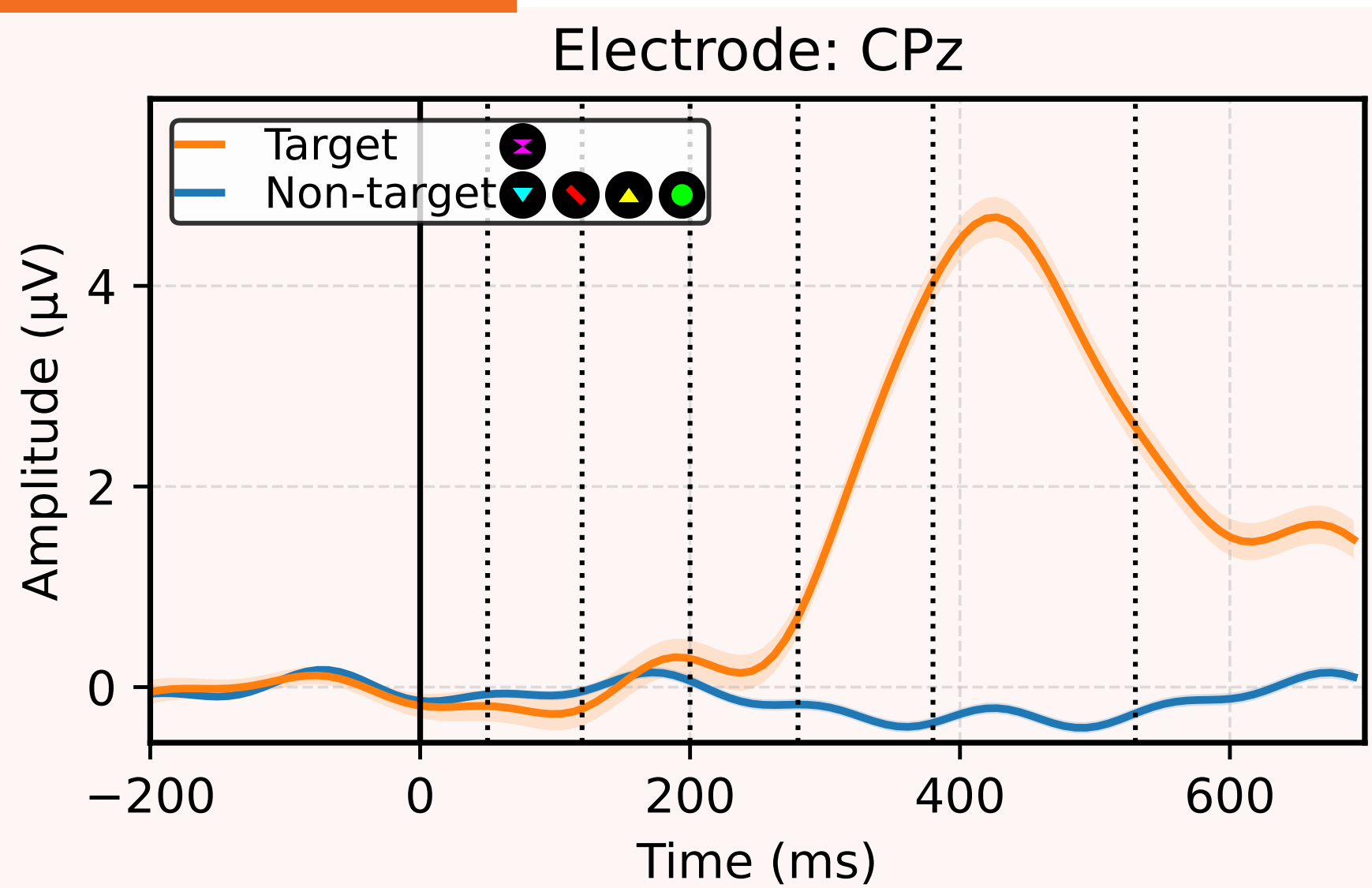


METHODS

P300 ERP DECODING WITH BT-LDA

We used a state-of-the-art P300 ERP decoding pipeline that included **block-Toeplitz linear discriminant analysis (BT-LDA)**^[3] to classify target from non-target epochs. Epoch classification was integrated over time using Pearson's correlation to classify left from right attended trials.

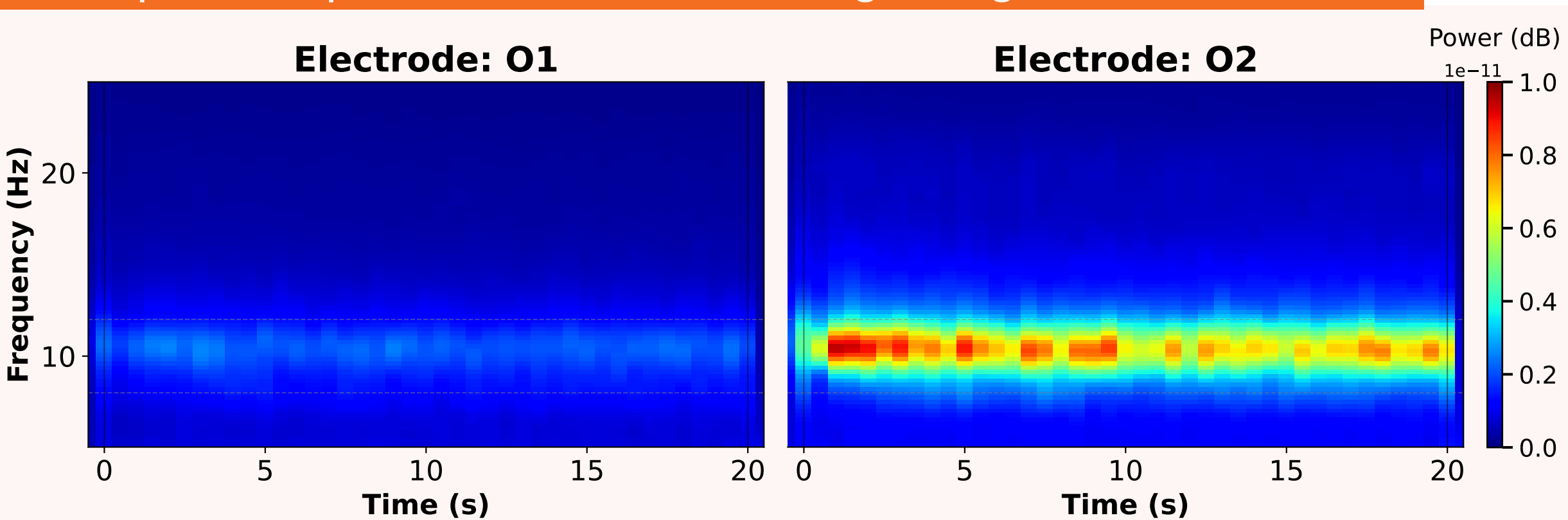
Example of the P300 ERP



ALPHA DECODING WITH CSP AND S-LDA

We used a state-of-the-art 10 Hz visual alpha-lateralization decoding pipeline^[4] that included **common spatial patterns (CSP)** and **shrinkage linear discriminant analysis (s-LDA)** to classify left from right attended trials.

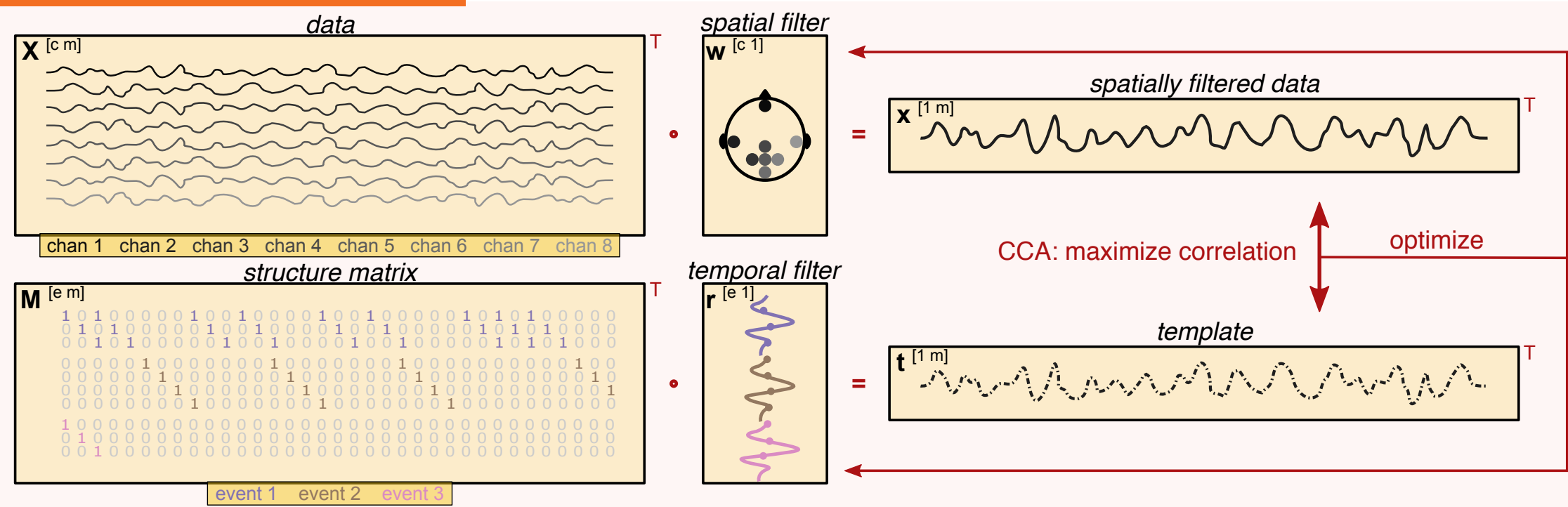
Example of Alpha lateralization during a Right Attended Trial



C-VEP DECODING WITH CCA

We used a state-of-the-art c-VEP decoding pipeline that included **reconvolution canonical correlation analysis (rCCA)** to classify left from right attended trials^[5].

Reconvolution CCA

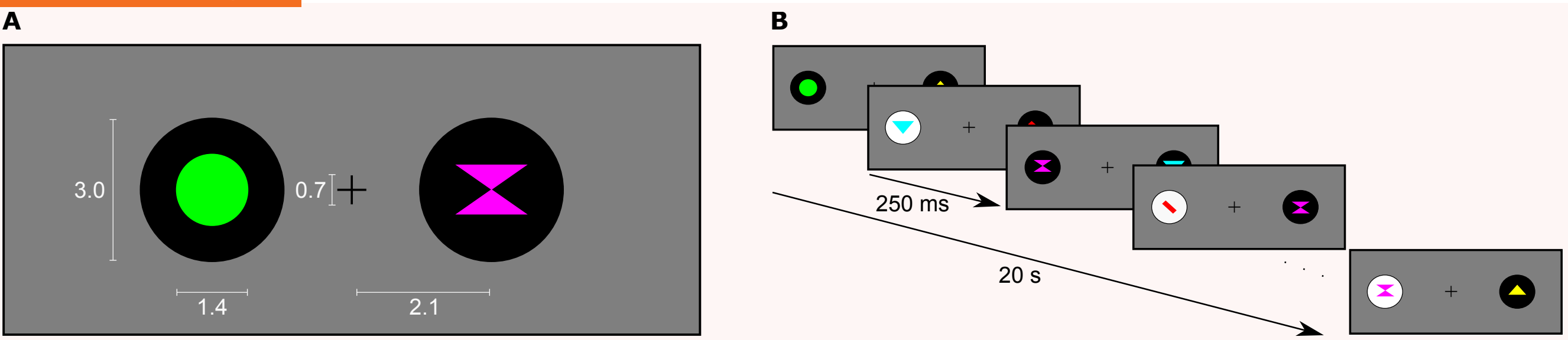


EVALUATION

Decoding pipelines were evaluated with **4-fold chronological cross-validation**. We derived **decoding curves** by incrementally extending each trial's decision window (1.25 s steps to 20 s) and computing classification accuracy at each step. Each pipeline was evaluated both with (w/) and without (w/o) independent component analysis (ICA)-based artifact removal.

EXPERIMENT

Task Design



Participants: 29 healthy adults

Task (per trial)

1. Fixate the center fixation cross; no eye movements.
2. Covertly attend cued side (left/right); ignore the other.
3. Count hourglasses (targets) on the attended side only.

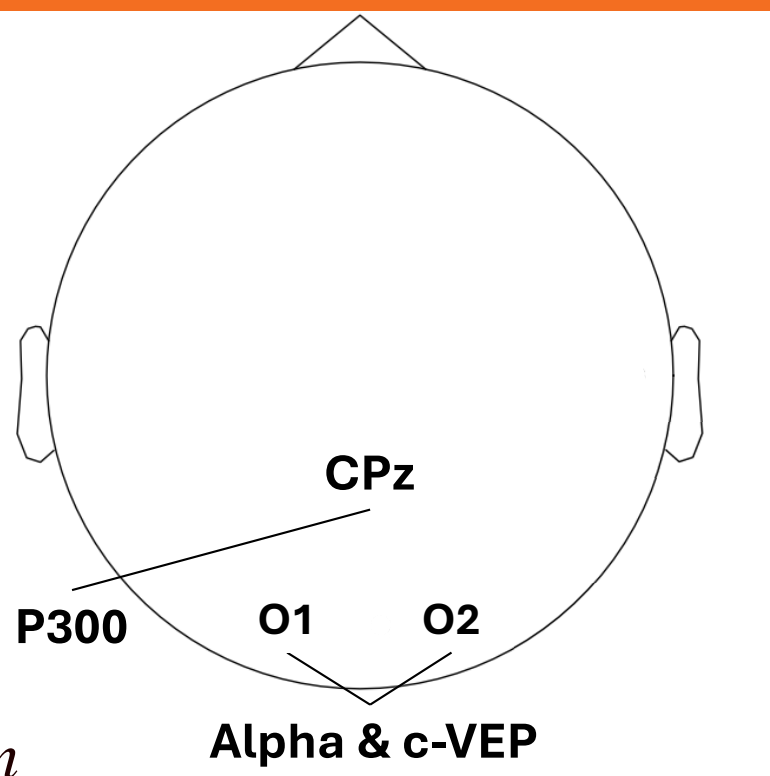
Stimulus protocol → Neural features

Foreground shape stream (5 shapes; 1 target) → *P300 ERP*

Background random black/white flickers → *c-VEP*

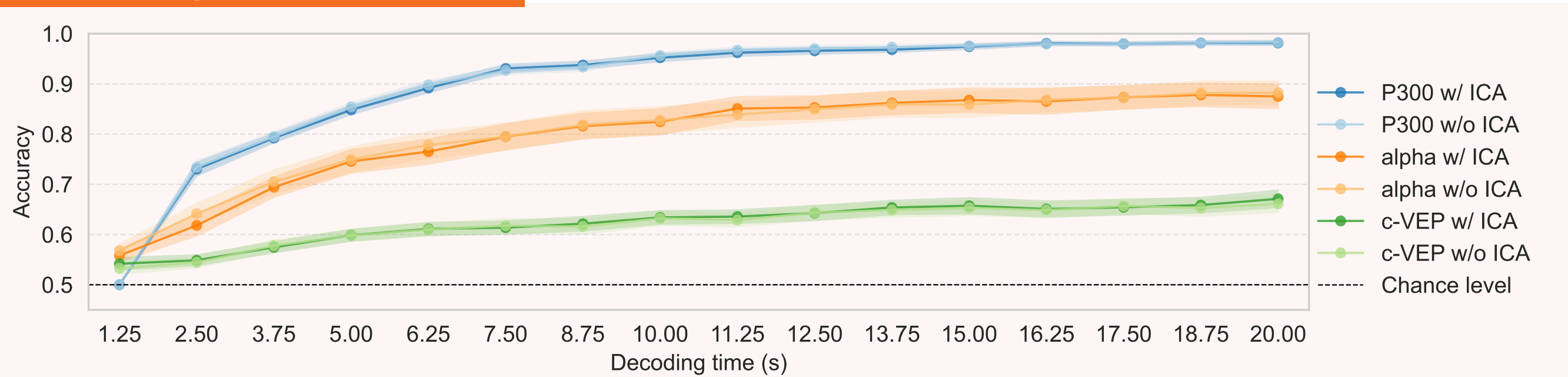
Covert spatial attention (left/right) → *Alpha lateralization*

Key EEG Electrodes



RESULTS

Decoding Performance



- Accuracy of P300 > alpha > c-VEP
- Accuracy increases over decoding time
- No difference in accuracy between w/ ICA and w/o ICA

Which method achieves the best accuracy over time?

Table 1. Mean classification accuracy (%) at each time interval w/ and w/o ICA.

Time (s)	c-VEP w/ ICA	c-VEP w/o ICA	alpha w/ ICA	alpha w/o ICA	P300 w/ ICA	P300 w/o ICA
5.0	59.9	59.8	74.6	75.0	84.8	85.4
10.0	63.4	63.2	82.5	82.8	95.2	95.6
15.0	65.7	65.3	86.8	85.9	97.4	97.6
20.0	67.1	66.1	87.5	88.2	98.1	98.3

When does each method reach key accuracy thresholds?

Table 2. Time (s) at which the mean accuracy reaches a threshold w/ and w/o ICA

Accuracy (%)	c-VEP w/ ICA	c-VEP w/o ICA	alpha w/ ICA	alpha w/o ICA	P300 w/ ICA	P300 w/o ICA
60.0	7.5	7.5	2.5	2.5	2.5	2.5
70.0	/	/	5.0	5.0	2.5	2.5
80.0	/	/	10.0	10.0	5.0	5.0
90.0	/	/	/	/	7.5	7.5

DISCUSSION

Our findings suggest:

- the feasibility of **gaze-independent c-VEP BCI**
- the **competitiveness** of c-VEP with SSVEP^[6]
- a **weak attentional modulation** for c-VEP during parallel stimulation^[7]
- that the results are **not caused by fixational eye movements**
- the high performance of **sophisticated decoding pipelines**

TAKE-AWAY

We showed for the first time the feasibility of a gaze-independent c-VEP BCI.

OPEN QUESTIONS

- Can we improve performance by combining ERP, alpha and c-VEP into a **hybrid decoding**?
- Can we improve c-VEP by **optimizing stimulation** parameters like size, distance, etc.?
- How well do the presented results generalize from a healthy to a **patient population**?
- Can we extend these results from 2 classes to **more classes**?
- Can we use **dynamic stopping**^[8] to shorten stimulus presentation?

REFERENCES

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Code is available at: https://github.com/rvodila/covert_cVEP_2025.

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