

Efficient Decoding of c-MVEP for BCI

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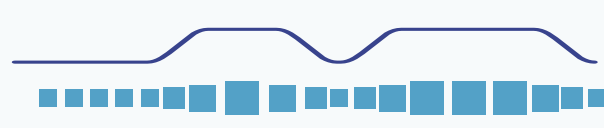
We investigated the decoding of the recently proposed flicker-free, **code-modulated motion visual evoked potential (c-MVEP)**, using efficient decoding approaches designed to reduce model complexity and calibration requirements. Given the code-modulated nature of c-MVEP and its similarity to the established flicker-based code-modulated visual evoked potential (c-VEP) paradigm, we hypothesized that c-MVEP could be decoded using

similar approaches. We evaluated several canonical correlation analysis (CCA)-based methods previously shown to perform well for c-VEP decoding. These methods progressively imposed stronger assumptions on the neural data. By reducing the number of free parameters and the amount of calibration data required, we aimed to identify efficient decoding strategies that maintain high c-MVEP classification performance.

The c-MVEP Paradigm

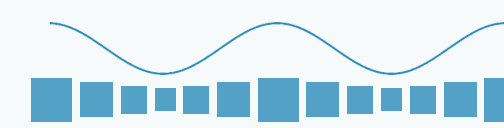
c-MVEP

- Code-modulated motion visual evoked potential
- Motion** using **pseudo-random sequences**^[1]
- Combines comfort and robust decoding



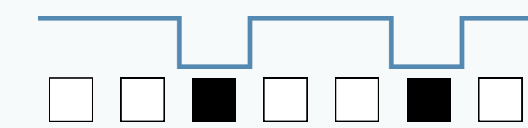
SSMVEP

- Steady-state motion visual evoked potential
- Motion** stimulation using specific **frequencies**^[2]
- Improved user comfort compared to SSVEP



c-VEP

- Code-modulated visual evoked potential
- Flickering** using **pseudo-random sequences**^[3]
- Reliable and robust decoding performances



Methods

Data:

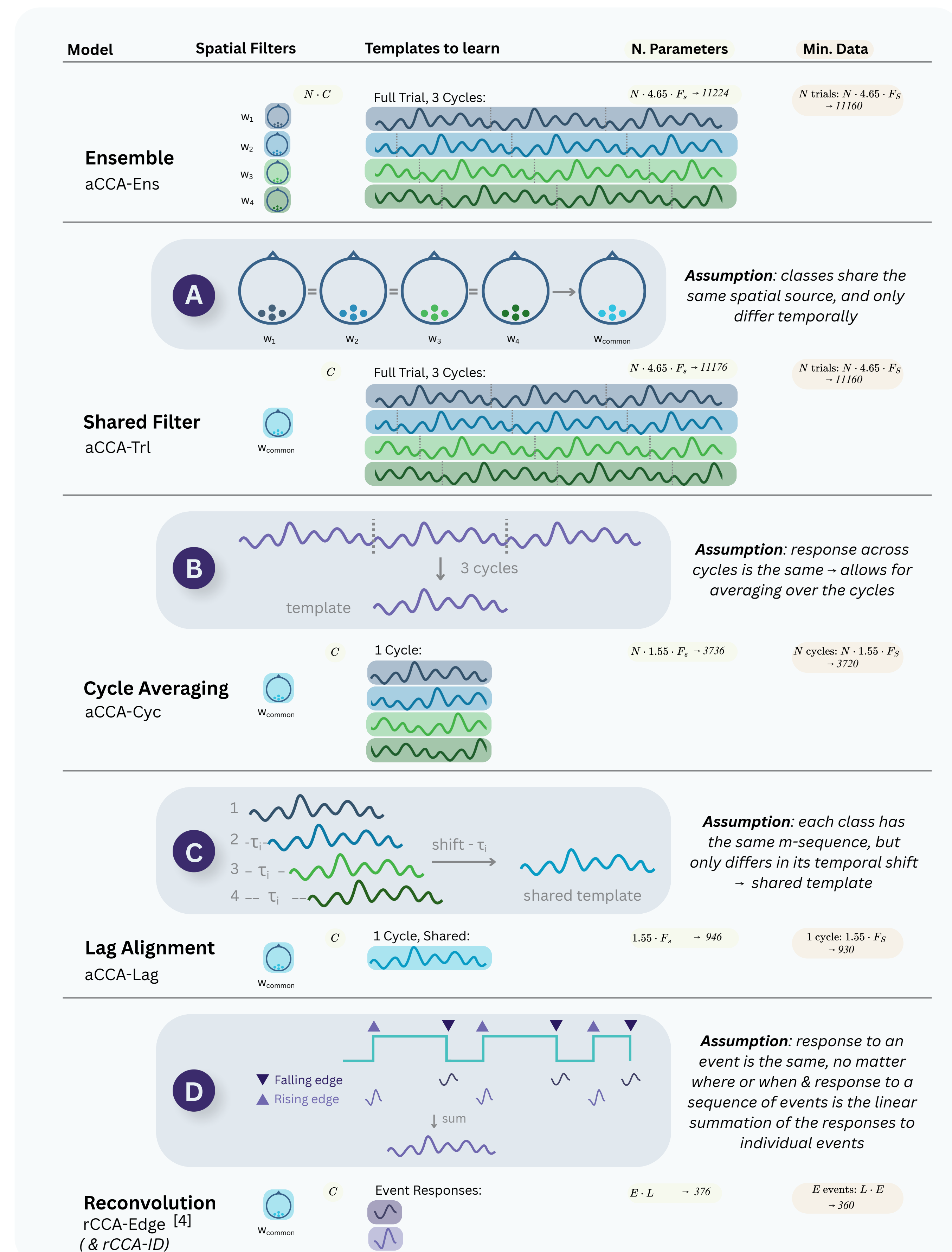
- 16-channel EEG (C), Fs = 600Hz
- 19 participants (14M, 5F; 23.7 ± 3.9 years)
- 2 conditions: c-MVEP and c-VEP
- 6 blocks of 4 trials (each condition)
- 31-bit m-sequence at 20Hz
- Cycle: 31/20 = 1.55s
- 4 classes (M): 0, 2, 4, 7, bits shifts
- trial: 3 cycles: 3 x 1.55s = 4.65s

Analysis:

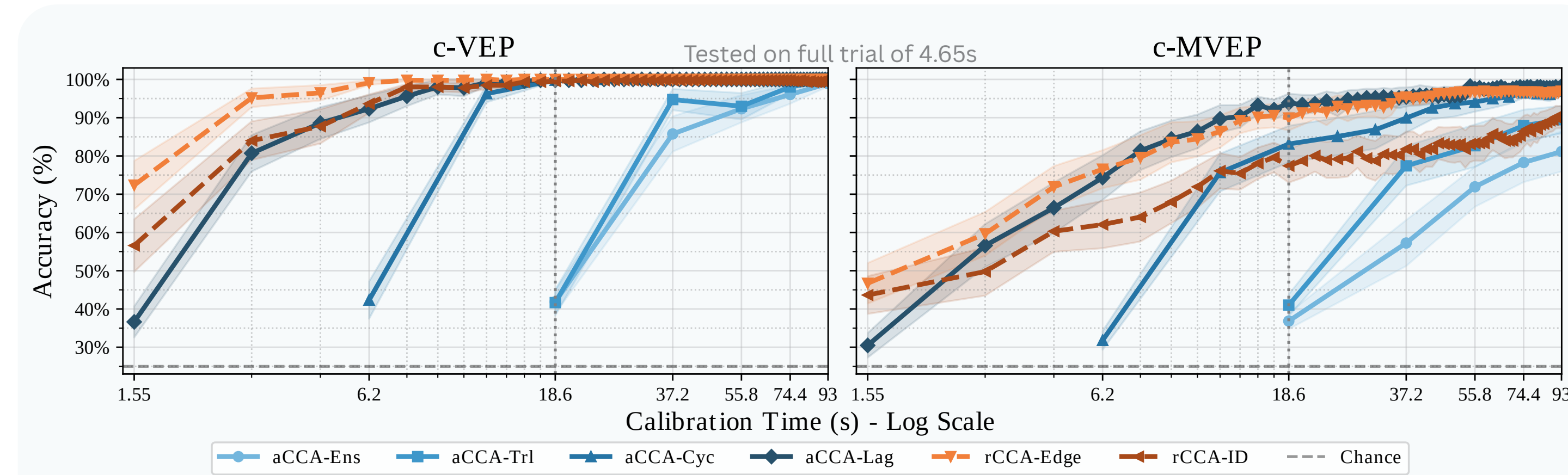
- Leave-one-block-out, six folds
- Test on full trial (one for each class)
- Six canonical correlation analysis (CCA) classification approaches
- Different minimum training data: One cycle (1.55s), one cycle per class (6.2s), trial per class (18.6s)
- Steps at the trial or cycle level

Optimizing Decoding by Reducing Parameters

To efficiently decode c-MVEP, we reduced the parameter space of the CCA approaches by making more and stricter assumptions about the neural data. Assumptions (**A-D**) were based on prior knowledge of brain responses or stimulus characteristics, as previously observed for the c-VEP paradigm. This led to six different CCA approaches:



Results: Learning Curve



Discussion

c-MVEP:

- Traditional:** *aCCA-Ens*, *aCCA-Trl* → **data-inefficient** 81.1% and 89.5% at maximum training time (93.0s)
- Cycle averaging:** *aCCA-Cyc* → **fewer parameters, efficient learning** 83.1% in just 18.6s
- Lag Alignment:** *aCCA-Lag* → **best overall trade-off** 93.9% in just 18.6s
- Reconvolution:** **high data efficiency through shared event responses**
 - rCCA-Edge*: 76.5% at 6.2s to 89.9% at 18.6s
 - rCCA-ID*: **lowest model complexity**, but likely **underfits the response** due to violated linearity assumption

c-VEP:

- Reconvolution:** **highly data-efficient** → 72.4% at 1.55s, and 99.1% at 6.2s
- All methods converge to 100% with sufficient calibration

c-MVEP vs c-VEP:

- c-VEP outperforms c-MVEP at 18.6s and 93.0s
- Current methods are optimized for c-VEP, without exploiting the continuous motion structure of c-MVEP

Open Questions

Decoding

- Leverage motion:** incorporate continuous motion characteristics
- Reconvolution events that capture c-MVEP responses

Stimulation

- Strengthen responses:** optimize motion types and event structure
- Stimulation sequence with **smoother motion** and **less adaptation**

Online Implementation

- Decoding c-MVEP in **real-time** with an increased number of targets

Take Home:

Comfortable Alternative: c-MVEP is a **viable alternative** to c-VEP, when high-contrast flickering is undesirable, despite the slightly lower performance.

Highly Efficient: c-MVEP achieves **high decoding accuracies with minimal calibration data** (6.2s) by using a universal template or stimulus reconvolution.

Key Finding: c-MVEP can be **effectively decoded without extensive calibration**, demonstrating its potential for practical BCI applications.

[1] Scheppink et al. "Beyond Flickering: Introducing Code-Modulated Motion Visual Evoked Potentials for Brain-Computer Interfacing" Front. Neuroergonomics 7:1884144 (2026)

[2] Xie et al. "Steady-state motion visual evoked potentials produced by oscillating newton's rings: implications for brain-computer interfaces." Plos one 7.6 (2012)

[3] Martínez-Cagigal et al. "Brain-computer interfaces based on code-modulated visual evoked potentials (c-VEP): a literature review" J. Neural Eng. 18 061002 (2021)

[4] Thielen et al. "From full calibration to zero training for a code-modulated visual evoked potentials for brain-computer interface" J. Neural Eng. 18 056007 (2021)

