Contrast-dependent decoding performance in classic and grating c-VEP stimuli

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INTRODUCTION

MOTIVATION

Brain responses differ across individuals. Personalized, adaptive BCIs should account for these differences when selecting stimulus parameters.

WHAT WE NEED

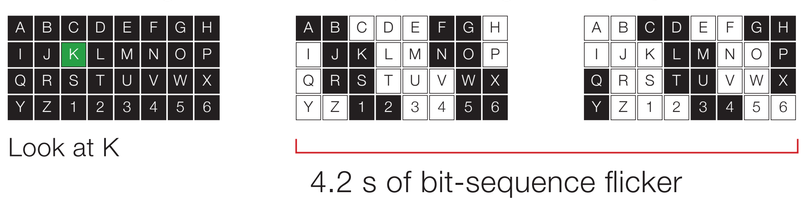
Closed-loop optimization requires an individual stimulus–response model. Noisy trials require separating the underlying response function, trial-to-trial variability, and uncertainty about that function.

THIS STUDY

Using contrast as a test case, we investigate whether Gaussian processes can estimate individual contrast–response functions from noisy single-trial decoding evidence in a c-VEP speller.

METHODS

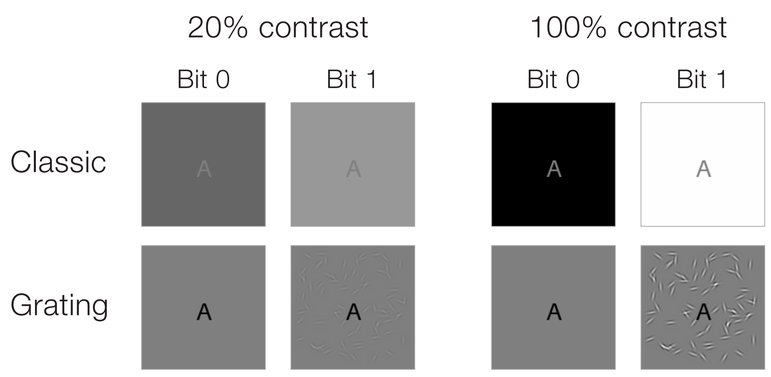
EXPERIMENT



Each key: a shifted 63-bit m-sequence. Schematic frames.

32-key c-VEP speller [1] · 4 participants
32 trials/setting · Randomized conditions
64-channel EEG · 6–21 Hz
Offline CCA–LDA · 4-fold cross-validation

STIMULI

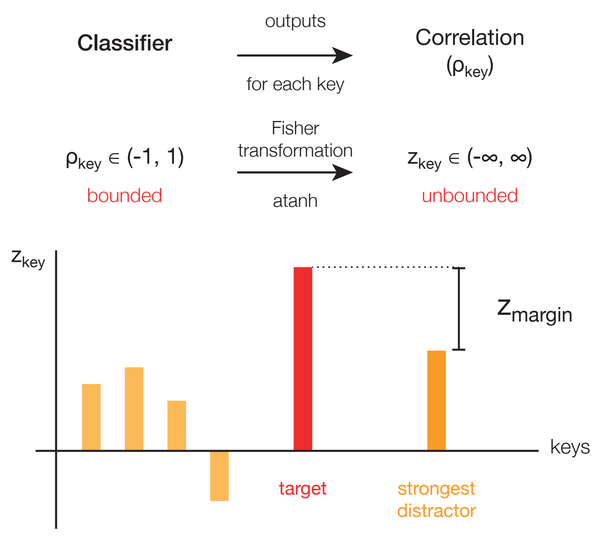


Six contrasts tested: 10, 20, 30, 40, 60, 100%

Examples: this study. Textured-stimulus background: [2].

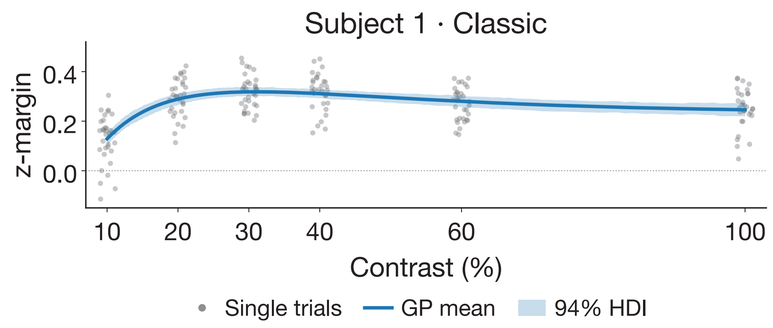
TRIAL-LEVEL EVIDENCE METRIC: z_{margin}

A positive z_{margin} means the cued (target) key ranks first; a larger margin means greater separation from the strongest distractor. Planned optimization uses this continuous margin, rather than single-trial correctness (0 or 1).



GAUSSIAN PROCESS (GP) MODELLING

z_{margin} = latent response + trial noise
Separate GP per participant and stimulus type: log contrast, squared-exponential kernel.
Constant vs contrast-specific trial noise.

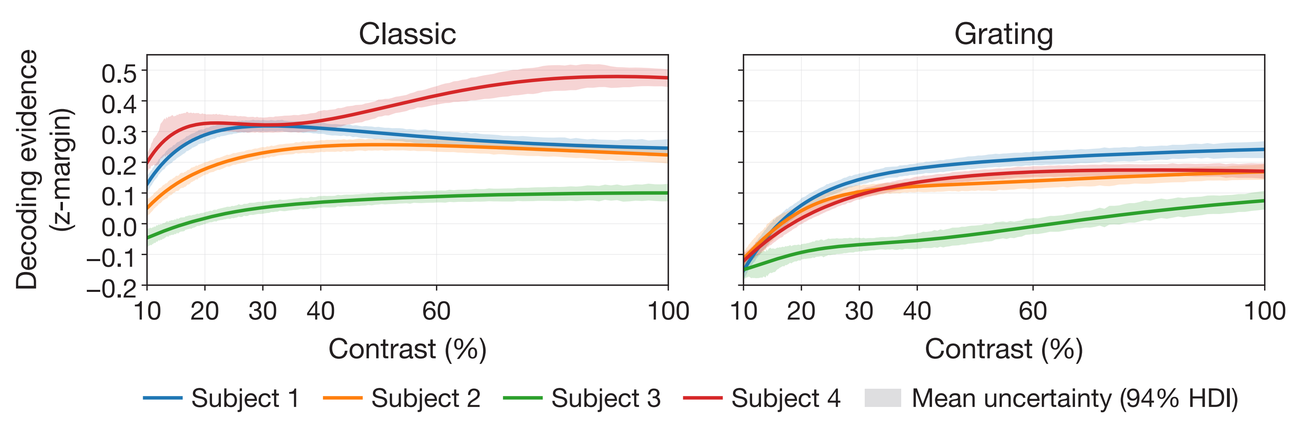


Retained trials after outlier filtering. Dots shifted horizontally for visibility. Band: mean uncertainty.

RESULTS

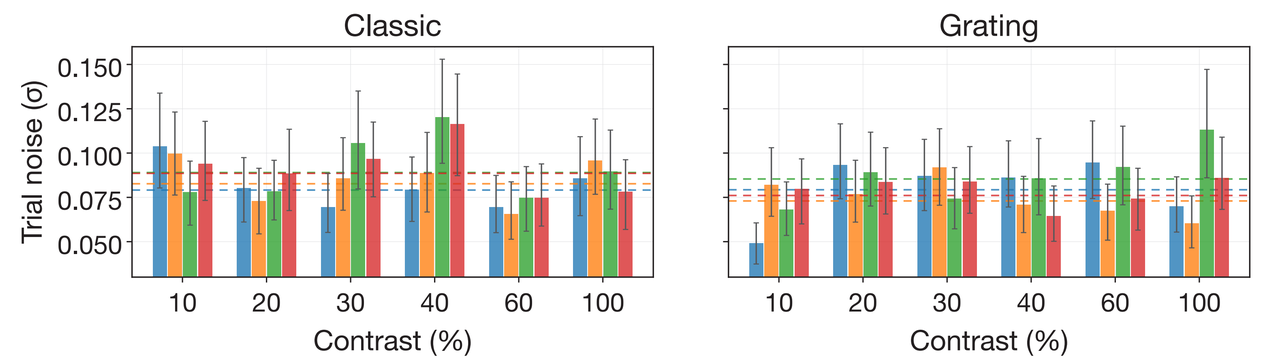
HIGHER CONTRAST GENERALLY INCREASES DECODING EVIDENCE

Contrast–response curves differed across participants and stimulus types. At high contrast, classic–grating differences were smaller for Subjects 1–2 than for Subject 4.



Lines: GP means · Shading: 94% highest-density intervals (HDIs) of the mean
The shaded band reflects uncertainty in the mean, not the spread of individual trials.

TRIAL-TO-TRIAL VARIABILITY SHOWS NO CONSISTENT CONTRAST TREND



Bars: contrast-specific trial noise · Dashed lines: constant-noise model
Error bars: 94% HDIs of the noise estimates.

DISCUSSION

GP MODELS CHARACTERIZE INDIVIDUAL RESPONSES FROM NOISY TRIALS

INDIVIDUAL DIFFERENCES

Contrast–response curves differed across participants and stimulus types, motivating individual modelling.

MEAN VS VARIABILITY

Higher contrast generally increased mean decoding evidence, without a consistent reduction in trial variability.

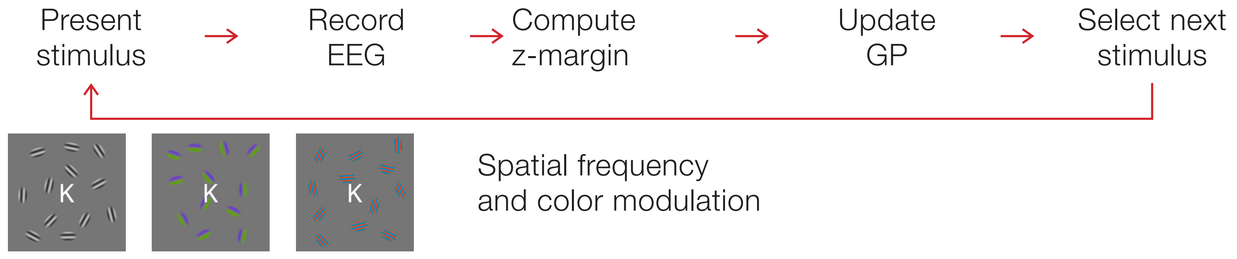
TOWARDS CLOSED-LOOP USE

Estimates of the response and its uncertainty could guide which stimulus setting to test next.

These offline fits provide a starting point for personalized stimulus optimization.
Whether model-guided stimulus selection improves decoding evidence remains to be tested.

ONGOING WORK

CLOSED-LOOP BAYESIAN OPTIMIZATION OF INDIVIDUAL STIMULUS SETTINGS



REFERENCES

[1] Martínez-Cagigal V et al. Brain–computer interfaces based on code-modulated visual evoked potentials (c-VEP): A literature review. J Neural Eng. 2021;18:061002. doi:10.1088/1741-2552/ac38cf
[2] Dehais F et al. Leveraging textured flickers: A leap toward practical, visually comfortable, and high-performance dry EEG code-VEP BCI. J Neural Eng. 2024;21. doi:10.1088/1741-2552/ad8ef7

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