

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

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ABSTRACT: Designing effective visual brain-computer interfaces (BCIs) requires careful selection of stimulus parameters that shape the strength and reliability of evoked neural responses. Stimulus contrast is one such parameter in code-modulated visual evoked potential (c-VEP) BCIs, yet its effects on decoding performance and reliability remain incompletely characterized. Here we investigate how stimulus contrast influences decoding performance in a c-VEP speller using two stimulus families: classic luminance flicker and grating-based textured stimulation. Four participants were tested across six contrast levels (10–100 %). Trial-level performance was quantified using a Fisher-transformed margin metric and modeled with Gaussian processes. In this exploratory dataset, performance generally increased with contrast, with larger decoding margins for the classic stimulus than for the grating stimulus. The magnitude and shape of these effects varied across participants, while estimated trial-to-trial noise changed only modestly across contrast levels. These findings suggest that trial-level Gaussian-process modeling can support exploratory characterization of stimulus-parameter effects in c-VEP BCIs.

INTRODUCTION

Designing an effective brain-computer interface (BCI) requires decisions not only about decoding methods, but also about how neural responses are elicited. In code-modulated visual evoked potential (c-VEP) BCIs, the design of stimuli shapes the evoked brain response and therefore the resulting decoding performance [1].

One important stimulus parameter is contrast. Across psychophysics and visual physiology, contrast is known to shape the strength of early visual responses, with neural activity in visual cortex increasing systematically with stimulus contrast over much of the tested range [2]. Human electrophysiology shows a similar pattern: visual evoked responses measured with EEG/VEP paradigms vary reliably with contrast, indicating that stronger contrast can produce stronger and more discriminable visually evoked activity [3–5]. In c-VEP BCIs, this suggests that increasing contrast could improve decoding performance by strengthening the stimulus-evoked response, although the magnitude of this benefit may vary across

participants and may need to be balanced against practical considerations such as visual comfort and usability [6–8], which may be higher for lower contrast levels.

However, contrast does not act independently of the stimulus design. In addition to conventional spatially uniform luminance flicker, recent work has considered textured stimulation patterns that introduce spatial structure into the stimulus [7]. In the present study, we compare a *classic* condition, consisting of spatially uniform luminance modulation around a mid-gray baseline, with a *grating* condition, in which the active state contains a textured pattern composed of multiple Gabor-like patches with different orientations. In the grating condition, modulation is therefore defined by the appearance of oriented spatial texture around a mid-gray baseline rather than a purely global luminance change. Consequently, it could be plausible that contrast effects may differ between the two stimulus families.

Most previous evaluations of c-VEP stimulation settings have focused on aggregate outcomes such as decoding accuracy or subjective ratings [1, 6–8]. While such measures are important, they do not fully capture how reliably a given stimulus setting produces usable responses across trials. For practical BCI design, a good parameter setting should not only yield high average performance, but should also produce strong trial-level performance with limited uncertainty and trial-to-trial variability [9, 10]. Therefore, it is important to characterize the contrast space not only in terms of performance but also in terms of trial-to-trial variability and uncertainty.

The present study examines how stimulus contrast affects c-VEP decoding in both classic and grating conditions using a trial-level performance metric derived from the class-wise trial scores. Rather than considering only average decoding accuracy, we model how this metric changes across contrast levels and quantify the associated uncertainty and trial-to-trial variability. To this end, we use Gaussian process regression to characterize subject- and condition-specific contrast-response functions. Specifically, we test whether trial-level performance generally increases with contrast, whether this effect differs between classic and grating stimuli, and whether variability remains approximately stable across contrast levels or differs across subjects and conditions. We expect higher contrast to generally yield stronger trial-level performance, although the shape of

the contrast-response function may vary with stimulus type and individual differences.

METHODS

Dataset and experimental design: Five healthy participants took part in the study (age 21–56 years, mean 34 years; 4 female). All had normal or corrected-to-normal vision and no history of neurological disorders. The study was approved by the Ethics Committee of the Social Sciences of the Radboud University, and written informed consent was obtained from all participants. One participant was excluded because of insufficient EEG data quality, leaving four participants for analysis.

The dataset comprised a visual speller experiment with two stimulation conditions: a *classic* condition and a *grating* condition. In the classic condition, stimulation consisted of spatially uniform luminance modulation around a mid-gray baseline. In the grating condition, the active state ($bit = 1$) consisted of a textured pattern composed of multiple Gabor-like patches with different orientations, producing a spatially structured stimulus rather than a uniform luminance field. In both conditions, the stimulus modulation was centered around the mean luminance of the display (see Figure 1).

Visual stimulation was presented on a 120 Hz display. Stimuli were presented in a c-VEP speller with 32 symbols arranged in a 4×8 grid. Each symbol in the speller was assigned a unique code derived from a 63-bit m -sequence, with circular shifts of 2 bits used to generate 32 distinct target codes. The codes were presented at a 60 Hz presentation rate for a cycle duration of 1.05 s.

The stimulus contrast parameter was defined relative to the mean luminance of the display. A contrast of 100% corresponds to a modulation of $\pm 50\%$ around the mean luminance, whereas 40% contrast corresponds to $\pm 20\%$ of modulation in both directions. Thus, across all conditions, the temporal modulation of each target was centered around the same mean luminance, such that the average brightness remained constant and only the modulation amplitude varied.

Six contrast levels, $c \in C = \{10, 20, 30, 40, 60, 100\}$, were tested in both classic and grating conditions, yielding 12 stimulus conditions in total. For each condition, 32 trials of 4.2 s duration (four m -sequence cycles) were collected, one for each target. The order of trials and conditions was fully randomized. Before stimulation, the target was cued to the participant by highlighting its background in green for 800 ms. The 384 trials collected per participant in a single session were divided into eight runs, between which self-paced breaks could be taken.

EEG acquisition and preprocessing:

EEG was recorded with a 64-channel BioSemi ActiveTwo system. Preprocessing was implemented in Python using MNE-Python (version 1.11.0) [11]. Continuous EEG was band-pass filtered from 6 to 21 Hz using MNE’s default zero-phase FIR filter with a Hamming window and `firwin` design; the filter length was au-

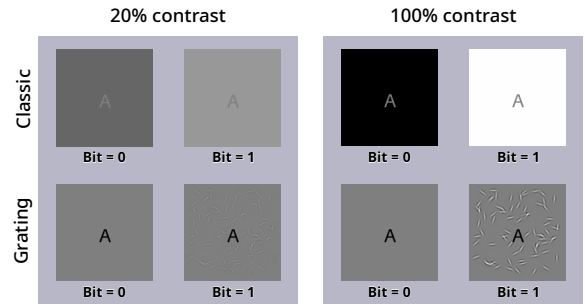


Figure 1: **Example stimuli used in the experiment.** Two contrast levels (20% and 100%) are shown. In the classic condition the stimulus consists of spatially uniform luminance flicker. In the grating condition the flicker is modulated by Gabor grating patterns.

tomatically determined from the transition bandwidths. Epochs were extracted from -0.5 to 4.7 s relative to trial onset, resampled to 120 Hz, and cropped to the analyzed 0 to 4.2 s stimulation interval. No baseline correction was applied.

Decoding: Decoding was performed offline, separately for each subject, stimulus condition, and contrast level, using a two-stage pipeline implemented in Python. Within each subject–condition–contrast combination, a 4-fold cross-validation procedure was used to estimate decoding performance.

Within each trial, overlapping encoding windows were extracted using an encoding length of 300 ms and a stride of $1/60$ s, that is, synchronized to the bit presentation rate. These epochs were first transformed using canonical correlation analysis (CCA) with one component and covariance regularization parameters γ_x and γ_y ($\gamma_x = \gamma_y = 0.1$) [12, 13].

The transformed epochs were subsequently vectorized and classified using a linear discriminant analysis (LDA) classifier with the *eigen* solver and Ledoit–Wolf shrinkage to regularize the covariance estimate, as implemented in scikit-learn (version 1.8.0) [14].

Epoch-level class probabilities were recombined across the trial and correlated with the tiled stimulus codebook to obtain class-wise trial scores ρ_{ij} , where ρ_{ij} denotes the score assigned to the target candidate symbol j in trial i [13]. The predicted symbol was $\hat{y}_i = \arg \max_j \rho_{ij}$.

Trial-level performance metrics:

Trial-level performance metrics were derived from the class-wise trial scores to quantify how strongly each trial supported the correct class. Let ρ_{i,y_i} denote the score of the true class for trial i . Two Fisher-transformed performance metrics were analyzed:

$$\begin{aligned} z_{\text{true},i} &= \text{atanh}(\rho_{i,y_i}), \\ z_{\text{margin},i} &= \text{atanh}(\rho_{i,y_i}) - \text{atanh}\left(\max_{j \neq y_i} \rho_{ij}\right). \end{aligned} \quad (1)$$

Both metrics are expressed on the Fisher-z scale, which stabilizes the variance of correlations and makes the values more suitable for regression and between-trial comparisons [15].

The two metrics capture complementary aspects of trial-level performance. z_{true} reflects the absolute strength of the match between the EEG response and the true stimulus code. In contrast, z_{margin} measures the separation between the true class and the strongest competing class, that is, the runner-up symbol, and therefore more directly reflects decision-relevant trial-level performance. As classification depends on this relative separation, z_{margin} was used as the primary target variable in the Gaussian process analysis.

Before GP modeling, we applied a shared trial-level outlier filter based on z_{margin} . Within each subject $\times$ condition $\times$ contrast group, trials with MAD-based robust z-scores exceeding 3.5 in absolute value were removed, where the robust z-score was computed relative to the group median and scaled by the median absolute deviation (MAD). The same exclusion mask was applied to all modeled targets.

Contrast-response modeling: The goal of the statistical analysis was to characterize how the trial-level performance metric varies with stimulus contrast. Contrast was modeled as $x_i = \log_{10}(c_i)$ and standardized as $\tilde{x}_i = (x_i - \mu_x)/\sigma_x$, consistent with psychophysics and visual-neuroscience work showing that contrast-response relationships are often more regular when expressed as a function of contrast than on the raw linear scale [2, 16]. For a given subject-condition pair, let

$$D = \{(\tilde{x}_i, y_i)\}_{i=1}^N$$

denote the retained trial-wise observations after outlier removal, where N is the number of retained trials and y_i is either $z_{\text{true},i}$ or $z_{\text{margin},i}$. The observed trial-level metric was modeled as

$$y_i = f(\tilde{x}_i) + \varepsilon_i, \quad (2)$$

where $f(\tilde{x})$ denotes the latent mean contrast-response function and ε_i is a zero-mean residual term capturing trial-to-trial deviations around that mean. Separate Gaussian process models were fit for each subject and stimulus condition.

Gaussian process contrast-response model: A Gaussian process prior was placed on the latent contrast-response function,

$$f(\tilde{x}) \sim \mathcal{GP}(0, k(\tilde{x}, \tilde{x}')), \quad (3)$$

where $k(\tilde{x}, \tilde{x}')$ is a squared-exponential covariance kernel,

$$k(\tilde{x}, \tilde{x}') = \eta^2 \exp\left(-\frac{(\tilde{x} - \tilde{x}')^2}{2\ell^2}\right), \quad (4)$$

with signal amplitude η and lengthscale ℓ . The kernel hyperparameters were assigned weakly regularizing positive priors,

$$\eta \sim \text{HalfNormal}(2), \quad \ell \sim \text{Gamma}(2, 1). \quad (5)$$

Posterior summaries were evaluated on a dense grid of 200 contrast values spanning the observed range. Figures

report the posterior mean together with 94 % highest-density intervals.

Two observation models were considered. First, a homoskedastic model:

$$y_i | f(\tilde{x}_i) \sim \mathcal{N}(f(\tilde{x}_i), \sigma^2), \quad \sigma \sim \text{HalfNormal}(1). \quad (6)$$

Second, a heteroskedastic model, in which the observation noise was allowed to differ across the discrete tested contrast levels. Let $c_i \in \mathcal{C}$ denote the raw contrast level associated with trial i . Then

$$y_i | f(\tilde{x}_i) \sim \mathcal{N}(f(\tilde{x}_i), \sigma_{c_i}^2), \quad \sigma_c \sim \text{HalfNormal}(1), \quad c \in \mathcal{C}. \quad (7)$$

Thus, the mean contrast-response relationship was modeled as a smooth function of standardized log-contrast $\tilde{x}_i$, whereas the observation noise was allowed to vary across the six discrete contrast conditions. Both models were fit for diagnostic purposes, but the main contrast-response curves reported in the results section are based on the homoskedastic model.

Posterior inference was performed in PyMC (version 5.28.0) using the No-U-Turn sampler with the NumPyro backend (version 0.20.0) [17]. Sampling used 1000 tuning iterations and 1000 posterior draws with a target acceptance probability of 0.95.

RESULTS

Trial-level performance as a function of stimulus contrast:

Figure 2 shows Gaussian process estimates of the trial-level performance metric z_{margin} as a function of stimulus contrast for each subject and stimulus condition. Across subjects, trial-level performance increased systematically with stimulus contrast. At low contrast levels (10–20 %), z_{margin} values were typically close to zero, indicating weak separation between the target and competing symbols. As contrast increased, the expected decoding margin increased monotonically, indicating more reliable decoding.

Analyses using z_{true} yielded the same qualitative conclusions, with fitted mean curves nearly identical to those for z_{margin} ($r \approx 0.995$ – 0.999). As z_{margin} directly reflects the separation between the true class and its strongest competitor, it was used as the primary metric in the figures and quantitative summaries, while analyses based on z_{true} yielded the same qualitative conclusions.

Homoskedastic Gaussian process fits revealed substantial variability between subjects and a clear interaction with the stimulus condition. In the classic condition, three of four subjects already showed positive trial-level performance at 10 % contrast. Across subjects, the mean posterior estimate increased from 0.08 at 10 % contrast to 0.26 at 100 % contrast. Subject 4 showed the strongest classic response, rising from 0.20 to 0.48 across the tested

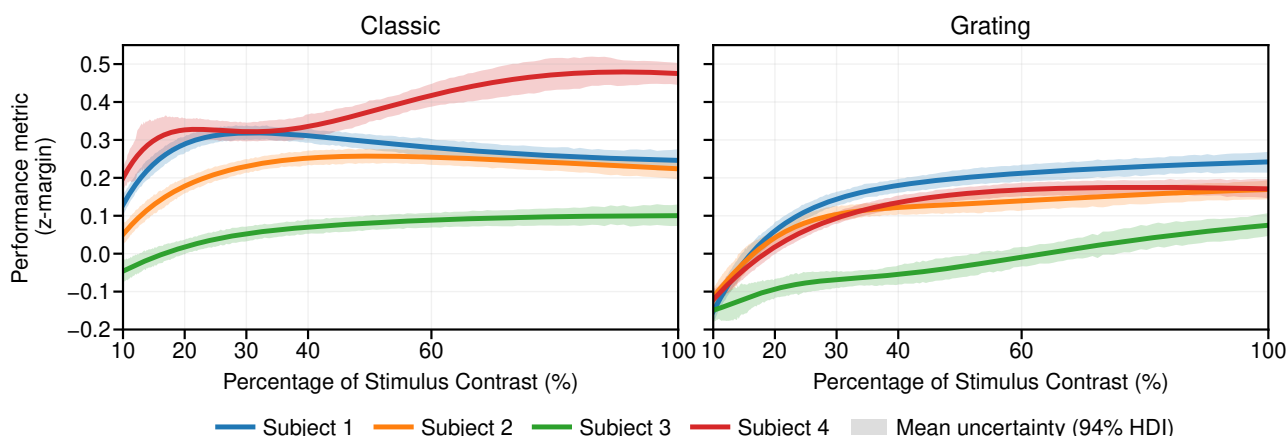


Figure 2: **Subject-wise trial-level performance curves as a function of contrast.** Gaussian process estimates of the trial-level performance metric z_{margin} are shown for each subject in the classic stimulus condition (left) and the grating stimulus condition (right). Higher values indicate stronger separation between the true target and competing targets. Solid lines show the posterior mean of the homoskedastic Gaussian process estimate of the expected trial-level performance as a function of contrast, and shaded regions indicate the 94 % highest-density interval.

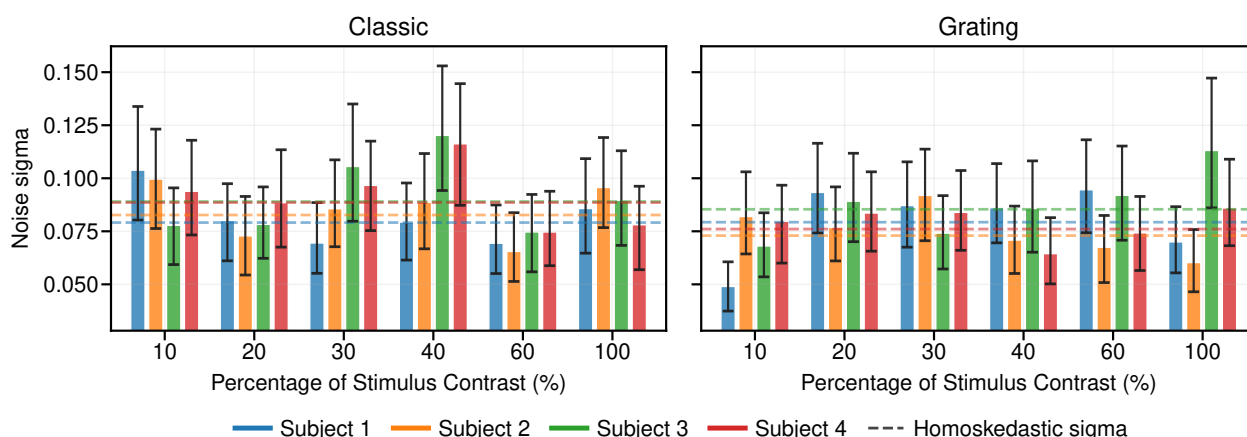


Figure 3: **Estimated observation noise by contrast and subject.** Estimated observation noise is shown across contrast levels for the classic (left) and the grating condition (right). Bars indicate posterior mean noise estimates with 94 % highest-density intervals.

contrast range, whereas Subject 3 remained weakest and reached only 0.10 at 100 % contrast.

The grating condition produced lower trial-level performance overall than the classic condition. All grating curves started near or below zero at 10 % contrast and increased more gradually with contrast, reaching a lower across-subject mean of 0.16 at 100 % contrast. The magnitude of the condition effect differed across subjects. Subject 1 showed nearly identical performance across conditions at high contrast (the difference between classic and grating at 100 % was only 0.004), whereas Subject 4 retained a strong classic advantage throughout the range (difference at 100 % contrast: 0.304).

Contrast-dependent observation noise:

Allowing the observation noise to vary by contrast revealed a modest level of heteroskedasticity in z_{margin} (Figure 3), although the pattern was subject- and condition-specific rather than globally monotonic.

At the individual level, noise in the classic condition was typically increased either at low contrast (Subjects 1–2: $\sigma \approx 0.10$ at 10 % contrast) or around mid contrast (Subjects 3–4: $\sigma \approx 0.12$ at 40 % contrast).

Noise levels in the grating condition were generally lower at 10 % contrast (mean across subjects = 0.070) and tended to increase toward intermediate or high contrasts. The clearest high-contrast increase was observed for Subject 3 in the grating condition, where σ reached 0.113 at 100 % contrast.

However, within-subject changes in noise across contrast were relatively small overall (ranges approximately 0.02–0.05), and many 94 % HDIs overlapped. This indicates that contrast-dependent noise effects were weaker and less systematic than the subject- and condition-dependent differences observed in the mean contrast-response curves in Figure 2.

DISCUSSION

We examined how stimulus contrast shapes trial-level performance in c-VEP stimulation, comparing a classic luminance-flicker condition with a spatially structured grating condition. Across subjects and conditions, trial-level performance generally increased with contrast, supporting the expectation that stronger stimulus contrast elicits more separable target-related responses. However, the results also showed that this effect is not captured well by a single global contrast rule: the shape and magnitude of the contrast–response relationship varied substantially across subjects and differed between the two stimulus families.

In this dataset, increasing contrast appeared to primarily improve the *mean* trial-level performance, while contrast-dependent changes in estimated trial-to-trial noise were comparatively modest. In other words, higher contrast mainly improved the separation between the true target and competing targets rather than strongly altering the variability of this trial-level performance metric across trials. This is consistent with the interpretation that contrast strengthens the evoked response itself, in line with known contrast effects in visual cortex and electrophysiology, and that the practical decoding benefit arises mainly from a stronger target-related signal rather than from a substantial reduction in uncertainty. In the present data, this effect was visible already at the level of subject-wise Gaussian process curves, where the increase in z_{margin} with contrast was clearer and more systematic than any corresponding pattern in the noise estimates.

A second observation is that the classic condition generally yielded stronger trial-level performance than the grating condition, with spatially uniform luminance modulation producing a larger decision-relevant margin than the textured grating stimulus. This contrasts with the findings of Dehaes and colleagues, who reported that textured flickers based on Gabor and Ricker patterns achieved higher classification accuracy than plain flicker stimuli, while also improving perceived visual comfort [7]. The discrepancy likely reflects differences in stimulus sequences, the user interface, the number of symbols, the spatial structure, and the decoding pipelines across studies, suggesting that the benefit of textured stimulation is not universal but depends on implementation details. Spatial structure is known to interact with contrast processing in the visual system, meaning that nominally identical contrast levels can drive different neural populations depending on stimulus texture and spatial frequency [18].

Importantly, the difference between the two stimulus families was not uniform across subjects. In some subjects, the grating condition approached the classic condition at higher contrast levels, whereas in others the classic condition retained a clear advantage across the entire range. This inter-individual variability is practically important, as it suggests that both the optimal contrast level and the preferred stimulus family may vary across

users. The present sample is too small to identify reliable predictors of these differences. Age could contribute, given known age-related changes in visual processing, but this cannot be tested with $N = 4$. Other factors, including visual acuity, attention, fatigue, cortical response strength, or preference for spatially structured stimulation, may also play a role. Larger studies should examine whether demographic, perceptual, or neurophysiological measures predict which users benefit from specific stimulus settings.

The margin-based metric z_{margin} provides a trial-level view of how strongly the neural response supports the correct decision within the decoder. Although it is not itself an online BCI performance measure, it is directly related to classification: larger positive margins indicate more robust correct selections, whereas margins close to zero indicate decisions that are more vulnerable to noise or changes in stopping time. This decoder-level perspective complements physiological stability measures, such as correlations or covariance between repeated EEG epochs, which capture response reproducibility more directly and have been shown to predict individual differences in c-VEP performance [10]. Future work could therefore combine signal-level stability measures with trial-level decision metrics when evaluating stimulus design.

Several limitations should be noted. First, the number of analyzed subjects was small ($N = 4$), and the study should therefore be interpreted as preliminary and exploratory. The goal was not to establish population-level effects, but to test whether trial-level modeling can characterize how stimulation parameters relate to both mean decoding performance and trial-to-trial reliability. Contrast level and stimulus family therefore served as example parameters for a broader goal: individualized stimulus-parameter selection in c-VEP BCIs. The observed between-subject differences should accordingly be viewed as possible individual trends, not as stable or generalizable group-level effects.

Second, the number of trials per stimulus setting was limited to 32. This limits the precision of absolute performance estimates, but the present analysis aimed to compare parameters rather than obtain a definitive performance value for each setting. Sosulski and Tangermann showed that reduced ERP-BCI datasets can still preserve information about which stimulation parameters are preferable, even when absolute estimates are noisy [19]. Thus, 32 trials per contrast level were considered sufficient for an exploratory within-subject comparison of contrast-dependent parameter effects, but not for precise population-level estimates.

Third, the analysis was performed offline and within a single decoding pipeline. Although the CCA–LDA approach was chosen as a standard and regularized c-VEP decoding pipeline, different preprocessing choices or classifiers could interact differently with stimulus structure, particularly for the grating condition. In addition, contrast was defined physically relative to display lu-

minance. Perceived contrast may differ across participants and could therefore contribute to the observed inter-individual variability. Finally, practical stimulus selection should also consider comfort, fatigue, and visual strain, which may favor stimuli that do not maximize decoding performance alone.

In summary, the present findings suggest that contrast can influence trial-level performance in c-VEP, primarily through its effect on the strength of the decision-relevant margin between the target and competing classes. In this dataset, the classic condition produced stronger trial-level performance overall, whereas the grating condition showed weaker but qualitatively similar contrast dependence. Modeling trial-wise performance with Gaussian processes provided an interpretable way to characterize both the mean contrast-response relationship and its uncertainty, and may be useful for future studies seeking to optimize visual stimulation parameters.

CONCLUSION

Overall, stimulus contrast influenced trial-level c-VEP decoding performance in this preliminary dataset, mainly by increasing the decision-relevant decoding margin. The effect was stronger for classic luminance flicker than for grating stimulation, while estimated trial-to-trial noise changed only modestly. These findings illustrate how trial-level evidence metrics and Gaussian process modeling can characterize stimulus-parameter effects beyond aggregate accuracy.

ACKNOWLEDGMENTS

This publication is part of the project Dutch Brain Interface Initiative (DBI2) with project number 024.005.022 of the research programme Gravitation which is (partly) financed by the Dutch Research Council (NWO).

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