tCFS: A new 'CFS tracking' paradigm reveals uniform suppression depth regardless of target complexity or salience

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Abstract

When the eyes view separate and incompatible images, the brain suppresses one image and promotes the other into visual awareness. Periods of interocular suppression can be prolonged during continuous flash suppression (CFS) - when one eye views a static 'target' while the other views a complex dynamic stimulus. Measuring the time needed for a suppressed image to break CFS (bCFS) has been widely used to investigate unconscious processing, and the results have generated controversy regarding the scope of visual processing without awareness. Here, we address this controversy with a new 'CFS tracking' paradigm (tCFS) in which the suppressed monocular target steadily increases in contrast until breaking into awareness (as in bCFS) after which it decreases until it again disappears (reCFS), with this cycle continuing for many reversals. Unlike bCFS, tCFS provides a measure of suppression depth by quantifying the difference between breakthrough and suppression thresholds. tCFS confirms that: (i) breakthrough thresholds indeed differ across target types (e.g., faces vs gratings, as bCFS has shown) – but (ii) suppression depth does not vary across target types. Once the breakthrough contrast is reached for a given stimulus, all stimuli require a strikingly uniform reduction in contrast to reach the corresponding suppression threshold. This uniform suppression depth points to a single mechanism of CFS suppression, one that likely occurs early in visual processing that is not modulated by target salience or complexity. More fundamentally, it shows that variations in breakthrough thresholds alone are insufficient for inferring unconscious or preferential processing of given image categories.

Significance statement

Research on unconscious vision has proliferated recently, often employing the continuous flash suppression (CFS) method in which flicker in one eye suppresses the other eye's image from awareness. That image is strengthened progressively until it breaks into visibility. Low breakthrough thresholds are claimed to indicate unconscious processing during suppression. We introduce a method that quantifies breakthrough and also suppression thresholds, thus providing a lower bound missing from previous CFS research. Comparing various image types, including those claimed to undergo unconscious processing, all images show equal suppression when both thresholds are measured. We thus find no evidence of differential unconscious processing and conclude reliance on breakthrough thresholds is misleading without considering suppression thresholds and leads to spurious claims about unconscious processing.

Introduction

The quest to understand visual processing outside of awareness is tantalising but notoriously challenging to implement (Breitmeyer, 2015; Hesselmann & Moors, 2015; Holender, 1986; Logothetis, 1998; Newell & Shanks, 2014; Schmidt, 2015). There are controversial claims of higher-level semantic processing (Lanfranco et al., 2022; Mudrik et al., 2014; Stein & Sterzer, 2014; Sterzer et al., 2014), object categorization (Kouider & Dehaene, 2007; Rees, 2007; Sterzer et al., 2014), and abstract reasoning (Hassin, 2013; Sklar et al., 2012) occurring outside of awareness. Several methods can be used to manipulate visual awareness (Kim & Blake, 2005), although interocular suppression in the form of binocular rivalry (Alais & Blake, 2014) or continuous flash suppression (CFS: (Fang & He, 2005; Tsuchiya & Koch, 2005) have been popular approaches, with CFS in particular having recently been very widely used. Interocular suppression arises when dissimilar images are presented independently to each eye, the result being only one eye's image is perceived, with the other suppressed. For images approximately matched in saliency, as is usually the case in binocular rivalry (Alais & Blake, 2014; Wang et al., 2022), monocular suppression lasts for no more than a few seconds before switching to suppress the other eye (and so on, alternating irregularly over time). With CFS, a highly salient stream of dynamic images seen by one eye suppresses a smaller, weaker target presented to the other for considerably longer periods of suppression that can last tens of seconds. The potency of CFS has great appeal when it comes to assessing residual effectiveness of different categories of visual stimuli blocked from awareness by CFS.

A commonly used variant known as "breaking CFS" (bCFS) was introduced by (Jiang et al., 2007) in which the suppressed target slowly ramps up from low contrast until it becomes sufficiently strong to break suppression and achieve visibility. Time to breakthrough has become a popular measure, and differences in breakthrough times among various image types have been used to support claims for unconscious processing of certain visual images. A shorter time to reach visual awareness is interpreted as evidence of unconscious processing of an image, or at least a preferential processing of that image. For example, emotional faces break suppression faster than neutral faces (or non-face) images (Alais, 2012; Jiang et al., 2007; Tsuchiya et al., 2006; Yang et al., 2007), as do emotionally relevant images compared to semantically neutral images (Alais, 2012; Jiang et al., 2007; Tsuchiya et al., 2006; Yang et al., 2007), and native words compared to foreign words (Jiang et al., 2007). Skeptics argue, however, that differences in breakthrough times can be attributed to low-level factors which vary between images, such as spatial frequency, orientation and contrast (Gayet et al., 2014; Moors, 2019; Moors et al., 2016, 2017; Moors &

Hesselmann, 2018; Stuit et al., 2023), and more fundamentally, that breakthrough times alone are insufficient to measure differential unconscious processing (Stein, 2019).

Conclusions based on a comparison of bCFS breakthrough times between different image categories suffer from a problem of unidirectionality and a false assumption of image equivalence[1]. Images producing faster breakthrough times (equivalently, lower breakthrough contrasts) are interpreted as undergoing residual processing outside of awareness, adding to their salience and weakening their interocular suppression (Mudrik et al., 2011; Sterzer et al., 2011; G. Zhou et al., 2010; W. Zhou et al., 2010)). An implicit assumption here is that as all images were initially invisible, the depth of interocular suppression was thus weaker for images with faster reaction times. Yet, the depth of interocular suppression is rarely measured in CFS paradigms (see Tsuchiya et al,. 2006 for an exception), and to our knowledge, has not been explicitly compared between image categories.

One method for measuring interocular suppression is to compare the threshold for change-detection in a monocularly suppressed or dominant target, as has been established in binocular rivalry research (Alais, 2012; Alais et al., 2010; Alais & Melcher, 2007; Nguyen et al., 2003). Suppression depth (or strength) is quantified based on the difference between detection thresholds during dominance/suppression, which is advantageously standardised as a relative change in contrast within the same stimulus. Ideally, the change should be a temporally smoothed contrast increment to the rival image being measured (Alais, 2012), which provides a natural complement to the linear contrast ramps that are standard in bCFS research. Here, we measure bCFS thresholds as the analog of change-detection during suppression, and as their complement, record re-suppression thresholds (reCFS) by including a bidirectional measure in which the contrast ramp decrements over time, eventually transitioning the target from dominance to suppression (Figure 1). By comparing the thresholds for a target to transition into and out of awareness, we recognise that the criterion for change is much higher, and as a result expect larger suppression depths (on average) than those recorded in rivalry research. More importantly, however, by averaging the difference between bCFS and reCFS thresholds, a key analogue of suppression depth that has been missing from the CFS literature can be provided and compared between image categories.

Here, we introduce a novel method termed 'tracking CFS' (tCFS) which combines

[1] An exception here is when the same image is compared under different contexts, such as after associative learning of value (Lunghi & Pooresmaeili, 2023) or fear conditioning (Gayet et al., 2016).

alternating down-ramped and up-ramped targets, to provide a measure of suppression depth that allows a more rigorous test of claims that certain images undergo less suppression than others (see Figure 2). The participant views a visible target as it declines in contrast until suppressed. When suppression is reported the contrast change reverses direction and the participant indicates when the target emerges out of dominance and is seen once again (triggering a contrast decrease again, and so on over many reversals). By continually tracking thresholds for breakthrough (bCFS) and re-suppression (reCFS) over time, tCFS is very efficient, makes no assumptions of image equivalence, and provides inherently bidirectional measures of CFS.

To foreshadow our results, across three experiments we find no evidence using the tCFS paradigm for differences in suppression depth among any of the image categories tested (e.g., faces, objects, noise). We do replicate the common observation that breakthrough thresholds differ across image categories, yet re-suppression thresholds were tightly linked to breakthrough such that suppression exhibited a constant difference (i.e., suppression depth) relative to breakthrough threshold. We therefore find no evidence to support differential unconscious processing among categories of suppressed images.

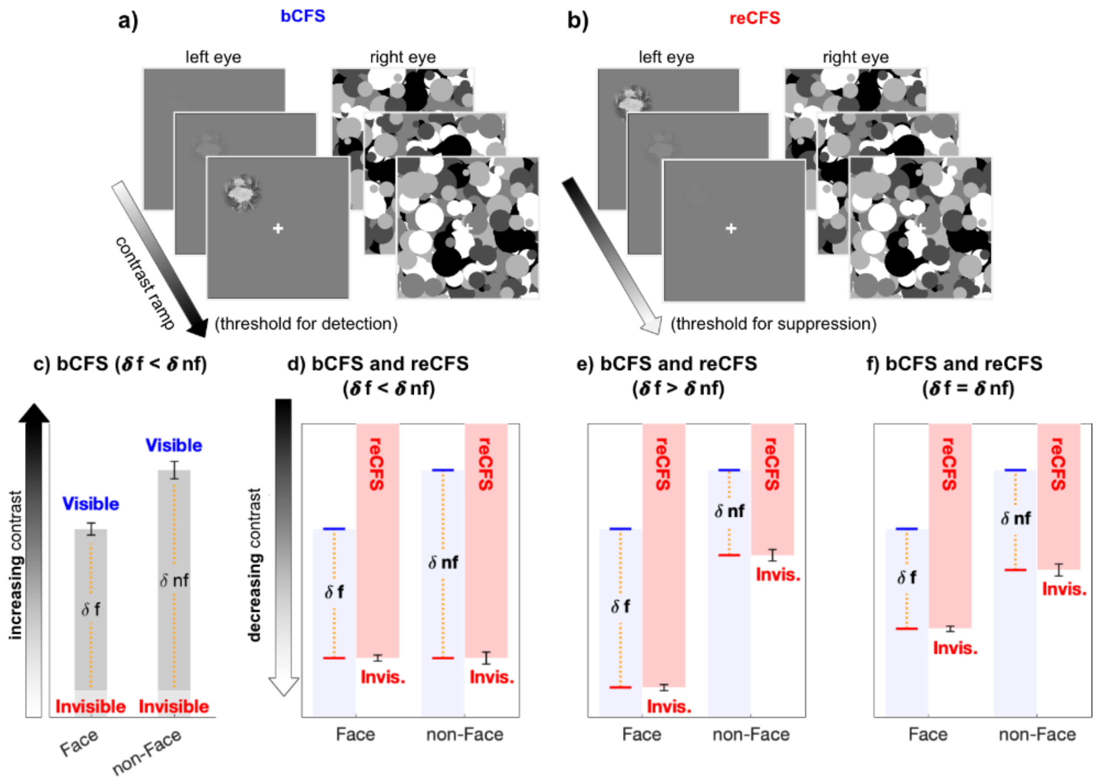


Figure 1. The critical measure of suppression depth remains untested in CFS. **a,b)** Example stimulus displays for the discrete trials, during which (a) a low-contrast target steadily increases in contrast until visibility is reported (bCFS), and (b) discrete reCFS trials, with a high-contrast target decreasing until target invisibility is reported. **c)** A typical bCFS result, in which a target image (here a face or non face) is initially weak and steadily increases until it breaks suppression. Faster breakthrough times (lower contrast) for face stimuli are often interpreted as evidence that faces undergo less suppression than non-faces. Without also measuring suppression thresholds for each stimulus, this conclusion is invalid. **d-f)** To define the magnitude of suppression during CFS, it is necessary to measure the contrast thresholds at which stimuli enter and exit from awareness, with the difference indicating suppression depth. Red bars display hypothetical results measuring the contrast at which an initially visible stimulus with decreasing contrast becomes suppressed by the mask (reCFS). The results of panel **c** are reproduced in d-f in light blue. **d)** If the reCFS thresholds for face and non-face images are the same, this would support reduced suppression depth for faces (as δ face < δ non-face). **e)** Alternatively, the reCFS thresholds for faces and non-faces might differ, with the face remaining visible at a lower contrast than non-face images (lower reCFS threshold), indicating more suppression for faces than non-faces (as δ face > δ non-face). **f)** Finally, the reCFS thresholds might differ between faces and non-faces but by an amount equivalent to their bCFS differences, indicating the same suppression depth for both image types (as δ face = δ non-face). Such a result would argue against enhanced unconscious processing of face stimuli.

General Methods

Participants

A total of 36 undergraduate psychology participants volunteered in exchange for course credit. All participated with informed consent and had normal or corrected-to-normal vision. Our sample size for Experiment 1 was based on power estimates to detect a moderate sized effect in a 2 x 2 repeated-measures design (Faul et al., 2009), while also exceeding the typical sample size used in bCFS studies to compensate for our novel paradigm (e.g., n = 10, Cha et al., 2019, n = 10–16, Han et al., 2021). We adjusted our power analysis after observing a strong effect size for the difference between bCFS and reCFS thresholds when using the tCFS method, resulting in fewer participants in Experiments 2 and 3. Experiment 1: N = 20, (15 females), Experiment 2: N = 16 (12 females), Experiment 3, N = 15 (11 females). All participants in Experiment 3 also did Experiment 2. This study was approved by the University of Sydney Human Research Ethics Committee (HREC 2021/048).

Apparatus

Visual stimuli were displayed on a Mac Pro (2013; 3.7 GHz Quad-Core Intel Xeon E5) computer, displayed on an Apple LED Cinema monitor (24 inch, 1920 x 1200 pixel resolution, 60 Hz refresh rate), running OS X El Capitan (10.11.6). All experiments were programmed using custom MATLAB code, and displayed using Matlab (ver R2017b) and Psychtoolbox (ver 3.0.13; Brainard et al., 1997). Responses were collected via the left mouse button of the right hand. A mirror stereoscope was used to partition participant's vision into separate left- and right-eye views, located approximately 51 cm from the screen, with a total optical path length of 57 cm.

Stimuli

Participants dichoptically viewed a high-contrast Mondrian mask pattern (400 x 400 pixels, 7° x 7°) with one eye and a small target stimulus (130 x 130 pixels, 2.2° x 2.2°) with the other eye. Two binocularly presented white squares surrounded the mask and served as a fusion lock to maintain stable fusion, and each eye had a central fixation cross (18 x 18 pixels; 0.3° x 0.3°). The Mondrian pattern was greyscale and consisted of overlapping circles of various sizes and intensities and was updated every fifth video frame (12 Hz). The mask's RMS contrast ranged between 0.07 and 0.09. As previous research has indicated that achromatic masks may be optimal to suppress achromatic targets (reviewed in (Pournaghdali & Schwartz, 2020), we opted for grayscale Mondrian patterns to match our targets.

In all experiments targets were viewed by the right eye and were selected at random from a set that was standardised in RMS contrast (20%) and mean luminance (before contrast ramping was applied). Target contrast was ramped up or down by scaling the target image's standard contrast within a range of .02 to 1.0. Importantly, all contrast scaling was done on a logarithmic scale in decibel units (i.e., conDb = 20 x log10(con)) to make the changes effectively linear, given the visual system's logarithmic contrast response function. Minimum (.02) and maximum (1.0) contrast values were thus -33.98 and 0 dB, respectively, and contrast steps were .07 dB per video frame. In experiment 3, where the rate of target contrast change was manipulated, the contrast steps were .035, .07, or .105 dB units per video frame. Target location varied between trials, drawn from a uniform distribution of 200 x 200 pixels centred on the fixation cross.

Procedure

Participants were given practice trials until they were familiar with CFS and the task used in these experiments. Participants were instructed to respond via mouse click the moment their subjective visibility of the target stimulus changed (either when a visible target became suppressed, or when a suppressed target became visible). The phenomenological quality of reversals may differ between participants (Moors et al., 2017; Zadbood et al., 2011), however we encouraged participants in the practice session to establish a criteria for target appearance/disappearance and to maintain it throughout the experiment. In all experiments, the dependent variable was the target contrast at the moment when a change in target visibility occurred (either breaking suppression or succumbing to suppression).

Experiment 1 - Using tCFS to measure suppression depth

Our first experiment was motivated to test for a difference between reCFS and bCFS thresholds, and to contrast the results obtained when using discrete trials – as is common in bCFS research, with results from the continuous tracking procedure. We hypothesised that a difference between bCFS and reCFS thresholds would provide evidence for a contrast range (i.e., suppression depth) between awareness and suppression, in contrast to the possibility of a given contrast threshold determining a narrow awareness/suppression border. By comparing the results between discrete and continuous methods, we sought to establish the feasibility of collecting multiple thresholds within a single-trial, allowing the rapid quantification of suppression depth in CFS paradigms. Experiment 1 compared CFS thresholds for targets increasing in contrast and decreasing in contrast (i.e., bCFS and reCFS thresholds) in discrete trials and in continuous tracking trials, in a 2 x 2 repeated-measures, within-subjects design. In the discrete conditions, participants completed eight blocks of eight trials, during which target contrast always changed in one direction - either increasing from low to high as is typically done in bCFS studies to measure breakthrough thresholds, or decreasing from high contrast to low to measure a suppression threshold. In the continuous condition, the target contrast tracked down and up continuously, reversing direction after each participant response. Continuous trials always began with the target decreasing from maximum contrast so that the participant's first response was to report when it disappeared, which caused target contrast to increase until breakthrough was reported, which caused it to decrease again until suppression, etc.. Continuous trials terminated after 16 reports of change in target visibility. When the contrast time series is plotted as shown in Figure 2b, the plot shows eight upper turning points where the target broke into awareness (bCFS thresholds) and eight lower turning points where the target became re-suppressed (reCFS thresholds). The order of discrete and continuous blocks was counterbalanced and randomized across participants. Images for the eight trials of each block type were drawn from the same set of four faces and four naturalistic objects, with no repetitions within a block. Before each block began, participants completed a series of practice trials that utilised an independent set of six images. They were able to complete practice trials as many times as they wished until they had confidently established interocular fusion and were comfortable with the requirements of the task.

Experiment 2 - The effect of image category

Experiment 1 demonstrated that the difference between bCFS and reCFS thresholds could be quantified rapidly using the tCFS procedure, and that this suppression depth of images could be quantified in an image-specific manner. In Experiment 2, we tested the suppression depth obtained for different image categories. Experiment 2 used only the continuous tracking 'tCFS' method and compared five image types (faces, familiar objects, linear gratings, phase scrambled images, and polar patterns that were radial lines or concentric circles). The trials contained 20 reports (10 bCFS and 10 reCFS thresholds) and the data were analysed in a 5 (image type) x 2 (bCFS vs reCFS thresholds) within-subjects, repeated-measures ANOVA. There were 10 tracking trials, with each trial containing a single target image from a subset of ten (two of each image category, randomly ordered for each participant).

Experiment 3 - Rate of contrast change on suppression depth

Experiments 1 and 2 introduced the tCFS method and demonstrated a uniformity of suppression depth across target image categories. This uniformity of suppression depth could indicate that neural events mediating CFS suppression are not selective for complexity or semantic meaning, and like popular models of binocular rivalry, could instead be based on low-level reciprocal inhibition and neural adaptation processes (Alais et al., 2010; Kang & Blake, 2010; McDougall, 1901)suppression depth would be sensitive to the rate of contrast change of the monocular target. More specifically, based on the adapting mutual inhibition model, we predicted that at a slower rate of contrast change neural adaptation for the monocular target would increase, lowering the amount of contrast change necessary to transition between visibility states. Similarly, a faster rate of target contrast change would reduce the time for neural adaptation of the monocular target, resulting in an increase in the required change in contrast necessary to transition a target into and out of awareness. Expressed in operational terms, the depth of suppression should increase with the rate of target change, which was the focus of Experiment 3.

Experiment 3 used the tCFS method and compared the rate of target contrast change (slow, medium, fast) across four image categories (faces, objects, linear gratings, and phase scrambled images). The trials contained 20 reports (10 bCFS and 10 reCFS thresholds) and the data were analysed in a 3 (contrast change rate) x 4 (image type) x 2 (bCFS vs reCFS thresholds) repeated-measures, within-subjects design. The medium rate of change was the same as used in Experiments 1 and 2, and the slow and fast rates were 0.5 and 1.5 times the medium rate, respectively. There were 12 tracking trials, given by the factorial combination of four target image types repeated at the three rates of target contrast change (in a randomised order for each participant).

Data Analysis

Data analysis was performed in Matlab (ver R2022a), and SPSS/JASP (ver 28). Initial inspection identified 1 participant for exclusion (from Experiment 3), based on failure to follow task instructions. For visualization and analysis, all contrast thresholds are expressed in decibel units.

Model Fitting

We additionally quantified the change in relative contrast over time, and evaluated a series of model fits to describe these data. For this analysis, bCFS and reCFS thresholds were first averaged within their respective response number, enabling a comparison of thresholds over the course of each trial. The modelling used the absolute change in contrast between each sequential threshold in the tracking series as its dependent variable, which we modelled after detrending, per participant, and at the group level.

We compared three basic models to this data. All models were fit with a non-linear least-squares approximation using a maximum of 400 iterations (lsqcurvefit.m in MATLAB) The first was a simple cubic polynomial with three free parameters:

1) $a\square^3 + b\square^2 + c\square$

where a, b and c are coefficients for the cubic, quadratic and linear term. We also fit a simple harmonic oscillator with three free parameters:

2) $a \times \sin(b \times t + c)$

Where a is amplitude, b is frequency, c is a phase offset, and t is time. We also fit a damped harmonic oscillator model with four free parameters:

3) $a \times e^{(-b \times t) \times \ \sin(c \times t + d)}$.

Where a and b describe the amplitude and damping coefficient of decay, and c and d describe the frequency and phase shift of the oscillatory response.

To fit each model, we linearly interpolated between the turning points (thresholds) in the tCFS time series of each trial to increase the observations to 1000 samples, and estimated the goodness of each fit through a series of steps. First, we calculated the sum of squared residual errors for each fit (SSE), and calculated the Bayesian Information Criterion (BIC) using equation 4:

4) $BIC = n \times \log(SSE/\ n\ ) + k \times \log(n)$;

Where n represents the number of observations in the dataset, SSE is the sum of squared errors, and k is the number of parameters in the model. The BIC allows a comparison of model fits while taking into account the goodness of fit and complexity of each model. It includes a penalty on the number of parameters in the model by including a term that scales with the logarithm of sample size. When comparing two models, the model with a lower BIC is considered favourable, with a change of 0 to 2 BIC as weak evidence in favour, and 6 to 10 as strong evidence in favour (Kass & Raftery, 1995),

Results

Experiment 1

Many previous bCFS studies have shown that *increasing* contrast eventually causes a target image to overcome interocular suppression. To our knowledge, however, none has investigated the contrast at which an initially visible image succumbs to suppression as its contrast is *decreased*. Experiment 1 uses the tCFS method to continuously track changes in target visibility as it rises and falls in contrast. As shown in Figure 2b, this provides a series of bCFS thresholds (upper turning points) as well as thresholds for the target's re-suppression (lower turning points: reCFS thresholds). We compare these thresholds to those obtained with a discrete procedure in which contrast either increased steadily from a low starting point until breakthrough (standard bCFS measure) or decreased steadily from a high starting point until suppression was achieved. On each trial the target image was either a face or a familiar object, with the images all matched in size, RMS contrast and mean luminance.

A repeated-measures ANOVA revealed a significant main effect of threshold, such that bCFS thresholds were significantly higher than reCFS thresholds ($F(1,19) = 50.38$, $p < .001$, $\eta_p^2 = .73$). There was also a significant interaction between threshold and condition ($F(1,19) = 41.19$, $p < .001$, $\eta_p^2 = .68$), indicating that the difference between bCFS and reCFS thresholds was influenced by whether they were recorded using the discrete trial procedure or the continuous trial procedure. Subsequent post-hoc tests revealed that bCFS and reCFS thresholds differed within each type of procedure (Discrete: $t(19) = 2.89$, $p = .009$, $d = 0.65$ Continuous: $t(19) = 12.12$, $p < .001$, $d = 2.7$). Overall, the suppression depth (i.e., the difference between bCFS and reCFS thresholds) was larger with the continuous procedure ($M = -15.40$ dB, $SD = 5.68$) compared to discrete procedure ($M = -5.74$ dB, $SD = 8.89$), $t(19) = 6.42$, $p < .001$). A finding we return to in the Discussion. Figure 2c displays a summary of these results.

After confirming a difference between bCFS and reCFS thresholds, we next compared suppression depth by image type. We repeated the analysis with the additional exploratory factor of image type (face vs object) in a 2 x 2 x 2 repeated-measures design (threshold, procedure, image type). We again found significant main effects of threshold ($F(1,19) = 47.72$, $p < .001$, $\eta_p^2 = .72$), and a threshold x condition interaction ($F(1,19) = 38.94$, $p < .001$, $\eta_p^2 = .67$), but no effect of image type ($p = .57$). In other words, there is a large disparity in contrast between targets breaking CFS and targets re-entering CFS, but the magnitude of this disparity is the same for objects and for faces. This potentially important finding is the focus of our next Experiment.

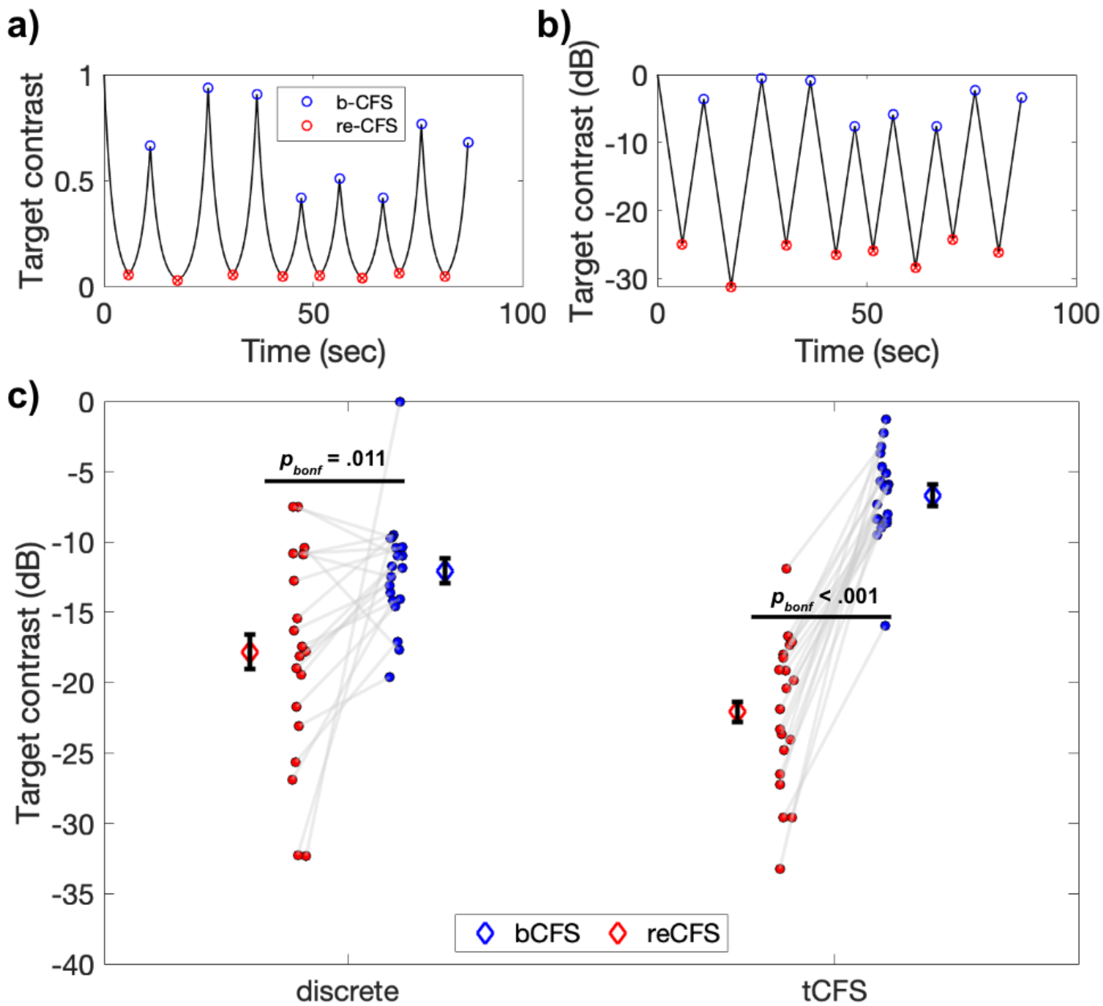


Figure 2. Example tCFS trial and comparison to discrete conditions**. a-b)** Example tCFS trial from one participant, showing the change in contrast over time. Red markers indicate the level at which a target with decreasing contrast became suppressed (reCFS) and blue markers indicate traditional bCFS responses (breakthrough of contrast-increasing target). The same trial is shown with target contrast in decibel scale in b. Because the human visual system has a logarithmic contrast response, it is appropriate to increase/decrease target contrast logarithmically as in b, to create a contrast change that is perceptually linear. **c)** Interaction between thresholds and condition type. Individual blue and red dots display participant means for bCFS and reCFS respectively. Grey lines link thresholds per participant, per condition. Blue and red diamonds display the mean across participants, and error bars plot ± 1SEM corrected for within participant comparisons (Cousineau, 2005).

Experiment 2

Experiment 1 disclosed that bCFS thresholds were not equivalent to reCFS thresholds, and demonstrated that the suppression depth of images could be quantified in an image-specific manner. Furthermore, Experiment 1 showed that suppression depth could be measured rapidly using the tCFS procedure and did not differ between faces and objects. In Experiment 2, we tested whether the constant suppression depth obtained in Experiment 1 for two image types would replicate across a larger variety of image categories.

We measured suppression depth for faces, objects, linear gratings, phase scrambled images, and radial/concentric patterns using the tCFS method. All have been used to investigate bCFS thresholds before (Stein, 2019). We included faces and objects as representative of salient and complex stimuli. Linear gratings and phase-scrambled images were used as simple stimuli. Phase-scrambled images were created from the object stimuli by randomising their FFT phase spectra. It acted as a control for the complex stimuli, devoid of semantic meaning and image structure while maintaining low-level stimulus content (Gayet et al., 2014). Finally, polar patterns (radial and concentric gratings) were included as intermediate stimuli that were globally defined (activating higher visual regions of the ventral visual stream such as area V4 (Wilkinson et al., 2000)) but lacking in semantic meaning (Hong, 2015).

A 2 x 5 repeated-measures ANOVA revealed a significant main effect of threshold (bCFS vs reCFS; $F(1,17) = 133.79$, $p < .001$, $\eta_p^2 = .89$), and image type ($F(4,68) = 13.45$, $p < .001$, $\eta_p^2 = .44$). Critically however, there was no significant interaction between thresholds and image type ($p = .1$), indicating that the relationship between bCFS and reCFS thresholds was invariant across image categories. This result is plotted in Figure 3, which clearly shows differences in bCFS thresholds (blue symbols in Figure 3a) over image type (1 x 5 repeated-measures ANOVA; $F(4,68) = 16.29$, $p < .001$, $\eta_p^2 = .49$), as has been reported in many studies. Scrambled noise images, for example, have a breakthrough threshold 5.3 dB higher than face images, and linear gratings breakthrough 3.0 dB higher than polar gratings. Critically, Figure 3 also shows that reCFS thresholds exhibit the same pattern of differences over image type (red symbols in Figure 3a), such that there is a constant degree of suppression depth across all image categories.

Replicating the result of Experiment 1, an approximately 15 dB of suppression depth was observed in Experiment 2 (Fig. 3b), which was practically identical across image types (Faces, $M = 14.35$ ($SD = 5.64$); Objects, $M = 14.61$ ($SD = 6.07$); Gratings, $M = 14.88$ ($SD = 5.55$); phase-scrambled images, $M = 14.70$ ($SD = 5.39$); polar patterns, M = 14.69 (SD = 6.50). A repeated-measures ANOVA confirmed that suppression depth did not differ across image categories ($F(4,68)= 0.1$, $p = .98$).

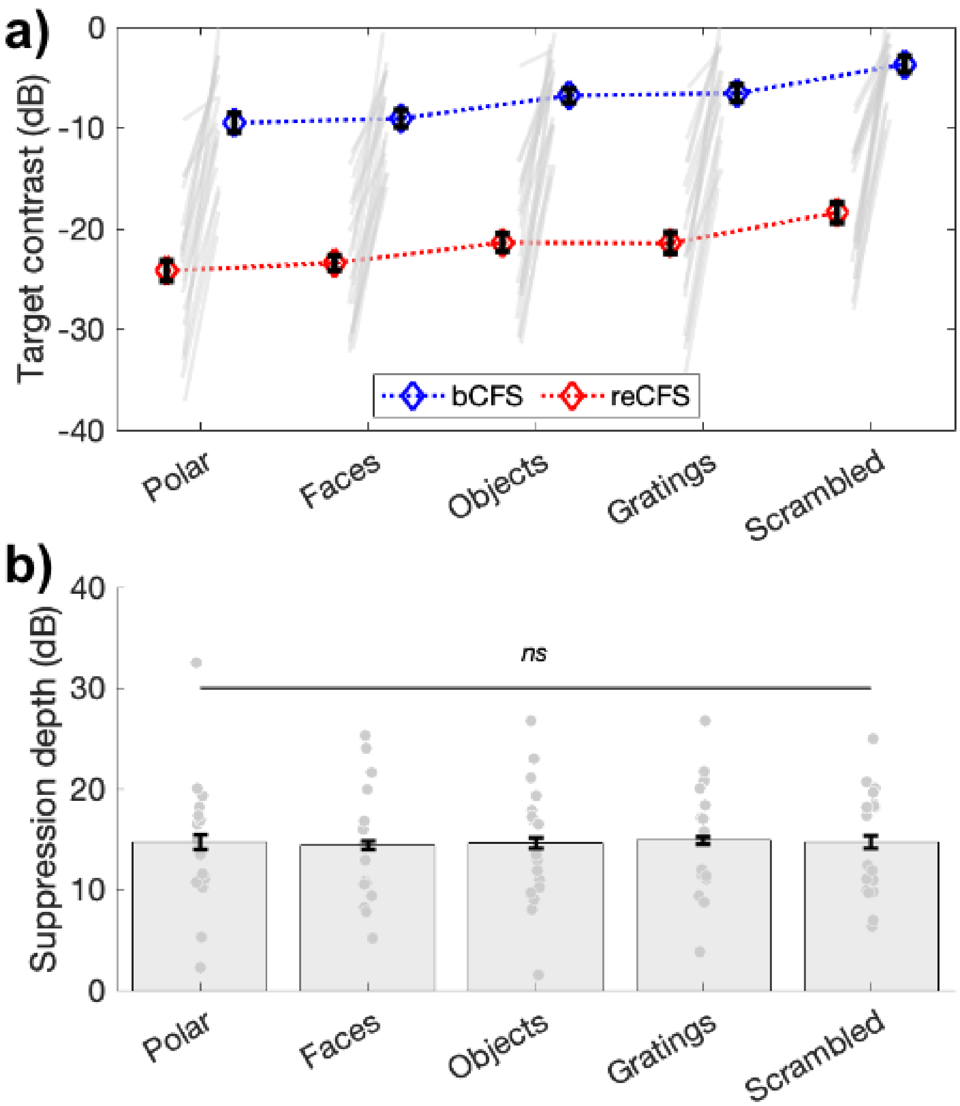


Figure 3. Suppression depth is uniform across image categories. a) bCFS and reCFS thresholds by image type. Blue and red diamonds display the mean across participants, and error bars plot ±1 SEM corrected for within participant comparisons (Cousineau, 2005). Grey lines link thresholds per participant, per image type. For visualization, we have linked the bCFS and reCFS thresholds with broken lines, to better indicate that both do vary according to image category. **b)** The difference in contrast between bCFS and reCFS thresholds is the same across image categories.

Experiment 3

Experiments 1 and 2 introduced the tCFS method and, using that new method, demonstrated that bCFS thresholds vary depending on target type, as many previous bCFS studies have shown. Importantly, reCFS thresholds varied in parallel with bCFS thresholds, which when expressed in terms of suppression depth, reveals that depth of suppression is strikingly uniform across target image categories in CFS. This uniformity of suppression depth could indicate that neural events mediating CFS suppression transpire within a common visual mechanism, one that is not selective for image type, complexity or semantic meaning, over a wide range of stimulus configurations. This view is compatible with popular models of binocular rivalry built around the concept of reciprocal inhibition and neural adaptation (Alais et al., 2010; Kang & Blake, 2010; McDougall, 1901), as well as with more recent Bayesian-inspired inference-based models in which perceptual alternations in dominance are triggered by accumulating residual error signal associated with competing stimulus interpretations (Hohwy et al., 2008). As pointed out elsewhere (Blake, 2022), steadily increasing error signal plays the same role as does steadily decreasing inhibition strength caused by neural adaptation in reciprocal inhibition models.

In the context of the tCFS method, the steady increases and decreases in the target's *actual* strength (i.e., its contrast) should impact its emergence from suppression (bCFS) and its reversion to suppression (reCFS) as it competes against the mask. Whether construed in terms of neural adaptation or error signal, we surmise that these cycling state transitions defining suppression depth should be sensitive to the rate of contrast change of the monocular target. Expressed in operational terms, the depth of suppression should covary with the rate of target change. Experiment 3 tested this supposition using three rates of contrast change.

A 3 x 2 x 4 repeated measures ANOVA compared three rates of contrast change (slow, medium, fast), on both thresholds (bCFS, reCFS) across four image categories (face, object, grating, phase scrambled) using the tCFS paradigm. There was a significant main effect of threshold (F(1,16) = 116.56, p < .001, η_p^2 = .88) again indicating that bCFS and reCFS contrasts differ. There was also a significant main effect of image type (F(3,48) = 9.40, p < .001, η_p^2 = .37), again with no interaction threshold. This result indicates that bCFS and reCFS thresholds vary in tandem regardless of image type. Critically, there was a significant interaction between rate of contrast change and thresholds (F(2,32) = 128.60, p < .001, η_p^2 = .89), as expected, indicating that the difference between bCFS and reCFS thresholds (i.e., suppression depth) depended on the target's rate of contrast change. **Figure 4** displays a summary of these results (averaged across image types), showing that as the rate of contrast change increases, so does suppression depth (Slow *M* = 9.64 dB, *SD* = 4.37, Medium *M* = 14.6 dB, *SD* = 5.43; Fast *M* = 18.97 dB, *SD* = 6.93). **Supplementary analyses** confirmed that these differences in suppression depth were not driven by fixed rates of perceptual alternation across the three levels of rate of contrast change (Figure 4c and Supplementary Figure 1)

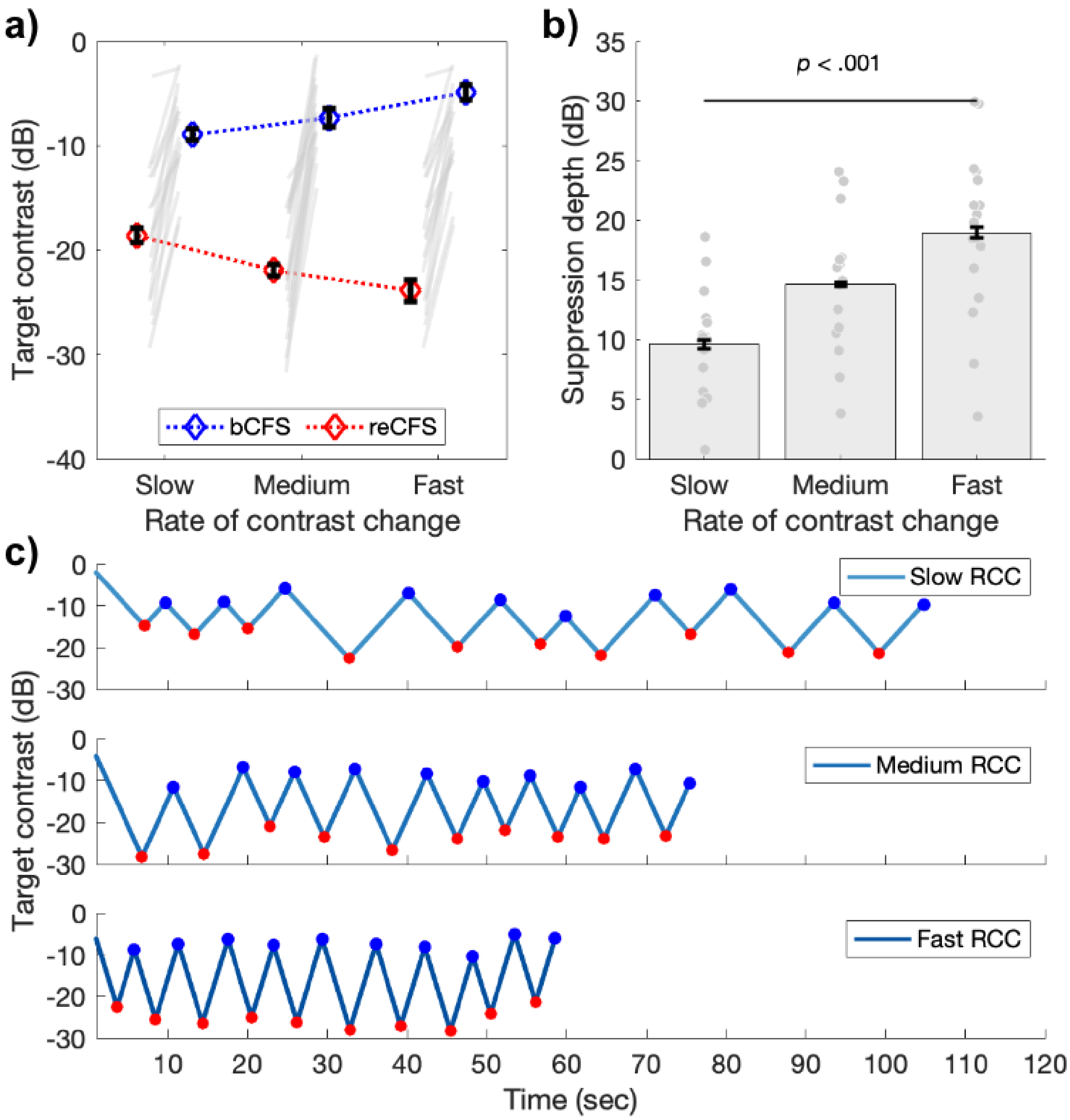


Figure 4. Suppression depth is greater with less time for adaptation. a) bCFS (blue) and reCFS (red) thresholds collected during tCFS with three rates of contrast change (RCC). Figure elements are the same as in Figure 3a. **b)** Suppression depth increases when the rate of contrast change increases during tCFS. All error bars correspond to ±1 SEM corrected for within participant comparisons (Cousineau, 2005). **c)** Example trials at each rate of contrast change from a single participant. Red markers indicate reCFS responses, blue markers show bCFS.

Perceptual switches during tCFS are described by a damped harmonic oscillator

The results of Experiment 3 demonstrated that when the opportunity for target adaptation is increased, as when the target's rate of contrast change was slow, that suppression depth is reduced and a smaller contrast decrease is needed for a visible target to reenter CFS (see Figure 4a). One possible account for this relates to the balance of excitation/inhibition in neural systems, which have been particularly fruitful models of interocular competition (Alais et al., 2010; Li et al., 2017). In these models, adaptation over time is a critical parameter governing changes in visual consciousness (Alais et al., 2010), which motivated us to explore in our final analysis whether suppression depths also fluctuated over time. Accordingly, our final analysis sought to model the temporal nature of perceptual switches during tCFS, to understand whether a balance of excitation and inhibition may be contributing to the sequential contrast thresholds that govern target visibility.

For this analysis, a key dependent variable is the contrast difference between sequential thresholds (i.e., from bCFS to reCFS, or reCFS to bCFS). As the number of thresholds was the same in each trial, we averaged each threshold over observers to obtain a sequence of mean thresholds that preserved the order across the trial. **Figure 5a** displays the mean result separately for each target rate of change condition. Importantly, pooling across the threshold order rather than each participant's time series avoids smearing the data due to observers differing in their perceptual durations (**cf. Supplementary Figure 1**). To investigate the balance between bCFS and reCFS thresholds, we calculated the absolute change in contrast between sequential thresholds, as plotted in **Figure 5b**. These sequential estimates of suppression depth show marked fluctuations early in each trial, followed by a stabilisation to the grand average suppression depth for each rate of contrast change (Slow ~10 dB, Medium ~ 15 dB, Fast ~ 19 dB).

We next tested whether these sequential changes in suppression depth could be described by models of excitation and inhibition. For each rate of change condition, we compared the goodness of fit of three models: a simple harmonic oscillator, a damped harmonic oscillator, and a cubic polynomial model. We assessed the relative goodness of fit using the change in Bayesian Information Criterion (BIC) between models (see **Methods**).

As can be appreciated in **Figure 5c,** sequential changes in suppression depth were well described by the damped harmonic oscillator model of excitation and inhibition, which well captured the modulations early in the trial. For each rate of target contrast change, the damped harmonic oscillator model was the superior fit to the data (Slow contrast change, $R^2 = 0.68$, BIC = -1847.2; Medium contrast change, $R^2 = 0.63$, BIC= -2125.29; Fast contrast change, $R^2 = 0.36$, BIC= -1041.29). In each case, the change in Bayesian Information Criterion between the damped harmonic oscillator and the next best fitting cubic polynomial model was large (Slow contrast change, ΔBIC = -1072.88; Medium contrast change, ΔBIC = -781.5; Fast contrast change, ΔBIC = -97.06). Supplementary Table 1 displays the assessments of each model fit for each rate of change condition.

The damped harmonic oscillator has been proposed to capture the response of neural populations governed by excitation/inhibition balance after external perturbation, with a given rate of decay. We return to the interpretation of these models in the Discussion.

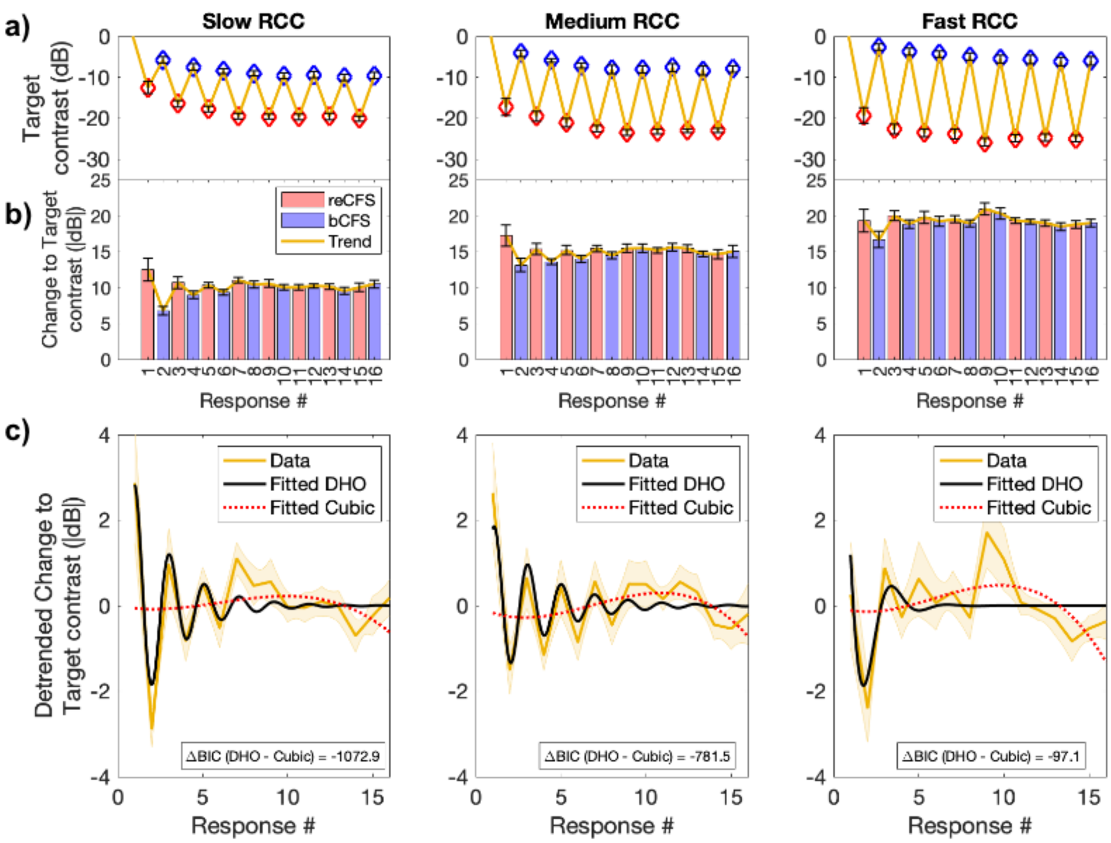


Figure 5. Suppression depth over time is well described by a damped harmonic oscillator. a) Top row: Mean bCFS (blue) and reCFS (red) thresholds averaged by threshold order over the trial. Each column displays the average for slow, medium and fast rate of contrast change (RCC), respectively. **b) Middle row.** Absolute change in target contrast between successive thresholds (i.e., suppression depth). Red bars indicate the decrease in target contrast needed for a visible target to reenter CFS. Blue bars indicate the increase in contrast for an invisible target to break CFS. **c) Bottom row:** Yellow lines and shading plot the average change in suppression depth between successive thresholds. The data in each RCC condition is best fit by a damped harmonic oscillator (DHO) model shown in black. The change in Bayesian Information Criterion relative to the next best (cubic polynomial) model is displayed in each panel. All error bars and shading denote ±1 SEM corrected for within participant comparisons (Cousineau, 2005).

Discussion

This study introduces a new CFS methodology that efficiently measures suppression depth based on a participant's responses to a target continually changing in contrast. In this new 'tracking CFS' method (tCFS), a visible target initially decreases from high contrast until it is reported as suppressed, then increases in contrast until breakthrough is reported, and so on in an ongoing cycle. By tracking visibility in this way, the method produces breakthrough thresholds (as in bCFS), but also suppression thresholds, as the weakening target reenters suppression (reCFS). By measuring the difference between both thresholds an image's suppression depth can be quantified, enabling a critical evaluation of whether previous claims of variations in suppression depth are supported. Experiment 1 introduced and validated the tCFS method to measure suppression depth. Experiment 2 applied tCFS to images from different categories and found a constant suppression depth across images, regardless of stimulus complexity or salience. Experiment 3 manipulated suppression depth by changing the rate of target contrast change.

The tCFS method offers two important advantages. First, it is fast and efficient. The data in Figure 2b, for example, show that 90 seconds is sufficient to collect a robust set of data comprising 16 thresholds, eight each for bCFS and reCFS. The second advantage is that in providing easy quantification of breakthrough and suppression thresholds, tCFS allows the strength of suppression to be calculated. This point has great theoretical importance because suppression depth is necessary to evaluate many claims in the CFS literature about the priority given to certain kinds of images, claims of preserved visual processing despite suppression, and claims of unconscious processing more generally. Here, using tCFS on a range of visual image categories, we find no evidence at all that suppression depth varies based on image category (e.g., faces vs gratings). This finding forces a reinterpretation of conclusions reached in a number of earlier studies inferring preserved unconscious processing from differences in breakthrough thresholds alone.

Thresholds for breaking and entering suppression quantify suppression depth

In Experiment 1, we used the tracking CFS method to measure bCFS and reCFS contrast thresholds, and compared them to those obtained using discrete unidirectional contrast changes – a series of measures with increasing target contrast to obtain bCFS thresholds as conventionally done, and also a series with decreasing target contrast to measure suppression thresholds. For both conditions, a significant difference between bCFS and reCFS thresholds was observed. This difference indicates that suppression is not a passive process where a given contrast threshold determines a narrow awareness/suppression border. Instead, there is a contrast range (i.e., suppression depth) between awareness and suppression. This is consistent with models of interocular suppression involving mutually inhibitory left- and right-eye processes. The fact that binocular rivalry produces a significant suppression depth is well known in that literature

(Blake & Camisa, 1979; Nguyen et al., 2003) but is rarely considered in CFS studies[2] where the focus is typically on the breakthrough threshold for awareness.

Intuitively, the average contrast threshold for reCFS should be lower than for bCFS, yet in the discrete conditions there were some participants who showed the inverse effect (n = 4; **Figure 2c**). One possibility is that saccades, blinks, or other oculomotor reflexes that differentially impact transitions during interocular rivalry (van Dam & van Ee, 2006a, 2006b) might have influenced the discrete bCFS and reCFS trials at separate times. Another possibility is that by using a blocked design in the discrete trials, a participant's motivation or attention to task might have changed between bCFS and reCFS blocks. These possibilities highlight inherent advantages and controls of the tCFS procedure, for which no participant showed an inverse effect: bCFS and reCFS thresholds are recorded in alternation, thus each threshold judgment is relative to the previous judgment on the same image. tCFS also helps maintain a level of engagement as the task is never repeated (bCFS and reCFS tasks alternate) and long periods of target invisibility that can occur in typical bCFS studies when the target is raised from near-zero contrast are avoided as target contrast hovers around the visibility/invisibility thresholds. Alternating between bCFS/reCFS tasks also means that any adaptation occurring over the trial will occur equivalently for each threshold, as will any waning of attention. As Figure 2c shows, tCFS produces an increased size of suppression depth compared to discrete trials. Moreover, it can be administered quickly, and provides threshold measures with less variance.

As an aside, the existence of distinctly different, complementary transition thresholds for bCFS and reCFS is reminiscent of the behavior termed hysteresis: a property of dynamical systems wherein output values, rather than being solely governed by corresponding input values, also exhibit lags or delays based on the valence of continuous changes in the input values, i.e., a form of memory of preceding states of the system. Other examples of hysteresis in visual perception include transitions between binocular fusion and binocular rivalry (Anderson, 1992; Buckthought et al., 2008; Julesz & Tyler, 1976), perception of motion direction in random-dot cinematograms (Williams et al., 1986), and repetition priming in perception of bistable configurations (Pastukhov et al., 2015). To paraphrase Maglio and Polman (Maglio & Polman, 2016), hysteresis can be construed as a form of memory whereby prior states influence the persistence of current states into the future.

No effect of image category on suppression depth

Having demonstrated a difference between bCFS and reCFS thresholds using the

[2] An exception to this rule is the study by Tsuchiya et al. (2006) using a briefly presented test probe to compare depth of suppression associated with CFS and BR.

tCFS procedure, Experiment 2 compared suppression depth across five different image categories. A number of previous studies have interpreted a difference in bCFS thresholds as a difference in suppression depth (Gayet et al., 2014; Jiang et al., 2007; Mudrik et al., 2011; Yang et al., 2007), yet made no attempt to measure suppression thresholds. We applied the tCFS method to assess whether bCFS thresholds would differ among image categories, and whether claimed differences in suppression depth would be obtained when reCFS thresholds were also measured. Importantly, our bCFS thresholds replicated the often reported finding that certain image types break into awareness at lower contrasts than others (see Figure 3a). For example, bCFS thresholds for faces were lower than for phase-scrambled images by 5.3 dB. Critically, however, while bCFS thresholds varied with image type, the reCFS threshold for all images was approximately 15 dB lower than bCFS, *regardless of image type*. In other words, all images produced a constant suppression depth of about 15 dB (see Fig. 3b), even though their bCFS thresholds varied.

It's natural to wonder whether this non-selectivity of CFS depth of suppression applies to binocular rivalry suppression, too. Blake and Fox (Blake & Fox, 1974) concluded that rivalry suppression is non-selective based on a task where observers were unable to notice large changes in the spatial frequency or orientation of a suppressed grating. On the other hand, Alais and Melcher (Alais & Melcher, 2007) found that the detectability of a brief, monocular probe presented to an eye during rivalry varied depending on the 'complexity' (e.g., grating vs face) of the stimulus being probed, with suppression being greater for complex images. Tsuchiya et al. (Tsuchiya et al., 2006) found that detection of a brief test probe was much more difficult to detect when presented to an eye during suppression phases of CFS compared to binocular rivalry. In a similar vein, durations of suppression phases associated with CFS are considerably longer than those associated with rivalry (15x longer, in the study by Blake et al., 2019). A clear next step will be to apply a variant of the tCFS paradigm to binocular rivalry, to assess the uniformity of rivalry suppression depth based on stimulus complexity.

An important caveat for interpreting suppression depth during tCFS is that our bCFS thresholds will be slightly overestimated due to the response time delay (a problem for most bCFS studies) and the reCFS thresholds will be slightly underestimated. This leads to a slight inflation of suppression depth. For example, if we assume an average reaction time of 200 ms for appearance and disappearance events, then suppression depth will be inflated by ~1.68 dB at the rate of contrast change used in Experiments 1 and 2. This cannot account for suppression depth in its entirety, which was many times larger at approximately 14 dB across image categories. We have no reason to suspect that reaction-times would differ when reporting on the appearance or disappearance of different image categories under CFS, and indeed found no significant evidence for an interaction between thresholds and image categories in our analyses. This leaves a constant suppression depth of approximately 14 dB to be explained, and the value of comparing between image categories remains. In Experiment 3, the rate of contrast change varied which led to corresponding changes in suppression depth, which we note could also not be attributed to a reaction-time delay (Supplementary Figure 1).Using the same assumptions of a 200 ms response time delay on average, when the rate was halved (slow condition) or increased by 50% (fast condition), we would expect response time effects on suppression depth of 0.84 and 2.52 dB, respectively. However, the changes in suppression depth attributable to rates of contrast change measured in Experiment 3 were far larger than this at 5.8 (slow) and 4.0 dB (fast).

Previous research has attributed faster CFS breakthrough (equivalently, lower contrast) to unconscious processing of suppressed images (Gayet et al., 2014; Mudrik et al., 2011). As the current study found uniform suppression depth for all tested images, even though bCFS thresholds varied, it is clear that differences in bCFS thresholds alone should not be interpreted in terms of preferential unconscious processing of semantically relevant images. Indeed, if image categories such as faces were processed unconsciously, they reasonably should be harder to re-suppress, and thus have a smaller suppression depth compared to neutral stimuli (see Figure 1) – which was not the case.

As an alternative to lower bCFS thresholds being due to unconscious processing of images with relevant semantic content, it may be that such images (here, faces and objects) break suppression at lower contrasts because they tend to rate highly in low-level image characteristics that contribute to image salience. Faces and objects will be more salient due to peaks in local image contrast (Parkhurst & Niebur, 2004) , contour integration (Kapadia et al., 2000), closed curvilinear form (concavity: (Schmidtmann et al., 2015), phase aligned spatial frequency spectra (Maehara et al., 2009), all of which would combine to make real-world images such as faces and objects more salient to early vision than linear gratings and scrambled noise and thus lead to lower bCFS thresholds in ways unrelated to semantic content. Others have pointed to this possibility before (Gayet et al., 2014; Moors, 2019; Moors et al., 2016, 2017; Moors & Hesselmann, 2018) and it appeals on the grounds of parsimony, yet an empirical means to quantify suppression depth has been missing. tCFS now provides a method to easily measure suppression depth and as these experiments show, once the bCFS threshold is determined, reCFS thresholds reveal a constant level of suppression depth. Different bCFS thresholds, therefore, cannot be taken to indicate different levels of suppression and unconscious processing, and thus favour an account based on low-level image features.

Some caution is warranted here, however. It is not clear that all variation in bCFS thresholds can be explained by low-level image properties. There may be important high-level factors that also contribute to the salience of a given target image that make it visible at lower contrasts than other images (Gayet et al., 2014; Jiang et al., 2007; Mudrik et al., 2011; Yang et al., 2007). For example, faces provide essential social information and we are very highly attuned to them. Face images may therefore be salient at lower contrasts than other images, such as random noise. Thus, without attributing any special access to awareness or partial processing during suppression, faces may simply have a higher effective contrast and become visible at lower contrasts, as seen in the lower bCFS face thresholds we report. A hybrid-model might therefore be needed for a full account of CFS, similar to those proposed for binocular rivalry (Cao et al., 2021; Wilson, 2003). Based on our results here, we imagine a hybrid model in which relative suppression depth for a given image arises from a low-level interocular mutual inhibition acting equivalently on any kind of image (yielding the uniform suppression depth we observe), and the absolute level of breakthrough threshold could be modulated down based on the degree of high-level salience. Careful manipulation of low- and high-level properties, in combination with the tCFS method, would be able to test this model (see *Future directions* below).

Suppression depth is modulated by rate of contrast change

Experiment 3 varied the rate of target contrast change with the expectation that this would alter the magnitude of adaptation during tCFS. We predicted that a faster contrast change would reduce the opportunity for adaptation to accrue, thereby requiring a greater change in contrast to overcome suppression during CFS. Similarly, a slower rate of change should increase the opportunity for adaptation, resulting in the inverse effect. We observed strong modulations of suppression depth based on the rate of contrast change, confirming these predictions (**Figure 4**). Follow-up analyses confirmed that all three rates of contrast change had distinct percept duration times (**Supplementary Figure 1**), indicating that the differences in suppression depth we observed were not due to an artefact such as participants responding with a fixed inter-response interval, which would spuriously increase suppression depth for a fast rate of change.

Damped harmonic oscillator model

We modelled the changes in contrast between successive bCFS and reCFS thresholds over a trail and found that a damped harmonic oscillator (DHO) provided an excellent fit to these sequential estimates of suppression depth. The applicability of this model is noteworthy for a number of reasons. First, in neuroscience, the DHO model provides a valuable mathematical framework for understanding the dynamics of neural systems and their responses to external stimuli, particularly with regard to the interplay between excitation and inhibition (Freeman, 1961; Hodgkin & Huxley, 1952; Spyropoulos et al., 2022). In the present context, the high starting contrast of the suprathreshold target in tCFS trials is analogous to the external perturbation. The asymptotic differences in thresholds over time are reminiscent of both earlier (Wilson, 2003), and more recent computational models (Cao et al., 2021) of interocular competition, models proposing that changes to visual awareness are driven by an out-of-equilibrium cortical network. We note that the locus of competing neural ensembles could reside in early visual stages (Alais et al., 2010; Lankheet, 2006; Li et al., 2017), late stages (Hohwy et al., 2008) or across hierarchical (Cao et al., 2021; Wilson, 2003) levels of visual processing. Although it is beyond the scope of the present work, future studies could vary the starting conditions of the tCFS procedure, or manipulate higher-order influences such as attention and expectation to examine whether the return to equilibrium we have revealed conforms to the predictions of competing models.

Future Directions

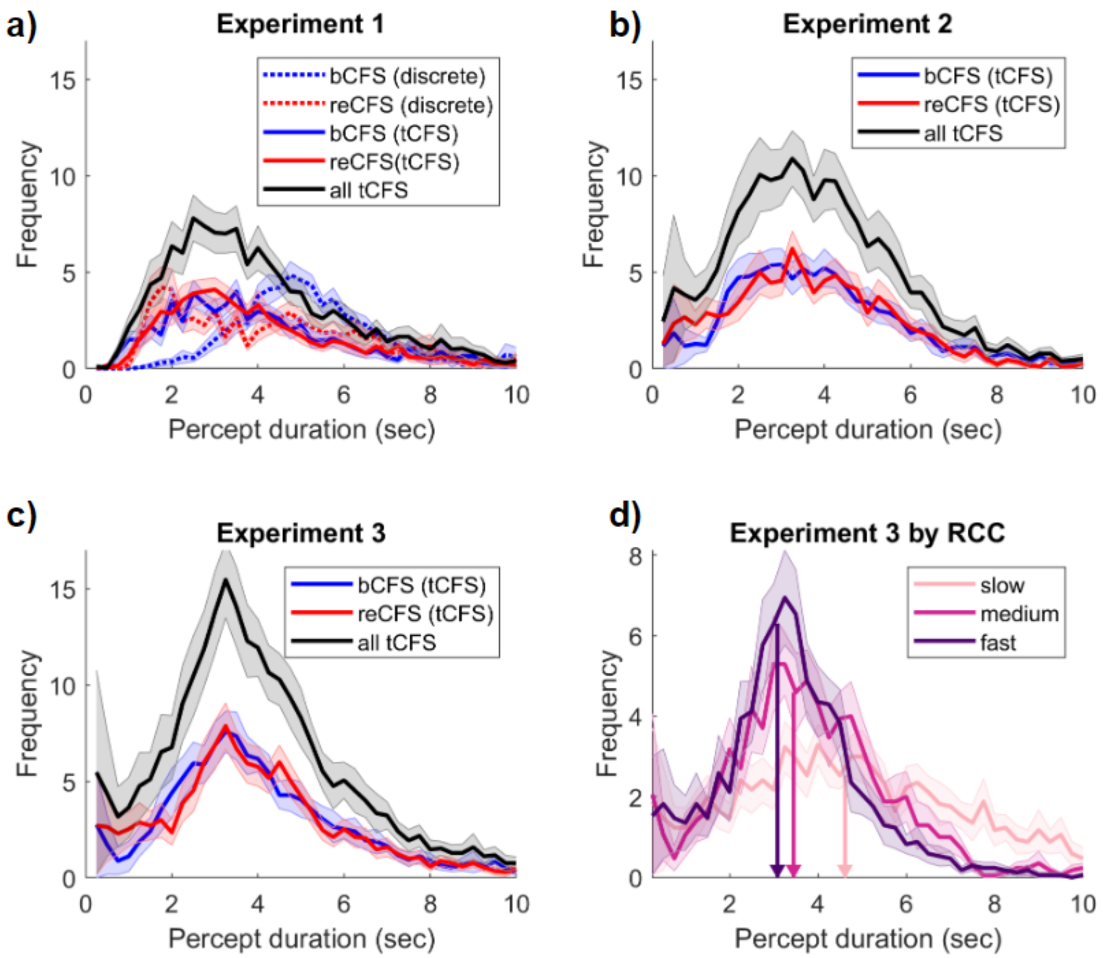
The tCFS method equips researchers with a convenient method to measure bCFS and reCFS thresholds, and thus suppression depth. We have used tCFS here to establish that a uniform suppression depth exists across image categories, and that differences in bCFS thresholds alone cannot provide strong evidence for unconscious processing. Many substantive questions remain. For example, the depth of interocular suppression is reported to partially depend on spatial feature similarity between the competing images (Alais & Melcher, 2007; Drewes et al., 2023) and their temporal frequency (Han et al., 2018; Han & Alais, 2018). These factors could be parametrically varied to examine specifically whether they modulate bCFS thresholds alone, or whether they also cause a change in suppression depth by asymmetrically affecting reCFS thresholds. Previous findings can easily be revisited, such as results showing that bCFS varies with manipulations of semantic content (e.g., face inversion, or manipulating a face's emotion), results which form part of the claimed evidence for preferential unconscious processing of certain suppressed images.

Conclusion

Across three experiments we have introduced the tCFS method and shown that traditional evidence for unconscious processing – based on differences in the threshold to reach awareness (bCFS threshold) – provide only half the story. Misleading conclusions about unconscious processing must be supported by measures of suppression depth, which can be calculated as the difference between both breakthrough (bCFS) and suppression (reCFS) thresholds. Using the tCFS method we have measured these thresholds, and found uniform suppression depth across five image five categories. Notably, this uniform suppression depth is increased with reduced opportunity for target image adaptation, as is the case when target contrast changes rapidly. Collectively, the three tCFS experiments refute existing claims of high-level semantic information or target complexity influencing the depth of unconscious processing during interocular suppression. Future findings may yet confirm differences in suppression depth in certain circumstances, yet this will require measurement of both breakthrough and suppression thresholds to demonstrate the requisite changes in suppression depth.

Supplementary Material.

We performed additional analyses to rule out an alternative explanation for the increased suppression durations demonstrated in Experiment 3. We reasoned that if alternations between bCFS and reCFS were happening with a regular periodicity, such that responses were made every 1 second (for example), then these consistent responses could result in smaller suppression thresholds when the rate of contrast change was slow, as we have observed. Similarly, larger suppression thresholds would be measured if the same 1 second interval had elapsed while the rate of contrast change was fast. Inspection of the raw tCFS time-series qualitatively indicated that perceptual durations were varying with the rate of target contrast change **(Figure 4c).** To test this possibility, we compared the group average perceptual durations across all experiments, to test whether the average duration of percepts was the same despite different rates of contrast change. **Supplementary Figure 1** displays the results of this analysis. The histograms of perceptual durations for Experiments 1 (all tCFS median *M* = 3.83, *SD* = 1.66) and Experiment 2 (*M* = 3.48, *SD* = 1.36) show similar means and distributions, with no significant difference between them ($t(36) = 0.72$, $p = .48$). This is unsurprising given their similar design and matched rate of contrast change. In Experiment 3, however, the distribution of percept durations is shown to vary by rate of contrast change. With shorter median percept durations for fast rates of contrast change (*M* = 3.08, *SD* = 1.07), and slower percept durations for slow rates of contrast change (*M* = 4.61, *SD* = 2.05) compared to medium (*M* = 3.45, *SD* = 1.29). A repeated measures ANOVA confirmed that median percept durations varied by rate of contrast change ($F(2,32) = 30.89$, $p < .001$, $\eta_p^2 = .66$).



Supplementary Figure 1. Perceptual durations in Experiments 1 to 3. a) Average histogram across participants for all percept durations by experimental condition. Solid lines show tCFS conditions, broken lines show discrete (unidirectional) conditions. Shading corresponds to ±1 SEM corrected for within participant comparisons (Cousineau, 2005). **b-c)** Average histograms for tCFS in Experiment 2, and Experiment 3, respectively. Figure conventions as in a). **d)** tCFS durations of Experiment 3 when split by rate of contrast change. Vertical lines and arrows indicate the mean of median percept durations across participants.

Model	Measure	Slow RCC	Medium RCC	Fast RCC
(cubic) 1	R^2	.07	.19	.29
	BIC	-774.31	1343.79	-944.23
(harmonic) 2	R^2	.005	.006	0
	BIC	-706.85	1138.595	-600.34
(dHO) 3	R^2	.684	.632	.361
	BIC	-1847.19	-2125.29	-1041.29
Comparison				
2-1	ΔBIC	67.46	205.195	343.89
3-1	ΔBIC	-1072.88	-781.5	-97.06
3-2	ΔBIC	-1140.34	-986.695	-440.95

Supplementary Table 1. Summary of results from model fits and comparisons.

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