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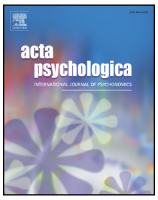

Repetition priming in selective attention: A TVA analysis

Árni Gunnar Ásgeirsson [a,c,*], Árni Kristjánsson [b], Claus Bundesen [c]

[a] Cognitive Psychology Unit, FSW, Leiden University, Wassenaarseweg 52, NL-2333 AK Leiden, Netherlands
[b] Department of Psychology, University of Iceland, Iceland
[c] Center for Visual Cognition, Department of Psychology, University of Copenhagen, Denmark

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ABSTRACT

Current behavior is influenced by events in the recent past. In visual attention, this is expressed in many variations of priming effects. Here, we investigate color priming in a brief exposure digit-recognition task. Observers performed a masked odd-one-out singleton recognition task where the target-color either repeated or changed between subsequent trials. Performance was measured by recognition accuracy over exposure durations. The purpose of the study was to replicate earlier findings of perceptual priming in brief displays and to model those results based on a Theory of Visual Attention (TVA; Bundesen, 1990). We tested 4 different definitions of a generic TVA-model and assessed their explanatory power. Our hypothesis was that priming effects could be explained by selective mechanisms, and that target-color repetitions would only affect the selectivity parameter (α) of our models. Repeating target colors enhanced performance for all 12 observers. As predicted, this was only true under conditions that required selection of a target among distractors, but not when a target was presented alone. Model fits by TVA were obtained with a trial-by-trial maximum likelihood estimation procedure that estimated 4–15 free parameters, depending on the particular model. We draw two main conclusions. Color priming can be modeled simply as a change in selectivity between conditions of repetition or swap of target color. Depending on the desired resolution of analysis; priming can accurately be modeled by a simple four parameter model, where VSTM capacity and spatial biases of attention are ignored, or more fine-grained by a 10 parameter model that takes these aspects into account.

1. Introduction

Priming occurs when an instance of stimulus presentation influences later responses. Priming effects are ubiquitous in the central nervous system and have been reported in simple neuro-computational processes (e.g. Breitmeyer, Ro, & Singhal, 2004), semantic processes (e.g. Dehaene et al., 1998; Neely, 1977) and even quite complex social situations (e.g. Klein et al., 2014). Repetition priming is a specific kind of priming that has primarily been studied in the context of visual attention (Kristjánsson & Campana, 2010). In such tasks, repetition of a recently important object or object-feature will facilitate target selection. Observers typically search for an object defined by a particular feature; e.g. a color singleton. If this target-defining feature remains the same on consecutive trials, performance will usually improve compared to trials when the feature changes (Maljkovic & Nakayama, 1994).

By some accounts, the priming is feature-based and part of perceptual stimulus processing. These accounts can explain results from a multitude of studies where repeated visual features have been shown to affect performance independently and simultaneously; i.e. that repetition of one feature is not affected by the repetition or alternation of another stimulus feature (e.g. Kristjánsson, 2006; Maljkovic & Nakayama, 1994). Not all studies have observed independent priming of features, however. Huang and Pashler (2005) found, for briefly displayed search arrays, that observers' performance (measured by localization accuracy) did not improve when a target feature was repeated, unless repetitions were expected due to non-random presentation contingencies. Therefore, they proposed a perceptual account of priming, specific to conditions where expectancy was heightened for feature repetitions, but concluded that feature priming in regular visual search arrays (specifically Maljkovic & Nakayama, 1994) reflected post-perceptual effects (Huang & Pashler, 2005, pp. 157).

In contrast, Yashar and Lamy (2010; see also Sigurdardottir, Kristjánsson & Driver, 2008) reported feature (shape) priming in briefly presented stimulus arrays, but only when the task required focused attention. They presented observers with identical stimulus arrays in two different conditions. In one, observers had to focus attention on fine details of a stimulus, but in the other they only had to judge whether a feature singleton was presented on the right or left side of a stimulus array. Priming effects were only observed in the former task. Ásgeirsson et al. (2014) generalized this result further by presenting observers with brief arrays of colored letters, where they were to report an odd-one-out letter among distractors. There were clear priming effects for both color

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[*] Corresponding author at: Faculteit der Sociale Wetenschappen, Leiden University, Wassenarseweg 52, NL-2333 AK Leiden, Netherlands
E-mail address: arnigunnarasgeirsson@gmail.com (Á.G. Ásgeirsson).

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and positions, and these were independent of each other, a finding at odds with some studies of priming in standard visual search (Campana & Casco, 2009; Pratt & Castel, 2001), and with the episodic retrieval view of priming.

Hillstrom (2000) also proposed that episodic representations are the unit of priming; arguing that priming operates on visual short-term representations of earlier trials. In another study, Huang, Holcombe, and Pashler (2004) demonstrated that stimulus features did not prime independently of each other but collectively, as an episode of feature and response repetition or alternation. The authors accounted for their result with a post-perceptual account, where the priming mechanism was hypothesized to exert its influence at a decision-making, rather than perceptual, stage of processing. They concluded that when all target features are repeated, along with the previous response, the decision about target identity is faster.

Ásgeirsson and Kristjansson (2011) made slight adjustments to the task used by Huang et al. (2004), and found that their episodic priming effects were contingent on task difficulty. When a target-defining feature was sufficiently salient, priming effects for that feature were independent of other features. When the target-defining feature was not very salient, the priming effect interacted with other features as if it was episode or object-based (see Kristjánsson, Ingvarsdóttir, & Teitsdóttir, 2008, for a study of feature versus object-based priming). Recently, the idea that priming reflects memory traces of episodes has resurfaced. Thomson & Milliken (2011) argued that since priming was affected by a switch in task (presumably a higher level effect), this was evidence for priming of episodes, likening this to the priming of event files (Hommell, 2011).

From the available literature, it seems unlikely that a single mechanism is responsible for all repetition priming. In fact, there are some noteworthy multi-stage theories of priming (Kristjánsson & Campana, 2010; Lamy, Yashar, & Ruderman, 2010), where perceptual and post-perceptual components are assumed. In the current context, it is important that there is an accumulation of priming over sequences of adjacent trials, independent of response demands, response mapping and speeded decision-making. In what follows, we limit our investigation to such effects.

1.1. Modeling priming in TVA

In this study, we investigate priming effects using a Theory of Visual Attention (TVA Bundesen, 1990). The theory treats visual selection and recognition as a problem of making perceptual categorizations of the form "object *x* has the feature *i*" where object *x* is a perceptual object, e.g. an alphanumeric character, and a feature *i* is a perceptual feature, e.g. a color or shape. Perceptual categorizations are made when a perceptual object enters visual short-term memory. Describing this process are two central equations; the rate equation (Eq. (1)) describes the rate of categorizations (objects/s) and the weight equation (Eq. (2)) describes the relative resources devoted to each visual object. The rate v for object x belonging to category i is given by Eq. (1):

$$v(x, i) = \eta(x, i)\beta_i \frac{\omega_x}{\sum_{z \in S} \omega_z} \tag{1}$$

where $\eta(x, i)$ is the strength of the sensory evidence that object x belongs to category i, β_i is the perceptual decision bias associated with category i, and w_x and w_z are the attentional weights of objects x and z. S represents the set of all elements in the visual field. The attentional weights in the rate equation are calculated for each visual object according to its pertinence and physical characteristics by Eq. (2):

$$\omega_x = \sum_{j \in R} \eta(x, j)\pi_j \tag{2}$$

where $\eta(x, j)$ is the strength of the sensory evidence that element x belongs to category j and π_j is the pertinence of category j. A concrete translation of the mathematical terms in the context of the current experiment is such that $v\ (x, i)$ is the rate of encoding into VSTM where x is a digit between 1 and 9; $\eta(x, i)$ represents the evidence that digit x belongs to one of the categories 1–9; π_j represents the current importance of a feature category, e.g. the color red, while $\eta(x, j)$ is the strength of sensory evidence that digit x is a red element. Finally, the weight w_x represents how resources are distributed to x. This value is only meaningful relative to the weight of other objects in the display. In the current study, the weights of visual objects are primarily interesting in that they form the basis of the selectivity parameter (α), which simply describes the ratio between a distractor and target weight, all other things being equal.

Our primary aim is to test several model definitions and see how repetition priming is best accounted for within TVA (Ásgeirsson et al., 2014). In our earlier paper, we demonstrated independence between color and position priming in a brief exposure selective attention tasks (partial report of a color singleton). We proposed a plausible account for the results by extending simple assumptions from TVA (Bundesen, 1990) to the obtained data, collapsed over all observers. Specifically, we suggested that color and position priming effects were obtained by the modulation of selectivity by increased *pertinence* of the primed attributes, i.e. the implicit importance of a repeated color or spatial position increase by repetition. Here, attempt to replicate and expand on those results by isolating the parameters necessary to describe color priming at an individual trial-by-trial level by fitting TVA-models to each participants data (see also Tseng, Glaser, Caddigan, & Lleras, 2014, for a perceptual decision-making approach to modeling response time benefits from color priming), whereby we may confirm or reject the viability of our earlier hypothesis (Ásgeirsson et al., 2014) by a much more detailed analysis. From earlier work (Goolsby & Suzuki, 2001; Meeter & Olivers, 2006; Yashar & Lamy, 2010) we simply hypothesize that priming can be described as an increase in selectivity for repeated features compared to feature "swaps"; when the target-defining feature is swapped with a distractor-defining feature, and vice versa. Goolsby and Suzuki (2001) demonstrated that color priming effects were virtually eliminated in "pop-out" visual search for an odd-one-out colored singleton when the position of a target was pre-cued, leaving selective attention almost untaxed. Meeter and Olivers (2006) went on to show that color priming effects are eliminated by presenting a target alone, without distractors (experiment 3). Because of these results, we hypothesize that color priming takes place only under circumstances of strong selection pressure (i.e. where multiple visual objects compete for selection) but not when selective pressure is minimal (Goolsby & Suzuki, 2001) or absent (Kristjansson, Saevarsson, & Driver, 2013; Meeter & Olivers, 2006; but see also Rangelov, Müller & Zehetleitner, 2011a,b). In terms of TVA, we may hypothesize the following: when a feature belongs to a target, it increases in pertinence, and, similarly, when a feature appears as a feature of a distractor, it decreases in pertinence. These changes are expressed in the π-values of Eq. (2). Consequently, the weight ratios between a distractor and target (defined as α) decrease and processing resources will be more concentrated on the target stimulus. Other things being equal, the repetition-contingent reduction in α leads to a higher rate of target encoding in the race towards visual categorization and consequently a higher probability of a target being reported. If this assumption holds, an increase in performance on feature repetition trials compared to swap trials should result in significant differences in α estimates between the two conditions (model 1).

Another hypothesis we tested by TVA-modeling was whether priming effects for brief masked displays are spatially contingent. Attention is usually not equally distributed in space and it is, therefore, far from certain whether color priming occurs uniformly in the visual field. There may be no relationship between repetition priming and spatial priorities, leaving the pattern of spatial deployment of attention unaltered by color repetitions. However, these parameters might also interact, say by a power law. In such cases performance on highly prioritized spatial positions might be boosted disproportionally to performance when the target is presented at a low priority positions. Or, alternately, the reverse pattern might emerge, where highly prioritized spatial locations might not be boosted to the same extent as low priority locations, due to ceiling performance. To answer these questions we tested whether the 6 stimulus positions in the experiment were weighted differently from each other (model 2) and whether the color priming effect interacted with those differences (model 3).

Finally, we tested whether a parameter representing VSTM capacity (K) improved the fit of our model. There is little doubt that visual attention is limited by VSTM (Awh, Vogel, & Oh, 2006; Carlisle & Woodman, 2011; Kristjansson et al., 2013). However, the significance of VSTM limitations is dependent on the task at hand (Woodman, Carlisle, & Reinhart, 2013). In a singleton recognition task, capacity limitations have the greatest effect on performance when selection of the target is difficult; e.g. when the defining feature is not salient. Under such conditions, an observer may regularly encode distractors by mistake, because the target-signal is weak and filtering inefficient. Conversely, when the defining feature of a singleton target is salient, selection becomes efficient and the likelihood of mistakenly encoding distractors reduces. Consequently, the likelihood of encoding multiple distractors, filling up the VSTM store, may become negligible if the target is sufficiently salient. Model 4 tests whether a model of performance in the current task is improved by taking VSTM limitations into account.

1.2. Summary

We tested the feasibility of modeling color priming within the TVA-framework (Bundesen, 1990) and assessed the importance of selectivity, perceptual thresholds, spatial distribution of attention and capacity limitations for model fits. We did this by a model selection procedure, where we start with the simplest possible model of repetition priming in TVA and then expand the analyses to more complex models.

2. Method

2.1. Participants

Twelve observers (7 male), aged 20–39 years. volunteered for the study. All observers reported normal or corrected-to-normal visual acuity and color vision. Observers were compensated with a gift-card worth approximately € 70.

2.2. Apparatus

Stimuli were presented on 20″ CRT monitors at a 100 Hz refresh rate. The screen resolution was set to 800 by 600 pixels. The experiment was run in Matlab using the Psychophysics Toolbox (Brainard, 1997; Pelli, 1997) on a desktop computer running the Windows XP operating system. Observers made responses on a standard USB-keyboard. For 8 of 12 observers (obs. 1–8), eye-movements were monitored with an EyeLink 1000 eye-tracker with monocular monitoring at a 500 Hz sampling rate. A chin rest supported these observers during the experiment to prevent head-movements. The eye-tracker was mounted on the desktop immediately in front of the stimulus presentation monitor at an 80 cm distance cm from the observers' eye. The remaining four observers were not restrained in any way while viewing the stimuli, but were at approximately the same viewing distance.

2.3. Stimuli

The targets and distractors in the experiment consisted of digits from 0 to 9 (height 2.8°, presented in Arial Bold). Target and distractor colors were chosen randomly for each trial — either red ($x = .585$, $z = .325$, 22 cd/m^2) or blue ($x = .161$, $z = .077$, 13 cd/m^2). Targets could appear in any of 6 positions on an imaginary circle (radius 7.0 visual angle) centered at fixation. The stimuli were masked by 4.5° by 4.5° pattern masks made from cropped pieces of Arial Bold letters (described in Vangkilde, Bundesen, & Coull, 2011) These were randomly rotated (0, 90, 180 or 270°) and mirrored for each trial independently for each stimulus position.

2.4. Procedure and design

All subjects performed 2880 (16 blocks of 180 trials) odd-one-out selection trials.

Here, a single target was present among 5 distractors. They also performed 540 (3 blocks of 180 trials) mixed odd-one-out selection trials and single target trials where 2 of the 3 were identical to the selection trials but 1 had only a single target stimulus (no distractors). The single target trials were included to anchor TVA-models to baseline performance, i.e. how a single digit is processed without any interfering stimuli. The single stimulus trials were interleaved among the selection trials to ensure that observers would not adopt a completely different strategy on the single stimulus trials.

For observers 1–8, each trial started with a fixation period during which the experimental loop was halted until the eye-tracker had registered central fixation for 700 ms (Fig. 1A). This was to ensure that performance could not be attributed to eye-movements away from central fixation. The stimuli were then presented for 10–200 ms (Figs. 1B and E). On odd-one-out selection trials, we sampled at 20, 40, 70, 110 and 200 ms exposure durations, whereas in the single-target recognition trials, where no distractors appeared, we sampled at 10, 20, 40 and 70 ms exposures.

Pattern masks were presented at all 6 stimulus positions for 500 ms (Fig. 1C) after which the observers' keyboards became active, and a blank screen prompted a response. When a response was registered, it was echoed centrally on screen, along with a feedback symbol (+ for correct, − for incorrect). Observers could only make a single response on the numbers pad of the keyboard (digits 1–9), before initiating the

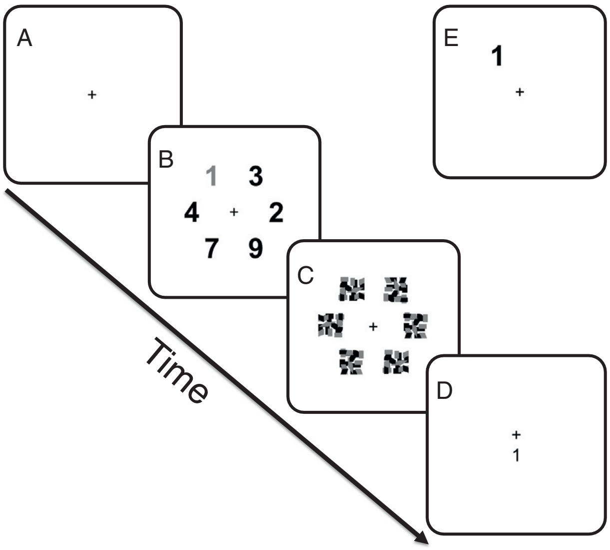

Fig. 1. An illustration of a typical trial progression. A. A fixation cross appeared centrally. B. When the eye-tracker had registered central fixation the stimuli appeared around on an imaginary circle around the fixation cross. C. 10–200 ms after stimulus onset, the stimulus positions were masked. D. When the masks disappeared, the observer responded by pressing the appropriate key(s), succeeded immediately by an echo of the response and a feedback symbol (+ or −). The next trial started a second after the onset of the feedback display. E. Example of single-stimulus trial. Stimuli are not drawn to scale (see Section 2 for details).

next trial or alternatively press the Enter key to signal that they had not recognized the target stimulus.

Observers were encouraged to keep guessing to a minimum and registered "don't know" responses by pressing the spacebar. They were instructed to try to keep the accuracy of committed responses between 80 and 90%. Every 30 trials, they were informed of their accuracy, and were encouraged to use this information to adjust their response criterion if they were overly conservative or liberal. The experiment was split into two test-sessions, of about 120 min each. The procedure was the same for observers 9–12, but without eye-tracking.

2.5. TVA modeling

We defined 4 models with the *MakeModel* program, developed by Kyllingsbæk (2006; p. 126–127). Table 1 provides an overview of the free parameters in each model.

Model 1 was the simplest one possible to account for differential selectivity within TVA, having 4 parameters; one representing processing speed (C; Bundesen, 1990; p. 524–525), one representing the threshold of visual perception (t_0; Kyllingsbæk, 2006; p. 124–125) and two parameters representing selectivity (α; see Kyllingsbæk, 2006; p. 125). The two α-parameters represented the distractor-to-target weight ratios when a target color was repeated (α_{repeat}) and when it swapped with distractor color (α_{swap}). Note that this model regards the whole stimulus array as spatially equivalent, and cannot account for any potential biases in the spatial deployment of attention.

Model 2 was based on model 1 with the addition of spatial attentional weights; one weight for each of the 6 possible stimulus positions. The weights allowed the model to represent different performance based on spatial biases of attention, but could not account for potential interactions between priming and spatial biases.

Model 3 was identical to model 2 with the exception of 6 extra weight parameters. In model 3, each stimulus position is represented by 2 weights; one each for swap and repetition trials. This allowed us to test whether spatial biases interact with repetition priming or whether the spatial distribution of attention remains the same regardless of condition.

Finally, Model 4 was based on model 2, with an added K-parameter (representing VSTM capacity limitations). The first 3 models are all unconstrained by storage capacity limitations. This means that there is a hidden assumption that the capacity of VSTM is never depleted in the experimental task. This could be the case for two reasons; 1) observers memory capacity is large enough to contain at least 6 stimuli (an unrealistic assumption; see e.g. Luck & Vogel, 1997; McAvinue et al., 2012) or, more realistically, that target selection is so efficient in the current task that observers never fill their VSTM with distractors before target entry.

To test whether VSTM limitations are relevant, when accounting for task performance, we added a single free parameter to represent the size of the memory store (K; see Kyllingsbæk, 2006; p. 125 and Appendix, for the calculations behind storage capacity estimations). The singleton recognition task only allows an indirect estimate of VSTM, since observers are only required to report one digit on each trial. A direct measure of capacity requires the number of targets to exceed the size of K. We therefore did not expect the K-parameter to give a realistic estimate of actual capacity. However, the model was expected to fit the data significantly better, if capacity limitations played an important role in the current task.

Parameter estimates were obtained by fitting these models with the *WinTVAFit* program (Kyllingsbæk, 2006; p. 127). The program seeks the best fit to the empirical data according to the assumptions of TVA (Bundesen, 1990) by maximizing the negative log-likelihood functions of each observer's data separately. It assumes an exponential race (Shibuya & Bundesen, 1988) based on the rates obtained by Eq. (1).

Table 1
Free parameters estimated by each of the 4 models.

Model	C	t_0	α_{swap}	α_{repeat}	w_{2-6}[a]	w_{7-12}	K
1	×	×	×	×			
2	×	×	×	×	×		
3	×	×	×	×	×	×	
4	×	×	×	×	×		×

[a] One attentional weight is always fixed to 1, while the remaining weights are estimated relative to it.

3. Results

In the selective condition, where an odd-one-out singleton was presented along with 5 distractors, all observers performed better when target color repeated from the previous trial. The mean difference in the proportion of correctly reported targets (out of all presented targets) between repeat and swap conditions, collapsed across exposure durations, was 5.0 percentage points ($t(11) = 9.928$, $p < .001$; between subject range: 2.4–7.6 pp). This result is consistent with Ásgeirsson et al. (2014) where the analogous main effect measured 6 pp. Fig. 2 shows the results from these conditions, collapsed over participants.

A number of control analyses were performed to rule out several alternative explanations for the observed data pattern. Analyses of committed response error rates (excluding "don't know" responses) by color repetition revealed a significant difference for 8 of 12 observers. The average error difference; i.e. $\text{P (error)}_{\text{swap}} - \text{P (error)}_{\text{repeat}}$, was .004 (range: −.009–.074; $\chi^2(1)$ range: .501–35.956). In all cases where subjects' error rates were significantly different by condition, the error rate was higher when the target color swapped compared to when it repeated. Consequently, the color priming effect cannot be explained by higher accuracy due to guessing in the repetition condition. If anything, this error pattern has reduced, rather than exaggerated, the priming effect.

Response repetition has been shown to have a large effect on response times in a number of studies (e.g. Hillstrom, 2000; Huang et al., 2004). However, this was not the case in the current study. We did not find a significant difference in performance on trials where the response on trial $n - 1$ matched the identity of the target on trial n ($t(11) = 1.238$, $p = .242$).

An analysis of reaction times did not reveal significantly faster responses in the repeat condition, compared to swap ($\text{RT}_{\text{rep}} - \text{Rt}_{\text{swap}} = 4$ ms; $t(11) = -.192$, $p = .852$). This negative finding was to be expected, since participants were instructed to emphasize accuracy only. However, it does demonstrate the lack of a speed-accuracy trade-off.

In the single target condition, where a target was presented alone, there was no difference by color repetition versus switch ($\Delta = .09$ pp; $t(11) = .515$, $p = .617$). This supports the notion that priming is an

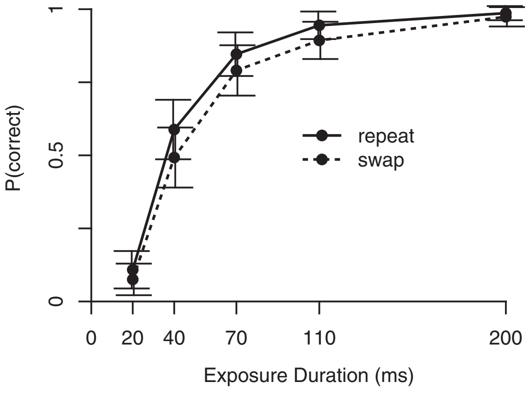

Fig. 2. Performance as a function of exposure duration, collapsed over observers, in the *selective* condition of the experiment. All observers performed better when target color was repeated, compared to when it changed (5 percentage points on average). The circles show the mean proportion pooled over participants, with error bars representing the standard error of the pooled mean proportions.

effect of improved selection between 2 items, and not general stimulus processing (see e.g. Goolsby & Suzuki, 2001; Yashar & Lamy, 2010; Meeter & Olivers, 2006; Kristjansson et al., 2013). In the theoretical context of TVA, this also counters an alternate explanation of repetition priming: a bias (ß-parameter) modulation (see Bundesen, Vangkilde, & Habekost, 2015, for a hypothesis regarding the composition of visual bias) and modulation of sensory evidence ($\eta(x,i)$). If repetition priming were caused by response bias modulation, e.g. an increased tendency to categorize digits as "red", we should see an effect of color repetition on encoding rates, regardless of competition for processing resources. Similarly, if the sensory evidence for certain categorizations was modulated by repetition, e.g. by a lower-level sensitization of feature sensitive neurons in the early visual pathway, this should affect processing independently of whether distractors are present. Both sensory evidence and bias are mathematically independent of stimulus competition. Here, the repetition effect depended on competition with other stimuli, so these alternative mechanisms do not explain repetition priming.

Analyses of error rates by color repetition in the single target conditions revealed no discernible pattern of errors by color repetition. Mean error difference was .003 (range: −.092–.134). There was insufficient power to analyze the errors for observers individually. A test of the pooled data did not reveal a significant difference between conditions ($\chi^2(1) = .336$; $p = .562$) and, therefore, no indication of any performance differences by repetition when observers were presented with a single digit.

We monitored the eye-movements of eight observers to ensure that the obtained effects could not be explained by fixation lapses. We compared their data to the remaining observers' data (9–12). Mean accuracy, collapsed over exposure durations, for the eye-movement control group was 64.1% and 69.4% correct in the color swap and repeat conditions, respectively. For the group without eye-movement control, the corresponding performance was 65.3% and 69.6% correct. These differences are miniscule giving no indication of between-group differences.

Table 2 shows the estimated parameters from all 4 models. The models are quite consistent in their estimates of overall processing rate (C; sd = 3.82) and the threshold for visual perception (t_0; sd = .27) and these estimates seem reasonable compared to analogous values in previous studies where TVA parameters are estimated using similar stimuli (e.g. McAvinue et al., 2012; Vangkilde et al., 2011).

The most important parameters; the conditional α-values, are also relatively consistent between models. Although the absolute values vary somewhat between models (table 2), the ratio between α_{swap} and α_{repeat} is very consistent between models (range: 1.43–1.57). This consistency shows that, although there are large differences in the explanatory power of the simplest model (1) and the more complex models (2–4), there is not much difference in how they account for the specific effects of color repetitions. We do not compare the α-values directly to other studies, in the way we have done with the t_0 and C parameters, since selectivity is, to a larger extent, dependent on the task at hand. A singleton recognition task may be performed using somewhat different strategies than a multiple target partial report task.

3.1. Model comparisons

The relative explanatory power of the models was assessed by log-likelihood ratio tests; where the χ^2-test statistic was $D = -2LL_1 + 2LL_2$ with $(k_2 - k_1) \times n$ degrees of freedom; where LL_1 is the log-likelihood for the null model, LL_2 is the log-likelihood for the alternative model, k_1 and k_2 are the number of free parameters in models 1 and 2 and n is the number of observers.

Table 2
Average parameter estimates from all 4 models. Attentional weight parameters are not shown (but see Fig. 5).

Model	k[a]	C	α_{swap}	α_{repeat}	t_0	K
1	4	77.57	.468	.324	12.7	
2	9	79.72	.395	.269	12.8	
3	15	79.38	.395	.251	12.8	
4	10	86.18	.420	.293	12.8	5.47

[a] Number of free parameters.

3.1.1. Models 1 and 2

Attention is usually not distributed evenly throughout visual space (e.g. Duncan et al., 1999; Nordfang, Dyrholm, & Bundesen, 2013). Models of attention are therefore typically improved by inclusion of parameters representing visual space. Our stimuli were presented at 6 different spatial locations, and to account for spatially biased attention, we included 6 independent weight parameters to represent the positions. These could vary based on spatially contingent performance. This addition improved the model fits greatly. Log-likelihood ratio tests revealed a significant difference in the χ^2 values for the difference between the models; collapsed over observers ($\chi^2(60) = 1446.6$, $p < .001$) and at the individual levels (see table 3).

3.1.2. Models 2 and 3

Model 2 improved on the explanatory power of model 1 by accounting for spatial biases in the deployment of attention. An implicit assumption behind that model is that spatial biases are unrelated to conditions of repetition or alternation of the target color; i.e. whether a feature is primed or not. Model 3 tested this assumption. The model had two weight parameters for each stimulus position, 12 in total. The new assumption in model 3 did not significantly improve the explanatory power of the model ($\chi^2(72) = 54.35$, $p = .94$), nor did it significantly improve model fits to any individual observers' data (table 3). The weight estimates from models 2 and 3 are illustrated in Fig. 5. It is clear that color priming did not change the overall spatial distribution of attention, and that the simpler model (model 2; 9 free parameters) is preferable to the more complex one (model 3; 15 free parameters).

3.1.3. Models 2 and 4

The first four models have all been unconstrained by visual short-term memory capacity. We built model 4 with the exact parameters as model 2, adding the K-parameter. This allowed estimation of ceiling performance and could account for the possibility of VSTM being filled with distractors before the entry of a target. The addition of this parameter improved the overall model fit ($\chi^2(12) = 31.01$, $p = .002$). At the individual level, 7 out of 12 observers' data was explained significantly better by a model including a K-parameter (table 3).

Table 3
Left: Maximized log-likelihood functions for each observer in each of the 4 models. Right: The difference (Δ) between the maximized likelihood functions when comparing the 4 models. Note that all other models are nested under model 1. The p-values are obtained by a likelihood ratio test, using the χ^2-statistic with $k_2 - k_1$ degrees of freedom, where k_1 and k_2 denote the number of free parameters in models 1 and 2, respectively.

	Model *LL*				*LL* difference		
Obs.	Model 1	Model 2	Model 3	Model 4	Δ 1–2	Δ 2–3	Δ 2–4
1	−1063.2	−1027.2	−1025.2	−1025.3	36.0**	2.0	1.9
2	−1072.1	−916.2	−914.5	−910.6	155.9**	1.7	5.6**
3	−1180.3	−1132.5	−1131.3	−1128.2	47.8**	1.2	4.3*
4	−863.6	−823.6	−818.3	−817.3	40.0**	5.3	6.2**
5	−1082.7	−1038.8	−1037.8	−1038.8	43.9**	1.0	<.1
6	−1074.6	−1017.8	−1016.3	−1017.8	56.7**	1.5	<.1
7	−1161.3	−1104.6	−1100.8	−1101.3	56.7**	3.8	3.3*
8	−1096.9	−1075.9	−1075.6	−1072.5	20.9**	.3	3.4
9	−1193.7	−1075.6	−1073.6	−1075.6	118.1**	2.0	.0
10	−1127.5	1097.9	−1094.5	−1097.8	29.6**	3.4	.1
11	−1120.1	−1035.1	−1031.1	−1031.9	85.0**	4.0	3.1*
12	−839.8	−807.2	−806.2	−804.1	32.6**	1.1	3.1*

LL = Log-likelihood. p-values are obtained from the likelihood ratio tests of each model comparison.

* $p < .05$.

** $p < .001$.

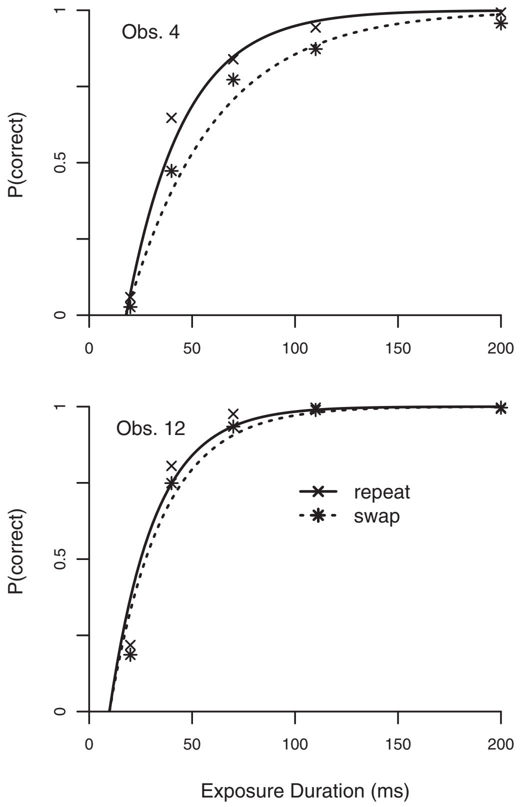

Fig. 3. Observed performance and model fits for observers 1 and 12 obtained by model 1. These observers show the strongest and weakest color priming effects, out of all 12 observers. Model 1 described the averaged data collapsed over spatial positions very well, but performed much worse than model 4 on a trial-by-trial basis.

Least square analyses showed that model 4 explained 94.7% of the variation in proportion of correct responses by color repetition, exposure duration and spatial position (between-subject range: 89.6–98.4%). The fits in Fig. 4 show observed data and model fits for two observers; the ones with the largest and smallest repetition contingent α difference (i.e. the largest and smallest color priming effects). Least square analysis of model 1 showed that it explained 98.2% of the variation in the proportion of correct responses by color repetition and exposure duration (between-subject range: 94.8–99.69%; see model fits in Fig. 3). However, this analysis is much coarser than one where positions are taken into account, and we have seen that the maximum likelihood estimation shows model 4 to have the greatest explanatory power at the trial-by-trial level of analysis. Model 1 only accounted for 67.8% of the variation (between-subject range: 42.3–87.1) in the full set of proportions; by color, exposure duration and spatial position.

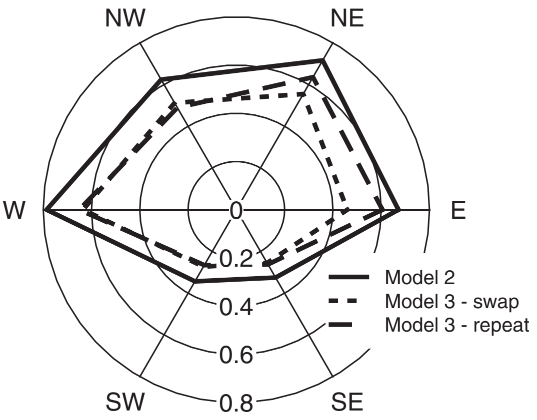

Fig. 5. The average spatial weight distribution by models 2 and 3. The solid line represents the spatial weight distribution in model 2. The dotted and dashed lines show the spatial weight distributions in model 3, under the *swap* and *repetition* conditions, respectively. Although attention was not distributed evenly to all stimulus positions, there was no interaction between spatial weights and color repetition. Weights are relative (see Eq. (2)) and presented on an arbitrary scale between 0 and 1, where 1 is the most highly weighted position of each participant.

The models presented were fitted to each observer's entire dataset. However, one can argue that this choice is not necessarily superior to other choices of data inclusion. Repetition priming is dependent on the previous trial and perception and/or behavior on that trial can only influence the current trial if there has been some registration of a stimulus. Incorrect responses, in the current context, can occur either when an incorrect letter identity is reported or when no identity is reported. However, incorrect responses might lend themselves to multiple categorizations based on observers' experience. Sometimes observers may erroneously report a distractor identity (intrusion), other times they may have confused similar letters, or guessed blindly. Analyzing the full datasets, as we do here, carries the implicit assumption that all trials can affect subsequent ones. This assumption is almost certainly wrong and may give an incomplete picture of priming effects. A simple solution to this problem would be to filter out all trials following incorrect responses. However, such filtering could compromise an important aspect of the experimental design; the random variation of all independent variables (i.e. target color, position and identity). Filtering out trials following incorrect responses would unevenly favor trials following long exposures that may lead to biased outcomes. Therefore, we choose the conservative option of fitting our models to the full dataset of each observer. Significance tests revealed a color priming effect following incorrect trials (2.3 pp; $t(11) = 3.634$; $p = .004$) but it was much smaller than the analogous effect following correct responses (6.3 pp; $t(11) = 9.031$; $p < .001$).

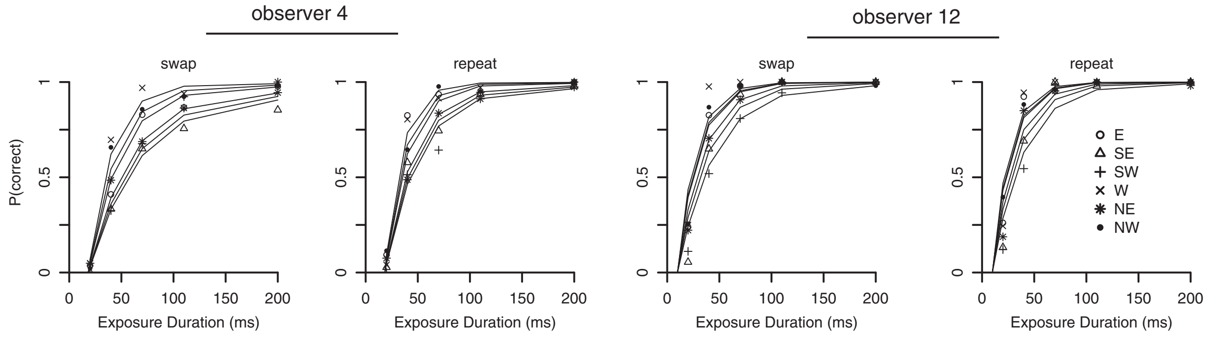

Fig. 4. Observed performance (points) and model fits (lines) by model 4. Observations and data are shown for two observers; observer 4 shows the largest priming effect and observer 12 showed the smallest. Each point type denotes a stimulus positions on an imaginary circle (see Fig. 1).

4. Discussion

There were clear performance benefits when a target color was repeated compared to when it swapped colors with the preceding distractors supporting the notion of perceptual repetition priming, as originally proposed by Maljkovic and Nakayama (1994, 1996) but questioned by researchers preferring a post-perceptual account (Hillstrom, 2000; Huang & Pashler, 2005; Huang et al., 2004). Our results also show that the priming effect is dependent on target selection during competition for attentional resources (target with distractors) and does not appear following a stimulus presented on its own. This result is in line with that of Goolsby and Suzuki (2001) who showed that eliminating uncertainty about a targets position with a spatial precue, virtually eliminating competition with distractors, yielded little or no priming on subsequent trials, in a typical “pop-out” visual search task (see also Meeter & Olivers, 2006; Yashar & Lamy, 2010). There are, however, notable contradictions to the selection dependent priming effect in the literature. Rangelov and colleagues have demonstrated priming effects in single target discrimination tasks, both when repeating the target-defining dimension (Rangelov, Müller, & Zehetleitner, 2011a,b) and when repeating the target-defining feature (Zehetleitner, Rangelov & Mülle, 2012). The important difference in the current study may be that these studies all used response time as their primary measure, and were, therefore, dependent on speeded target and response selection. In the current study, we avoided speeded response selection and simultaneously eliminated competition between visual elements. Under those circumstances, single target processing was not affected by repetition of target color.

It is notable that results from repetition priming of feature values (e.g. certain colors or orientations) are sometimes directly at odds with the literature on priming of feature dimensions, i.e. when the target-defining dimension of singleton is randomly varied. For example, Zehetleitner et al., (2011) demonstrated in a brief presentation localization task, where the target was a singleton defined by either oddness in orientation or luminance, was improved by repeating the defining dimension between trials (Zehetleitner et al., 2011). The localization task was very similar to that of Yashar and Lamy (2010), where no priming effects were found. However, in the latter study, the primed attribute was the feature value (circle or diamond), while Zehetleitner et al. measured priming in terms of repetition of feature dimension. Yet, both feature and dimension priming effects seem to operate by changes in the efficiency of target selection. This has been demonstrated behaviorally, but also by demonstrations of modulations in the size (Töllner et al., 2008 in dimension repetition) and onset (Eimer, Kiss, & Cheung, 2010) of the N2pc ERP component.

The presented models demonstrate that generic TVA-based model definitions account well for color priming on a trial-by-trial basis. Model 4 had 10 free parameters; representing the threshold for visual perception (t_0), overall processing capacity (C), conditional selectivity parameters (α_{swap} and α_{repeat}), VSTM capacity (K) and spatial distribution of attention to the 6 stimulus positions (w_{1-6}, where one $_{\mathrm{w}}$ is fixed to 1). Good fits were obtained with these parameters only, and variation by color priming was well accounted for by the separate α-parameters for the repeat and swap conditions. This supports the notion that perceptual feature priming can be explained by variations in selectivity. In addition to the success of model 4, it must be noted that even model 1, the simplest one possible for explaining priming as a function of stimulus exposure and selectivity, could explain performance over exposure durations very well. In fact, this model accounts for the data just as well as a large proportion of studies in the priming literature; comparing performance on repeat vs. swap trials, independent of the spatial biases of individual observers (e.g. Huang et al., 2004; Meeter & Olivers, 2006; Yashar & Lamy, 2010).

Based on the results, we will hold onto the account of repetition priming in brief displays, proposed in Ásgeirsson et al. (2014), where, other things being equal, the occurrence of feature j (e.g. a color) as a target feature on trial n increases the pertinence (π) of feature j on trial $n + 1$. The viability of this account will be determined by further testing of priming under data-limited conditions, such as brief stimulus displays. A particularly salient point to address in terms of validating the proposed account of priming is whether it holds when multiple targets are presented simultaneously. If the pertinence of a target feature j on trial n automatically increases on trial $n + 1$, we should see improved performance in situations where observers select multiple targets among distractors, as is often the case in brief presentation partial report experiments (e.g. McAvinue et al., 2012; Vangkilde et al., 2011). The difference between these experiments and the current one is that here we define the target category by color oddness, but in the cited experiments the selection category is constant throughout (i.e. report red characters). Defining the target as the odd-one-out may play a causal role in repetition priming. Therefore, this must be tested in an experiment where there are multiple reportable targets, but the defining category can vary between trials.

4.1. Limitations

We should note that while our results provide little evidence for episodic priming (e.g. Huang et al., 2004, Huang & Pashler, 2005; Hillstrom, 2000; Thomson & Milliken, 2011), they do not rule out such priming effects under other circumstances. Two recent accounts of priming of visual search allow for priming at two or more levels of processing (Kristjánsson & Campana, 2010; Lamy et al., 2010).

Additionally, the type of model presented here suffers from some weaknesses when it comes to explaining repetition priming and attention in general. First, the models have a memory of only 1-trial back. That is to say, the benefit in selectivity, induced by color repetition, is only modeled as a consequence of the latest trial. Priming effects are not limited to 1-trial back. They accumulate over multiple repetitions (Brascamp, Pels, & Kristjánsson, 2011; Kristjansson, 2006; Maljkovic & Nakayama, 1994, 1996). Reports of priming effects are often limited to describing the effects of trial $n - 1$ on trial n (e.g. Ásgeirsson & Kristjansson, 2011; Huang et al., 2004; Yashar & Lamy, 2010) when the primed feature(s) is randomly chosen from trial-to-trial and there are few long sequences of the feature repetitions. The statistical power of such analyses shrinks strongly for each step taken further back into past trials. It is, consequently, not very practical to apply statistical tests on data from such paradigms, if they are to test hypotheses about effects stemming from trials far back in a sequence of repetitions. Some authors have partially solved this problem by presenting search items non-randomly to increase the probability of feature repetitions (Huang & Pashler, 2005; Kristjánsson, Wang, & Nakayama, 2002; Maljkovic & Nakayama, 1994; Sigurdardottir, Kristjansson, & Driver, 2008). Applying non-random repetition probabilities markedly increases the statistical power of a study and allows a look further back in terms of repetition sequences. However, when the repetition probabilities have been altered, it is not clear whether the resulting priming effect reflect perceptual effects (e.g. Ásgeirsson & Kristjansson, 2011; Ásgeirsson et al., 2014; Maljkovic & Nakayama, 1994; Yashar & Lamy, 2011) or whether they are a result of learning the inherent statistics of a task (Huang & Pashler, 2005; Kristjánsson & Nakayama, 2003). In the current experiment we randomized target color for each trial to avoid any possibility of learning task contingencies. We are, therefore, constrained by the same lack of statistical power as many other studies. We do, however, propose that repetition priming in briefly presented visual arrays may be described by a model where pertinence values are dynamically updated on each trial; where repeating a feature of a target heightens the pertinence of that feature, while swapping features between targets and distractors reduces it.

4.2. Conclusions

Perceptual repetition priming is becoming a well-established characteristic of selective visual attention. Here we have lent further support to earlier studies (Ásgeirsson et al., 2014; Kristjánsson, 2006; Maljkovic & Nakayama, 1994; Sigurdardottir et al., 2008; Yashar & Lamy, 2010; Yashar & Lamy, 2011) where priming effects were accounted for perceptually. We have shown that color priming only takes place under conditions where a target must be selected among distractors, but not when it is presented alone.

We have modeled our data with different model definitions based on TVA (Bundesen, 1990, see Bundesen & Habekost, 2008 for a more complete overview of TVA research) and shown which parameters are affected by priming, in particular selectivity parameters (α). The most precise model of TVA requires taking spatial biases and VSTM capacity into account. We have also shown that a very simple 4 free parameter models suffice to describe color priming quite well, albeit at a cost of resolution.

There is an outstanding question regarding the generality of our model. In two separate investigations (Ásgeirsson et al., 2014, and the current investigation) we have concluded that priming can be described in terms of TVA by assuming that when a feature j is a target feature on trial n, its pertinence (π) will increase on trial $n + 1$. Similarly, when a feature j is a distractor feature on trial n, its pertinence on trial $n + 1$ will be reduced. These pertinence values affect the model estimates by TVA through the weight equation (Eq. (2)). The viability of this very simple account of priming remains to be tested with different types of stimuli, under more varied conditions of target-distractor similarity and with multiple targets, rather than in odd-one-out target recognition tasks only. For now, however, the account proposed here is the simplest and most parsimonious one for perceptual priming of briefly presented stimuli.

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