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Statistical learning of distractor shape modulates attentional capture

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ABSTRACT

Physically salient but task-irrelevant stimuli have high attentional priority, although observers are able to capitalize on statistical regularities in the environment to more efficiently ignore such stimuli. Physically salient distractors that more frequently appear in a particular location are less distracting when they appear in this high probability location. Likewise, colors and orientations that are frequently associated with distractors become preferentially ignored with learning. Such statistically learned distractor suppression has been examined with respect to the frequency of elementary features across trials, and less is known about how statistics concerning the composition of distractor features within a trial influence attention, particularly with respect to how orientations combine to form shapes. Color, orientation, and location are also represented very early in vision, whereas more complex features such as shape are represented further downstream in the visual system; it remains unclear whether statistically leaned distractor suppression can operate over such downstream visual representations. In the present study, we demonstrate attentional capture by physically salient, shape-defined distractors that is reduced in magnitude for a high probability shape. Our findings demonstrate that statistical learning can modulate attentional priority at least at the level of basic shapes and is not restricted to modulations of priority at the earliest stages of visual information processing tied to elementary features.

1. Introduction

The representational capacity of the human visual system is limited and selective attention is the mechanism by which the brain effectively manages this limitation, prioritizing some perceptual input over others (Desimone & Duncan, 1995). The attentional priority of different sources of visual input reflects the joint product of goal-directed mechanisms driven by the relationship between stimulus features and task-specific goals (e.g., Anderson & Folk, 2010; Folk, Remington, & Johnston, 1992; Folk & Remington, 1998), stimulus-driven mechanisms driven by the physical salience of stimuli (e.g., Theeuwes, 1992, 2010), and learning-dependent mechanisms driven by selection history, or how attention has been allocated in past situations and the outcomes experienced in the context of those situations (Anderson et al., 2021; Awh, Belopolsky, & Theeuwes, 2012). It is also the case that both goal-contingent and stimulus-driven attentional orienting are shaped by selection history. For example, in the case of goal-contingent attentional orienting, prioritization of a target stimulus or target-defining feature is facilitated by statistical learning, being more efficient when a target appears in a high probability location (e.g., Jiang, Swallow, & Rosenbaum, 2013; Jiang, Swallow, Rosenbaum, & Herzig, 2013; Jiang, Won, & Swallow, 2014; Jiang & Swallow, 2013) or in a high probability color (Cosman & Vecera, 2014). Stimulus-driven attentional capture, the involuntary prioritization of a physically salient but task-irrelevant stimulus, can also be mitigated as a result of statistical learning.

When a physically salient distractor is more likely to appear in one particular location in a search array compared to others, ignoring of the distractor at this location is facilitated, with a reduced magnitude of attentional capture observed for distractors appearing at the high probability distractor location (e.g., Britton & Anderson, 2020; Kim & Anderson, 2021, 2022; Wang & Theeuwes, 2018a, 2018b, 2018c; Wang, Samara, & Theeuwes, 2019; Wang, van Driel, Ort, & Theeuwes, 2019). Such facilitated distractor ignoring persists after the biased spatial probabilities are removed (Britton & Anderson, 2020), suggesting a learning-dependent influence that cannot be accounted for by inter-trial priming. A similar phenomenon has been observed with respect to distractor color, with the magnitude of stimulus-driven attentional capture reduced for distractors appearing in a more frequent color (Adam & Serences, 2021; Stilwell, Bahle, & Vecera, 2019; Won, Venkatesh, Witkowski, Banh, & Geng, 2022; see also Vatterott & Vecera, 2012). It is also the case that location and color probabilities can be integrated to facilitate ignoring when different color distractors are more likely to

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appear in different locations (Failing, Feldmann-Wustefeld, Wang, Olivers, & Theeuwes, 2019).

The efficiency of visual search is influenced by the statistics concerning the color and orientation of targets and distractors (Hansmann-Roth, Kristjánsson, Whitney, & Chetverikov, 2021; Witkowski & Geng, 2022). Particularly pertinent to the present study, attention is influenced by the distribution of distractor orientations, with orientations within the range that more frequently characterize distractors receiving reduced attentional processing (e.g., Chetverikov, Campana, & Kristjánsson, 2016; Chetverikov, Campana, & Kristjánsson, 2017; Chetverikov, Campana, & Kristjánsson, 2017; Tanrıkulu, Chetverikov, & Kristjánsson, 2021). In prior studies examining the influence of distractor-related statistics on distractor suppression, however, the *frequency* with which different distractor features (e.g., color, orientation) are encountered over trials varies. Far less is known with respect to how the statistics concerning the *composition of distractor features within trials* influence distractor suppression, particularly with respect to how different distractor features combine to form unique shapes. A plethora of studies have examined the role of simple shape in the guidance of attention, including the learning-dependent control of attention (e.g., Della Libera & Chelazzi, 2009; Wang, Yu, & Zhou, 2013); however, the role of shape-level information in statistically-learned distractor suppression has been less explored. In the present study, we examined whether specific configurations of distractor orientations and the shapes that they form are suppressed as a function of the frequency with which they are encountered in the task.

2. Experiment 1

To better understand the scope of statistically learned distractor suppression, we examined attentional capture as a function of the shape of physically salient but task-irrelevant stimuli. Participants searched for a shape-defined target (upside-down or right-side-up pentagon) amidst circle non-targets and, on distractor-present trials, a diamond or square distractor. Importantly, one shape distractor was considerably more frequent than the other. Simple shape is represented later in the visual system, as early as area V4 (e.g., Pasupathy & Connor, 1999, 2001, 2002), with simple shapes reflecting unique combinations of more elementary features, such as edge orientations, represented in V1 (e.g., Victor, Purpura, Katz, & Mao, 1994; Mazer, Vinje, McDermott, Schiller, & Gallant, 2002). Reduced attentional capture by high probability shape distractors would extend the principle of statistically learned distractor suppression beyond statistical learning tied to elementary visual features and correspondingly early-stage visual representations.

2.1. Methods

2.1.1. Participants

33 participants (15 female, 17 male, 1 non-binary), between the ages of 18 and 35 inclusive (M = 18.8, SD = 1.07), were recruited from the Texas A&M University community. Participants were compensated either with course credit or $10 USD. All participants were English-speaking and reported normal or corrected-to-normal visual acuity and normal color vision. All procedures were approved by the Texas A&M University Institutional Review Board and were conducted in accordance with the principles expressed in the Declaration of Helsinki. Written informed consent was obtained for each participant. The obtained sample provided power $(1 - \beta) > 0.99$ with $\alpha = 0.05$ to detect a difference between the high and low probability distractor condition of $d_z = 0.88$ (computed using G*Power 3.1), which reflects the effect size for the influence of statistical learning on feature-based distractor suppression in the context of color (Stilwell et al., 2019, Experiment 2).

2.1.2. Apparatus

A Dell OptiPlex 7040 (Dell, Round Rock, TX, USA) equipped with Matlab software (Mathworks, Natick, MA, USA) and Psychophysics Toolbox extensions (Brainard, 1997) was used to present the stimuli on a Dell P2717H monitor. The participants viewed the monitor from a distance of approximately 70 cm in a dimly lit room. Responses were entered using a MilliKey response box.

2.1.3. Stimuli, design, and procedure

Participants first completed a 32-trial practice session, then completed 1056 trials which were equally divided into four runs. Each trial consisted of a fixation display (400–600 ms, randomly determined on each trial), a search display (1500 ms or until response), a blank display (1000 ms), a feedback display (1000 ms), and a blank display (500 ms; see Fig. 1). The background of all displays was black. The search display included one pentagon target and seven distractors, each rendered in one of eight colours (blue, cyan, grey, orange, pink, purple, white and yellow). Each shape stimulus was approximately $3.1^\circ \times 3.1^\circ$ in size and was presented on an imaginary circle with a radius of 9.1°. The target pentagon could be either upside-down or right-side-up, and contained either a horizontal or vertical line. The non-targets were circles, and contained a tilted line (randomly tilted 45° left or right). On distractor-present trials, one of the non-target circles was replaced by either a square or diamond, one of which served as a high probability shape distractor.

The target and distractor location were fully crossed and counterbalanced for each distractor shape. Trials were presented in a random order. The high probability shape distractor was present on 74.2 % of total trials and the low probability shape distractor was present on 10.6 % of total trials (15.2 % of total trials were no-distractor trials). Which shape served as the high probability distractor alternated across participants. Participants were instructed to find either an upside-down or right-side-up pentagon regardless of colour and indicate whether the line inside it is horizontal or vertical by pressing the corresponding key on the response box. The line segment inside the target was randomly determined with the constraint that it was equally-often vertical and horizontal, and colours were assigned to shapes randomly without replacement on each trial. A multicolored display was used to examine whether any effect of statistical learning of distractor shape would be sufficiently robust as to be detected in spite of variability in a different feature dimension. The feedback display and the blank display that follows were presented only when participants made an incorrect response ("Incorrect") or failed to make a response before the trial timed out ("Too slow").

2.1.4. Data analysis

Response times (RTs) were computed from the onset of the search display. RTs faster than 200 ms or exceeding 3 SDs of the mean for each condition for a given participant were excluded. When appropriate, we report Greenhouse-Geisser corrected *p*-values.

2.2. Results

RT and accuracy data were subjected to a repeated-measures analysis of variance (ANOVA) with distractor condition (high probability shape, low probability shape, no distractor) as a factor. There was an effect of distractor condition on RT, $F(2, 64) = 130.34$, $p < 0.001$, $\eta_p^2 = 0.80$ (see Fig. 2). Planned contrasts revealed that RTs were slower when high and low probability shape distractors were present compared to when there was no distractor, $ts > 13.4$, $ps < 0.001$, $ds > 2.35$. Importantly, RTs were faster on high probability shape distractor trials than low probability shape distractor trials, $t(32) = 4.16$, $p < 0.001$, $d = 0.72$, indicative of learned distractor suppression.

There was a similar pattern for accuracy, $F(2, 64) = 32.95$, $p < 0.001$, $\eta_p^2 = 0.51$. Accuracy was lower when high and low probability shape distractors were present relative to when there was no distractor, $ts > 6.61$, $ps < 0.001$, $ds > 1.15$. Higher accuracy was observed on high probability shape distractor trials compared to low probability shape distractor trials, $t(32) = 2.65$, $p = 0.012$, $d = 0.46$.

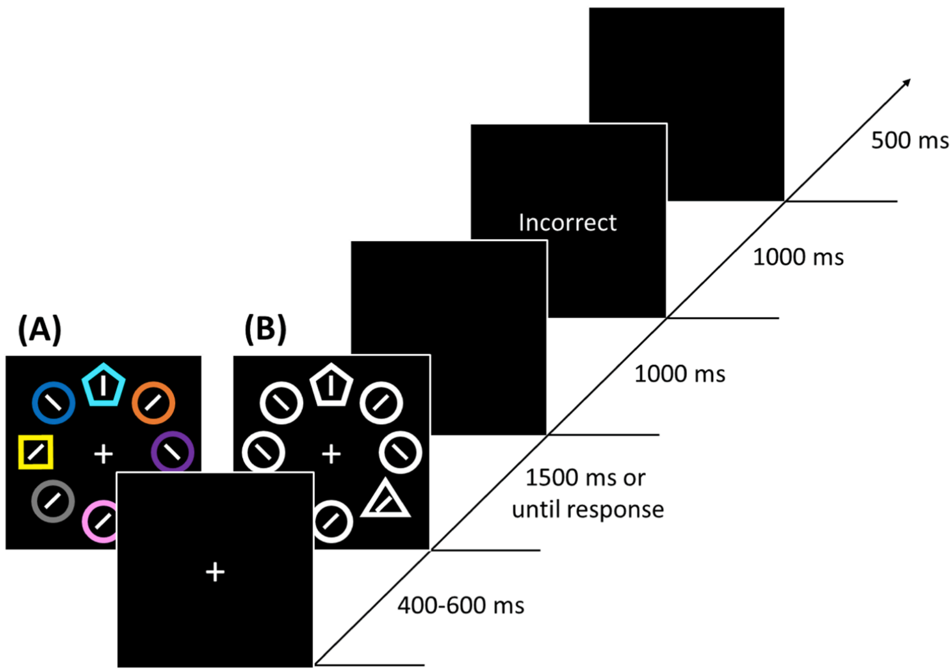

Fig. 1. Sequence of trial events for Experiment 1 (A) and Experiment 2 (B).

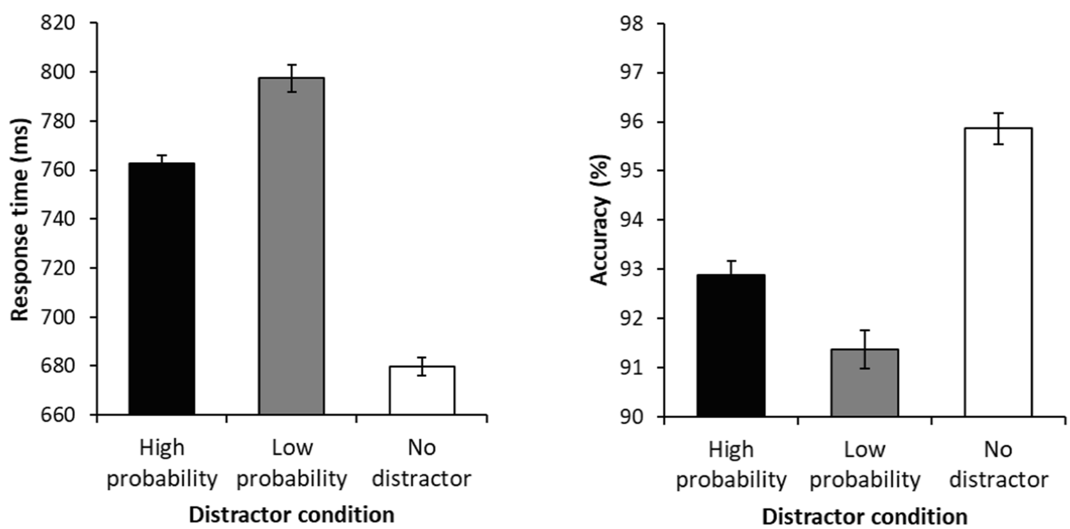

Fig. 2. Mean response times (left) and accuracy (right) from Experiment 1. Error bars represent the within-subjects SEM.

Follow-up analyses examined the speed with which the effect of statistical learning on distractor suppression emerged and whether this effect could be explained entirely by intertrial priming. The RT difference between the high and low probability shape distractor was evident as early as the first block of trials, $t(32) = 3.45$, $p = 0.002$, $d = 0.60$, consistent with prior reports of a rapid influence of statistical regularities on distractor suppression (Stilwell et al., 2019; Vatterott & Vecera, 2012; Wang et al., 2019). The RT difference between the high and low probably shape distractor remained significant when trials on which the distractor shape on trial *n* repeated from trial *n-1* were removed from analysis, $t(32) = 4.18$, $p < 0.001$, $d = 0.73$, consistent with an effect of statistical learning beyond the immediate consequences of intertrial priming (e.g., Stilwell et al., 2019; Wang et al., 2019; Wang & Theeuwes, 2018b; see also Britton & Anderson, 2020; Kim & Anderson, 2021).

3. Experiment 2

In Experiment 1, when the distractor was the high probability shape, it impaired performance to a lesser extent than the lower probability shape, consistent with statistically learned distractor suppression at the level of stimulus shape. However, diamonds contain only oblique lines and squares only vertical and horizontal lines, such that a modulation of orientation-selective cells in V1 (e.g., Victor et al., 1994; Mazer et al., 2002) could explain the results, which would be consistent with statistical learning at an earlier stage more in line with prior demonstrations of statistically learned distractor suppression (e.g., Adam & Serences, 2021; Chetverikov et al., 2016; Stilwell et al., 2019; Tanrıkulu et al., 2021; Wang & Theeuwes, 2018a, 2018b, 2018c; Witkowski & Geng, 2022; Won, Forloines, Zhou, & Geng, 2020). To more definitively link statistically learned distractor suppression to distractor shape, in Experiment 2 we used two distractor shapes that contained the same three line segments, which differed only in their spatial configuration.

Specifically, the critical distractor was either a right-side-up or upside-down triangle, one of which was presented significantly more frequently than the other. Configural processing of contours is evident specifically at the level of V4 (e.g., Pasupathy & Connor, 1999, 2001, 2002) and given that both distractor shapes used in the experiment contained the same three oriented lines, the mere presence of a particular orientation was not diagnostic of the shape of the distractor. That is, the elementary distractor features (e.g., colors, orientations) to which participants were exposed were held constant over trials, and what varied across trials was the composition of these distractor features to form specific shapes. Thus, any observed modulation of distractor processing by statistical learning in Experiment 2 would not be reducible to distractor suppression at the level of stimulus orientation (e.g., Chetverikov et al., 2016; Tanrıkulu et al., 2021) and would be uniquely attributable to configural processing at the level of simple shape.

3.1. Methods

3.1.1. Participants

35 new participants (26 female, 8 male, 1 no response), between the ages of 18 and 35 inclusive (M = 21.8, SD = 4.4), were recruited from the Texas A&M University community, matching the sample size of Experiment 1.

3.1.2. Apparatus

Identical to Experiment 1.

3.1.3. Stimuli, design, and procedure

Identical to Experiment 1 with the exception that the two distractor shapes were a right-side-up and upside-down triangle, and all of the shapes were rendered in white in order to more specifically isolate variability tied to distractor shape.

3.1.4. Data analysis

One participant was excluded from the analysis because the RT difference between high and low probability shape distractor trials exceeded 2.5 SD from the mean difference.[1] Otherwise, everything was identical to Experiment 1.

3.2. Results

As in Experiment 1, there was an effect of distractor condition on RT, $F(2, 66) = 116.51$, $p < 0.001$, $\eta_p^2 = 0.8$ (see Fig. 3). Planned contrasts revealed that RTs were slower when high and low probability shape distractors were present compared to when there was no distractor, $ts > 11.59$, $ps < 0.001$, $ds > 2.03$. Importantly, RTs were faster on high probability shape distractor trials than low probability shape distractor trials, $t(33) = 3.27$, $p = 0.003$, $d = 0.57$, indicative of learned distractor suppression.

There was a similar pattern for accuracy, $F(2, 66) = 43.71$, $p < 0.001$, $\eta_p^2 = 0.57$. Accuracy was lower when high and low probability shape distractors were present relative to when there was no distractor, $ts > 8.15$, $ps < 0.001$, $ds > 1.29$. There was no significant difference between high probability shape distractor trials compared to low probability shape distractor trials, $t(33) = 1.17$, $p = 0.25$.

The RT difference between the high and low probability shape distractor was again evident as early as the first block of trials, $t(33) = 3.47$, $p = 0.001$, $d = 0.6$, and remained when trials on which the distractor shape repeated were eliminated from analysis, $t(33) = 3.93$, $p < 0.001$, $d = 0.68$.

[1] Excluding the participant from the analysis does not change the statistical conclusions.

4. Discussion

The present study straightforwardly extends the mechanism of statistically learned distractor suppression beyond elementary features such as color, orientation, and location, to encompass representations of stimuli at the level of simple shape. Beyond statistical learning tied to the presence of a single feature or visual information at a single location, the attentional priority of stimuli can be modulated by statistical learning tied to distinctly configural processing. Likewise, the present study demonstrates that distractor suppression is not only sensitive to the probably of encountering specific distractor features, but also to the probability of different configurations of distractor features occurring within trials, particularly with respect to how those features combine to form shapes. Such a finding is consistent with the idea that statistical learning has a broad influence on the computation of visual information. Although the full extent of this mechanism has yet to be delineated and remains a topic of future investigation, for example with respect to distractors that differ in complex/meaningful shape as represented in the lateral occipital cortex (LOC; Grill-Spector et al., 1999; Grill-Spector, 2003; Malach, Reppas, Benson, Kwong, Jiang, & Kennedy, 1995), it is clear that the mechanism cannot be localized to a single level of representation within the visual hierarchy.

Using color singleton distractors, it has been shown that such distractors evoke weaker activation in the visual system as early as V1 as a function of their frequency (Adam & Serences, 2021; Won et al., 2020). Although reduced distractor-evoked activity was evident later in the visual system, such reduced activation may simply reflect downstream effects of reduced stimulus-driven activation evident in V1 (see Adam & Serences, 2021). The orientation of stimuli is prominently represented in the activity of V1 cells as well (e.g., Victor et al., 1994; Mazer et al., 2002). Shape, as manipulated in the present study, reflects a more complex visual feature dependent upon configural processing of more elementary features that is not represented until V4 (Pasupathy & Connor, 1999, 2001, 2002), arguing against a common locus of suppression operating over V1 or earlier.

There are many important questions left to address with respect to statistically learned distractor suppression. Among the foremost of these questions reflects the mechanisms by which the probabilities of different visual inputs are tracked and stored in the brain as a form of memory. Is there a domain-general learning mechanism that takes different sensory representations as input and in turn influences information processing at the locus of input? Or is the mechanism more modular and essentially built into the architecture of a sensory system itself, operating within a level of representation? It is also an open question how late in the visual system the effects of statistical learning can be realized and where such effects truly originate from. For example, can the influence of location-dependent probability learning operate principally at the level of a spatial priority map (e.g., Balan & Gottlieb, 2006; Bisley & Goldberg, 2003; Thompson & Bichot, 2005), with learning-dependent consequences then feeding back to earlier-stage representations, or do learning-dependent effects emerge in sensory areas prior to such priority integration? Or perhaps learning-dependent changes can occur at both levels, even simultaneously. The present study informs and helps to motivate future investigations into these and related questions by broadening the scope with which learning-dependent influences on statistically learned distractor suppression have been documented to operate.

5. Author's contribution

BAA, HK and AO conceived of the experiment. HK and AO programmed the experiment and led data collection efforts. BAA, HK and AO analysed the data. HK and AO drafted the manuscript, which BAA edited.

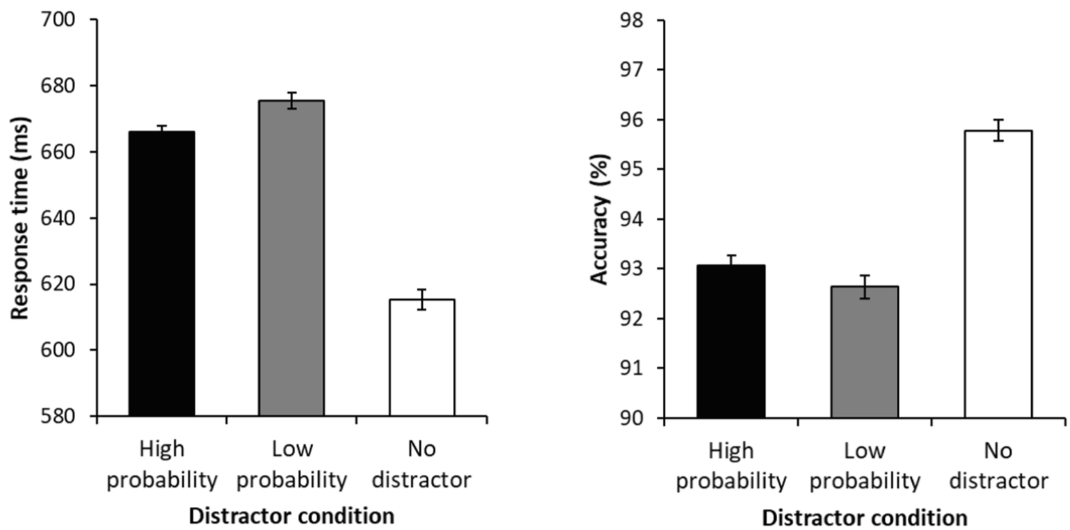

Fig. 3. Mean response times (left) and accuracy (right) from Experiment 2. Error bars represent the within-subjects SEM.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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