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Overt attention in contextual cuing of visual search is driven by the attentional set, but not by the predictiveness of distractors

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Abstract

Two experiments examined biases in selective attention during contextual cuing of visual search. When participants were instructed to search for a target of a particular color, overt attention (as measured by the location of fixations) was biased strongly towards distractors presented in that same color. However, when participants searched for targets that could be presented in one of two possible colors, overt attention was not biased between the different distractors, regardless of whether these distractors predicted the location of the target (repeating) or did not (randomly arranged). These data suggest that selective attention in visual search is guided only by the demands of the target detection task (the attentional set) and not by the predictive validity of the distractor elements.

Humans and other animals are able to cope with the complexity of the surrounding environment by filtering the incoming information, such that cognitive processes are directed only to stimuli of primary importance. This is the role of selective attention, to determine the selective processing of information both within and across different modalities (e.g., Broadbent, 1958; Evans & Craig, 1991; Rock & Gutman, 1981). What exactly receives the focus of selective attention is determined by a number of factors, commonly and broadly partitioned into bottom-up stimulus features and top-down goal-directed processes (for reviews, see Awh, Belopolsky, & Theeuwes, 2012; Theeuwes, 2010). This article is concerned with the latter and primarily how the goals of the agent, brought about either by instruction or by experience with a task, come to determine the focus of attention.

The interdependency of the processes of learning and attention is demonstrated in many common cognitive tasks. For example, when solving categorisation problems with exemplars comprising multiple features, those features that are learnt to be most diagnostic are allocated preferential attentional processing in the future (e.g., Rehder & Hoffman, 2005). Young infants will tend to direct gaze towards the face of a parent over a stranger, presumably as a result of learning about the rewarding properties of that stimulus. Even in simple and rapid visual detection tasks, attention is automatically captured by a rewarding stimulus, even when this attentional capture is counterproductive to the task demands (Le Pelley et al., 2015).

We focus here on the process of visual search, in which the cognitive task is to locate and respond to one stimulus positioned within an array of many. The mechanisms of attentional selection are well studied in this task. Triesman’s feature integration theory (Triesman & Gelade, 1980) has provided the basis for modern theorising on the processes of visual search. Briefly, the model states that features of the visual input are extracted in parallel by pre-attentive processing mechanisms, with attention acting to guide the focus of further processing to enable appropriate feature binding. Thus, in any complex visual search tasks that require the resolution of a conjunction of features (e.g., search for a red vertical line among blue vertical and red horizontal lines), the attentive process moves the spotlight of attention serially from stimulus to stimulus until the target object is detected. Such searches are relatively inefficient and determined by the number of distracting stimuli in the configuration (the “set size”). In contrast, when searching for a single feature (e.g., a red target among blue distractors) rather than a conjunction, the pre-attentive processing mechanisms receive a unique hit and attentional resources can be allocated directly towards the unique object (search times are not a function of the set size). This simple dichotomy of search into discrete pre-attentive and attentive processes has been challenged in recent years by findings showing that the set size effect varies for both conjunction and feature searches, suggesting that there are parallel processes influencing conjunction search, and conversely that serial processes can play a role in feature search. These data led Wolfe and colleagues to propose the Guided Search model (e.g., Wolfe, 1994; Wolfe, Võ, Evans, & Greene, 2011), which suggests that the role of pre-attentive processing is to *guide* the attentive process by restricting the range of to-be-searched objects to those that contain features consistent with the target.

Visual search in the real world will engage not just attentional mechanisms, but also the encoding and recall of memory for past search experiences. Indeed, many experiments to date have shown that a stored representation for the configuration of the distractors can lead to a substantial decrease in the time taken to locate and respond to the target. This “contextual cuing” effect (Chun & Jiang, 1998) is thought to derive from a perceptual saving that results from the processing of fewer distractors prior to the localisation of the target (although see Kunar, Flusberg, Horowitz, & Wolfe, 2007). This is perhaps best shown in data from eye-tracking studies of contextual cuing, which have found that fewer fixations are made when searching repeating configurations compared to random configurations (Harris, & Remington, 2017; Peterson & Kramer, 2001; Tseng & Li, 2004; Zhao et al., 2012).

It has been demonstrated that selective attention plays an important role in contextual cuing. Jiang and Chun (2001) presented participants with a visual search task in which configurations comprised green and red stimuli. Importantly, the target (a T shape) was the same color on every trial, say red (though this was counterbalanced across participants), and this ensured that the distractors (L shapes) presented in that color would receive preferential attentional processing, even though participants were not explicitly instructed about this regularity. An effective search strategy in this task would therefore be to ignore all green items. Jiang and Chun presented repeated configurations for which just the red items comprised the repeating configuration (while the green stimuli were randomly arranged), while for other configurations the green (but not the red) stimuli were repeated. Thus, the former repeating configurations contained useful information for detecting the target presented in the attended color, while the latter repeating configurations only contained useful information presented in the unattended color. This manipulation had a significant effect on contextual cuing: learning was only observed for those configurations with repeating distractors presented in the attended color, while no learning was observed for configurations with repeating distractors presented in the unattended color. These experiments demonstrate the impact of top-down control on the processing of distractors in the contextual cuing task. By fixing the color of the target and therefore the “attentional set” that participants engage in the task, the possible search space is narrowed to only those objects that constitute plausible targets (c.f. Guided Search; Wolfe, 1994). This results in preferential processing of those stimuli, permitting associative learning to occur only between these processed elements and the target position (for a recent discussion of associative models of contextual cuing, see Beesley, Vadillo, Pearson, & Shanks, 2015, 2016).

The current article aims to address two questions that arise from Jiang and Chun’s (2001) results. Firstly, to what extent is this modulation of the contextual cuing effect driven by a preferential allocation of attention to the distractor stimuli of a particular color? It seems likely that overt shifts of attention to relevant stimuli will occur, given it is well known that a standard conjunction visual search of the type used in these studies results in a preferential allocation of attention to those features of the configuration that are shared with the target (e.g., Motter & Belky, 1998). Our study attempts to confirm this hypothesis in the contextual cuing task. The second and more important aim of this work is to examine to what extent these biases in top-down control of attentional selection are driven *only* by the attentional set determined by the visual search task, or whether the allocation of attention can also be driven by *learning* which elements of the configurations are most useful for finding the target, as determined by their predictiveness.

A number of experiments in the human associative learning literature have demonstrated that when a stimulus becomes a reliable predictor of events in the environment, that stimulus will receive a biasing of attention towards it in the future (e.g., Beesley & Le Pelley, 2011; Beesley, Nguyen, Pearson, & Le Pelley, 2015; Le Pelley, Beesley, & Griffiths, 2011; Le Pelley, Beesley, & Griffiths, 2014; Livesey, Harris & Harris, 2009; Mitchell, Griffiths, Seetoo, & Lovibond, 2012). These attentional effects are thought to be elicited reflexively by the appearance of the stimuli (e.g., Le Pelley, Pearson, Griffiths, & Beesley, 2015; Le Pelley, Vadillo & Luque, 2013; Luque, Vadillo, Le Pelley, & Beesley, 2017) and such learned biases in processing have also been observed in implicit learning tasks (Beesley & Le Pelley, 2010). These studies demonstrate a reciprocal relationship between associative learning and attentional processing: as we learn about the usefulness of certain stimuli in our environment (e.g., for predicting rewards), these stimuli come to be allocated greater attentional processing; in turn this enhanced attentional processing will bias any future learning episodes involving these stimuli (i.e., learning more about these stimuli compared to stimuli which are not the focus on attention).

By mapping this to the contextual cuing task, we see that Jiang and Chun’s experiments test the latter aspect of the relationship (attention modulates associative learning), but it is unclear whether the former aspect (associative learning modulates attention) plays a role in contextual cuing. The current experiments examined this question directly.

Experiment 1

In Experiment 1 we sought to establish that the effects ascribed to selective attentional processes in Jiang and Chun's (2001) study truly reflected a biasing of attention towards those stimuli that contained relevant features, as determined by the demands of the visual search task. As we have noted, given that effects of preferential eye movements of this kind have already been demonstrated in visual search tasks, a measurable bias in eye movements was expected. Nevertheless, by examining this in a similar procedure to that used by Jiang and Chun (2001), we were able to establish that our procedure, measurements and analysis could reliably detect differences in participants' eye-movements, which would provide a suitable baseline for assessing biases in attentional processing between the stimuli of our task.

The second aim was to examine whether such biases in attention could be driven by learning to attend to relevant elements of the repeated configuration. Here we used a condition in which the attentional set determined by the visual search task did not dictate a top-down biasing of attention to one color over another, however the configuration of stimuli consisted of distractors that were predictive of the target position (repeating) and distractors that were non-predictive of the target position (random). Several tasks in our lab have established that participants can learn about such *semi-repeating* configurations of context (e.g., Beesley & Shanks, 2012), and so the question of interest was specifically whether such learning effects result in a biasing of attention to those distractors that are predictive of the target.

Method

Participants

The experiment was approved by the local UNSW Sydney ethics committee. Sixty-eight undergraduate psychology students from UNSW Australia participated in exchange for course credit. This sample size yields 81% power to detect a moderate-to-large effect size of Cohen's *d* = 0.7 in a between groups contrast, and 98% power to detect effects of the same size in a within group contrast. All participants had normal color vision and normal or corrected-to-normal visual acuity. Participants were randomly allocated to one of two between-subject conditions: instructed or learning. The experiment was approved by the ethics committee of the School of Psychology, UNSW Australia, and all participants gave informed consent.

Materials and Apparatus

Participants were tested individually in a quiet room with a standard desktop computer and a 58.4 cm widescreen eye tracking monitor (TX-300, Tobii Technology, Danderyd, Sweden) which samples eye gaze at 300 Hz. Participants sat at an average viewing distance of 59 cm (*SD* = 2.8cm), using a chin rest to maintain a fixed position. The eye tracker was calibrated using a five-point procedure at the start of the experiment. Stimulus presentation was controlled by MATLAB using the Psychophysics Toolbox extensions (Brainard, 1997; Kleiner, Brainard & Pelli, 2007; Pelli, 1997). Responses to the target stimulus were made by pressing the ‘m’ or ‘z’ key on a standard keyboard.

Distractor stimuli were an ‘L’ shape (rotated 0°, 90°, 180°, or 270°) while the target stimulus was a ‘T’ shape (rotated at either 90° or 270°). Stimuli were arranged in a square grid of 144 evenly spaced cells (12 x 12) which was positioned centrally on the screen and was 240 mm (23°) square. The grid itself was invisible to participants. The fixation cross (displayed centrally before each trial) was 11 mm (1.1°) square. The stimuli were 13 mm (1.3°) square. The background of the screen was grey (RGB: .6, .6, .6) and the stimuli were presented in either red (RGB: .7, .13, .13) or blue (RGB: .25, .41, .88). There was a small offset in the vertical line of the ‘L’ distractors, which increased the similarity between the ‘L’ distractor and the target ‘T’, making the search task more difficult (Duncan & Humphreys, 1989).

Design

Experiment 1 employed a 2 x 2 x 4 mixed-model design, with a between-subjects factor of task instruction (instructed vs. learning) and within-subject factors of configuration (repeated vs. random) and epoch (1 to 4). The two between-subject conditions experienced both repeated and random configurations over four epochs of 120 trials. All search configurations contained 16 distractors and one target stimulus, with equal numbers of red and blue distractors in each configuration. Four “repeated” search configurations were trained, each of which contained a subset of distractors for which the position and orientation was maintained across multiple presentations (termed predictive). These repeated search configurations contained eight such predictive distractors presented in one color (for example, red) which were intermixed with a set of eight distractors that were placed and orientated randomly on each trial in the alternative color (blue). For the instructed condition, the color of the target was always the same as the color of the predictive distractors within the repeated configurations (red). For the learning condition, the target was presented in one color on half the trials and in the alternative color on the remainder of trials. For the purely “random” configurations, all 16 distractors were randomly arranged on each trial with an equal number of red and blue distractors. For both the instructed and learning conditions the targets in purely random configurations were colored in the same manner as for repeating configurations. Table 1 shows the design of the experiment; a schematic illustrating the differences between the conditions is also presented in Figure 1.

Two red and two blue distractors were placed in each quadrant of the screen. Eight target locations were used, with one from each quadrant assigned to the repeated configurations and one from each quadrant assigned to the random configurations. These eight target positions were chosen at random from one of five locations within each quadrant that were approximately equidistant from the centre of the screen. Distractors could not appear in these target locations.

The four repeated configurations were presented 60 times each (15 times in each epoch) across the course of the experiment. The same number of random trials was used, resulting in 480 trials in total. The same repeated configuration or the same target position could not occur on consecutive trials. Target orientation was determined randomly but an equal number of presentations of each orientation was maintained within each epoch.

Procedure

Participants were seated with a chin rest adjusted according to the participants' height. The eye-tracker was then calibrated and participants received instructions about the nature of the search task: in the instructed condition, participants were told that the target would always be in one color (i.e., they were *instructed* to attend to one color), while in the learning condition, participants were told that the target could be in either color (i.e., they may *learn* to attend more to one color on the basis of the predictiveness of the distractors, but were not instructed to do so). An example of a search trial was presented and participants were shown the two correct responses for the two possible orientations of targets.

Each trial commenced with a fixation cross presented in the centre of the screen for 1000 ms, which was then replaced immediately by the search configuration. Participants searched for the target stimulus and responded with a left or right response depending on its orientation. RTs were recorded from the onset of the search configuration. Following a valid response (z or m) the configuration was removed from the screen. The response-stimulus interval (hereafter RSI) was 1000 ms. If participants made an incorrect response to the target orientation, “ERROR!” appeared in the centre of the screen for 2000 ms, prior to the RSI. A rest-break of 20 seconds was given every 120 trials (splitting the experiment into 4 equal parts). Trials started automatically after these breaks.

Measuring the distribution of attention from fixations

For our analysis of how attention was distributed across the different distractors, we took each fixation that was made during the task and calculated two metrics of distractor processing. The first was the number of distractors present within the “attentional spotlight” region surrounding the centre point of each fixation. We defined the width of this spotlight as 300 pixels (7.7°) in diameter, but very similar ordinal results were observed for analyses conducted with smaller spotlights of (at least) 100 pixels (2.6°) in diameter. A distractor was deemed to be "attended" if the centre point of that distractor fell within the area of the attentional spotlight (i.e., the Euclidian distance from the fixation to the distractor was less than the radius). The number of distractors attended was summed across all fixations for a given trial, with the metric reflecting the mean number attended on each trial. The second metric was simply the average distance of the nearest distractor of each type to the position of each fixation. If attention is biased towards one type of distractor over another, we would expect more distractors to fall within the attentional spotlight and for the nearest distractor of that type to be closer to the points of fixation. We had no a priori reason to anticipate different patterns of results from these two metrics, but we include both to provide a more comprehensive examination of the attentional effects.

Results

Three participants in the instructed condition and two in the learning condition produced accuracy that was below 90% and were removed from the final analysis. Accuracy of responses for the remaining sample was high in both the instructed (*N* = 31; 97.8%; standard error of the mean, *SE* = 0.4) and learning conditions (*N* = 32; 97.9%; *SE* = 0.3). Data from trials on which an inaccurate response was made or the reaction time was 2.5 standard deviations or more from the participant mean (2.8%; *SD* = 0.55) did not contribute to the analyses.

For each trial, the percentage of missing samples resulting from tracking errors (e.g., due to blinks) was calculated, and the data from the eye with the lowest proportion of missing samples were used for that trial. Missing data that spanned a gap of no more than 75 milliseconds were replaced by interpolating between the data immediately preceding and following the gap. The average proportion of missing samples following this interpolation procedure was 2.2% (*SD* = 2.4). Fixations were determined by a displacement method (Salvucci & Goldberg, 2000). The range of values of both the vertical and horizontal coordinates of the gaze data were analysed in 150-ms windows. If neither coordinate deviated beyond a range of 75 pixels (1.9°), then the analysed window was deemed a fixation. Fixation length was determined by extending this window until a displacement exceeded this threshold. Fixation position was determined by the mean horizontal and vertical pixel values across the fixation sample. Trials without any detected fixations did not contribute to the analysis. This led to an exclusion of 48% of the data for one participant in the learning condition and the data from this participant were therefore not included in any analyses; for the remaining participants, 1.3% (*SD* = 2.33) of trials on average were removed.

Figure 2 shows the average RT (panel A) and average number of fixations per trial (panel B). Reaction times decrease across the course of the experiment and are shorter for repeated compared to random configurations, demonstrating the typical contextual cuing effect. While the pattern of data looks similar in the instructed and learning conditions, RTs are longer in the learning condition and the contextual cuing effect seems to be weaker. The pattern in the number of fixations per trial is remarkably similar to the RT data.

The RT data were subjected to a mixed model ANOVA with within-subjects factors of configuration (repeated vs. random) and epoch (1-4), and a between-subjects factor of condition (instructed vs. learning). This revealed a main effect of configuration, $F(1,60) = 49.38$, $\eta_p^2 = .45$, $p < .001$, reflecting a mean contextual cuing effect (RT for random configurations minus RT for repeated configurations) of 163 ms (*SD* = 191). There was also a main effect of epoch, $F(3,180) = 76.03$, $\eta_p^2 = .56$, $p < .001$, reflecting a decline of RT across blocks, as well as a main effect of condition, $F(1,60) = 50.40$, $\eta_p^2 = .46$, $p < .001$, indicating that responses were faster in the instructed (Mean = 2023 ms; *SD* = 504) than in the learning condition (Mean = 2911 ms; *SD* = 480). There was an interaction between configuration and epoch, $F(3,180) = 3.85$, $\eta_p^2 = .06$, $p = .011$, suggesting that the contextual cuing effect increased in magnitude across epochs. The configuration by condition interaction was significant, $F(1,60) = 6.10$, $\eta_p^2 = .09$, $p = .016$, indicating that the contextual cuing effect was stronger in the instructed condition (221 ms; SD = 170) than the learning condition (106 ms; SD = 195). The epoch by condition interaction was also significant, $F(3,180) = 7.55$, $\eta_p^2 = .11$, $p < .001$, suggesting that improvements in RT across epoch were greater for the learning condition compared to the instructed condition. The three-way interaction was not significant, $F(3,180) = 1.13$, $p = .34$. To examine whether contextual cuing was present for each condition, the data were separately subjected to a Repeated Measures ANOVA with factors of configuration and epoch. In each condition there were main effects of configuration and epoch, $F\text{s} \geq 9.13$, $p\text{s} \leq .005$. However, the interaction effect was significant only in the instructed condition, $F(3,90) = 5.19$, $\eta_p^2 = .15$, $p = .002$, and not in the learning condition, $F(3,90) = 1.54$, $p = .21$[1].

The fixation data were subjected to an identical overall ANOVA, which revealed a main effect of configuration, $F(1,60) = 50.57$, $\eta_p^2 = .46$, $p < .001$, demonstrating a contextual cuing effect, with a saving of 0.58 fixations (*SD* = 0.66), on average, for repeated compared to random configurations. There was also a main effect of epoch, $F(3,180) = 86.26$, $\eta_p^2 = .59$, $p < .001$, reflecting a decline in the number of fixations across epochs, as well as a main effect of condition, $F(1,60) = 73.16$, $\eta_p^2 = .55$, $p < .001$, indicating that fewer fixations were made in the instructed condition (5.5; *SD* = 1.2) than in the learning condition (8.5; *SD* = 1.6). There was an interaction between configuration and epoch, $F(3,180) = 3.15$, $\eta_p^2 = .05$, $p = .026$, revealing that the contextual cuing effect increased in magnitude across epochs. Unlike in the RT data, the configuration by condition interaction was not significant, $F(1,60) = 4.20$, $\eta_p^2 = .06$, $p = .057$. The epoch by condition interaction was also significant, $F(3,180) = 6.89$, $\eta_p^2 = .10$, $p < .001$, suggesting that the decrease in the number of fixations across epochs was greater for the learning condition compared to the instructed condition. The three-way interaction was not significant, $F < 1$. To examine whether contextual cuing was present for each condition for the fixation data, the data were separately subjected to a Repeated Measures ANOVA with factors of configuration and epoch. In each condition there were main effects of configuration and epoch, $Fs \geq 10.94$, $ps \leq .002$. However, the interaction effect was significant in the instructed condition, $F(3,90) = 3.52$, $\eta_p^2 = .11$, $p = .018$, but not in the learning condition, $F(3,90) = 1.44$, $\eta_p^2 = .05$, $p = .24$.

Figure 3 shows data pertaining to the distribution of fixations to the different distractor types for repeated and random configurations across the two conditions. Recall that each configuration contained two different sets of distractors, with each set appearing in a distinct color. For "repeated configurations" half of the distractors (those in one color) were predictive of the target location, while the other half of the distractors were randomly arranged and therefore nonpredictive. For entirely random configurations, we continue to demarcate these into two sets referred to as "predictive" and "nonpredictive" (although both sets of distractors are nonpredictive of the target location) since these different sets of distractors were colored in a manner that corresponded to the two sets of distractors in repeated configurations. Thus the fixation data in random configurations provides a baseline for overt attention towards stimulus features in the absence of any predictive information. It is clear that for the instructed condition, attention was biased towards the distractors that were in the same color as the target (P). This effect was consistent across configurations with repeating elements and those that were entirely random. However, in the learning condition there was no clear attentional bias to either set of distractors, in either the configurations with repeating elements or those that were entirely random.

These data were assessed with a mixed-model ANOVA (for each metric) with within-subject factors of configuration (repeating vs. random) and distractor type (P vs. NP) and a between-subjects factor of condition (instructed vs. learning). For the attentional spotlight metric, this revealed a main effect of configuration, $F(1,60) = 40.81$, $\eta_p^2 = .41$, $p < .001$, with a greater number of distractors falling within the attentional spotlight of the fixations on trials with random configurations compared to trials with repeated configurations (mirroring the earlier results of more fixations overall for random configurations). There was a main effect of distractor type, $F(1,60) = 200.75$, $\eta_p^2 = .77$, $p <$

.001, indicating that predictive distractors were more likely to fall within the attentional spotlight (on average 7.1 per trial; *SD* = 1.8) than non-predictive distractors (5.9, *SD* = 2.5). There was also a main effect of condition, $F(1,60) = 92.57$, $\eta_p^2 = .61$, $p < .001$, with a greater number of fixations on distractors overall in the learning condition (again mirroring the finding of a greater number of fixations made and longer RTs in this condition). There was a significant configuration by condition interaction, $F(1,60) = 4.72$, $\eta_p^2 = .07$, $p = .034$, revealing that the difference in the processing of repeated and random configurations was driven primarily by the data from the instructed condition. There was a significant distractor type by condition interaction, $F(1,60) = 189.50$, $\eta_p^2 = .77$, $p < .001$, indicating that the attentional bias towards predictive distractors in the instructed condition (on average 2.3 more predictive distractors attended; SD = 0.14) was greater than that in the learning condition (0.0; SD = 0.1). The configuration by distractor type interaction was not significant, $F(1,60) = 2.34$, $\eta_p^2 = .04$, $p = .13$. The three-way interaction was significant, $F(1,60) = 5.26$, $\eta_p^2 = .08$, $p = .025$. This three-way interaction appears to result from a difference in the magnitude of attentional bias towards P distractors over NP distractors between repeated and random configurations across the two conditions. In the instructed condition, the attentional bias towards P distractors over NP distractors was actually greater in random configurations compared to that in repeated configurations (2.5 vs 2.1), $t(30) = 3.40$, $d = .61$, $p = .002$. In the learning condition, there was no difference in the size of the attentional bias across repeated and random configurations (0.1 vs 0.0), $t < 1$.

An identical ANOVA on the distance metric found no effect of configuration, $F < 1$, but did find an effect of distractor type, $F(1,60) = 296.13$, $\eta_p^2 = .83$, $p < .001$, and condition, $F(1,60) = 12.90$, $\eta_p^2 = .18$, $p = .001$. The distractor type by condition interaction was significant, $F(1,60) = 267.99$, $\eta_p^2 = .82$, $p < .001$, indicating that the difference in the distance of P and NP distractors to the point of fixation was greater in the instructed condition (a difference of 1.4°; SD = 0.08°) than in the learning condition (0.04°; SD = 0.03°). No other interaction effects were significant, $F\text{s} \leq 1.05$, $p\text{s} \geq .31$.

These data suggest that attention was biased towards P distractors and away from NP distractors in the instructed condition, but not in the learning condition. To test the null hypothesis that the contextual cuing effect for repeated configurations does not result in a bias of attention in the learning condition, the P and NP data for repeated configurations in this condition were subjected to Bayesian paired *t*-tests[2] separately for the two metrics. These revealed $BF_{01} = 4.8$ and $BF_{01} = 4.0$ for the attentional spotlight and distance metrics, respectively. The conclusions were the same ($BF_{01} \geq 2.9$) when the data were analysed over epochs 3 and 4, or epoch 4 alone (i.e., where we would expect contextual cuing to be at its strongest). There is therefore evidence to suggest that the contextual cuing effect in the learning condition does not result in an attentional bias.

Discussion

Experiment 1 examined whether contextual cuing results in attentional biases to distractor stimuli that differ in terms of their surface feature similarity to the target stimulus (i.e., color) and in their ability to predict the position of the target. It was observed that when the distractors shared stimulus properties that were relevant to the search task (i.e., they were presented in the same color as the target), and participants were instructed about this regularity, then attention was biased towards the processing of those distractors. However, this attentional bias was present for both repeated and random configurations, indicating that it did not differ as a function of the relevance of the specific set of distractors (i.e., with respect to locating the target). In other words, distractors that were predictive of the target position were not favored over those that were non-predictive. In fact, the attentional bias to distractors presented in the target color was larger in random configurations compared to repeated configurations in the instructed condition. This is the opposite of the result that would be predicted if participants had developed a bias towards predictive distractors and is possibly the result of there being fewer fixations for repeated configurations overall (i.e., a floor effect may have reduced the observed attentional bias). When the color of the distractors was rendered irrelevant to the search task by making the target appear in each color with equal frequency (the learning condition), no attentional bias was observed to the different distractor types. Overall, these results suggest that the learning of predictive information in the configurations does not lead to changes in the allocation of overt attention to that information during contextual cuing.

It is noteworthy that contextual cuing was observed in both the instructed and the learning condition. That is, even in the learning condition, which showed no attentional bias towards predictive distractors, a contextual cuing effect was observed. Thus, an attentional bias towards predictive distractors is not a necessary condition for contextual cuing. However, it does appear that the selective processing of distractors, as brought about by the attentional set determined by the visual search task in the instructed condition, led to an enhancement in the contextual cuing that occurred, in so much that the contextual cuing effect was greater in this condition compared to that observed in the learning condition.

One possible explanation as to why a bias in selective attention failed to develop in the learning condition could be that paying attention to the predictive distractors might provide a disadvantage in the search task. That is, on half of all trials, the target in repeated configurations appeared in the opposing color to that of the predictive distractors. In contrast, in the instructed condition, there was no disadvantage to focusing attention on the predictive distractors, since the target was always presented in the same color as these distractors. Consequently, Experiment 2 examined this possibility by attempting to minimise this disadvantageous aspect of selective attention in the learning group.

It is also worth noting that the clear demonstration of a contextual cuing effect in the fixation data (Figure 2B) lends support to the attentional guidance theory of contextual cuing. Chun and Jiang (1998) suggested that contextual cuing is driven by the guidance of attention towards the target location in the repeated configurations. Other researchers (Kunar, Flusberg, Horowitz, & Wolfe, 2007) have proposed that the contextual cuing effect might be driven instead by response selection mechanisms. This non-attentional account denies that attention arrives at the target location earlier in repeated configurations; rather, it proposes that repeated configurations permit a faster response to the target by lowering the response threshold. However, given that our data showed that fewer fixations were required in the repeated configurations than in random configurations and that eye-gaze has been shown to be tightly coupled with attention (Deubel & Schneider, 1996), our data seem to be incompatible with such a non-attentional account of contextual cuing (see also Harris, & Remington, 2017; Peterson & Kramer, 2001; Tseng & Li, 2004; Zhao et al., 2012).

Experiment 2

The data from the learning condition of Experiment 1 suggest that contextual cuing can occur in the absence of an attentional bias towards predictive distractors. However, we have suggested that for the learning condition, shifting overt attention towards the predictive distractors may have been at odds with conducting an efficient search for the target, since for half of the trials in this condition, the target was not presented in the same color as the predictive distractors. It is possible that this potential detrimental effect on target search may have hindered the development of a strong attentional bias to predictive distractors in the learning condition.

We addressed this issue in Experiment 2 by training a modification of the learning condition – here termed the “split” condition – in which the distractors were red and blue, but in repeated configurations the color of the predictive distractors matched that of the target. For example, if a participant was trained with repeating configurations that contained predictive red distractors, then the target was always presented in red in these configurations (and the target was always presented in blue for random configurations). Thus, attending to the predictive distractors would now be beneficial in terms of the primary task of visual search, at least for these trials. Consistent with this prediction, Geyer, Shi and Muller (2010) have shown that the relationship between the target and distractor colors plays a crucial role in contextual cuing. Geyer et al. trained participants with configurations containing both predictive and nonpredictive distractors (as in the current conditions). Stronger contextual cuing effects were observed when those predictive elements were trained in the same color as the target, compared to when they were colored differently from the target. This result demonstrates the importance of perceptual features in contextual cuing, and on the basis of these findings we would predict greater contextual cuing in the split condition compared to the learning condition of Experiment 1.

Recall that in Experiment 1, despite the absence of any effect on overt attention in the learning group, a contextual cueing effect was still observed for this condition. It is possible that grouping the predictive elements together by color is in some way beneficial for the encoding of the configuration in memory. We sought to examine this in Experiment 2 in two ways. Firstly, we compared learning in the split condition to that in a “mono” condition in which all of the stimuli (all of the distractors and the target) were presented in one color. This mono condition was otherwise identical to the split condition: for repeating configurations, half of the distractors were predictive of the target position and half were randomly arranged. Secondly, in a final test phase of the experiment, we presented the configurations of the split condition in both the training configuration of colors and the reverse of these colors. That is, for “switched” trials, all of the blue elements (e.g., the predictive distractors and the target) were now presented in red, while the red elements (e.g., the random distractors) were presented in blue. Should color grouping information play an important role in the encoding or retrieval of stored representations in contextual cuing, we might expect that this disruption of color would have a significant impact on performance in these switch trials. The mono condition also provides a further test of the process of selective attention in contextual cuing, in the sense that it provides a means to observe whether selective attention to predictive distractors occurs in the absence of any biases that may be brought about as a result of the attentional set that is determined by the visual search task.

Method

Participants

The experiment was approved by the local UNSW Sydney ethics committee. Sixty-two undergraduate psychology students from The University of New South Wales participated in the experiment in exchange for course credit. This sample size yields 77% power to detect a moderate-to-large effect size of $d = 0.7$ in a between groups contrast, and 96% power to detect effects of the same size in a within group contrast. All participants had normal color vision and normal or corrected-to-normal visual acuity. Participants were randomly allocated to one of the two between-subject conditions (split vs. mono). The experiment was approved by the ethics committee of the School of Psychology, UNSW Australia, and all participants gave informed consent.

Design

The first phase of Experiment 2 employed a 2 x 2 x 3 mixed-model design. The between-subject factor was color condition (split vs. mono) and the within-subject factors were configuration (repeated vs. random) and epoch number (1 to 3). The search array in the ‘split’ group consisted of 8 red and 8 blue distractors, with a red target presented for all repeated configurations and a blue target presented for all random configurations (see Table 2). In contrast, the search array in the ‘mono’ group consisted of 16 red distractors and 1 red target. The training phase lasted for 3 epochs of 120 trials. All colors were counterbalanced across participants. This phase of the experiment continued in the mono condition for one additional epoch of 120 trials. For comparison between the two between-subject conditions, the trials from the 4th epoch in the mono condition are not analysed but are shown in Figure 4.

The split condition received a final epoch of 120 trials (the 4th epoch) which we term the “switch phase”. Here the colors of all the stimuli (both sets of distractors and the target) in the repeated configurations were switched (as described above). Since we presented both repeated (non-switched) and switched trials equally often in this phase, this meant there were both repeated configurations with blue targets and repeated configurations with red targets. Therefore, for the trials that presented random configurations, the target was presented in red for one half of the trials and in blue for the other half. This ensured that there was an equal distribution of red and blue targets throughout the experiment in this condition. Repeated (non-switched), switched and random configurations were presented in an intermixed manner during this phase (40 trials each).

Materials & Procedure

Experiment 2 used the same materials and procedure as Experiment 1, with the addition of the switched configurations in the fourth epoch of the split condition. For the split condition, the transition from the training phase to the switch phase occurred seamlessly without any signal to the participant.

Results

Three participants in the split condition and four in the mono condition produced accuracy rates that were below 90% and were therefore removed from the final analysis. For the remaining participants, accuracy of responding was high in both the split (*N* = 28; 98.7%; *SE* = 0.2) and mono (*N* = 27; 97.8%; *SE* = 0.4) conditions. Data from trials on which an inaccurate response was made or on which the reaction time was 2.5 standard deviations or more from the participant mean (3.0%; *SD* = 0.6) did not contribute to the analyses. The processing of eye gaze data into fixations was conducted in an identical manner to Experiment 1. The average proportion of missing samples following the interpolation procedure was 2.0% (*SD* = 2.8). Two participants (one in each condition) had more than 15% of trials without any eye-gaze data and were not included in the final analysis; on average, 0.8% (*SD* = 1.5) of trials did not contain a single fixation and were therefore not analysed.

Figure 4 shows RTs (A) and number of fixations (B) for repeated and random configurations for the split and mono conditions. The data show a contextual cuing effect in both conditions, but this appears stronger in the split condition compared to the mono condition. This difference in the extent of contextual cuing is also observed in the fixation data.

The RT data were analysed with a mixed-model ANOVA with within-subject factors of configuration (repeated vs. random) and epoch (1-3) and between subject-factor of condition (split vs. mono). This revealed a main effect of configuration, $F(1,51) = 24.18$, $\eta_p^2 = .32$, $p < .001$, reflecting a mean contextual cuing effect of 228 ms (*SD* = 350). There was also a general decrease in RTs as revealed by a main effect of epoch, $F(2,102) = 154.90$, $\eta_p^2 = .75$, $p < .001$. There was no main effect of condition, $F < 1$. There was a significant interaction between configuration and epoch, $F(2,102) = 4.61$, $\eta_p^2 = .08$, $p = .012$, suggesting that contextual cuing increased with training, and also a significant interaction between configuration and condition, $F(1,51) = 5.97$, $\eta_p^2 = .11$, $p = .018$, indicating that contextual cuing was stronger in the split condition (338 ms; *SD* = 383) than in the mono condition (114 ms; *SD* = 275). The epoch by condition interaction was not significant, $F(2,102) = 2.88$, $p = .061$, nor the three-way interaction, $F(2,102) = 1.57$, $p = .21$.

To assess the contextual cuing effect in each condition, two repeated-measures ANOVAs were conducted with within-subject factors of configuration and epoch. In the split condition this revealed main effects of configuration, $F(1,26) = 21.03$, $\eta_p^2 = .45$, $p < .001$, and epoch, $F(2,52) = 129.02$, $\eta_p^2 = .83$, $p < .001$, and a significant interaction effect, $F(2,52) = 6.37$, $\eta_p^2 = .20$, $p = .003$. In the mono condition there was a significant main effect of configuration, $F(1,25) = 4.45$, $\eta_p^2 = .15$, $p = .045$, a significant main effect of epoch, $F(2,50) = 46.98$, $\eta_p^2 = .65$, $p < .001$, but no interaction between these factors, $F < 1$[3].

The fixation data were analysed with an identical overall ANOVA, which revealed a main effect of configuration, $F(1,51) = 23.66$, $\eta_p^2 = .32$, $p < .001$, demonstrating a contextual cuing effect, with a saving of 0.79 fixations (*SD* = 1.20), on average, for repeated configurations compared to random configurations. There was also a main effect of epoch, $F(2,102) = 151.63$, $\eta_p^2 = .75$, $p < .001$, but no main effect of condition, $F < 1$. There was a significant interaction between configuration and epoch, $F(2,102) = 6.94$, $\eta_p^2 = .12$, $p = .001$, and also importantly between configuration and condition, $F(1,51) = 4.50$, $\eta_p^2 = .08$, $p = .039$, which confirms in the fixation data that the contextual cuing effect was larger in the split condition (a saving of 1.11 fixations; $SD = 1.32$) compared to the mono condition (a saving of 0.45 fixations; $SD = 0.97$). The remaining interaction effects were not significant, Fs ≤ 2.12, ps $\geq .13$. We also assessed whether the contextual cuing effect was present in the fixation data in each condition. In the split condition this revealed main effects of configuration, $F(1,26) = 19.31$, $\eta_p^2 = .43$, $p < .001$, and epoch, $F(2,52) = 97.85$, $\eta_p^2 = .79$, $p < .001$, and a significant interaction effect, $F(2,52) = 8.58$, $\eta_p^2 = .25$, $p = .001$. In the mono condition there was a significant main effect of configuration, $F(1,25) = 5.27$, $\eta_p^2 = .17$, $p = .030$, a significant main effect of epoch, $F(2,50) = 58.33$, $\eta_p^2 = .70$, $p < .001$, but no interaction between these factors, $F < 1$.

Figure 5 shows the attentional spotlight and distance metrics, as described in Experiment 1, for the data from epochs 1-3. As was the case for the learning condition of Experiment 1, there was very little evidence of differential distractor processing in either the split or the mono condition. The attentional spotlight data were subjected to a mixed-model ANOVA with within-subjects factors of configuration (repeated vs. random) and distractor type (predictive vs. non-predictive) and between-subjects factor of condition (split vs. mono). This revealed a main effect of configuration, $F(1,51) = 30.29$, $\eta_p^2 = .37$, $p < .001$, which mirrors the finding from the main fixation analysis, that a greater number of distractors were fixated for random configurations than for repeated configurations. The main effects of distractor type and condition were not significant, Fs < 1, and none of the interaction effects were significant, Fs ≤ 2.86, ps $\geq .10$.

The data for the distance metric were subjected to the same analysis process. There were no main effects nor any significant two-way interaction effects, Fs ≤ 1.44, ps $\geq .24$, however the three-way interaction was significant, $F(1,51) = 4.06$, $\eta_p^2 = .07$, $p = .049$. It is noteworthy that for repeated configurations in the split condition, fixations were (numerically at least) closer to predictive compared to non-predictive distractors, while the reverse is true for the mono condition. A two-way ANOVA on the data from the split condition found no main effects, *F*s ≤ 1, but did find a significant interaction effect, $F(1,26) = 4.89$, $\eta_p^2 = .16$, $p = .036$. However, the difference in distractor distance was not significant in either the repeated or random configurations, *t*s ≤ 1.63, *p*s $\geq .11$. A two-way ANOVA on the data from the mono condition found no main effects nor an interaction effect, *F*s < 1.

Figure 6 shows RTs and numbers of fixations to different configurations in the "test" phase for the split condition. In both RTs and fixations, it is clear that a contextual cuing effect is observed on trials in which the trained arrangement of colors was used, as well as on trials in which those colors were switched. Paired samples *t*-tests supported these conclusions with significant differences in RTs for trained vs. random, $t(26) = 2.53$, $d = .49$, $p = .018$, switched vs. random, $t(26) = 3.96$, $d = .76$, $p = .001$, but not for trained vs. switched trial types, $t < 1$. A similar pattern of results was observed for the fixation data: trained vs. random, $t(26) = 2.60$, $d = .50$, $p = .015$; switched vs. random, $t(26) = 4.12$, $d = .79$, $p < .001$; trained vs. switched, $t < 1$.

Discussion

In Experiment 2, all participants experienced repeated configurations that contained both distractors that were predictive and distractors that were non-predictive of the target position. We observed contextual cuing effects in both of these conditions. However, as was observed for the learning condition in Experiment 1, significant contextual cuing effects (present in both RT and fixation data) did not occur as a result of an attentional bias to predictive distractors over non-predictive distractors. While we observed a significant three-way interaction in the fixation distance metric, our follow up analyses, as well as the lack of any such effects in the attentional spotlight metric, suggests that we should be cautious about interpreting these effects as related to a specific attentional bias towards predictive distractors. We can therefore conclude that the ability to detect the target at a more rapid rate (and after fewer fixations) when presented with a repeated configuration is not a result of selectively fixating on the predictive information within that configuration. An exploratory analysis of the eye-gaze data is presented in the General Discussion to examine in more detail the time-course and efficiency of search through repeated and random configurations.

Experiment 2 also examined the role of color segmentation in contextual cuing. Participants were either trained with predictive and non-predictive distractors in different colors (split condition) or with all distractors in the same color (mono). We found that the cuing effect was stronger when the predictive and non-predictive distractors were segmented by color (split) compared to when they were presented in the same color (mono). This suggests that in our task, perceptual segmentation leads to a stronger trace of the repeated configuration of distractors in memory, perhaps by facilitating the formation of a configural representation of these similar elements (Beesley, et al., 2015, 2016). This finding is at odds with the results of a series of experiments presented by Conci and von Mühlenen (2011), in which they examined how perceptual segmentation of the distractors modulates contextual cuing. When the search task ensured the target features were not preferentially attended, Conci and von Mühlenen found that the contextual cuing effect was significantly weaker when the configuration was segmented by perceptual features (compared to cuing for homogenous configurations). This is inconsistent with our finding of enhanced cuing for segmented configurations, but may be explained by the different amounts of predictive context in the two designs. In our experiments, repeated configurations contained both predictive and nonpredictive distractors, while in Conci and von Mühlenen’s experiments the repeated configurations were entirely predictive. Therefore perceptual segmentation may be beneficial when it constrains the processing of information to a relevant set (and avoids processing irrelevant information), but is a hindrance when processing is necessary across information presented in two distinct perceptual features. Indeed, similar benefits of segmentation have been observed for partially predictive configurations (Geyer, Shi, & Müller, 2010).

In a final phase of the experiment, for those in the split condition, the colors of the distractors in these repeating configurations were switched in a final phase. We found that this had no detrimental effect on the size of the contextual cuing effect that was observed. One interpretation of these data is that the representation of the repeating configuration exists in a form that is independent of the surface level features of the distractor elements (e.g., distractor colors). Taken together with the more substantial cuing effect in the split condition compared to the mono condition, these data may suggest that color information acts to modulate the encoding of repeated configurations in visual search but the subsequent behavior elicited by these configurations is driven by the spatial configuration and not the surface features.

Statistical comparisons of the data from Experiments 1 and 2

As a means to elucidate the variables affecting contextual cuing and attentional processing, we provide a statistical analysis of the four between-subjects conditions conducted across the two experiments. Since the two experiments were drawn from different samples, and the data were collected in different time periods, the conclusions should be taken as tentative at best; full experimental control of these variables is necessary to be conclusive about their importance. Nevertheless, it is notable that across experiments there were substantial differences in the size of the contextual cuing effects. Of particular note is that the split condition in Experiment 2 showed a comparable contextual cuing effect to that of the instructed condition in Experiment 1, while the remaining two conditions showed comparably small contextual cuing effects. To simplify the analysis we took the data from the first 3 epochs of trials (trials 1-360) and computed a contextual cuing score for each condition of interest by subtracting the reaction time for repeated configurations from that for random configurations. We observed that the cuing effect for the Split condition in Experiment 2 (338 ms, *SE* = 74 ms) was somewhat similar in size to that of the Instructed condition in Experiment 1 (208 ms, *SE* = 32 ms), though there was little evidence in favor of the equivalence of these cuing effects, BF_{01} = 1.15. In contrast, the cuing effect in the Split condition of Experiment

2 was stronger than that observed for the Learning condition in Experiment 1 (72 ms, *SE* = 37 ms), and there was considerable evidence in support of this difference, $BF_{10} = 23.46$. A similar pattern of results was observed in the fixation data (Split vs. Instructed, $BF_{01} = 1.60$; Split vs. Learning, $BF_{10} = 3.78$).

These comparisons appear to suggest that the Split condition showed a stronger contextual cuing effect than the Learning condition. The only difference between the two conditions was that in the Split condition, the target was always presented in the same color as the predictive distractors, while in the Learning condition the target could be in either color (across trials). This suggests that the coincidence of the distractor and target colors promotes the learning of associations, a finding which is consistent with data presented by Geyer, Shi, and Müller (2010). Note that despite these suggested differences in the size of the cuing effects in the Split and Learning conditions, the profile of eye-movements was identical in the two conditions: in neither condition did we observe greater processing of predictive over non-predictive distractors.

General Discussion

The four conditions across these two experiments paint a very consistent pattern. Selective attention (fixations) towards particular sets of distractors was prioritised according to the attentional set determined by the nature of the search task, but showed no sensitivity to the predictiveness of distractors. When participants were explicitly instructed to search for a target that always appeared in a single color and to ignore distractors of a different color (Experiment 1: instructed condition), overt attention was strongly biased towards distractors appearing in the same color as the target. The eye gaze analyses of the instructed group of Experiment 1 show this bias clearly, regardless of whether those distractors were predictive (on repeated configuration trials) or nonpredictive (on random configuration trials). In contrast, when the task was to search for a target that could appear in one of two colors, but distractors in just one color were predictive on repeated trials, participants did not fixate the predictive distractors any more than the non-predictive distractors in either a configuration-specific manner (i.e., on repeated trials only) or a feature-general manner (i.e., on all trials). This was the case in the learning condition of Experiment 1, when the predictive distractors predicted the location but not the color of the target, and in the split condition of Experiment 2, when the predictive distractors conveyed information about both the location and color of the target. Furthermore, when only a single color was used for all distractors and targets in the mono condition of Experiment 2, thus removing uncertainty about the color of the target without producing the strong task-driven biases in selective attention seen in Experiment 1, there was again no bias towards fixating predictive compared to non-predictive distractors.

These results clearly suggest that selection biases in contextual cuing are driven by the top-down demands of the search task and not the learned predictiveness of the distractors within repeated configurations. To provide further support for this conclusion, the data from the selective attention metrics were combined for the three conditions which appeared to show no bias in selective attention (epochs 1 to 4 in the learning and mono conditions, and epochs 1 to 3 in the split condition). These data were subjected to Bayesian paired samples *t*-tests to compare attention to predictive and non-predictive distractors for repeated configuration trials. This revealed that for both the attentional spotlight, $BF_{01} = 7.96$, and the distance metric, $BF_{01} = 5.00$, there was considerable support for the null hypothesis that there was no effect of selective attentional processing.

Given the evidence that there is no bias in overt attention towards predictive distractors in repeated configurations, it is especially noteworthy that this predictive information clearly *did* improve the efficiency of target detection during search in all of the conditions tested. In every condition, participants required fewer fixations to locate the target on repeated configuration trials than on random configuration trials. Thus, despite their inherent usefulness for improving visual search, predictive distractors appear to receive no bias in selective processing. One explanation for this somewhat paradoxical finding might be that the demonstration of equivalent fixation profiles to repeated and random distractors does not necessarily equate to equivalent processing of the two sets of distractors. In other words, more weight may be placed on the *processing* of predictive distractors without this leading to a higher probability of those distractors being fixated. Indeed, learning in the absence of overt attentional processing has been suggested by Jiang and Leung (2005), who gave participants a task similar to that used by Jiang and Chun (2001), in which repeated configurations contained predictive distractors in both “attended” and “unattended” colors (as determined by the color of the target). In a later stage, Jiang and Leung reversed the assignment of colors for the distractors (as in the switch phase of Experiment 2) and found that once the unattended distractors became the focus of attention, contextual cuing was observed. This result suggests that learning about predictive elements of the search configuration may occur even when those elements are not the focus of overt processing. Indeed, contextual cuing can occur even in the presence of attention demanding stimuli such as color singletons (Conci & von Mühlenen, 2009; Harris & Remington, 2017). These findings are consistent with our own, which demonstrate that strong contextual cuing effects occur without a strong biasing of attention to the relevant predictive content.

There remains a question as to why repeated configurations have fewer fixations: does the fixation profile of repeating configurations tell us anything about the efficiency of search in contextual cuing? To examine this further, we subjected the fixation data from the learning (epochs 1 to 4), split (epochs 1 to 3), and mono conditions (epochs 1 to 4) to an exploratory analysis. Figure 7 shows the data grouped by the number of fixations within a trial. Figure 7A shows the mean pixel distance from the target of each fixation within these different trial types. Firstly, it is quite clear that across the trials of different length (3 fixations to 10 fixations), the pattern of data is remarkably similar between the repeated and random search configurations. Secondly, in line with the previous analyses conducted by Tseng and Li (2004), our data suggest that visual search performance in these tasks has two characteristic components: an inefficient search process in which attention moves in a non-productive manner, failing to move towards the target and consistently away from the target location in trials with more fixations, followed by an efficient search process in which consistent monotonic increments are made towards the target position (the final 3-4 fixations). The latter efficient search process is extremely consistent across the different trial types, suggesting that once this phase is reached, the trial terminates in a similar manner across paths of different lengths. In contrast, the trials differ in the length of the first, inefficient search process.

Figure 7B shows the proportion of trials containing a given number of fixations for the repeated and random configurations. As the data clearly show, the benefit of search through repeated configurations is driven by a greater number of trials having fewer fixations, particularly in the range of 1-5 fixations. Conversely, there is a consistent pattern of repeated configurations being less likely to have trials with more fixations (6-20). To provide some statistical basis to these claims, we subjected the data to a two-way Repeated Measures ANOVA with factor of configuration (repeated vs. random) and fixations (1-20), which importantly revealed a significant interaction between the factors, $F(19,1577) = 7.73$, $\eta_p^2 = .09$, $p < .001$, suggesting that the pattern in the proportion of trials with different numbers of fixations differed between the repeated and random configurations. An analysis of the data on trials with fewer than 6 fixations revealed that there was a greater proportion of these trials for repeated compared to random configurations, $t(83) = 5.52$, $d = .60$, $p < .001$ (a complementary analysis of the RT data is presented in the Appendix).

Thus, these data suggest that for repeated configurations, the inefficient period of visual search is more likely to cease at an earlier stage in the search process and there will therefore be an earlier transition into the efficient search process (over the final 3 or 4 fixations, as suggested by Figure 7A). For each participant, we calculated the maximum distance from the target of all the fixations in a trial, and calculated the mean of these maximal distances for repeated and random configurations. This revealed that search tends not to stray as far from the target location for repeated configurations (maximum distance = 17.7°, $SE = 0.12$) compared to search through random configurations (maximum pixel distance = 18.0°, $SE = 0.11$), $t(83) = 2.63$, $d = .29$, $p = .010$.

Overall, our data suggest that participants search directly for the perceptual features that define the target (as demonstrated in the instructed condition), and not for the cues that might inform them as to where the target is located. In doing so, they fixate distractors that occur in the repeated configurations, which provide information about where the target is located, but this sampling is not strategic and thus participants do not prioritise selection of these predictive distractors over non-predictive distractors in future encounters with the same repeated configuration.

Search through repeated configurations appears to progress, at least initially, in a somewhat random fashion, with fixations evenly distributed towards predictive and non-predictive distractors. Once some beneficial predictive information has been encountered (i.e., when a match is made with a stored representation in memory), this leads to a termination in the inefficient search at an earlier time point (Figure 7), and also to a reduction in the maximal distance that fixations drift from the target location.

Why would the predictive distractors in contextual cuing fail to receive prioritised attention when there is evidence of biases in attention on the basis of learned predictiveness in a wide range of other tasks? There are other visual cognition paradigms that exhibit oculumotor biases towards predictive distractors (e.g., Le Pelley et al., 2015) and other learning tasks that exhibit learned predictiveness biases towards multiple spatially discrete predictive and nonpredictive features (e.g., Livesey & McLaren, 2007). Thus the procedure we employed in the contextual cuing task in which predictive and nonpredictive information were spatially distributed and simultaneously presented would be expected to lead to such biases.

Although it may seem somewhat counterintuitive, our contention is that it may be optimal in tasks like contextual cuing for attention to be strongly controlled by a search for the defining features of the target, even at the expense of attending to predictive cues. On a typical contextual cuing trial, the target is presented simultaneously with the predictive distractors, and search times are typically relatively brief. Repeated configurations also possess reasonably high similarity with random configurations, meaning that the learned components of a repeated array may not be immediately apprehended. These properties of the task are important because they may limit the usefulness of selecting predictive distractors for further attention relative to simply investing attention in those perceptual features that define the target itself. The predictive information that repeated distractors convey essentially directs the participant to look to another location to find the target. Thus by the time the specific components of a repeated configuration are processed, biasing attention more strongly towards them may serve little purpose and in fact may actually hinder rapid target selection (if predictive distractors capture attention, they may prevent attention from reaching the target quickly). Indeed, the benefits that are provided by intentionally encoding the predictive content of the displays are minimal (a saving in the order of 200 ms or 1 fixation in the conditions examined here).

That is not to say that predictive information is neglected in the encoding of the display; our data quite clearly show that predictive information was learnt and had significant control of behavior in terms of producing shorter search times. Like all implicit learning tasks, the learning that occurs in the contextual cuing task might be best considered incidental, in the sense that it is arguably superfluous to the explicit demands of the task (i.e., to respond accurately to the target orientation). Our data certainly support this notion that participants learn incidentally and do not strategically encode greater amounts of predictive information in the displays as they search; if anything, it would appear that search is somewhat random until the point at which predictive information is encountered, and then transitions rapidly to an efficient search process which results in target detection within 3 or 4 fixations. It is possible that the learning of predictive information occurs somewhat covertly (that is, not determined exclusively by the spatial location of the fixations), either by an initial (perhaps rapid) global processing of the whole scene, or sequentially through the non-strategic search process we have identified.

This account suggests that an attentional bias to predictive distractors fails to emerge in contextual cuing because it is not optimal for the individual to develop one. This account thus implies that learned predictiveness effects are strategic and initiated voluntarily, which is a description that may not characterise the general attentional consequences of learned predictiveness particularly well (for a review see Le Pelley et al., 2016). An alternative explanation is simply that in visual search, selective attention is so strongly dominated by searching for the defining physical properties of the target that biases to other features (voluntary or otherwise) are extremely difficult to observe. Biasing stimulus selection towards the unique features of the target may be the single most important factor in determining good performance in visual search, and this differs from most learned predictiveness tasks, where attending to the specific features of the predicted outcome can occur sometime after attending to the predictive cues. This may be why the reciprocal relationship between predictive learning and attention that is observed in many other experimental contexts does not appear to hold in this one.

While our data suggest that attentional selection is controlled exclusively by the attentional set determined by the search task, the data from Experiment 2 reveal that the perceptual features of the distractors and their relationship with the target features did have a significant effect on the contextual cuing that developed. In Experiment 2, the cuing effect (in both RTs and the number of fixations) was greater in the split condition compared to that in the mono condition. That is, while grouping the predictive and non-predictive distractors by color did not lead to an overt attentional bias towards those predictive distractors, it had a clear effect on the strength of the memory representation that formed for those configurations.

Furthermore, the data from our final test phase suggest that this representation may well be stored in a form independent from (or at least insensitive to) the color information in which it has been presented: when the colors of the predictive and non-predictive distractors were switched in this final phase, intact cuing was observed in both RTs and fixations. It would seem therefore that the benefit of segregating the predictive and nonpredictive information occurs during the initial encoding of the configuration, rather than the recall of that information from memory. While further experimental evidence will be needed to support these conclusions, these findings may well have important implications for the manner in which surface feature information is realized in formal models of contextual cuing (e.g., Brady & Chun, 2007; Beesley et al., 2015, 2016).

In conclusion, the data from these experiments illuminates the interaction between associative learning and overt attentional processes in the contextual cuing task. Overt attentional biases are driven by physical properties of the stimuli governed by the target search template and are not preferentially directed by the associative strength of distractors contained within repeating configurations. Furthermore, in line with the findings of Tseng and Li (2004), our data suggest that the contextual cuing effect occurs when a stored representation is activated following an unsystematic (i.e., random) search process, which leads to an early termination of inefficient search, and an earlier engagement of efficient search.

Footnotes

1. A mixed-model ANOVA with the same factors was conducted on the accuracy data of Experiment 1 and found only a main effect of epoch, $F(3,180) = 6.59$, $\eta_p^2 = .10$, $p < .001$, with accuracy increasing across epochs from 96.6% in epoch 1 to 98.3% in epoch 4. No other main effects or interactions were significant, $F\text{s} \leq 2.16$, $p\text{s} \geq .10$.
2. Bayesian statistics were conducted in JASP (Version 0.8.0.0) with the default Cauchy prior width of 0.707.
3. A mixed-model ANOVA with the same factors was conducted on the accuracy data of Experiment 2 and found only a main effect of epoch, $F(2,102) = 4.96$, $\eta_p^2 = .09$, $p = .01$, with accuracy increasing across epochs from 97.5% in epoch 1 to 98.4% in epoch 3. No other main effects or interactions were significant, $F\text{s} \leq 2.53$, $p\text{s} \geq .09$.

Appendix

The RT data for epochs 1-3 from the learning, split, and mono conditions were subjected to further analysis in order to evaluate the observed contextual cuing effect across the range of RTs (Figure 8). In Figure 8A, RTs are split into 10 bins by each decile of reaction time for both the repeated and random configurations. At each decile, the reaction times were faster in the repeated than the random configurations, $ts(83) \geq 2.70$, $ds \geq .15$, $ps \leq .01$. As in the fixation data presented in Figure 7B, a similar pattern of data emerged in the reaction time data, with a greater percentage of trials having faster reaction times in the repeated configurations compared to the random configurations. An ANOVA with factors of configuration and bin found a significant interaction, $F(21,1743) = 5.52$, $\eta_p^2 = .06$, $p < .001$, supporting this conclusion. These analyses are consistent with those presented by Johnson, Woodman, Braun, and Luck (2007).

Author note

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Table 1.

Condition	Distractors	Target color (% of trials)
Instructed (Repeated)	8 red repeated + 8 blue random	Red (100%)
Instructed (Random)	8 red random + 8 blue random	Red (100%)
Learning (Repeated)	8 red repeated + 8 blue random	Red (50%) or blue (50%)
Learning (Random)	8 red random + 8 blue random	Red (50%) or blue (50%)

Note: The manipulations of predictive and randomised distractors, their colors, and the colors of the targets for Experiment 1. The colors of the stimuli were counterbalanced, such that in the instructed condition half of the participants searched for a blue target with blue predictive distractors, while in the learning condition half the participants were trained with blue predictive distractors and red random distractors.

Table 2.

Condition	Distractors	Target color (% of trials)
Split (Repeated)	8 red repeated + 8 blue random	Red (100%)
Split (Random)	8 red random + 8 blue random	Blue (100%)
Mono (Repeated)	8 red repeated + 8 red random	Red (100%)
Mono (Random)	16 red random	Red (100%)

Note: The manipulations of predictive and randomised distractors, their colors and the colors of the targets for Experiment 2. The colors of the stimuli were counterbalanced, such that in the split condition half of the participants searched for a blue target with blue predictive distractors.

Figure 1. A schematic of the different conditions in Experiments 1 and 2. All configurations actually contained 16 distractors and the different sets of distractors were evenly distributed across the screen. Distractors presented in boxes reflect those that repeated across trials and therefore were predictive of the target location. For simplicity, the same configurations are presented in all four conditions, but note that both repeated and random configurations were generated randomly for each participant in each condition.

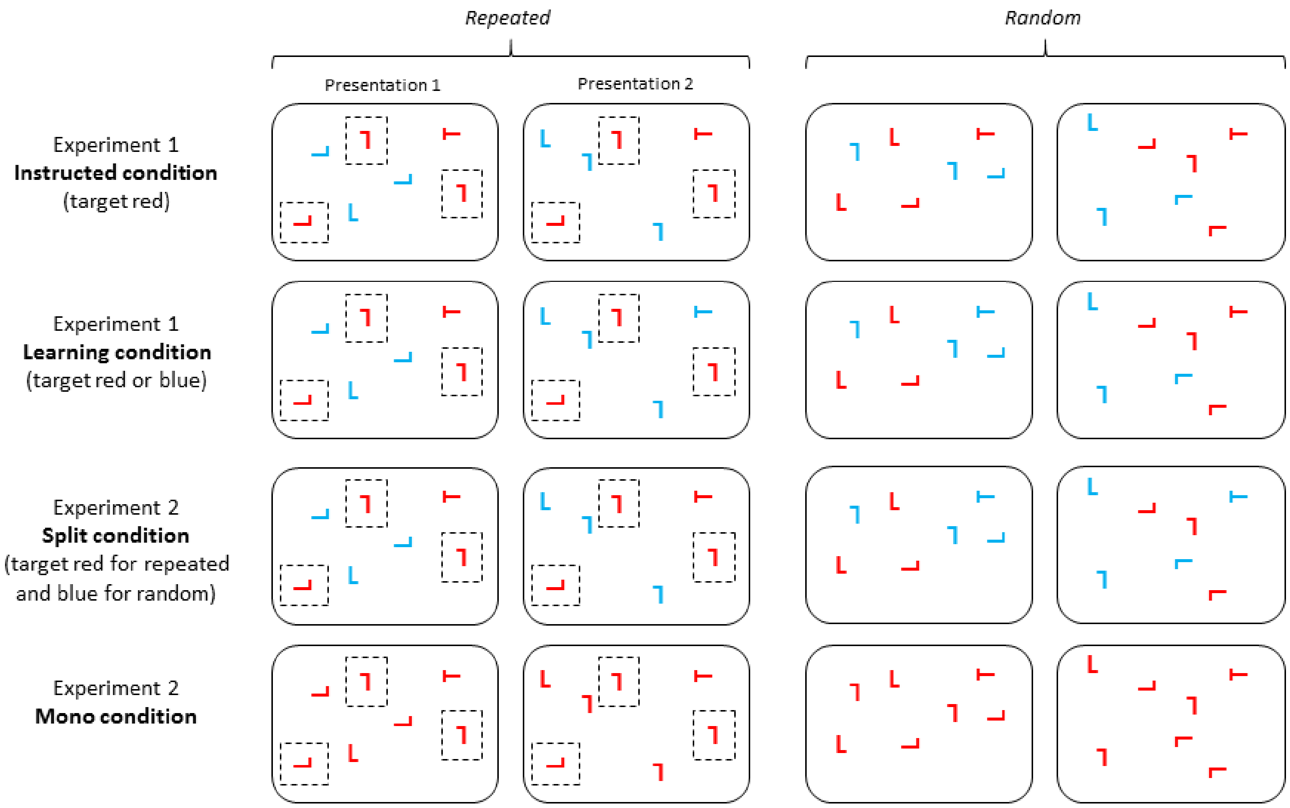

Figure 2. Reaction time (A) and number of fixations (B) to repeated and random configurations in the instructed and learning conditions of Experiment 1. Error bars show standard error of the mean.

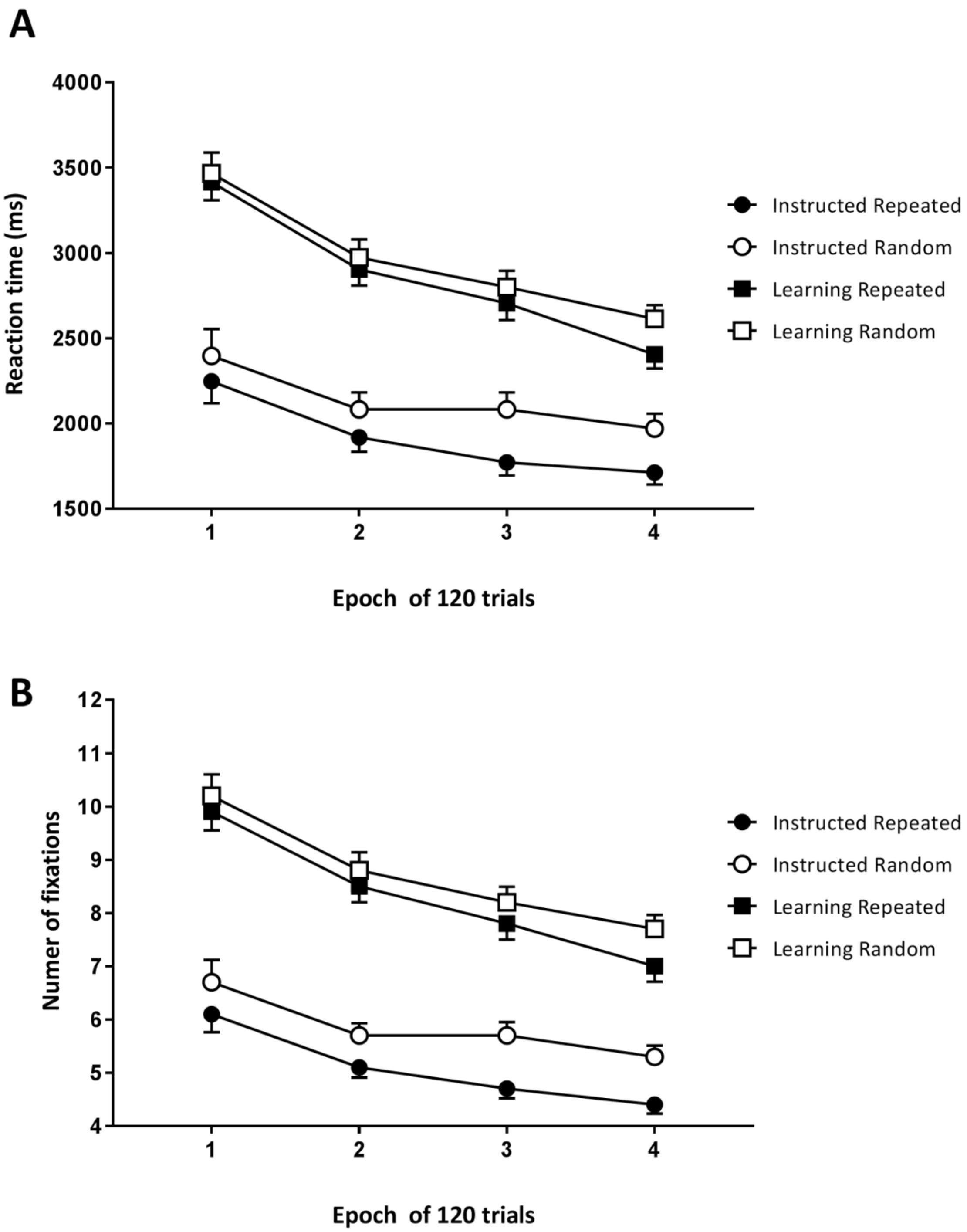

Figure 3. Attention to distractor types “P” (predictive) and “NP” (nonpredictive; see text for description) in repeated and random configurations for the instructed and learning conditions of Experiment 1. A: mean number of distractors falling within the “attentional spotlight” of all fixations of a trial. B: mean distance of the nearest distractor of each type to each fixation. Error bars show standard error of the mean.

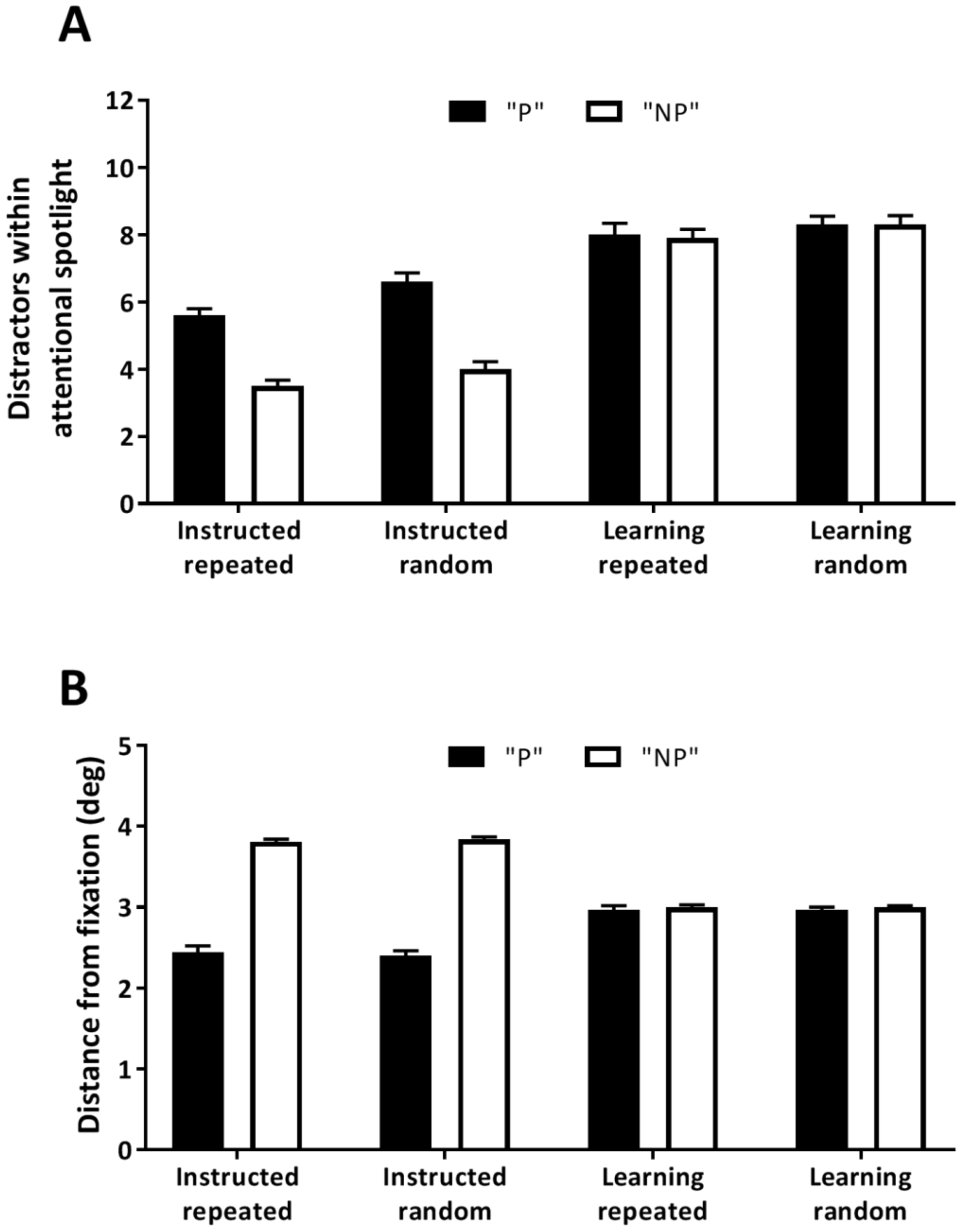

Figure 4. Reaction time (A) and number of fixations (B) to repeated and random configurations in the split and mono conditions of Experiment 2. Error bars show standard error of the mean.

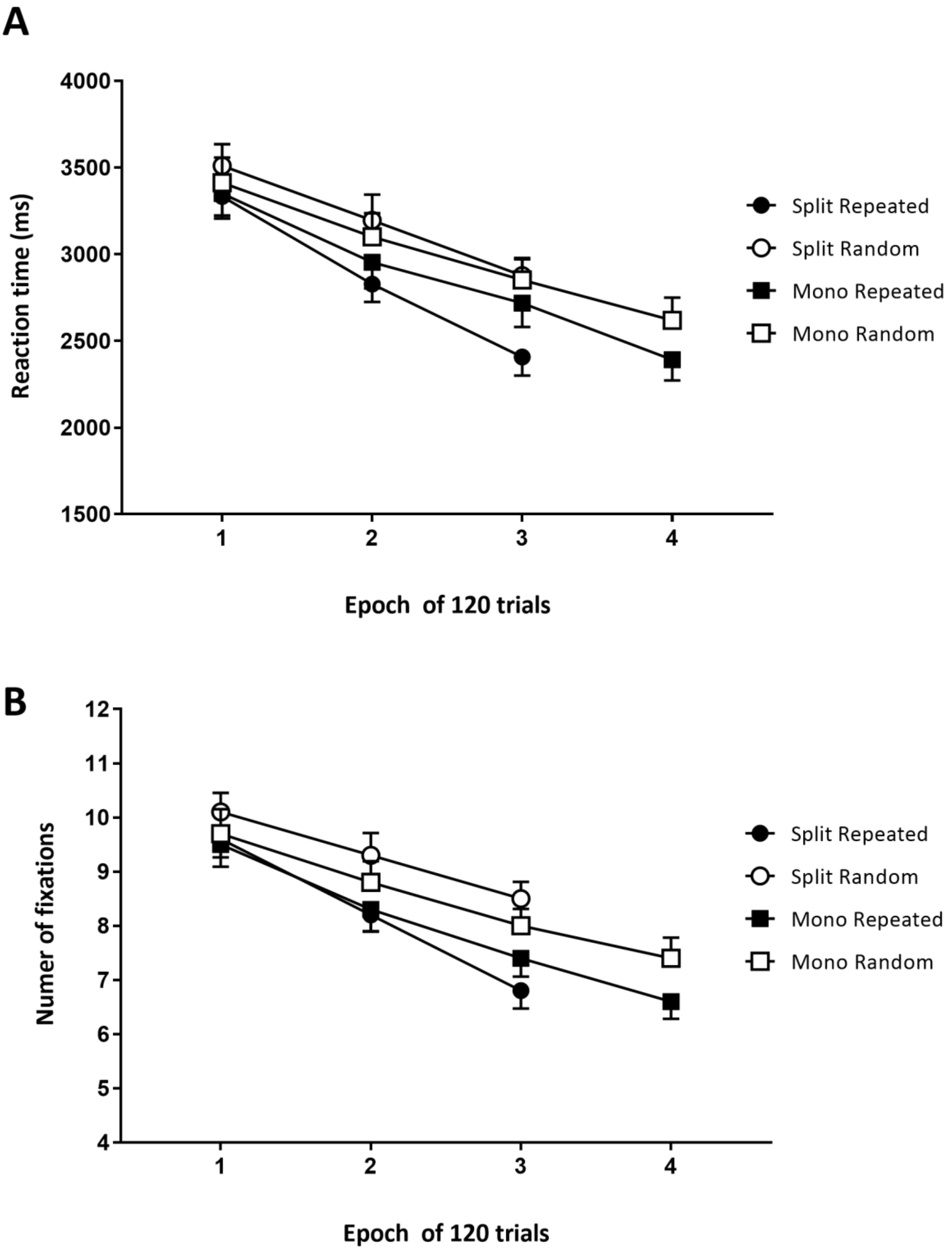

Figure 5. Attention to distractor types “P” and “NP” (see text for description) in repeated and random configurations for the split and mono conditions of Experiment 2. A: mean number of distractors falling within the “attentional spotlight” of all fixations of a trial. B: mean distance of the nearest distractor of each type to each fixation. Error bars show standard error of the mean.

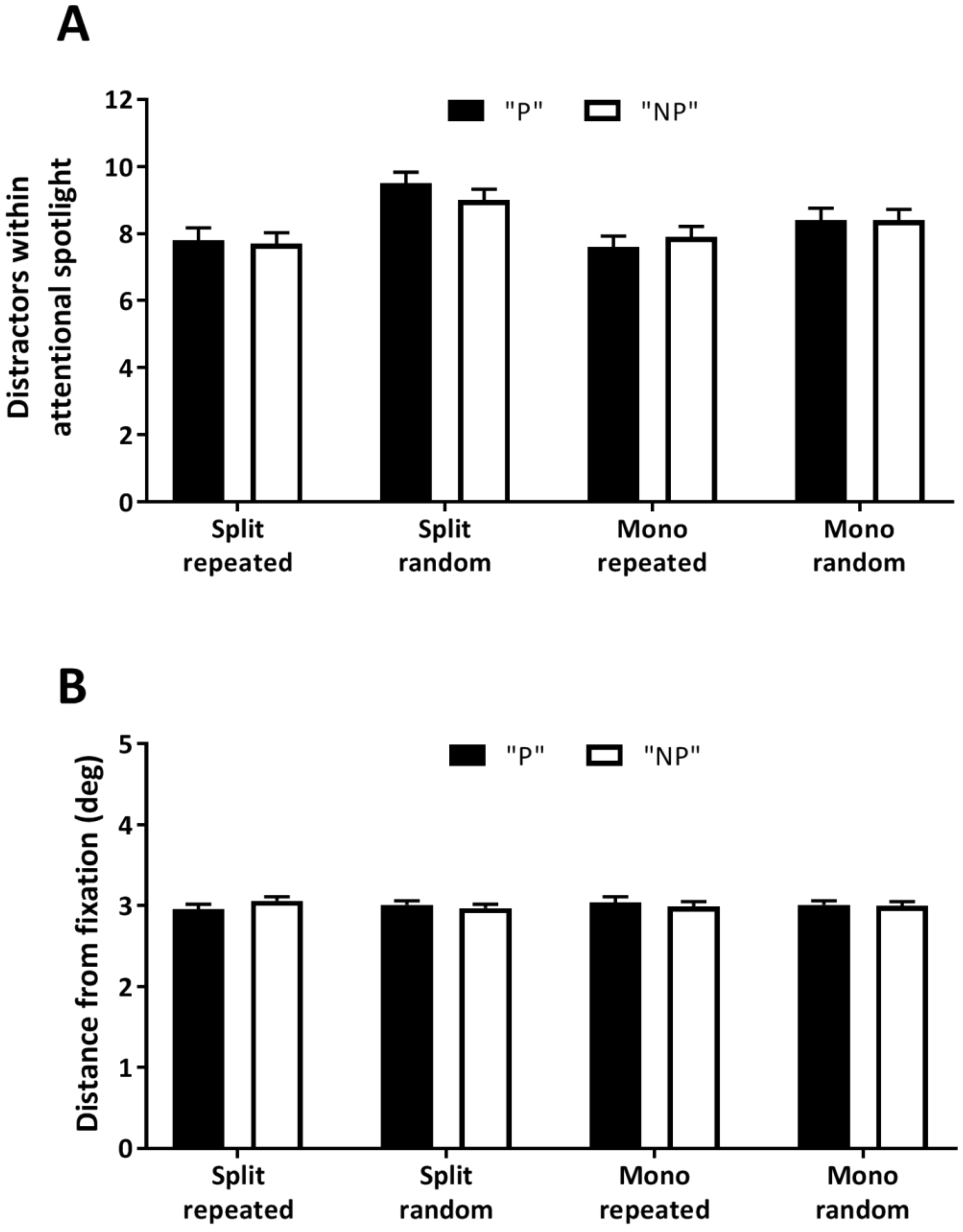

Figure 6. Detailed analysis of the reaction time (left) and number of fixations (right) in epoch 4 of the split condition in Experiment 2. Trained and switched configurations were different presentations of the same set of repeated configurations, with the labels reflecting whether the distractors were presented in the same color arrangement as presented in epochs 1-3 (trained) or in the reverse arrangement of colors (switched). Error bars show standard error of the mean.

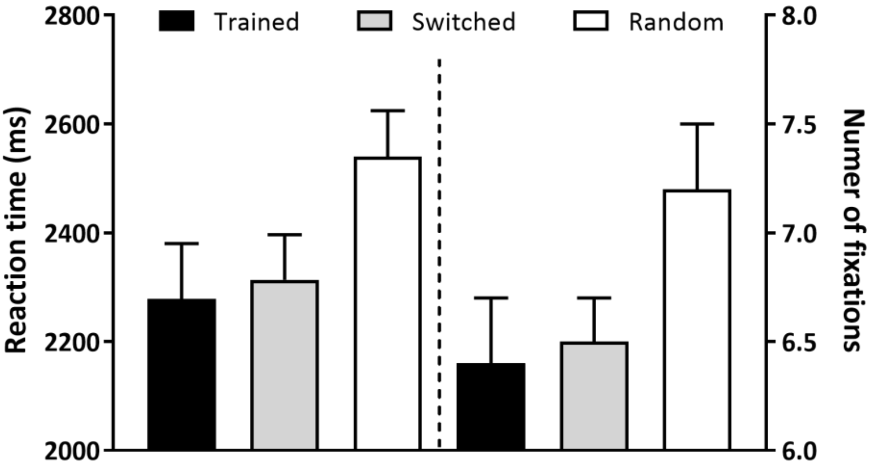

Figure 7. Fixation data for correct responses from the learning, split and mono conditions, grouped according to the number of fixations per trial and separately for repeated and random configurations. A: mean pixel distance from the target of each fixation in turn (left to right); for clarity of presentation the data for random configurations are offset horizontally from those for repeated configurations. B: percentage of trials containing a given number of fixations (error bars show standard error of the mean).

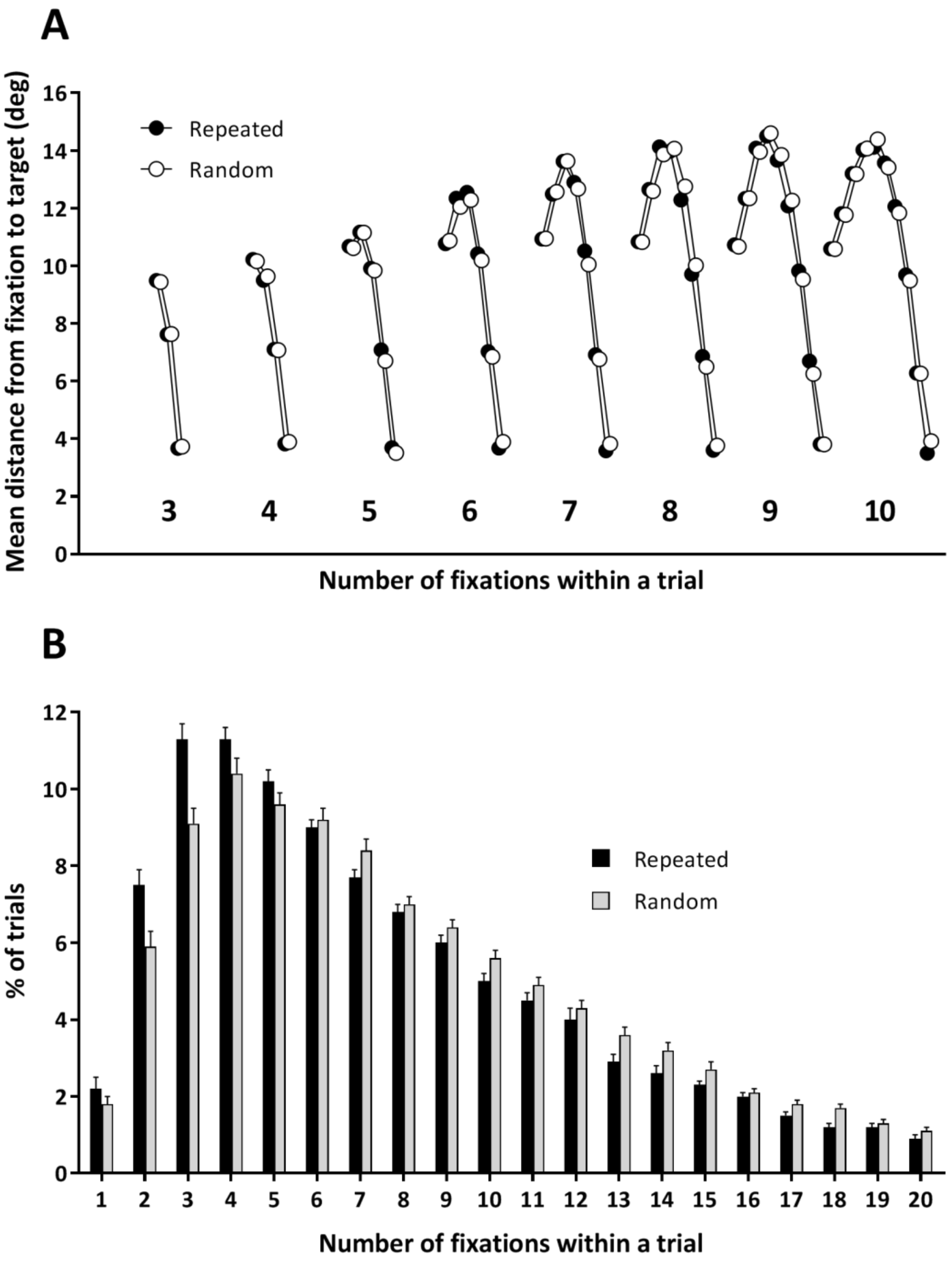

Figure 8. Reaction time data for correct responses from the learning, split, and mono conditions. A: data presented separately by each decile of reaction time and for repeated and random configurations. B: percentage of trials within a given reaction time bracket (200 ms bin) for repeated and random configurations.