

Contextual cuing survives an interruption from an endogenous cue for attention

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Abstract

This document is a template.

Keywords: keyword1, keyword2, keyword3

Contextual cuing survives an interruption from an endogenous cue for attention

It is well established that the process of visual search is guided by past experience. When we encounter a scene, the extent to which the stimuli within that scene match representations in memory will determine the effectiveness of the stimulus processing and subsequent search through the scene. This cognitive process is studied in the lab using the contextual cuing (CC) task: participants typically experience a standard visual search task (i.e., serial processing; slow search), such as searching for a T amongst L shapes. A set of search configurations is repeated across trials, and response times to targets are faster compared to those in configurations that do not repeat. Thus, the repetition of the search configurations leads to the formation of a representation of the configuration in memory, and future processing of the same configuration activates this representation, driving more efficient behaviour within that scene.

Much work has focused on the nature of the memory and attention processes responsible for contextual cuing. The effect was initially suggested to be implicit in nature, with repeated configurations seemingly guiding search unconsciously: typically participants are unable to articulate their knowledge of the repeated configurations, and show poor ability to recognise learnt configurations in memory tests (e.g., Chun & Jiang, 1998; Colagiuri & Livesey, 2016), although this view of CC has been strongly contested (e.g., Smyth & Shanks, 2008; Vadillo et al., 2016). There are also a number of plausible computational models of how memory representations of repeated configurations are formed and result in the CC effect (e.g., Beesley et al., 2015; Brady & Chun, 2007). The predominant view is that the memory representations are best characterised as associative in nature, whereby distractors (or groups of distractors, see Beesley et al., 2016) form associations that activate more strongly the contingent target position within each repeated configuration.

The exact nature of how repeated configurations come to facilitate visual search is the focus of much debate within the literature. Broadly there are two quite distinct theoretical accounts of why responses are faster for repeated configurations: the early attentional guidance account, and the late response facilitation account. According to the early account, recognition of

the configuration leads to a more efficient search process through the distractor array, such that the target is localised (fixated) at an earlier time point in search. Perhaps the clearest (and arguably simplest) evidence in support of this account comes from studies of eye-tracking during CC. For example, search through repeated configurations results in fewer fixations prior to target localisation (e.g., Beesley et al., 2018; Tseng & Li, 2004). According to the late response facilitation account, the benefit for repeated configurations comes about as a result of enhanced target processing once it has been localised by attention. One conceptualisation of this process is that repeated configurations lead to a reduction in the evidence threshold required to ascertain that the target is present in its location, such that responses can be initiated earlier. Such an account has been put forward by Sewell et al. (2018), in order to explain the evidence supporting the late account from response time modelling of the CC effect.

It seems likely that the both early and late processes contribute to the overall CC effect (for a review see Sisk et al., 2019). The current article focuses on exploration of the early-stage attentional account of CC. The term “early” here reflects the fact that the CC benefit is present prior to the detection of the target and the initiation of the response to the target. Analysis of eye-movements has shown that serial visual search can be defined as having two distinct phases: an initial ineffective search in which the direction of saccades is not consistent (arguably random) and a secondary effective phase in which each saccade will draw attention closer to the target. CC appears to result from having more trials with a shorter ineffective phase.

One interpretation of these data is that CC is initially random, and that the initial distractor processing is not beneficial for CC. Supporting evidence for this account comes from Olson and Chun (2002), where participants were trained on a CC task in which either all the distractors repeated, those in the half of the screen containing the target (short-range-context), or those in the half of the screen that didn't contain the target (long-range-context). CC was observed in the short-range-context, but not in the long-range-context condition. Thus it would appear that the distractors further from the target are not critical to the generation of a CC effect.

Brady and Chun (2007)'s computational account features a mechanism that ensures spatial

constraints are placed on the learning of associations with relation to their proximity to the target. If the spatial constraints are tuned to modulate learning and restrict associative formations to only those distractors close to the target, this model can accurately model the data from Olson and Chun (2002). Since the only consequential mechanism in the model for CC is the associative weights (and their modulation by spatial constraints), then one prediction that follows from this account is that the initial phase of search is inconsequential for observing CC.

The current article provides a test of this prediction by significantly interrupting the search process with an endogenous cue for attention. In all experiments participants complete a contextual cuing visual search task but are also presented with an arrow that signals the side of the screen on which the target will appear. Thus, this cue disrupts the natural search process, eliminating entirely the early phase of search. In contrast to the localised facilitation account, it's possible that contextual cuing involves learning of a procedural template that guides eye-movements in a consistent pattern for each repeated configuration. While the initial process may be inefficient in nature, it may nevertheless be an important part of the procedural response in terms of the sequence of eye-movements. Recent experiments from (Seitz 2023?) suggests that more generic scanning behaviour forms part of the procedural knowledge that contributes to CC.

In the current experiments we explored how CC is affected by the interruption of the search process by a clear direction of attention from an endogenous cue. In Experiment 1 we examine whether a learnt pattern of behaviour is disrupted due to the onset of the endogenous cue, while in Experiment 2 we seek to establish whether the CC effect is weaker under these conditions. Experiment 3 explores the underlying drivers of the CC effect, in terms of the distractor-target associations, during these procedures.

Transparency and Openness

The raw data, analysis scripts, experimental materials, and the manuscript source files, are available at http://github.com/tombeesley/CC_Control. The analyses reported in this manuscript are computationally reproducible from the manuscript source files (using R v4.4.0), which are available at the github repository. The study design and analyses were not pre-registered.

Experiment 1

Experiment 1 sought to examine whether the learnt attentional behaviour that develops during contextual cuing is still expressed when participants are directed by an endogenous (instructional) cue to search in a particular region of the visual scene. Participants were first trained with a set of four repeating configurations in phase 1 across 5 epochs of 32 trials each. Then prior to phase 2, participants were told that an arrow would appear before every trial indicating the side of the screen on which the target would be located. This arrow was valid on every trial. In phase 2, the repeating configurations were presented in two forms: “consistent”, where the target appeared in the same position as it has appeared for that configuration in phase 1; and “inconsistent”, where the target appeared in a position in the opposite quadrant of the screen from where it had appeared in phase 1. Random configurations were also presented in this phase. If the contextual cues within the repeated configurations continue to guide attention in the presence of the instructional cue, then we would expect that response times would be faster on consistent trials compared to random trials. In addition, we would also expect that the contextual cues would guide attention *away* from the (new) target quadrant on inconsistent trials, and so response times should be slower on these trials compared to those on random trials.

Method

Participants

Thirty-one undergraduate students from Lancaster University were recruited (mean age = 20.1, SD = 1.1; 17 identified as female and 14 as male) via the Psychology Research Participation System in the Department of Psychology at Lancaster University, in return for the opportunity to use the recruitment system for their own research in future years.

Materials

Participants were tested individually in a quiet room with a Dell laptop with a 15.6” screen, a screen resolution of 1920 x 1080, and a full size external keyboard for participants to use to respond to the task. Participants sat approximately 50 cm from the screen. 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 ‘c’ or ‘n’ key on a standard keyboard. All experimental materials are available at the github repository for this study.

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 8 mm square and arranged in a square grid of 144 evenly spaced cells (12 x 12) which was positioned centrally on the screen and was 170 mm square. The grid itself was invisible to participants. The fixation cross (displayed centrally before each trial) was 4 mm square. The background of the screen was grey (RGB: .6, .6, .6) and the stimuli were presented in black (RGB: 1, 1, 1). There was a small offset in the vertical line of the ‘L’ distractors, which increased the similarity between the ‘L’ distractors and the target ‘T’, making the search task more difficult (Duncan & Humphreys, 1989).

Design

Phase 1 employed a within-subjects design with factors of epoch (1-5) and configuration (repeated and random). All configurations contained 16 distractors, equally divided between the four quadrants of the display, and one target. Four repeated configurations were trained. Four target locations were used, with one from each quadrant assigned to each of the repeated configurations. These same four target positions were used for the random configurations throughout the task. Each of these four target positions was chosen at random from one of five locations within each quadrant, that were approximately equidistant from the center of the screen. Distractors could not appear in these target locations.

Phase 2 employed a within-subjects design with factors of epoch (6-10) and configuration (repeated: consistent; repeated: inconsistent; random: consistent; random: inconsistent). On each trial, there was a .5 probability that an “inconsistent” version of the configuration would be presented. This meant that the target was relocated to a diametrically opposed target position such as to maximise the displacement from the trained target position (see Figure 1). This could occur for both the repeated and random configurations, hence creating four unique trial types for this

phase. While random configurations did not have a “trained”, associated, target position, it is necessary to divide the random trials into consistent and inconsistent trial types in this way in order to assess any target frequency effects that may occur, since the inconsistent target locations used in this phase were novel.

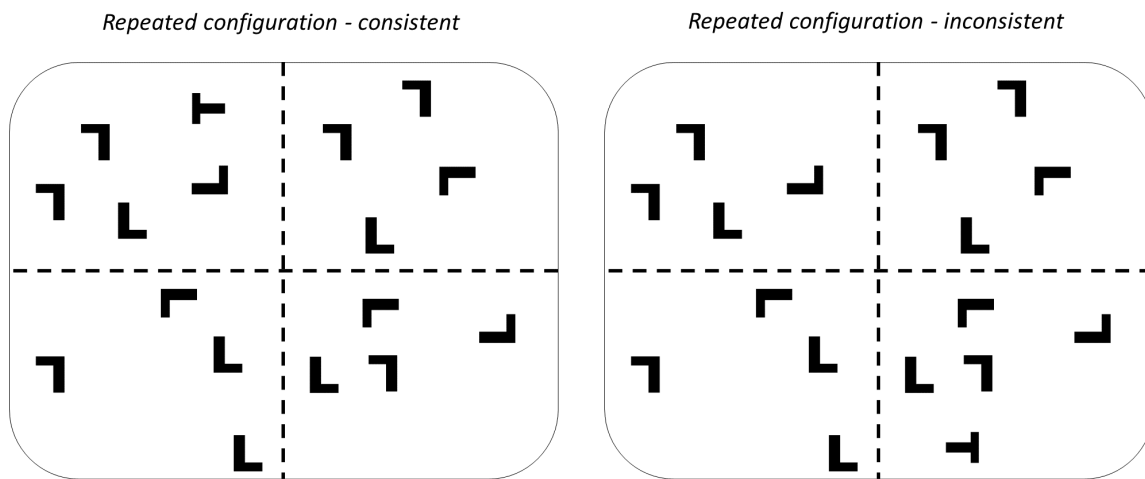


Figure 1

Schematic of the manipulation of target position in consistent and inconsistent trials of phase 2. The dashed lines show the division of the stimuli into quadrants, but were not present in the task procedure.

Procedure

Participants were tested individually in a quiet testing room. They were given instructions on how to complete the task, including the presentation of an example of a search trial. Participants were shown the two correct responses for the two possible orientations of targets.

Each trial commenced with a fixation cross presented in the center of the screen for 500 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. Reaction times (RTs) were recorded from the onset of the search configuration. Following a valid response (c or n), the configuration was removed from the screen. The ITI was 1000 ms. If

participants made an incorrect response to the target orientation, “INCORRECT RESPONSE” appeared in red in the center of the screen for 3000 ms, prior to the ITI. If participants did not respond within 6000 ms, “TIMEOUT - TOO SLOW” appeared in red in the center of the screen for 3000 ms, prior to the ITI.

Each block of eight trials contained each of the four different repeated configurations and four random configurations. These eight configurations could appear in any order with the constraint that the position of the target did not repeat across trials or across consecutive blocks.

A rest break of 30 seconds was given every 80 trials. Trials started automatically after these breaks.

After 160 trials, prior to phase 2, participants were given an instruction screen which detailed the arrow that would appear on the screen prior to the configuration. They were able to ask any questions they had at this stage and then proceeded to phase 2. The arrow appeared for 1000ms following the fixation cross, before the presentation of the search configuration. The task was otherwise identical to that used in phase 1.

Results

Our criterion for removing outlier data, at both the participant level and the trial level, was 2.5 standard deviations above or below the mean of the sample. On average, trials ended with a timeout on 1.97% of trials ($SD = 2.53$). Two participants had an unusually high proportion of timeouts and were removed from the analysis. The mean accuracy of participants (not including timeout trials) was 98.10% ($SD = 1.65\%$). One participant had an unusually low proportion of accurate trials and was also removed. The only participant deemed to be an outlier in terms of mean response time (hereafter RT) was also excluded on the basis of the timeout criterion, noted above.

For the remaining twenty-eight participants we removed trials with a timeout and inaccurate trials, before removing outliers from the RT data. On average, the proportion of outliers removed was 3.03% ($SD = 0.79\%$). Zero participants had an unusual proportion of trials removed as outlier RTs (greater than 2.5 SDs above the mean).

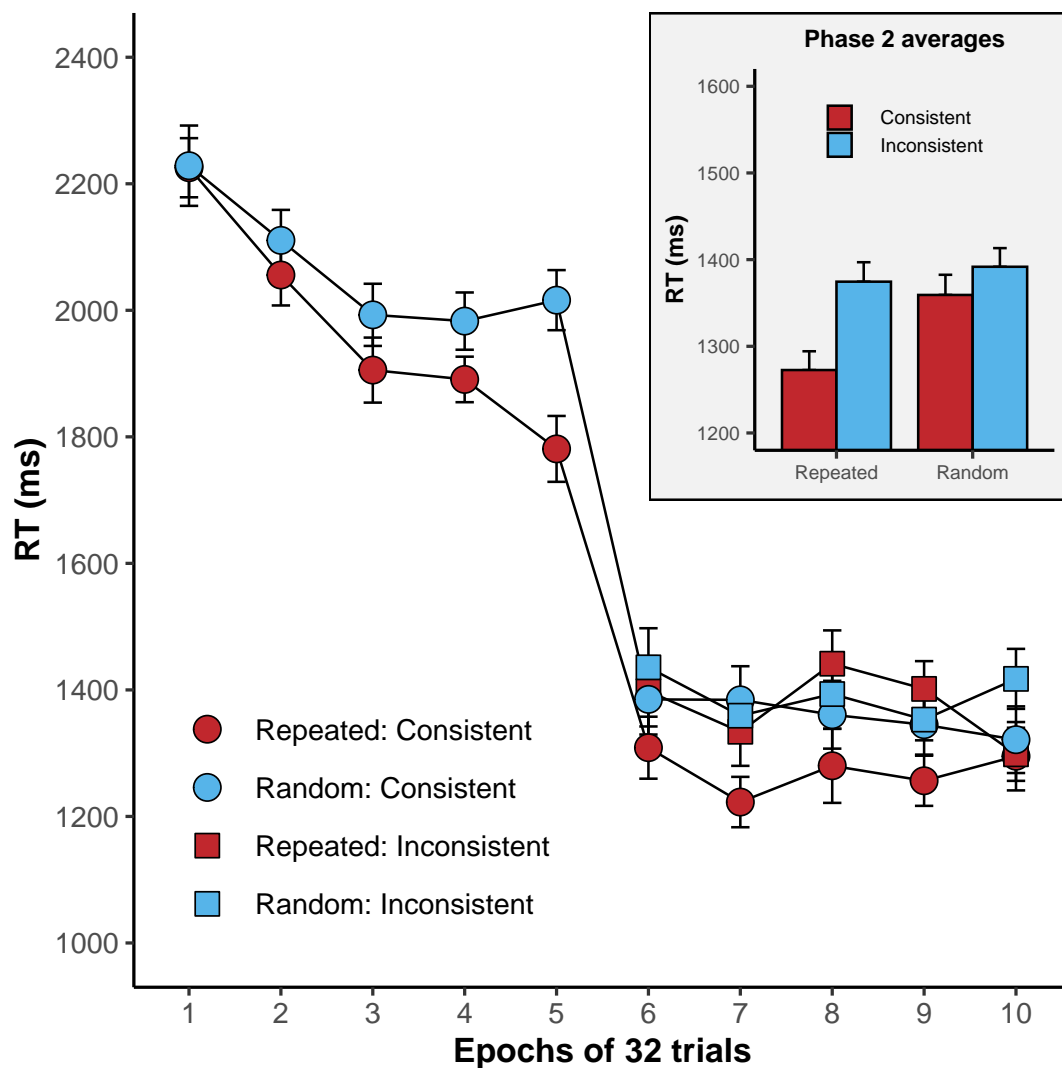


Figure 2

RT data for Experiment 1. The phase 2 averages across the four trial types are shown inset.

Within-subject error bars were computed by a process of normalising the RT data for the sample (cousineau2005?).

Figure 2 shows the RT data across the 10 epochs of the experiment. In phase 1 (epochs 1-5) a contextual cuing effect emerged, with faster responses to repeated over random configurations. In phase 2, the presence of the guiding arrow led to a clear reduction in the response times. For all participants, the mean RT across epochs 4 and 5 was higher than the mean

RTs across epochs 6 and 7. Despite the clear evidence for the processing of the endogenous cue, the underlying search configuration continued to play a role in the guidance of attention, with faster response times for (consistent) repeated configurations compared to random configurations.

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These data were analysed with a Bayesian ANOVA¹, using the *BayesFactor::anovaBF()* function in R. All analyses in this study used the default parameters for the priors, which “places mass in reason-able ranges [of effect sizes] without being overcommitted to any one point” (Rouder et al., 2017, p. 317). First taking the data from phase 1 (epochs 1-5), there was strong support for the model containing the factors of epoch and configuration (repeated vs. random), $BF_{10} = NA^{\pm} NA\%$. The addition of the interaction term did not improve the model fit, $BF = NA^{\pm} NA\%$, though there was no evidence for the absence of the interaction. The best fitting model was a better fit than the two models containing only one of the factors, smallest $BF = NA^{\pm} NA\%$, providing strong support for both the effects of configuration and epoch. Partial eta-squared (n_p^2) effect sizes were calculated using *effectsize::eta_squared*, giving values of: 0.22 for the effect of

¹ The Bayesian analyses here follow the process outlined in Rouder et al. (2017). Briefly, we present the best fitting model evaluated against the null model, and then compare this fit to that of other models. Where the comparison of two models (i.e., A against B) reveals a Bayes Factor of greater than 3, this is taken as support for the components of model A that are not present in model B. Bayes Factors of less than 0.33 are taken as evidence in support of the equivalence of two models. Following Wetzels et al. (2011) we use the terms “substantial” ($BF > 3$; $BF < 1/3$), and “strong” ($BF > 10$; $BF < 1/10$) to reflect the levels of support for the results of the model comparisons.

configuration; 0.39 for the effect of epoch; and 0.1 for the interaction effect.

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A Bayesian ANOVA on the data from phase 2 (epochs 6-10) found strong support for the model containing the factors of configuration (repeated vs. random) and target position (consistent vs. inconsistent), $BF_{10} = NA \pm NA\%$. The next best fitting model contained these two factors and the interaction term, and was not a substantially worse fit to the data, $BF = NA \pm NA\%$. The best fitting model (with factors of configuration and target position, but no interaction) was a substantially better fit to the data than the model containing only the factor of configuration $BF = NA \pm NA\%$ providing evidence that RTs were faster on consistent than inconsistent trials. There was no evidence for a difference between the best fitting model and the model containing only the factor of target position, $BF = NA \pm NA\%$. The relevant effect sizes (n_p^2) were: 0.14 for the effect of configuration; 0.22 for the effect of target position; and 0.14 for the interaction of these two factors.

To further explore responses to the different trial types in phase 2, Bayesian t-tests were run using `BayesFactor::ttestBF` (using the default Cauchy prior) for comparisons between the repeated and random configurations, across the two target position conditions (consistent and inconsistent). This revealed substantial support for a difference between the response times on “repeated: consistent” trials and those on the respective random trials (random: consistent), $BF_{10} = 4.14 \pm 0\%$. There was also substantial evidence to suggest there was no meaningful difference

between the response times for the “repeated: inconsistent” trials and the respective random trials, $BF_{10} = 0.24 \pm 0.03\%$.

To compare the size of the CC effect across phases 1 and 2, we calculated a “CC effect score” by subtracting the RT on consistent repeated trials from the RT on consistent random trials. Positive values reflect a CC effect. There was a CC effect score of 142.724939987091 ms (SD = 202.675331193791) for the end of phase 1 (epochs 3-5) and a CC effect score of 106.761916074753 ms (SD = 176.116337547221) for the start of phase 2 (epochs 6-8). A Bayesian t-test of the effect of phase on CC effect found moderate support for the null result, 0.25, suggesting that the CC effect was not attenuated in the second phase.

Discussion

In Experiment 1 we established a contextual cuing effect in the first phase, before introducing an endogenous cue for attention that directed the participants consistently towards the side of the screen on which the target was presented. Unsurprisingly, this had a dramatic effect on reducing RTs in all participants, but there remained a significant contextual cuing effect in this second phase. Thus, disrupting a substantial part of the early search process did not appear to affect the performance of the contextual cuing that had been established: notably there was evidence to suggest that the contextual cuing effect in phase 2 was of a similar magnitude to that which was observed in phase 1. On some repeated trials in phase 2, we positioned the target in a diametrically opposed location on the screen. On these trials there was no impact of the repeated configuration on performance.

These findings together support a view of contextual cuing in which the initial process of search is inefficient and seemingly random, not being guided in any way by the repeated context. Only when attention lands within a region of space approaching the target does the repeated configuration take over to guide search efficiently towards the target. The maintenance of a robust contextual cuing effect in phase 2 in the presence of the endogenous cue also suggests that CC is a robust and flexible behaviour. The apparent ability to entirely disrupt and negate the early part of the search process, whilst maintaining an intact CC effect, is somewhat at odds with the “general

procedural learning” that has been suggested to occur in CC (seitz2023?). According to this account, “...what may look an ineffective phase [of search] actually constitutes an important period during which procedural learning of a general scanning scheme becomes functional.” (seotz2023?). The present data suggest that this aspect of search can be removed at no cost to CC.

Experiment 2

In Experiment 1 we demonstrated that an established effect of contextual cuing is maintained even when attention is being guided by the presence of a valid endogenous cue. That is, we found that the *performance* of an established search behaviour in contextual cuing is not disrupted by the guidance of attention. In Experiment 2 we wanted to explore whether the *learning* of the contextual cue itself was affected by the presence of a valid endogenous cue. That is, does the presence of a valid endogenous cue, which leads to a controlled command of attention, limit the development of a contextual cuing effect. To do this, we trained each participant on two sets of repeating configurations. One of these sets was always presented in the presence of a valid endogenous cue, while the other set was always presented in the absence of the endogenous cue. The extent to which there is a “cue-competition” effect between the endogenous cue and the contextual cues can be examined by comparing the contextual cuing effect we observe for the two sets of configurations. Given the clear difference in RTs we observed in Experiment 1 between the trials with the endogenous cue present and the cue being absent, we anticipated the same difference in responding in Experiment 2. Therefore we also included a second phase of Experiment 2 in which we removed the endogenous cue entirely from the task. This second phase therefore allowed us to directly compare the contextual cuing for the two sets of configurations when RTs were at a comparable level.

Given the results of Experiment 1, we would anticipate that the size of the CC effect would be comparable in the two conditions. That is, Experiment 1 suggests that the CC effect is unaffected by the presence of the endogeneous cue, and therefore that the effect is reliant on the cuing that occurs by distractors later in the search process. Removal of the inefficient period of search should not dramatically affect the development of CC.

We can also consider the predictions from an associative learning perspective: so called “cue-competition” effects have been examined previously in contextual cuing. Endo and Takeda (2004) trained participants with a contextual cuing task composed of distractor location configurations and repeating distractor identities. Their experiments suggested that the stronger configural (spatial) cue out-competed the cue provided by the distractor identities. Similarly, Kunar et al. (2014) found that when colour cues and configural cues both predicted the target location, configural cues were dominant and tended to overshadow the weaker colour cue. Beesley and Shanks (2012) looked at the cue-interaction effects *within* a configuration of distractors. Participants were first trained with half a configuration of repeating distractors that predicted the target (8 out of 16 distractors). In a later stage these distractors were paired with a new half-configuration, such that the whole configuration now predicted the same target location. In contrast to the predictions of the vast majority of models of contingency learning, learning about these new predictive distractors was facilitated, rather than impaired in this second phase (relative to a control condition). Thus, Beesley and Shanks (2012) found that cue-competition was not observed within a configuration of equally predictive distractors. Together these studies suggest that the spatial configuration serves as a strong cue for the target and will out-compete non-configural cues for access to the learning mechanism. The dominance of the configuration in these situations may therefore lead to the prediction that the endogenous cue would not “block” the learning of the configuration in the current task.

Method

Participants

Thirty-four undergraduate students from Lancaster University were recruited (mean age = 20.74, SD = 5.29; 28 identified as female and 6 as male) via the Psychology Research Participation System in the Department of Psychology at Lancaster University, in return for the opportunity to use the recruitment system for their own research in future years.

Materials

Participants were tested in a quiet laboratory testing cubicle, with a standard PC and a 24" monitor set at a resolution of 1920 x 1080 pixels. Since the monitor was larger for this experiment, the dimensions of the presented stimuli had a proportional increase in size: Distractor stimuli were 11 mm square; the search grid was 240 mm square; the fixation cross was 6 mm square. In all other respects, the materials were the same as those detailed in Experiment 1.

Design

Four repeated configurations were created in an identical manner to those used in Experiment 1. For each participant, two of these configurations were used for the "cue-competition" condition, in which the arrow cue was presented before the configuration, while two were used for the "control" condition (no arrow presented). As in Experiment 1, the four repeated configurations were paired with unique target positions from each of the four quadrants. We counterbalanced the use of the target quadrants across the factors of configuration type (repeated and random) and cue condition (cue-competition and control). For half of the participants, targets in the top left and bottom right were used for the repeated configurations presented with the arrow (cue-competition) condition, with targets in the top right and bottom left used for repeated configurations in the no-arrow (control) condition. For these participants, random configurations presented with the arrow had targets in the top right and bottom left, and random configurations without the arrow had targets in the top left and bottom right. For the other half of the participants these assignments were reversed (repeated-arrow: top-right and bottom-left; repeated-no arrow: top-left and bottom-right; random-arrow: top-left and bottom-right; random-no arrow: top-right and bottom-left).

Procedure

The procedure was the same as Experiment 1 with the following differences. Participants received 320 trials in total. For the first 160 trials, the arrow was presented for the relevant conditions. For the final 160 trials, the arrow was never presented. Rest breaks were given every 60 trials.

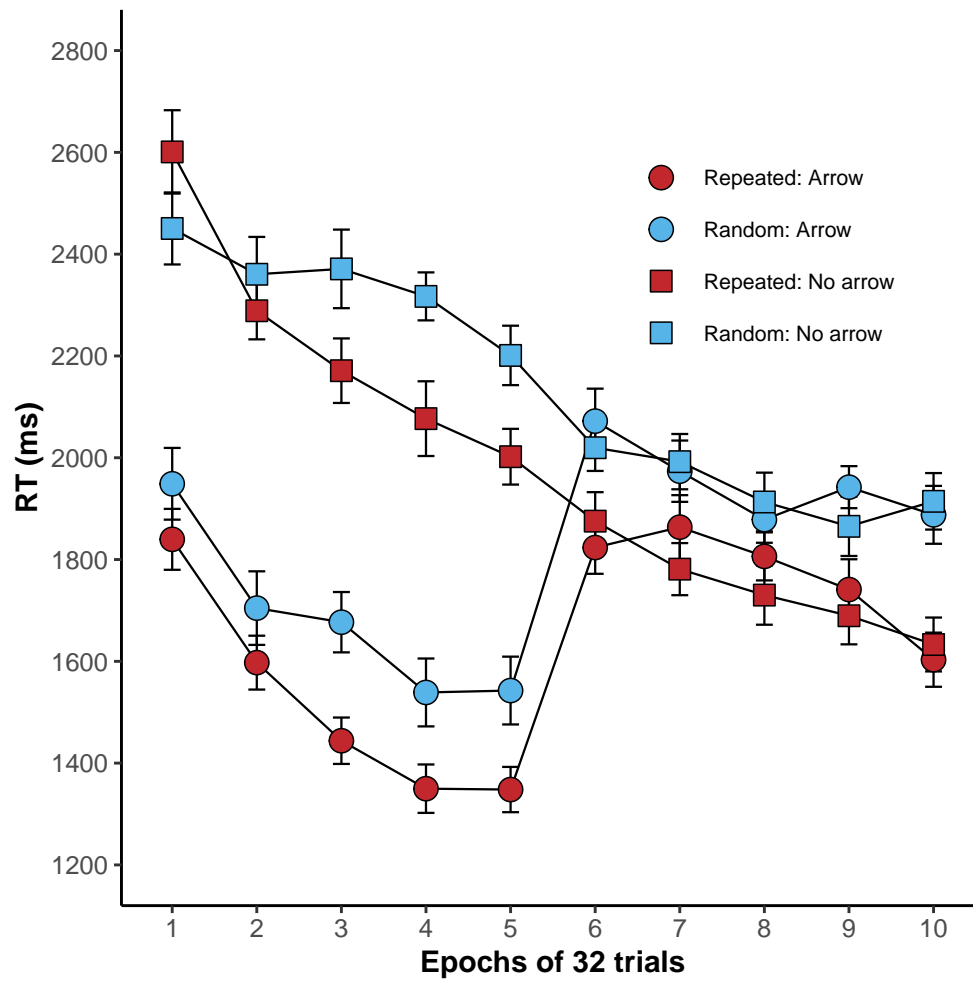
Results

Our criteria for removing outlier data were identical to Experiment 1. On average, trials ended with a timeout on 2.13% of trials ($SD = 1.83$). Zero participants had an unusually high proportion of timeouts. The mean accuracy of participants (not including timeout trials) was 95.85% ($SD = 6.10\%$). One participant had an unusually low proportion of accurate trials and were removed from the sample. Zero participants were deemed to be an outlier in terms of mean RT.

For the remaining thirty-three participants we removed trials with a timeout and inaccurate trials, before removing outliers from the RT data. On average, the proportion of outliers removed was 2.81% ($SD = 1.04\%$). One participant had an unusual proportion of trials removed as outlier RTs and were not included in the final analysis.

Figure 3

RT data for Experiment 2. Error bars show standard error of the mean on normalised data.



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Figure 3 shows the RT data across the 10 epochs of the experiment. Contextual cuing emerged rapidly in both the arrow and no-arrow conditions, with little suggestion that the CC effect was different in the two conditions. The phase 1 data were explored with a Bayesian ANOVA, which revealed that the best fitting model contained the factors of epoch, configuration (repeated vs. random), and endogenous cue (arrow present vs. arrow absent), with no interaction terms, $BF_{10} = NA^{\pm} NA\%$. The next best fitting model contained all three factors and the interaction of epoch and configuration, $BF_{10} = NA^{\pm} NA\%$, and this model was not a substantially worse fit to the data, $BF = NA \pm NA\%$. All other models were substantially worse fits than the best fitting model, largest $BF = NA \pm NA\%$. Importantly, the interaction term between the factors of endogenous cue and configuration did not improve the fit of the model, providing substantial support for the absence of this interaction, $BF = NA \pm NA\%$. The relevant effect sizes (n_p^2) were: 0.02 for the effect of epoch; 0.4 for the effect of configuration; 0.85 for the effect of endogenous cue; 0.12 for the interaction effect between configuration and epoch; and 0.02 for the interaction between configuration and endogenous cue.

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When the endogenous cue was removed in the second half of the experiment, RTs were equivalent across the two conditions. An effect of configuration was seen for both cuing conditions, with little discernible difference between the size of the cuing effects. We conducted a

Bayesian ANOVA with factors of epoch, configuration and endogenous cue condition (arrow vs. no-arrow). The best fitting model was that with just the factors of epoch and configuration with no interaction between the factors, $BF_{10} = NA^+ \pm NA\%$. There was substantial support for this model over the next best fitting model, $BF = NA \pm NA\%$. To examine the interaction of the configuration and endogenous cue factors, we compared the model containing those two factors to the model containing the two factors plus the interaction of configuration and endogenous cue, which revealed substantial support for the absence of an interaction, $BF = NA \pm NA\%$. The relevant effect sizes (n_p^2) were: 0.62 for the effect of configuration; and 0.25 for the effect of epoch.

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To provide further support for the absence of the interaction between the factors of configuration type and endogenous cue, the data from across the experiment (epochs 1-10) were analysed with a Bayesian ANOVA with only the factors of configuration and endogenous cue. The best fitting model was that with the two factors and no interaction, $BF_{10} = NA^+ \pm NA\%$. The addition of the interaction term did not strengthen the model, with substantial evidence for the absence of the interaction, $BF = NA \pm NA\%$. The relevant effect sizes (n_p^2) were: 0.77 for the effect of the endogenous cue; and 0.61 for the effect of configuration.

Discussion

Experiment 2 sought to examine whether the presence of a valid endogenous cue would impair the acquisition of a contextual cuing effect. In the first phase, two sets of configurations

were trained, one of which was always presented in the presence of the endogenous cue, and one set which was presented without the endogenous cue. Overall there was considerable evidence that the cue was processed and acted upon, as response times to the target were much faster on cued trials. However, there was no evidence to suggest that the instructed guidance of attention impaired the acquisition of the configurations on those trials. Furthermore, when the endogenous cue was never presented in the final phase of the experiment, the size of the contextual cuing effect was equivalent between the two sets of configurations; the Bayesian analyses found support for the equivalence of these CC effects.

The lack of competition effects seen in Experiment 2 are at odds with some findings in the CC literature (i.e., Endo & Takeda, 2004; Kunar et al., 2014), where competition has been seen by more dominant or salient features of the displays. Instead, the findings point towards a more automatic nature to contextual cuing, whereby associations form ubiquitously, so long as they receive the focus of attention at some point within the search process (e.g., Beesley & Shanks, 2012).

Taken together with the findings of Experiment 1, these data suggest that when attention is cued in an endogenous manner, the underlying search configuration will still play a significant role in guiding search for the target. Since the endogenous cue appears at the point of fixation, the most plausible interaction of these processes is that the guidance by the endogenous cue is followed by the guidance by the repeated context. The equivalence of the CC effects in the two conditions (cued and uncued) would therefore suggest that the guidance by the context was driven largely (or perhaps entirely) by the distractors that appear close to the target. Accordingly, the longer search times in the uncued condition suggest that more distractors are processed in this condition, but that the influence of the repeated distractors on attentional guidance may be limited to those occurring later in the search process, and therefore those nearer to the target. Alternatively, the interaction of these two processes (endogenous and configuration-driven attention) need not interact in this order. It is at least possible that the configuration is processed rapidly at the onset of the trial, before the effects of the endogenous cue on attention are observed. If this is the case,

then those repeated distractors that influence search (producing the CC effect) need not be localised around the target. Experiment 3 provided a test of these two possible accounts.

Experiment 3

Existing data from studies of contextual cuing has pointed towards a localised learning effect for repeated configurations, with those distractors closest to the target being preferentially weighted in the learning process over those located further from the target. For example, Olson and Chun (2002) trained participants with three sets of repeating configurations that differed in terms of which distractors repeated across trials. For one set, the entire global context (all of the distractors) repeated, while for the other two sets only the short-range (those close to the target) or the long-range distractors (those far from the target) repeated across trials. They found no difference between the CC effect in the short-range and global configurations, while the CC effect was not significant for the long-range context. Similar results have been shown by Brady and Chun (2007) which led to the development of the spatial constraints model of contextual cuing, in which distractor-target associations occurring in close proximal space are weighted more heavily in the learning process (over those occurring across greater spatial distance).

It is important to consider how the bias towards local learning may interact with the attentional scanning process during contextual cuing. The analysis of eye-movements during contextual cuing tasks (Beesley et al., 2018; Tseng & Li, 2004) has revealed a characteristic scanning pattern comprising two phases: search initially occurs in a seemingly random manner, as the eyes move between distractors in the central region of the distractor field, before then moving in a more directed manner towards the target position. Contextual cuing appears to result from a cessation of the first (random) search phase at an earlier time point in the entire search process, such that processing of repeated distractors will, on average, result in fewer fixations. With respect to the current study, in Experiments 1 and 2 we have initially directed attention towards the side of the screen that contains the target on cued trials. This may bring about an early cessation of the first phase of the search process. From here, however, it seems that search is still facilitated by the repetition of the context.

To test this characterisation of the interaction between the endogenous cue and the repeated context, we exposed participants to the same procedure as used in phase 1 of Experiment 1, which establishes a contextual cuing effect prior to the use of the endogenous cue. In a second phase we then presented the endogenous cue on every trial (as in Experiment 1), but we manipulated the presence of the repeated distractors within the configurations. For each repeated configuration we created two variations: in the “proximal” configurations, only the distractors in the quadrant containing the target match those from the full repeated configuration, while the distractors in the other three quadrants were randomly arranged on each trial; in the “distal” configurations, the distractors closest to the target were randomised, while the distractors in the other three quadrants were the same as those in the full repeated configuration. During this phase we also presented fully repeated configurations and fully randomised configurations. Comparison of the response times across these four trial types will allow us to determine the contribution of proximal and distal distractors to the CC effect when attention is cued endogenously.

Method

Participants

Forty-two undergraduate students from Lancaster University were recruited (mean age = 18.64, SD = 2.84; 28 identified as female and 14 as male) via the Psychology Research Participation System in the Department of Psychology at Lancaster University, in return for the opportunity to use the recruitment system for their own research in future years.

Materials

All materials, including stimuli and testing environment were identical to Experiment 2.

Design

The design of phase 1 was identical to Experiment 1, with four repeated configurations created and presented with random configurations during this phase. For phase 2, each of the four configurations was manipulated to create two alternative conditions. In the “Repeated distal” condition, the four distractors in the target quadrant were randomly arranged on each trial, while

the 12 distractors in the other three quadrants were presented in the same positions as had been trained in phase 1. Thus, slower response times for this condition (compared to the fully repeated configurations) would indicate the extent to which participants CC was governed by the distractors closest to the target. For the “Repeated proximal” condition, the four distractors in the target quadrant were presented in the same positions as had been trained in phase 1, while the 12 distractors in the other three quadrants were randomly arranged on each trial. Thus, slower response times for this condition (compared to the fully repeated configurations) would indicate the extent to which CC was governed by the distractors further from the target. Comparison of the RTs for these different configurations with those of the random configurations would allow for the assessment of whether these subsets of distractors had *any* contribution to the CC effect that had developed during phase 1.

Procedure

The procedure was identical to Experiment 1.

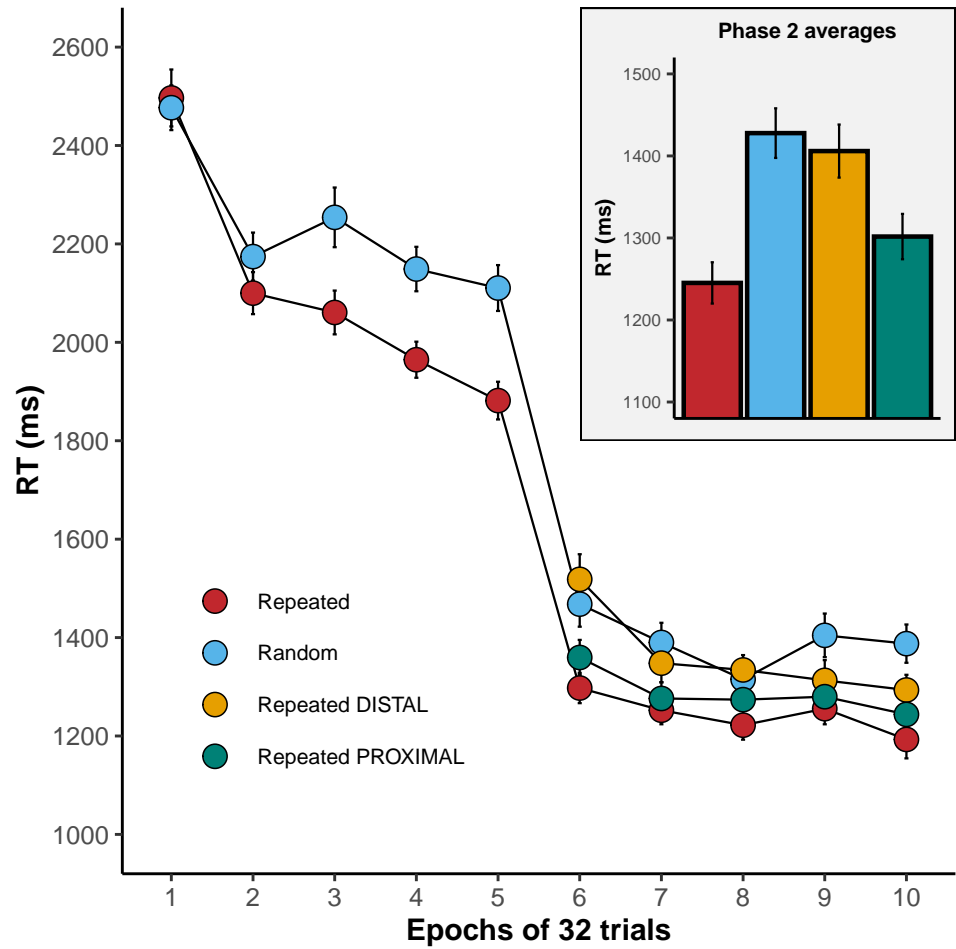
Results

Our criteria for removing outlier data were identical to Experiment 1. On average, trials ended with a timeout on 2.81% (SD = 2.25) of trials. Two participants had an unusually high proportion of timeouts and were removed from the sample. The mean accuracy of participants (not including timeout trials) was 96.09% (SD = 8.57%). Two participants that had an unusually low proportion of accurate trials and were also removed. Zero participants were deemed to be an outlier in terms of mean RT.

For the remaining thirty-eight participants we removed trials with a timeout and inaccurate trials, before removing outliers from the RT data. On average, the proportion of outliers removed was 3.17% (SD = 0.71%). Zero participants had an unusual proportion of trials removed as outlier RTs.

Figure 4

RT data for Experiment 3. Error bars show standard error of the mean on normalised data.



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Figure 4 (main panel) shows the RT data across the 10 epochs of Experiment 3. As in Experiment 1, contextual cuing was readily established in phase 1. These data were subjected to a Bayesian ANOVA which revealed that the best fitting model contained the factors of configuration (repeated vs. random) and epoch, and an interaction between those factors, $BF_{10} = NA^{\pm} \pm NA\%$. However, the model without the interaction provided a strong fit to the data, $BF_{10} = NA^{\pm} \pm NA\%$, and a comparison between the two models did not find any evidence in support of the interaction term, $BF = NA \pm NA\%$. There was strong support for the best fitting model over the remaining models, smallest $BF = NA \pm NA\%$, providing strong support for the factors of epoch and configuration. The relevant effect sizes (n_p^2) were: 0.38 for the effect of the endogenous cue; and 0.47 for the effect of configuration; and 0.08 for the interaction of these two factors.

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The response times decreased significantly with the presentation of the valid endogenous cue in phase 2. Response times to the fully repeated configurations were somewhat comparable to those when just the proximal repeated distractors were present. Response times for the distal repeated distractors appeared to be slower and comparable to the fully random configurations. The phase 2 data were subjected to a Bayesian ANOVA which found that the best fitting model contained the factors of configuration and epoch but no interaction between the factors, $BF_{10} = NA^{\pm} \pm NA\%$. This model provided a superior fit to the data compared to the next best fitting model that included the two factors and the interaction term, $BF = NA \pm NA\%$, providing strong support for the contribution of the two factors and the absence of an interaction between the two

factors. The relevant effect sizes (n_p^2) were: 0.37 for the effect of configuration; and 0.16 for the effect of epoch.

The inset graph in Figure Figure 4 shows the mean RTs to the four types of configuration, averaged across the 5 epochs of phase 2. To explore the differences in response times, Bayesian t-tests were run for all pairwise comparisons. The response times to repeated and repeated-proximal configurations were both faster than those to random configurations, smallest $BF_{10} = 10313.81 \pm 0\%$. In contrast, there was no evidence that the response times to repeated-distal configurations were different from those to random configurations, $BF_{10} = 0.39 \pm 0.04\%$. Response times to repeated configurations were faster than those to repeated-proximal configurations, $BF_{10} = 4.67 \pm 0\%$. Response times to repeated-proximal configurations were faster than those to repeated-distal configurations, $BF_{10} = 31.88 \pm 0\%$.

Discussion

Experiment 3 explored the localisation of the distractors driving contextual cuing when attention is guided by an endogenous cue. As expected, there was substantial evidence that contextual cuing was present when the distractors close to the target were maintained, but not when these distractors were randomly arranged. These data suggest a particular order to the interplay between the two drivers of attention: initially attention is guided by the endogenous cue towards one half of the screen, and then search is refined by the presence of the valid configural cues (the repeated distractors). Like in Experiment 1, the phase 2 data demonstrate the resilience of the CC effect to changes in the search process. Despite visual search never commencing in a cued manner during the initial acquisition period of phase 1, a CC effect was readily observed in phase 2. Thus it seems that the stored representations of configurations surrounding target positions are very flexibly deployed in visual search. Notably the fully repeated configurations exerted more of a benefit on search than those containing only the proximal distractors, suggesting that the repeating distractors beyond the target quadrant have some (but possibly lesser) influence on search (Brady & Chun, 2007).

These data lend support to the notion that the effect of the repeated configuration is a late

process within visual search, and that each trial commences with a random search process that is not guided by the repeated configuration (Beesley et al., 2018; Tseng & Li, 2004). In some ways, these findings represent a paradox of CC: the cuing effect occurs almost at the point at which target detection has been made. One interpretation would be that this exemplifies the role of spatial contiguity in the formation of visual associations (Renaux et al., 2017). Alternatively, it provides support for the proposed “decision threshold” accounts of CC (Kunar et al., 2007; Sewell et al., 2018), which posit that the repeated distractors close to the target ensure a reduced threshold for target detection, resulting in faster response times.

General Discussion

Three experiments explored the impact of a central endogenous cue on the contextual cuing of visual search. In Experiment 1, having established a contextual cuing effect, each trial was preceded by an central endogenous cue of attention in the form of an arrow, directing attention towards the side of the screen in which the target was positioned (this arrow cue was always valid in each of the three experiments). Despite participants clearly using this cue, visual search was still facilitated by the presence of the repeating pattern of visual search. This experiment demonstrated that, once acquired, the activation of the memory representation and its impact on performance of visual search remains intact in the presence of a top-down instruction to guide attention. Experiment 2 examined the storage of these contextual representations, and whether these were impaired by an endogenous cue guiding search. We found equivalent levels of contextual cuing for two sets of configurations, one of which was paired with the cue and one which was not. Together, these two experiments suggest a seamless interplay between these two factors governing attention in visual search: the endogenous cue initially guides attention and the repeated configuration continues to refine and guide attention towards a fixation on the target. In Experiment 3 we therefore explored whether the localised distractors around the target were sufficient to generate CC following the guidance by the endogenous cue. Indeed, there was a significant CC effect in the case of the proximal distractors, albeit slightly weaker than that generated by the entire repeated configuration. Importantly, those repeated configurations that did

not contain the proximal distractors failed to generate a CC effect, suggesting that the proximal distractors play a crucial role in search following the guidance of attention by the endogenous cue.

The effect of CC on visual search has frequently been characterised as an automatic influence on behaviour (e.g., Chun & Jiang, 1998; Chun & Nakayama, 2000; Geyer et al., 2021). This characterisation of CC comes from multiple aspects of the observed effect. Updating of the associations is somewhat slow and seemingly inflexible to changes in the acquired associations (Makovski & Jiang, 2011; Manginelli & Pollmann, 2009; e.g., Zellin et al., 2013), and therefore perhaps reflects a habitual form of behaviour. In addition, contextual cuing has frequently been observed in the absence of above-chance recognition memory for the repeating search configurations (e.g., Colagiuri & Livesey, 2016), which suggests a non-conscious, automatically evoked form of behaviour. Despite this persistent characterisation, the automaticity (or controllability) of CC has rarely been directly tested in the literature. To our knowledge, only the experiments of Luque and colleagues (Luque et al., 2017; Luque et al., 2021) have directly assessed this aspect of CC, by placing the influence of the configuration in competition with top-down goals in the task. Their findings supported the conclusion that CC performance can be controlled and will not guide search for the target when another aspect of the task governs attentional control. In the current study, the repeated configurations continued to have an influence on search performance even when attention had been guided by the endogenous cue. These results are therefore somewhat at odds with the conclusions of Luque and colleagues (Luque et al., 2017; Luque et al., 2021).

To what extent is this behaviour best characterised as “automatic” in nature? Arguably the clearest demonstration of an automatic effect of a stimulus on behaviour is when the associated behaviour is elicited even when it is counter-productive to the current goals (Moors & De Houwer, 2006). Such a test was constructed in the repeated inconsistent trials of Experiment 1, in which the repeated configuration was associated with a target that was previously located in a position on the opposite side of the screen to the direction indicated by the endogenous cue. If the repeated configuration had an effect on behaviour on these trials, we would have expected to see slower

response times compared to random trials. This was not the case: response times were equivalent in these two conditions. As such it is hard to claim here that the configuration is having an *automatic* effect on behaviour, according to this strict characterisation of such an effect. Nevertheless, the experiments here reveal an interplay between top-down processes and stimulus driven effects on attention in CC.

The current data reveal that the influence of repeated contexts has a relatively late control on behaviour in visual search. Previous analysis of eye-movements during CC (Beesley et al., 2018; Tseng & Li, 2004) has shown that contextual cuing (and visual search more generally) has two characteristic components. The first of these is an inefficient search process where search fails to move towards the target in trials with more fixations. This is followed by a phase in which monotonic, positive increments are made toward the target position in the final 3 to 4 fixations. CC reduces the frequency of trials with the initial (random) search period (there are more of such trials for random configurations and fewer for repeated configurations). Thus, the effect of the endogenous central cue in the current study is to eliminate, or considerably reduce, the engagement with this first phase of the search process. The results of this study strongly imply that the positive associative information in the repeating configurations is extracted in the final stages of search and is localised to the target. This is true both in terms of the performance of an acquired configuration (Experiments 1 and 3) and the acquisition of the representation for that configuration (Experiment 2). Perhaps paradoxically, the benefit of repeated configurations in search occurs shortly before the target is fixated. These data therefore support the view that late-stage “response threshold” processes may play an important role in the CC of visual search (Sewell et al., 2018). Notably, the results of Experiment 2 show that the curtailing of the initial (random) search process, which significantly reduces search times, does not limit the development of an adequate contextual cuing effect.

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