Local and global context repetitions in contextual cueing

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In contextual cueing tasks, participants can use a repeating local context to learn to detect the target, yet most contextual cueing studies have relied on repeating global context properties. We examined whether observers can use local context repetitions in a similar manner as they use global context repetitions. In addition, we examined how reward-predicting context features modulate the use of local and global contexts. Participants searched through contexts in which either the entire context configuration or only a local context around the target repeated, intermixed with novel contexts. Half of the context items appeared in a color signaling either low or high reward. We found that local context repetitions led to comparable benefits in response times and fixation count as global context repetitions did. Surprisingly, reward magnitude did not affect performance in local nor in global contexts. The results suggest that a local chunk of distractors can be used for context learning and attention guidance in a similar manner as the global context configuration. We suggest that the proportion of repeated and novel context trials is crucial for context learning and that our combination of locally and globally repeating contexts provided an environment that facilitated learning in both context types because it allowed predicting the target location from the context in most of the trials.

Introduction

Unlike in many visual search tasks in the laboratory, visual information in our natural environment rarely comes arranged completely random. Instead, visual information is often arranged in a similar manner in similar contexts, which helps our visual system to quickly assess the situation and to decide what to do next. For example, when searching for particular objects in a kitchen scene (e.g., a sponge), we can use knowledge we have acquired in similar kitchen scenes for optimizing search (see Võ & Wolfe, 2012). For instance, we know that sponges are likely to appear near the sink in a kitchen because we frequently found sponges near sinks in the past. As a result, we can now use this information for guiding visual attention more efficiently to the target, that is, we look near the sink first. Similarly, observers were reported to use environmental regularities in visual search; for instance, they responded faster to targets appearing in high compared to low probability locations (Ferrante, Patacca, Di Caro, Della Libera, Santandrea, & Chelazzi, 2018). This process of extracting statistical regularities from the environment is referred to as *statistical learning* (e.g., Ferrante et al., 2018; Goujon, Didierjean, & Thorpe, 2015; Theeuwes, 2018). Statistical learning helps organisms to overcome the problem of limited encoding capacity and facilitates focusing on locations that provide observers with relevant information (Li & Theeuwes, 2020; Theeuwes, 2018; Wang & Theeuwes, 2020).

One influential paradigm frequently used for investigating the statistical learning of repeated contexts in visual search is contextual cueing (Chun, 2000; Chun & Jiang, 1998). In the original paradigm, participants search for a “T”-shape among distractor contexts of “L”-shapes. Unbeknownst to the participants, half of these context configurations repeat in each experimental block, while the other half is generated randomly. Chun and Jiang (1998), who first reported the effect, observed that participants became faster in reporting the target in repeated contexts than in novel contexts—although they were unable to explicitly recognize repeated contexts after having performed the experiment. Studies using eye tracking in contextual cueing suggest that the faster responses are due to more efficient attention guidance to the target because not only response times get shorter in repeated contexts but also eye movements are guided more efficiently to the target (e.g., Harris & Remington, 2017; Peterson & Kramer, 2001; Tseng & Li, 2004; Zhao, Liu, Jiao, Zhou, Li, & Sun, 2012).

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Learning of local and global context information

While there is growing evidence for more efficient attention guidance in repeated than in novel contexts, the mechanisms underlying this facilitation are less clear (see Goujon et al., 2015, for a review). One possibility is that observers implicitly learn a global representation of repeated contexts, that is, an association of the complete repeated distractor configuration and the location of the target. When the context reappears, observers might guide their attention to the target, based on this global representation.

There is empirical evidence that global characteristics of the search contexts are learned and linked to the target location. Kunar, Flusberg, and Wolfe (2006), for instance, observed that associating the background color of distractor contexts with particular target locations led to contextual cueing effects. In addition, there is evidence that participants learn associations between the different distractor elements irrespective of the enclosed target, which also speaks for global learning. When participants search through repeated contexts in which the distractor configuration remains invariant over trials but the target randomly changes its location, participants show increased contextual cueing when these contexts are consistently paired with a target location in a subsequent phase (Beesley, Vadillo, Pearson, & Shanks, 2015). Observers thus benefit from prior exposures to repeated contexts, even when associations with a certain target location were prevented at that time. These results suggest that global characteristics of the distractor context are encoded as part of contextual cueing.

On the other side, there is also evidence that observers might only learn a local chunk of information surrounding the target location, which might be sufficient for producing contextual cueing effects. Olson and Chun (2002), for instance, conducted a contextual cueing task in which they used four different context types. In addition to the usual repeated and novel contexts, the authors used contexts in which they only repeated a part of the displays in each block. They repeated either the left or the right side of the context, whereas the other side was generated newly in each trial. The target could either be contained in the repeated side of the display (“short-range context”) or in the novel side (“long-range context”). The authors observed a response time benefit in completely repeated contexts compared to novel contexts, that is, the classical contextual cueing effect. However, when only the target’s side of the display repeated and the other side was novel, the authors could also observe a response time benefit. Interestingly, this effect was absent when the target was placed in the novel side of the display. The authors concluded that the participants only learned a local context surrounding the target, and not a complete global representation of repeated contexts (see also Brady & Chun, 2007; Song & Jiang, 2005; Zang, Jia, Müller, & Shi, 2015). They further suggested that when the target appeared on the novel side, the separation of the target and repeated distractors by randomly generated items hindered the association of the repeated items and the target location.

The local context surrounding the target seems not only sufficient for contextual cueing to evolve, but it also determines whether contexts can be associated with a new target location after contextual cueing had already been established (“adaptation of contextual cueing”, Annac, Conci, Müller, & Geyer, 2017). Previous studies had reported that contextual cueing was heavily impaired when the target was moved to a new location in repeated contexts after learning had already emerged, and that context learning only recovered slowly and with an extensive amount of context repetitions (e.g., Zellin, Mühlenen, Müller, & Conci, 2014). Annac and colleagues (2017) proposed that the item density in the target’s local context might explain why adaptation of contextual cueing can be limited. They conducted a contextual cueing experiment with (global) repeated and novel contexts and observed a reliable contextual cueing effect after participants had performed 24 blocks. Thereafter, the target was moved to a new location in repeated contexts, while the repeating distractor configuration remained unchanged. This manipulation allowed examining whether contextual cueing adapted to the new location in two conditions: when the target moved to a location in which the local distractor context was arranged sparsely, with only one distractor in a local context patch surrounding the target, or when it moved to a dense local context patch of similar size with three distractors. For the sparse context patch, a reliable contextual cueing effect was observed across the blocks 25 through 48, but not for the dense context patch. Interestingly, however, responses were *faster* to targets in the dense compared to the sparse patch. The authors suggested that items in the dense target patches were spontaneously grouped (Duncan & Humphreys, 1989), and automatically caught the observer’s attention. This facilitated target detection in the dense target patch, explaining the faster target responses, but grouping also hindered learning to associate the context with the new target location, because fast target detection reduced the time available for learning a new association. In a control experiment, the authors presented the target in either a dense or sparse local context patch right from the start of the experiment, without moving the target location. The results showed a contextual cueing effect for targets in patches with both densities. This finding suggests that the item configuration in local contexts can be crucial for learning a new association, especially when an association has already been established.

There is evidence that global and local context learning are not mutually exclusive, but determine contextual cueing in combination. Brady and Chun (2007), for instance, found that local contexts were learned only when the local context configuration did not change its relative location in the global context. Their experiments showed that a local chunk of two distractors in the target quadrant was sufficient for contextual cueing to occur; however, their Experiment 4 showed that observers could not benefit from local context repetitions when the repeating patch varied its location in the global configuration. Local context learning thus seems to require location binding to the larger-scale global context to become effective.

Attention determines context learning

An important factor determining which parts of repeated contexts are learned in contextual cueing is attention (e.g., Jiang & Leung, 2005; see also Beesley, Hanafi, Vadillo, Shanks, & Livesey, 2018; Jiang & Chun, 2001; Jiang & Song, 2005). In their contextual cueing task, Jiang and Leung (2005) composed the search display of black and white distractors; the target was constantly white throughout the experiment (black for half of the participants; the following sentences apply to white targets). This manipulation separated the context into two sets. The set of white items always contained the white target among white distractors, whereas the set of black items never contained the target. The authors repeated either the complete display, or only the black, or only the white items, whereas the other set was generated newly in each trial. These completely or partly repeated contexts were presented among novel contexts in which both sets were generated newly. The authors observed reduced response times in completely repeated contexts and also in repeating white items contexts. When only the black items repeated, no response time benefit was found. The authors concluded that participants attended the white items only, as this set always contained the target. As a result, an association was only established for white item context and the target location. Because the black items seemed not relevant when searching for the target item, they were not attended, and even when black items repeated, an association between black context items and the target was not established.

Reward influences attention guidance in contextual cueing

Attention, crucial for contextual cueing, is susceptible to reward (for reviews, see Anderson, 2016; Chelazzi, Perlato, Santandrea, & Della Libera, 2013; Failing & Theeuwes, 2018; Theeuwes, 2018). Assigning reward increases the perceived visual salience of a stimulus (Hickey, Chelazzi, & Theeuwes, 2010) and reward can bias visual selection even against the observers' intentions (e.g., Feldmann-Wüstefeld, Brandhofer, & Schubö, 2016; Le Pelley, Pearson, Griffiths, & Beesley, 2015).

Also in contextual cueing, reward-predicting stimuli can influence attention guidance. Salient reward-predicting colors in the display were reported to lead to an increased contextual cueing effect and increased the efficiency of attention guidance in repeated contexts (Bergmann, Koch, & Schubö, 2019; see also Bergmann, Tünnermann, & Schubö, 2020; Pollmann, Eštočinová, Sommer, Chelazzi, & Zinke, 2016; Schlagbauer, Geyer, Müller, & Zehetleitner, 2014; Sharifian, Contier, Preuschhof, & Pollmann, 2017; Tseng & Lleras, 2013). Bergmann and colleagues (Bergmann et al., 2019) used a contextual cueing task in which half of the items were presented in one of three colors, whereas the other half was gray. The color was consistently associated with a reward that participants received for correct responses, and present in both novel and (globally) repeated contexts. Thus, participants could predict the reward from the color with display onset. Results showed that a color signaling high reward decreased response times in repeated but not in novel contexts. High reward also led to more efficient eye movements: Participants made fewer fixations in repeated compared to novel contexts and the first fixation landed closer to the target in high reward trials—interestingly, only when the color predicted high but not medium or low reward. High reward thus increased task performance by facilitating attention guidance to the target in repeated contexts.

Rationale of the present study

In the present study, we investigated whether observers use local context repetitions in a similar manner as global context repetitions to detect the target, and whether colored stimuli signaling reward facilitate attention guidance in local context configurations in a similar manner as has been reported for global ones. If reward-predicting context features facilitate attention guidance on the global context level, they might also facilitate the use of local context repetitions. On the other side, it is also possible that reward does favor global more than local context configuration learning, because repeating only few items might be less efficient to learn to guide attention to the target. To investigate these alternatives, we conducted a contextual cueing task using three context configuration types. We repeated either the complete global context configuration or only a local patch of three distractors that surrounded the target – a number of context items that has been reported to be the minimum for successful

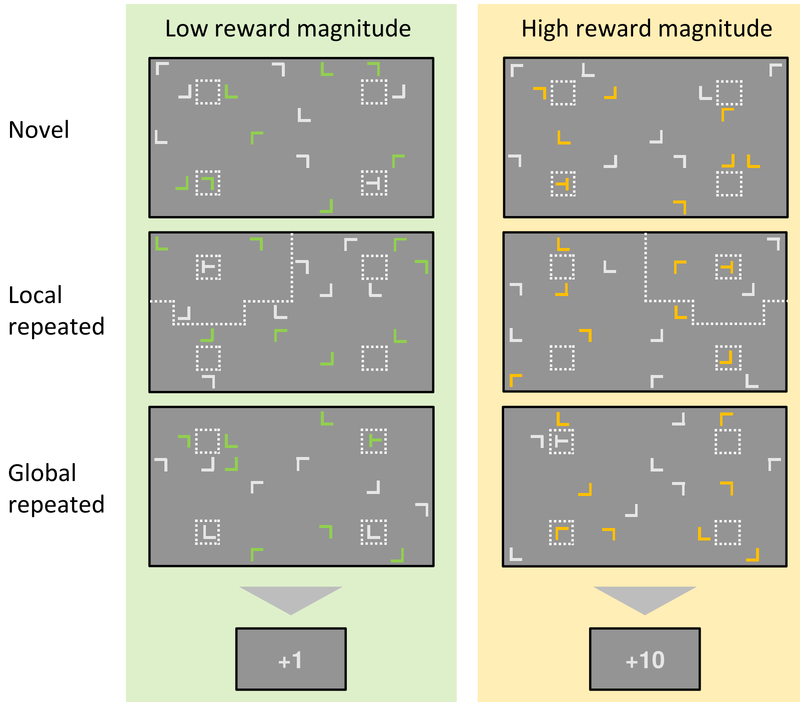

Figure 1. Exemplary search context configurations in novel (upper row), local (middle row), and global contexts (lower row) associated with low (left column) and high reward (right column). In global contexts, the entire context configuration repeated with each block. In local contexts, only a patch surrounding the target repeated (indicated by the dotted lines, not visible to participants). This patch always contained two colored and two gray items. The location of the repeating patch varied in the global configuration, and was balanced across experimental conditions. In novel contexts, the entire context configuration was generated newly in each trial. The same four target locations were used for all context types (dotted squares, not visible to participants). The color-reward association was balanced across participants.

context retrieval (Brady & Chun, 2007; Song & Jiang, 2005). These global repeated and local repeated contexts were randomly intermixed with novel contexts in each block. Half of the items in each context configuration type—global, local, and novel—were presented in a color that signaled a high or a low reward given for correct responses (cf., Figure 1).

We expected that participants would show context configuration learning in global contexts and, presumably, also in local contexts, which should manifest in faster target response times in local and global compared to novel contexts. In addition, we examined whether observers benefited from a local context repetition in a similar manner as from global context repetitions. Because global contexts contained a good deal more repeating distractors as local contexts (15 vs. 3, see Figure 1), however, one may alternatively assume that target response times in global contexts are faster than response times for targets presented in local contexts. We also examined the number of fixations until the target was fixated, a measure that has been frequently related to the efficiency of attention guidance in contextual cueing (e.g., Harris & Remington, 2017; Peterson & Kramer, 2001; Tseng & Li, 2004). If observers can use local contexts in a similar manner for finding the target as global ones, this should manifest in fewer fixations in local and global compared to novel contexts, which should be comparable for local and global contexts. If, however, participants use global contexts more than local ones for finding the target, one would expect to observe fewer fixations in global than in local contexts. Reward might boost context configuration learning, which should be visible in faster response times and fewer fixations for high compared to low reward contexts for both, local and global contexts similarly. If, however, reward facilitates learning of global context configurations more than for local contexts, a color signaling high reward should lead to larger reductions of responses times and fixation count in global than in local contexts.

Method

Participants

We recruited sixty volunteers (42 female; 18–30 years, $M = 21.6$, $SD = 2.61$) that participated for payment or course credit. All participants were naïve to paradigm and objective of the experiment, had normal or corrected-to-normal visual acuity, and showed no signs of color blindness (confirmed with Oculus Binoptometer 3). We removed one participant from the analyses because of high error rates (>3 *SD* from the group mean). Before the experiment started, participants gave written consent in line with the ethical standards of the Declaration of Helsinki. The experiment was approved by the local Ethic Committee of the Faculty of Psychology at Philipps-University Marburg.

Apparatus

The participants were placed 100 cm in front of an LCD-IPS screen (Cambridge Research Systems, Display++ LCD Monitor 32″, 1920 × 1080 pixels, 120 Hz) and responded with the buttons of a gamepad (Microsoft Xbox 360 Gamepad). Eye movements were recorded using an EyeLink 1000 Plus eye tracker (SR Research Ltd., spatial resolution 0.01°, sampling rate 1000 Hz). Head movements were prevented with a chin rest aligned to the center of the screen. The eye tracker was calibrated with the EyeLink 13-point calibration procedure. We used E-Prime Professional (2.0.10.356) routines for stimulus presentation and response collection.

Stimuli

The search contexts consisted of 15 L-shaped distractors and 1 T-shaped target, aligned on an invisible 12 × 7 grid (35.5° × 20.7°) with a minimum of 1.7° between two items. The distractors (Ls) were rotated 0°, 90°, 180°, or 270° and the target (T) was tilted to either the left or right. All items were presented in the same size (1.4° × 1.4°). In every trial, the target appeared in one of four fixed locations, each located in one quadrant of the screen (12.4° eccentricity from screen center, cf., Figure 1). To rule out target location probability effects, the same target locations were used in novel, local, and global contexts, and in contexts associated with low and high reward. Using the same locations ensured that the target location was unpredictive of context novelty and of reward magnitude. Of the 16 items, eight were gray (RGB 128, 128, 128; 56.75 cd/m^2), and eight were homogeneously colored. The background was dark gray (RGB 64, 64, 64; 28.23 cd/m^2). The search contexts were generated by randomly placing seven distractors on the target's side of the display and eight on the other side. We distributed the colored items equally to both sides of the display, four colored items on the left and four on the right side. The colored items were green (RGB 29, 173, 69; 56.65 cd/m^2) or orange (RGB 252, 104, 4; 56.78 cd/m^2), both colors were isoluminant to the gray items. The target was either gray or colored. We defined a 21-cell patch surrounding the target (cf., Figure 1). This patch always contained three distractors and the target. Two items within the patch were always colored and two were gray. The target patch covered one quarter of the grid's cells (21 of 84) and contained one quarter of the items (four of 16). All contexts were generated individually for each participant.

Procedure

Trial procedure

Participants started the trial by fixating a fixation dot (Thaler, Schütz, Goodale, & Gegenfurtner, 2013) shown at screen center. The dot was surrounded by a thin line, which disappeared when the dot was fixated. After 400 ms, the search display was shown. Participants were asked to press one of two buttons on the gamepad's back to indicate the orientation of the target, which varied randomly in each trial. The search display was removed with response, or replaced by a blank screen after 1000 ms.

After the response, the achieved reward points were shown at screen center for 600 ms. When participants responded correctly within the time limit of 1600 ms, they were rewarded with "+1" or "+10" points, which depended on the color contained in the search display (see Figure 1). They received "+0" feedback after incorrect responses or responses slower than 1600 ms. We instructed participants that they could earn points for responding correctly, but we did not inform them that color predicted the reward magnitude. We converted the collected points into a monetary bonus (max. 5.28 EUR).

Experimental procedure

The experiment consisted of two sessions on separate days (max. one day in between). Session 1 contained 12, session 2 contained 8 blocks with 48 trials each. Within each block, 16 global contexts, 16 local contexts, and 16 novel contexts were presented in random order. In global contexts, the entire context configuration repeated with each block. In local contexts, only the patch surrounding the target repeated, whereas the remaining context configuration was generated newly in each trial. In novel contexts, the entire context configuration was generated newly in each trial. Half of all contexts in each context configuration type—global, local, and novel—contained the color signaling high, the other half the color signaling low reward (cf., Figure 1). Individual configurations were generated for contexts containing a colored and contexts containing a gray target so that half of all contexts contained a colored and the other half contained a gray target.

The first experimental session started with one block of practice trials. The practice contained only novel contexts without reward feedback. The block was repeated if participants did not reach an average response accuracy of at least 65%. After each experimental block, participants received performance feedback (mean response accuracy, mean response time, amount of points they had collected). After the block feedback, participants made a short pause of at least 10 seconds.

Data analysis

Response times and error rates

For response time (RT) analyses, we removed all trials with incorrect or too slow responses (12% of trials) and all trials exceeding ± 2 *SD* from the mean of each participant in each block (another 3%). The remaining RTs were collapsed for each participant and block, separately for each context type and each reward magnitude. The error rates were aggregated like the RTs.

Eye movements

We extracted fixations, saccades, and blinks using SR Research Data Viewer (Version 3.1.97). As for RT, we analyzed only trials with correct responses. In addition, we removed trials without eye movements, with blinks, and in which participants moved their eyes faster than 100 ms after stimulus onset (another 9 % of trials removed). We then calculated the number of fixations (fixation count) until a fixation landed in an area of 8.3° around the target location. This area also included the cells next to the target, since in some trials participants responded correctly although they had not fixated the target directly. Only trials in which participants reached the area during display presentation were used and the fixation count was aggregated like RTs and error rates. All analyses were calculated using IBM SPSS Statistics 25 (IBM, Armonk, NY, USA).

Recognition task

After the main experiment, participants performed a recognition task consisting of one block (48 trials). Participants encountered the 16 global, 16 local, and 16 novel contexts in random order and decided for each context whether they had seen it before or whether it was novel. Before the task started, we informed the participants that some of the contexts were repeating during the experiment. We however did not reveal that, in some trials, only the target patch repeated. There was no time restriction for this task.

Mixed model analysis

To quantify context learning in local and global contexts, we calculated a linear mixed model analysis, a modern form of statistical models that yield several advantages compared to traditional analyses. Mixed model analyses extend regular linear regression by including random effects that allow to control for variability from different sources (e.g., participants) in addition to the fixed effects that represent the overall effects on the dependent variables, similar to main effect (or interaction) in analyses of variance (ANOVAs). Fixed effects can be used to test specific hypotheses; when being significant, a fixed effect can be interpreted the same way as a significant test result in a standard ANOVA. Mixed models are robust to sphericity violations, do not increase the complexity of the analysis, and do not bear the risk of inflating Type I errors. For a detailed description of mixed models in experimental psychology, see (Singmann & Kellen, 2019).

In contextual cueing, mixed model analysis allows describing the data, such as response times, by estimating slopes based on the response times measured over the course of the experiment. Crucially, the data need not be aggregated into larger 'epochs' of arbitrary size as often done by traditional analyses. Linear mixed model analyses allow including the linear trend as continuous predictor instead of using discrete factors, thereby avoid multiple testing, and provide a more accurate estimate of the RT decrease compared to traditional approaches that rely on data collapsed across several blocks.

The model includes random effects in addition to fixed effects, that is, random intercepts and random slopes. Random intercepts allow that initial RT values vary across participants, thereby accounting for individual response speeds. The random slopes relate to the experimental conditions and allow the slope steepness (i.e., the RT decrease) to vary across participants. Random effects together with fixed effects that serve to examine the effect of experimental manipulations, make our mixed models a powerful analysis tool (Barr, Levy, Scheepers, & Tily, 2013), which we consider especially useful for the analysis of contextual cueing experiments.

The specific mixed model implemented in the present study is visualized in Fig. 2. It estimates the average response times (RT) in block 1 as a shared intercept for all experimental conditions. This value is assumed to be identical for all context configurations, because all contexts are "novel" to the participants at the beginning of the experiment. The model describes the decline of RTs by estimating slopes. The slope of RTs in novel contexts is used as a reference for comparisons with the slopes in local and global contexts (Fig. 2, left panel). A steeper slope in local or global compared to

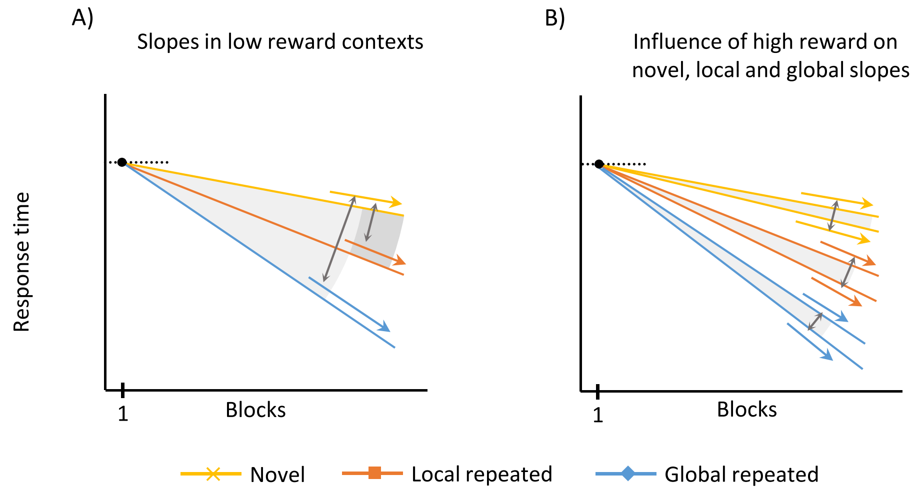

Figure 2. Visualization of the mixed model analysis. (A) Novel contexts are depicted as yellow lines, local contexts as orange, global contexts as blue lines. The model uses a shared intercept in block 1 (depicted as black dot) and describes the decrease of RTs by estimating linear slopes. The slope of novel low reward contexts is considered a reference (yellow line). The model compares the slope of local low reward contexts (orange line) to this reference, as well as the slope of global low reward contexts (blue line). (B) For estimating differences between low and high reward, the model compares the slopes of high and low reward contexts, separately for novel (yellow lines), local contexts (orange lines), and global contexts (blue lines).

novel contexts indicates that context learning emerges, i.e., that RTs decrease more in these contexts than in novel contexts. To examine whether reward facilitated learning of local and global context configurations, the model investigates potential modulations of reward magnitude on the slopes by using low reward as the reference (Fig. 2, right panel). The model estimates the difference of the slopes in high reward compared to low reward contexts, separately for novel, local, and global contexts. The model also includes random intercepts and slopes. For investigating differences between global and local contexts, we recoded the mixed model using global (instead of novel) contexts as a reference. The identical mixed model was applied to the error rates and fixation count.

Results

Response times

Mixed model analysis

The observed RTs are depicted in Figure 3, upper panels. The mixed model estimated that RTs decreased by 4.5 ms with each block in novel contexts ($b = -4.5$ [$-5.6, -3.4$], $t(75) = -8.09$, $p < 0.001$). The slope in global contexts was estimated 1.7 ms steeper, $\Delta b = -1.7$ [$-2.3, -1.2$], $t(6962) = -6.00$, $p < 0.001$. Also the slope in local contexts was estimated steeper than the slope in novel contexts, but the difference was estimated only 1 ms, $\Delta b = -1.0$ [$-1.6, -0.4$], $t(6962) = -3.43$, $p = 0.001$. These results indicate that RTs decreased faster in both local and global contexts than in novel contexts, that is, contextual cueing emerged in both context types. Slopes in low and high reward contexts did not differ (all $ps \geq .515$).

To investigate whether observers benefited from a local context repetition similarly as from global repetitions, we compared the slopes in local and global contexts. We recalculated the model, now with *global* contexts coded as a reference, which revealed that the slope in local contexts was 0.7 ms shallower than in global contexts, $\Delta b = 0.7$ [0.2, 1.3], $t(6962) = 2.57$, $p = 0.010$.

Follow-up: Separate mixed models

There has been evidence that contextual cueing can differ when the task is performed in two sessions separated by sleep (e.g., Geyer, Müller, Assumpcao, & Gais, 2013). Thus, estimating one single slope for both experimental sessions might have been not sensitive enough to detect specific changes which happen either in the first or the second session. We therefore performed an additional analysis of the data: we recalculated the model separately for each session and each reward magnitude. The models were the same as the main model but now with the global context coded as a reference. In addition, they excluded the effects of reward because each reward magnitude was analyzed separately. The resulting slope estimates are visualized in Figure 3 (lower panels). Interestingly, the slope was significantly shallower in local than in global contexts, but only in the second session and only in low

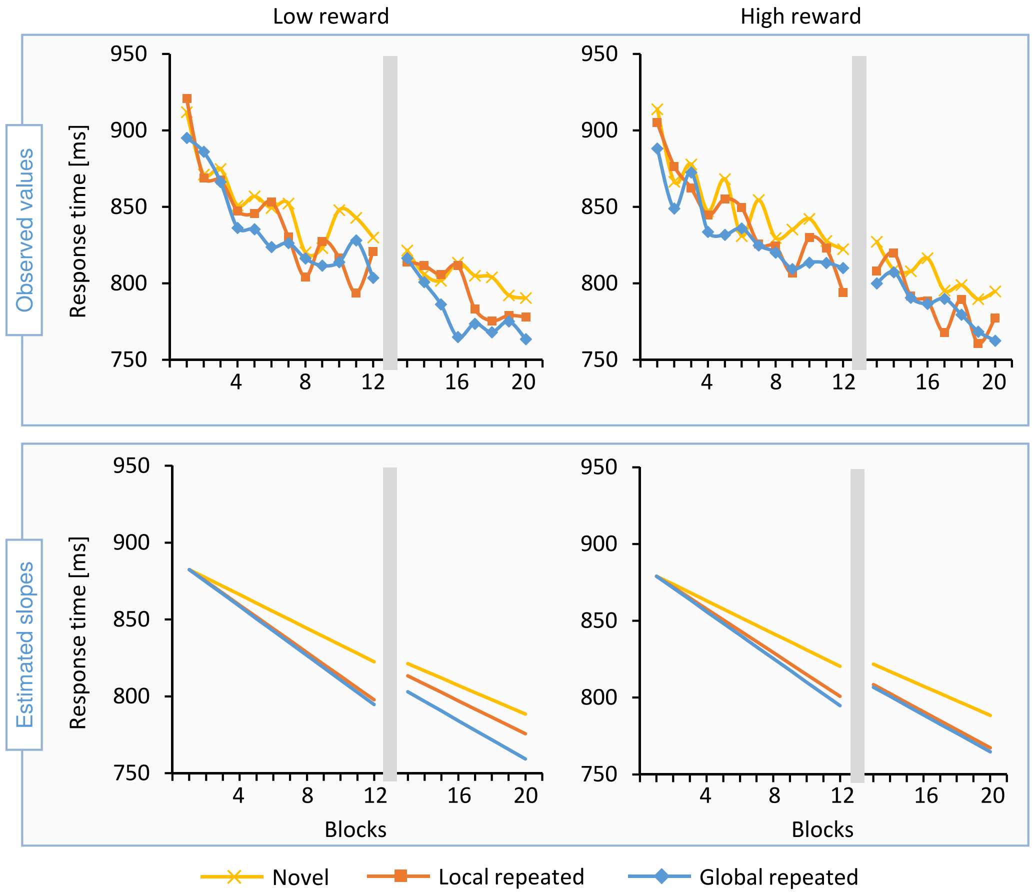

Figure 3. Response times observed during the experiment (upper panels) and estimated slopes of the mixed models (lower panels). Separate panels depict RTs for low (left column) and high reward (right column). RTs measured for novel contexts are shown as yellow, RTs for local contexts as orange, and for global contexts as blue lines. The gray bar stands for the time gap between the sessions.

reward contexts, $\Delta b = 0.9$ [0.3, 1.4], $t(1298) = 3.07$, $p = 0.002$. In the other conditions, there were no significant differences between local and global context slopes (all *p*s ≥ 0.385).

In sum, the analysis of RT slopes revealed that participants showed contextual cueing in local and global contexts and that local contexts mostly led to similar benefits in RT slopes as global contexts did. When considering the impact of reward, no facilitation of the use of local or global contexts was observed, as RT slopes of low and high reward contexts were comparable. However, we observed that the *difference* between local and global contexts depended on the reward magnitude in session 2: While in session 1, participants benefited from local contexts in a similar manner as from global contexts, in session 2, the slopes in local contexts were shallower than in global contexts in low reward contexts (see Figure 3, lower left panel). In high reward contexts, the slopes in local and global contexts were comparable.

Error rates

Error rates were higher in novel contexts ($M = 12.39\%$, $SEM = 0.37$) compared to local ($M = 11.63\%$, $SEM = 0.37$) and global contexts ($M = 11.04\%$, $SEM = 0.34$), and similar for both reward magnitudes (low reward: $M = 11.73\%$, $SEM = 0.29$, and high reward: $M = 11.64\%$, $SEM = 0.30$). The mixed model estimated that the error rates decreased 0.6 % with each block in novel contexts ($b = -0.6$ [−0.7, −0.5], $t(101) = -10.98$, $p < 0.001$). The difference between the slopes in global and novel contexts missed significance ($\Delta b = -0.07$ [−0.15, 0.006], $t(6962) = -1.82$, $p = 0.069$), and so did the difference between local and novel contexts ($\Delta b = -0.08$ [−0.16, 0.001], $t(6962) = -1.94$, $p = 0.052$). There were no differences between reward magnitudes (all *p*s $\geq .522$). When we recalculated the model with global contexts coded as a reference, neither the difference between the slopes in global and local contexts was significant ($\Delta b = -0.005$ [−0.08, 0.07], $t(6962) = -0.12$, $p = 0.902$). These results indicate that participants made fewer errors when the experiment proceeded, but there were differences between neither context types nor reward magnitudes.

Fixation count

The fixation count is depicted in Figure 4. Similar to the response times, the mixed model estimated that the average fixation count decreased with each block in novel contexts ($b = -0.008$ [-0.012, -0.004], $t(108) = -3.85$, $p < 0.001$). Again, the slope in global contexts was estimated steeper than in novel contexts ($\Delta b = -0.006$ [-0.009, -0.003], $t(6937) = -3.64$, $p < 0.001$). Also the slope in local contexts was steeper than the slope in novel contexts ($\Delta b = -0.004$ [-0.007, -0.0005], $t(6937) = -2.25$, $p = 0.025$). There were no differences between slopes with low and high reward contexts (all $ps \geq 0.402$). As for RT, we re-calculated the model with global contexts coded as a reference, which showed that the difference between the slope in global and local contexts was not significant ($\Delta b = 0.002$ [-0.001, 0.005], $t(6937) = 1.39$, $p = 0.164$).

In sum, these results show that participants used both local and global contexts to direct their eyes to the target because they needed fewer fixations than in novel contexts. This benefit was similar for local and global contexts. Reward affected the fixation count neither in local nor in global contexts.

Differences between gray and colored targets

In the present study, half of the context configuration items were gray and half were colored. Thus the target was colored in half of the trials and gray in the other half, and searching for the target in either the subset of gray or colored items was not particularly efficient. However, as color, as a salient feature, predicted reward magnitude, participants might have relied on color to search for the target. Moreover, former studies reported color to influence the size of contextual cueing when some context items were colored and others not (Conci & von Mühlenen, 2011). Conci and von Mühlenen found that displays that can be segmented into separate color or size subsets lead to reduced contextual cueing effects compared to uniform displays, likely because segmenting the display reduces the number of items available for cueing the target. If so, this might have particularly affected performance in local contexts, because the local context patch only contained two colored and two gray items (3 distractors and 1 target; cf., Figure 1). Focusing on the colored items would reduce the number of items available for context learning even further, that is, from four to two, whereas in global contexts still half of the items would be considered. Consequently, focusing on color would have a stronger impact on local contexts, that is, longer response times for contexts with a gray compared to a colored target.

To examine this consideration, we compared RTs in contexts with gray and colored targets separately for sessions 1 and 2. We collapsed RTs in session 1 (blocks 1-12) and session 2 (blocks 14-20), and calculated a repeated measure ANOVA with the factors *target color* (colored vs. gray), *context type* (novel vs. local vs. global), and *reward* (low vs. high). Block 13 was excluded because participants directly started with this block after the break without additional practice. Results in session 1 showed no differences between contexts with gray and colored targets; the main effect of target color ($p = 0.600$) and all interactions including target color missed significance ($ps \geq .270$).

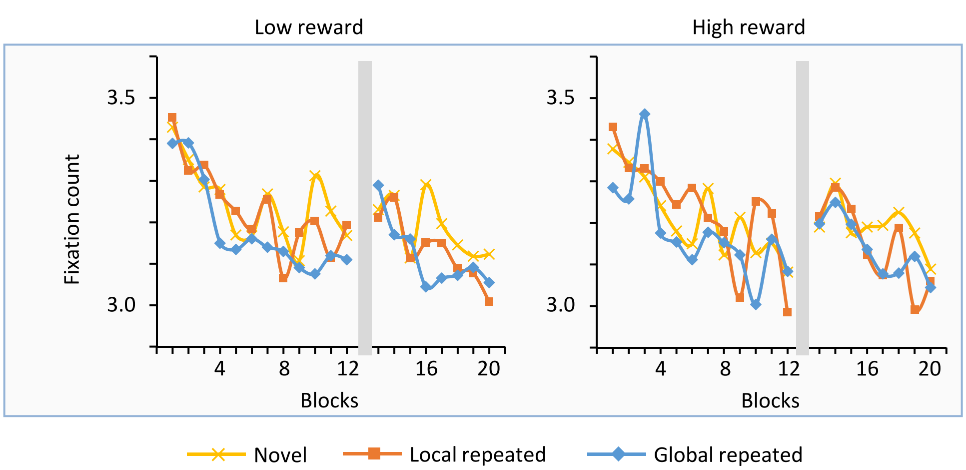

Figure 4. Fixation count during the experiment in low reward (left panel) and high reward contexts (right panel). Fixation count for novel contexts is shown in yellow, for local contexts in orange, and for global in blue. The gray bar stands for the time gap between the sessions.

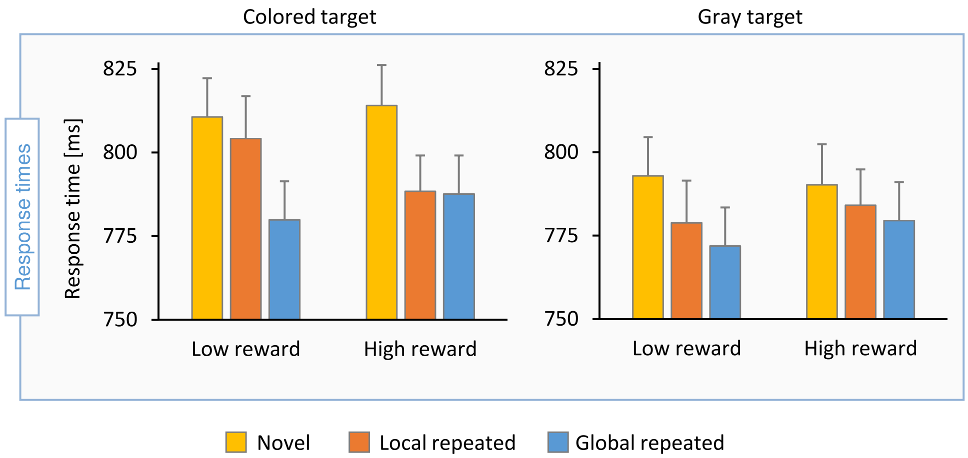

Figure 5. Response times in blocks 14 to 20, separately for contexts with colored targets (left panel) and gray targets (right panel). Novel contexts are depicted as yellow, local as orange, and global as blue bars. The error bars show the standard error of the mean.

Results in session 2 (see Figure 5) showed a main effect of target color ($F(1, 58) = 7.44$, $p = 0.008$, $\eta^2_p = .114$) indicating faster RTs in contexts with gray ($M = 783$ ms, $SEM = 11$) compared with colored targets ($M = 797$ ms, $SEM = 12$), and a significant main effect of context type ($F(2, 116) = 21.18$, $p < 0.001$, $\eta^2_p = .267$). Pairwise comparisons based on estimated marginal means revealed that RTs in local and global contexts were faster than in novel contexts ($\Delta M_{local} = 13$ ms, $SEM = 4$, $p = 0.001$; $\Delta M_{global} = 22$ ms, $SEM = 4$, $p < 0.001$), and that global contexts were searched faster than local contexts ($\Delta M = 9$ ms, $SEM = 3$, $p = 0.017$; p values are Bonferroni corrected for multiple comparisons). No other effect reached significance ($ps \geq .141$). In sum, these results show that participants responded *slower* in contexts with colored compared to gray targets in session 2, which would suggest that participants focused on gray items rather than on items in color in that session.

Although not significant, Figure 5 visually suggests a differential effect of reward in local contexts with a colored target (orange bar in left panel of Fig. 5). To examine this possibility, we calculated the mixed model for session 2, separately for low and high reward as visualized in Figure 3, and separately for contexts with gray and colored targets. For low reward contexts with colored targets, the local slope was estimated more shallowly than the global slope (difference: $\Delta b = 1.4$ [0.6, 2.2], $t(1298) = 3.49$, $p < 0.001$), whereas the slopes were similar for high reward contexts ($p = 0.712$), and for contexts with gray targets ($p_{low\ reward} = 0.543$, $p_{high\ reward} = 0.469$). The separate mixed models therefore confirm that in low reward contexts with a colored target, local contexts had shallower slopes than global contexts in session 2.

Recognition task

Accuracy in the recognition task was analyzed using a repeated measure ANOVA with the factor context type (novel vs. local vs. global) and reward (low vs. high). The recognition accuracy was higher in global and local contexts compared to novel contexts, indicated by a main effect of context type ($F(1, 80) = 8.84$, $p = 0.001$ [Greenhouse-Geisser corrected], $\eta^2_p = .132$). Pairwise comparisons based on estimated marginal means confirmed that the accuracy was significantly lower in novel ($M = 45$ % correctly identified contexts, $SEM = 2$) than in local ($M = 56$ %, $SEM = 2$), $p = 0.009$, or in global contexts ($M = 57$ %, $SEM = 2$), $p = 0.006$. The recognition accuracy in local and global contexts did not differ, $p = 1$ (p values are Bonferroni corrected). The main effect of reward missed significance ($F(1, 58) = 3.33$, $p = 0.064$), and also the interaction was not significant ($F(1, 116) = 0.29$, $p = 0.751$).

General discussion

The present study examined if observers use local and global context repetitions for finding the target in a similar manner and how reward-predicting context features influence context learning in local and global contexts. Because reward-predicting context features were reported to facilitate attention guidance in global contexts, we speculated that they might also facilitate attention guidance in local contexts. We used search contexts in which either the complete context configuration repeated (global contexts), only a local patch surrounding the target repeated while the remaining context was arranged randomly (local contexts), or in which the complete context was random (novel contexts). Half of the context items were presented in a color signaling high or low reward magnitude for correct responses. As we assumed, we found contextual cueing (CC) in both local and global contexts, measured as faster response times and fewer fixations compared to novel contexts. In addition, local contexts led to comparable CC effects as global contexts did, which suggests that observers could use local and global context repetitions in a similar manner to detect the target.

Unexpectedly, reward had not much impact on performance, as the slopes observed for high and low reward response times did not differ. We only observed a small effect on local contexts with colored targets in session 2. These results were surprising, since reward has been reported to facilitate task performance in global contexts and we had expected to observe a similar facilitating effect in local and global contexts.

Local and global context repetitions

Our results showed that local contexts led to comparable CC effects as global contexts: RTs decreased faster in both local and global contexts than in novel contexts, and their slopes did not differ (except for colored targets signaling low reward in session 2, which will be considered at a later point in this discussion). Contextual cueing emerged similarly in both context types (s. Figure 3, lower panels), suggesting that the repetition of only three distractors surrounding the target was sufficient to produce CC effects comparable to repeating all 15 distractors in the display. Fixation count points in the same direction, because the slopes of the fixation count were comparable in local and global contexts, but steeper than in novel contexts. This suggests that attention guidance, as indexed by the fixation count, was comparably efficient in local and global contexts.

At first glance, it seems surprising that the repetition of only three distractors led to similar contextual cueing as seen with repeating the entire context configuration. Song and Jiang (2005) reported that, once a context has been learned, the repetition of a minimum of three context items (two distractors and the target) was sufficient to produce a contextual cueing effect. In their study, however, the authors first repeated the entire context configurations in a training phase, which allowed learning to emerge. In a subsequent testing phase, they repeated three items of the previously shown contexts but arranged the remaining items randomly. Testing with these partially repeated contexts was thus explicitly separated from learning. In an additional experiment, the authors examined whether three items would also suffice for learning to emerge. Similar to our experiment, the study implied partially repeated contexts with three repeating items, completely repeated contexts, and novel contexts. While participants showed contextual cueing for completely repeated contexts, performance in contexts with three repeating items was as slow as in novel contexts. The authors concluded that the repetition of three items was sufficient for retrieval of an already learned context configuration, but was not enough for learning to evolve.

In contrast to Song and Jiang (2005), we observed contextual cueing also in local contexts with only three distractors repeating during learning. One reason for this difference might be that our local contexts contained three repeated distractors (and the target), whereas Song and Jiang used one object less. Another reason might be that the three distractors of our local contexts were arranged in a spatially defined patch surrounding the target. Novel context items appeared only outside the patch but not within. In Song and Jiang's study, randomly placed distractors also appeared between the three repeating items. These novel items might have hindered learning an association of the repeating items and the target location (see Olson & Chun, 2002). Our local contexts showed contextual cueing because random items never occupied the space between the three repeated distractors and the target.

Our local contexts however not only showed contextual cueing, but the effect was of similar size as compared to global contexts. One may argue that this resulted from the limited display presentation time in our experiment (max. 1000 ms). One might think that participants had not enough time for processing the complete global configuration in this time span, and that they therefore only associated a limited patch with the target also in global contexts. However, it seems more likely that the target patch simply contained sufficient information for guiding attention to the target and that learning the complete global configuration did not provide a significant advantage for the observers. This would also suggest that observers learned a restricted context patch also in global contexts, despite the global context repetition. Brady and Chun (2007) implemented a modeling approach investigating to what extent repeated context configurations are learned in contextual cueing. Their results suggested that, even when the context repeats globally, observers might only learn a local context, provided that the local context configuration did not shift its relative location in the global context. These findings point to the relevance of local context as being responsible for the facilitation of attention guidance to the target, while the global context layout (i.e., the local context's relative location in the larger-scale global context) might have helped orienting toward the relevant local context patch (see

Zinchenko, Conci, Töllner, Müller, & Geyer, 2020, for the role of context layout in orienting). In the study of Brady and Chun (2007) the local context covered about one *quadrant* of the search display. Since the target patch of our local contexts approximated the quadrant of the target (see Figure 1), it seems very likely that the local contexts provided the observers with sufficient information for context learning to emerge.

In sum, our results suggest that observers use the distractors in the local context of the target to learn to guide attention to the target location. Local contexts were as effective as global contexts, presumably because the target patch was large enough, covering approximately one quadrant of the screen, and because the space between the repeating distractors and the target was never occupied by random novel items.

Proportion of repeated vs novel context trials: The role of predictions in context learning

An aspect that might have facilitated learning of local and global context configurations is the overall proportion of local and global contexts in the experiment. Each experimental block contained one third global, one third local, and one third novel contexts (cf., Figure 1). Thus two thirds of trials contained contexts in which (at least some) items were repeating, and only one third of trials was entirely novel. This is an important difference to most contextual cueing studies, in which usually only half of the trials contain repeating context items (50% global and 50% novel trials, Chun & Jiang, 1998).

The ratio of repeated and novel contexts has a strong impact on the emergence and size of the CC effect (Yang & Merrill, 2015). Zinchenko, Conci, Müller, and Geyer (2018) showed that CC was even absent when contexts repeated in only a small proportion of trials (20 % repeated, 80 % novel). Based on the theory of predictive coding (e.g., de Lange, Heilbron, & Kok, 2018; Friston, 2005), the authors proposed that learning of repeated contexts can only emerge when observers can generate predictions about regularities in the visual environment, and when they are able to evaluate these predictions by processing prediction errors, which are crucial for learning to evolve. Applied to contextual cueing, this would imply that participants use context configurations to generate predictions about potential target locations. Based on prediction errors, they learn to associate repeated context configurations with the embedded target locations. We assume that, after having performed several search trials through different contexts, observers generated predictions about the likely target location which were evaluated in the subsequent trials. By comparing the predicted to the actual target location, participants could update and refine their predictions.

This mechanism requires that the visual environment (here: the contexts) has a consistent and reliable structure that can be perceived by the observer (de Lange et al., 2018; Feldman & Friston, 2010). Although organisms are highly sensitive in registering regularities in space and time (e.g., de Lange et al., 2018; Goujon et al., 2015; Summerfield & de Lange, 2014), an unstructured environment with regularities appearing in only a few trials might not allow for reliable predictions. In contextual cueing tasks, regularities can be registered in repeated contexts but not in novel ones, making the proportion of repeated versus novel contexts crucial for learning: The higher the proportion of trials in which the contexts repeat, the higher the frequency of trials in which observers can successfully evaluate their predictions, providing the ground for learning. A low proportion on the other hand does mostly not allow for reliable predictions, which hinders learning.

In our experiment, two thirds of the trials were repeated trials, with either the entire context configuration repeating, or the configuration around the target. This combination of local and global repeated contexts constituted a reliable visual environment, as both context types provided prediction error signals adequate for learning. As a result, learning emerged in both context types. Presumably, the fact that participants received feedback about their task performance in each trial might have further contributed to the perceived reliability and the observed contextual cueing effects.

Also Zinchenko et al. (2018) found contextual cueing with a high proportion, but not with a low proportion of repeated contexts. According to our notion, the high proportion of repeated contexts has constituted an environment that allowed for an efficient processing of prediction errors and, accordingly, favored the emergence of context configuration learning. A low proportion, however, was suggestive of an unstructured environment and hindered context learning. Zinchenko et al. (2018) also explained their results with the processing of predictions. However, their explanation focused on predictions (or "expectations") about the presence vs absence of repeated contexts in the experiment rather than on prediction error processing within individual contexts and trials. The authors assumed that a high proportion of repeated context trials would result in the (implicit) expectation that contexts were repeating in the experiment which subsequently allowed for the buildup of context memory. They came to this conclusion based on another study (Jungé, Scholl, & Chun, 2007) that observed that starting the experiment with a short phase of only novel contexts abolished contextual cueing in a typical contextual cueing task. Jungé et al. (2007) assumed that context learning requires some sort of learning resources and that the visual system acts economically by stopping to search for regularities when it regularly fails to detect them. Zinchenko et al. (2018) suggested that participants learned to expect the absence of repeated contexts when repeated contexts were rare in their experiment, which abolished context learning when only a low proportion of the contexts repeated.

Our interpretation extends the ideas of Zinchenko et al. (2018): While the authors assumed that expectations about global regularities (i.e., the presence vs. absence of repeated contexts in the experiment) are crucial for context learning to evolve, we suggest that the processing of predictions within individual contexts and trials is crucial as well.

Lack of reward effects in the present study

Although participants showed robust contextual cueing, reward magnitude seemed to have played no role for context learning. Expecting a high reward did not speed responses in any of the contexts when compared to expecting a low reward. This was an unexpected finding that stands in contrast to prior findings reporting faster responses with high reward in global contexts (e.g., Bergmann et al., 2019; Pollmann et al., 2016). Accordingly, we had assumed that expecting a high reward would increase contextual cueing by facilitating attention guidance in local and in global contexts, and by strengthening the association of the repeated context configuration and the target location in learning (Bergmann et al., 2019; Tseng & Lleras, 2013). This would have been beneficial for task performance in global and in local contexts, since attention could be guided more efficiently to the target when the contexts reappeared.

The results, however, suggest that participants did not learn to expect a high or a low reward based on the color in the display. When asked for having noticed any regularities during the experiment in the post-experimental questionnaire, only about one quarter of the participants (15 of 59) reported the correct color-reward association. This suggests that the color-reward association was rather subtle and not easily recognized. Several studies have shown that participants need not be aware of the reward scheme for reward to become effective in attention guidance (Failing & Theeuwes, 2018; Feldmann-Wüstefeld et al., 2016). However, it seems striking that the color-reward association went unnoticed by so many participants, although it was consistent, and reward feedback was provided after each response and in each trial. Although immediate feedback usually facilitates learning, most of our participants missed to associate color with reward magnitude.

One aspect that might shed light on this point comes from a contextual cueing study by Zellin and colleagues (Zellin, von Mühlenen, Müller & Conci, 2013). Zellin et al. (2013) examined whether observers can transfer target location probability learning and contextual learning across contexts. In their study, the target was relocated to a new location after an initial learning phase. Target relocation was done either between two repeated contexts, or between one repeated and one novel context in which the target location was fixed and had been repeated. Results showed successful performance adaptation to relocated targets for changes between two repeated contexts, and a reversal of contextual cueing (i.e., faster RTs for novel contexts and contextual cost for repeated contexts), when the target location was exchanged between repeated and novel contexts. These findings show that learning can appear on several levels in contextual cueing tasks, namely as probability learning of target location probabilities, which accounts for learning a repeated target location also in novel contexts with non-repeating context configuration, and as contextual learning of context configurations, which accounts for the association of the target location in repeating contexts. The authors point to a third level, namely the different "contextual past" of a target: they suggest that observers also learn whether a target location has been presented in a repeated or novel context. This third-level learning explains why relocation of a target with a history of being associated with a predictive (repeated) context results in a search performance benefit, while relocation of a target without such a history resulted in contextual cost. Taken together, these findings show that a target's contextual past contributes to future search performance and thereby affects learning in contextual cueing tasks.

With regard to the present study, one might speculate whether the lack of reward effects was in part resulting from observers not being able to acquire distinct "contextual pasts" for individual target locations. In our experimental design, target locations and context types were combined in such a way that target location probability learning was explicitly prevented and observers had to focus on contextual learning. As a consequence, the design also prevented that a history of target locations that were uniquely associated with particular contexts developed (i.e., a contextual past in the sense of Zellin et al., 2013). In view of the findings of Zellin et al. (2013), for reward effects to become effective, observers might, however, need such third-level learning. In other words, observers might not only need to learn that a particular context is predictive for a target location, but the target location needs to come with a history of being bound with a unique repeating context configuration (but see Bergmann et al., 2019; Bergmann et al., 2020). Further research will help in clarifying this point.

As outlined in the previous section, the large proportion of local and global contexts in the experiment (2/3 of trials) presumably facilitated context learning. However, there was not only a large proportion, but also a large absolute number of individual local and global contexts in a block. One block contained 16 local and 16 global contexts, considerably more than in previous studies (Bergmann et al., 2019 used 24 repeated contexts; other studies used only 12). Learning that many different configurations required a lot of learning resources and, when assuming that resources are limited, learning the color-reward association might have received less priority and fewer resources, or there might have been no resources left. In line with this idea, there is evidence that resources for context configuration learning are limited, at least within one experimental session (Schlagbauer, Müller, Zehetleitner, & Geyer, 2012; Smyth & Shanks, 2008).

Interestingly, several studies reported that learning resources can become available again after contextual cueing has evolved and context learning has been consolidated. When participants perform several contextual cueing sessions separated by sleep, they have been reported to be able to learn a large amount of context configurations (Jiang, Song, & Rigas, 2005, see also Geyer et al., 2013). Thus participants might have no resources left for learning at the end of a long contextual cueing session, but regain them when starting a second contextual cueing session on the next day.

Contexts with gray and colored items

Although highly speculative, regained resources might explain why we observed differential results in session 2, but not in session 1. Because performance improved equally well with local and global contexts in session 1 (as indexed by the similar slopes), participants might have used the regained resources for focusing on other aspects of the experiment in session 2. For instance, they might have tried to figure out the role of the colored items in the experiment, or a potential relation of color and reward magnitude.

This would explain the counterintuitive finding that participants became slower in responding to colored targets than to gray targets in that session. In addition, gray was the most frequent item color, as all displays contained a set of gray items. Other colored items were less frequent and less predictive as they varied between orange and green. Accordingly, participants might have been more prepared to search though gray items, what can explain the faster responses to gray targets.

Using a contextual cueing task, Conci and von Mühlenen (2011) showed that displays with colored and non-colored items can lead to reduced contextual cueing, likely because the display is segmented into separate subsets and this segmentation interferes with contextual learning. They argue that contextual cueing is much weaker in such displays, because there are fewer items available to guide the observer to the target. It seems not unlikely that item color also led to display segmentation in the present experiment, although gray and colored items were matched in luminance and were distributed randomly across displays. This might explain why local contexts with colored targets were searched more slowly than global contexts in session 2: Because the local target patch contained only few items, segmentation was more detrimental than in global contexts. However, these considerations are speculative, and the causes of the color effects in session 2 remain open at this point.

Conclusion

The present study shows that repeating few items in contextual cueing leads to contextual cueing effects of comparable size as seen when repeating the entire context configuration. This result suggests that observers can use a repeating local target patch in a similar manner as the entire context configuration to find the target, provided that the patch retains its relative location in the global context. Our results further suggest that the proportion of local and global contexts in an experiment is crucial in context learning, because a large proportion enabled observers to successfully evaluate their predictions in the majority of the trials. This suggests that contextual cueing could be explained by mechanisms of predictive coding theories (cf., Zinchenko et al., 2018).

Keywords: contextual cueing, local and global context repetitions, reward

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