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RESEARCH ARTICLE | *The Role of Eye Movements in Perception, Cognition, and Action*

On the representational nature of value-driven spatial attentional biases

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Anderson BA, Kim H. On the representational nature of value-driven spatial attentional biases. *J Neurophysiol* 120: 2654–2658, 2018. First published October 10, 2018; doi:10.1152/jn.00489.2018.—Reward learning biases attention toward both reward-associated objects and reward-associated regions of space. The relationship between objects and space in the value-based control of attention, as well as the contextual specificity of space-reward pairings, remains unclear. In the present study, using a free-viewing task, we provide evidence of overt attentional biases toward previously rewarded regions of texture scenes that lack objects. When scrutinizing a texture scene, participants look more frequently toward, and spend a longer amount of time looking at, regions that they have repeatedly oriented to in the past as a result of performance feedback. These biases were scene specific, such that different spatial contexts produced different patterns of habitual spatial orienting. Our findings indicate that reinforcement learning can modify looking behavior via a representation that is purely spatial in nature in a context-specific manner.

NEW & NOTEWORTHY The representational nature of space in the value-driven control of attention remains unclear. Here, we provide evidence for scene-specific overt spatial attentional biases following reinforcement learning, even though the scenes contained no objects. Our findings indicate that reinforcement learning can modify looking behavior via a representation that is purely spatial in nature in a context-specific manner.

looking behavior; real-world scenes; reward learning; selective attention; spatial attention

INTRODUCTION

Attention determines which of multiple perceptual inputs are represented in capacity-limited regions of the brain (Desimone and Duncan 1995). Although attention can be directed to features and locations endogenously, in goal-directed fashion (e.g., Posner 1980; Wolfe et al. 1989), the orienting of attention can be powerfully shaped by selection history (e.g., Awh et al. 2012; Failing and Theeuwes 2018). One important component of selection history in the control of attention is reward learning (see Anderson 2016, for a review). Previously, reward-predictive stimuli automatically captured both covert (e.g., Anderson et al. 2011; Failing and Theeuwes 2014) and overt (e.g., Anderson and Yantis 2012; Theeuwes and Belopolsky 2012) attention.

Although the guidance of attention on the basis of reward-associated features (e.g., Anderson et al. 2011; Anderson and Halpern 2017; Anderson and Yantis 2012; Failing and Theeuwes 2014; Laurent et al. 2015; Theeuwes and Belopolsky 2012) and objects (e.g., Della Libera and Chelazzi 2009; Donohue et al. 2016; Hickey and Peelen 2015; Kim et al. 2015) has been well-established, controversy has arisen concerning the degree to which reward learning can bias spatial attention to valuable locations. When scenes contain objects and a correspondingly rich spatial layout, robust attentional biases are observed for regions of a given scene that participants have been consistently reinforced for orienting toward during a prior training phase (Anderson and Kim 2018). When the task involves searching for stimuli against a uniform (e.g., blank) background, however, differentially reinforcing participants for orienting toward particular regions of space does not produce a measurable bias (e.g., Anderson and Kim 2018; Jiang et al. 2015a; Won and Leber 2016; although see Chelazzi et al. 2014). Although spatial reward contingencies can bias spatial choices in a decision-making task under such objectless conditions, potentially reflecting position–reward contingencies guiding goal-directed attentional selection, such biases have not been shown to persist once the reward contingencies are no longer in play (Anderson and Kim 2018; Jiang et al. 2015a, 2015b; Won and Leber 2016). Furthermore, while spatial attentional biases in object-containing scenes have been shown to be context-specific, with different scenes evoking different spatial biases (Anderson and Kim 2018), it is unclear whether such specificity could extend to situations in which objects are not available to serve as cues to the attention system.

In light of this evidence, it could be argued that value learning does not have a direct influence on the spatial attention system that extends beyond orienting motivated by current reward considerations (see Jiang et al. 2015b; Won and Leber 2016). Although scene-based information may serve as a context for activating particular stimulus-reward associations that then guide attention (Anderson 2015a, 2015b; Anderson and Kim 2018), value-driven biases would depend fundamentally on associations linking outcomes to the features and/or objects that predict them (e.g., Anderson et al. 2011; Anderson and Yantis 2012; Della Libera and Chelazzi 2009; Donohue et al. 2016; Failing and Theeuwes 2014; Kim et al. 2015; Theeuwes and Belopolsky 2012). Furthermore, to the degree that the spatial orienting system can in fact be shaped by reinforcement

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learning in an enduring way, it is unclear what the representational basis of space would be in this situation. Different spatial contexts can give rise to different directional biases when scenes contain objects (Anderson and Kim 2018), but any direct influence of reward learning on the spatial attention system may reflect context-independent reorganization of the spatial priority map (see Chelazzi et al. 2014) rather than scene-specific orienting biases.

In the present study, we sought evidence of enduring spatial attentional biases resulting from reinforcement learning that *1*) could not be attributed to associations between reward and objects within the scene and *2*) are flexibly bound to particular scene contexts, allowing multiple different scene-specific biases to emerge. Our specific approach was informed both by situations in which enduring spatial attentional biases have not been observed using objectless scenes as well as approaches that have successfully demonstrated robust spatial biases using naturalistic scenes that do contain objects. Concerning the circumstances in which enduring value-dependent spatial biases have not been evident, all such experiments have measured attention posttraining in the context of a concurrent visual search task (Anderson and Kim 2018; Jiang et al. 2015a, 2015b; Won and Leber 2016). It is possible that reward contingencies experienced in a spatial choice task can in fact produce an enduring oculomotor bias, but this bias does not robustly transfer to the context of goal-directed visual search.

A potentially more sensitive measure of selection bias is provided by a free-viewing task, in which there is no explicit goal-directed process to compete with any effect of selection history. Highly reliable biases arising from selection history have been demonstrated in a free-viewing task using naturalistic scenes containing objects and a clearly defined spatial layout (Anderson and Kim 2018). In the present study, we applied the same approach to objectless scenes, using the same scenes that were shown to be insensitive to the consequence of selection history when measured in the context of a visual search task (Anderson and Kim 2018). These texture scenes contain a rich and naturalistic spatial context, which may be important in linking representations of space to reward (Anderson and Kim 2018), and offer a more ecologically valid manipulation of space-reward contingencies, which might facilitate spatial learning (see Won and Leber 2016).

In our experiment, participants were provided performance feedback encouraging them to orient toward a particular quadrant of four different objectless texture scenes, which we refer to as the "high-value" quadrant. The high-value quadrant was different for each scene, requiring context-specific learning (Anderson 2015a, 2015b; Anderson and Kim 2018). The consequence of this repetitive selection history was then measured using eye movements in a free-viewing task. We hypothesized that both saccades and fixations would be biased toward the region of a given texture scene that participants were previously reinforced for orienting toward, reflecting context-specific spatial attentional biases in the absence of guidance from object information.

METHODS

Participants. Thirty-six participants were recruited from the Texas A&M University community. Participants were compensated with course credit and provided written and informed consent. All reported normal or corrected-to-normal visual acuity and normal color vision. The sample size was selected to match that of all five experiments reported in Anderson and Kim (2018). All procedures were approved by the Texas A&M University Institutional Review Board and conformed with the principles outlined in the Declaration of Helsinki.

Apparatus. A Dell OptiPlex equipped with Matlab software and Psychophysics Toolbox extensions (Brainard 1997) was used to present the stimuli on a Dell P2717H monitor. The participants viewed the monitor from a distance of ~70 cm in a dimly lit room. Manual responses were recorded in the training phase using a standard computer mouse. Eye position was monitored throughout the test phase using an EyeLink 1000 Plus eye tracker running at 1,000 Hz. Head position was maintained using a chin and forehead rest (SR Research).

Training phase. Each trial began with the presentation of a scene image that filled the entire computer screen (Fig. 1). The scene remained on screen until participants clicked on it using the mouse cursor. Five-hundred milliseconds after a click was registered, feedback was presented at the center of the screen within a black box for 1,500 ms. The feedback consisted of the words "Not good," "Good!," or "Excellent!!." The feedback then disappeared while the scene remained on screen for an additional 1,000 ms, which was followed by a blank 500-ms intertrial interval.

Participants were informed that they would receive feedback each time they clicked on a scene and that this feedback would depend on where they clicked. Participants were instructed that certain locations were better to click on than others and to use the feedback to try to find the best possible locations to click on.

Four different scenes were presented, 40 times each in a random order for a total of 160 trials. The scenes were taken from images freely available on the internet and were identical to those used in

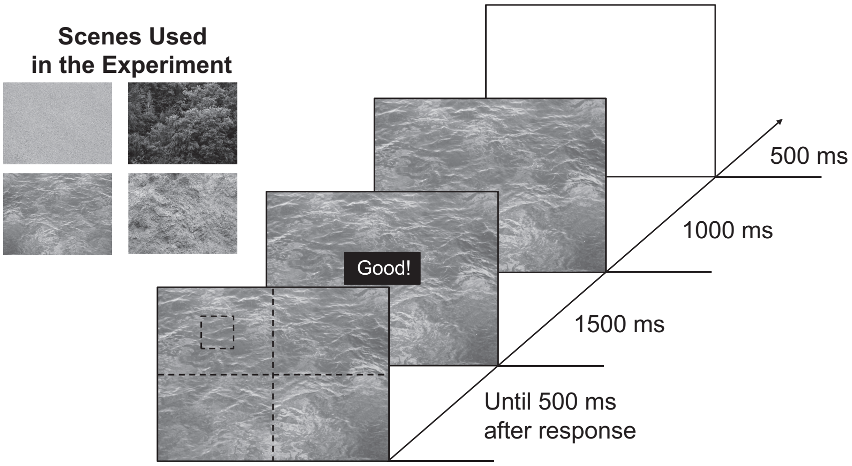

Fig. 1. Time course of trial events during the training phase. Participants clicked on a pixel each time a scene was presented, and were given performance feedback contingent upon which quadrant of the picture they had clicked on. In this example, the top left quadrant is the high-value quadrant, and clicking within the center box in that quadrant yielded the most positive feedback. The dotted lines were not visible to participants and are provided for illustrative purposes. During the subsequent test phase, participants freely viewed the scenes from training while eye position was recorded. Note that the desert scene differs slightly from the one used in the actual experiment. Scenes are availiable online: https://www.deviantart.com/roskvape/art/Rock-Texture-307459462; https://www.deviantart.com/pagan-stock/art/forest-texture-01-478458985; https://commons.wikimedia.org/wiki/File:Sand.jpg; http://textures101.com/view/3528/Plain/Ocean_Water.

experiment 3 of Anderson and Kim (2018). For each scene, one quadrant was designated as the high-value quadrant. Any click outside of the high-value quadrant yielded "Not good" feedback. If participants clicked within an imaginary 2.7 × 2.7° box centered within the high-value quadrant of a given scene, "Excellent!!" feedback was provided, and any click within this quadrant but outside of the center box was met with "Good!" feedback. The position of this 2.7 × 2.7° box was not informed by the appearance of the scenes and was arbitrarily chosen to be centered within each high-value quadrant. Participants were assigned to one of four training conditions in counterbalanced fashion, with each quadrant of each scene serving as the high-value quadrant in one of the four conditions.

Test phase. The test phase consisted of two blocks of 32 trials, during which each of the scenes used during training was presented 8 times for 5,000 ms each in a random order. Eye position was calibrated at the beginning of each block using nine disks presented sequentially on a 3–3 grid spanning the range of the monitor (9-point calibration). Participants were informed that there was no specific task to perform and that they were free to look around the images however they wished. Due to a programming error, the last trial in each block was not presented (and therefore not analyzed).

Data analysis. To assess learning, in the training phase, the percentage of clicks in the high-value quadrant was computed for each presentation of each scene, and then averaged across the four different scenes. For the test phase, we compared two indexes of attentional bias between the previously high-value quadrant and the average of the three previously low-value quadrants. The first was total fixation time, summed over all fixations within each quadrant, and the second was the number of gaze shifts to each quadrant. Saccades were defined as occurring when velocity exceeded 35°/s and acceleration exceeded 9,500°/s^2. Fixation durations did not include blinks or epochs during which the image of the pupil was otherwise distorted or lost (which were registered as blinks). Saccades landing and fixations occurring outside of the boundaries of the area covered by the monitor were discarded. In defining gaze shifts and fixation time, four areas of interest were drawn, each encompassing an entire quadrant of the screen minus a 0.5° band separating the quadrants (to minimize ambiguity arising from margin-for-error in measured eye position); fixations occurring or saccades landing within this 0.5° band were not counted toward any of the four quadrants. A gaze shift was defined as when a saccade landed within a different area of interest than where it originated. In a follow-up analysis examining the first shift of gaze, only trials on which eye position did not begin in the high-value quadrant were analyzed, and the percentage of gaze shifts to the high-value quadrant was measured for each participant (as in Anderson and Kim 2018).

RESULTS

Training phase. The percentage of clicks on the high-value quadrant differed across scene presentation [$F(39,1365) = 21.59$, $P < 0.001$, $\eta^2_p = 0.381$], exhibiting a learning curve that was well accounted for by a linear trend [$F(1,35) = 68.21$, $P < 0.001$, $\eta^2_p = 0.661$; see Fig. 2]. By the 18th presentation of each scene, participants asymptoted at ~85% selection of the high-value quadrant. All but three participants selected the high-value quadrant at least 60% of the time, selecting it on 95% of the trials over the last 10 presentations of each scene, indicating robust learning of the contingencies. The highest value region within the center of the high-value quadrant was only clicked on 10.2% of trials across participants, and 20 of the 36 participants never clicked on this region on any trial.

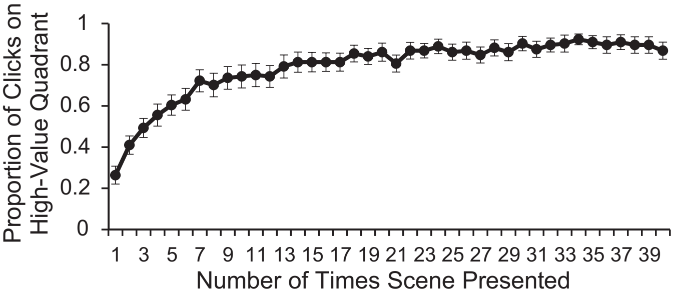

Fig. 2. Mean proportion of clicks on the high-value quadrant across each of forty presentations of each scene (averaged over the 4 different scenes used). Error bars are means ± SE.

Test phase. Eye movements were robustly biased toward the previously high-value quadrant during free viewing. Participants spent a longer amount of time fixating the previously high-value quadrant ($M = 1498$ ms, SD = 767 ms) compared with the other three quadrants [$M = 777$ ms, SD = 224 ms, $t(35) = 4.54$, $P < 0.001$, $d = 0.76$]. Participants also shifted gaze more frequently to the previously high-value quadrant ($M = 1.063$, SD = 0.288) compared with the other three quadrants [$M = 0.841$, SD = 0.297, $t(35) = 4.49$, $P < 0.001$, $d = 0.75$; see Fig. 3].

Discovering the highest value region during training was associated with significantly larger oculomotor biases. The difference between the high- and low-value quadrants was larger for participants who clicked on the highest value region at least once during training ($n = 16$) than it was for those who never clicked on it ($n = 20$) for both fixation duration [$t(34) = 2.06$, $P = 0.047$, $d = 0.67$ (1,071 vs. 441 ms)] and shifts of gaze [$t(34) = 2.39$, $P = 0.023$, $d = 0.79$ (0.347 vs. 0.123)]. Even for participants who never clicked on the highest value region, both indicators of bias were still significantly greater than zero ($P < 0.03$).

The observed oculomotor biases were evident as early as the initial shift of gaze. When eye position began in a low-value quadrant, 48.6% (SD = 17.8%) of initial gaze shifts were made to the high-value quadrant, which was significantly more than would be expected from unbiased selection [33.3%, $t(35) = 5.16$, $P < 0.001$, $d = 0.86$].

DISCUSSION

The representational nature of space-based attentional biases, as shaped by selection history, has been the subject of debate. Robust spatial attentional biases, capable of transferring to a goal-directed attention task, have only been evident using naturalistic scenes where objects can be used to anchor spatial representations (Anderson and Kim, 2018; Jiang et al. 2015a; Won and Leber 2016). Whether and how reinforcement learning can bias spatial attention without guidance from object-based representations are not known, and questions have been raised concerning the extent to which the spatial attention system is itself sensitive to reward history (see Won and Leber 2016).

The present study suggests that selection history can shape the attention system in an enduring way that is distinctly spatial in its representation; even when there are no objects present to guide learning or attention, regions of scenes that participants have been previously reinforced for orienting toward show evidence of elevated priority in a subsequent test phase. This distinctly spatial bias is context specific, as it differed for different scenes, thus attesting to its ecological validity (see

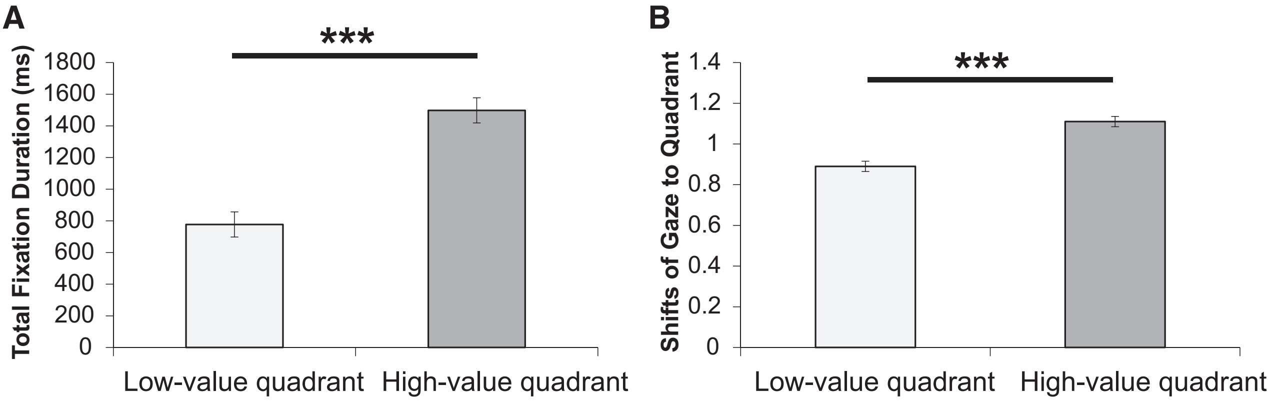

Fig. 3. Eye position data. *A*: total fixation duration, summed over all fixations within a quadrant, for the high-value compared with the average of the low-value quadrants, averaged over each scene presentation. *B*: number of saccades made to the high-value compared with the average of the low-value quadrants, averaged over each scene presentation. Error bars are within-subjects SE. ***$P < 0.001$.

Won and Leber 2016). Participants who discovered the highest value region to click on showed the largest biases, attesting to the value dependence of the effect. When in a familiar environment, rather than direct overt attention to previously less-explored regions of a space (novelty bias: Johnston et al. 1990; Johnston and Schwarting 1997), humans exhibit a robust tendency to direct their gaze to regions they have been reinforced for frequently orienting to in the past, engaging in habit-like orienting behavior.

The information contained within scenes has previously been shown to serve as a rich source of spatial guidance. In particular, eye movements are drawn toward regions of scenes where targets have been found more frequently in the past, a phenomenon referred to as scene-based contextual cueing (Brockmole and Henderson 2006a, 2006b; Brockmole et al. 2006; see also Chun and Jiang 1998). In the present study, we extend this phenomenon to learning from performance feedback and further demonstrate that objects within scenes are neither necessary to promote the value-dependent learning and expression of attentional bias nor to provide a context with which to link different spaces with outcomes.

The present study involved a spatial choice task in which participants were explicitly required to orient to and select different regions of scenes in an effort to maximize the quality of performance feedback. An interesting question for future research concerns the necessity of this spatial decision-making component and whether more incidental relationships between spatial orienting and outcomes would be sufficient to bias future eye movements (Jiang et al. 2015a; Won and Leber 2016). Unlike prior studies using a spatial choice task during training and a visual search task during extinction (Jiang et al. 2015b; Won and Leber 2016), including a study using the same scene images (Anderson and Kim 2018), we demonstrate an enduring spatial attentional bias using a free-viewing task. One possible explanation for these different outcomes is that any value-dependent spatial biases learned in a spatial choice task are overridden by the engagement of active search routines during goal-directed visual search, limiting the influence of such biases.

Another interesting question concerns the timing of spatial orienting and corresponding feedback. The design of the training phase involved presenting feedback very quickly after orienting to and selecting a region of the scene, and the task encouraged a close temporal relationship between scene presentation and selection-for-reward, promoting a state of response readiness (see, e.g., Langner et al. 2018; Los et al. 2017; Steinborn et al. 2017). The degree to which the learning or expression of the observed biases depends on such conditions is unclear, and future research might explore the boundary conditions for linking scenes to the orienting responses that produce the greatest reward.

Concerning the specific representational nature of the spatial learning evident in the present study, two possibilities must be considered. One possibility is that participants associated a specific region of space in a cognitive map (O'Keefe and Nadel 1978) or gridlike representation (Hafting et al. 2005) with reward, while a second possibility is that participants associated reward with the act of generating a contextually specific directional saccade, akin to the distinction between place vs. response learning in the animal learning literature (e.g., Packard and McGaugh 1996; Tolman 1948). Another unanswered question concerns the manner in which objects and space-based considerations interact when the two are simultaneously present in displays, both in the context of learning (are rewards preferentially associated with objects over space when both simultaneously predict reward, with one overshadowing the other?) and the expression of learning (if a reward-associated object is placed outside of a high-value region of a scene and competes for selection, would one of these two associations preferentially guide attention?). Finally, the present study used four different scenes in the manipulation of spatial context, and an open question remains the upper bound of memory capacity for such scene-specific spatial memories. To the degree that the observed spatial biases rely on activated long-term memory representations (e.g., Woodman et al. 2013), a massive storage capacity might be expected (Wolfe 2012), which would attest to the ecological validity of the underlying system (see Won and Leber 2016).

The results of the present study speak to the manner in which individuals direct their gaze when exploring the visual world. Visual exploration is shaped by selection history through abstracted spatial representations that can influence gaze without having to interface with representations of objects. Scenes activate contextually specific memories for regions of space that an organism has been more highly rewarded for orienting toward in the past, and such memories bias eye movements during visual exploration.

GRANTS

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DISCLOSURES

No conflicts of interest, financial or otherwise, are declared by the authors.

AUTHOR CONTRIBUTIONS

B.A.A. and H.K. analyzed data; B.A.A. and H.K. interpreted results of experiments; B.A.A. and H.K. prepared figures; B.A.A. drafted manuscript; B.A.A. and H.K. edited and revised manuscript; B.A.A. and H.K. approved final version of manuscript; H.K. performed experiments.

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