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Egocentric Coding of Space for Incidentally Learned Attention: Effects of Scene Context and Task Instructions

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Visuospatial attention prioritizes regions of space for perceptual processing. Knowing how attended locations are represented is critical for understanding the architecture of attention. We examined the spatial reference frame of incidentally learned attention and asked how it is influenced by explicit, top-down knowledge. Participants performed a visual search task in which a target was more likely to appear in one, "rich," quadrant of the screen than in the others. The spatial relationship between the display and the viewer's perspective changed partway through the experiment. Because incidentally learned attention is persistent, the spatial bias that developed during training was present following the change in viewer perspective. Despite the presence of multiple environmental landmarks including a background scene, participants prioritized rich regions relative to their perspective, rather than relative to the environment. Remarkably, the egocentric attentional bias was unaffected by explicit knowledge of where the target was likely to appear. Although participants used this knowledge to prioritize the region of space they were told was likely to contain a target, a strong egocentric bias to a region that was unlikely to contain a target persisted. These data indicate that incidental attention differs fundamentally from attention driven by explicit knowledge. We propose that attention takes 2 forms. One is declarative, based on maps that explicitly prioritize some regions of space over others. The other is procedural, influenced by implicit knowledge that modulates how attention is moved through space.

Keywords: attention, location probability learning, probability cuing, spatial reference frame, explicit and implicit learning

A fundamental problem of spatial attention is characterizing the way attended locations are coded. At least two possibilities have been proposed. First, spatial attention may be conceptualized as a priority map, driven by perceptual salience and the observer's goals, that enhances the perceptual representation of attended objects (Bisley & Goldberg, 2010; Egeth & Yantis, 1997; Fecteau & Munoz, 2006; Itti & Koch, 2001; Treisman, 1988; Wolfe, 2007). Second, the relationship between attention and action has been emphasized with the suggestions that attention piggybacks on motor planning systems or is primarily for the control of action (Allport, 1989; Driver, 2001; Rizzolatti, Riggio, Dascola, & Umiltà, 1987). Two major dimensions on which *attention maps* and *attention-for-action* may differ are in their spatial reference frame and in their accessibility to conscious awareness. Whereas the perceptual system commonly codes visual input in an object-centered reference frame, the action system is egocentric and less accessible to awareness (Goodale & Haffenden, 1998). This study characterizes the spatial reference frame of attention in a visual search task.

Spatial Reference Frame of Attention

Studies of numerous attentional phenomena suggest that spatial attention relies on multiple frames of reference (Behrmann & Tipper, 1999). When lying down, patients with hemifield neglect have difficulty identifying stimuli on the left side of their body and the left side of space assuming an upright posture (Calvanio, Petrone, & Levine, 1987; Farah, Brunn, Wong, Wallace, & Carpenter, 1990). In inhibition of return (Posner & Cohen, 1984), inhibited locations sometimes remain in the same position relative to the eyes soon after an eye movement (i.e., they are coded *retinotopically*; Abrams & Pratt, 2000; Mathôt & Theeuwes, 2010). However, with sufficient time, inhibited locations can be coded spatiotopically (Cavanagh, Hunt, Afraz, & Rolfs, 2010; Wurtz, 2008), with inhibition remaining at the original screen location following a saccade (Mathôt & Theeuwes, 2010; Maylor & Hockey, 1985; Pertzov, Zohary, & Avidan, 2010; Posner & Cohen, 1984). The use of multiple reference frames also occurs with negative priming (Tipper, 1985; Tipper, Driver, & Weaver, 1991; Tipper, Howard, & Houghton, 1998), spatial memory (Golomb, Chun, & Mazer, 2008; Golomb, Pulido, Albrecht, Chun, & Mazer, 2010), and spatial priming (Ball, Smith, Ellison, & Schenk, 2009, 2010). For example, when a spatial location is encoded into memory, attention stays at the same retinal location

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after a saccadic eye movement (Golomb et al., 2008). However, attention to the remembered screen location emerges when that location is task relevant and when there is sufficient time for spatiotopy to develop (Golomb et al., 2010).

The use of multiple reference frames is consistent with the idea that attention is a heterogeneous construct (Chun, Golomb, & Turk-Browne, 2011; Driver, 2001; Egeth & Yantis, 1997; Pashler, 1994; Treisman, 2009). Different types of attention may rely on different frames of reference. This study investigates the spatial reference frame of incidentally learned attention and asks how it is influenced by scene context and explicit instructions.

Incidentally Learned Attention

Incidental learning of the statistical regularities of the environment is a powerful mechanism in perception and attention. The human visual system is sensitive to the co-occurrence of objects (Fiser & Aslin, 2001; Turk-Browne, Junge, & Scholl, 2005), locations (Chun & Jiang, 1998), and motion trajectories (Makovski, Vazquez, & Jiang, 2008). Statistical learning also affects spatial attention. In contextual cuing, participants are faster at finding a target when it appears in a search display that occasionally repeats (Chun & Jiang, 1998). In probability cuing, participants develop a spatial bias toward locations that frequently contained a target in the past (Druker & Anderson, 2010; Geng & Behrmann, 2002, 2005; Jiang, Swallow, Rosenbaum, & Herzig, 2013; Miller, 1988). Incidental learning of statistical regularities changes standard signatures of spatial attention. In contextual cuing, the *N2pc* component of the event related potential (Luck, 2006), an indicator of spatial attention, is greater for repeated displays than for unrepeated ones (Johnson, Woodman, Braun, & Luck, 2007). In probability cuing, visual search is more efficient when a target appears in high-probability locations than in low-probability locations (Jiang, Swallow, & Rosenbaum, 2013). Incidentally learned attention is also highly persistent, with both contextual cuing and probability cuing lasting for at least one week (Chun & Jiang, 2003; Jiang, Song, & Rigas, 2005; Jiang, Swallow, Rosenbaum, & Herzig, 2013).

How are attended locations coded during incidental learning? One possibility is that because incidental learning reflects stable properties of the environment, the attended locations may be coded relative to the external world. However, it is also possible that incidentally learned attention is coded relative to the viewer. The parietal cortex, which is critical for spatial attention, codes space in a viewer-centered framework (Andersen, Snyder, Bradley, & Xing, 1997; Saygin & Sereno, 2008).

Several studies have examined the viewpoint specificity of one form of implicitly learned attention–contextual cuing–but with inconsistent results. Chua and Chun (2003) asked participants to conduct visual search on computer-generated 3-D displays. Some displays were shown repeatedly, and incidental learning of these displays facilitated search. After the displays were learned, they were rotated in depth. Chua and Chun found that contextual cuing was abolished after a 30° rotation. In a second study, Tsuchiai, Matsumiya, Kuriki, and Shioiri (2012) contrasted the effect of display rotations with viewer movements. They found that contextual cuing was disrupted by a 30° display rotation. However, it persisted when a 30° viewpoint change was produced by viewer movement. Although the contrast between display rotation and viewer movement is important, the ability to interpret these data is compromised by the complexity of contextual cuing. Contextual cuing occurs in response to a display that has been previously encountered. For this to occur, the current display must be matched to a learned configuration. Even if attentional cuing itself is viewpoint invariant, implicit learning and retrieval of the display may be viewpoint specific. This complexity diminishes the utility of contextual cuing in the investigation of the spatial reference frame of attention.

In contrast to contextual cuing, probability cuing occurs for randomly generated displays. When a target is more frequently found in some locations than in others over multiple trials, a general attentional bias toward these high-probability locations develops (Druker & Anderson, 2010; Geng & Behrmann, 2002, 2005; Jiang, Swallow, Rosenbaum, & Herzig, 2013; Miller, 1988). Probability cuing yields large effects in visual search, comparable to those of goal-driven attention (e.g., directed by a central arrow; Jiang, Swallow, & Rosenbaum, 2013). In a recent study, Jiang and Swallow (2013) examined the spatial reference frame used in probability cuing. Participants conducted visual search on displays that were laid flat on a tabletop. In the first phase of the task (training), the probability that the target would appear in a high-probability "rich" quadrant was 50%, significantly higher than chance. By the end of training, participants found the target more quickly when it appeared in the rich quadrant than in any of the sparse quadrants.

Two changes in the task were made for the second, testing phase of the experiment. First, the target was equally likely to appear in any quadrant (25%). Any spatial bias during testing therefore would reflect the persistence of incidentally learned attentional biases. Second, participants were reseated to another side of the table to produce a 90° change in viewpoint. Jiang and Swallow (2013) found that the spatial bias that developed during training rotated with the viewer. Rather than being directed to the region of the screen that was likely to contain the target, the spatial bias was now directed to a part of the display that rarely contained the target during training. The same pattern of data occurred when the display was presented briefly to curtail saccadic eye movements, ruling out oculomotor learning as an explanation.

Jiang and Swallow (2013)'s findings are among the clearest evidence, to date, of the egocentric nature of spatial attention. Two major limitations, however, constrain the generalizability of the findings. First, although participants could use the room furniture to establish an environment-centered representation, rich environmental cues were far from the visual search display and irrelevant to the task. The viewer-centered representation may have dominated simply because the environmental cues were weak. To demonstrate that probability cuing is egocentric and not updated following a viewpoint change, it is necessary to conduct experiments in which the environmental cues are strong. To address this limitation, we placed search items over a rich visual scene in the current study. Previous studies on scene-based contextual cuing have shown that a background scene is highly salient in visual search (Brockmole & Henderson, 2006a, 2006b; Rosenbaum & Jiang, 2013), increasing the likelihood that it will be used to establish an environment-centered representation.

The second feature that limits the generalizability of Jiang and Swallow's (2013) findings is the nature of awareness: Participants in that study acquired probability cuing via incidental learning.

This condition differs from many real-world search situations in which people are aware of the locations that are likely to contain important items (Brockmole, Castelhano, & Henderson, 2006; Brockmole & Henderson, 2006a, 2006b; Rosenbaum & Jiang, 2013). Awareness could change the nature of location probability learning, possibly yielding an environment-centered rather than viewer-centered representation (Liu, Lungu, Waechter, Willingham, & Ashe, 2007).

Overview of Experiments

The present study investigated the impact of background scenes and task instructions on the spatial reference frame of probability cuing. In particular, we examined whether the egocentric attentional bias generalizes to conditions in which a natural scene is displayed in the background and participants are explicitly told where to find the target-rich locations. If the egocentric nature of probability cuing is restricted to situations with impoverished search displays and under conditions of incidental learning, the viewer-centered bias should not be present in these experiments.

We conducted five experiments using a monitor laid flat on a table. In all experiments, participants searched for a T target among L distractors. The items were displayed against a natural scene that remained constant throughout the experiment. All experiments consisted of training and testing phases. In the training phase, the target was more likely to appear in one quadrant of the screen than in the others. Across multiple trials, the target was found in the rich quadrant 50% of the time and in any one of the sparse quadrants 16.7% of the time. Which quadrant was rich was counterbalanced across participants but was fixed for a given participant. In the testing phase, the target was equally likely to appear in any quadrant (it appeared in each quadrant 25% of the time; see Figure 1). Between the training and testing phases, the experimenter turned the monitor or the participants moved to another side of the table. We examined whether the spatial bias toward the rich quadrant persisted in the testing phase. Of critical importance, however, was whether the spatial bias was stable relative to the external environment or relative to the viewer.

Participants in Experiments 1 and 2 received no information about where the target was likely to appear. In Experiment 1, participants sat at the same place in the training and testing phases. However, the experimenter turned the monitor 90° as the participants watched. In Experiment 2, participants moved their chair to another side of the table. If probability cuing is viewer centered, then in both conditions the bias should result in the prioritization of a new part of the scene. If the presence of the background scene facilitates spatial updating or leads to an environment-centered representation of attended locations, the spatial bias should stay in the part of the scene where the target was most often found. Experiments 1 and 2 differed primarily in whether the rotation occurred to the display or to the participant's perspective.

At the beginning of the experiment, participants in Experiments 3 and 4 were explicitly told where the target was likely to appear and were encouraged to prioritize the rich quadrant. This instruction added an intentional component to probability cuing. Following training, participants moved to another side of the table, producing a 90° viewpoint change. We examined whether probability cuing remained egocentric under conditions of intentional learning. The two experiments differed in the instructions given to participants in the testing phase. In Experiment 3, participants were told that the target would be equally likely to appear in any quadrant during testing and encouraged to abandon any systematic biases toward parts of the display. In Experiment 4, participants were encouraged to continue favoring the part of the screen where the target was most often found during training. Experiments 5a and 5b were identical to Experiments 3 and 4, except that explicit instructions were given only in the testing phase. These experiments therefore tested whether probability cuing was egocentric when learning was intentional and whether the bias was sensitive to different task strategies imposed on the participants.

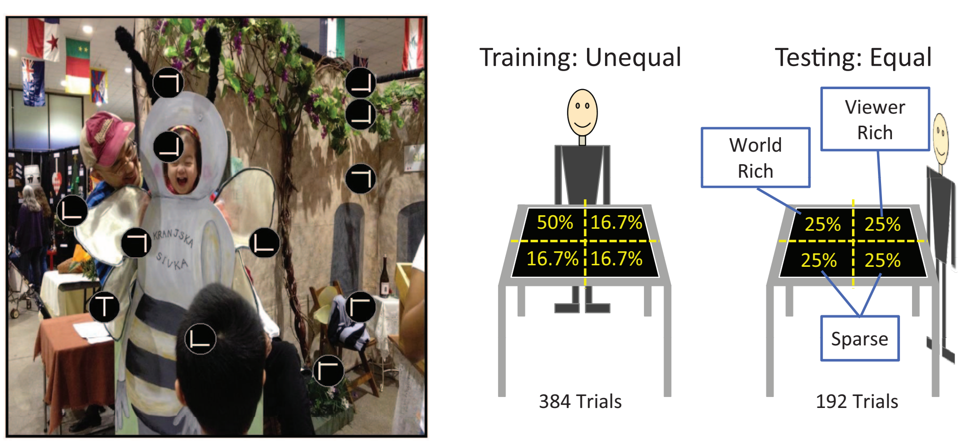

Figure 1. Left: A sample display. Participants searched for a T target among L distractors and reported its color (slightly red or slightly green) over a natural scene. Items were displayed on a monitor laid flat on a table. Right: Experimental setup and design. The likelihood that the target would appear in each quadrant of the display was unequal in the training phase but equal in the testing phase. Participants moved to a new search position between the two phases (Experiments 2–5), or they stayed in the same position but watched the experimenter turn the monitor 90° (Experiment 1).

Section 1: Incidental Learning

The first two experiments examined whether incidentally learned attention was environment-centered or viewer-centered.

Experiment 1: Incidental Learning Followed by Display Rotation

The presence of a natural scene in visual search provides a stable landmark for spatial attention. Previous research on scene-based contextual cuing has shown that even though the scene is not part of the search task, participants often notice the scene and associate it with the target's location (Brockmole et al., 2006; Brockmole & Henderson, 2006a, 2006b; Rosenbaum & Jiang, 2013). In Experiment 1, we examined whether the presence of a single scene during the search task changes the nature of probability cuing. In particular, we examined whether probability cuing moves with the scene when the display is rotated (scene-centered), or whether it remains in the same location relative to the viewer (viewer-centered).

Method.

Participants. Participants in this study were students at the University of Minnesota (age range = 18–35 years). A prespecified sample size of 16 was tested in all experiments. All participants provided informed consent, had normal or corrected-to-normal visual acuity, passed a color blindness test, and received $10/hour or extra course credit for their time. There were 5 male and 11 female participants in Experiment 1, with a mean age of 19 years.

Equipment. Participants were tested individually in a dimly lit room. A 19-in. LCD monitor (1,168 × 876 pixels) was laid flat at one corner of a rectangular table. Viewing distance was unconstrained (approximately 35–60 cm) and varied according to the participant's height. Visual angles in the method section are provided with an assumed distance of 57 cm. The experiment was programmed with MATLAB (www.mathworks.com) and Psychophysics Toolbox (Brainard, 1997; Pelli, 1997).

Materials. Participants conducted visual search for a T target among L distractors (1.20° × 1.20°), which were each lightly tinted red or green and presented in a black circle (1.70° radius). Items were presented at randomly selected locations within a 10 × 10 invisible matrix (18° × 18°). The orientation of each item was randomly selected from four possible orientations (0°, 90°, 180°, and 270°), which ensured that the items did not change their appearance after the display rotation (or after viewer movement in subsequent experiments). Items were displayed over a natural scene that was constantly in view throughout the experiment.

At the start of the experiment, half of the participants sat at the side of the table near the long edge of the monitor. The other half sat at the side near the short edge of the monitor. An indoor or outdoor scene was displayed constantly in the background of the search display. The scene was upright for half the participants but sideways for the other half. In all experiments we obtained the same pattern of results for people who sat at different positions. After the monitor rotation (see below), the scene was sideways for the first group of people and upright for the second. For each participant, a random scene was chosen from a set of 48 (35 indoor and 13 outdoor scenes, each 24° × 24°) sampled from the Internet or personal collections. This scene remained the same throughout the experiment.

Design. After 10 practice trials involving a different scene, participants were tested in the main experiment in 576 trials. The first 384 trials constituted the training phase; the last 192 trials were the testing phase. In the training phase, the target appeared in a "rich" quadrant on half of the trials (50% probability) and in each of the other three "sparse" quadrants on 16.7% of the trials. Which quadrant was rich was counterbalanced across participants but kept constant throughout the training phase. At the end of the training phase, an experimenter turned the monitor 90° while the participants watched. The testing phase then began, during which the target appeared in each quadrant 25% of the time. As in our previous published work (Jiang & Swallow, 2013), we did not provide a cover story to participants regarding the display rotation (this experiment) or viewer rotation (subsequent experiments).

Participants should acquire probability cuing during training, and this learned spatial bias should persist during testing (Jiang & Swallow, 2013; Jiang, Swallow, Rosenbaum, & Herzig, 2013). Of interest is where that bias is directed after the display rotation, which dissociated the scene/monitor reference frames (referred to as *scene-rich* for brevity) from the viewer/room reference frames (referred to as *viewer-rich*). After rotation, the part of the scene where the target was most often found during training was the scene-rich quadrant. The part of the scene that was now in the same location as the previously rich quadrant relative to the viewer (e.g., the viewer's lower right) was the viewer-rich quadrant. The other two quadrants were the sparse quadrants.

Task and procedure. Each trial started with a central fixation square (0.6° × 0.6°) appearing at random locations within the central 1.5°. Participants clicked on the square to initiate a trial. The mouse click required eye–hand coordination and ensured that eye position was roughly centered before each trial. A display of one T and 11 Ls was then presented. The items were nearly white displayed against a black circle (see Figure 1). There were always three items in each quadrant. Half of the items were tinted slightly red (RGB values [255 245 245], and the other half were tinted slightly green (RGB values [230 250 230]). The participants' task was to find the T and report its color by pressing one of two keys as quickly and as accurately as possible. The search items were erased after the keypress response, but the scene remained on the display. The color discrimination task was unaffected by changes in viewpoint. The very light tinting of the items ensured that participants were not searching through just one set of items (e.g., judging whether T was among the red items). A correct response was followed by three rising tones that lasted for a total of 300 ms. An incorrect response was followed by a buzz (200 ms) and a 2-s timeout.

Scene recognition. Because we were interested in the effect of the background scene on probability cuing, we tested scene recognition memory to ensure that participants noticed and remembered the scene. Four scenes, including the one displayed in the experiment, were shown in four quadrants of the display. The foils were chosen randomly from the entire set of 48 scenes. Participants selected the scene that was present during the search task. Although all scenes were visually distinct, some were semantically similar (e.g., several living room scenes). Participants did not know that their memory would be tested and could not anticipate the nature of the foils. Because the foils were chosen randomly, a correct response could be based on conceptual memory, perceptual memory, or both.

Location probability recognition. After the scene recognition response, participants were asked whether they thought the target was evenly distributed or whether it was more often found in some locations than in others. Regardless of their response, participants were then told that the target was not evenly distributed and were asked to click on where they thought they found the target most often. The scene remained in view during the location probability recognition test.

Results and Discussion. We first examined recognition accuracy for the background scene. Fifteen of the 16 participants accurately identified the scene. We excluded the participant who failed the scene recognition test from the analysis. The same exclusion criterion was applied to all experiments. In no experiments did the exclusion of participants change the pattern of results.

Training phase. Although the color discrimination task was difficult, participants achieved 97% accuracy in the training phase. Accuracy was slightly but not significantly higher when the target was in the rich quadrant (97.5%) rather than in one of the sparse quadrants (96.5%, $p = .10$). For this and all subsequent experiments, we focused on reaction time (RT), excluding incorrect trials and trials with an RT under 200 ms (0.38% of the trials in Experiment 1) or over 10,000 ms (0.13% of the trials in Experiment 1). Few trials were eliminated as outliers in subsequent experiments (0.19% in Experiment 2, 0.58% in Experiment 3, 0.30% in Experiment 4, 0.47% in Experiment 5a, and 0.15% in Experiment 5b). Figure 2 shows mean RT from the training phase, separately for trials in which the target appeared in the rich and sparse quadrants. Trials were divided into 32 blocks to show the progression of training.

An analysis of variance (ANOVA) with condition (rich or sparse) and block (1–32) revealed a significant main effect of condition, $F(1, 14) = 41.53$, $p < .001$, $\eta_p^2 = .75$. Participants found the target faster when the target was in the rich quadrant rather than in a sparse quadrant. The main effect of block was also significant, $F(31, 434) = 2.88$, $p < .001$, $\eta_p^2 = .17$. RT declined as the experiment progressed. The interaction between the two factors was not significant, $F(31, 434) = 1.07$, $p > .30$. The gradual increase in probability cuing was revealed by a significant linear trend in the interaction between block and condition, $F(1, 14) = 8.19$, $p < .013$, $\eta_p^2 = .37$. The RT difference between sparse and rich conditions increased as training progressed.

Testing phase. Accuracy in the testing phase was 96.9% ($SE = 0.7\%$) in the sparse quadrants, 95.7% ($SE = 1.2\%$) in the scene-rich quadrant, and 96.9% ($SE = 0.6\%$) in the viewer-rich quadrant. The difference was not significant, $F(2, 28) = 1.59$, $p > .20$.

Mean RT for correct trials, excluding outliers (see training data analysis), was calculated for each participant. The average across the entire testing phase is shown in Figure 3A. An ANOVA on target quadrant condition (sparse, scene-rich, or viewer-rich) revealed a significant main effect, $F(2, 28) = 22.01$, $p < .001$, $\eta_p^2 = .61$. Planned contrasts showed that the viewer-rich condition was significantly faster than both the sparse condition, $t(14) = 5.56$, $p < .001$, and the scene-rich condition, $t(14) = 6.55$, $p < .001$. The latter two did not differ from each other, $t(14) = 0.22$, $p > .50$.

Because the target was equally likely to appear in any quadrant during the testing phase, the effects of target quadrant reflected the long-term persistence of probability cuing. To examine whether probability cuing weakened in the testing phase, we divided the 192 trials into eight epochs of 24 trials each. As shown in Figure 3B, RT was significantly affected by target quadrant condition, $F(2, 28) = 22.47$, $p < .001$, $\eta_p^2 = 0.62$. The spatial bias toward the viewer-rich quadrant remained strong throughout the testing phase, leading to a lack of an interaction between quadrant condition and epoch ($F < 1$).

Location probability recognition. Valid location probability recognition data were obtained from seven participants,[1] among which one person indicated that the viewer-rich quadrant was where the target was most often found. Three people identified the scene-rich quadrant, and three others identified a sparse quadrant as the high-probability quadrant. Because only one person identified the quadrant in which search was faster during testing, recognition performance did not correspond to the pattern of visual search performance.

The data from Experiment 1 are consistent with the claim that incidentally learned attentional biases to high-frequency locations are coded within a viewer-centered reference frame but not relative to the background scene. The presence of clear landmarks failed to induce a scene-based attentional bias. However, it is also possible that the bias was coded relative to the larger environment (e.g., the room), which remained stable after display rotation, or that the participants failed to update the location of the rich quadrant within the scene. The next experiment addresses these two issues.

Experiment 2: Incidental Learning Followed by Viewer Locomotion

Spatial updating is often more successful with viewer movement than with display rotation (Rieser, 1989; Simons & Wang, 1998; Wang & Simons, 1999). With viewer movement, participants may be better able to update the spatial bias to redirect attentional prioritization to the environment-rich regions. To test this possibility, in Experiment 2 participants moved to a seat that changed their viewpoint by 90°. The design of this experiment is illustrated in Figure 1. Viewer movement also dissociates the viewer-centered reference frame from multiple environment-centered reference frames, including the room, the monitor, and the background scene. If the presence of a scene enhances spatial updating, probability cuing should be directed to the part of the monitor, scene, and world where the target was most often found in the past.

Method.

Participants. Sixteen new participants completed Experiment 2. There were 4 male and 12 female participants, with a mean age of 19.6 years.

Design and procedure. The training phase of Experiment 2 was identical to that of Experiment 1. At the end of training, an experimenter asked participants to move their seat to an adjacent edge of the table. Half of the participants moved clockwise, and

[1] Eight of the participants viewed the display sideways during testing. These participants turned the monitor back to an upright orientation to read the recognition test instructions. By doing so they realigned the scene-based and viewer-based reference frames, making it impossible to tell whether their choice was scene-based or viewer-based.

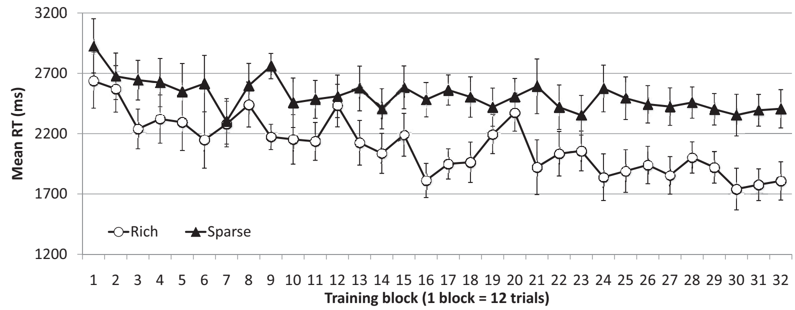

Figure 2. Results from the training phase of Experiment 1. Error bars show ±1 *SE* of the difference between the rich and sparse quadrants. RT = reaction time; *SE* = standard error.

the others moved counterclockwise. Nothing else in the room changed. Participants then completed the testing phase. Just like Experiment 1, the likelihood that a target would appear in each quadrant was unequal in the training phase but equal in the testing phase (see Figure 1). Following viewer movement, the target could fall into three types of quadrants: The environment-rich quadrant was the quadrant on the monitor (as well as in the scene and room) where the target was often found; the viewer-rich quadrant was in the same location as the previously rich quadrant relative to the participant (e.g., to their upper left); and the sparse quadrants were the other two quadrants (see Figure 1).

We tested memory for the scene at the completion of the experiment. Participants also clicked on the display to report where they thought the target was most often found.

Results. Thirteen of the 16 participants correctly identified the scene used in the experiment. Our analysis was restricted to these participants, as evidence suggested that they had noticed and attended to the scene.

Training phase. Accuracy in the training phase was 96.5% in both the rich and sparse conditions. RT data were analyzed in the same way as in Experiment 1. Figure 4 shows data from the training phase.

An ANOVA on target quadrant condition and block revealed significant main effects of quadrant condition, $F(1, 12) = 33.26$, $p < .001$, $\eta_p^2 = .74$; and block, $F(31, 372) = 4.59$, $p < .001$, $\eta_p^2 = .28$; as well as a significant interaction, $F(31, 372) = 2.25$, $p < .001$, $\eta_p^2 = .16$. The linear trend in the interaction term was also significant, $F(1, 12) = 8.42$, $p < .013$, $\eta_p^2 = .41$. Thus, probability cuing toward the rich quadrant developed during training.

Testing phase. Search accuracy in the testing phase was 94.6% ($SE = 0.8\%$) in the sparse condition, 96.2% ($SE = 0.9\%$) in the environment-rich condition, and 95.2% ($SE = 1.0\%$) in the viewer-rich condition. Accuracy was statistically equivalent among the three conditions, $F(2, 24) = 1.09$, $p > .35$.

Probability cuing persisted in the testing phase: Target quadrant significantly affected RT across the entire testing phase (see Figure 5A), $F(2, 24) = 5.69$, $p < .01$, $\eta_p^2 = .32$. Planned contrasts showed that participants were significantly faster in the viewer-rich condition than both the sparse condition, $t(12) = 3.97$, $p < .002$, and the environment-rich condition, $t(12) = 2.17$, $p = .05$. The latter two conditions did not differ significantly, $t(12) = 0.62$, $p > .50$.

In an additional analysis, we split testing data into eight epochs (see Figure 5B). The interaction between condition and epoch failed to reach significance ($F < 1$).

Location probability recognition. Although probability cuing persisted in the viewer-rich quadrant, only one of the 13 participants selected that quadrant as the rich quadrant. Three other participants chose the environment-rich quadrant, and the remaining nine selected a sparse quadrant.

Discussion. The first two experiments demonstrated that incidental learning of a target's likely location yielded an egocentric attentional bias. The presence of a scene in the background of visual search did not induce an environment-centered representation of attended locations, nor did it facilitate spatial updating. This

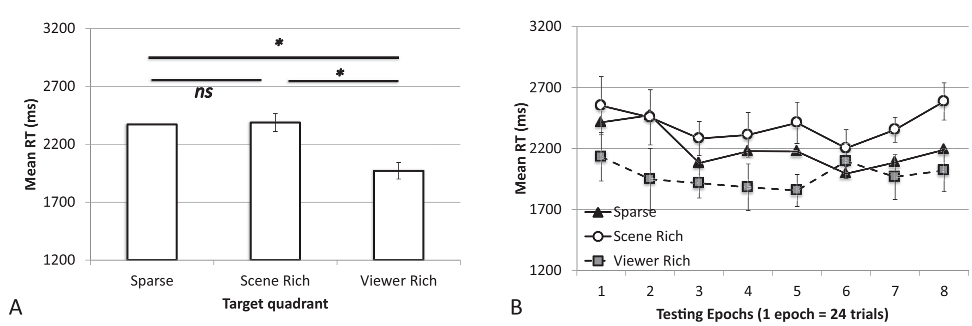

Figure 3. Results from the testing phase of Experiment 1. (A) Average across the entire testing phase. ns = not significant; * $p < .05$. (B) Testing phase data split into eight epochs. Error bars show ±1 *SE* of the difference between each of the rich conditions and the sparse condition. RT = reaction time; *SE* = standard error.

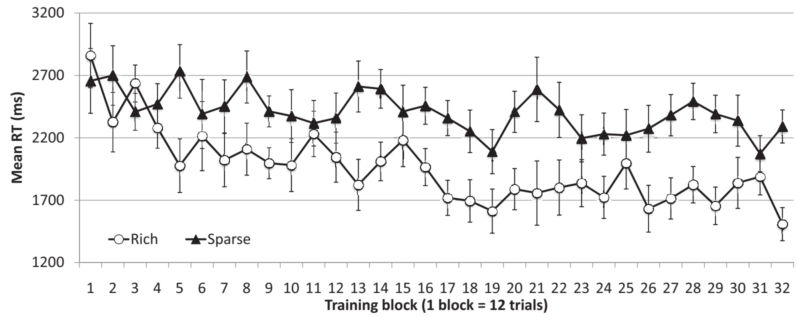

Figure 4. Results from the training phase of Experiment 2. Error bars show ±1 *SE* of the difference between the rich and sparse quadrants. RT = reaction time; *SE* = standard error.

was the case both after a display rotation and after viewer movement. Although spatial updating is more successful following viewer movement than following a display rotation (Rieser, 1989; Simons & Wang, 1998; Wang & Simons, 1999), neither resulted in the prioritization of the environment-rich locations. These data support the claim that incidentally learned attention is egocentric and is not successfully updated with viewer movement.

Section 2: Intentional Learning

In intentional learning, attention is effectively guided by top-down goals. Task instruction is commonly used to create such goals. Unlike incidentally learned attention, goal-driven attention can be flexibly adjusted to reflect changes in the cue's utility (Jiang, Swallow, & Rosenbaum, 2013; Vickery, King, & Jiang, 2005). Given that previous studies have demonstrated that attention can be both retinotopically and spatiotopically mapped (Ball et al., 2009, 2010; Behrmann & Tipper, 1999; Golomb et al., 2008, 2010; Mathôt & Theeuwes, 2010; Maylor & Hockey, 1985; Pertzov et al., 2010; Posner & Cohen, 1984; Tipper et al., 1991, 1998), it is possible that the spatial reference frame used by top-down attention differs from that of incidental learning.

Experiments 3 and 4 examined the spatial reference frame of location probability learning under explicit instructions. In these experiments, participants were told where the target was likely to appear at the beginning of the training phase. In addition, participants received explicit instructions that modulated their search strategy in the testing phase. Participants in Experiment 3 were told to distribute attention equally, whereas participants in Experiments 4 were asked to prioritize the environment-rich quadrant. Finally, participants in Experiments 5a and 5b received explicit instructions before the testing phase but not before the training phase.

Even with explicit knowledge of where a target is likely to appear during training, participants in Experiments 3 and 4 may also implicitly learn where the target is likely to appear. The effects of explicit instructions on implicit learning tasks have been diverse (Stadler & Frensch, 1998). In serial reaction tasks (Nissen & Bullemer, 1987), learning has two components, one of which is facilitated by explicit instructions (Curran & Keele, 1993; Frensch & Miner, 1994). Similar enhancement from explicit instructions has been observed with artificial grammar learning (Dulany, Carlson, & Dewey, 1984). However, when the underlying statistics are complex, such as in contextual cuing or probabilistic perceptual-motor sequence learning, explicit instructions do not enhance learning (Chun & Jiang, 2003; Flegal & Anderson, 2008; Sanchez & Reber, 2013). Because the statistics that support probability cuing are simple, the acquisition of probability cuing may be enhanced by explicit instructions. In addition, explicit instructions may change the nature of spatial representation, potentially leading to an environment-centered rather than viewer-centered attentional bias. In fact, a previous study using the serial reaction time task demonstrated increased allocentric coding of spatial sequences when participants become aware of the repetition (Liu et al., 2007). This suggests that awareness may change the nature of the spatial representation.

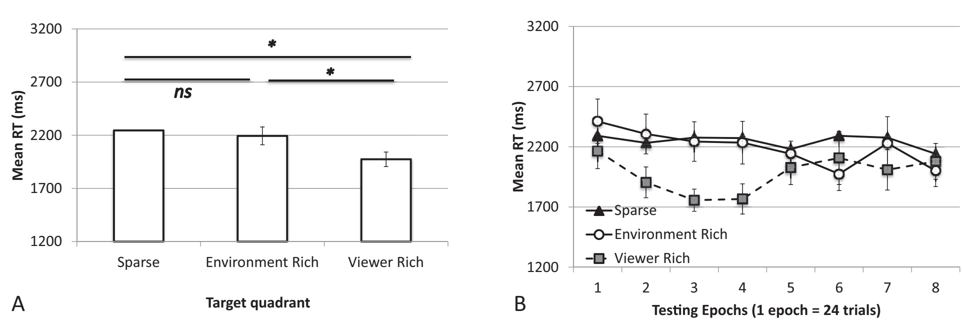

Figure 5. Mean RT from the testing phase of Experiment 2. (A) Average across all trials. ns = not significant; * $p < .05$. (B) RT data for the eight epochs of trials. Error bars show ±1 *SE* of the difference between each of the rich conditions and the sparse condition. RT = reaction time; *SE* = standard error.

Experiment 3: Explicit Instructions Before Training and Testing

The goal in Experiment 3 was to examine whether explicit knowledge about where a target is likely to appear yields an environment-centered representation of those locations. Before training, participants were told where the target was likely to appear. In addition, we told participants before testing that the target now would be equally likely to appear in all quadrants. This experiment therefore differed from Experiment 2 in (a) the nature of learning (incidental vs. intentional) and (b) explicit prioritization during testing. It is possible that intentional learning may change the nature of spatial coding, such that the target-rich quadrant would be coded relative to the external environment rather than relative to the viewer. In addition, the instruction to distribute attention equally in the testing phase may override any persisting attentional biases. If probability cuing is still egocentric under these conditions, it would provide strong evidence that spatial attention is viewer-centered and that this component is cognitively impenetrable.

Method.

Participants. Sixteen new participants completed Experiment 3. There were two male and 14 female participants, with an average age of 19.7 years.

Design and procedure. This experiment was the same as Experiment 2 except for the instructions. At the start of the experiment, participants were told where the target was likely to appear. A blue box the size of a visual quadrant highlighted the rich quadrant. The blue box appeared against a blank screen when it was shown for the first time, but it was displayed over the scene in subsequent repetitions. The instruction stated: "It is important to keep in mind that the T is not evenly distributed. The T is more often located in the region indicated by the blue square. The T will be in that quadrant 50% of the time, and in each of the other quadrants 17% of the time. It helps to prioritize that quadrant." An experimenter also verbally encouraged participants to prioritize the rich quadrant during search. This instruction was displayed once every 96 trials over the scene as a reminder in the training phase.

After reseating, participants were told, "It is important to keep in mind that the T is evenly distributed for the following blocks. The T will be in each quadrant 25% of the time." An experimenter verbally reinforced this message and encouraged participants to abandon any spatial preferences. The instruction appeared again halfway through the testing phase. As in Experiments 1 and 2, the target's location was uneven in the training phase but was randomly chosen in the testing phase.

At the end of visual search, participants selected the scene they saw in the experiment. They also clicked on where the target was most often found.

Results and Discussion. Fourteen of the sixteen participants correctly recognized the scene used in the experiment. Data from the other two participants were excluded.

Training phase. Accuracy in the training phase was 96.6% (SE = 0.9%) when the target was in the rich quadrant and 95.4% (SE = 0.8%) when it was in the sparse quadrants. These values were not significantly different ($p > .14$).

Mean RT (see Figure 6) was significantly influenced by quadrant condition, $F(1, 13) = 46.77$, $p < .001$, $\eta_p^2 = .78$, and block, $F(31, 403) = 2.84$, $p < .001$, $\eta_p^2 = .18$. The interaction between the two factors failed to reach significance, $F(31, 403) = 1.32$, $p > .10$. Trend analysis on the interaction term revealed a marginally significant linear trend, $F(1, 13) = 3.54$, $p = .08$, $\eta_p^2 = .21$. Thus, probability cuing was observed in Experiment 3. Owing to explicit instructions, the effect was large even early in the experiment.

Testing phase. Accuracy in the testing phase was 95.1% (SE = 1.0%) in the sparse condition, 95.5% (SE = 1.0%) in the environment-rich condition, and 93.2% (SE = 1.8%) in the viewer-rich condition. These values were not significantly different, $F(2, 26) = 1.41$, $p > .25$.

Although participants were told that the target was now equally likely to appear in any quadrant, probability cuing persisted in the testing phase (see Figure 7A). Averaged across the entire testing phase, RT was significantly influenced by quadrant condition, $F(2, 26) = 19.96$, $p < .001$, $\eta_p^2 = .61$. Planned contrasts showed that RT was significantly faster in the viewer-rich condition than both the sparse condition, $t(13) = 5.77$, $p < .001$, and the environment-rich condition, $t(13) = 4.84$, $p < .001$. The latter two conditions did not differ significantly, $t(13) = 1.39$, $p > .18$.

As shown in Figure 7B, RT differences among different quadrant conditions were maintained throughout the testing phase. The interaction between quadrant condition and epoch was not significant, $F(14, 182) = 1.20$, $p > .25$.

Recognition test. When participants were asked where they thought the target was most often found, six chose a sparse quadrant, two chose the viewer-rich quadrant, and five chose the environment-rich quadrant. All groups showed a viewer-centered

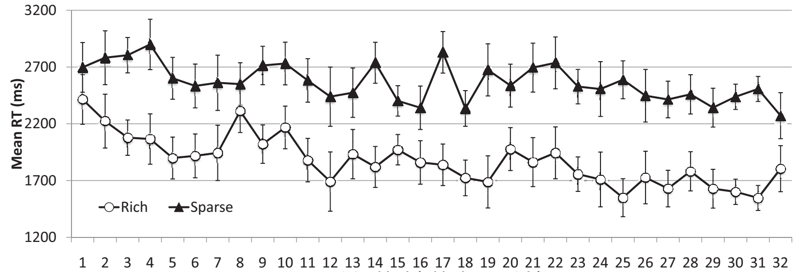

Figure 6. Results from the training phase of Experiment 3. Error bars show ±1 SE of the difference between the rich and sparse conditions. RT = reaction time; SE = standard error.

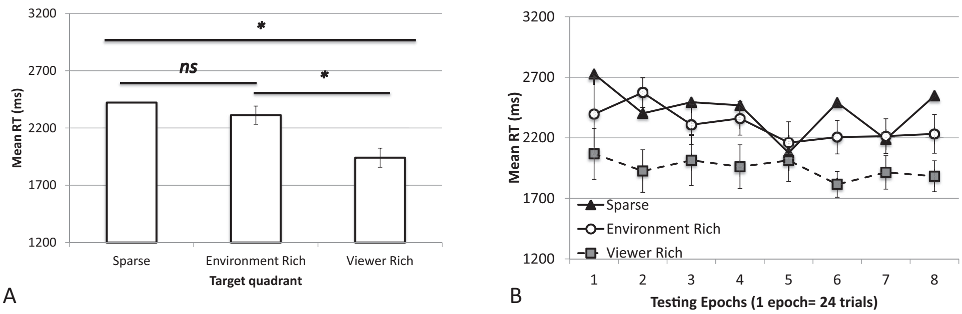

Figure 7. Mean RT from the testing phase of Experiment 3. (A) Average across all trials. ns = not significant; $^{*}p < .05$. (B) RT data for the eight epochs of trials. Error bars show ±1 *SE* of the difference between each of the rich conditions and the sparse condition. RT = reaction time; *SE* = standard error.

attentional bias but no environment-centered bias ($F < 1$) for the interaction between testing condition and recognition choice.

In this experiment, explicit instructions did not alter the nature of spatial coding or persistence in probability cuing. Intentional learning did not change how the target-rich region had been encoded. If it had, the attentional bias should not have persisted in the viewer-rich quadrant. Furthermore, knowing that the target's location would be random did not eliminate the spatial bias toward the quadrant that was previously likely to contain it. Importantly, the bias was now exclusively directed to the viewer-rich quadrant. Thus, explicit knowledge did not disrupt the viewer-centered bias, suggesting that the latter was driven by mechanisms that are cognitively impenetrable.

Experiment 4: Intentional Learning and Prioritization of the Environment-Centered Quadrant

Our purpose in Experiment 4 was to examine whether task instructions could strengthen the attentional prioritization of the environment-rich locations and eliminate the viewer-centered attentional bias. The experiment was the same as Experiment 3, except that after reseating, participants were told to continue to favor the environment-rich quadrant. This manipulation could potentially override the attentional bias toward the viewer-rich quadrant, replacing it with an attentional bias toward the environment-rich quadrant.

Method.

Participants. Sixteen new participants completed this experiment. There were six male and 10 female participants, with an average age of 22 years.

Design and procedure. This experiment was the same as Experiment 3 except that participants were instructed to prioritize the same quadrant on the monitor/scene throughout the experiment. After reseating, the same instruction that participants received at the beginning of the task appeared again (see Experiment 3). This instruction included a blue outline square that enclosed the rich quadrant. The blue square's location remained the same in the external world/scene regardless of where participants sat. An experimenter also verbally reinforced the instructions, asking participants to prioritize the quadrant with the blue square.

Results and Discussion. One participant failed to recognize the scene used in the study. We analyzed data from the other 15 participants.

Training phase. Accuracy was 96.0% ($SE = 0.6\%$) in the rich quadrant and 96.0% ($SE = 0.5\%$) in the sparse quadrants ($p > .50$).

Probability cuing was large (see Figure 8). The main effect of quadrant condition was significant, $F(1, 14) = 73.86$, $p < .001$, $\eta_p^2 = .84$, as was the main effect of block, $F(31, 434) = 4.27$, $p < .001$, $\eta_p^2 = .23$. These two factors did not interact significantly, $F(31, 434) = 1.11$, $p > .30$. The linear trend in the interaction term was marginally significant, $F(1, 14) = 3.22$, $p = .09$, $\eta_p^2 = .19$. As was the case in Experiment 3, probability cuing occurred immediately in the training phase, driven by task instructions.

To examine the impact of explicit knowledge on probability cuing, we conducted an analysis that compared the training phase data between incidental learning (Experiments 1–2) and inten-

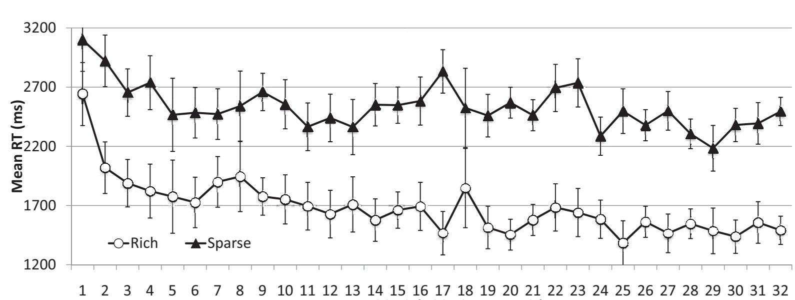

Figure 8. Results from the training phase of Experiment 4. Error bars show ±1 *SE* of the difference between the rich and sparse conditions. RT = reaction time; *SE* = standard error.

tional learning (Experiments 3–4) experiments. An ANOVA on condition (rich or sparse), block (1–32), and instructions (incidental or intentional) revealed a significant interaction between these two factors, $F(1, 55) = 15.60$, $p < .001$, $\eta_p^2 = .22$. Intentional learning nearly doubled the size of probability cuing, suggesting that participants effectively used the instruction.

Testing phase. Accuracy was 97.0% ($SE = 0.5\%$) in the sparse condition, 96.9% ($SE = 0.6\%$) in the environment-rich condition, and 95.4% ($SE = 0.7\%$) in the viewer-rich condition. An ANOVA revealed a marginally significant difference among the three conditions, $F(2, 28) = 2.76$, $p = .08$. This difference raised concerns about a potential speed–accuracy trade-off. Therefore, in the following analyses RT was converted to an "inverse efficiency" index (Akhtar & Enns, 1989; Christie & Klein, 1995) by dividing it by the percent correct. This procedure increases the RT value more for conditions with lower accuracy. Raw RT produced the same pattern of results as adjusted RT.

Figure 9A shows the adjusted RT averaged across the entire testing phase. An ANOVA revealed a significant main effect of quadrant condition, $F(2, 28) = 9.91$, $p < .001$, $\eta_p^2 = .41$. Planned contrasts showed that RT was significantly faster in the viewer-rich condition than in the sparse condition, $t(14) = 5.79$, $p < .001$. In contrast to previous experiments, RT was also significantly faster in the environment-rich condition than in the sparse condition, $t(14) = 3.11$, $p < .007$. The viewer-rich and environment-rich conditions did not differ significantly, $t(14) = 1.47$, $p > .15$.

Breaking testing data down to eight epochs (see Figure 9B) revealed persistence of probability cuing over time. The interaction between condition and epoch failed to reach significance, $F(14, 196) = 1.09$, $p > .35$.

Recognition. When asked to identify the target-rich quadrant, participants did not uniformly choose the environment-rich quadrant, suggesting that their subjective impression differed from the instruction. Five chose the environment-rich quadrant, six chose the viewer-rich quadrant, and the other four chose a sparse quadrant. Recognition choice did not interact with testing phase performance, $F(4, 24) = 1.88$, $p > .14$.

Experiment 4 showed that although explicit instructions to prioritize the environment-rich quadrant were effective in inducing such a bias, they failed to eliminate the egocentric bias to the viewer-rich quadrant. The RT difference between the viewer-rich condition and the sparse condition was similar across the first four experiments, $F(4, 66) < 1$ for the interaction between experiment and condition (sparse or viewer-rich). The difference in Experiments 3 and 4 (481 ms and 503 ms), which actively discouraged participants from prioritizing the viewer-rich quadrant, was no smaller than in the first two experiments (399 ms and 272 ms). The viewer-centered bias to the rich quadrant therefore was unaffected by explicit instructions to prioritize another region of the screen.

Experiment 5. Incidental Learning Followed by Explicit Instructions Before Testing

Experiment 5 examined whether the effects of testing-phase instructions replicate when probability cuing is acquired incidentally. Participants in this experiment received no information about the target's location probability before the training phase. Following training, they were given an instruction to either distribute attention equally (similar to Experiment 3) or favor the environment-rich quadrant (similar to Experiment 4). A replication of Experiments 3 and 4 would strengthen the conclusion that spatial attention has two dissociable components, only one of which is sensitive to explicit knowledge. In addition, it would generalize results from intentional learning (Experiments 3 and 4) to incidental learning (Experiment 5).

Method.

Participants. Thirty-two participants completed this experiment. There were 11 male and 21 female participants, with a mean age of 20.2 years. Half of the participants completed Experiment 5a, and the other half completed Experiment 5b.

Design. All participants completed the training phase under incidental learning conditions, as in Experiments 1 and 2. At the end of the training phase, they moved their seat to another side of the table and received explicit instructions about the search target. Participants in Experiment 5a received the same instructions as those of Experiment 3. They were asked to distribute their attention equally to all regions of the screen. Participants in Experiment 5b received the same instructions as those of Experiment 4. They were asked to prioritize the environment-rich quadrant. Similar to the other experiments, the target was unevenly distributed across the four quadrants in the training phase but was equally likely to appear in any quadrant in the testing phase. To reduce the awkwardness of holding the keyboard, responses were made with a mouse click (left for red, right for green).

The recognition test in Experiment 5a was the same as before. In Experiment 5b, participants were asked to recall the location of

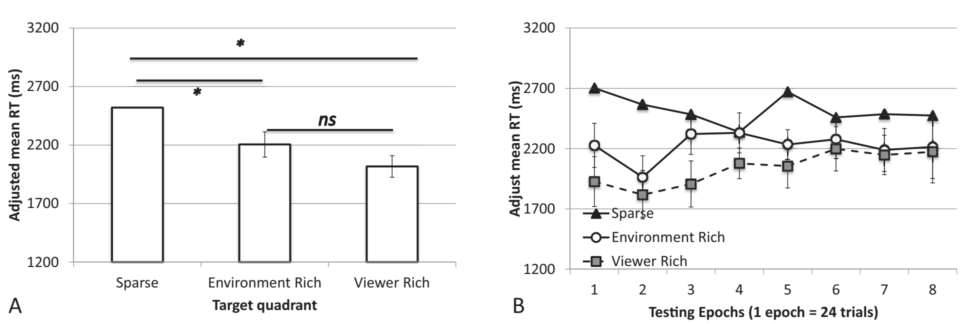

Figure 9. Adjusted mean RT from the testing phase of Experiment 4. (A) Average across all trials. ns = not significant; * $p < .05$. (B) RT data for the eight epochs of trials. Error bars show $\pm$ 1*SE* of the difference between each of the rich conditions and the sparse condition. RT = reaction time; *SE* = standard error.

the quadrant that they were instructed to prioritize. After testing four participants, we included an additional recognition question. Beside recalling the instruction, the last 12 participants reported where they thought the target was most often found.

Results. Data from three participants were excluded due to a failure to recognize the scene ($N = 1$ in Experiment 5b) or low accuracy (below 85% and below 3 *SD* of the mean; one each in Experiments 5a and 5b). The final sample included 15 participants in Experiment 5a and 14 in Experiment 5b.

Training phase. Because the training phase was identical for Experiments 5a and 5b, data were combined. Mean accuracy was 97.6% ($SE = 2.0\%$) in the rich quadrant and 97.1% ($SE = 2.0\%$) in the sparse quadrant, a nonsignificant difference, $t(28) = 1.44$, $p > .15$.

Replicating Experiments 1–2, probability cuing was observed in the training phase (see Figure 10). An ANOVA on condition (rich or sparse), block (1–32), and experiment (5a or 5b) indicated that the main effect of condition was significant, $F(1, 27) = 80.09$, $p < .001$, $\eta_p^2 = .75$. RT was faster in the rich condition than the sparse condition. RT also improved as training progressed, leading to a significant main effect of block, $F(31, 837) = 4.97$, $p < .001$, $\eta_p^2 = .16$. Finally, there was a significant interaction between quadrant condition and block, $F(31, 837) = 2.38$, $p < .001$, $\eta_p^2 = .08$, demonstrating the gradual acquisition of probability cuing with training. None of the experimental factors interacted with experimental version (all ps $> .30$).

Testing phase.

Experiment 5a. Search accuracy was unaffected by quadrant condition in the testing phase ($F < 1$). Mean accuracy in Experiment 5a was 97.8% ($SE = 0.5\%$) in the sparse condition, 98.1% ($SE = 0.7\%$) in the environment-rich condition, and 98.2% ($SE = 0.5\%$) in the viewer-rich condition.

RT was significantly influenced by testing condition (see Figure 11A), $F(2, 28) = 27.49$, $p < .001$, $\eta_p^2 = .66$. The viewer-rich condition was significantly faster than both the sparse condition, $t(14) = 6.50$, $p < .001$, and the environment-rich condition, $t(14) = 5.46$, $p < .001$. The latter two conditions did not differ significantly, $t(14) = 0.98$, $p > .30$. This pattern of data held across eight testing epochs (see Figure 11B), revealing no interaction between condition and epoch ($F < 1$).

Thus, when instructed to pay equal attention to all regions of the display, participants continued to show a strong attentional bias toward the viewer-rich quadrant and no bias toward the environment-rich quadrant. These data replicated those of Experiment 3.

Experiment 5b. Search accuracy in Experiment 5b was unaffected by quadrant condition in the testing phase, $F(2, 26) = 1.36$, $p > .25$. The mean accuracy was 96.7% ($SE = 0.5\%$) in the sparse condition, 96.4% ($SE = 0.6\%$) in the environment-rich condition, and 95.1% ($SE = 0.9\%$) in the viewer-rich condition.

RT data (see Figure 12A) revealed a significant main effect of testing condition, $F(2, 26) = 10.26$, $p < .001$, $\eta_p^2 = .44$. Planned contrasts showed that the sparse condition was significantly slower than both the environment-rich condition, $t(13) = 3.78$, $p < .002$, and the viewer-rich condition, $t(13) = 4.51$, $p < .001$. The latter two conditions did not differ from each other, $t(13) = 0.43$, $p > .50$. Breaking down the data into eight epochs (see Figure 12B) revealed no interaction between condition and epoch, $F(14, 182) = 1.19$, $p > .25$.

Additional evidence for the impact of task instructions came from an ANOVA that included testing condition as a within-subject factor and experimental version (5a or 5b) as a between-subject factor. This analysis showed a significant interaction, $F(2, 54) = 7.47$, $p < .001$, $\eta_p^2 = .22$. Whereas the viewer-centered component was equally strong between experiments, the environment-centered component was present only in Experiment 5b.

These data replicated Experiment 4: Explicit instruction to prioritize the environment rich quadrant effectively led to an attentional preference for that quadrant, yet it did not affect the bias toward the viewer-rich quadrant.

Recognition. In Experiment 5a, the number of participants choosing the sparse quadrant, the environment-rich quadrant, and viewer-rich quadrant was 6, 3, and 6, respectively. Regardless of their choice, however, all participants demonstrated a strong bias toward the viewer-rich quadrant and no bias toward the environment-rich quadrant. This led to a lack of interaction between recognition choice and testing condition ($F < 1$).

In Experiment 5b, all participants correctly recalled the quadrant that we had instructed them to prioritize. However, of the 12 participants who were asked where they thought the target was most often found, all avoided the instructed quadrant. Four chose the viewer-rich quadrant, and the other eight chose a sparse quadrant. Recognition choice did not correlate with testing phase performance ($p > .20$). Although participants did not believe that the

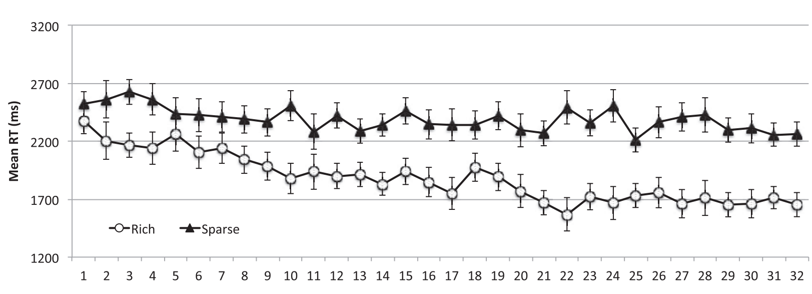

Figure 10. Results from the training phase of Experiment 5, including participants from Experiments 5a and 5b. Error bars show ±1 *SE* of the difference between the rich and sparse conditions. RT = reaction time; *SE* = standard error.

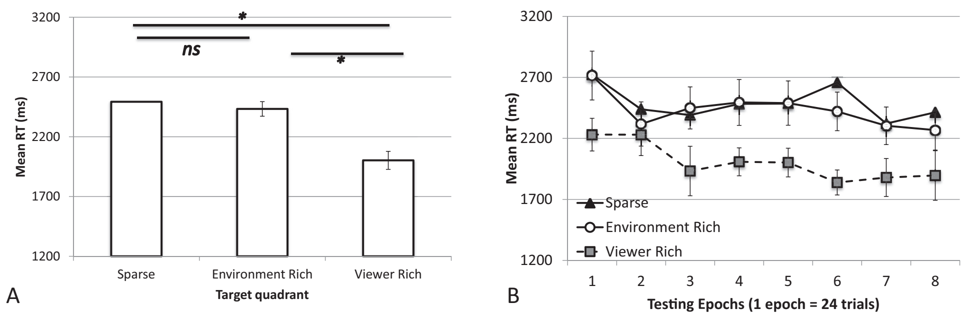

Figure 11. Mean RT from the testing phase of Experiment 5a. (A) Average across all trials. ns = not significant; $^{*}p < .05$. (B) RT data for the eight epochs of trials. Error bars show ±1 *SE* of the difference between each of the rich conditions and the sparse condition. RT = reaction time; *SE* = standard error.

instructed quadrant was more likely to contain a target, they nonetheless prioritized that quadrant as instructed.

Together, Experiments 5a and 5b generalized the results from Experiments 3 and 4. Regardless of whether participants had acquired probability cuing incidentally or intentionally, they demonstrated an egocentric bias toward the viewer-rich quadrant. Instructions influenced attention toward the environment-rich quadrant without reducing the egocentric bias toward the viewer-rich quadrant.

General Discussion

Spatial attention prioritizes the processing of selected regions of space, ensuring that behaviorally relevant information is processed (Desimone & Duncan, 1995). A fundamental characteristic of spatial attention is its spatial reference frame. Attended locations may be coded relative to the external environment or relative to the viewer. Under many circumstances, these reference frames are aligned. However, they are dissociated when the viewer moves through space. Although large movements through space take too long to affect more transient forms of attention (e.g., Abrams & Pratt, 2000; Ball et al., 2009, 2010; Cavanagh et al., 2010; Golomb et al., 2008, 2010; Mathôt & Theeuwes, 2010), the persistent nature of incidental attention makes its reference frame an important factor in how it is used in everyday cognition. Understanding the reference frame of incidentally learned attention may therefore further our understanding of the nature of this kind of attention. It may also provide new insight into how attention may be both a system that prioritizes locations in space and a system that is fundamentally tied to action.

Environment-centered and viewer-centered reference frames have complementary advantages and disadvantages that make them suitable for solving different computational problems (Farah et al., 1990). An environment-centered representation is stable as a person moves through that environment. This type of representation is ideal for navigation through large-scale environments that provide few constraints on a person's location. However, an environment-centered reference frame must be inferred from sensory and perceptual information that is initially acquired from viewer-centered sensory systems. Neurons in the occipital cortex and the parietal lobe, which are critical for vision and spatial attention, code space relative to the viewer (Andersen et al., 1997; Engel, Glover, & Wandell, 1997; Golomb & Kanwisher, 2011; Saygin & Sereno, 2008). In contrast, a viewer-centered representation is relatively easy to compute. Although they may be viewpoint dependent, viewer-centered representations can be useful in navigation and visual search when the environment places constraints on the viewer's navigation path.

In the five experiments reported here, we took advantage of the persistence of incidentally learned attention to examine its spatial reference frame. Our study makes broad connection to research on spatial attention, implicit learning, and spatial cognition, yet it is clearly distinct from prior work on each topic. By focusing on

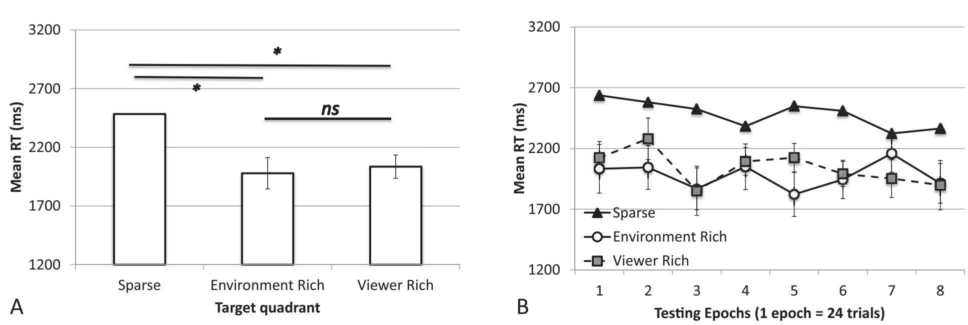

Figure 12. Mean RT from the testing phase of Experiment 5b. (A) Average across all trials. ns = not significant; $^{*}p < .05$. (B) RT data for the eight epochs of trials. Error bars show ±1 *SE* of the difference between each of the rich conditions and the sparse condition. RT = reaction time; *SE* = standard error.

incidentally guided attention rather than on voluntary and salience driven attention (Wolfe, 2007), this study has broad implications for the architecture of spatial attention. Studies on implicit learning have examined both the effects of explicit instructions (Stadler & Frensch, 1998) and allocentric versus egocentric coding of spatial stimulus–response sequences (Liu et al., 2007; Witt, Ashe, & Willingham, 2008). However, sequence learning in these experiments involves learning a series of actions as well as a series of spatial locations. To the extent that spatial locations are learned, learning appears to be explicit (Witt & Willingham, 2006). As a result, implicit sequence learning is not considered a strong modulator of *spatial attention*. Finally, studies on spatial cognition have generally focused on the representation of space, rather than on the representations that are used for attention (Wang, 2012). Our study therefore brings together diverse research topics in unique ways.

Our findings can be summarized as follows.

Observation 1: Location Probability Learning Is Egocentric

Despite reflecting stable features of the external world, representations of where a target was frequently found in the past are coded relative to the viewer. In all five experiments a clear landmark with which the rich locations could be coded was provided in the form of an indoor or outdoor scene, and only those participants who recognized this scene were included in the analysis. Yet, dissociating the scene and viewer-centered reference frames revealed that representations that support probability cuing do not appear to use this information. In all five experiments a robust egocentric bias toward the viewer-centered rich quadrant was observed.

The egocentric bias was observed even under conditions that should have weakened it. First, in addition to the scene, other landmarks, including the room and furniture, provided evidence that the spatial relationship between the participant and rich locations had changed. Moreover, in most experiments the viewpoint change occurred as a result of viewer movement, which should facilitate spatial updating (Simons & Wang, 1998; Wang & Simons, 1999). Second, explicit instructions that actively discouraged the use of an egocentric attentional bias did not eliminate it. A strong egocentric bias was observed both when participants were told not to prioritize any region of the screen (Experiments 3 and 5a) and when they were told to prioritize the environment-rich quadrant (Experiments 4 and 5b). Finally, the egocentric bias persisted in the testing phase despite the presence of visual statistics that neither matched nor reinforced it. During the 192 trials in the testing phase, the target was no more likely to appear in the viewer-rich quadrant than in the other quadrants. Yet, the egocentric bias persisted even under these conditions.

Observation 2: Task Instructions Can Drive Explicit Attention but not Incidental Attention

Informing participants that a target was likely to appear in one region of the screen facilitated visual search beyond the effects of incidental learning alone. Probability cuing during the training phase was greater when participants encoded the visual statistics intentionally rather than incidentally. These data are consistent with the broader literature on the relationship between implicit learning and explicit knowledge (Chun & Jiang, 2003; Curran & Keele, 1993; Dulany et al., 1984; Flegal & Anderson, 2008; Frensch & Miner, 1994; Sanchez & Reber, 2013; Stadler & Frensch, 1998).

The data from the testing phase also indicate that explicit instructions can influence the pattern of voluntary attention. When told that the target would be evenly distributed, participants followed the instructions and showed no bias toward the environment-rich quadrant. When told that the target was likely to appear in the environment rich quadrant, participants prioritized that quadrant. Thus, a location in the environment can be prioritized on the basis of explicit goals. Although many previous studies have shown that instruction influences attention, the present data clearly contrast these effects with those of incidental learning. Whereas the former was environment-centered and altered by instruction, the latter was egocentrically coded and was not effectively modulated by instruction.

Understanding the degree to which probability cuing can be influenced by explicit knowledge provides unique insights into the nature of spatial attention. Our data showed that at least one form of attention is informationally encapsulated from the influence of explicit knowledge. In particular, one might suppose that telling participants that a target is likely to appear within a particular region of the scene might lead them to encode that information relative to the scene itself, rather than relative to their own perspective. However, the data suggest that this characterization is too simplistic. In both experiments involving explicit instructions, an egocentric attentional bias persisted during the testing phase. The encapsulation of implicit probability cuing from explicit instructions is strong evidence for the existence of two dissociable systems (Reber & Squire, 1998; Sanchez & Reber, 2013).

Combined, these data suggest that although participants are able to use explicit knowledge to prioritize some regions of the scene over others, they cannot use this information to reduce their use of the incidentally acquired, egocentric spatial attention.

Theoretical Implications

Our study has strong implications for the architecture of spatial attention. Although previous studies have identified many sources of spatial attention (e.g., goals and perceptual salience), these sources can all be described as modulating the attentional prioritization of different locations (Bisley & Goldberg, 2010). Our study suggests, contrary to the single-system view, that spatial attention consists of two components—a declarative component driven by task goals and a procedural component driven by implicit learning.

Many studies have shown that spatial attention can be directed based on both the observer's goal and stimulus saliency (Egeth & Yantis, 1997; Itti & Koch, 2001; Treisman, 1988; Wolfe, 2007). However, these two sources of information guide attention in similar ways. Attentional capture by an abrupt onset and goal-driven attention by a central arrow produce underadditive effects: attentional capture is reduced when the target appears at a location that was already validly cued by a central arrow (Yantis & Jonides, 1990). Underadditivity implies that stimulus-driven attention and goal-driven attention mobilize the same system (Sternberg, 2001). The fundamental distinction between goal- and stimulus-driven attention is in where the attentional bias originates and how it triggers the orienting system (Corbetta & Shulman, 2002). For both, where attention goes is determined by a priority map, which represents the relevance and salience of objects in various spatial locations (e.g., Bisley & Goldberg, 2010; Fecteau & Munoz, 2006; Gottlieb, Balan, Oristaglio, & Schneider, 2009; Itti, Rees, & Tsotsos, 2005; Wolfe, 2007).

In contrast, our data suggest that spatial attention has at least two dissociable components, one that is *declarative* and the other that is *procedural*. The declarative component of spatial attention is dictated by top-down goals. It specifies which locations should be prioritized in a given task and can code these locations relative to the environment (e.g., Experiments 3 and 4). The output of declarative attention may interface with action planning, but, crucially, declarative attention prioritizes locations and objects before the actual shift of attention. The procedural component of spatial attention reflects learning the vectors of attentional shifts that allow a person to find a relevant item. This component relies on learning and memory. Once acquired, its influence on spatial attention is instantiated "online," in the active process of moving attention. The vectors of attentional shifts that result in the detection of the target are reinforced. In experiments where the target is more often found in some places than others, the vectors of attentional shifts toward the high-probability regions are strongly reinforced, increasing the likelihood that they will occur again.

It is possible to distinguish procedural and declarative attention on several dimensions. By definition, declarative attention is dictated by top-down knowledge, but procedural attention is impenetrable by such knowledge. Furthermore, whereas declarative attention is accessible to conscious awareness, the procedural component of spatial attention is largely implicit. Declarative attention can be flexibly modified: One may prioritize completely different locations from moment to moment to reflect current goals (Jiang, Swallow, & Rosenbaum, 2013; Vickery et al., 2005). In contrast, procedural attention persists over long periods of time and is slow to adjust to changes in the underlying statistics in the environment (Jiang, Swallow, Rosenbaum, & Herzig, 2013; current study). Finally, whereas declarative attention may be flexibly referenced to the external world, procedural attention is egocentric.

By using the terms *declarative* and *procedural,* we suggest that the division of spatial attention bears some similarity to the division of human memory (Schacter, 1996; Squire, 1992, 2004). Whereas declarative memory encompasses semantic, episodic, and autobiographical memory, procedural memory includes skill and habit learning, priming, and conditioning. Like declarative memory, declarative attention is flexible and accessible to consciousness. Like procedural memory, procedural attention is inflexible, specific, and not consciously accessible (Squire, 1992). However, it is not our intent to suggest that declarative and procedural attention are identical to declarative and procedural memory. Indeed, the neural systems involved in each are likely to differ. Whereas contextual cuing, a form of implicit attention, relies on both the medial temporal lobe and basal ganglia (Chun & Phelps, 1999; Manns & Squire, 2001; van Asselen et al., 2009), procedural memory relies on the basal ganglia and other perceptual-motor systems (Doyon et al., 2009; Graybiel, 2008; Schacter, 1996; Squire, 1992, 2004). Similarly, goal-driven (declarative) attention relies heavily on the dorsal parietofrontal network rather than on the hippocampus and the broader medial temporal lobe (Corbetta & Shulman, 2002; Dosenbach, Fair, Cohen, Schlaggar, & Petersen, 2008; Duncan, 2010).

Our dual-system view of attention echoes the two-systems theory of vision proposed by Goodale and Milner (1995). Goodale and Milner's theory proposes that perceptual systems involved in identifying objects in the environment are separate from those that use visual information to guide action. According to Goodale and Milner, the occipitotemporal ventral stream supports object perception, whose outcome is usually accessible to conscious awareness. The occipitoparietal stream supports visually guided motor action, and its computation is largely inaccessible to conscious awareness (Milner & Goodale, 2008). Both streams contribute to action but in different ways. The ventral stream allows one to plan an action in an offline fashion (e.g., based on memory), but the dorsal stream is engaged in online visuomotor computation. The perceptual and visuomotor systems also differ in their spatial reference frame (Goodale & Haffenden, 1998; Milner & Goodale, 2008).

We believe, similar to Goodale and Milner's theory of vision, that attention has both a declarative component and a procedural component. Declarative attention is more accessible to conscious awareness and hence is more likely controlled by an observer's goal. However, we also believe that declarative attention is not only involved in establishing a priority map (see also Findlay & Walker, 1999; Tubau, Hommel, & Lopez-Moliner, 2007). It can also be used to set up an action plan prior to the actual movement of attention. Procedural attention, in contrast, is instantiated in the actual process of performing an attention task and moving attention through space (cf. Jiang, Sigstad, & Swallow, 2013).

Our framework suggests that in addition to being a priority map, attention is closely tied to action (Allport, 1989; Rizzolatti et al., 1987). According to the premotor theory of attention, covert attention originates from planned overt responses, including saccades or hand movements. Consistent with this proposal, neurophysiological and psychophysical studies have found common mechanisms for attention and action (Craighero, Fadiga, Rizzolatti, & Umiltà, 1999; Moore & Fallah, 2001; Song & Nakayama, 2009). Others have suggested that an important function of attention is to sample sensory information for the purpose of guiding action (Allport, 1989). Although probability cuing does not rely on overt saccades (Geng & Behrmann, 2005; Jiang & Swallow, 2013), localizing the target ultimately allows the observer to respond to it. In addition, the visuomotor system may use a viewer-centered reference frame to code object shapes (Goodale & Haffenden, 1998). A clear advantage of coding attended locations in relation to oneself is for visuomotor action (Milner & Goodale, 2008).

In addition to facilitating the interface between attention and visuomotor action, egocentric attention has several advantages. First, because a viewer-centered representation is easy to compute, egocentric attentional biases can be rapidly acquired during incidental learning. In one recent study (Jiang, Swallow, & Capistrano, 2013), the ability to incidentally learn an environment-centered rich quadrant was examined. In one experiment, the rich quadrant was fixed in the environment but random relative to the viewer (search was performed at a random location on each trial). In another, the rich quadrant was fixed relative to both the environment and the viewer. Although incidental learning of the target rich location was rapid when it was stable relative to the viewer and the environment (emerging after about 20 trials of training), it failed to develop when the rich location was stable only in the environment, even after 384 trials of training. Thus, the egocentric coding of space supports the rapid incidental acquisition of visual statistics. The learned attentional bias persists over time but gradually adjusts to reflect new visual statistics (Jiang, Swallow, Rosenbaum, & Herzig, 2013). These data also suggest that viewer-centered attentional biases are acquired in situations when they are most likely to be useful: when the rich regions are stable relative to the viewer. These situations may occur more frequently than one might think. Man-made and natural environments constrain navigational paths and the locations at which a person is likely to look for relevant items (e.g., one is more likely to approach a certain tree from only one or two directions). Moreover, goal-driven attention, which can be flexibly directed to a region of space in the external world (Experiments 3 and 5b), can compensate for the relative inflexibility of procedural attention and even override it under some conditions (Jiang, Swallow, & Rosenbaum, 2013).

Probability Cuing Influences Attention

Given that our theoretical framework divides attention into declarative and procedural components, it is important to consider whether studies on incidental attention are indeed studying attention, or whether they are studying something entirely different. For example, one may wonder whether probability cuing is simply a matter of learning an oculomotor routine. Perhaps participants simply learned to saccade in a specific direction. However, several other studies suggest that oculomotor learning is unlikely to be a major component of probability cuing. First, probability cuing occurs even when participants maintain fixation throughout search (Geng & Behrmann, 2005). In addition, probability cuing emerges and persists in a viewer-centered rich quadrant even when displays are presented so briefly that there is no time to make a saccade (Jiang & Swallow, 2013). Finally, making frequent saccades toward a specific quadrant is insufficient to establish probability cuing (Jiang, Swallow, & Rosenbaum, 2013). Although covert attention correlates with the direction of eye movement, probability cuing is attentional rather than, or in addition to, oculomotor.

Perhaps most important, much like goal-driven attention, probability cuing scales with set size. The more items are on the display, the larger is the benefit of probability cuing (Jiang, Capistrano, Esler, & Swallow, 2013; Jiang, Swallow, & Rosenbaum, 2013). In addition, probability cuing guides attention as effectively as a central arrow cue (Jiang, Swallow, & Rosenbaum, 2013). Enhanced search efficiency is considered a hallmark of attentional guidance (Wolfe, 2007). Therefore, while probability cuing clearly differs from goal-driven attention, it should be considered a form of attention.

A final objection may arise from the fact that incidental attention depends on learning and memory and therefore may simply be another form of procedural memory. However, although learning and memory are critical to probability cuing, characterizing it as another example of procedural memory misses its greater impact on our understanding of attention. It has long been known that people can learn the statistical structure of the environment (Fiser & Aslin, 2001; Geng & Behrmann, 2005; Makovski et al., 2008; Turk-Browne et al., 2005) and that they can even use this information to facilitate task performance (e.g., Chun & Jiang, 1998; Geng & Behrmann, 2005). What these and other recent data on incidentally learned attention demonstrate, however, is that learned information about the environment does not simply operate as another source of top-down attentional guidance (Experiments 3–5; Jiang, Swallow, & Rosenbaum, 2013). Learning about the structure of the environment in the context of performing an attentional task influences attention directly, by increasing the likelihood that it moves through space in particular ways.

Open Questions

Although the dual-system view of attention is consistent with our data, it requires additional testing before it can be fully accepted. Direct evidence for the dual-system view could come from future studies that measure procedural attention (e.g., by analyzing scan paths or by manipulating task demands). Tests on neuropsychological patients with different kind of brain damage (e.g., basal ganglia vs. parietal) may also yield new insights into the fractionation of attention.

It is also the case that this study has not been generalized to more naturalistic situations, such as when people search for an object in the real world rather than on a computer screen. Although we expect the dual-system view of attention will apply to real-world search, the relative contributions of each component may change. In natural environments where search targets are fully integrated with the scene, performance may rely more heavily on explicit awareness (and the declarative component) than what we have found here (Summerfield, Lepsien, Gitelman, Mesulam, & Nobre, 2006).

Our study also leaves open several empirical questions about the persistence of the egocentric attentional bias. For example, would the bias persist when the background scene has changed following the viewpoint change? Would the egocentric bias readjust if the target is often found in another region? The dual-system view makes several testable predictions. First, because procedural attention is encapsulated from top-down knowledge, the egocentric attentional bias should persist when the background scene changes, as long as participants perform the same visual search task. Changing the nature of the visual search task, however, should disrupt procedural attention and the egocentric bias. Second, when the egocentric bias is incongruent with where targets are actually likely to appear, probability cuing should gradually move toward the target-rich region, facilitating the extinction of the previously acquired attentional bias (see Jiang, Swallow, Rosenbaum, & Herzig, 2013, for such an adjustment).

Conclusion

Visual search is sensitive to both explicit and implicit knowledge about where a target is likely to appear. High-probability locations were prioritized regardless of whether participants were aware of the target's likely locations. Importantly, however, incidentally acquired attentional biases were coded egocentrically. When the participant moved to a new search position, the bias moved with the participant. This egocentric bias was not influenced by explicit instructions to prioritize a different region of the screen. However, explicit instructions could be used to attend to a region of space based on an environment-centered reference frame. We propose that whereas goal-directed attention affects which locations in space are prioritized and can be flexibly referenced, incidental learning affects the vector of attentional shifts in a specific task and is intrinsically egocentric.

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