Cognition 115 (2010) 147–153

Contents lists available at ScienceDirect

Cognition

journal homepage: www.elsevier.com/locate/COGNIT

The role of experience in location estimation: Target distributions shift location memory biases

John Lipinski [a,*], Vanessa R. Simmering [b], Jeffrey S. Johnson [b], John P. Spencer [c]

[a] Institut für Neuroinformatik, Ruhr-Universität Bochum, Germany
[b] Department of Psychology, University of Wisconsin–Madison, Madison, WI, USA
[c] Department of Psychology and Delta Center, University of Iowa, Iowa City, IA, USA

ARTICLE INFO

Article history:
Received 25 February 2009
Revised 23 November 2009
Accepted 15 December 2009

Keywords:
Categorization
Spatial cognition
Spatial memory

ABSTRACT

Research based on the Category Adjustment model concluded that the spatial distribution of target locations does not influence location estimation responses [Huttenlocher, J., Hedges, L., Corrigan, B., & Crawford, L. E. (2004). Spatial categories and the estimation of location. *Cognition, 93*, 75–97]. This conflicts with earlier results showing that location estimation is biased relative to the spatial distribution of targets [Spencer, J. P., & Hund, A. M. (2002). Prototypes and particulars: Geometric and experience-dependent spatial categories. *Journal of Experimental Psychology: General, 131*, 16–37]. Here, we resolve this controversy by using a task based on Huttenlocher et al. (Experiment 4) with minor modifications to enhance our ability to detect experience-dependent effects. Results after the first block of trials replicate the pattern reported in Huttenlocher et al. After additional experience, however, participants showed biases that significantly shifted according to the target distributions. These results are consistent with the Dynamic Field Theory, an alternative theory of spatial cognition that integrates long-term memory traces across trials relative to the perceived structure of the task space.

1. Introduction

Categories help people carve up experience into meaningful units. Consequently, category formation processes have been a central focus of cognitive science (e.g. Casasola, 2008; Murphy, 2002; Rogers & McClelland, 2004). Categories are often formed via inductive processes where classification responses reflect the distribution of exemplars within a set of items. This is adaptive in that people will classify objects most accurately if they base their decisions primarily on high- vs. low-density regions of the sampled stimulus space. Several recent Bayesian categorization models formalize this view (e.g. Ashby & Alfonso-Reese, 1995; Griffiths, Sanborn, Canini, & Navarro, 2008; Huttenlocher, Hedges, & Vevea, 2000). Although reliance on high-density regions can optimize accuracy, it can also distort responses toward such regions. Thus, people often optimize overall accuracy but exhibit systematic biases.

The present study focuses on a particular type of categorization—spatial categorization. Just as people carve up sets of objects into meaningful units, they also carve up space into categories. Moreover, spatial categories create systematic response biases. For instance, in one common task, people reproduce the location of a dot in a circle following a short memory delay. Data suggest that people divide the circle into quadrants, forming four spatial categories. Location estimates within the circle are biased away from horizontal and vertical axes toward the centers of the four categories. Such 'geometric' biases have been reported in a host of studies (e.g. Crawford, Regier, & Huttenlocher, 2000; Huttenlocher, Hedges, & Duncan, 1991; Spencer & Hund, 2002, 2003; Spencer, Simmering,

* Corresponding author. Institut für Neuroinformatik, Ruhr-Universität Bochum, Universitätsstr. 150, Gebäude ND, Raum NDEF 04/589b, 44780 Bochum, Germany. Tel.: +49 234 32 24201; fax: +49 234 32 14209.
E-mail address: 2johnlipinski@gmail.com (J. Lipinski).

0010-0277/$ - see front matter © 2009 Elsevier B.V. All rights reserved.
doi:10.1016/j.cognition.2009.12.008

& Schutte, 2006) and have been formally modeled using two different models of spatial memory—the Category Adjustment Model (CAM; Huttenlocher et al., 1991) and the Dynamic Field Theory (DFT; Schutte & Spencer, in press; Simmering, Schutte, & Spencer, 2008; Spencer, Simmering, Schutte, & Schöner, 2007).

Although *geometric* category biases are prevalent across tasks, recent research suggests that spatial memory is impervious to *induced* (i.e. experience-based) category biases. In particular, Huttenlocher, Hedges, Corrigan, and Crawford (2004) tested whether spatial memory biases changed relative to the distribution of targets probed in the circle-dot task. Across conditions targets were clustered around the horizontal and vertical axes (HV condition) or the diagonal axes (X condition). According to Huttenlocher et al., if spatial memory is subject to induced category biases, then spatial memories for locations in the HV condition should exhibit biases towards the cluster of target instances presented along the horizontal and vertical axes. In four experiments, Huttenlocher et al. showed that geometric category biases persisted regardless of the target distribution. Thus, they concluded that spatial category formation is not influenced by inductive processes. This is consistent with the CAM which has no mechanism for accumulating memories over experience and, hence, no mechanism for induced category effects.

Nevertheless, these data contradict an earlier study by Spencer and Hund (2002) showing that target distributions influence spatial memory biases. Specifically, location estimates of a target 40° from a vertical axis shifted systematically relative to the distribution of other targets probed. When the 40° target was paired with targets *farther* from the axis, bias away from vertical *increased*. When the 40° target was paired with targets *closer* to the axis, bias *decreased*. Thus, location memory biases shifted towards the center of the target distribution. Subsequent studies showed that spatial memory estimates are also influenced by location frequency (Hund & Spencer, 2003; Spencer & Hund, 2003). The DFT has captured these effects by positing that people actively maintain location information in working memory and this leaves a trace in long-term memory (LTM). Such traces accumulate with experience and create biases in working memory, such as attraction toward an average remembered location (Simmering et al., 2008; Spencer et al., 2007). Thus, the DFT provides an explicit mechanism by which memories can accumulate and systemically influence spatial memory. This contrasts with the CAM which provides no such mechanism for accumulating memories across different experiences.

How do we reconcile these conflicting results and theories? We see three possibilities. First, induced category effects may only occur in spatial tasks with sparse distributions. The distribution in Spencer and Hund (2002) included three targets separated by 20°. By contrast, Huttenlocher, Hedges, Corrigan, and Crawford, 2004 used more densely packed distributions with 120 or 144 targets, separated by as little as 2°. Second, the experience-dependent manipulation in Huttenlocher et al. may not have been strong enough to yield measurable effects because each target was only presented once. Spencer and Hund presented each target 16 times, which may have created stronger LTM of the distribution. Third, the conflict across studies could reflect differences in the range of possible responses. In Spencer and Hund, people estimated three locations within a large (.91 m by 1.22 m) homogeneous space after delays up to 20 s. By contrast, Huttenlocher et al. used a circle with a 7.5 or 8.5 cm radius and a 4 s memory delay. Response variations within the circle after this short delay may have been too small to detect subtle induced category effects.

The present experiment tested these possibilities using the Huttenlocher et al. task[1] (2004; Experiment 4), but with a 12.75 cm circle radius and a 10 s memory delay. Additionally, we presented each target four times instead of once. Based on the DFT, we expected to find evidence of induced category effects in spatial recall, with participants' category biases *shifting over trials* according to the target distribution. Note that the DFT does not predict a complete reversal of geometric bias. Rather, two effects should be superimposed—bias away from the vertical and horizontal axes and bias based on the LTM of the target distribution. If location memory biases are not sensitive to the target distribution, as the CAM predicts, however, our modifications should not affect response patterns differentially across conditions.

2. Methods

2.1. Participants

Forty undergraduates (23 males) participated in exchange for course credit or payment. All were right-handed and reported normal or corrected-to-normal vision.

2.2. Materials

Participants sat in front of a 19-in. monitor with a large white circle (12.75 cm radius, 1 mm border) centered on it. Stimuli consisted of white dots (~1 mm in diameter) presented 6.38 cm from the center of the circle. At the time of location estimation, a yellow dot (~1 mm in diameter) appeared at the center of the monitor. Participants responded by moving the yellow dot to the remembered location.

Stimuli differed in two ways from Huttenlocher et al.'s (2004) Experiment 4. First, the circle radius was larger (12.75 cm vs. 8.5 cm) to allow estimation responses to vary across a greater spatial range. Second, we decreased the target size from 2 mm to 1 mm to provide for more precise localization.

2.3. Procedure

Each trial consisted of the 2 s presentation of a white target dot at one of the target locations, followed by a 10 s delay, then the appearance of the yellow response dot at the center of the screen. To prevent fixation at the

[1] Huttenlocher et al. also included an explicit categorization task, which we eliminated to avoid potential cross-talk between explicit and implicit category processes.

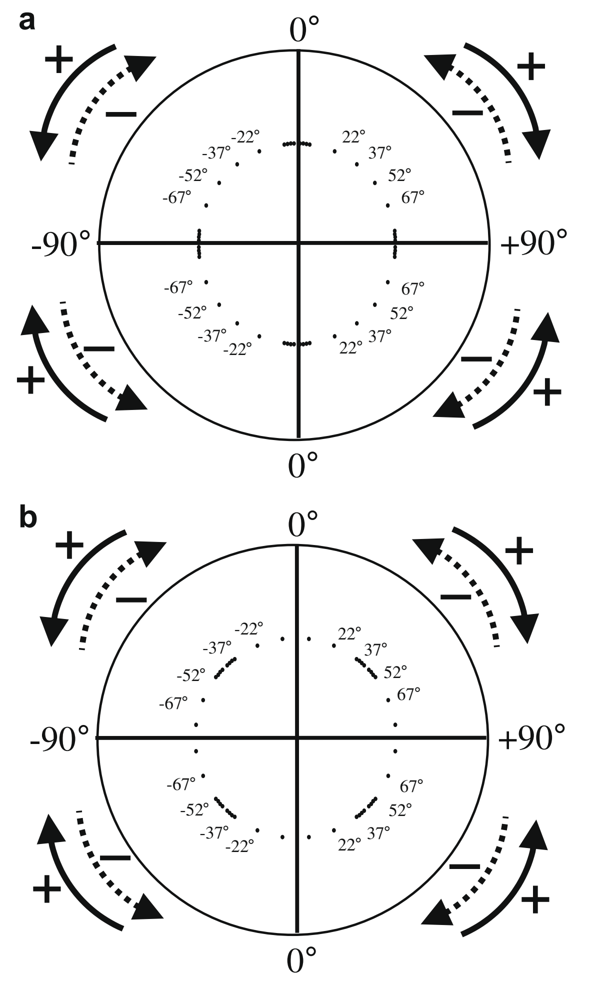

Fig. 1. Target locations presented in the (a) HV and (b) X distribution conditions. Labeled target locations indicate the four common targets analyzed in each quadrant (±22°, ±37°, ±52°, ±67°). Positive memory biases (solid line arrows) indicate errors in the direction away from the vertical axis. Negative memory biases (dotted line arrows) indicate errors in the direction toward the vertical axis.

target location, participants were instructed to look at the monitor edges throughout the delay, reorienting to the screen when the computer said "Ready, Set, Go!". Participants then moved the response dot to the remembered location and clicked the mouse button. The inter-trial interval varied randomly between 1.5 and 3.5 s.

Participants were randomly assigned to either horizontal–vertical (HV) or diagonal (X) distribution conditions. Target locations were clustered along the horizontal and vertical axes in the HV condition, and the diagonal axes in the X condition (Fig. 1). We presented four trial blocks, with each target presented once per block in random order. Note that Huttenlocher et al. (2004) presented targets at one-half (4.25 cm) and three-fourths (6.38 cm) of the circle radius whereas we presented targets only at one-half the circle radius (6.38 cm). This allowed us to present each target four times while still retaining a manageable total experiment time.

2.4. Data analysis

As in Huttenlocher et al. (2004), we analyzed responses only for the 16 target locations that were shared across the distributions and more than 7.5° from the horizontal and vertical axes. Note that location estimation responses tend to be more strongly biased away from the vertical axes than from the horizontal axes (see Huttenlocher et al., 2004; Spencer & Hund, 2002). Thus, to facilitate comparisons across quadrants, locations were labeled by their deviation from the vertical axis (Fig. 1). Errors were computed such that positive errors indicate biases away from the vertical axis. We analyzed performance for the first presentation of each target (Block 1) for comparison with Huttenlocher et al., and the fourth presentation (Block 4) to examine the effect of target repetition.

Directional errors exceeding the mean response ±2 SDs for a specific target across participants in each condition were removed as outliers. The minimum SD allowed was 5° to prevent removal of accurate responses due to low variability; the maximum SD allowed was 15° to prevent extreme errors from inappropriately influencing the distribution. In Block 1, 25 outlier responses were removed (3.9%; 11 for the HV condition, 14 for the X condition); in Block 4, 24 responses were removed (3.8%; 12 for HV, 12 for X).

3. Results

Fig. 2 shows the Block 1 response pattern for the 4 common targets in each quadrant. Consistent with Huttenlocher et al. (2004), responses were biased *away from* the vertical axis (positive errors) when the targets were near this axis (±22° from vertical), and *toward* the vertical axis (negative errors) when the targets were near the horizontal axis (±67° from vertical).

We fit regression lines to the data within each quadrant for each distribution. Table 1 reports these slopes, along with those from Huttenlocher et al. (2004). As in Huttenlocher et al., there were no significant slope differences across conditions, and the regressions provided a robust fit to the data. Thus, Block 1 replicates the pattern from Huttenlocher et al., suggesting that our modifications did not meaningfully alter performance. Given the similar performance profiles across quadrants in Block 1 (see Table 1), we collapsed the data in each block across targets equidistant from the vertical axis (i.e., ±22°, ±37°, ±52°, ±67°).

The critical question is whether repetitions to each target altered performance across conditions and blocks. Fig. 3 shows mean location memory performance for the four targets (collapsed across quadrants) in Block 1 and Block 4 for the HV (Fig. 3a) and X (Fig. 3b) conditions. Overall, both distributions show the same characteristic bias profile across blocks, namely bias *away from* the vertical axis for targets near this axis (i.e., ±22°) and bias *toward* the vertical axis for targets far from this axis (i.e., ±67°). Moreover, Table 2 shows that the regression slopes and correlation values across conditions in each block are comparable. Using this statistical criterion—as used by Huttenlocher et al. (2004)—we would conclude that the target distributions did not significantly impact performance.

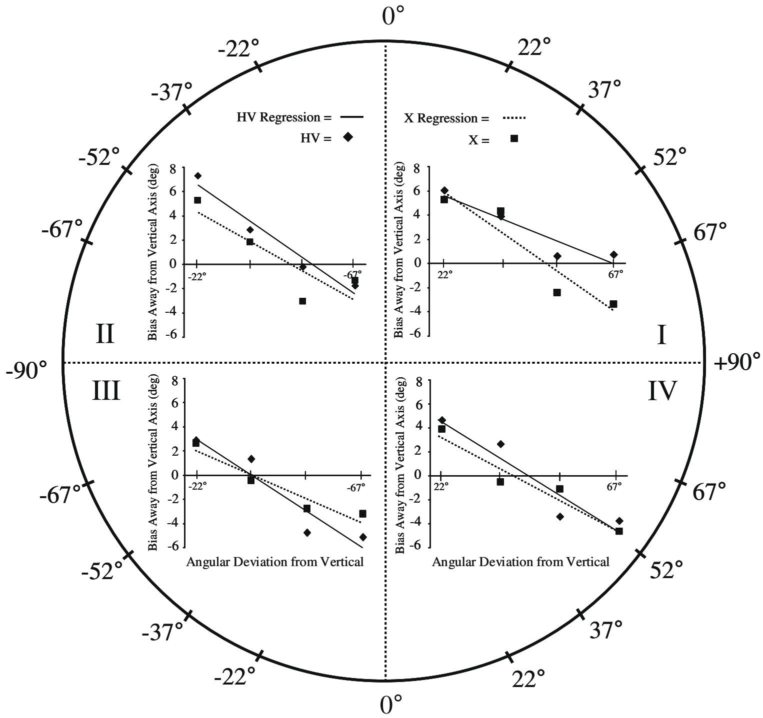

Fig. 2. Mean location memory responses in Block 1 across target locations and conditions, shown separately for each quadrant. Positive values indicate errors away from the vertical axis; negative values indicate errors toward the vertical axis (away from the horizontal axis). To facilitate comparisons between quadrants and preserve the relevant relations from the directional coding scheme used by Huttenlocher et al. (2004), target locations are plotted according to their angular deviation from the vertical axis.

Table 1
Regressions of Block 1 location memory biases, separated by distribution condition and quadrant for target locations appearing in both the HV and X distributions.

	HV distribution		X distribution		Difference in slope			
	Experiment[a]	Huttenlocher et al.[b]	Experiment[a]	Huttenlocher et al.[b]	Experiment		Huttenlocher et al.[b]	
					t	p	t	p[c]
Quadrant I								
Slope	−0.127	−0.193	−0.218	−0.102	1.43	0.23	−4.10	NS
r	−0.942	−0.992	−0.943	−0.982				
Quadrant II								
Slope	−0.201	−0.188	−0.165	−0.051	0.5	0.64	−3.16	NS
r	−0.978	−0.993	−0.87	−0.671				
Quadrant III								
Slope	−0.201	−0.195	−0.133	−0.108	−1.16	0.31	−1.35	NS
r	−0.94	−0.984	−0.955	−0.785				
Quadrant IV								
Slope	−0.208	−0.124	−0.175	−0.149	0.55	0.61	0.41	NS
r	−0.948	−0.881	−0.966	−0.959				

[a] Errors were computed such that positive errors indicate memory biases away from the vertical axis, negative errors biases toward the vertical axis (away from the horizontal axis). To facilitate comparisons between quadrants and preserve the relevant relations from the directional coding scheme used by Huttenlocher et al. (2004), correlations and slopes were calculated relative to the targets' absolute deviation from the vertical axis.
[b] Results from Huttenlocher et al. (2004), Experiment 4.
[c] Precise p values were not reported; all p values >.05.

Nevertheless, Fig. 3 shows that the regression lines shift systematically over blocks *in opposite directions across conditions*: downward for targets in the HV condition and upward for targets in the X condition. To quantify this difference, we computed a difference score (Block 4–Block 1) within each condition (see Fig. 3c). Regression analyses on these difference scores revealed a significant intercept difference across conditions ($b = -3.17$, $t = 4.43$, $p = .007$), confirming the significant impact of target distribution on performance across blocks. We also conducted a mixed-model ANOVA with Block (1, 4) and Target as within-subjects factors and distribution as a between-subjects

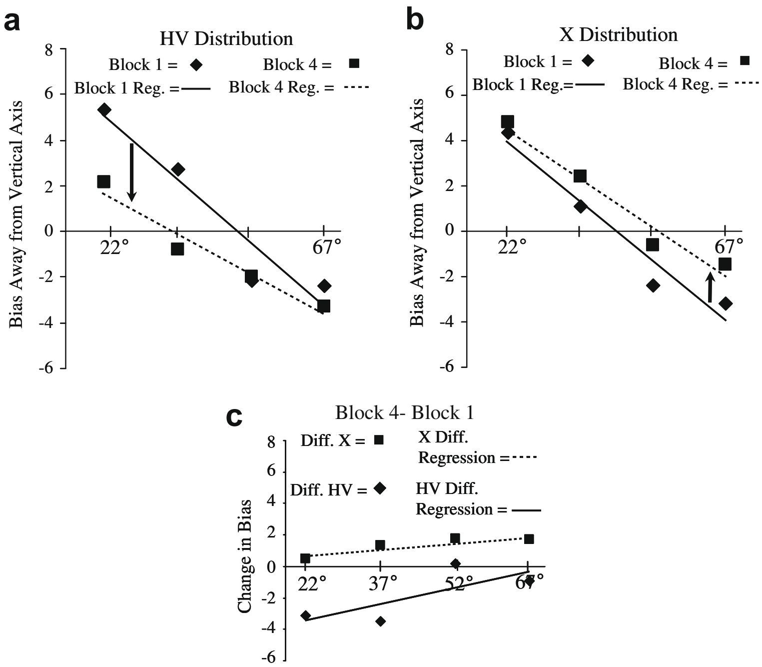

Fig. 3. Comparison of performance between Block 1 and Block 4 for (a) HV and (b) X distributions, collapsed across targets equidistant from the vertical axis in each quadrant (see text and Table 2 for details). (c) Change in location memory biases from Block 1 to Block 4 across conditions.

Table 2
Regressions of location memory biases for target locations appearing in both the HV and X distributions, collapsed across quadrants and separated by distribution condition and trial block.

	HV distribution	X distribution	Difference in slope	
			t	*p*
Block 1				
Slope	−0.186	−0.174	0.24	0.83
r	−0.955	−0.974		
Block 4				
Slope	−0.117	−0.146	0.99	0.38
r	−0.972	−0.980		

factor. Results yielded a main effect of Target, $F(3, 114) = 43.6$, $p < .001$, indicating a significant bias away from the horizontal and vertical axes across targets in both conditions (see Fig. 3). Critically, there was also a significant Distribution × Block interaction, $F(1, 38) = 10.6$, $p = .002$ (all other $ps > .15$). Simple effects tests showed a significant Block effect in the HV condition, $F(1, 19) = 5.4$, $p = .031$, confirming a downward shift in memory bias between Block 1 ($M = 0.90$, $SE = 0.60$) and Block 4 ($M = -0.97$, $SE = 0.57$). By contrast, there was an upward shift in memory bias in the X condition, $F(1, 19) = 5.5$, $p = .03$, between Block 1 ($M = -0.03$, $SE = 0.47$) and Block 4 ($M = 1.28$, $SE = 0.34$). These results verify that the target distributions significantly influenced spatial recall over blocks.

4. Discussion

Research from Huttenlocher et al. (2004) motivated by the CAM suggested that location memory is not affected by inductive category processes. These findings contrast with earlier work from Spencer and Hund (2002) motivated by the DFT. One possible explanation for this discrepancy is that target distribution effects are limited to sparsely populated distributions (as in Spencer and Hund). Another possibility suggested by the DFT is that induced category effects emerge over repeated trials.

We tested these alternatives here in a task based on Experiment 4 in Huttenlocher et al. (2004) but increased the number of presentations per target, the memory delay, and the circle size. Our results revealed opposite shifts in location memory bias over experience across the HV and X conditions. These distribution-based changes indicate the presence of an inductive process in spatial cognition that operates over both sparsely and densely populated distributions.

What are the implications for existing theories of spatial memory? The CAM is not consistent with our results because this model has no mechanism by which experience can modulate performance. However, recent extensions of

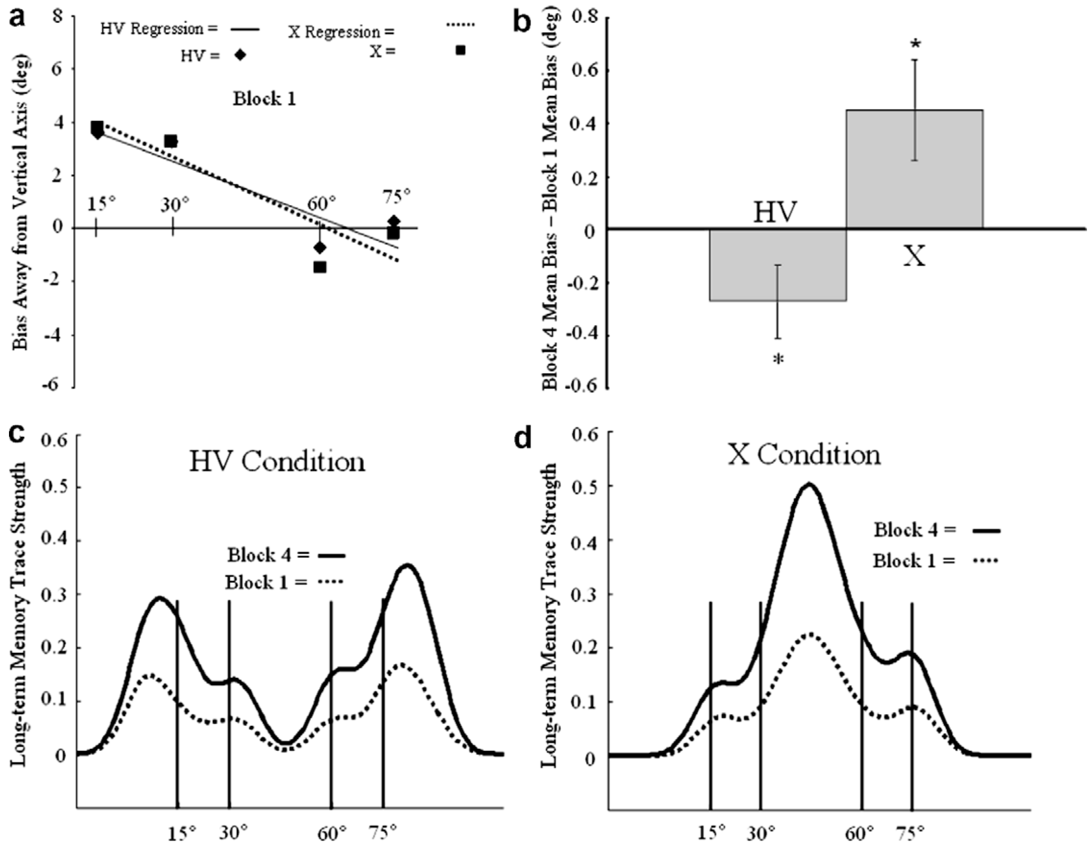

Fig. 4. (a) Simulation results for HV and X distributions in Block 1. (b) Differences in mean bias between Block 1 and Block 4 for HV and X distributions, where * indicates $p < .05$. Accumulation of traces in LTM across blocks for HV (c) and X (d) conditions.

this approach can capture inductive biases found in object estimation tasks (e.g., Crawford, Huttenlocher, & Hedges, 2006; Huttenlocher et al., 2000). Thus, in principle, the more general Bayesian framework to which the CAM belongs might be able to capture our reported effects. Future elaborations of the CAM model will be required to evaluate this possibility. Note, however, that the CAM model has a number of other short-comings that we have discussed elsewhere. For instance, this model does not capture the pattern of response variability near category boundaries (see Schutte & Spencer, in press), it is not a process model and therefore has no mechanism to explain why spatial memory biases increase systematically over delays (see Spencer & Hund, 2002), and it does not capture changes in geometric biases over development (see Schutte & Spencer, in press). Thus, there is a growing suite of phenomena not adequately addressed by this model.

The DFT presents a compelling alternative. The DFT captures working memory for a target location through a peak of neural activation that is actively maintained via recurrent interactions during delays. Importantly, such patterns of neural activation must be coupled to activation patterns associated with perceptual cues in the local workspace (e.g., reference frames). This keeps working memories in register with the local surrounds as a person moves, as objects move, and so on. Geometric biases arise in the DFT as a consequence of these two demands—actively maintaining the target location, on one hand, and actively staying in register with perceived reference frames on the other. In particular, perceptual peaks *repel* working memory peaks when the to-be-remembered location is relatively close to the reference frame. This occurs as a natural consequence of the surround inhibition associated with each activation peak and the fact that perceptual peaks are anchored to perceived cues. This repulsion of memory peaks away from perceived reference frames accounts for geometric biases, including the pattern of lower response variability near reference frames and the increase in bias over delays (see Schutte & Spencer, in press).

In addition to capturing the details of working memory processes, a peak in the DFT also leaves a trace in LTM which is reciprocally coupled to working memory. This reciprocal interaction implements a form of Hebbian learning (Spencer, Dineva, & Schöner, 2009), and can create biases toward an average remembered location (Spencer & Hund, 2002) or toward more frequent locations (Hund & Spencer, 2003).

To demonstrate this, we simulated the present results using the model of Schutte and Spencer (in press), with the addition of a LTM mechanism that captures changes in spatial recall over learning in a supervised learning task (Lipinski, Spencer, & Samuelson, in preparation). We used the parameters from Schutte and Spencer and two modified LTM parameters from Lipinski et al. to reflect the unsupervised nature of the present task: we slowed the time-scale of accumulation in LTM (from 3000 to 70000 time steps) and reduced the strength of the LTM contribution to working memory (from .2 to .1). We also modified the vertical input from Lipinski et al. to increase repulsion for common targets near the vertical axis, and added a horizontal input to weaken repulsion for targets near the horizontal boundary. Finally, to make the simulation task more tractable, we used simpler target distributions (HV: 3°, 7°, 15°, 30°, 60°, 75°, 83°, 87°; X: 15°, 30°, 38°, 42°, 48°, 52°, 60°, 75°). The simulated target distributions had eight targets in the quadrant we simulated—four common targets (15°, 30°, 60°, 75°) and four shifting targets. We maintained the central characteristics of the original target set used by Huttenlocher et al. (2004) by averaging the locations of adjacent targets used here. We ran 100 simulations in each condition across four blocks of trials with a 10 s delay on each trial. *The simulations were identical across conditions with the exception of the target distribution (HV vs. X).*

Fig. 4a shows simulation results for Block 1 for the four common targets. The negative regression slope replicates the pattern from Huttenlocher et al. (2004). There were no significant slope differences across conditions ($t = .35$; $p = .74$) and the regressions provided a robust fit to the data ($r = .9$; cf. Table 1). Critically, changes in recall errors between Block 1 and Block 4 differed significantly across conditions (Fig. 4b): mean errors for the common targets in the HV condition significantly *decreased* over experience ($M = -0.27$; $p = .049$), while errors to these targets in the X condition significantly *increased* over experience ($M = 0.45$; $p = .02$). Thus, the DFT produces the same direction of distribution-dependent change over blocks as seen in our data.

Fig. 4c and d shows the LTM traces across conditions at the end of Blocks 1 and 4. The LTM distributions clearly differed, even at the end of Block 1, but this did not significantly affect performance because LTM was still relatively weak. However, larger differences in LTM, capable of influencing performance, emerged by Block 4. What explains the differential direction of bias across blocks? In the HV condition (Fig. 4c), errors to the 15° and 30° targets were both biased inward, whereas responses to 60° and 75° changed little because 60° was located on a flat part in LTM and 75° was close to the average remembered location for the outer targets (the weak bias away from horizontal pushed this average closer to 75°). Thus, there was an overall inward bias in the HV condition, largely driven by the common targets closer to the vertical axis. In the X condition (Fig. 4d), errors to the 15° and 30° targets were biased outward by Block 4, whereas responses to the 75° target were, once again, near a bump in LTM and showed little change over blocks. The 60° target also showed little change—it was balanced between attraction inward and a pull toward the bump at 75°. Thus, there was an overall increase in outward bias in the X condition.[2]

In summary, the present results provide clear evidence that inductive processes operate within the spatial memory system, as reported by Spencer and Hund (2002). Critically, these findings are not consistent with the CAM but—as our simulation results demonstrate—they are consistent with the DFT. The present work, therefore, provides a critical test of these two spatial memory theories.

[2] Note that the model produced smaller biases than were found empirically. In our view, this is acceptable given that the model produced the correct qualitative pattern using parameters from two other studies.

Acknowledgements

This research was supported in part by NSF-HSD 0527698 and NIH-RO1MH62480 awarded to John P. Spencer.

References

Ashby, F. G., & Alfonso-Reese, L. A. (1995). Categorization as probability density information. *Journal of Mathematical Psychology, 39*, 216–233.

Casasola, M. (2008). The development of infants' spatial categories. *Current Directions in Psychological Science, 17*, 21–25.

Crawford, L. E., Huttenlocher, J., & Hedges, L. (2006). Within-category feature correlations and Bayesian adjustment strategies. *Psychonomic Bulletin & Review, 13*, 245–250.

Crawford, L. E., Regier, T., & Huttenlocher, J. (2000). Linguistic and non-linguistic spatial categorization. *Cognition, 75*(3), 209–235.

Griffiths, T. L., Sanborn, A. N., Canini, K. R., & Navarro, D. J. (2008). Categorization as nonparametric Bayesian density estimation T. In M. Oaksford & N. Chater (Eds.), *The probabilistic mind: Prospects for rational models of cognition*. Oxford: Oxford University Press.

Hund, A. M., & Spencer, J. P. (2003). Developmental changes in the relative weighting of geometric and experience-dependent location cues. *Journal of Cognition and Development, 4*(1), 3–38.

Huttenlocher, J., Hedges, L., Corrigan, B., & Crawford, L. E. (2004). Spatial categories and the estimation of location. *Cognition, 93*, 75–97.

Huttenlocher, J., Hedges, L. V., & Duncan, S. (1991). Categories and particulars: Prototype effects in estimating spatial location. *Psychological Review, 98*, 352–376.

Huttenlocher, J., Hedges, L. V., & Vevea, J. L. (2000). Why do categories affect stimulus judgement? *Journal of Experimental Psychology: General, 129*, 220–241.

Lipinski, J., Spencer, J.P., & Samuelson, L.K. (in preparation). Biased feedback in spatial recall yields a violation of delta rule learning.

Murphy, G. L. (2002). *The big book of concepts*. Cambridge: MIT Press.

Rogers, T. T., & McClelland, J. L. (2004). *Semantic cognition*. Cambridge: MIT Press.

Schutte, A. R., & Spencer, J. P. (in press). Tests of the dynamic field theory and the spatial precision hypothesis: Capturing a qualitative developmental transition in spatial working memory. *Journal of Experimental Psychology: Human Perception & Performance.*

Simmering, V. S., Schutte, A. R., & Spencer, J. P. (2008). Generalizing the dynamic field theory of spatial cognition across real and developmental time scales. *Brain Research, 1202*, 68–86.

Spencer, J. P., Dineva, E., & Schöner, G. (2009). Moving toward a unified theory while valuing the importance of the initial conditions. In J. P. Spencer, M. S. Thomas, & J. L. McClelland (Eds.), *Toward a unified theory of development: Connectionism and dynamic systems theory re-considered* (pp. 354–372). New York: Oxford University Press.

Spencer, J. P., & Hund, A. M. (2002). Prototypes and particulars: Geometric and experience-dependent spatial categories. *Journal of Experimental Psychology: General, 131*, 16–37.

Spencer, J. P., & Hund, A. M. (2003). Developmental continuity in the processes that underlie spatial recall. *Cognitive Psychology, 47*(4), 432–480.

Spencer, J. P., Simmering, V. S., & Schutte, A. R. (2006). Toward a formal theory of flexible spatial behavior: Geometric category biases generalize across pointing and verbal response types. *Journal of Experimental Psychology: Human Perception & Performance, 32*, 473–490.

Spencer, J. P., Simmering, V. S., Schutte, A. R., & Schöner, G. (2007). What does theoretical neuroscience have to offer the study of behavioral development? Insights from a dynamic field theory of spatial cognition. In J. M. Plumert & J. P. Spencer (Eds.), *Emerging landscapes of mind: Mapping the nature of change in spatial cognition* (pp. 320–361). Oxford: Oxford University Press.