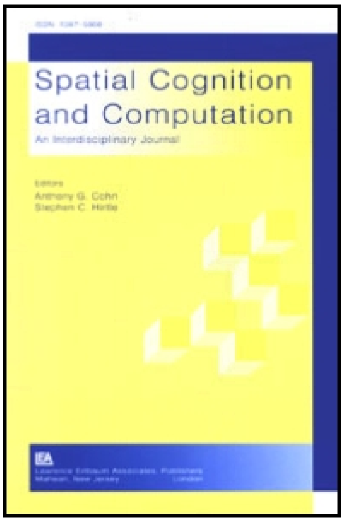

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External Cue Effects on Memory for Spatial Location within a Rotated Task Field

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Abstract: Fitting, Wedell and Allen (2007) demonstrated that although memory for location within a small two-dimensional task field is largely independent of cues when orientation is fixed, it is highly dependent on cues when orientation varies by rotating the task field on a majority of trials. Their analysis focused only on 0° rotation trials. The current investigation aimed to understand the spatial estimation process under conditions of actual rotation and thereby analyzed the cue effects for the 30°, 90°, and 160° rotation trials of that experiment. Results indicated strong cue-based angular bias effects, which were modeled as resulting from use of cues as category prototypes. Unique to rotation trials, the number of inferred protypes did not generally correspond to the number of cues. In the one-cue condition, there was evidence that an additional prototype was generated at a location opposite the single cue, representing a "phantom" prototype. In the three-cues condition, there was evidence that only two cues served as prototypes biasing estimation. Absolute error in spatial memory was also strongly reduced as a function of proximity to cues, implicating the role of cues in anchoring fine-grain memory. In contrast to the bias measure, effects on absolute error were more directly tied to actual cue locations.

Keywords: spatial memory, place memory, categorical coding, fine-grain memory, external cues, mental rotation

Researchers have studied spatial memory in a variety of ways, with different procedures often leading to the use of different spatial representations. For example, studies of the Morris water maze, in which place memory is determined by spatial relations among distal cues and to-be-remembered locations, demonstrate that external cues play a critical role in coding the location of the hidden platform or the to be remembered object in both humans and animals (Morris, 1981; Morris & Parslow, 2004; Nadel, 1990), a cue-based representation.

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In contrast, spatial representations can also utilize an environmental frame of reference other than cues, such as features of the background or the shape of the task field (Cheng, 1986; Huttenlocher, Hedges, & Duncan, 1991; Mou & McNarmar, 2002; Wedell, Fitting, & Allen, 2007), a cue-independent representation. Such lack of responsiveness to cues occurs even when use of the cues would greatly improve accuracy. Such contrasting results indicate that the role of cues in spatial memory representations is highly task dependent. A key issue for reseachers then is to determine what conditions support different spatial representations and processes in memory. In particular, this article delineates how cues are used when orientation to a small spatial task field is rotated to different degrees on each trial.

This study derives from a recent set of studies by Fitting, Wedell, and Allen (2007), which explored conditions that might promote a cue-based representation of spatial location within the simple task of remembering a point location in a small 2-dimensional circular task field. Prior research using this task had typically not included any manipulation of external cues (e.g., Huttenlocher et al., 1991). That research had demonstrated that memory for spatial location of a dot presented briefly in a circular task field was biased toward the central tendency of the quadrant in which the dot appeared. This parsing of the space supports the use of either a viewer-based frame of reference or a geometric-based frame of reference to divide the circular task field into four quadrants or spatial categories, with uncertainty about the location of the dot resolved toward the relevant prototype location.

Experiment 1 of Fitting et al. manipulated whether zero, one, or three salient external cues surrounded the circular task field and found that the cue manipulation had no effect on any of the reported dependent variables (angular bias, radial bias, or absolute error). Thus, in the fixed orientation version of the task typically used, external cues appear irrelevant and play little or no role in memory for the spatial representation. In a subsequent followup set of experiments, Fitting, Wedell, and Allen (in press) systematically varied the number of cues surrounding the fixed orientation task field and found that these did not affect the categorical parsing of the space, although they did lead to some changes in memory accuracy and radial bias.

However, Experiment 2 of Fitting et al. (2007) demonstrated dramatically different results from these using a procedure in which the task field was rotated either 0°, 30°, 90°, or 160° on any given trial. Figure 1 presents a schematic representation of the four rotation conditions along with the 32 dot locations used. On all trials the dot location was presented in the 0° orientation for 1.5 s, followed by an alternating checkerboard pattern filling the circle for 3.0 s. The rotation became apparent in the response phase of the trial when the task field was presented in one of the four orientations shown in Figure 1. The circled target in each panel of Figure 1 provides an example of how the location shifted with rotation, along with the corresponding shifts of cue locations. Fitting et al. analyzed the 0° rotation condition because it represented the exact display parameters used in the fixed orientation

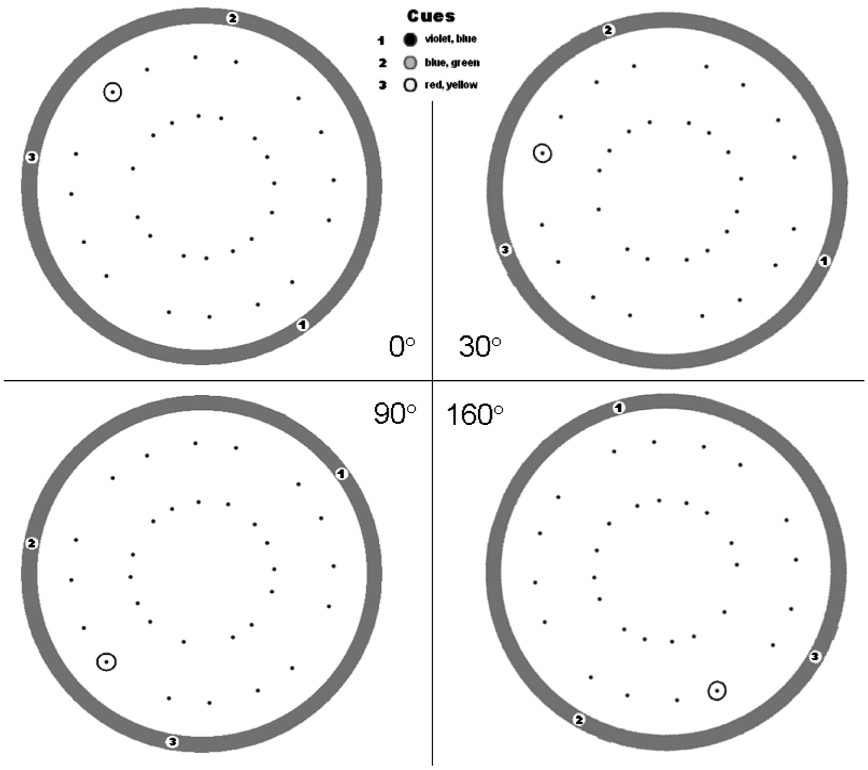

Figure 1. Circular task field (radius of 212 pixels) with 32 target dot locations distributed over the circular area (16 dots located at a radius of 92 pixels and 16 located at a radius of 168 pixels). Within each of four quadrants, dots were located at one of four different angles (3°, 25°, 43°, and 75°). A black border 20 pixels in width defined the circle. Numbers refer to cue locations at 80°, 170°, and 305°. Reference cues were small circles presented in two different colors as indicated. The different degrees of rotation are illustrated in the corner of each panel. The circled target illustrates how location varies with rotation. Note: The size of the dots does not correspond to the actual scale of presentation.

version of the task and thus was most comparable. They found that cues strongly affected the inferred category structure, as reflected in the types of errors and biases observed. The rotation data were not analyzed in that report because they were deemed not directly comparable to fixed orientation trials and because of greater proportions of data being excluded for blatant misremembering.

In this article, we first describe the theoretical model developed for the 0° rotation data in the fixed and variable orientation tasks and how the data conformed to it. We then justify additional modeling changes needed to explain the data for rotation trials. We then present the method and results for the 30°, 90°, and 160° rotation conditions as analyzed using our modeling procedures.

PRIOR MODEL DEVELOPMENT

Our modeling of bias derives from the category-adjustment model developed by Huttenlocher et al. (1991). The core idea of this model is that spatial location is coded at two levels, fine-grain and categorical, with both being involved in the estimation process of an object's location. Following Huttenlocher et al. the expected value of the response in an estimation task ($E[R]$) is characterized as a weighted average of fine-grain and categorical information. Consequently, the expected bias (E[Bias]) is determined by subtracting the actual value from the response and can be described as follows:

$$E[\text{Bias}] = E[R] - \mu = \lambda\mu + (1 - \lambda)p - \mu \tag{1}$$

where μ is the mean of the distribution of fine-grain memory values for the object and is assumed to be unbiased and hence equated with the true location of the object. Similarly, p is the mean of the distribution of prototype locations for the relevant category. The parameter λ, which varies from 0 to 1, represents the relative weight of the fine-grain information. Typically the data are modeled in polar coordinates so that bias may be angular or radial. The model of Equation 1 provides a reasonable approximation to both biases typically observed in the dot location task, assuming that each of the four quadrants of the circle describe different spatial categories represented by a centrally located prototype (Huttenlocher et al., 1991; Huttenlocher, Hedges, Corrigan, & Crawford, 2004; Newcombe & Huttenlocher, 2000). In this study we are primarily focused on angular bias.

Our modeling of angular bias differs from that of Huttenlocher et al. (1991) in two basic ways. First, we include parameters that reflect a tendency for targets near the boundaries to exhibit reduced bias. Like the uncertain boundaries version of the Huttenlocher et al. model, our fuzzy-boundary version attributes this reduction in bias to the tendency of targets near the border to recruit the respective prototypes for the adjacent categories, with the categorical effects then largely cancelling out. Second, our fuzzy-boundary model includes two possibilities for constructing spatial categories. In the first version, these may be specified a priori, as when we designate the four quadrants defined by the horizontal and vertical segmentation of the space (consistent with viewer-based or geometric-based frames of reference). In the second version, the location and number of categories are inferred from the modeling procedure, providing a useful test and description of cue-dependent category representations. The former model is referred to as the fixed-quadrants fuzzy-boundary model and the latter as the cue-based fuzzy-boundary model. In this paper we will focus on the cue-based fuzzy-boundary model (for detailed description of the fixed-quadrants fuzzy-boundary model, see Fitting, Wedell, & Allen, 2005; Fitting et al., 2007).

Angular bias for the cue-based fuzzy-boundary model can be expressed as follows:

$$E[\text{Bias}] = \lambda\mu + (1-\lambda)\sum \Pr(p_j|\mu)p_j - \mu \qquad (2)$$

The key difference between Equations 1 and 2 is that the prototype weighting $(1-\lambda)$ is applied to each prototype in Equation 2, as modified by the probability of prototype retrieval given the stimulus. The prototype recruitment equation is based on the angular similarity of the stimulus location to the prototype location as follows:

$$\Pr(p_j|\mu) = \frac{\exp(-c|\mu - p_j|)}{\sum \exp(-c|\mu - p_k|)} \qquad (3)$$

Equation 3 assumes that similarity is a negative exponential function of distance (Shepard, 1987) and prototype recruitment follows a proportional strength rule (Luce, 1959). In Equation 3, the only new parameter estimated is c, which represents the sharpness of the boundaries.[1] As c increases, the fuzzy-boundary model tends to recruit only one prototype for a given target. Note that the form of Equation 3 means that boundaries are posited to fall at equal distances from the category prototypes. The cue-based fuzzy-boundary model incorporates Equation 3 into Equation 2, modifying prototype weighting by the probability of prototype recruitment, $\Pr(p_j|\mu)$. The fuzzy-boundary model essentially adds just one parameter to the basic category-adjustment model, c, which determines the sharpness of the boundary.[2]

The cue-based fuzzy-boundary model provided a good fit to the angular bias data for the one-cue and three-cues conditions (0° rotation) of the Fitting et al. (2007) Experiment 2. Figure 2 shows the theoretical functions inferred by the model for those conditions. Panel A presents the functions fitting the one-cue condition in which the cue appeared at 305° (see Figure 1 for cue locations). Tests of additional variance explained justified separate functions for short radius and long radius targets, with the only difference being the value of the fine-grain weighting parameter, $\lambda = 0.916$ for short radius targets and $\lambda = 0.939$ for long radius targets. The same value of the boundary parameter, $c = 0.025$ and prototype location, $p = 281°$ were used for all

[1]In Equation 3, c is a constant. In fitting different versions of this model to the data, we allowed c to vary with stimulus (long and short radius) or with prototype. These distinctions are described in detail when we report the model fitting procedures in the *Results* section.

[2]In modeling the actual data, we include "virtual" prototypes for the lowest and highest categories so that recruitment may be conducted in a clockwise or counterclockwise fashion in the same way for each quadrant.

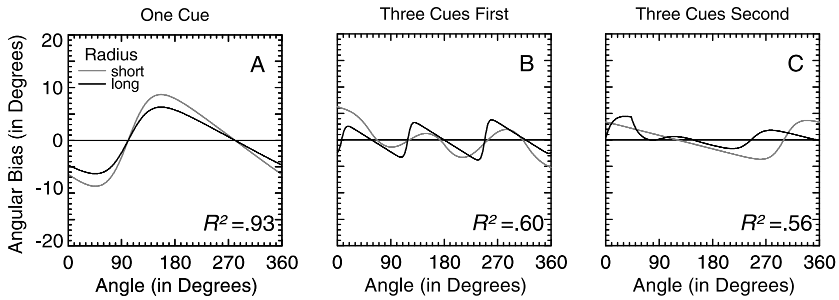

Figure 2. Fit to the mean angular bias data for the 0° rotation condition of Fitting et al. (2007). Functions represent the fit of the cue-based fuzzy-boundary model separately for the short and long targets. Panel A shows a 4-parameter fit to the one-cue data. Panel B shows a 7-parameter fit to the three-cues-first data. Panel C shows a 6-parameter fit to the three-cues-second data.

targets, with a resulting high proportion of variance in mean angular bias explained, $R^2 = 0.93$.

As depicted in Figure 2, the bias function crosses the X-axis (i.e., $X = 0$) in two places, at 281°, corresponding to the prototype location, and at $281° - 180 = 101°$, corresponding to the inferred boundary location. The pattern of bias shown in panel A is considerably at odds with the pattern typically obtained with fixed orientation, as represented by four downward sloping functions, each intersecting the X-axis at the prototype location within a given quadrant. Instead, there is a single downward sloping function for these data, with the inferred location of the prototype close to the actual location of the cue. This pattern of data provides compelling evidence for the use of a cue-based prototype when the task field is rotated on a majority of trials.

Panel B of Figure 2 presents the functions fitting the conditions in which three cues appeared (at 80°, 170°, and 305°) and participants made their estimates in this condition prior to making estimates in the one-cue condition. Once again, tests of the additional variance explained justified separate functions for short radius and long radius targets. The functions reflect a model with seven parameters. Inferrred prototype locations were held constant across radius conditions and were determined to be located at 58°, 180° and 317°, values fairly close to the actual cue locations. The data were fit best by allowing both the fine-grain memory weighting parameter and the boundary sharpness parameter to vary with radial location of targets. For short radius targets, inferred values were $\lambda = 0.651$ and $c = 0.015$; for long radius targets, inferred values were $\lambda = 0.930$ and $c = 0.160$. Thus, the short radius targets depended more on categorical information, but that information was obscured more by reduced sharpness of boundaries. The proportion of variance in the mean angular bias of estimates explained by the model was $R^2 = .60$. Once again, the pattern of data obtained in the three-cues condition is at odds with the typically obtained pattern of four quadrant-based prototypes because instead of four downward sloping functions there are just three (one for each prototype).

Panel C of Figure 2 presents the functions fitting the conditions in which the same three cues appeared but participants made their estimates in this condition after making estimates in the one-cue condition. Statistical analyses showed a carry-over effect in this condition (but none was obtained for estimates in the one-cue condition as a function of order). The pattern of data appeared to conform to the general idea that for short radius target locations, participants used essentially one prototype, but for long radius target locations they tended to use three prototypes.

This model provided a good account of the data using six free parameters ($R^2 = 0.56$). In modeling these data, the values of fine-grain memory weighting and boundary sharpness were held constant across radius conditions ($\lambda = 0.972$ and $c = 0.043$), with only inferred prototypes differing across conditions. For the short radius targets, a single prototype location was inferred at 120°. For the long radius targets, the three inferred prototypes were located at 43°, 144° and 349°. As with the other conditions, the pattern of data obtained in this condition is at odds with the typically obtained pattern of four quadrant based prototypes when the task field is not rotated.

In summary, Fitting et al. (2007) demonstrated that when the task field is rotated on the majority of trials, cues tend to serve as prototypes, even on the trials in which the task field was not rotated (i.e., 0° rotation trials). These results stand in strong contrast to results they obtained when the task field is not rotated. Furthermore, the cue-dependent fuzzy-boundary model provided a reasonable account of these data. In this article, we examine how well the cue-based fuzzy-boundary model explains the pattern of bias in rotation conditions. Overall, we did not change the form of the model to explain these data. However, we did find that just as in the modeling of the data shown in Panel C of Figure 2, the number of inferred prototypes does not necessarily correspond to the number of cues.

MODELING ADDITIONAL EFFECTS

In addition to effects of cues on angular bias, Fitting et al. (2007) noted cue effects on absolute error, as measured by the pixel distance between the estimated location and the actual location. Although absolute error is influenced by both bias and random error, the modeling of the data indicated that these effects went beyond those predicted by the bias effects. The observed reductions in absolute error as a function of proximity to cues were consistent with the literature on the effects of cues on error (Cook & Tauro, 1999; Kamil & Cheng, 2001; Werner & Diedrichsen, 2002). Fitting et al. used a simple regression model to characterize these effects based on the idea that cues serve as memory anchors and thus reduce variability in the fine-grain representation. To characterize the localized effects of anchors, absolute error was predicted by the log of the distance of the target to the nearest cue. Thus, the following equation was used to predict the expected absolute error, $E[\text{AE}]$:

$$E[\text{AE}] = b_0 + b_1 \text{ Log}(d_{ij}) \quad (4)$$

where b_0 is an intercept representing a baseline amount of absolute error, b_1 is a regression coefficient that weights the effects of cues as represented by $\text{Log}(d_{ij})$, the logarithm of the distance between the target and the nearest cue. According to the anchoring hypothesis, the weighting of distance to nearest cue should be negative, resulting in less absolute error in a location when the target is proximal to a cue. Figure 3 presents the functions resulting from the fit of Equation 4 to the absolute error data in the 0° rotation conditions of Fitting et al. (2007). Note that only two parameters are free to vary in this model, b_0 and b_1. This model provided a parsimonious fit to the error data, with $R^2 = .59$ for the one-cue data and $R^2 = .60$ for the three-cues data. In support of the anchoring hypothesis, b_1 was inferred to be negative.

In anticipation of differences in the recruitment of cues to anchor error in the rotation conditions, we present a more general model that can be reduced to Equation 4 under specific constraints. The model is expressed as follows:

$$E[\text{AE}] = b_0 + \sum \text{Pr}(x_j|s_i)b_j \text{ Log}(d_{ij}) \quad (5)$$

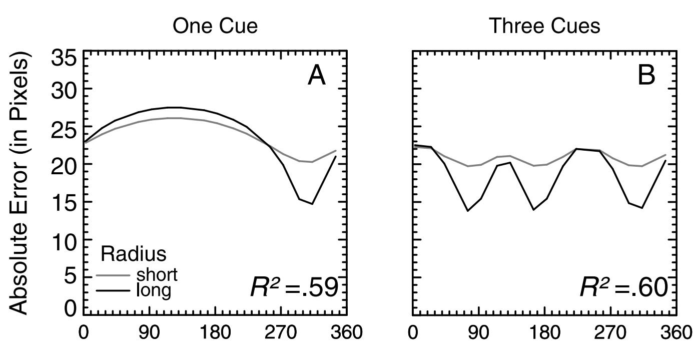

Figure 3. Fit to the mean absolute error for the 0° rotation condition of Fitting et al. (2007). The different functions shown for the short and long radius targets were generated without any parameters fit to the radius condition. Functions show the fit of a 2-parameter regression model based on proximity to the nearest cue. Panel A shows the fit to the one-cue data and panel B the fit to the three-cues data.

in which a probabilistic recruitment function is added to the equation, in a similar way as in the fuzzy-boundary model of Equations 2 and 3. However, one difference in the recruitment function is that recruitment is based on objectively defined external locations, x_j, rather than inferred prototype locations. A second difference is that the probabilistic recruitment function allows for the case where the sensitivity parameter varies with cue (c_j). When the sensitivity parameter is set at a high value, essentially just the nearest cue location will be recruited and Equation 5 will reduce to Equation 4.[3]

EXPERIMENTAL HYPOTHESES

Our focus in this article is on the non-0° rotation trials. In this section we describe a number of hypotheses that will be tested. Several of our hypotheses are predicated on the idea that mentally rotating the target location to correspond to the rotated cue locations is mentally taxing. The literature on mental rotation experiments supports this assertion, indicating that mental rotation is associated with an angle dependent increase in the demands placed on working memory (Harris et al., 2000; Shepard & Metzler, 1971; Silberstein, Danieli, & Nunez, 2003, Vasta, Belongia, & Ribble, 1994). It follows that degree of rotation should increase the cognitive cost of encoding, resulting in the location's coordinates being less exactly remembered and hence increases in error and bias. This assertion leads to several testable hypotheses.

Hypothesis 1: The number of blatantly misremembered locations will increase with increase in angle of rotation. This will be tested by a main effect of rotation on an Analysis of Variance (ANOVA) conducted on the number of data points inferred to be blatantly misremembered.

Hypothesis 2: Bias effects will increase with increase in angle of rotation. This will be tested in an ANOVA by an Angle × Rotation interaction on angular bias and by a Radius × Rotation interaction on radial bias.

Hypothesis 3: Mean absolute error will increase with increase in angle of rotation. This will be tested by a main effect of rotation in an ANOVA on absolute error.

Based on the results from the 0° rotation condition reported by Fitting et al. (2007), we hypothesize similar cue-based effects on bias and accuracy as shown in Figures 2 and 3.

[3]In Equation 5, the probabilistic recruitment function essentially falls out of the equation if c is fixed at 0.0. In this case, the equation becomes a simple regression equation on the different log distances. We describe the use of this variation of Equation 5 later in the *Results* section.

Hypothesis 4: The number and locations of spatial prototypes affecting angular bias will tend to correspond to the number and locations of external cues. This will be tested by an Angle × Cue interaction in the ANOVA on angular bias data.

Hypothesis 5: Absolute error should decrease as proximity to the nearest cue decreases. This will be tested by an Angle × Cue interaction in the ANOVA on the absolute error data.

Hypothesis 6: The radial prototype will tend to be located between the short and long radius targets, as typically found in dot location tasks (Huttenlocher et al., 1991; Fitting et al., 2007). This will be tested by a main effect of radius in the ANOVA on radial bias.

Finally, previous findings (Schmidt, Werner, & Diedrichsen, 2003; Werner & Diedrichsen, 2002) suggest that landmarks may systematically distort estimates of targets in close proximity to those landmarks. We interpret this as reflecting possible cue effects on radial bias.

Hypothesis 7: The radial prototype will tend to shifted toward external cues. This will be tested by an Angle × Cue interaction in the ANOVA on radial bias.

METHOD

Participants and Task

Participants were fifty-four undergraduate students from the University of South Carolina psychology department participant pool who attempted to reproduce dot locations.

Materials and Apparatus

All materials and instructions were presented on computers with using E-prime software (Version 1.1). A white circular region (212 pixels in radius) was separated from the white background by a black circular outline (20 pixels thick) presented in video graphics array mode at a resolution of 640 × 480 pixels. Dot locations were represented by a red dot (5 pixels in diameter). The reference cue for the one-cue condition was violet and blue in color and located at 305° along the circle. The reference cues for the three-cues condition included the same cue at 305° along with a blue and green cue located at 80° and a red and yellow cue located at 170° (see Figure 1). The locations of the cues were chosen to create markedly different patterns of bias for cases in which the cues are used as prototypes as opposed to the use of the standard four-quadrant representation.

Task and Procedure

One to five participants were tested at the same time within a laboratory room. Altogether, 32 target locations were distributed within a circular area on the screen to provide sufficient data for modeling the predicted biases. Short radius targets consisted of 16 dots located at a radius of 92 pixels, and long radius targets consisted of the other 16 dots located at a radius of 168 pixels. For both radii, four different angles were used (3°, 25°, 43°, and 75°) and presented in each of the four quadrants as shown in Figure 1. Dot locations were presented successively one at a time in random order. After the presentation of a dot, a checkerboard mask appeared followed by the rotated response task field. The task field was rotated 0°, 30°, 90°, or 160° by moving the locations of the peripheral cues around the field as illustrated in Figure 1. Number of cues was a within-subjects variable and consisted of either one external cue (at 305°) or three different peripheral cues (at 80°, 170°, and 305°) as shown in Figure 1. The order of cue presentation was a between-subjects variable (one cue first or three cues first). Participants were randomly assigned to the between-subjects conditions ($n = 27$ in each condition).

After the general instructions, participants experienced two learning trials with no rotations followed by a specific instruction about the rotation process. Feedback was given for two rotation-learning trials followed by five rotation-learning trials without feedback. Learning trials were followed by two experimental test sets with 128 different dot locations (32 dots in each of the four rotations). A dot appeared on screen for 1 s, followed by a dynamic checkerboard mask that covered the circular task field for 1.5 s, which was followed by a blank circle in the rotated position. The checkerboard mask consisted of alternating white and black squares (10×10 pixels in size) covering the circular region. To avoid fixation a moving pattern was created by exchanging the colors of the squares three times after 0.5 s. The participant used a mouse to move a cross-hairs cursor that appeared at the center of the circle to the remembered locations and clicked the mouse button to indicate their response (in pixel location on the screen). In the second set, which followed a 3-minute break, the cue condition was changed and participants rated the same dot locations presented successively in random order.

Spatial memory was assessed by three dependent variables. Absolute error corresponded to overall inaccuracy of place memory and consisted of the Euclidean distance in pixels between the actual and the observed dot location. Angular bias (in degrees) corresponded to the signed angular inaccuracy and was computed by subtracting the angle of the actual location from the angle of the reproduced location. Negative values indicate a clockwise bias and positive values indicate a counter-clockwise angular bias. Radial bias (in pixels) corresponded to signed radial inaccuracy and was computed by subtracting the radial distance of the actual point from the radial distance of the observed point. Negative radial values indicate bias towards the center of the circle and positive values indicate bias towards the circumference of the circle.

RESULTS

The observed dot locations were used to generate the dependent variables in all analyses. Because a blatant misremembering of a location can obscure systematic effects, we developed methods for identifying these data points and eliminating them from later analyses. An observed value was designated a blatantly misremembered location for all three dependent variables on the basis of absolute error and angular bias. For absolute error, a deviation of more than two standard deviations (SD) from the mean of estimates for that dot location across all participants within the corresponding cue condition indicated the observation was an outlier.

For angular bias a deviation of more than 90° in either direction was a blatantly misremembered location because deviations of this magnitude were likely due to gross errors of memory. Combining both methods, these blatantly misremembered locations were defined and recorded separately for each of the field rotations (0°, 30°, 90°, and 160°) and for each of the cue conditions, as shown in Table 1. The blatantly misremembered data points were replaced by the mean of the remaining values for the specific point in the corresponding condition (i.e., the Rotation × Cue × Order × Radius × Angle condition).

A 2 (Order) × 2 (Cue) × 4 (Rotation) × 2 (Radius) mixed factorial ANOVA was conducted on the frequency of blatantly misremembered data points identified for each subject. It revealed a significant main effect of rotation, $F(3, 156) = 32.36$, $p < .001$, indicating that blatant misremembering increased with increase in rotation. The main effect of rotation supports H_1, indicative of greater memory demands with increase in angle of rotation.

Table 1. Number and percentage values of replaced blatantly misremembered locations by rotation, cue, order and radius

	One cue first		One cue second		Three cues first		Three cues second	
Radius	Short	Long	Short	Long	Short	Long	Short	Long
0° rotation	22	15	13	11	14	12	16	12
	5.09%	3.47%	3.01%	2.55%	3.24%	2.78%	3.70%	2.78%
30° rotation	30	29	21	20	19	19	24	22
	6.94%	6.71%	4.86%	4.63%	4.40%	4.40%	5.56%	5.09%
90° rotation	73	64	61	55	49	43	64	52
	16.90%	14.81%	14.12%	11.34%	11.34%	9.95%	14.81%	12.04%
160° rotation	112	89	137	116	72	60	99	95
	25.93%	20.60%	31.71%	26.85%	16.67%	13.89%	22.92%	21.99%

The total number of trials in each cell of the table seen by all subjects was 432.

There was a significant radius effect, $F(1, 52) = 16.58$, $p < .001$, and a significant Rotation × Radius interaction, $F(3, 156) = 2.87$, $p < .05$. These effects generally indicate greater misremembering of short radius targets, especially in the 160° condition. No other significant effects were noted.[4]

[4]Because missing data points increase with increases in degree of rotation, as shown in Table 1, a potential confound arises for the analyses we report. Namely, the differential amounts of missing data mean that the more accurate subjects may be overrepresented in high rotation conditions compared to low rotation conditions, potentially confounding interpretation of effects of rotation. Note that this confound would likely work against finding rotation effects that we report, because bias and error increase with rotation. To investigate this issue, we conducted ANOVAs on a restricted set of subjects who showed less than 7% missing data for the three rotation conditions in a given cue condition. This resulted in restricting the analyses to 13 participants in the one-cue-first condition, 13 in the one-cue-second condition, 17 in the three-cues-first condition, and 18 in the three-cues-second condition. These analyses then look only at one group of subjects across the three rotation conditions, namely, the ones who perform the best on this spatial task. In these analyses, the number of extreme data points that have been replaced by the mean of remaining subjects' data was much smaller and distributed more equally across rotation conditions. Overall, percentages of missing data were 3.49% (30° rotation), 4.21% (90° rotation) and 6.85% (160° rotation) in the one-cue condition, and 2.57% (30° rotation), 3.82% (90° rotation), and 2.97% (160° rotation) in the three-cues condition.

We conducted parallel 2 (Cues) × 3 (Rotation) × 2 (Radius) × 16 (Angle) mixed factorial ANOVAs on this restricted data set, separately for the first cue-set encountered and the second cue-set encountered (thus, cue was a between subjects factor in these analyses). The patterns of significance from these ANOVAs were quite similar to those reported for the whole data set, despite the much lower power due to fewer subjects and cues being analyzed as a between subjects factor. We summarize these below.

For angular bias, nine significant effects were reported for the within subjects analysis of the full data set (Table 2). Five of these were replicated in the cues-first restricted set and eight were replicated in the cues-second restricted set. Each restricted data set had one significant effect that was not significant in the full data set. For absolute error, 10 significant effects were reported in Table 2. Six of these were replicated in both the cues-first and the cues-second sets, with the latter set producing one significant effect not found in the full set. For radial bias, five significant effects were reported in Table 2. Two of these were replicated in the cues-first set and three in the cues-second set, with each restricted set producing two significant effects not found in the full data set.

Overall, the effects most critical to our hypotheses and modeling in the full data set were replicated in analyses for both restricted data sets. These critical effects include the effect of rotation on absolute error, the effect of angle, the Cue × Angle interaction effect, and the Rotation × Cue × Angle interaction effect on both angular bias and absolute error, and the radius effect on radial bias. In conclusion, the patterns of significance were quite similar for analyses of the restricted and full data sets. Therefore, we are confident that the reported results are not due to a potential confound resulting from differential mortality across rotation conditions.

In this paper our analyses focus on the 30°, 90°, and 160° rotation trials, as the results for 0° rotation trials are extensively reported in Fitting et al. (2007). To guard against the inflated type I error that results from artificially reducing variability by substitution of misremembered data points with means, we conservatively reduced our criterion for statistical significance to $\alpha = .01$ for all ANOVA tests. For change in R^2 tests that we report when comparing nested models, we used a .05 criterion in order to maintain more powerful tests. These models were designed to explain the pattern of effects for the 32 means in each condition. Violations of sphericity were addressed via the use of the Greenhouse-Geisser degrees of freedom correction factor (Greenhouse & Geisser, 1959). The rotation trials 30°, 90°, and 160° afford the use of a cue-based frame of reference in order to locate the dot in the circular region. Overall, we hypothesized that as in the 0° rotation trials, different patterns would be observed for one- and three-cues conditions (H_4, H_5 and H_7). In addition, we hypothesized that memory for fine-grain information would degrade with increases in degree of rotation so that bias and absolute error would increase (H_2 and H_3, respectively).

For each dependent variable, we begin with a 2 (Cues) × 3 (Rotation) × 2 (Radius) × 16 (Angle) within factorial ANOVA. For bias measures, the key tests of interests are any interactions with cue condition. For absolute error, the main effect of cue is also of interest. These results are presented in Table 2. Because of the extensive number of interactions with cue, we then conducted

Table 2. Degrees of freedom and F-values for 2 (cues) × 3 (rotation) × 2 (radius) × 16 (angle) within factorial ANOVAs

Source	DF	Angular bias	Absolute error	Radial bias
Cue (C)	(1, 53)	3.18	169.01***	0.74
Rotation (Rot)	(2, 106)	6.61**	43.01***	0.75
Radius (Rad)	(1, 53)	1.16	6.65	445.70***
Angle (A)	(15, 795)	16.64***	23.36***	1.68
CxRot	(2, 106)	1.09	5.53**	0.64
CxRad	(1, 53)	6.10	3.80	0.57
CxA	(15, 795)	18.98***	34.80***	1.33
RotxRad	(2, 106)	5.09**	6.16**	21.18***
RotxA	(30, 1590)	6.86***	3.61***	5.21***
RadxA	(15, 795)	5.68***	2.92***	1.91
CxRotxRad	(2, 106)	1.29	3.30	0.64
CxRotxA	(30, 1590)	5.48***	4.96***	2.31**
CxRadxA	(15, 795)	5.24***	3.41***	1.18
RotxRadxA	(30, 1590)	2.13**	1.38	0.96
CxRotxRadxA	(30, 1590)	1.87	1.79	2.03**

**$p < .01$, ***$p < .001$.

Table 3. Degrees of freedom and F-values for 2 (order) × 3 (rotation) × 2 (radius) × 16 (angle) mixed factorial ANOVAs for the one-cue condition

Source	DF	Angular bias	Absolute error	Radial bias
Order (O)	(1, 52)	0.29	0.88	0.01
Rotation (Rot)	(2, 104)	6.52**	42.19***	0.14
Radius (Rad)	(1, 52)	4.73	9.39**	391.93***
Angle (A)	(15, 780)	25.09***	44.44***	1.43
OxRot	(2, 104)	0.05	2.35	3.15
OxRad	(1, 52)	2.61	0.30	5.28
OxA	(15, 780)	1.44	0.72	2.74**
RotxRad	(2, 104)	4.84	3.86	12.01***
RotxA	(30, 1560)	8.64***	5.15***	4.34***
RadxA	(15, 780)	8.66***	3.55***	2.17
OxRotxRad	(2, 104)	1.71	0.26	0.95
OxRotxA	(30, 1560)	1.35	2.22**	2.02**
OxRadxA	(15, 780)	1.16	1.44	2.11
RotxRadxA	(30, 1560)	2.72***	1.28	1.83
OxRotxRadxA	(30, 1560)	1.95	1.22	1.39

$^{**}p < .01$, $^{***}p < .001$.

2 (Order) × 3 (Rotation) × 2 (Radius) × 16 (Angle) mixed factorial ANOVAs for one- and three-cues conditions, separately. These results are presented in Tables 3 and 5. Finally, we modeled the data for angular bias and absolute error and the results for angular bias in Tables 4 and 6.[5]

Angular Bias

The key finding of the initial ANOVA on angular bias was that cue is involved in half of the possible cue interactions, indicating different angular bias patterns across cue conditions (see the corresponding column of Table 2). The Angle × Cue interaction is consistent with the idea that the number or location of spatial prototypes differ as a function of number and location of external cues, providing preliminary support for H_4. Also key to our focus is the fact that there were two significant interactions with rotation, suggesting

[5] Although response times were collected, a programming error led to a substantial loss of response time data. Therefore, we have chosen not to report analyses for response times in the main text. However, an ANOVA that was conducted on the available response times indicated highly significant effects for rotation, with response times increasing as expected from 30° to 90° to 160° rotation. Because of the incomplete nature of the data set, we do not feel it worthwhile to pursue further analyses on these data.

Table 4. Parameter values and fit indices for the fit of a 5-parameter cue-based fuzzy-boundary model to each rotation condition (one cue case)

Rotation	p_1	λ	c_1	p_{2L}	c_{2L}	R^2	Effects remaining significant
30° rotation	255.80°	0.906	0.016	151.74°	0.024	0.676	0 of 1
90° rotation	306.34°	0.685	0.012	113.06°	0.031	0.741	0 of 2
160° rotation	295.49°	0.723	0.020	99.02°	0.047	0.724	2 of 3

Note: p_1 = first prototype value, p_{2L} = second prototype value for the long radius only, λ = weight of fine-grain memory, c_1 = sensitivity parameter for the first prototype, c_{2L} = sensitivity parameter for the second prototype for the long radius only.

that the estimation process is moderated by degree of rotation (H_2). Effects of one and three cues are described separately below.

One-cue Condition. Results from the ANOVA on angular bias in the one-cue condition are shown in the corresponding column of Table 3. Two significant rotation interactions were noted, demonstrating that the estimation process was affected by degree of rotation. Because there were two interactions with

Table 5. Degrees of freedom and F-values for 2 (order) × 3 (rotation) × 2 (radius) × 16 (angle) mixed factorial ANOVAs for the three-cues condition

Source	DF	Angular bias	Absolute error	Radial bias
Order (O)	(1, 52)	0.55	1.04	9.48**
Rotation (Rot)	(2, 104)	4.23	34.69***	1.82
Radius (Rad)	(1, 52)	1.68	1.81	321.62***
Angle (A)	(15, 780)	4.80***	11.80***	1.75
OxRot	(2, 104)	2.13	1.22	3.53
OxRad	(1, 52)	2.93	7.81**	1.81
OxA	(15, 780)	0.89	2.68**	2.31
RotxRad	(2, 104)	0.78	7.14**	12.36***
RotxA	(30, 1560)	3.17***	3.56***	3.25***
RadxA	(15, 780)	1.55	2.82**	0.83
OxRotxRad	(2, 104)	0.64	0.42	0.15
OxRotxA	(30, 1560)	1.24	1.71	1.53
OxRadxA	(15, 780)	1.09	1.54	1.25
RotxRadxA	(30, 1560)	1.08	1.92	1.07
OxRotxRadxA	(30, 1560)	0.76	1.21	0.72

**$p < .01$, ***$p < .001$.

Table 6. Parameter values and fit indices for the model fit of cue-based fuzzy-boundary models in each of the rotation conditions (three cues case)

Rotation	Radius	λ	p_1	p_2	c_1	c_2	R^2	Effects remaining significant
30°	Short	0.898	229.28°	45.51°	0.011	0.031		
	Long	0.979	″	″	0.003	″	0.392	1 of 2
90°	Combined	0.856	286.32°	46.77°	0.026	0.013	0.584	0 of 1
160°	Combined	0.709	321.22°	53.06°	0.015	0.007	0.368	0 of 1

Note: ″ = same values as above, p_1, p_2 = first prototype value, p_2 = second prototype value, λ = weight of fine-grain memory, c_1 = sensitivity parameter for the first prototype, c_2 = sensitivity parameter for the second prototype.

rotation we conducted a 2 (Radius) × 16 (Angle) within factorial ANOVA on angular bias for each rotation. A significant angle effect for the 30° rotation was noted, $F(15, 795) = 4.91$, $p_{GG} < .001$. For the 90° rotation, there was a significant angle effect, $F(15, 795) = 11.99$, $p_{GG} < .001$, and a significant Radius × Angle interaction, $F(15, 795) = 2.68$, $p_{GG} < .01$. For the 160° rotation there were three significant effects, a radius effect, $F(1, 53) = 16.80$, $p < .001$, an angle effect, $F(15, 795) = 11.99$, $p_{GG} < .001$ and a Radius × Angle interaction, $F(15, 795) = 2.68$, $p_{GG} < .01$.

The ANOVA results noted above provide justification for modeling the data combined across order but separately for each rotation condition. Fits of the cue-based fuzzy-boundary model of Equations 2 and 3 started with six parameters free to vary in each of the three rotation conditions (λ, c, p for each radius). As illustrated in Figures 4A–C, the long radius targets in quadrants 1 and 2 (0°–180°) do not behave as predicted by a one prototype model. We speculated that in rotation conditions subjects might mentally

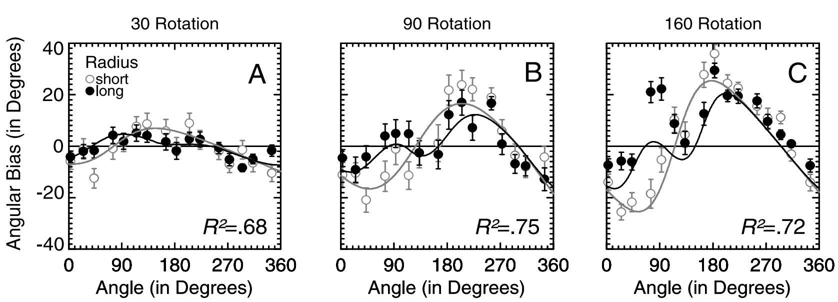

Figure 4. Fit to mean signed angular bias (rotation conditions, one-cue condition). Error bars represent one standard error and functions represent the 5-parameter fit of the cue-based fuzzy-boundary model. Panel A shows fit to the 30° rotation condition. Panel B shows fit to the 90° rotation condition. Panel C shows fit to the 160° rotation condition.

project a "phantom" cue at the border opposite to the actual cue to help to locate targets near this position. We modeled this effect for all rotation conditions by including a second prototype value p_{2L} and a second sensitivity parameter c_{2L} for the "phantom" cue operating on only the long radius targets. A larger value for c_{2L} than for c_1 would mean the influence of the "phantom" prototype is not as general as that of the available cue, but occurs primarily for proximal targets. Note that this unequal probability of prototype retrieval requires that Equation 3 is changed so that the sensitivity parameter, c, includes subcripts tied to the prototype and target. Following this line of reasoning, a 5-parameter cue-based fuzzy-boundary model was fit to the data, with parameter estimates shown in Table 4.

To further assess the fit of the model, a 2 (Radius) × 16 (Angle) within factorial ANOVA was conducted on the residuals from the model for each of the different rotation conditions. If the model is accounting for the systematic variance in the data, then significant effects should become nonsignificant. The ANOVA revealed no remaining significant effects for 30° and 90° rotations, indicating that the model sufficiently explained angular bias effects for these rotation conditions. For the 160° rotation condition, the significant Radius × Angle interaction was accounted for by the model, indicating that the integration of the "phantom" cue for the proximal targets explained the Radius × Angle interaction. However, the radius effect, $F(1, 53) = 10.14$, $p_{GG} < .01$, and angle effect, $F(15, 795) = 3.00$, $p_{GG} < .01$, remained significant. Although the significant angle effect could not entirely be explained by the 5-parameter model, the F-value was reduced by approximately 89%, and thus the model accounted for the bulk of this effect in the 160° rotation condition.

In each of the three rotation conditions, R^2 indices revealed a good fit to the data (see Table 4). Figure 4A–C illustrates the fit of the 5-parameter cue-based fuzzy-boundary model for each of the three rotation conditions. The "phantom" cue effects can be seen in the negative dip in the angular bias measure for long radius targets near 125°, which is the point opposite to the cue location. The justification for using a 5-parameter model that included a "phantom" cue in the modeling equation rather than a 3-parameter model (λ, c, p) that included just one prototype was further justified by significant differences in R^2 for nested models within each of the rotation conditions. The 5-parameter models explained significantly more variance than the 3-parameter models in each case.

The effect of the "phantom" cue was clearly limited to long radius targets, as shown by the smooth function for the short radius targets in Figure 4. Both long and short radius targets show little bias at the approximate cue location (305°), consistent with the cue being used as a prototype. Finally, increasing the degree of rotation clearly led to stronger bias effects, as indicated by the increasingly greater deviation of the data points from the centerline in Figure 4A–C. The model attributed this difference to reduced fine-grain memory resolution resulting in increased weighting of prototypes (see the values of λ in Table 4).

Three-cues Condition. Results from the ANOVA on angular bias in the three-cues condition are shown in the corresponding column of Table 5. This analysis revealed only a significant main effect for angle and a significant Rotation × Angle interaction. A 2 (Radius) × 16 (Angle) within factorial ANOVA was conducted on angular bias for each rotation. For the 30° rotation there was a significant angle effect, $F(15, 795) = 5.00$, $p_{GG} < .001$ and a significant Radius × Angle interaction, $F(15, 795) = 2.49$, $p_{GG} < .01$. For the 90° rotation there was only a significant angle effect, $F(15, 795) = 2.85$, $p_{GG} < .01$, which was also true for the 160° rotation, $F(15, 795) = 4.60$, $p_{GG} < .001$.

The ANOVA results noted above provide justification for modeling the data combined across order but separately for each rotation condition. Fits of the cue-based fuzzy-boundary model of Equations 2 and 3 started with 11 parameters free to vary in each of the three rotation conditions (three p, two λ varying with radius, six c that varied with both prototype and radius). However, tests of the change in R^2 for each rotation revealed that three prototype models did not fit significantly better than corresponding nested two prototype models, and hence each condition was fit with just two prototypes. The best fit for the 90° and 160° rotation conditions was a 5-parameter model with one λ, two prototypes (p_1 and p_2), and two c parameters, each tied to the corresponding prototype. The best fit for the 30° rotation condition was a 7-parameter model with two prototypes (p_1 and p_2), three c parameters (two for the long and short radius for the first prototype and one for the second prototype), and two λ separate for radius (see Figure 5A–C). One of the reasons for why separate λ for radius and additional c parameters separated by radius for the first prototype had to be used is because R^2 indicated to be

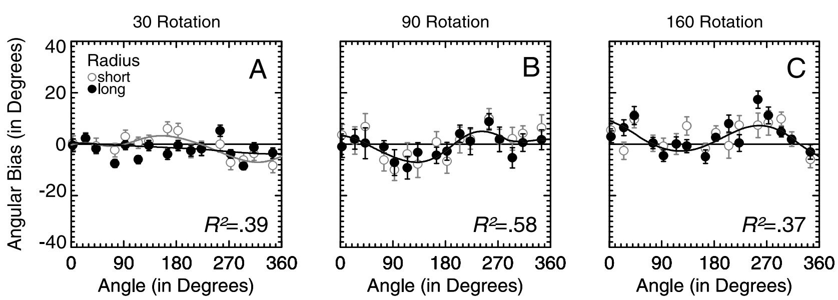

Figure 5. Fit to mean signed angular bias (rotation conditions, three-cues condition). Error bars represent one standard error and functions represent the fit of the cue-based fuzzy-boundary model. Panel A shows the 7-parameter fit to the 30° rotation condition. Panel B shows the 5-parameter fit to the 90° rotation condition. Panel C shows the 5-parameter fit to the 160° rotation condition.

significant higher for the 7-parameter model compared to 5-parameter model in the 30° rotation.

This might indicate that specifically in low rotation conditions radius appears to have a high impact on the estimation process. This is supported by model fits in the 0° rotation condition where the inclusion of separate parameters for the short and the long radius provided a better fit to the angular bias data (Fitting et al., 2007). The 2 (Radius) × 16 (Angle) within factorial ANOVAs conducted on the residuals separately for the different rotation conditions did not reveal any remaining significant effects for 90° and 160° rotations, indicating that the models sufficiently explained angular bias effects. For the 30° rotation the significant Radius × Angle interaction disappeared and thus was explained by the 7-parameter model, whereas the significant angle effect could not be explained by the model, $F(15, 795) = 3.08$, $p_{GG} < .001$. Thus, the cue-based fuzzy-boundary model accounted for most but not all of the effects in the data (see Table 6).

For each of the models described above, change in R^2 tests revealed that the corresponding three-prototype models did not add any significant improvement over the two-prototype models that were used. The finding that only two prototypes were needed to fit the data in the three-cues rotation conditions implicates increased task demands of rotation leading to limits on the ability to use all three cues, as three prototypes were inferred for the corresponding 0° rotation conditions shown in Figure 2 (Fitting et al., 2007). Table 6 presents the estimated parameter values for each of the three rotation conditions. Note that R^2 for the rotation condition was overall not as high as for the 0° rotation condition, perhaps due to greater task demands resulting in more error in estimation.

Nevertheless, results indicate that the cue-based fuzzy-boundary model provided a reasonable fit of the observed estimation data in the three-cues condition for each of the three rotation conditions. Figure 5A–C illustrates the model fit for the cue-based fuzzy-boundary model for each of the three rotation conditions. These models provided good fits of the bias in estimation in all three rotation conditions and supported the interesting theoretical interpretation of reliance on fewer cues under conditions of rotation. As shown in Table 6 and Figure 5A–C the locations do not directly correspond to particular cue locations but seem to represent some compromise. This stands in strong contrast to the 0° rotation (Fitting et al., 2007) in which there was close correspondence to cue location and prototype locations that were estimated by the model.

Possible reasons for why the estimated prototype locations in the rotation conditions do not correspond to any of the available cue locations are that different subjects might use different prototypes. Another possibility is that there may be a bias introduced by the rotations, so that the locations are systematically underestimated. To investigate the hypothesis it would require individual analyses. However, individual data for rotation trials were not reliable enough for modeling purposes and thus an individual analysis was not possible for this data set. Finally, note once again that bias increases dramatically with rotation as indicated by the increasingly greater deviation of the data points from the centerline in Figure 5A–C. The difference can be attributed to reduced fine-grain memory discrimination leading to increased reliance on prototype information as shown in the values of λ in Table 6.

Absolute Error

It was hypothesized that cue condition would have an impact on accuracy of human spatial memory, with a decrease in absolute error when more peripheral cues were available (H_5). We also predicted a main effect for rotation, with absolute error increasing with degree of rotation (H_3). This prediction derives from the idea that fine-grain memory would be less accurate under conditions of rotation. We also expected interaction effects of cue with radius and angle indicative of greater accuracy as the target is more proximal to a cue.

Results of the initial ANOVA on absolute error are shown in the corresponding column of Table 2. The significant cue effect reflected reduced absolute error in the three-cues condition ($M = 47.72$) compared to the one-cue condition ($M = 62.41$). When comparing the results of the rotation conditions with the 0° rotation condition reported by Fitting et al. (2007), mean absolute error was twice as great in the three-cues condition and three times as great for the one-cue condition, supporting the interpretation that fine-grain memory, and thus accuracy, decreased profoundly with rotation. Further, a significant main effect of rotation and four out of seven significant interactions involving rotation indicated that increases in rotation strongly increased absolute error, consistent with H_3. Four out of seven possible interactions with cue were significant, indicating that cue condition is an important factor in determining absolute error. The significant Angle × Cue interaction was consistent with H_5, which posits that absolute error decreases as distance to the nearest cue decreases.

One-cue Condition. Results from the ANOVA on absolute error for the one-cue condition are shown in the corresponding column of Table 3. There was one significant interaction involving order of presentation (Order × Rotation × Radius). A significant main effect of rotation was found along with two interactions of rotation out of seven (Angle × Rotation, and Order × Angle × Rotation). In addition, a significant angle effect was noted that was moderated by radius.

Because there was just one significant interaction with order, we combined data across the two order conditions in modeling the data to provide a more parsimonious presentation. We modeled these data in order to test the plausibility that the pattern of error reduction is well predicted by proximity to cues. Our modeling used a simple regression analysis on absolute error

(Equation 4) as well as a regression analysis with a probabilistic recruitment of proximal cues as described in Equations 3 and 5. Comparing both types of modeling procedures, the localized effects of anchors were best described with a probabilistic recruitment.

Accordingly, the closer a target is to a cue, the greater anchoring of fine-grain memory and hence reduced absolute error. In our application to the one-cue condition, we posited a "phantom" cue at 180° from the actual cue, consistent with the bias data. Different weighting and sensitivity parameters for the actual cue and the "phantom" cue were used, as the "phantom" cue was expected to have a weaker impact than the actual cue. In this context, the "phantom" cue is interpreted as the reliance on additional information in a task with an increased difficulty level that requires mental rotations. Note that a key difference between modeling of absolute error and modeling of bias was that our modeling of absolute error used the actual cue locations rather than inferring those locations from the data.

Figure 6A–C illustrates the model fit to absolute error separately for each rotation condition. For each panel of Figure 6, the 5-parameter model of Equation 5 (combined with Equation 3) was used to account for the data (with an intercept, two regression parameters, and two sensitivity parameters). Impressively the differences between the functions for the short and the long radius are based entirely on the different proximities of the targets to the cues and do not depend on any fitted parameters. Note that the R^2 for these data are quite high, ranging from .82 to .89 (see Figure 6A–C). The good fits of the model to the data suggest that in the one-cue condition observers tend to rely on the available peripheral cue location as the prototype and may generate a "phantom" cue at the boundary. Evidence for this lies in the steep dipping of the functions at 305° and 125° as predicted by the model (see Figure 6A–C). Note that modeling of the data in the 0° rotation condition

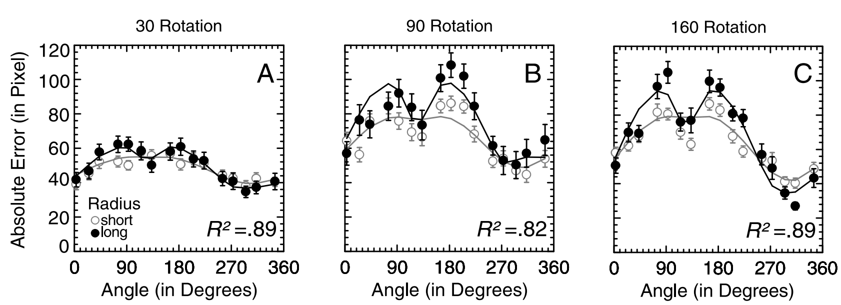

Figure 6. Fit to the mean absolute error for one-cue condition. Error bars represent one standard error and functions show fit of model based on proximity to nearest cue using three parameters. Panel A shows the fit to the 30° rotation condition. Panel B shows the fit to the 90° rotation condition. Panel C shows the fit to the 160° rotation condition.

did not show evidence of a phantom cue in either angular bias or absolute error (see Figures 2A and 3A).

Three-cues Condition. Results from the ANOVA on absolute error for the three-cues condition are shown in the corresponding column of Table 5. There were significant Order × Radius and Order × Angle interactions, indicating that order partially affected the estimation process. There was a significant main effect for angle that was not only influenced by order, but also by rotation and radius. There was also a significant main effect of rotation with two significant interaction effects (Rotation × Radius and Rotation × Angle), suggesting an impact of rotation on the estimation process.

The various order interactions clearly make it difficult to characterize the data generally. To examine how well proximity to cues described the data, separate regression analyses were conducted for each order and rotation. Comparing both types of modeling procedures (simple regression versus regression with probabilistic recruitment), the data were more parsimoniously described by the simple regression model. We began with an 8-parameter model for each rotation condition, consisting of an intercept along with regression weights for each cue at each radius. The reduced model we report did not significantly reduce R^2 and consisted of three parameters, including one intercept and two cue weights as one of the cue weights was equated for two cues.

Two exceptions were revealed for the 30° and the 90° rotations in the three-cues-second condition, with a 4-parameter model being significantly better compared to the 3-parameter model. The fourth parameter was the addition of separate intercepts for the two radii. Figures 7A–F illustrates the model fits for the three-cues-first and the three-cues-second conditions. Although a similar pattern was found in both three-cues conditions, the significant interactions with order made it inappropriate to combine these. In contrast to the 0° rotation condition (see Fitting et al., 2007), the three cues were each weighted in rotation trials. When probabilistic recruitment of cues was included, the model did not fit any better (and a model that recruited only the nearest cue fit worse).

This suggests that the high memory demands on rotation trials may have prompted a strategy to stabilize memory by using all three cues when possible. One clear difference between the results for the 0° rotation condition (see Figure 3B) and the rotation conditions (see Figure 7A–F) is that in the 0° rotation condition absolute error for the long radius is always predicted to be less than or equal to the corresponding short radius condition. This is not true in the rotation conditions. The reason this occurs is that in the 0° rotation condition only proximity to the nearest cue is weighted. Because proximity to the nearest cue is always greater for long radius than short radius targets in this condition, error is predicted to be less for long radius targets. Our model of the rotation conditions does not include probabilistic recruitment of cues but rather all cue proximities operate on each target.

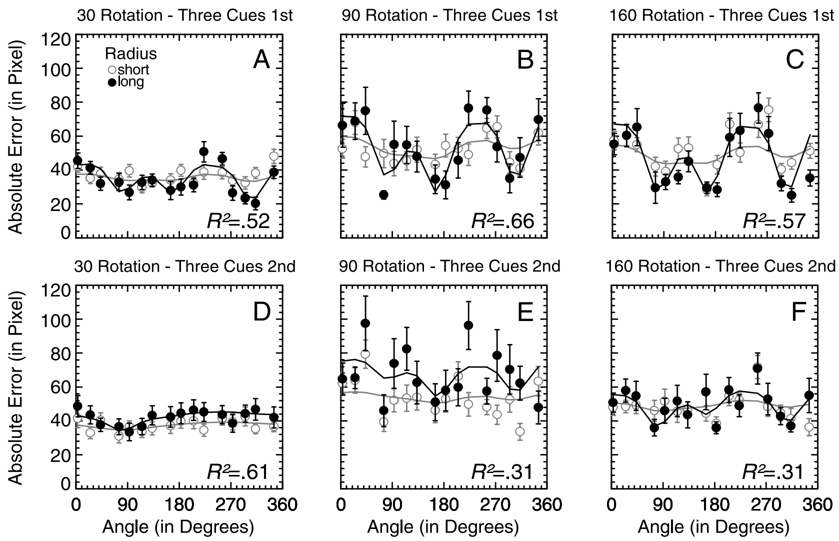

Figure 7. Fit to the mean absolute error (rotation conditions, separate for three-cues-first and three-cues-second data). Error bars represent one standard error and functions show fit of model based on proximity to nearest cue. Panel A–C show 3-parameter model fit to absolute error of the three-cues-first condition to each of the rotation conditions, 30° rotation condition (A), 90° rotation condition (B), 160° rotation condition (C). Panel D–F show the fit to absolute error of the three-cues-second condition to each of the rotation conditions, a 4-parameter model fit to the 30° rotation condition (D), a 4-parameter model fit to the 90° rotation condition (E), a 3-parameter model fit to the 160° rotation condition (F).

This means that the summed proximity for long radius targets is sometimes less than for corresponding short radius targets, and hence absolute error is predicted to be greater. Nevertheless, the pattern of absolute error clearly shows strong reductions when the targets are proximal to the cues in these rotation conditions, especially for the long radius targets.

Radial Bias

Following the category-adjustment model's predictions, the prototypic radius was assumed to fall between the short radius and the long radius (H_6). Further, radial bias effects were predicted to increase with increase in angle of rotation, as indicated by a Radius × Rotation interaction (H_2). It also seemed plausible that cue condition would have an impact on the radial prototype so that there would be a tendency to be biased toward the external cues (H_7).

Results from the initial ANOVA on the radial bias data are shown in the corresponding column of Table 2. A significant radius effect was noted, with estimates being biased toward the circumference (+) for the short radius

($M = 14.52$) and toward the center (−) for the long radius ($M = -10.70$), supportive of H_6. For rotation, four interactions were noted, a significant Rotation × Radius, a Rotation × Angle, a Rotation × Cue × Angle, and a Rotation × Cue × Radius × Angle interaction. Compared to the size of the significant radius effect ($\eta^2 = .894$), the effects of these four interactions were fairly small [Rotation × Radius: partial $\eta^2 = .286$, Rotation × Angle: partial $\eta^2 = .089$, Rotation × Cue × Angle: partial $\eta^2 = .042$, Rotation × Cue × Radius × Angle: partial $\eta^2 = .037$].

The largest and most interesting effect was the Rotation × Radius interaction that represented greater radial bias with greater rotation, consistent with reduced fine-grain memory resolution (H_2). Figure 8 illustrates the radial bias scores combined across cue conditions for the 30° rotation condition (A) the 90° rotation condition (B), and 160° rotation condition (C). The Rotation × Radius interaction is illustrated by the widening gap between short and long radius functions with an increase in angle of rotation.

Note that H_7 predicts a significant Cue × Angle interaction. This effect was not significant as shown in Table 2. However, as noted above, two of the significant rotation interactions included cue (Rotation × Cue × Angle; Rotation × Cue × Radius × Angle), indicating that cue had an impact on radial bias, at least to some extent. Despite the significant interactions with cue, the effects did not occur in the form of an increase in bias toward the external cues, as predicted in H_7. Because both of the cue interactions were very small and η^2 did not exceed .05, we do not further discuss them. Overall, the key findings were the significant radius effect for radial bias as predicted by the category-adjustment model and the increase of this effect with rotation, consistent with reduced fine-grain memory discrimination with rotation. Unlike angular bias, which was greatly reduced with an increase of cues, radial bias was unaffected by the number of available cues.

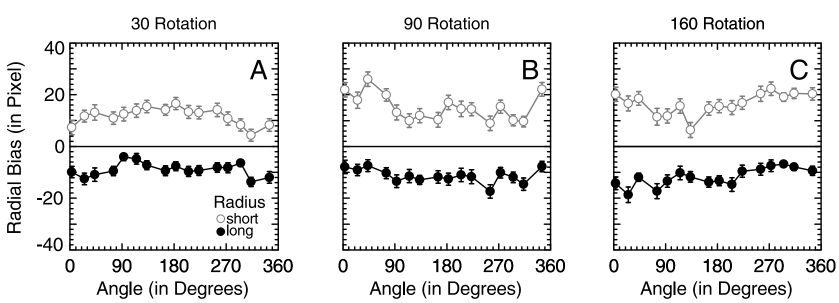

Figure 8. Mean radial bias scores combined across cue conditions. Error bars represent one standard error. Panel A shows radial bias scores for the 30° rotation condition. Panel B shows radial bias scores for the 90° rotation condition. Panel C shows radial bias scores for the 160° rotation condition.

DISCUSSION

In previous research (Fitting et al., 2005, 2007, in press) we have demonstrated that when field rotation is absent, memory for spatial location in the classic dot location procedure is largely cue-independent rather than cue-dependent. This occurs even when ample peripheral cues are available. However, when field rotation is present and likely, observers tend to base their memory on available peripheral cues, even in instances when the field is not rotated. The purpose of the present analyses was to examine the influence of cues on spatial memory for a dynamically changing environment on trials when an actual rotation had to be performed. The analyses of the 30°, 90°, and 160° rotation trials indicated that all the effects on bias and accuracy examined in the 0° rotation condition of the experiment were dramatically increased by rotation.

Thus, these results reinforced the conclusion that estimation of spatial location from memory strongly depends on available external cues within a dynamically changing environment. Indeed, reliance on cues for rotation trials is so prevalent that observers appeared to insert them when they were insufficient, as in the appearance of the so-called "phantom" cue in the one-cue condition. On the other hand, the increased task demands associated with increased rotations appeared to lead to using fewer cues than were available in determining angular location, as implied by our model fitting of the three-cues conditions.

In addition to the strong effects on angular bias, cues had pervasive effects on absolute error. These effects were well described by a model in which increased proximity of the target locations to the available cues enhanced fine-grain memory and hence decreased absolute error. While radial bias significantly increased with angle of rotation it did not have any clear relationship with the number or location of cues.

Rotation and Cue Effects

Consistent with the literature on mental rotation (Harris et al., 2000; Shepard & Metzler, 1971; Silberstein, Danieli, & Nunez, 2003; Vasta, Belongia, & Ribble, 1994), our study supported the finding that degree of rotation increased the cognitive demands of the test. As rotation increased, the location's coordinates were less exactly remembered, leading to greater error and bias. Consistent with H_1, poor memory performance was clearly shown by the greater instances of blatant misremembering with rotation (see Table 1). Further, increases in rotation led to increases in bias effects that were indicated by an Angle × Rotation interaction on angular bias and a Rotation × Radius interaction on radial bias (H_2). A main effect of rotation on absolute error indicated poor accuracy increased with rotation (H_3). These effects are all consistent with the idea that rotation leads to poorer memory for fine-grain information, thus making participants more reliant on categorical stimuli. We suggest that one source of this increased error is the greater demands upon spatial working memory.

Because rotation conditions also prompted a cue-based categorization scheme, interactions involving cue condition often increased with rotation. An exception to this general conclusion occurred for radial bias, which was largely cue independent. The increased cue effects for angular bias and absolute error with rotation are consistent with the idea that rotation degrades fine-grain memory, possibly through increased working memory demands, and thus increases the reliance on cue-based categories. Consistent with this interpretation, findings indicated that absolute error was well modeled as a function of proximity of the target to the cue as shown in Figures 6 and 7, with greater errors associated with larger rotations.

The categorical structure imposed on the dynamic task field was inferred to be cue-based, with the structure differing as a function of number of cues. The cue-based fuzzy-boundary model proved useful in describing the underlying angular bias effects quantitatively, successfully explaining most interactions with cue conditions. A similar cognitive model of how people reorient to their environment is presented in a previous in a recent study by Gugerty and Rodes (2007). The authors report a cognitive model of strategies for cardinal direction judgments that supports the idea of categorical and perceptual information are held in memory and then rotated to a new orientation. This work and ours support the general conclusion that people are successfully able to combine a number of complex processes, such as categorical encoding, analog encoding, and rotational transformations, in response to changing orientation within an environment.

An additional proximity based cue-anchoring model was developed to describe effects of cues on absolute error. This model asserted that proximity to a cue served to anchor the fine-grain memory representation and hence reduce absolute error. The model explained the majority of variance in absolute error for each target by the target's proximity to the cue.

Cue Utilization

Somewhat surprisingly, modeling approaches supported the idea that in the rotation conditions, participants tended to project a "phantom" cue in the one-cue condition. Evidence for the "phantom" cue was found in modeling both angular bias and absolute error. In both cases, the "phantom" cue did not have a wide range of influence as the actual cue (this was modeled as an increased sensitivity parameter that limited its recruitment to proximal targets). In retrospect, the finding of a "phantom" cue in the one-cue condition can be seen as a logical result of a strategy that participants might employ. With a single cue, one can easily divide the circle in half with an imaginary line running through the circle from the cue. Indeed, we used this representation to help formulate a boundary for the single category condition.

For most targets, one simply codes their locations relative to the cue. However, if one sees that the target is fairly proximal to the intersection of the boundary with the circumference of the circle, it makes sense to project an imaginary cue at that border and code location relative to it. The exaggerated "phantom" prototype effects for the long radius but not short radius targets in the 90° and 160° rotation led to the Radius × Angle interaction observed there. Even though the best model explaining the data for the 30° rotation condition integrated a "phantom" prototype for the long radius, the relatively small effect of this prototype produced no significant Radius × Angle interaction in that condition. The pattern of data for both angular bias and absolute error is consistent with this notion. Note that other researchers have also found evidence for use of virtual or "phantom" landmarks near a border (Schmidt et al., 2003).

For the three-cues condition the cue-based fuzzy-boundary modeling of the data indicated that under rotation conditions, participants were not able to fully utilize three cues. Instead the modeling implied the effective use of just two prototypes, as seen in Figure 5. Presumably, the limits upon spatial memory imposed by rotation apply at least partially to number of cues used in the categorical representation and not just to fine-grain memory resolution. Furthermore, we can conclude these effects did not occur at encoding, as the 0° rotation conditions show clear evidence for the use of three prototypes (Figure 2B and 2C). These findings speak to the flexibility of generating spatial coding strategies in a cue-sparse environment: When cues were too few an additional cue could be generated, but when cues were too numerous, some cues could be ignored. This particular experiment suggests a magic number "2" in that with one cue participants appear to generate a second "phantom" cue but with three cues they tend to ignore one of them. Naturally this preliminary result requires investigation across a wider set of environments and cue conditions.

Results from rotation trials reported here fortify the conclusion that cues have at least some effects on absolute error measures that are independent of effects on angular bias measures. This conclusion is most easily reached by comparing the pattern of data for the three-cues conditions (Figures 5 and 7). In modeling angular bias, there appear to be just two cue-based prototypes used, as evident in the two peaks shown for each bias function. However, for absolute error all three cues are generally used as evidenced by the three dips in the functions illustrated in Figures 7A–F. Further evidence is gleaned from the fact that there appear to be much larger effects of cues for long radius targets on absolute error, but this is not the case for angular bias. Thus, a complete understanding of the effects of cues cannot focus solely on their use in determining category prototypes but must also include their role in bolstering fine-grain spatial memory.

We also introduced a simple modeling scheme for absolute error based on the logarithmic distance between the target and the cues. While absolute error is partially determined by angular bias and radial bias, it also has a component that is attributable to error in fine-grain memory. The effects of cues were shown to be somewhat independent of angular bias, as there was clear evidence of the influence of three cues for absolute error but only two cues for several conditions relating to angular bias. These results support the conclusion that fine-grain memory for targets is bolstered in areas proximal to external cues, as these cues may serve to anchor the representation (Schmidt et al., 2003; Werner & Diedrichsen, 2002). The success of these modeling enterprises argues for further exploration of these models in future research.

Implications for Other Spatial Tasks

The impact of how cues in the visual environment afford the viewer a different categorical structure is an issue that needs to be considered in future research. In particular, a question that needs further investigation is the applicability of our models to a large-scale space. How do the spatial memory processes proposed by the fuzzy-boundary versions of the category-adjustment model come into play when location memory is tested in a large-scale space? This question raises interesting issues regarding the process by which observers parse the environment into categorical regions, the role of environmental geometry and peripheral cues in this parsing process, and the role of human information-processing limitations in cue selection and use.

Our research on a human analogue of the Morris water maze provides some support for the generality of these effects in a vista space (Fitting, Allen, & Wedell, 2007). In this study, individuals were asked to indicate a remembered location in a 3 m diameter arena over different intervals of time and with different memory loads. The role of peripheral cues on the spatial estimation process were assessed by varying number of cues as a between-subjects variable. Results indicated that the process by which observers parse the environment into categorical regions is highly influenced by the available peripheral cues, with remembered locations being biased toward the nearest cue.

This finding is consistent with cues being used as category prototypes and uncertainty about location being resolved toward the prototype, as proposed by the category-adjustment model (Huttenlocher et al., 1991). Further, our human analogue of the Morris water maze study indicated that error and bias decreased with increase in number of cues. Because that study did not examine multiple target locations it is difficult to make conclusions about the issue regarding the human information-processing limitations in cue selection and use in large-scale or vista spaces.

Virtual environments, such as computer-generated navigation tasks, might be a useful tool to investigate this problem, and have already been indicated to be increasingly popular to study place learning and memory more generally (e.g., Jacobs, Laurance & Thomas, 1997; Laurance, Learmonth, Nadel, & Jacobs, 2003; Maguire, Frith, Burgess, Donnett, & O'Keefe, 1998; Moffat & Resnick, 2002; Skelton, Bukach, Laurance, Thomas, & Jacobs et al., 2000; Skelton, Ross, Nerad, & Livingstone, 2006). The obvious advantages of this approach include that one can freely design environments according to study requirements, avoid of the large costs in terms of effort, logistics, and control associated with studying behavior in vista space or large real environments, and precisely track participants' movements in the environment.

If taxing working memory is the key to using cues for spatial encoding, then we might expect cue effects to emerge in a fixed orientation environment under certain circumstances. A condition in which cues would have utility to structure an environmental task field in a fixed orientation could be when multiple target locations are presented and have to be held in memory. Clearly, the more target locations have to be held in memory, the greater the demands on working memory, as verified by studies in which having to remember more object locations results in poorer memory for location (Dent & Smyth, 2005). Holding multiple locations in memory might then induce the reliance on available cues in order to maintain memory for multiple targets and enhance memory performance. Another situation in which cues could help to structure a fixed orientation task field might be if long delays occurred between encoding and retrieval. Following this line of reasoning, increased delay intervals would tax memory, prompting the use of cues to provide a more robust categorical structure for memory retrieval.

It may also be interesting to examine circumstances under which cues may take precedence over geometric information. The lack of external cue use in a fixed orientation environment is consistent with the "modular hypothesis," suggesting the operation of an autonomous geometric module in spatial coding processes that takes presidency over cue-based processes. This geometric module appears to be present early in development (Hermer & Spelke, 1996; Wang et al., 1999) and the dominance of geometric spatial coding is further supported by animal studies (Cheng, 1986). According to the "modular hypothesis," spatial coding is based on geometric information, such as the shape of the environment, with people ignoring non-geometric information, such as available external reference cues. The interplay of geometric-based and cue-based spatial representations across different tasks and task manipulations is an important area for future research. The present study indicates the key role of orientation of the environment to the cues.

Finally, it may be instructive to use rotation or orientation manipulations to test for cases in which geometric structuring of the environment takes precedence over egocentric structuring. Wedell et al. (2007) varied the geometric shape of the task field in a fixed orientation version of the dot location task. They reasoned that if geometric properties determined the number of prototypes, then one would expect different numbers of prototypes for triangle, square and pentagon shaped task fields. However, in each case four prototypes emerged, corresponding to an egocentric up-down and left-right parsing of the geometric task field.

Given the pervasive effects of rotation on inducing cue-based encoding, it would be instructive to examine whether geometric encoding would be engaged when rotation or dynamic orientation is introduced to the task. More generally, the present results suggest the value of manipulating orientation to the task field across a variety of spatial tasks to examine the effects on the spatial representations encoded in memory. Just as manipulating orientation in the Water maze task determines whether spatial memory is based on procedural memory or place memory, manipulations of orientation may be a key determinant of whether egocentric, cue-based, or geometric-based points of view are used in coding spatial categories for memory for location.

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