Reorienting when cues conflict: A role for information content in spatial learning?

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In two experiments, human participants searched in dynamic three-dimensional virtual-environment rectangular enclosures. Unlike previous studies involving learning of features and geometry, we trained features and geometry separately before placing them in conflict. Specifically, participants learned to respond to rewarded features located along the principle axis of a rectangular search space and to respond to rewarded geometry of a rectangular search space in separate training phases followed by a single test trial. During the test trial, features and geometry were placed in conflict by situating rewarded bins during feature training in unrewarded geometric corners from geometry training and unrewarded bins during feature training in rewarded geometric corners from geometry training. Results of Experiment 1 indicated that although all participants learned features and geometry at an equivalent rate and to an equivalent level, performance during the test trial indicated no preferential responding to features or geometry. However, choice reaction time was significantly longer during the test trial compared to that of last feature and last geometry training trials. Experiment 2 attempted to dissociate information content of features and geometry from their acquired associative strength by rewarding only one geometric corner during geometry training. Results of Experiment 2 indicated that although features had presumably acquired greater associative strength relative to that of geometry by the end of training, performance during the test trial indicated no preferential responding to features or geometry. As in Experiment 1, choice reaction time was significantly longer during the test trial compared to that of last feature and last geometry training trials. Collectively, results seem to provide converging evidence against a view-based matching account of spatial learning, appear inconsistent with standard associative-based accounts of spatial learning, and suggest that information content of spatial cues may play an important role in spatial learning.

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A long-standing issue in the spatial learning literature surrounds the extent to which features (objects in the environment) and geometry (shape of an enclosure) compete during learning for behavioral control (for reviews, see Cheng and Newcombe, 2005; Spetch and Kelly, 2006; see also Doeller and Burgess, 2008; Doeller et al., 2008). Although it appeared as though geometry extracted from enclosures was learned incidentally by a dedicated geometric module (Cheng, 1986; Gallistel, 1990; for a review, see Cheng and Newcombe, 2005), recent empirical evidence suggests that geometry may be learned associatively like that of other environmental cues (e.g., Miller and Shettleworth, 2007; see also Cheng, 2000, 2008; Collett and Zeil, 1998; Cheung et al., 2008; Gillner et al., 2008; Sturzl et al., 2008; Wystrach and Beugnon, 2009).

According to associative-based accounts of spatial learning, geometry of an enclosure is treated as any other environmental cue (e.g., features) capable of acquiring independent associative strength (Miller, 2009; Miller and Shettleworth, 2007). Behavioral control is suggested to be determined by the cue with the largest value when the associative strength of each cue is divided by the sum total of the associative strength of all other cues present in that trial. Such an associative-based account seems to explain many observed phenomena in enclosure search tasks such as differential influences (i.e., cue competition or lack thereof) of features and/or geometry (Alexander et al., 2009; Wilson and Alexander, 2008; for a review, see Cheng, 2008). However, associative-based accounts are not exempt from problems in accounting for geometry learning (for a review, see Cheng, 2008). For example, explaining behavioral control by geometry when enclosure size is manipulated between training and testing seems problematic for such an account because the enclosure size is not considered as an element (Miller, 2009; see also Chiandetti et al., 2007; Kelly and Spetch, 2001; Learmonth et al., 2002; Sovrano et al., 2005, 2007; Sturz and

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Kelly, 2009; Vallortigara et al., 2005). In addition, an associative-based account appears unable to explain results of experiments in which features (e.g., colors of walls) move randomly during training (see Graham et al., 2006; see also Cheng, 2008).

According to view-based matching accounts of spatial learning, geometry of an enclosure is stored as a representation from the goal location in memory and involves reducing the discrepancy between an organism’s current retinal image and this stored representation. Behavioral control is suggested to be determined by the best match of current perception with this stored representation. For example ants and honeybees appear to search until their current retinal image matches that of an image stored in memory (for reviews, see Cheng, 2000, 2008; Collett and Zeil, 1998; see also Cheung et al., 2008; Gillner et al., 2008; Stürzl et al., 2008; Wystrach and Beugnon, 2009). However, view-based matching accounts are also not exempt from problems in accounting for geometry learning (for a review, see Cheng, 2008). For example, explaining behavioral control by features or geometry when view-points change from training to testing seems problematic for such an account because view-based matching requires a view-point dependent representation (see Nardini et al., 2009).

More recently, some empirical and theoretical efforts have shifted focus to the relative weighting of spatial cues (Nardini et al., 2008; Newcombe and Ratliff, 2007; Ratliff and Newcombe, 2008). This adaptive-combination model suggests that spatial cues are weighted by factors such as reliability, validity, saliency, strength, and prior experience. Specifically, based on recent evidence that suggests humans integrate visual and haptic information in a statistically optimal fashion (Ernst and Banks, 2002; for a review, see Denève and Pouget, 2004), mechanisms that adhere to information-processing principles have been proposed as underlying a process of the weighting of spatial information (Cheng et al., 2007; see also Nardini et al., 2008, 2009; Newcombe et al., 2009; Newcombe and Ratliff, 2007). Behavioral control is suggested to be determined by the reliability, validity, saliency, and strength of a spatial cue in predicting a goal location.

Oftentimes however, associative-based and information-processing accounts of spatial learning appear to make identical predictions which render them theoretically difficult to differentiate. Importantly though, the predictions themselves are derived through different means. Specifically, associative-based accounts suggest that the acquired associative strength of features and geometry is the source of their relative behavioral control whereas information-processing accounts suggest that the acquired information content of features and geometry in predicting a goal location is the source of their relative behavioral control. As a result, differentiating between these two theoretical accounts of spatial learning requires acquired information content of spatial cues to be dissociated from their acquired associative strengths.

The purpose of the present experiments was to test these theoretical accounts of spatial learning. However, unlike previous studies involving learning of features and geometry, we trained features and geometry separately before placing them in conflict (see Fig. 1). Specifically, participants learned to respond to rewarded features located along the principle axis of a rectangular search space and to respond to rewarded geometry of a rectangular search space in separate training phases followed by a single test trial. As a result, we attempted to either maintain equivalence of the acquired information content of features and geometry with their individually acquired associative strengths (Experiment 1) or dissociate acquired information content of feature and geometry from their acquired associative strengths (Experiment 2). We believe that such a method allowed us to place predictions derived from view-based matching, associative-based accounts, and an adaptive-combination account of spatial learning in direct conflict for theoretical diagnostic purposes.

1. Experiment 1

Participants searched in a dynamic three-dimensional virtual-environment rectangular enclosure, and we rewarded both geometrically equivalent corners during geometry training and a particular color during feature training (see Fig. 1). Specifically, during feature training four colored bins were located along the principle axis of a rectangular search space, and during geometry training four identically colored bins were located one in each corner of the same-sized rectangular search space. According to associative-based accounts of spatial learning, the rewarded color during feature training would acquire strong positive associative strength while the unrewarded color would acquire weak negative associative strength. Similarly, during geometry training, rewarded geometry would acquire strong positive associative strength while unrewarded geometry would acquire weak negative associative strength. Although associative strength cannot be measured directly, acquired associative strength of features and geometry can be inferred from performance. Assuming performance measures suggest equivalence in acquired associative strength of features and geometry, an associative-based account of spatial learning would predict equivalent responding to features and geometry during a test trial in which features and geometry are placed in conflict because each corner would contain both a strong positive and a weak negative element (i.e., the value of rewarded features divided by the total available associative strength would be equivalent to that of the value of the associative strength of rewarded geometry divided by the total available associative strength).

In contrast, a view-based matching account of spatial learning would suggest that the contours of the test enclosure would more closely match that of an image of the geometry training enclosure (i.e., four bins arranged with one bin in each corner) compared to that of an image of the feature training enclosure (i.e., four bins equally spaced along the ‘principle axis’); therefore, the geometrically correct corners during the test trial would best match a view-based representation of the goal location (even despite a change in feature color at the corners) and as a result would predict preferential responding to the geometrically correct corners.

Like an associative-based account, an adaptive-combination account would also predict equivalent responding to features and geometry during a test trial in which features and geometry are placed in conflict. However, an adaptive-combination account would suggest that lack of preference during a conflict trial would result from the equivalency in information content of features and geometry in predicting a goal location. Specifically, the information content of rewarded geometry would be equivalent to that of the rewarded features, and the information content of unrewarded geometry would be equivalent to that of unrewarded features. More specifically, rewarded features and rewarded geometry would be 100% reliable in predicting a goal location whereas unrewarded features and unrewarded geometry are 0% reliable in predicting a goal location. The resulting expected values of the reliability in predicting the goal location for each corner would be 50%.

It is clear that these theoretical accounts of spatial learning generate divergent predictions regarding choice location during a conflict trial, but it is also apparent that the predictions from associative-based and adaptive-combination accounts result in the prediction of no preference for features or geometry during a conflict trial (i.e., a null effect). Although basing theoretical conclusions on empirical null effects often result in conceptual and interpretational difficulties, recent efforts have advocated for the importance of such effects for theoretical diagnostic purposes (see Gallistel, 2009). Despite the potential benefits of null effects for theoretical diagnostic purposes, we sought an additional dependent measure.
to provide converging evidence for and against these predictions, and although movement trajectories have been successfully used as qualitative measures in support of theoretical accounts of spatial learning (e.g., Wystrach and Beugnon, 2009), we adopted choice reaction time (a purely quantitative measure) for its obvious statistical advantages.

Despite the fact that the aforementioned theoretical accounts of spatial learning appear to be silent with respect to choice reaction time, we selected choice reaction time for its potential to provide converging evidence to assist in discriminating between these theoretical predictions. Specifically, it seems reasonable to assume that if a view-based matching strategy were employed by participants, choice reaction time during the test trial would be equivalent to that of choice reaction time during the last geometry training trial because of the similarity of the test view with any representation that may be stored in memory from training. In contrast, however, it seems reasonable to assume that if an associative-based or adaptive-combination strategy were employed by participants, choice reaction time during the test trial should be longer than that of both last feature and last geometry training trials because all of these spatial cues would have acquired equivalent associative strength and information content, respectively. Specifically, under the assumption that the presence of a cue with strong associative strength or information content would expedite time-to-choice, it seems reasonable to assume that the absence of a spatial cue with greater relative associative strength or information content would result in longer choice reaction time.

2. Method

2.1. Participants

Twenty-one Armstrong Atlantic State University (AASU) undergraduate students (9 males and 13 females) served as participants. Five participants (1 male and 4 females) did not meet training criteria (see below) and therefore were excluded from analyses. The
remaining 16 participants (8 males and 8 females) were included in all analyses. All participants received extra class credit.

2.2. Apparatus

An interactive, dynamic three-dimensional virtual environment was constructed and rendered using Valve Hammer Editor and run on the Half-Life Team Fortress Classic platform. A personal computer, 19-inch liquid crystal display (LCD) monitor, optical mouse, keyboard, and speakers served as the interface with the virtual environment. The monitor (1152 \times 864 pixels) provided a first-person perspective of the virtual environment. The arrow keys of the keyboard, the mouse, and the left mouse button navigated within the environment. Speakers emitted auditory feedback. Experimental events were controlled and recorded using Half-Life Dedicated Server on an identical personal computer.

2.3. Stimuli

Dimensions are length \times width \times height and measured in virtual units (vu). Three virtual enclosures (Geometry, Feature, and Test), all measuring 568 vu \times 284 vu \times 281 vu were created (see Fig. 1). Each enclosure contained four raised bins (86 vu \times 86 vu \times 38 vu). The four bins were arranged with one in each corner for the Geometry and Test enclosures. The four bins were arranged equally spaced along the principle axis for the Feature enclosure. Bins were colored red, blue, or yellow depending on enclosure type (see below). The enclosures were illuminated by a light source centered 64 vu below the ceiling. All walls were white in color with the exception of the floors (grey) and ceilings (black).

2.4. Procedure

Participants were informed to locate the bin that transported them to the next virtual room and moved via keyboard keys: ↑ (forward), ↓ (backward), ← (left), and → (right). Movement of the mouse changed the view in the environment. Auditory feedback indicated movement (footstep sounds). Participants selected a bin by jumping into it (simultaneously moving forward [↑] and jumping [left mouse button]). Auditory feedback indicated a jump occurred (“uhuh” sound). Selection of a rewarded bin resulted in auditory feedback (transport sound from Super Mario Bros.TM ) and a 1 s inter-trial interval (ITI) in which the monitor went black and participants progressed to the next trial. Selection of a non-rewarded bin resulted in different auditory feedback (game over sound from Super Mario Bros.TM ) and required participants to jump out of the current bin and continue searching.

Participants experienced two training phases followed by one test trial. The order of training phases was counterbalanced across participants. In each training phase, participants were required to meet the criteria of four correct first choices out of the last six trials to ensure sufficient learning of both features and geometry. All training trials and the test trial were conducted in one continuous session lasting approximately 30 min.

2.4.1. Feature training

Feature training consisted of 15 trials. Participants were randomly assigned to one of two rewarded colors (blue or yellow). Participants began each trial in the center of the enclosure and entered it at random orientations from 0° to 315° in increments of 45°. For each trial, two bins were colored blue and two bins were colored yellow. Arrangement of the bin colors along the principle axis varied randomly from trial to trial among the six possible combinations (see Fig. 1).

2.4.2. Geometry training

Geometry training consisted of 15 trials. Participants were randomly assigned to one of two rewarded geometric corners (goal locations at corners with a short wall on the left and a long wall on the right or goal locations at corners with a long wall on the left and a short wall on the right). Participants began each trial in the center of the enclosure and entered it at random orientations from 0° to 315° in increments of 45°. All bins were colored red (see Fig. 1).

2.4.3. Testing

Testing consisted of one trial. Participants began the test trial in the center of the enclosure oriented to one of the long walls so that all bins would be out of view. The color of the rewarded bins from feature training was located in the unrewarded geometric corners from geometry training, and the color of the unrewarded bins from feature training was located in the rewarded geometric corners from geometry training. Participants made a single choice during the test trial which resulted in no auditory feedback and termination of the session (see Fig. 1).

3. Results

3.1. Training

Fig. 2 shows the mean proportion of participants’ correct first choices plotted by five-trial blocks for feature (filled circles) and geometry (unfilled circles) training trials of Experiment 1. Dashed line represents chance performance (i.e., 0.5). Error bars represent standard errors of the mean.

2.4.2. Geometry training

Geometry training consisted of 15 trials. Participants were randomly assigned to one of two rewarded geometric corners (goal locations at corners with a short wall on the left and a long wall on the right or goal locations at corners with a long wall on the left and a short wall on the right). Participants began each trial in the center of the enclosure and entered it at random orientations from 0° to 315° in increments of 45°. All bins were colored red (see Fig. 1).

2.4.3. Testing

Testing consisted of one trial. Participants began the test trial in the center of the enclosure oriented to one of the long walls so that all bins would be out of view. The color of the rewarded bins from feature training was located in the unrewarded geometric corners from geometry training, and the color of the unrewarded bins from feature training was located in the rewarded geometric corners from geometry training. Participants made a single choice during the test trial which resulted in no auditory feedback and termination of the session (see Fig. 1).

3. Results

3.1. Training

Fig. 2 shows the mean proportion of participants’ correct first choices plotted by five-trial blocks for feature (filled circles) and geometry (unfilled circles) training trials of the 15 trials of training. As shown, participants’ choices rapidly came under control of rewarded features and rewarded geometry. A three-way mixed analysis of variance (ANOVA) on mean proportion of first choices to the rewarded bins with Gender (male, female), Trial Type (feature, geometry), and Block (1–3) as factors revealed only a main effect of Block, F(2, 28) = 34.23, p < .001. No other main effects or interactions were significant, Fs < 2.2, ps > .05. Post hoc tests revealed each block was significantly different from all other blocks (ps < .05). Additionally, Block 3 for both feature and geometry trials were significantly greater than chance performance (i.e., 0.5), one-sample t-tests, ts(15) > 10.1, ps < .001.

3.2. Testing

Two separate analyses were used collectively as converging evidence to determine search strategy during testing: (1) choice location and (2) choice reaction time.
3.2.1. Choice location

We calculated the proportion of participants’ choices to rewarded feature bins from feature training and rewarded geometry from geometry training during the test trial. Proportions of choices were equivalent to rewarded features (0.625) and rewarded geometry (0.375), as confirmed by a chi-square, $\chi^2(1, N = 16) = 1.0, p > .05$.

3.2.2. Choice reaction time

We analyzed choice reaction time for participants during the test trial and compared it to the choice reaction times for the last feature training and last geometry training trials. As with most reaction time data, choice reaction times were positively skewed ($M = +1.79, \text{SEM} = 0.55$), and as a result, we subjected all reaction time data to a square-root transformation (see Sheskin, 2004). Fig. 3 shows the mean transformed choice reaction time plotted by trial type. As shown, participants took longer to make a choice during the test trial compared to that of last feature and last geometry training trials. These results were confirmed with a one-way repeated measures ANOVA on transformed choice reaction time with Trial Type (last feature, last geometry, test) as a factor and revealed a main effect, $F(2, 30) = 3.42, p < .05$. Post hoc tests revealed that choice reaction time for the test trial was significantly longer than that of last feature and last geometry training trials ($ps < .05$). However, choice reaction times for last feature and last geometry training trials were not significantly different from each other ($p > .05$).

4. Discussion

Results of training indicated that participants learned features and geometry at an equivalent rate and to an equivalent level. During the test trial in which these separately trained features and geometry were placed in conflict, participants selected features and geometry equally—indicating no preference for features or geometry. However, choice reaction time during the test trial was longer than that of last feature and last geometry training trials. Although we acknowledge that in isolation a lack of preferential responding during the test trial must be interpreted with caution, it is nonetheless in accordance with predictions derived from both associative-based and adaptive-combination accounts but not view-based matching accounts of spatial learning. Specifically, associative-based and adaptive-combination accounts predict equivalent responding to features and geometry during the test trial because performance during training allows for the inference that features and geometry had acquired equivalent associative strength and information content respectively. One potential issue often arises with respect to equivalence in saliency of spatial cues, but the fact that features and geometry were learned at an equivalent rate also allows for the inference that they possessed equivalent saliencies. However, view-based matching accounts predict preferential responding to the geometrically correct corners regardless of feature color at those corners due to a better match of these corners with any representation of the goal location that may have been stored in memory.

Furthermore, it seems reasonable to assume that if a view-based matching strategy were employed by participants, choice reaction time during the test trial should have been equivalent to that of choice reaction time during geometry training because of the similarity of the test view with any representation that may have been stored in memory. However, choice reaction time was significantly longer during the test trial compared to not only the last geometry training trial but also to that of the last feature training trial. Although we also acknowledge that in isolation evidence for differences in reaction time must be interpreted with caution because these theoretical accounts of spatial learning are silent with respect to such a measure, the results appears consistent with both an associative-based and adaptive-combination account of spatial learning because these spatial cues had acquired equivalent associative strength and information content, respectively. As a result, a spatial cue with greater relative associative strength or information content was absent and thus unable to immediately influence search behavior.

From a view-based matching perspective, one could argue that despite the similarity of the test view with the training view, the test view was, in fact, different from the training view. It seems possible that such a difference (regardless of how slight) may increase choice reaction time. However, when both choice reaction time and choice location are taken into account, these collective results suggest against such a possibility. As a result, collectively, these results appear inconsistent with a view-based matching account of spatial learning but consistent with both associative-based and adaptive-combination accounts of spatial learning.

As mentioned, both associative-based and adaptive-combination accounts of spatial learning oftentimes make identical predictions; however, the predictions themselves are derived through different means. Specifically, an associative-based account suggests the associative strength of features and geometry are the source of their relative behavioral control whereas an adaptive-combination account suggests the information content of features and geometry in predicting a goal location is the source of their behavioral control (see Miller and Shettleworth, 2007; Newcombe and Ratliff, 2007). The purpose of Experiment 2 was to attempt to dissociate acquired information content of features and geometry from their individually acquired associative strengths in an effort to test divergent theoretical predictions of these two accounts of spatial learning.

5. Experiment 2

Using a similar procedure to Experiment 1, we attempted to dissociate associative strength of spatial cues from their information content. Specifically, we only rewarded one geometric corner during geometry training while continuing to reward both feature bins during feature training. Under these training conditions, an associative-based account of spatial learning would predict that the rewarded color during feature training would acquire strong positive associative strength while the unrewarded color would acquire weak negative associative strength. However, during geometry training, rewarded geometry would acquire weak positive associative strength while unrewarded geometry would acquire weak...
negative associative strength. As a result, an associative-based account of spatial learning would predict preferential responding to features during a test trial in which features and geometry are placed in conflict because the associative strength of the rewarded features divided by the total available associative strength would be greater than that of the associative strength of rewarded geometry divided by the total available associative strength. As with Experiment 1, a view-based matching account would predict preferential responding to rewarded geometry during a test trial in which spatial cues are in conflict because the contours of the test enclosure would more closely match that of an image of the geometry training enclosure compared to that of an image of the feature training enclosure; therefore, the geometrically correct corners during the test trial would best match a view-based representation of the goal location. An adaptive-combination account, however, would predict equivalent responding to features and geometry during a test trial in which features and geometry are placed in conflict because features and geometry have acquired equivalent information content in predicting a goal location. Specifically, the information content of the red bins in the rewarded geometry corners would be equivalent to that of the rewarded features in unrewarded geometry corners in predicting a goal location because the rewarded geometry corner is indistinguishable from its rotational equivalent, and therefore, the expected reliability of each geometric correct corner is 50%—one geometrically correct corner predicts the goal location with 100% reliability while its rotational equivalent predicts the goal location with 0% reliability. Similarly, rewarded features are 100% reliable whereas unrewarded geometry is 0% reliable—resulting in an expected value of 50%.

As with Experiment 1, the aforementioned theoretical accounts of spatial learning are silent with respect to choice reaction time; however, application of the same logic concerning reaction time from Experiment 1 can be applied to Experiment 2. Specifically, it seems reasonable to assume that if a view-based matching strategy were employed by participants, choice reaction time during the test trial would be equivalent to that of choice reaction time during the last trial of geometry training because of the similarity of the Test view with any representation that may be stored in memory. It also seems reasonable to assume that if an associative-based strategy were employed by participants, choice reaction time during the test trial would be equivalent to that of choice reaction time during the last feature training trial because of the relatively greater associative strength of features compared to that of geometry. In other words, a spatial cue with greater relative associative strength would be present to immediately influence search behavior. In contrast, however, it seems reasonable to assume that if an adaptive-combination strategy were employed by participants, choice reaction time during the test trial would be longer than that of both last feature and last geometry training trials because of the equivalency of the information content of these spatial cues. In other words, a spatial cue with greater relative information content would be absent and thus unable to immediately influence search behavior.

6. Method

6.1. Participants

Thirty-two AASU undergraduate students (11 males and 21 females) served as participants. Sixteen participants (3 males and 13 females) did not meet training criteria (which was identical to the criteria used in Experiment 1) and therefore were excluded from analyses. The remaining 16 participants (8 males and 8 females) were included in all analyses. All participants received extra class credit.

6.2. Apparatus and stimuli

The apparatus and stimuli were identical to those used in Experiment 1.

6.3. Procedure

The procedure was identical to Experiment 1 with two exceptions: (1) for geometry training, only one of the geometrically correct corners was rewarded and varied randomly from trial to trial, and (2) during the test trial, bins in the geometrically correct corners were colored red, and bins in the geometrically incorrect corners were the color of the rewarded feature during feature training (see Fig. 1). It should be noted that although only one of the geometrically correct corners was rewarded during geometry training, the performance criteria remained the same as Experiment 1 (i.e., participants were required to make four correct first choices out of the last six trials for both feature and geometry training). Therefore, with respect to geometry training, rotational errors (although unrewarded) were considered correct for the purposes of the performance criteria of Experiment 2.

7. Results

7.1. Training

Fig. 4 shows the mean proportion of participants’ first choices to the rewarded feature bins (filled circles) and both geometrically correct corners (unfilled circles) plotted by five-trial blocks for the 15 trials of training. As shown, participants’ choices rapidly came under control of rewarded features and rewarded geometry (along with its rotational equivalent). A three-way mixed ANOVA on mean proportion of first choices to rewarded feature bins and rewarded geometry (and its rotational equivalent) with Gender (male, female), Trial Type (feature, geometry), and Block (1–3) as factors revealed only a main effect of Block, $F(2, 28) = 14.64, p < .001$. No other main effects or interactions were significant, $F s < 1.5$, $p s > .05$. Post hoc tests revealed Block 1 was significantly different from all other Blocks ($p s < .01$), but Blocks 2 and 3 did not differ from each other ($p s > .05$). Additionally, Block 3 for both features and geometry were significantly greater than chance performance (i.e., .5), one-sample t-tests, $t s(15) > 9.7, p s < .001$. As in Experiment
as with Experiment 1, two separate analyses were used collectively as converging evidence to determine search strategy during testing: (1) choice location and (2) choice reaction time.

7.2.1. Choice location

As with Experiment 1, we calculated the proportion of choices to rewarded features during feature training and rewarded geometry during geometry training during the test trial. As with Experiment 1, proportions of choices were equivalent to rewarded features (0.313) and rewarded geometry (0.688), as confirmed by a chi-square, $\chi^2(1, N=16)=2.25, p>.05$.

7.2.2. Choice reaction time

As with Experiment 1, we analyzed choice reaction time for participants during the test trial and compared it to the choice reaction times for the last feature training and last geometry training trials. Also, as with Experiment 1, reaction time data were positively skewed ($M=+1.46, SEM=0.87$), and therefore were subjected to a square-root transformation (see Sheskin, 2004). Fig. 6 shows the mean transformed choice reaction time plotted by trial type. As shown, participants took longer to make a choice during the test trial compared to that of last feature and last geometry training trials. These results were confirmed with a one-way repeated measures ANOVA on transformed choice reaction time with Trial Type (last feature, last geometry, test) as a factor and revealed a main effect, $F(2, 30)=8.75, p<.01$. Post hoc tests revealed that choice reaction time for the test trial was significantly longer than that of last feature and last geometry training trials ($ps < .01$). However, choice reaction time for last feature and last geometry training trials were not significantly different from each other ($p > .05$).

8. Discussion

Results of training in Experiment 2 indicated that participants learned features and geometry at an equivalent rate and to an equivalent level. However, because we were able to train features and geometry separately, we believe this allowed the information content in predicting a goal location of these spatial cues to be dissociated from their individually acquired associative strengths. Specifically, although features and geometry were equivalent in information content in predicting a goal location during the test trial (i.e., expected value of both was 50%), features had acquired greater associative strength during training. During the test trial in which these separately trained features and geometry were placed in conflict, participants selected features and geometry equally—indicating no preference for features or geometry. However, the choice reaction time during the test trial was longer than that of last feature and last geometry training trials. Again, we acknowledge that in isolation a lack of preferential responding during the test trial must be interpreted with caution, but it is nonetheless in accordance with a prediction derived from an adaptive-combination but not view-based matching or associative-based accounts of spatial learning. Specifically, an adaptive-combination account predicts equivalent responding to features and geometry during the test trial because the information content of features and geometry were equivalent in predicting a goal location. A view-based matching account predicts preferential responding to rewarded geometry because of a better match of these corners with any representation stored in memory, and an associative-based account predicts preferential responding to feature corners because the acquired associative strength of features was greater relative to that of geometry.

Furthermore, it seems reasonable to assume that if a view-based matching strategy were employed by participants, choice reaction
time during the test trial should have been equivalent to that of choice reaction time during the last geometry training trial because of the similarity of the Test view with any representation that may have been stored in memory. Moreover, it seems reasonable to assume that if an associative-based strategy were employed by participants, choice reaction time during the test trial should have been equivalent to that of choice reaction time during the last feature training trial because of the relatively greater associative strength of features compared to that of geometry. As a result, a spatial cue with greater relative associative strength was present and thus able to immediately influence search behavior. However, choice reaction time was significantly longer during the test trial compared to not only the last feature training trial but also to that of the last geometry training trial. Again, we acknowledge that in isolation evidence for differences in reaction time must be interpreted with caution because these theoretical accounts of spatial learning are silent with respect to such a measure, but such a result appears to be only consistent with an adaptive-combination account of spatial learning. Collectively, we interpret these results to suggest that these spatial cues were equivalent in information content in predicting a goal location during the test trial. In other words, a spatial cue with greater relative information content was absent and thus unable to immediately influence search behavior.

9. General discussion

Results of training in Experiment 1 indicated that participants learned features and geometry at an equivalent rate and to an equivalent level. During the test trial in which these separately trained features and geometry were placed in conflict, participants selected features and geometry equally—indicating no preference for features or geometry. This result is consistent with associative-based and adaptive-combination accounts of spatial learning because performance during training allows for the inference that features and geometry had acquired equivalent associative strength and information content in predicting the goal location, respectively. However, this result appears inconsistent with a view-based matching account of spatial learning because participants should have responded preferentially to the geometrically correct corners regardless of feature color at those corners due to a better match of these corners with any representation of the goal location that may have been stored in memory. Such an interpretation appears to be bolstered by the choice reaction time data that indicated participants took significantly longer to make a choice during the test trial compared to that of the last feature and last geometry training trials.

Results of training in Experiment 2 indicated that participants learned features and geometry at an equivalent rate and to an equivalent level. However, because we were able to train features and geometry separately, this allows for the inference that the information content in predicting a goal location of these cues was dissociated from their individually acquired associative strengths. During the test trial, participants selected features and geometry equally despite potential greater relative associative strength of features. This suggests that the expected information content of geometry in predicting a goal location was equivalent of that of features. As with Experiment 1, such an interpretation appears to be bolstered by the choice reaction time data that indicated participants took significantly longer to make a choice during the test trial compared to that of the last feature and last geometry training trials.

As an aside, it is worth noting the role of both choice location and choice reaction time data in the interpretational process. Despite the fact that these theoretical accounts of spatial learning appear silent with respect to choice reaction time, the use of both measures was critical to providing converging evidence when drawing theoretical conclusions. Specifically, the aforementioned theoretical accounts of spatial learning often appear to make identical predictions concerning one measure; however neither appears to make identical predictions with respect to both measures. Thus, it appears that analysis of choice reaction time data could continue to serve as a useful measure in discriminating theoretical accounts of spatial learning.

In conclusion, present results appear inconsistent with view-based matching accounts of spatial learning because, according to these models, participants should have preferentially responded to geometry during the test trials due to a better match of this view with any representation that may have been stored in memory from training. These results appear consistent with recent evidence against view-based matching accounts of spatial learning in children over the age of five years (Nardini et al., 2009). Thus, there appears to be some generality to our obtained result, and, at least for humans over the age of five years, provide converging evidence against a view-based matching account of geometry learning. Present results also appear inconsistent with associative-based accounts of spatial learning because according to these models, participants should have preferentially responded to features during the test trial of Experiment 2 due to their relatively larger associative strength compared to that of geometry. However, results appear consistent with an adaptive-combination model of spatial learning (Cheng et al., 2007; Nardini et al., 2008, 2009; Newcombe and Ratliff, 2007; Ratliff and Newcombe, 2008). Specifically, by attempting to dissociate information content of spatial cues from their individually acquired associative strengths, we believe we were able to maintain equivalent information content of features and geometry while reducing the acquired associative strength of geometry relative to that of features during the test trial of Experiment 2. Under these conditions, participants showed no preference for features or geometry but took significantly longer to make a choice response compared to last feature and geometry training trials. We interpret these results as suggesting that, at least in adult human participants, information content of spatial cues may play an important role in spatial learning.

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