Spatial Visualization Training Using Interactive Animation

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Abstract

In two experiments, we investigated the benefits of using interactive animation and virtual geometric solids for spatial visualization training. Individuals with low spatial ability were trained to recognize the cross section of a three-dimensional (3D) object using interactive animations in which they passed a plane through a 3D object, observed, and drew the resulting cross section. In both experiments, trained participants showed significantly greater pre-posttest improvement compared to controls on a test of inferring cross sections. Effects of training transferred to untrained stimuli. We propose mechanisms of learning and transfer and suggest how these results can be further developed and applied to spatial visualization training in science education.

Keywords: spatial visualization; training, interactive animation; virtual models; cross-sections

Objectives

Multiple sources of evidence suggest that spatial abilities can be developed through spatial activities and training. For example, meta-analyses of the literature on spatial experience (Baenninger, & Newcombe, 1989) indicate that: 1) participation in spatial activities such as sports, crafts and other hobbies is positively related to scores on spatial ability measures; and 2) performance on spatial ability tests can be improved through training. This evidence for the mutability of spatial skill raises questions of what are the most effective approaches to train spatial visualization ability. Here we investigate the benefits of *spatial visualization* training using interactive animations of virtual objects for a task that involves inferring the 2D cross section of a 3D geometric figure.

Theoretical Perspectives

Cross sections as an example of spatial visualization. Spatial visualization is defined as the cognitive ability to understand, mentally encode and manipulate 3D visuo-spatial forms (Carroll, 1993). Some spatial visualization tasks involve inferring 2D representations of 3D structures, and vice versa. One such task, inferring the cross section (or 2D slice) of a 3D structure, is an essential skill in many disciplines of science. For example, inferring cross sections of anatomical structures is critical for biology students (Rochford, 1985) and inferring cross-sectional contours of landforms is essential in geology (Kali & Orion, 1996).

Theory motivating training. Figure 1 shows a sample trial from the task used in our experiments. Test instructions direct the participant to imagine the cross section that would result when a criterion figure is intersected by a cutting plane. An informal task analysis suggests that one method of accomplishing this task is to construct a mental image of the figure, imagine the figure being sliced, and change one's view perspective (or mentally rotate the sliced figure) to imagine the cut cross section from a perspective perpendicular to the sliced surface. However if the cross section is of a familiar object, the inference might also be made by retrieving a stored image from memory.

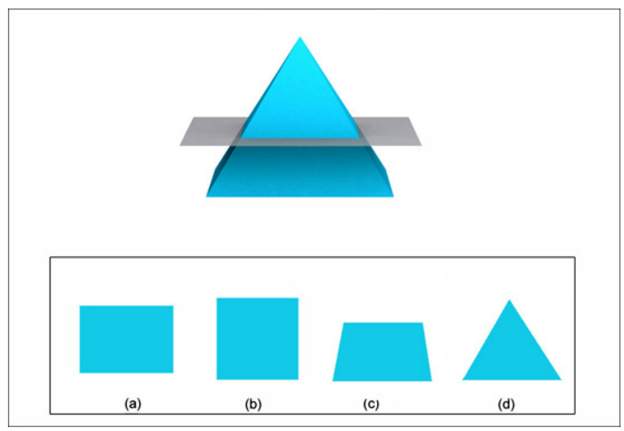

Figure 1: A sample problem from the pre-posttest

The dominant model of mental imagery holds that images can be produced from recently acquired visual percepts, representations previously stored in long-term memory, and verbal descriptions (Kosslyn, 1980; Kosslyn, Brunn, Cave, & Wallach, 1984). In our training manipulation, participants predict a cross-sectional shape that would result from the intersection of a geometric figure and a cutting plane. Next they manipulate a corresponding virtual geometric form and view the resulting cross-sectional shape. We hypothesized that the experience of manipulating geometric forms and viewing the images that result from their manipulations would improve participants' performance on a cross section task by providing them with memories they could draw on in this task.

Kosslyn (1980) also proposes that images retained in the short-term visuospatial buffer represent objects as seen from particular points of view. The task in our experiments requires participants to change their current view perspective with regard to the criterion figure. Compared to high spatial participants, low spatial individuals have more difficulty changing their view perspective (Kozhevnikov & Hegarty 2001; Hegarty & Waller, 2004). The interactive animations in our experiments demonstrate this perspective transformation by showing the cross sections of geometric figures *as if* the participant had successfully changed their view perspective.

Our training design was also motivated by evidence for the association between motor processes and mental imagery. For example, computer-based environments have been used to train adults and children to improve the speed and accuracy of mental rotation (Wiedenbauer, Schmid & Jansen-Osmann, 2007; Widenbauer & Jansen-Osmann 2008). As participants rotated a joystick, they viewed images that rotated in synchrony with their hand movements. In both studies, the authors attributed participants' improved mental rotation performance at posttest to their congruent updating of movement and vision. Similarly, participants in our experiments receive online visual updating on the results of their manual manipulations of virtual objects.

Demonstrations of training effects in spatial task performance raise the question of what aspects of performance are affected by training and how far this training generalizes. Some studies have found that training effects are quite specific to the stimuli and spatial transformations that were practiced (e.g., Kail & Park, 1990, Tarr & Pinker, 1989). These studies suggest that what is developed is the ability to recognize specific shapes in different orientations, rather than ability to perform spatial transformations per se. Kail & Park (1990) accounted for this training effect by reference to *instance theory* (Logan, 1988), which proposes that practice on a task increases the strength or number of memory representations of to-be-learned material. However, other studies have found that spatial training generalizes to transformations of new objects and new spatial transformations (Leone, Taine, & Droulez, 1993; Wallace & Hofelich, 1992). We investigate whether our training effects are specific to trained stimuli or whether they generalized to untrained objects.

In Experiment 1, participants interacted with virtual models that revealed orthogonal and oblique cross sections of five simple solids (cone, cube, cylinder, prism, and pyramid) pictured in our pre-post test. They were tested on cross sections of these objects and of complex objects made up of these solids. We predicted that on posttest: 1) experimental participants would outperform controls on recognition of trained items; 2) experimental participants would outperform controls on recognition of more complex test items composed of trained figures; and 3) experimental participants would make significantly fewer egocentric errors than controls.

Experiment 1

Method

Participants. Twenty low-spatial undergraduate students from the Department of Psychology, University of California, and Santa Barbara were identified on the basis of their pretest scores on the Santa Barbara Solids Test[1] and were randomly assigned to experimental or control groups (ten per group).

Materials

Pretest/posttest measure. The criterion task in our experiments is the Santa Barbara Solids Test, which measures individual differences in the ability to infer cross sections of three-dimensional solids (Cohen & Hegarty, 2007). Three levels of geometric complexity are represented in the test: simple figures are primitive geometric solids: cones, cubes, cylinders, prism, or pyramids. Joined figures consist of two simple solids attached at their edges. Embedded solids are composed of one single solid enmeshed inside another. Each test item shows a criterion figure and four answer choices (Figure 1). In addition to the correct answer (Figure 1b), one of the four answer choices in each problem is an egocentric distracter (Figure 1c), which represents the slanted shape participants might imagine if they failed to change their view perspective relative to the criterion figure.

Drawing trials and interactive animations. Training materials consisted of ten 2D drawing trials and ten corresponding interactive animations. The drawing trials were color images, printed on 8½" x 11" paper, of the five simple solids (cone, cube, cylinder, prism, and pyramid) at orthogonal and oblique orientations. The interactive animations were virtual 3D visualizations of the five solids created using Autodesk® 3ds Max® software. In each animation, the virtual geometric solid remained stationary while the cutting plane could be advanced through the figure with a slider bar that was manipulated with a mouse. As the cutting plane advanced through the virtual figure, a 2D image of the resulting cross section appeared to the left of the virtual figure (Figure 2).

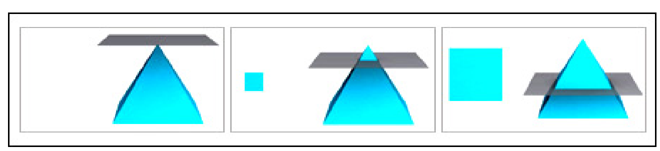

Figure 2: A succession of screen shots from an interactive animation.

[1] Low spatial ability was defined as a pretest score of 15 ≥, which represented the lower half of the distribution of scores.

Procedure

Pretest. Participants were pretested on the Santa Barbara Solids Test (SBST) either in a previous testing session or at the beginning of the experiment.

Training intervention. The participant was shown a drawing trial and was asked to draw the cross-sectional shape that would result from the intersection of the indicated cutting plane and geometric solid (Figure 3).

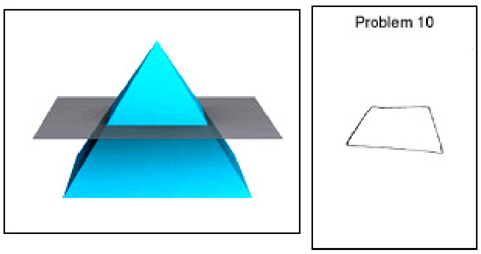

Figure 3: Drawing trial (left); participant's first attempt to draw cross section (right).

The participant then moved the cutting plane of the interactive animation through the virtual figure to the location shown in the drawing trial. Next the participant copied the cross-sectional shape shown in the animation beneath the first drawing. The experimenter then asked the participant to compare the first and second drawings and to grade, with a + or – sign, the accuracy of the first with respect to the second (Figure 4).

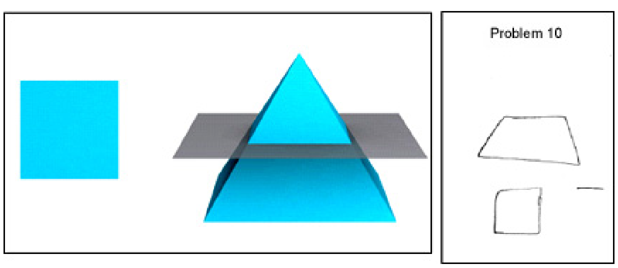

Figure 4: Screen shot from interactive animation (left); participant's drawing of correct cross section under first attempt (right).

This procedure was completed for the 10 simple figures; the entire training cycle was then repeated until the participant drew the correct cross sectional shape for each solid on the first attempt. Control participants read non-fiction prose for 15 minutes (the approximate amount of time used for the training).

Posttest. After this manipulation, experimental participants and controls completed the posttest administration of the SBST.

Results and Discussion

Overall pretest scores on the Santa Barbara Solids Test were similar for the experimental (M= .31, SD = .01) and control (M=.38, SD = .01) groups.

The 30 problems in the test were classified into three categories for analysis of training and transfer effects. The 10 test figures showing cross sections (orthogonal or oblique) of simple geometric solids were categorized as trained figures. Seventeen of the remaining 20 test figures were classified as similar figures, as they are composed of one or more trained cross sections. The remaining three figures were classified as new figures, as they did not contain any trained cross sections (they were made up the same solids but untrained sections of these solids). The score on the test and each subset of items was the proportion correct.

Gain scores for each category of items (trained, similar and new) were computed by subtracting pretest from posttest performance scores. Figure 5 gives the means and standard deviations for these gain scores for the experimental and control groups, which were compared with separate independent samples t-tests. For the trained figures, the gain scores of the experimental group were higher than those of the control group, $t(18) = 4.88$, $p<.001$, supporting our first hypothesis. The control group also outperformed the control group on the 17 similar figures, $t(18) = 4.04$, $p= .001$, supporting our second hypothesis. Finally, this group had greater gain scores than the control group on the three new figures, $t(18) =2.19$, $p<.05$.

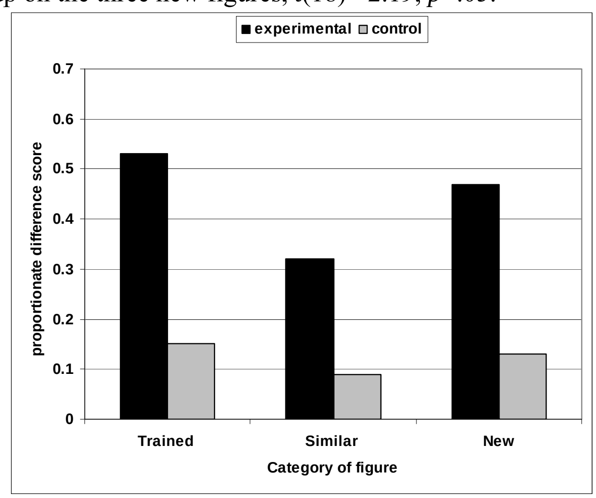

Figure 5: Gain scores by condition and category of test figure, Experiment 1.

The reduction in egocentric errors was computed by subtracting the proportion of pretest from posttest egocentric errors. The pre-posttest reduction in egocentric errors was significantly greater for experimental participants (M = -.41, SD= .09) than for controls (M = -.10, SD= .10), $t(18) = 7.31$, $p<.001$, supporting our third prediction and suggesting that experimental participants learned to reject egocentric errors as answer choices.

What do these results suggest about the benefits of the interactive animation training used in Experiment 1? The significant increase in performance on trained items suggest that experimental participants encoded the images of cross-sectional shapes that they learned during training, and that they retained these images long enough to recognize trained shapes on the posttest. Furthermore, the significant result for similar figures suggests that experimental participants could identify the trained shapes when they appeared in more complex figures. Both of these results can be accounted for by instance theory (Logan, 1988). The significant reduction in egocentric errors made by experimental participants vs. controls suggests that experimental participants learned to reject egocentric errors, as these 'slanted shapes' were never shown as correct cross sections of any figure.

Although statistically significant, the results for new figures were preliminary, given the small number of new figures in this experiment. In order to investigate the extent to which the participants learned something *beyond* the ability to identify the shapes of trained figures (instance theory) and to reject egocentric errors, in Experiment 2 experimental participants were trained on only four interactive animations: orthogonal and oblique cross sections of the cone and the cube. The reduced number of trained shapes allowed us a better opportunity to assess transfer.

Our hypotheses for Experiment 2 were that, on posttest: 1) experimental participants would outperform controls on four trained problems; 2) experimental participants would outperform controls on 12 similar problems; 3) experimental participants would outperform controls on 14 new items; and 4) experimental participants would make significantly fewer egocentric errors than controls on posttest.

Experiment 2

Method

Participants. Twenty–three undergraduate students, screened and identified as low spatial participants as in Experiment 1, were randomly assigned to experimental or control groups.

Materials. Four of the drawing trials from Experiment 1 and four corresponding interactive animations (orthogonal and oblique orientations of the cone and the cube) were used as the training materials. The Santa Barbara Solids Test (SBST) was the pretest and posttest measure.

Procedure

Participants were pretested on the SBST at the beginning of the experimental session. Participants in the experimental condition were trained with the four interactive animations using the same procedure as in Experiment 1. Control participants read non-fiction prose for approximately the same amount of time. After this manipulation, experimental participants and controls completed the posttest administration of the SBST.

Results and Discussion

Overall performance on the Santa Barbara Solids Test across all types of figures was nearly identical for the experimental (*M*= .35, *SD* = .01) and the control (*M*=.36, *SD* = .12) groups.

The 30 problems from this test were reclassified for analysis of training and transfer effects. The items involving orthogonal and oblique cutting planes of the cone and the cube were categorized as trained figures. The cross sections in 12 additional items contained one or more cross-sections that participants viewed during training; these 12 test figures were categorized as similar figures. The cross sections of the remaining 14 test figures did not contain any cross sections seen during training; these were categorized as new figures. Gain scores were computed and compared using the same procedures as in Experiment 1.

Figure 6 shows the means and standard deviations of the gain scores for the different categories of items. The experimental group improved more than the control group on the four trained test items, $t(21) = 6.38$, $p<.001$, supporting our first prediction. As in Experiment 1, this result provides evidence that training improved ability to identify cross sections of trained figures. The experimental group also had significantly greater gain scores for the 12 similar figures, $t(21) = 3.79$ $p<.001$, supporting our second prediction. As in Experiment 1, this result suggests that experimental participants could identify the trained shapes as parts of the more complex similar figures. Finally, the experimental group also improved more on the 14 new figures, $t(21) = 4.89$, $p<.001$, suggesting that they learned something beyond merely identifying shapes they were exposed to during training, supporting our third prediction.

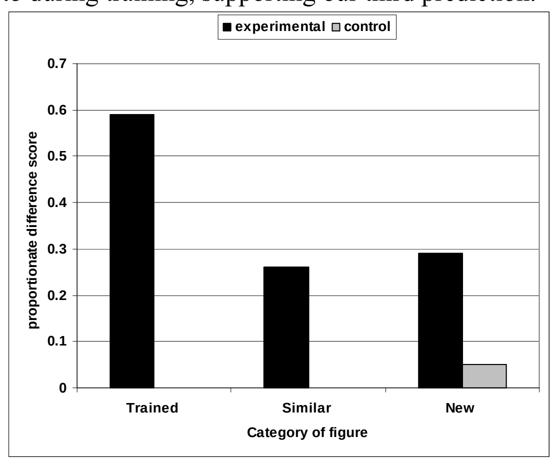

Figure 6: Gain scores by condition and category of test figure, Experiment 2.

The pre-posttest reduction in egocentric errors was significantly greater for experimental participants (*M* = -.30, *SD*= .14) than for controls (*M* = -.05, *SD*=.15), $t(21) = 4.17$, $p<.001$, supporting our fourth prediction. As in Experiment 1, this result suggests that the spatial visualization training manipulation was effective in teaching experimental participants to reject egocentric distracters.

General Discussion

Across both studies, experimental participants learned to identify trained cross sections, and to recognize trained shapes as parts of more complex joined and embedded figures. Additionally, experimental participants choose significantly fewer egocentric answers, compared to controls, on the posttest. Together, these results suggest that interacting with virtual geometric figures enabled experimental participants to later identify the correct cross sections of primitive geometric solids when they were presented as discrete shapes and as parts of more complex figures. The significant decline in egocentric errors among experimental participants suggests that they learned to reject a common misrepresentation about the shape of cross sections.

The significant improvement on new figures in Experiment 2 suggests that participants learned something beyond the ability to identify trained cross-sectional shapes in novel contexts. Experimental participants were trained to recognize orthogonal and oblique cross sections of a cone and a cube. Yet their posttest performance was significantly better than controls on problems that contained cross-sectional shapes they had not learned: oblique and orthogonal cross sections of cylinders, prisms and pyramids. It is possible that experimental participants were able to infer the shapes of untrained figures by noting similarities among the spatial features of criterion figures and remembering the shapes of their cross sections. For example, having learned that the oblique cross section of a cone is an ellipse, they could infer that the oblique cross section of a figure with a *similarly* curved side (a cylinder) would also be an ellipse. This explanation is consistent with Kosslyn's (1980) model of imagery, which holds that new images can be combined from verbal descriptions and visual representations stored in long-term memory.

One limitation of these experiments is their multiple choice format, which allows participants to use process of elimination strategies to choose answers. In current research we are investigating if similar gains in performance are seen with a production task (drawing), rather than a multiple choice task. Another limitation of these experiments is that transfer was measured by performance on previously seen geometric solids only. Future experiments will introduce additional transfer measures using more novel forms.

In summary, these experiments provide further evidence that spatial visualization skill can be improved through training and provide evidence for the usefulness of interactive computer visualizations in this training. Additionally, they demonstrate training effects on a relatively unstudied skill: the ability to infer the 2D cross section of a 3D figure. An open question is whether this form of training may be useful when applied to specific domains of science education, for example, in biology, geology, and engineering. Future research will apply this training methodology to specific domains of science and mathematics education.

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