Exploring the generalizability of visual search strategies

Undergraduate Research Thesis

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Abstract

When searching our visual environment, we often have multiple strategies available. For example, when looking for apples on a supermarket shelf, you can look for red things, round things, or you can just search serially through all items. How do we choose a strategy? Recent research on this question has revealed substantial variation across individuals in attentional control strategies when approaching visual search tasks, and the strategies have been found to be reliable within subjects. However, strategies on one visual search task have failed to generalize across different paradigms that assess various components of strategy use (Clarke et al., 2018). Thus, evidence for whether strategies generalize beyond a single paradigm remains scarce. While previous tests of generalizability used paradigms that vary in many ways, we focused on a single strategy component that could be preserved across tasks, with several other changes. In two experiments, we assessed the correlation between individuals' strategies in the Standard Adaptive Choice Visual Search (Standard ACVS; Irons & Leber, 2018) and a modified novel visual search task, Spatial ACVS. In the Standard ACVS, participants seeking to perform optimally have to enumerate subsets of different colored squares and identify the smaller subset to choose a target from. Similarly, in the Spatial ACVS, participants seeking optimal performance have to enumerate spatially separate subsets of squares (one on the left and one on the right side of the display), choosing the target in the smaller subset. Participants finished both tasks in the same order in one experimental session. Results showed a positive correlation in optimal target choices between the two tasks (r = .38), indicating similar strategy usage. Future studies can focus on what strategy components tend more to be generalized across tasks and whether an individual's strategy can generalize to tasks with a combination of several strategy

components. The ultimate goal is to fully understand how people choose their attentional control strategies in unconstrained, real-life environments.

Keywords: visual search, attentional control, strategy, individual difference, numerosity

Introduction

Imagine when you walk into a grocery store trying to find some fresh apples. On the shelves crowded with different kinds of fruits, it is not always an easy task to find them. If you search from one corner of your visual field to another, the search will be rather inefficient. Alternatively, if you try to use some attentional control to help your search, for example by selectively attending to the red things or round things, the search will be much faster. While there are multiple strategies to control attention in visual search, different strategies sometimes yield significantly different performances. Suppose if apples are surrounded by a majority of red items, or they are located on red shelves, then a strategy of searching for the red color will not be as efficient as searching for shapes, sizes, or other features.

How do people choose their attentional control strategies to help visual search? Studies have found that people's strategy selection is overall suboptimal and results in ineffective control (e.g., Bacon & Egeth, 1994; Leber & Egeth, 2006a, 2006b). Research using eye-tracking has also found that participants do not always make fixations that will optimize the information gain and their visual search behaviors could be better explained by a stochastic model (Boot, Becic, & Kramer, 2009; Clarke, Green, Chantler, & Hunt, 2016).

Researchers have offered several speculations regarding why people choose suboptimal strategies in visual search. Bacon and Egeth (1994), for example, proposed that participants adopted less optimal attentional control settings to avoid effort. Kool, McGuire, Rosen, and Botvinick (2010) extended findings supporting the *law of less work*, which had pertained mostly to demands for physical work, to cognitive demands. Pauszek and Gibson (2016, 2018) also proposed a *least cost hypothesis* of voluntary attentional control by showing that participants often abandoned valid symbolic cues in their Posner-like cueing paradigms to avoid effort in processing.

The Adaptive Choice Visual Search (ACVS) Task

While research has found overall suboptimal attentional control strategies, a number of existing studies showed large variation within their samples (e.g., Hogeboom & van Leeuwen, 1997; Kristjánsson, Jóhannesson & Thornton, 2014; Lleras & von Mühlenen, 2004; Muhl-Richardson et al., 2018; Nowakowska, Clarke & Hunt, 2017). More recently, studies using the Adaptive Choice Visual Search (ACVS; Irons & Leber, 2016, 2018) demonstrated the broad individual differences were test-retest reliable. The ACVS task was based on a subset search (Green & Anderson, 1956; Egeth, Virzi, & Garbart, 1984). The task display had two targets, each belonging to a subset of red or blue squares. Participants were free to search for whichever subset they like to find the target. Crucially, one of the targets, refered to as the optimal target, belonged to a subset that is less numerous than the other subset (see Fig. 1). Throughout the course of the experiment, if participants selected more optimal targets, their responses tended to be faster. The extent to which participants were optimal was assessed by *Proportion Optimal*, the proportion of trials in which they selected the optimal target.

A striking finding with the ACVS paradigm is the broad and stable individual differences in search strategy. While a substantial proportion of participants selected the optimal target at chance level, many others adopted the optimal strategy, and a few participants even deliberately chose the suboptimal target more often. These variations showed good test-retest reliability over two session separated 1-10 d apart (*M* = 3.1), as reported in Irons and Leber (2018).

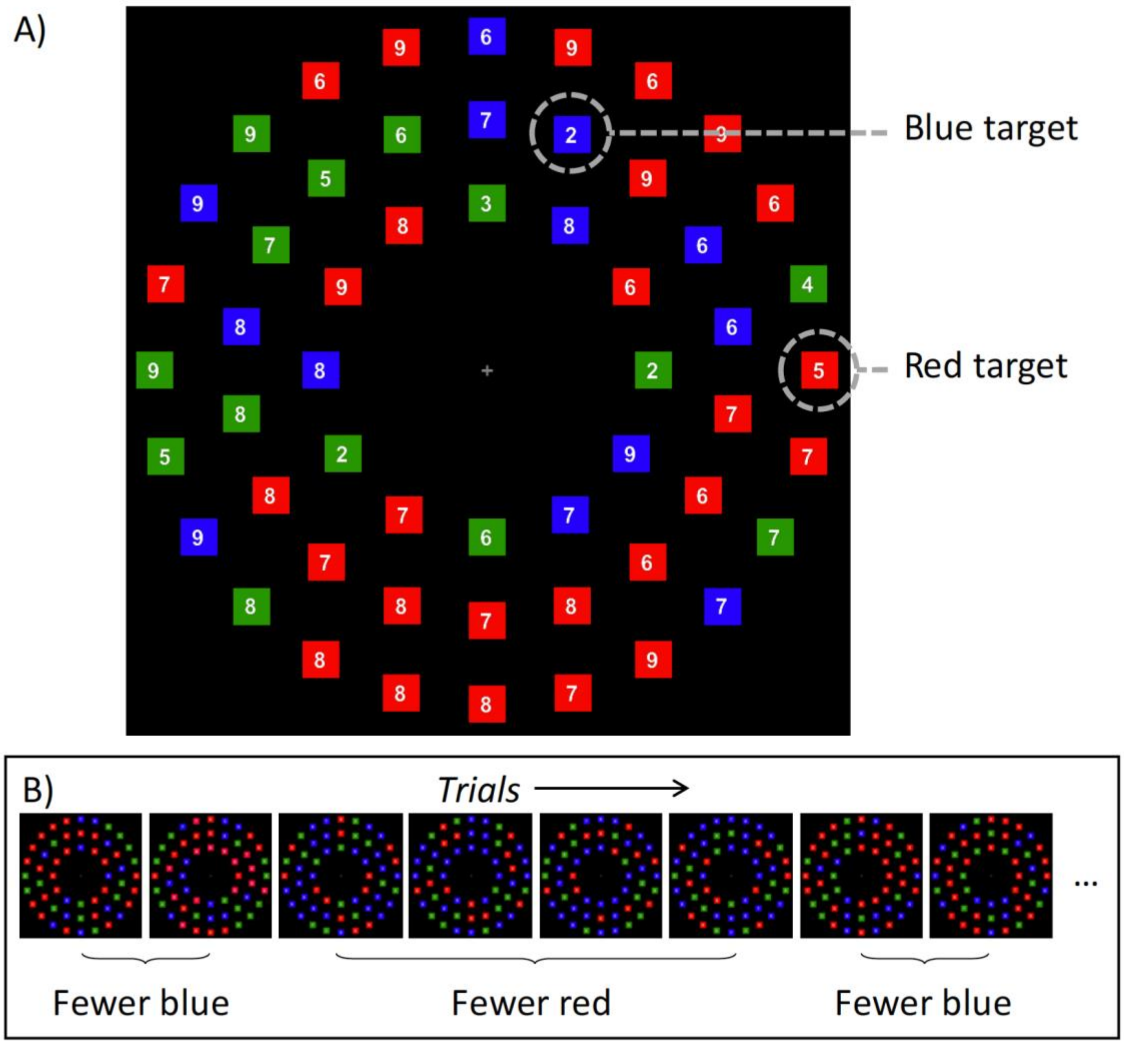

Figure 1. The ACVS paradigm (Irons & Leber, 2019). A) In a sample trial as shown, participants are asked to search freely for either a red or a blue target with digits between 2 and 5. Since there are fewer blue squares than red ones in the display, the blue target is considered the "optimal" choice. Whether the red or the blue square is the optimal target changes periodically (randomized every 1-6 trials), requiring monitoring the display and switching search goals. If an individual frequently makes optimal choices

throughout the experiment, the search speed will be significantly faster than those who make fewer optimal choices.

Do Individuals Generalize Visual Search Strategies?

Having found broad and stable individual differences in attentional control strategies that contributed to different search speeds, it would be interesting to ask if each individual's strategy generalizes to different visual search tasks. In other words, if an individual reliably uses the optimal strategy in one task, will they do so in other visual search tasks? For non-optimal observers, will the extent to which they are optimal in one task correlate with that in another task?

Clarke and colleagues (2018) made the only attempt so far to try to investigate this question. In their study, they had participants complete three different visual search tasks that varied their ways to assess strategies. One of them was the split-half line segment task previously used by Nowakowska, Clarke, and Hunt (2017), where participants had to identify a target line segment among various distractor line segments. The display contained a homogeneous side in which most line segments tilted towards a similar direction, and a heterogeneous side where most line segments tilted towards different directions. If the target appeared on the homogeneous side, it would pop out of the display and take a very short time to identify. Therefore, the optimal strategy to complete the task is to examine the homogeneous side covertly, without making eye movements that would slow the search speed. In another visual foraging task developed by Kristjánsson, Jóhannesson, and Thornton (2014; see also Jóhannesson, Thornton, Smith, Chetverikov, & Kristjánsson, 2016), participants had to search for a sequence of targets of certain features in every display. When a target was defined by a conjunction of two features, the optimal strategy was to exhaustively find one type of target and then move on to another type of target (e.g., searching for all green squares followed by all red circles). Together with ACVS, these three paradigms were completed by participants in two sessions and their optimalities were measured. The results did not show correlations in optimality between any of the two tasks.

Not being able to find a correlation in strategies across tasks does not necessarily mean a failure in finding the generalizability of visual search strategies. The three tasks in Clarke et al. likely involve different sub-tasks, some are important for an individual to adopt a certain strategy. Just like a world-class runner or swimmer may not choose to actively engage in triathlon races, an individual who does not excel at all sub-components of a particular visual search task could fail to perform optimally overall. In real-world visual search scenarios, even more complex components can contribute to more confounds in characterizing an individual's strategy. If this is indeed what caused the null result in the previous study while trying to find a correlation in strategy between tasks, then it is meaningful to investigate the sub-components which could make a difference in individuals' strategy choices. For the same reason, a full understanding of individual search strategy cannot be achieved without tackling these individual components.

Thus, given the scarcity of research that tries to correlate strategies between tasks, we cannot yet conclude whether an individual's visual search strategy is truly generalizable. Nevertheless, a reasonable speculation would be that strategies generalize to some extent, depending on the sub-components of a particular task. In tasks that contain the same sub-components, individuals likely generalize their strategies. Changing some sub-components might result in a change in strategies, but we still do not know which of these sub-components are critical for the generalizability of visual search strategies.

Overview of the Present Study

The present study aims to test the sub-component account of strategy generalization and to find if an individual's strategy in the ACVS generalizes to visual search tasks that have some and all sub-components with the ACVS paradigm.

What are the sub-components of the ACVS? To make an optimal choice in the ACVS, participants should first appraise the display and extract relevant statistical summary information. Participants complete this step by either discriminating the numerosity difference between red and blue subset or estimating which color takes up more space in the display. Then, they need to deploy feature-based attention to a subset of squares of a certain color, searching through the subset until one of the squares have a digit that belongs to the target digit set held in working memory. They will also need to periodically update the attentional sets across trials in order to always choose the optimal target. At least one of these stages has been shown to be crucial in making optimal choices: by disrupting the appraisal phase with an irrelevant task, participants showed reduced optimality (Hansen, Irons, & Leber, 2019).

In the present study, we modified the previously adopted ACVS paradigm (Standard ACVS) and made it a space-based one (Spatial ACVS). The new paradigm differed from the Standard ACVS only by one factor—whether subsets are feature-based or space-based. Specifically, instead of having red and blue subsets of squares, the new task had two sets of gray squares located on the left and right sides of the display. Each side contained one target square, and by changing the numerosity of the two subsets, there was always an optimal target which belonged to a subset with fewer squares.

We then planned to have participants complete the Spatial ACVS followed by the Standard ACVS and assess strategy generalizability by calculating the correlation between individuals' optimality on two tasks. If an individual's strategy generalizes between the two tasks, we should see a positive correlation in the proportion of optimal choices.

Experiment 1

We started by creating a novel visual search task that could also reveal a wide range of individual differences in strategies. Importantly, this task should provide participants with some degree of freedom in choosing different strategies to approach the task and also allow us to objectively measure their strategies.

To this end, we modified the ACVS paradigm to create a new task. We kept the task as a subset search, so that participants could complete every trial by searching for only a subset of the display. Different from the original task where subsets were defined by color features, subsets in the new task were located in spatially different regions in the display. Specifically, there were two sets of squares, located on the left and the right side of the display, and one side always had fewer squares than the other side. Thus, choosing the target on the side with fewer squares was the optimal strategy. We called this modified task the "Spatial ACVS."

Since we planned to test the strategy correlation between Spatial ACVS and the original ACVS task, we wanted to find out a ratio that would give us an average optimality similar to that of the original task, and still preserve sufficient individual variations. As a result, we tried three different ratios in Experiment 1.

Since it is increasingly difficult to identify the numerosity contrast between two sets of stimuli, when that contrast gets smaller (Feigenson, Dehaene, & Spelke, 2004), we predicted that the proportion of optimal choices would increase as the numerosity contrast increases. There still should be individuals who reliably adopt the optimal strategy even for the Small contrast condition because it is larger than the just noticeable difference (Dehaene, Izard, Spelke, & Pica, 2008). Previous studies also found that human adults can reliably discriminate different numerosities of at least a 7:8 ratio (Barth, Kanwisher, & Spelke, 2003; Dehaene, Izard, Spelke, & Pica, 2008; Halberda & Feigenson, 2008; van Oeffelen & Vos, 1982). Thus, participants in our experiment would be able to find the less numerous side under such ratio if they were sufficiently motivated.

Method

Participants. Twenty-four individuals (10 male, 14 female) aged 18 to 26 (*M* = 18.63) from The Ohio State University's Research Experience Program (REP) participated in this study. All participants had self-reported normal or corrected-to-normal visual acuity and normal color vision.

Apparatus. Participants completed the experiment in a dimly lit, sound-attenuated room. The experiment was programmed with Psychophysics Toolbox (Brainard, 1997; Pelli, 1997) implemented in MATLAB (Mathworks, Natick, MA, USA). Stimuli were presented using a Mac Mini computer and a 24-inch LCD monitor. Participants were seated at a viewing distance of approximately 60 cm from the screen.

Stimuli. The stimuli were based on previous versions of the ACVS (Irons & Leber, 2016, 2018; Hansen, Irons, & Leber, 2019), with some spatial modifications. Different number of gray squares (sized 1° x 1°, RGB: 97, 97, 97) were placed at different sides (i.e., the left side and the right side) of each display on three concentric rings with 6.3°, 9.4°, and 12.4° eccentricity from the innermost to the outermost.

All squares had a small white digit between 2 and 9 superimposed on the center. Each search array contained two targets, one on each side of the display. All target squares had digits between 2 and 5, and all distractor squares had digits between 6 and 9 superimposed on them. Target digits were chosen pseudorandomly such that each digit appeared equally often on both targets, and the two targets on each trial always contained different digits to enable us to determine which target was chosen by the participant.

Procedure. The experiment used a blocked design with Small, Medium, and Large contrast conditions, corresponding to a 1.2:1, 1.5:1, and 2.0:1 non-optimal to optimal side ratio, respectively. This gives three types of display, with the non-optimal side always having 20 squares, and the optimal side having 17, 13, and 10 squares, with respect to each contrast. All targets were generated in a pseudorandom manner that held the total target eccentricity constant for all participants. All distractors were generated randomly. Two blocks of the same ratio were grouped, making up a total of six blocks of 72 trials (432 total trials). The order of the ratios presented was counterbalanced across participants, with four participants completing each possible order. The number of times that the optimal target appeared on each side was balanced for each participant, and no more than three times did the optimal target appear on the same side of the display.

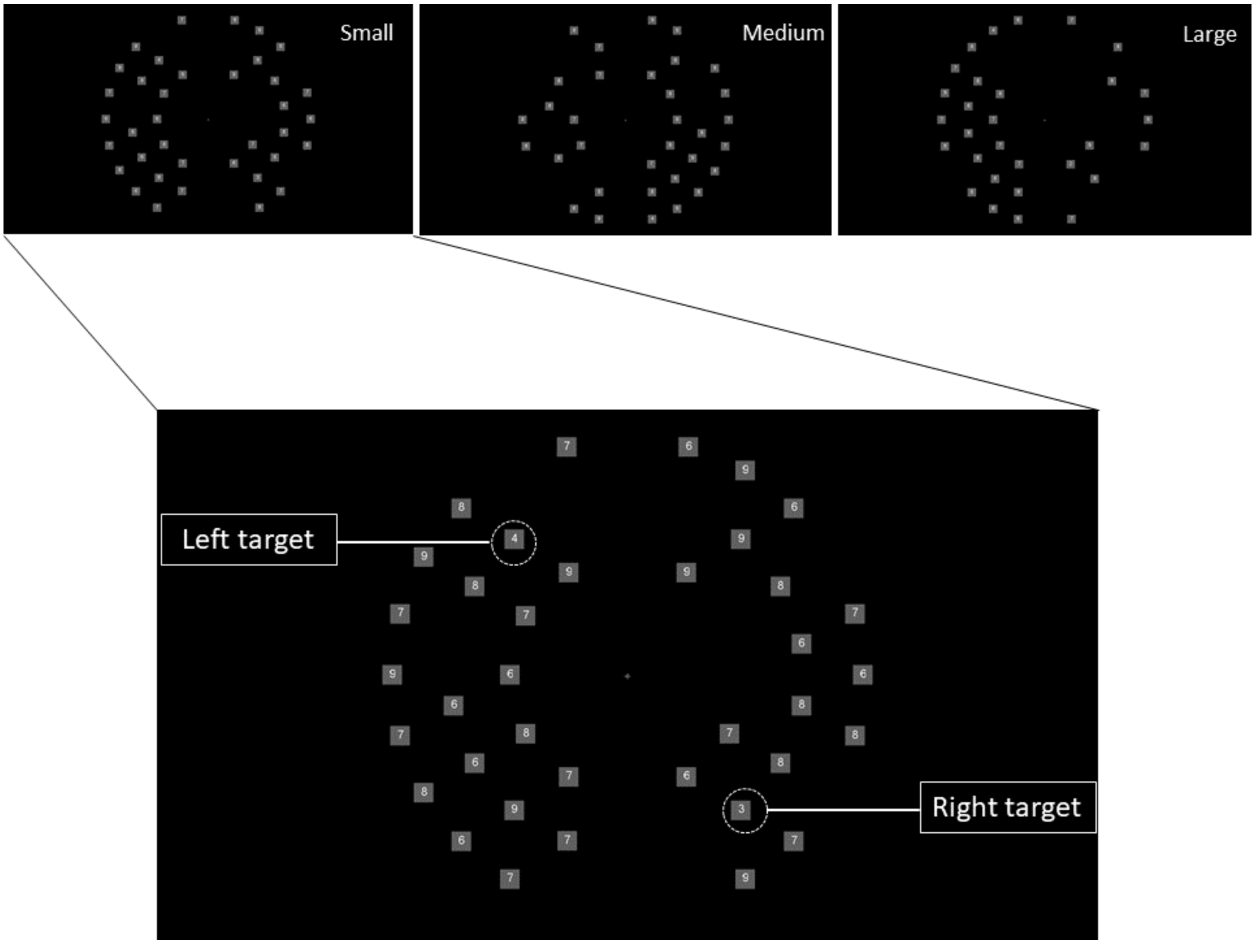

Figure 2. Sample displays with three different numerosity contrasts. The Small, Medium, and Large contrast displays have ratios 1.2:1, 1.5:1, and 2.0:1, respectively. In every display, there is a left target and a right target. The side on which there are more squares is counterbalanced across trials.

Results

Data from one participant whose accuracy was more than three standard deviations below the group mean was removed from analyses. Incorrect trials and trials in which participants responded in less than 300 ms or more than 3 SD above the participant's mean were removed from analyses. Overall, the accuracy of the task was close to ceiling (M = 97.93%).

Proportion Optimal increases with numerosity contrasts, with Small contrast the lowest (range 42.34% - 65.69%, *M* = 52.04, *SD* = 5.273), followed by Medium (range 51.77% - 86.23%, *M* = 60.12, *SD* = 8.192), and Large (range 51.82% - 96.40%, *M* = 70.44, *SD* = 12.75).

In the Small contrast condition, proportion optimal was still above chance ($t(23) = 1.899$, $p = .035$, one-tailed). In the Large contrast condition, proportion optimal was still below 100% ($t(23) = 11.355$, $p < .001$).

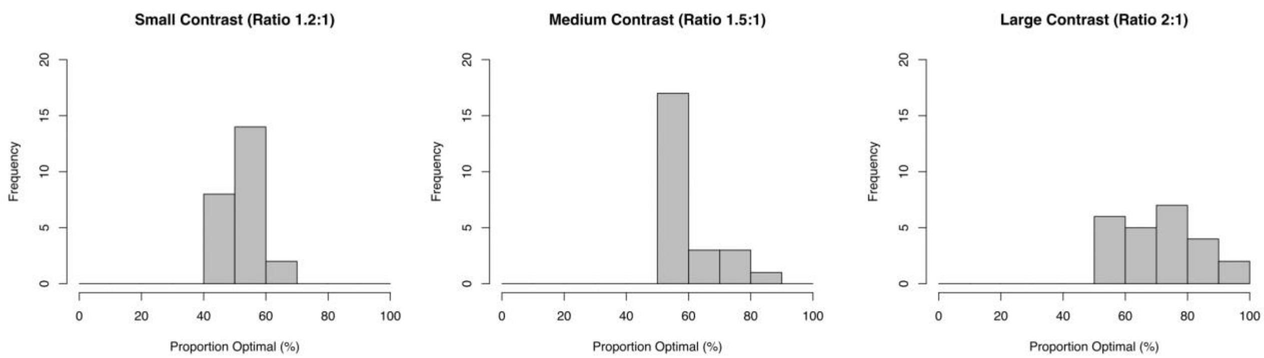

Figure 3. The frequency distributions of proportion optimal under three different contrast ratios.

A linear regression was calculated to predict proportion optimal based on ratio (Fig. 4). A significant regression equation was found ($F(1, 70) = 47.7$, $p < .001$), with an R^2 of .405. The proportion optimal (P) changed with optimal-nonoptimal side ratio (r) with the following function.

$$P = 0.223\,r \; + \; 0.258$$

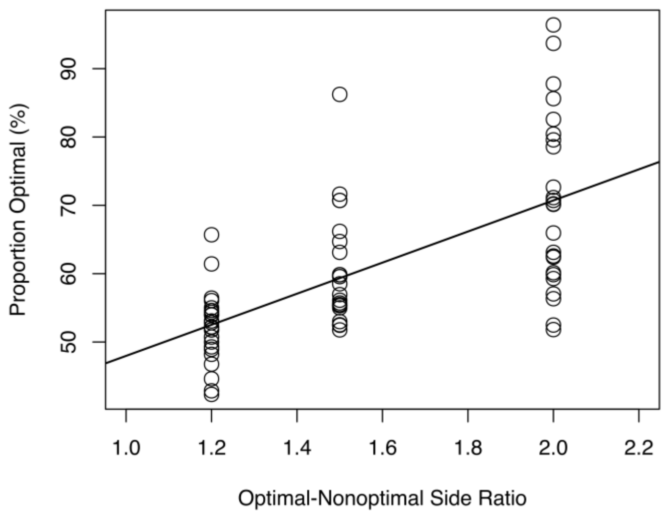

Figure 4. Individual proportion optimal data under each contrast ratio.

Discussion

As predicted, with increased numerosity contrasts, participants made more optimal choices. The results showed that proportion optimal in Large contrast condition (i.e., the 2.0:1 ratio) was closest to that in the Standard ACVS experiments previously conducted in our lab.

One limitation is that a linear model might not have sufficiently captured the relationship between proportion optimal and numerosity contrast. While error rates when making numerosity comparisons do seem to change linearly with the contrast between two numerosities (Feigenson, Dehaene, & Spelke, 2004), we could not ascertain a linear relationship between the difficulty in numerosity discrimination and proportion of optimal choices.

Nevertheless, for the purpose of this experiment, we were able to conclude that for ratios within the range we chose, a 2.0:1 ratio yielded optimality most comparable to Standard ACVS.

Experiment 2

In Standard ACVS, the feature of the optimal target was determined by intermixed "runs" of 1-6 (i.e., one to six successive optimal targets of the same color). This required participants to switch on 28.57% of the trials when they consistently selected the optimal target. However, in Spatial ACVS task the run numbers were set to be 1-3, which increased the switch rate when adopting the optimal strategy.

In Experiment 2, we further modified the Spatial ACVS to make it more comparable to Standard ACVS by making the optimal side switching periodically in runs of 1-6.

Method

Fifteen individuals (5 male, 9 female, 1 non-binary) aged 18 to 22 (*M* = 19.00, *SD* = 1.31) from The Ohio State University participated in the experiment. All participants had self-reported normal or corrected-to-normal visual acuity and normal color vision.

In this newer version of the task, the optimal side alternated in random runs of one to six trials, giving an optimal switch rate of 28.57%. Except for the number of runs, the methods were the same as Experiment 1.

Results

Proportion Optimal increases with Small contrast (range 43.48% - 61.15%, *M* = 51.67%, *SD* = 5.35%), Middle constrast (range 50.00% - 82.73%, *M* = 60.98%, *SD* = 10.07%), and Large constrast (range 50.71% - 93.66%, *M* = 68.02%, *SD* = 16.10%).

A cross-experiment analysis with Experiment 1 found that proportion optimal collapsed across ratios did not differ in two experiments ($t(34) = 0.23$, $p = .82$). No main effect of ratios and interaction between tasks and ratios were found. Similarly, the overall switch rate of the two tasks did not differ ($t(34) = 0.29$, $p = .77$).

Discussion

The results demonstrated no significant change in participants' proportion of optimal choices when the optimal side was made in runs of one to six, as in Standard ACVS.

This indicated that an increase in required target switching might not influence optimality significantly. Indeed, in a within-subject manipulation on Standard ACVS on required switching showed that it did not influence an individual's tendency to choose the optimal target in ACVS, neither did task-switching ability predict the optimal strategy (Shaw, Hansen, McKinney, Irons, & Leber, 2020).

Together with Experiment 1, these two experiments allowed us to find a stimuli ratio (i.e., 2.0:1) between two sides of the displays on Spatial ACVS that yielded an average and standard deviation of optimality comparable to Standard ACVS.

Experiment 3

Experiment 3 was preregistered (osf.io/rx2c5). Participants completed the Standard ACVS task (Irons & Leber, 2018; McKinney, Hansen, Irons, & Leber, 2019), followed by the Spatial ACVS task with the established 2:1 ratio.

Method

Participants. 57 individuals (29 female) aged 18 to 32 ($M = 19.23$) participated in this study. All participants had self-reported normal or corrected-to-normal visual acuity and normal color vision. Data from one participant was excluded because she completed the two tasks with a different order than predetermined. Seven participants whose overall accuracy was three standard deviations lower than average were excluded from analyses. The final sample included 50 participants, as specified in the preregistration, which would give us a power of .98 of finding a medium effect size (*r* = .50).

Equipment. Participants sat in a dimly lit, sound-attenuated room without restraint approximately 60 cm from the display. The stimuli were presented using Psychophysics Toolbox (Brainard, 1997; Pelli, 1997) implemented in MATLAB (Mathworks, Natick, MA, USA) and were displayed on a 24-inch LCD monitor with a 60 Hz refresh rate.

Stimuli. The Standard ACVS used displays that were based on Irons & Leber (2018). Each search display contains 54 squares (13 red, 13 blue, 14 green, and 14 “variable”). On every trial, the targets are a red and a blue square containing a digit between 2-5 (all other red, blue, and variable squares contain digits 6-9). On half of the trials, the variable distractors were red, and on the other half the variable distractors were blue. Short runs of one to six trials with red variable distractors were interleaved with short runs of 1-6 trials with blue variable distractors (see Fig. 1). In Spatial ACVS, on every trial, 20 squares appeared on one side (i.e., left or right) of the display and 10 squares appeared on the other side, with every square positioning at one of the 54 locations where the squares in Standard ACVS appear, except for the 6 locations closest to the vertical midline of the display. All squares are colored gray and contain a digit between 2-9. Two targets, one on each side, each have digits between 2-5. On half of the trials, more squares appeared on the left side and on the other half, more squares appeared on the right side. Short runs of one to six trials with more squares on the left side are interspersed with short runs of 1-6 trials with more squares on the right side.

Procedure. Participants completed three blocks of Standard ACVS task followed by three blocks of Spatial ACVS task. This order was preserved across all participants to minimize intersubject variability driven by the design, for the purposes of individual differences analysis (cf. Irons & Leber, 2018). Participants were informed that a blue and a red target will be presented on every trial and that they were always free to search for either one. The targets contained a digit between 2 and 5, and participants responded using the keys V, B, N, and M corresponding to each of the possible target digits. The four response keys were covered by four stickers with handwritten corresponding digits. Participants completed ten practice trials followed by three blocks of 84 trials, with short breaks in between. At the end of these blocks, participants were told to notify the experimenter, and they were given the chance to take a short break. Then, the experimenter explained instructions of Spatial ACVS. Participants were informed that all the squares would be of the same color, that they could always find one target on each side of the screen, and that they were always free to search for either one. The targets contained a digit between 2 and 5, and participants responded using the same keyboard as used in the first task with the keys V, B, N, and M corresponding to each of the possible target digits. The four response keys were covered by four stickers with handwritten corresponding digits. Participants completed ten practice trials followed by three blocks of 72 trials.

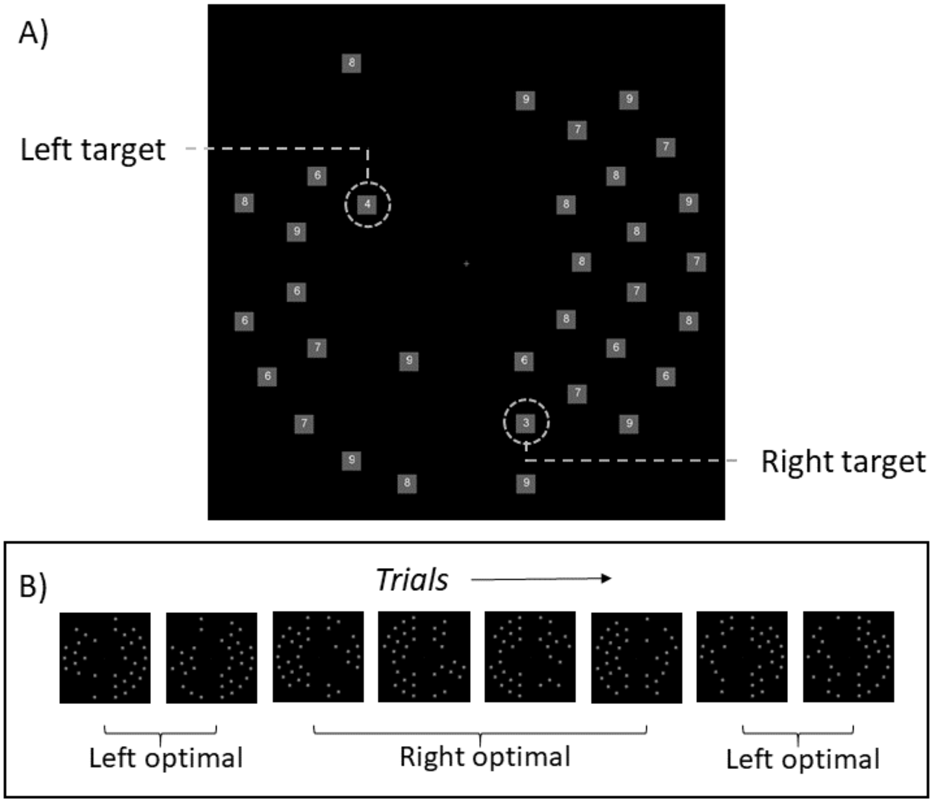

Figure 5. A) Example search display from the Spatial ACVS task. Each display contains a left and a right target, with a digit (2, 3, 4, or 5) on them. There is always an “optimal” target which is located on the side with fewer squares. B) Example sequence of trials. All sequences in the task contained runs of 1-6 trials with fewer squares on the left and fewer squares on the right.

Results

The search accuracy was close to ceiling for both tasks (Standard ACVS M = 98.42%, Spatial ACVS M = 98.56%). In the following analyses, we excluded error trials and trials with search response times (RTs) less than 300 ms more than three standard deviations above the mean (3.03% of Standard ACVS trials, 2.69% of Spatial ACVS trials).

Standard ACVS. The result of Standard ACVS replicated the main findings of the classical ACVS paradigm (Irons & Leber, 2018). There was a broad range of individual differences in the proportion of optimal choices, from 10.79% to 96.77% (M = 65.37, SD = 19.47). Overall, participants made more optimal choices than chance (one-sample t-test against 50%; $t(49)$ = 5.58, $p < .001$) but also made a large proportion of suboptimal choices (one-sample t-test against 100%; $t(49)$ = 12.58, $p < .001$). The proportion of optimal choices were negatively correlated with search response times (r = -.57, $p < .001$) (Fig. 7).

Spatial ACVS. The proportion optimal on Spatial ACVS ranged from 50.95% to 98.10% (M = 82.24, SD = 13.85). Proportion optimal was negatively correlated with search response times (r = -.36, p = .011).

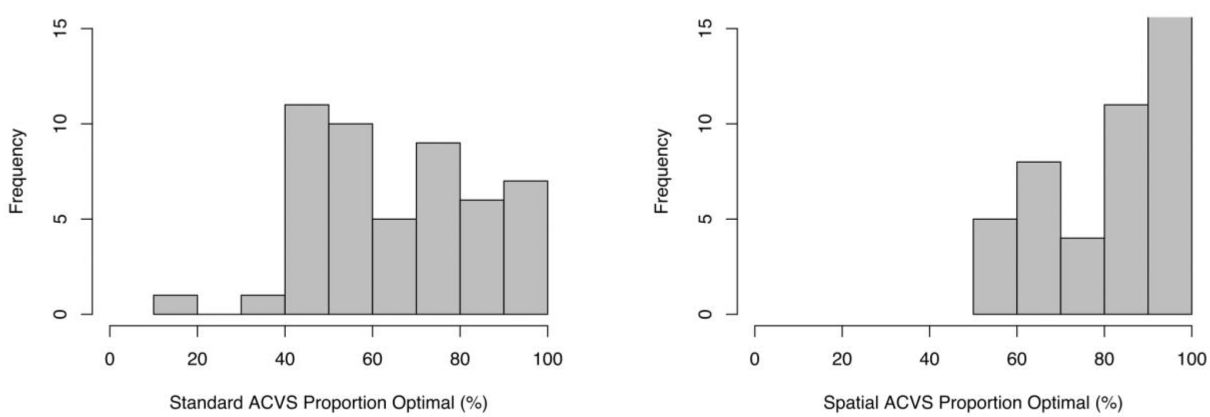

Figure 6. Frequency distributions for individuals' proportion optimal in both tasks.

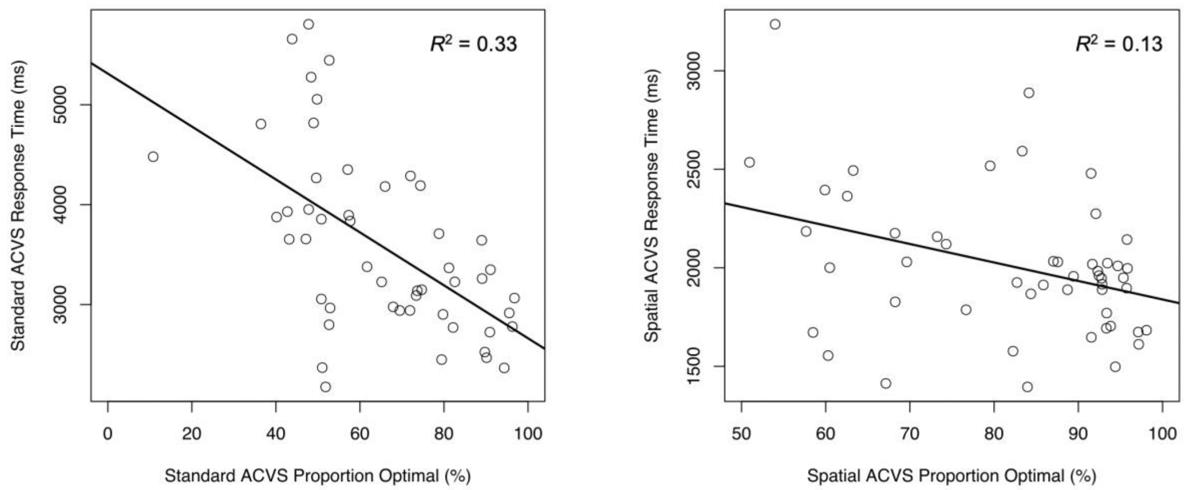

Figure 7. Response times negatively correlated with proportion optimal in both tasks.

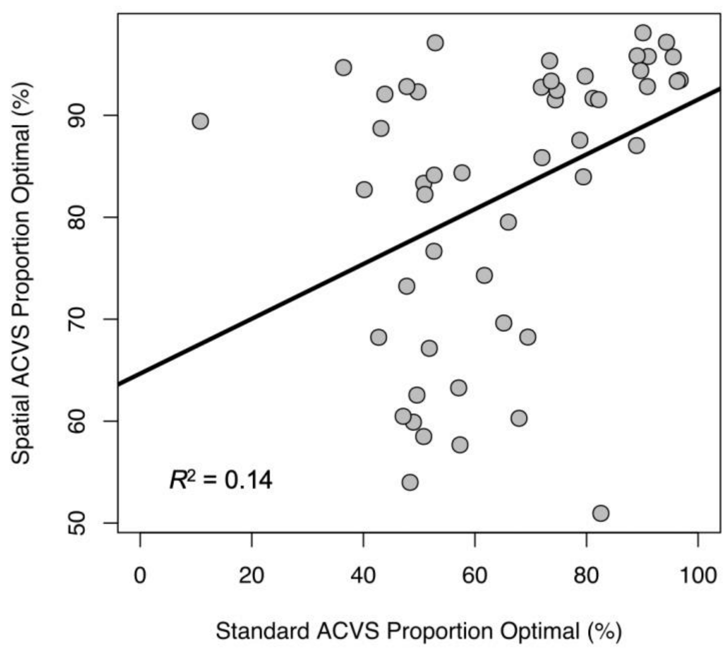

Figure 8. A positive correlation between proportion optimal in Standard ACVS and Spatial ACVS.

Correlation Between Tasks. There was a positive correlation between individuals' proportion optimal in two tasks (r = .38, p = .007).

Discussion

We found a positive correlation between participants' proportion of optimal choices in two tasks. This means that the extent to which an individual is optimal in Standard ACVS correlates with the extent to which an individual is optimal in Spatial ACVS. In other words, participants transferred their visual search strategies from one task to another. This finding marks that visual search strategies are generalizable at least between tasks that have similar strategy subcomponents.

We also note that the correlation in an individual's optimality between two tasks was weaker than that of the test-retest reliability of the Standard ACVS, as reported in Irons & Leber (2018). There are some speculations regarding what resulted in this weaker correlation. In Experiment 3, participants completed the two tasks in the same order in one sitting. While keeping the task order allowed us to better assess the correlation between tasks, it is not clear whether the first task influenced the performance in the second task, and whether different individuals were influenced by this task order in different ways. We found that a cluster of individuals who performed optimally in Spatial ACVS were at chance optimal in Standard ACVS (Fig. 8). One explanation is that some participants were not aware of the optimal strategy until the second task. However, one piece of evidence that is inconsistent with this possibility is that optimality did not differ—i.e., increase—across blocks in both Standard ACVS ($F(2, 147) = 1.365$, $p = .259$) and Spatial ACVS ($F(2, 147) = 0.043$, $p = .958$). A two-way repeated-measures ANOVA showed no main effect of blocks ($F(2, 294) = 0.963$, $p = .383$) nor interactions between blocks and tasks ($F(2, 294) = 0.874$, $p = .418$). An alternative explanation would be that Spatial ACVS has weaker test-retest reliability and the noise added to the correlation was due to momentary states of the participants. It is difficult to rule out this possibility with existing data.

As a result, we also plan to carry out studies to explore the strategy test-retest reliability in different paradigms in the future. Another, more interesting alternative is that some participants were more motivated to use the optimal strategy in Spatial ACVS. If this is true, then we need to find whether the only different strategy sub-component—adopting feature-based attention or directing spatial attention—could contribute to some individuals' motivation to make optimal choices.

General Discussion

Over the past few decades, researchers have been trying to understand the factors that control attention (Egeth & Yantis, 1997). While previous research has focused on individuals' ability to apply specific types of goal-direction attentional control, strategy is overlooked but it contributes to a meaningful variation in performance. This has inspired researchers to investigate strategies using various visual search paradigms, many of which yielded broad and stable individual differences.

A complete understanding of individual differences in attentional control strategies and how they can contribute to people's visual search performance in real-life settings, however, must take into account whether strategies are generalizable beyond a single visual search paradigm. Here we show evidence for strategy generalization by showing a positive correlation in individuals' strategy measurements across two visual search tasks. We modified the standard Adaptive Choice Visual Search (ACVS) task and developed a space-based subset search task which still allowed participants to approach it with different strategies.

In Experiment 1, we found that in the Spatial ACVS task where two targets could be found in two unequal-sized subsets of gray squares located on two sides of the display, the proportion of optimal choices increased with an increased numerosity contrast between the two subsets. With a ratio of 2:1, the proportion of optimal choices was well above chance but below 100%, and exhibited large individual variation comparable to Standard ACVS.

In Experiment 2, we attempted to make the Spatial ACVS paradigm more comparable to the Standard ACVS by requiring the optimal strategy to have the same number of switches between target types. This change, however, did not influence the proportion of optimal choices.

Finally, in Experiment 3, we had participants complete Standard ACVS and Spatial ACVS in one session and measured their proportion of optimal choices in both tasks. The results showed a positive correlation between optimality on both tasks, indicating participants generalized their strategies from Standard ACVS to Spatial ACVS.

We offer several suggestions for future research investigating the generalizability of visual search strategies. The results obtained from the present study, together with those included in Clarke et al. (2018), suggest that individuals generalize strategies in some, but not all, visual search tasks. Perhaps individuals adopt the optimal strategy in one task because they are willing to carry out all sub-components required by the optimal strategy. The absence of strategy generalization between visual search tasks can be contributed to different sub-components that constitute a task.

Strategy generalization also has the potential to provide evidence for effective cognitive training. Since over a century ago, researchers have been interested in whether improvement in one specific cognitive function would benefit other cognitive functions (Woodworth & Thorndike, 1901). The debate continues since studies keep showing contradictory results (e.g., Anguera et al., 2013; Boot, Blakely, & Simons, 2011; Jaeggi, Buschkuehl, Jonides, & Shah, 2011; Melby-Lervåg, Redick, & Hulme, 2016; Morrison & Chein, 2011; Owen et al., 2010;

Redick et al., 2013; Schmiedek, Lövdén, & Lindenberger, 2010; Sala & Gobet, 2017; Simons et al., 2016). The existence of "far transfer", or skill generalization between domains that are loosely connected, is of particular significance for topics like brain training. The scarcity of evidence supporting far transfer makes it difficult for brain training programs to conclude that training in a specific cognitive task might benefit consumers in general cognitive abilities. However, it seems that strategy is more amenable to training. By simply informing participants of the optimal strategy and giving them a chance to appraise the display, we could see a significant increase in proportion of optimal choices in the ACVS paradigm, which would boost the speed in finding the targets (Hansen, Irons, & Leber, 2019).

In conclusion, the present study shows evidence for visual search strategy generalization and offers some directions for future research. Future work can be aimed at a more complete understanding of the strategy subcomponents and the mechanisms underlying their interactions. A full understanding of how individuals strategically configure their control settings in different types of unconstrained environments will eventually give us more insight into people's goal-directed attentional control behaviors.

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