TESTING THE PROFILE OF OBJECT-BASED ATTENTION

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A THESIS

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

Psychology – Master of Arts

2025

ABSTRACT

Previous work on feature-based attention has established two prominent models of the selection profile: feature-similarity gain and surround suppression. The former predicts a monotonic decrease in task performance as the target feature becomes more different from the attended feature, whereas the latter predicts a non-monotonic performance pattern where the lowest performance occurs for targets close to the attended feature with a rebound in performance for more distant features. While support for both models have been found using simple features, it is unclear whether the selection profile for object-based attention aligns with either model. The current study assessed the selection profile for simple shapes, as a first step toward more parametric investigations of object-based attention. The study used a newly developed standardized circular shape space that allowed object difference to be quantitatively measured. In two experiments, participants were directed to attend to two target shapes that systematically varied along the shape circle. Two distractor shapes then appeared, overlapping with the target shapes, and one shape in each pair underwent a brief luminance change. Participants reported the status of each target shape (no change, dimmer, brighter). Experiment 1 used finer sampling of the shape space with a maximum target difference of 90°, and Experiment 2 used a coarser sampling with maximum target difference of 180°. For both experiments, performance accuracy peaked when the two target shapes matched and then decreased in a monotonic manner as the two shapes became more different. These results align more with the feature-similarity gain model and suggest that an analogous shape-similarity gain effect operates at a higher level of complexity. Such a gain effect may support object-based selection to differentiate target objects along higher-order, holistic dimensions like shape.

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INTRODUCTION

In daily life, our brains sift through vast amounts of perceptual information through a process of focusing and filtering. The process of filtering through this information to emphasize relevant items is referred to as selective attention. Regarding visual attention specifically, our visual system utilizes this process to aid in a variety of visual tasks we might perform, from simply looking through cabinets for the right snack to looking for abnormalities in medical imaging. For this reason, understanding the complex neural machinery and the behaviors that result from this process can have an important impact on both theoretical and applied research. While decades of studies have been dedicated to this topic, there are still components of it that are not fully understood(Cavanagh et al., 2023; Chapman & Störmer, 2024; Martinez-Trujillo & Treue Stefan, 2004). Specifically, study of the profile of selective attention, the way in which attention enhances relevant information and suppresses irrelevant information to find a target, has been a topic of interest. Behavioral methods that define the shape of this profile have been done with location-based attention and feature-based attention; however, there is still a significant gap involving object-based attention. The current study helps to fill this gap by examining whether object-based attention follows the selection profiles that have been identified for feature-based selective attention: feature-similarity gain and surround suppression.

The dominant model for the profile of selective attention has been the feature-similarity gain model, which suggests that when we choose to attend to a feature, for example the color red, attention enhances all red colored items in the scene and such enhancement gradually declines as an item's color becomes less similar to red (blue curve in Figure 1)(Martinez-Trujillo & Treue Stefan, 2004). However, more recent research has found that selective attention may follow a different pattern of results called *surround suppression*. In this case, instead of decreasing

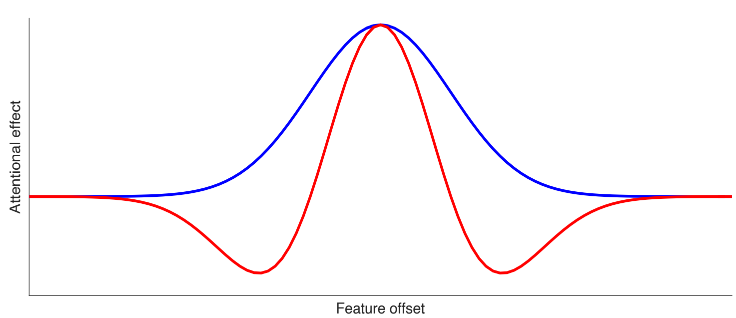

Figure 1 A comparison of hypothetical data patterns for a feature-similarity gain model (blue) and surround suppression (red).

monotonically, attention most strongly suppresses items that are similar to the attended feature but lessens suppression for very dissimilar features to the target (red curve in Figure 1)(Tsotsos, 1990). While this newer data pattern has been found in simple features like color, orientation, and motion direction, as well as for location-based attention, it has yet to be found for object-based attention (Cavanagh et al., 2023).

Some of the first evidence for the feature-similarity gain hypothesis was found in single unit recording studies done on monkeys (Martinez-Trujillo & Treue Stefan, 2004; Treue & Martinez-Trujillo, 1999). These studies found that neurons showed enhanced response when attending to an individual neuron's preferred motion direction and a suppressed response when attending to the anti-preferred direction. This effect was even present in neurons whose receptive field did not overlap with the attended stimulus but had a probe stimulus moving in various directions. This led the researchers to conclude that feature-based attention globally modulates neuron behavior in a monotonic fashion, where when a neuron's preferred feature is similar to an attended feature, its activity is enhanced. Conversely, neurons with preferred features less like the attended feature, are subject to less enhancement and more suppression. Since then, behavioral (Bondarenko et al., 2012; Boynton et al., 2006; Lankheet & Verstraten, 1995; Liu & Hou, 2011; Liu & Mance, 2011; Wang et al., 2015; Zhang & Luck, 2008) and neuroimaging (Liu et al., 2007; Saenz et al., 2002; Serences & Boynton, 2007) studies have generally found supporting evidence for this conclusion in humans. Most of these early studies focused on motion (Boynton et al., 2006; Lankheet & Verstraten, 1995; Liu & Mance, 2011; Saenz et al., 2002; Serences & Boynton, 2007) like in the original monkey studies but, others have used features like orientation and color and yielded similar results (Bondarenko et al., 2012; Liu et al., 2007; Liu & Hou, 2011; Wang et al., 2015; Zhang & Luck, 2008). While not feature specific, several studies also found this monotonic pattern of results when examining location-based attention, where a cue indicates the likely position of a target and performance is compared between neutral, valid, and invalid cues (Bashinski & Bacharach, 1980; Downing, 1988; Handy et al., 1996; Hawkins et al., 1990; H. J. Müller & Humphreys, 1991; Posner et al., 1980). The most significant drawback of these studies was that their methods typically used a very coarse set of stimuli, often a target stimulus and its maximally different counterpart. This limits the applicability of the results because it did not explore a finer sampling of feature spaces and locations. Studies that did utilize a finer sampling of a studied space yielded results that hinted at a potential nonmonotonic pattern of results (Downing, 1988; Handy et al., 1996; Wang et al., 2015). This suggests that the feature-similarity gain hypothesis and the similar pattern of results for location-based attention may not be a complete picture of the shape of the selection profile for attention.

More recently, behavioral studies using human subjects and finer sampling of feature spaces have found a different pattern of results. In this newer research, the decrease in performance as the presented feature becomes more different from the attended feature does not happen monotonically. This pattern of center-surround suppression is predicted by the Selective Tuning Model of attention (Tsotsos, 1990; Tsotsos et al., 1995) which suggests that rather than attention to a feature causing inhibition of the feature opposite to the target to create a monotonic decrease, attention to a target causes inhibition of similar features/nearby locations which decreases as the stimuli become more different from the target. This pattern of results has been found for both feature-based attention (Bartsch et al., 2017; Fang et al., 2019; Fang & Liu, 2019; Ho et al., 2012; Liu et al., 2023; Störmer & Alvarez, 2014; Tombu & Tsotsos, 2008; Yoo et al., 2018) and location-based attention (Caputo & Guerra, 1998; Cutzu & Tsotsos, 2003; Fang, Ravizza, & Liu, 2019; Hopf et al., 2006, 2010; Mounts, 2000; N. G. Müller et al., 2005; N. G. Müller & Kleinschmidt, 2004; Yoo et al., 2018). However, beyond simply exploring a finer sampling of stimulus spaces, it has been found that specific components of task design influence the presence of the suppressive surround (Hopf et al., 2010; Liu et al., 2023; Tombu & Tsotsos, 2008; Yoo et al., 2018). Specifically, Liu et al., (2023) found that increasing task difficulty by using highly competitive distractors results in a pattern of surround suppression in the same task where low competition distractors do not but, that guiding participants to develop a highly precise target template also results in a suppressive surround pattern even with low distractor competition. The fact that task design influences the presence of surround suppression potentially explains why this pattern of results was not found in initial study of this topic, even when there was finer sampling of stimulus spaces.

In addition, it seems the exact location of where within the feature space the inhibitory zones occur varies between and within feature-spaces. For example, Störmer & Alvarez (2014) found surround suppression at about 30° difference (approximately 17% of the maximum possible difference) between two target colors. In contrast, Fang et al. (2019) found the area of suppression to be at a 15° (8%), 30° (17%), and 45° (25%) difference for red, green, and blue color categories respectively. Additionally, a pattern consistent with surround suppression has been found for orientation, motion direction, and spatial frequency (Fang & Liu, 2019), with suppression for orientation and motion direction occurring at 45° (50%) and at 1 octave of offset for spatial frequency. This shows that while the presence of near-target inhibition occurs across features, it does not necessarily occur in the same relative location in the feature space. Similarly, when a stimulus is near an attended target, both in physical space and in feature space, there is evidence for stronger suppression than when the stimulus only shares physical proximity with the target (Yoo et al., 2018). This suggests that when object-location and object-feature information interact, enhancement and suppression effects also interact. While historically presented as competing theories, it has also been suggested that both feature-similarity gain and center-surround suppression could function in tandem (Fang et al., 2019). This model resembles surround suppression near a target with enhancement of the target, suppression of similar distractors, and rebound for more dissimilar distractors; however, this hybrid model then predicts another decrease in performance beyond the rebound for the most dissimilar distractors, rather than a leveling off of performance that a pure surround suppression model would predict. Yoo et al. (2021) have described this as a narrow strong enhancement effect at the area of the target with a wider and weaker suppression effect centered around the target as well. This reconciliation of theories shows that it is possible for both mechanisms to be at play and, together, impact the shape of the selection profile.

Based on this accumulation of evidence, it appears that feature-similarity gain is not the only mechanism at play when allocating attention and that a suppressive surround is at least present, if not dominant, for feature and location-based attention. The Selective Tuning Model suggests that rather than simply enhancing and suppressing specific neural representations based on top-down target information, the brain first selects the most salient representations available from the initial feedforward (bottom-up) perceptual response at the most complex level of neural representation. Then in a feedback process, the brain more carefully narrows down these potential targets and suppresses the neural representations not selected. As feedback continues through layers of decreasing complexity, more neural representations are attenuated because other representations better match the attentional template and this continues until there is only one representation, ideally the target, remaining unattenuated (Cutzu & Tsotsos, 2003; Tsotsos, 1990; Tsotsos et al., 1995). This results in fully irrelevant stimuli not being suppressed because they never passed through any layers in the feedback system, whereas partially relevant or similar stimuli may pass through some layers which causes inhibition of those related neurons. This is beneficial because it helps isolate a target from distractors that are more likely to cause false positives rather than just suppressing distractors that are clearly distinct from a target. While the implications of this structure seem easy to imagine for simple location-based and feature-based attention (a physical space of suppression surrounding a target area or suppression of similar features to a target within a feature space) this seems less clear for objects that are potentially composed of multiple complex features and can appear across multiple locations. However, the process of moving from more complex to less complex layers of information lends itself well to object-based attention by allowing stimuli/neurons to be attenuated at multiple layers for both global components of an object and local features.

Even though the Selective Tuning Model predicts surround suppression in object-based attention and seems like a natural extension of the pattern observed for location and feature-based attention, this has yet to be found (Cavanagh et al., 2023; Tsotsos, 2011). One reason for the difficulty in finding this expected effect is that there is no one consensus on what constitutes an object or object-based attention (Cavanagh et al., 2023). While it seems easy to know what an object is when looking at one, it is not always clear cut. Objects could be defined as a closed area of space, but this excludes objects with poorly defined borders or partially occluded objects. Even when an object can be clearly defined as separate from others, there is debate over whether object-based attention is distinct from feature-based attention or if they are the same process operating over different representational spaces (Chapman & Störmer, 2024). Despite this difficulty, there have been some experimental paradigms that have proven successful at studying object-based attention (Cavanagh et al., 2023; Chapman & Störmer, 2024; Duncan, 1984; Egly et al., 1994). From these studies, it is known that cueing an object facilitates identifying orthogonal features of that object or features within the space of the object when compared to non-cued objects. This demonstrates that objects receive enhanced processing when attended to in a similar manner to both features and locations which allows object-based attention to be studied with similar experimental designs. The second reason for this difficulty is the lack of a calibrated object space that can be used like many standard feature spaces, e.g., color space (360 deg around a color wheel) or orientation space (180 deg rotation). While simple shapes can be classified as a group of objects, the difference between a triangle and a square is not as cleanly and continuously quantifiable as the difference between a 30° line and a 60° line. However, recently, Li et al. (2020) created a “shape wheel” with a similar structure to a standard color wheel. This space was created through a process of digital editing of prototype shapes, collection of subjective similarity ratings of those shapes, digital reconstruction of the shape space from these ratings, and statistical assessments of circularity of the space. This standardized space contains 360 shapes that can be used as unique objects whose difference can be measured in the same way as color and orientation. Thus, we reasoned that this standardized circular shape space can be used to explore the selection profile for visual objects.

The current study aims to identify a general shape of the selection profile for object-based attention. These experiments rely on the idea that when the two object features match, an orthogonal task involving both objects can be done most successfully, but when the features do not match the attentional templates of those objects conflict, causing interference which decreases task performance (Störmer & Alvarez, 2014). This interference increases as the features gradually differ until there is a point of maximum interference which is interpreted as the area of center-surround suppression (Yoo et al., 2021). Using the shape wheel as a stimulus set, two attended target shapes can be made to systematically differ, therefore, changing the level of interference at the object level. The experiments also make sure to overlap each target with a distractor so that the object itself must be attended and not just the space it occupies, since, when two objects overlap, people can more easily identify orthogonal features of one selected object than across objects (Duncan, 1984). Combining these principles results in the general design of the current experiments, where participants are shown two target shapes overlapped by distractors and asked to respond to luminance changes of the targets. In Experiment 1, the difference between the two targets could range from 0°-90 ° while in Experiment 2 this range was expanded to 0°-180°. It was hypothesized that evidence for both a pattern of feature-similarity gain, and surround suppression would be found in participants accuracy results. Both experiments demonstrated a monotonic decrease in task performance as target offset grew, demonstrating that the shape space has a parametric quality, and supporting presence of a feature-similarity gain-like model for attentional selection at the object-level which could be considered an object-similarity gain effect. No clear surround suppression effect was found.

EXPERIMENT 1

Methods

Participants

Participants (N = 16, 10 female, 6 male) were collected primarily from the community of undergraduate and graduate students and Michigan State Univeristy and were compensated at a rate of $12 per hour. An a priori power analysis for a repeated measures ANOVA was conducted using G*Power version 3.1. (Faul et al., 2007) based on data from Störmer & Alvarez (2014), which compared target feature (color) offset to task accuracy. The effect size was $\eta^2 = 0.42$ (Cohen's $f = 0.85$), considered to be large using criteria from Cohen (1988). With a significance criterion of $\alpha = .05$ and power = .80, the minimum sample size needed with this effect size is N = 16. Thus, the obtained sample size was adequate to test the study hypothesis. Informed consent was obtained from every participant. To participate, participants needed to be over the age of 18 and have normal or corrected-to-normal vision. All experimental protocols were approved by the Institutional Review Board at Michigan State University.

Apparatus

This study was conducted using Matlab (MathWorks, Natick, MA) with the MGL toolbox (Gardner et al., 2018). The stimuli were presented on a 34 in. LCD Ultrawide Display

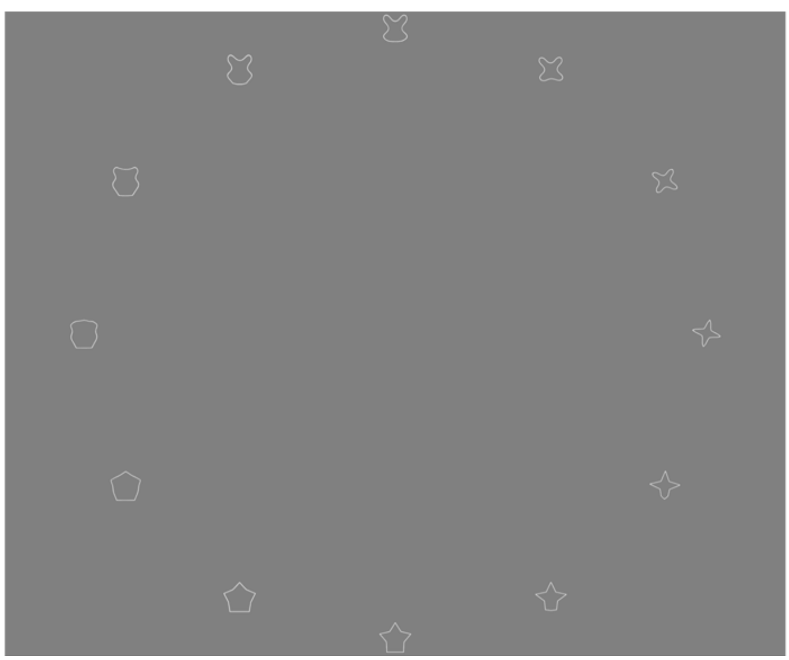

Figure 2 An example shape space of stimuli that could appear in the study. This space shows 12 shapes all 30° apart from each other, spanning the entire scale of possible shapes. This is representative of all shapes that could be used on a single trial but on each trial the exact set of possible shapes will be randomly different.

(2560 x 1080 pixels, 60hz refresh rate) at a viewing distance of 50cm. The gamma for the monitor was set at 2.2 to approximately linearize the display luminance.

Stimulus

The stimuli were composed of 360 closed line drawings of 2D shapes (see Fig. 2 for examples). They were accessed from the OSF public repository provided by the original authors (Li et al., 2020 https://osf.io/d9gyf/). All shapes were resized to 90% to 110% its size relative to the other shapes. The exact resizing parameter for each shape was chosen to minimize the number of overlapping pixels among shapes. This was done to make them more distinct when overlaid one over another. The background is set at a grayscale value of 127. The original shapes had a maximum grayscale value of 255 but this has been decreased using this formula

$$floor(\left(1 + \left(\frac{(pixel_{value} - 127)}{127}\right) * .7\right) * 127)$$

which results in the maximum grayscale value of 216 so shapes could become both brighter and dimmer. The shapes to be used in the experiment were chosen randomly on each trial and a sample of shapes that could be used in the study can be found in Figure 2. The two target shapes varied between ±0-90° difference on the shape wheel in increments of 18°. This created 11 stimulus groups but since only the absolute value of the target offset was visually distinguishable, the trials for the 0° condition were doubled and the other groups were merged based on the absolute value of the target offset, leaving 6 groups of trials. The distractor shapes were always ±45° different from the location on the shape wheel that is maximally different from both target shapes. The distractor that was more different from a particular target appeared overlapping that target.

Procedure

Participants performed the task in three phases: practice, luminance detection thresholding, and main attention task. All three of these phases use the same task structure with small differences between them. On a single trial, two target shapes appeared 3.25 degrees to the left and right of a central fixation respectively. Participants were told to pay attention to these shapes and to respond only to changes that occur to those two target shapes. After 1000ms of these shapes present by themselves, two distractor shapes appeared overlapping the targets. Participants were told to ignore these distractor shapes. The four shapes were presented together on the screen for a total of 1700 ms. The first luminance change occurred between 600-1200 ms after the appearance of the distractor shapes, an interval with all four shapes unchanged was shown for 50-650ms after each luminance change, and the luminance changes themselves lasted 200ms. After the changes occurred, the participants were prompted to respond randomly to the left or right target shape by making key presses that equated to no change, dimmer, or brighter. They were then prompted to respond about the other target. The time course of a single trial can be found in Figure 3. The luminance change condition varied independently for both the left and the right set of shapes to encourage attention to both sets, as attending to only one set did not provide information about the other. For all trials within a block, for each side independently, on 30% of trials the target dimmed, on 30% of trials the target brightened, on 30% of trials the distractor changed, and on 10% of trials no luminance change occurred at all. The order of the luminance changes between the left and right side varied randomly with half of all trials having the luminance change occur first of the left side and the other half occurring first on the right

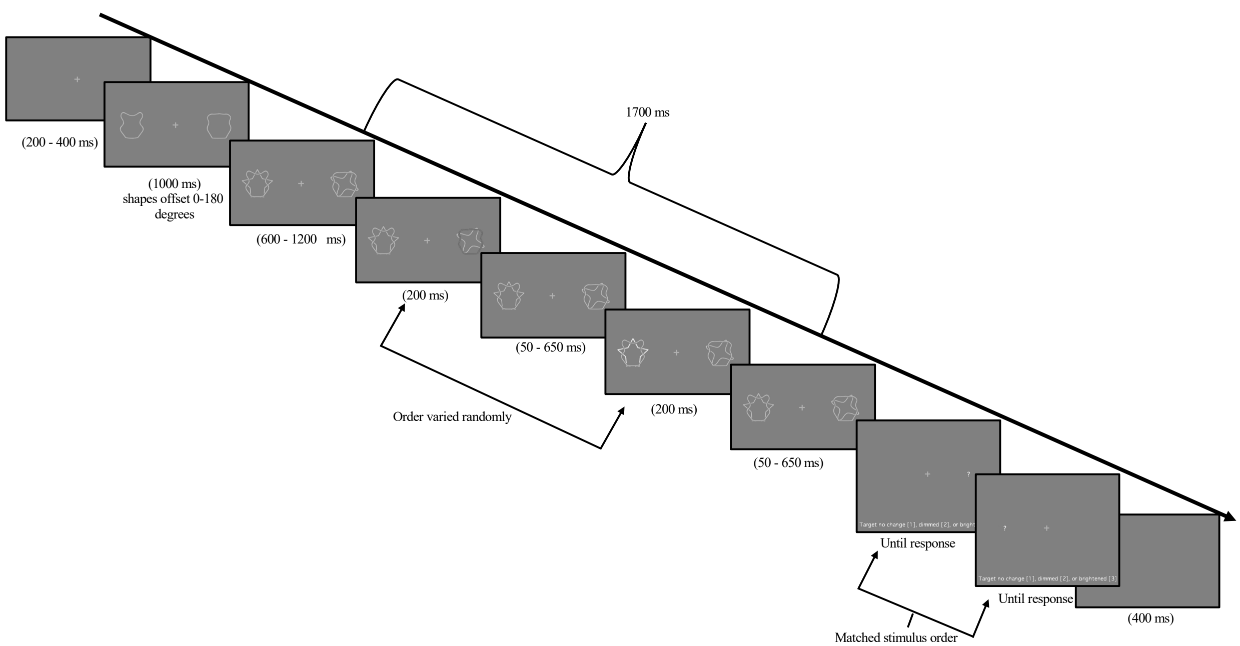

Figure 3 The time course of one trial both Experiment 1 and Experiment 2. The trial begins with 200-400ms of fixation before the two target shapes appear and are present for 1000ms. The distractor shapes then overlay the targets. There is then a viewing period (600-1200ms) before both potential luminance changes occur (200ms each) and the intervals between and after the luminance changes can endure for 50-650ms. This period where all 4 shapes are presented always lasts for a total of 1700ms. The two luminance changes occur in a random order. The participants are then cued to respond to what type of luminance change occurred for both the left and right side (matching the order that the changes themselves occurred) and this cue persists until a response is made. There is then an intertrial interval of a blank screen that lasts 400ms.

side. The order in which the participant was asked to respond to the left or right stimulus always matched the order in which the luminance changes occurred.

In the practice phase, participants were given the opportunity to practice the task the experimenter has explained to them verbally. Participants ran through a block of 22 trials (2 exemplars of each possible target offset) and were asked if they felt comfortable enough with the task structure to move forward. The participant continued practice blocks until they indicated they were comfortable with the task structure.

In the luminance detection threshold blocks, participants performed the same task described above but the difficulty of the task was changed based on correctness of response. This was done to find a threshold value for both dimming and brightening trials that would result in the participants getting approximately 71% of trials correct. This was done with two separate 2-down 1-up staircasing procedures (Levitt, 1971), one for dimming trials and one for brightening trials. The staircases had starting values of .36 with a maximum value of .99 and a minimum value of .01. This value represents the percent change from the starting luminance value to the maximum brightness or maximum dimness. Participants ran 3 blocks of 60 trials each and, for each block, 10 trials for each of the 6 target offset conditions was randomly interleaved throughout.

The main attention task had the same design as the previous two phases, except now the luminance change values for dimming and brightening were fixed based on the results of the staircasing procedure in the previous phase. Participants completed 4 blocks of 120 trials with a programmed break halfway through each block to allow for rest to limit fatigue. Within each block, 20 trials of each of the 6 target offset conditions were randomly interleaved.

Analysis

To evaluate how shape offset impacts performance, participant task accuracy when presented with each of the 6 target offset conditions was compared. Initial analysis was conducted using a one-way repeated measures ANOVA to examine if there was an overall effect of target offset on task accuracy. Regardless of if the data follow a pattern consistent with the feature similarity gain model or a model of center-surround suppression, a main effect of target offset is expected, with the 0° offset condition having the highest accuracy. To test this, planned comparisons (at alpha level 0.05) with a Bonferroni correction were done for all conditions compared to the 0° offset condition. To test for whether a feature-similarity gain or surround suppression model better fits the data, additional planned comparisons would be done between key offsets of interest. Relative comparisons would be made with a Bonferroni correction between any local minimum and a local maximum value that occurs at a point of greater target offset. If these comparisons are present and significant, this would provide support for a surround suppression effect for object-based attention. If these comparisons are either not possible to perform due to the data pattern or are insignificant, then the data would only support an object-similarity gain model.

A complementary analysis approach that may provide additional insight is a model fitting approach adapted from Fang et al. (2019). This method used two models, a monotonic (Gaussian) and a nonmonotonic (Ricker Wavelet) function, and test whether the data better fits one model or the other. The monotonic model expressed by this function:

$$Pc = \frac{A}{w} e^{-\frac{x^2}{2w^2}} + b$$

where *A*, *w*, and *b* are free parameters of the Gaussian function, *x* is the target offset, and *Pc* is the accuracy of the task, would analyze whether a feature-similarity gain based model better fits the data. The nonmonotonic model expressed by this function:

$$Pc = \frac{2A}{\sqrt{3w}\,\pi^{1/4}} e^{-\frac{x^2}{2w^2}} \left(1 - \frac{x^2}{w^2}\right)$$

where *A* and *w* are free parameters of the Ricker Wavelet function, *x* is the target offset, and *Pc* is the accuracy of the task, would analyze whether a surround suppression based model better fits the data. Non-linear regression was used to find the fit of each model to the data and produce a residual sum of squares. To compare these models directly, a Bayes information criterion (Raferty, 1995, 1999; Wagenmakers, 2007) was calculated for each model from the residual sum of squares and then the two Bayes information criteria were compared to produce a Bayes factor (Raferty, 1995, 1999) where a factor greater than 1 would support a monotonic model and a factor less than one would support a nonmonotonic model.

Results

The trend observed in the data was that, as the difference between the target offset grew, task performance decreased monotonically (Figure 4a). At the group level, there was no numerical rebound in performance between any tested difference. A one-way repeated measures ANOVA was conducted to examine the effect of shape offset on task performance. The main effect of target offset was significant, $F(5,75) = 11.09$, $p < .001$. Using follow up, planned comparisons, paired samples t-tests with a Bonferroni correction (at alpha level 0.05) were conducted. All other groups would be compared to the 0° condition to test for a cueing effect expected from both the feature-similarity gain and surround suppression hypotheses and then additional comparison tests would compare any local minimum values to any local maximum values with a larger target offset value to test for the presence of a suppressive surround predicted by the surround suppression hypothesis. The group performed significantly better on the 0° condition than the 54°, $t(15) = 3.98$, $p = 0.0012$, d = 1.00, CI = (0.030, 0.099), 72°, $t(15) = 4.76$, $p = 0.0002$, d = 1.19, CI = (0.042, 0.110), and 90°, $t(15) = 3.97$, $p = 0.0012$, d = 0.99, CI

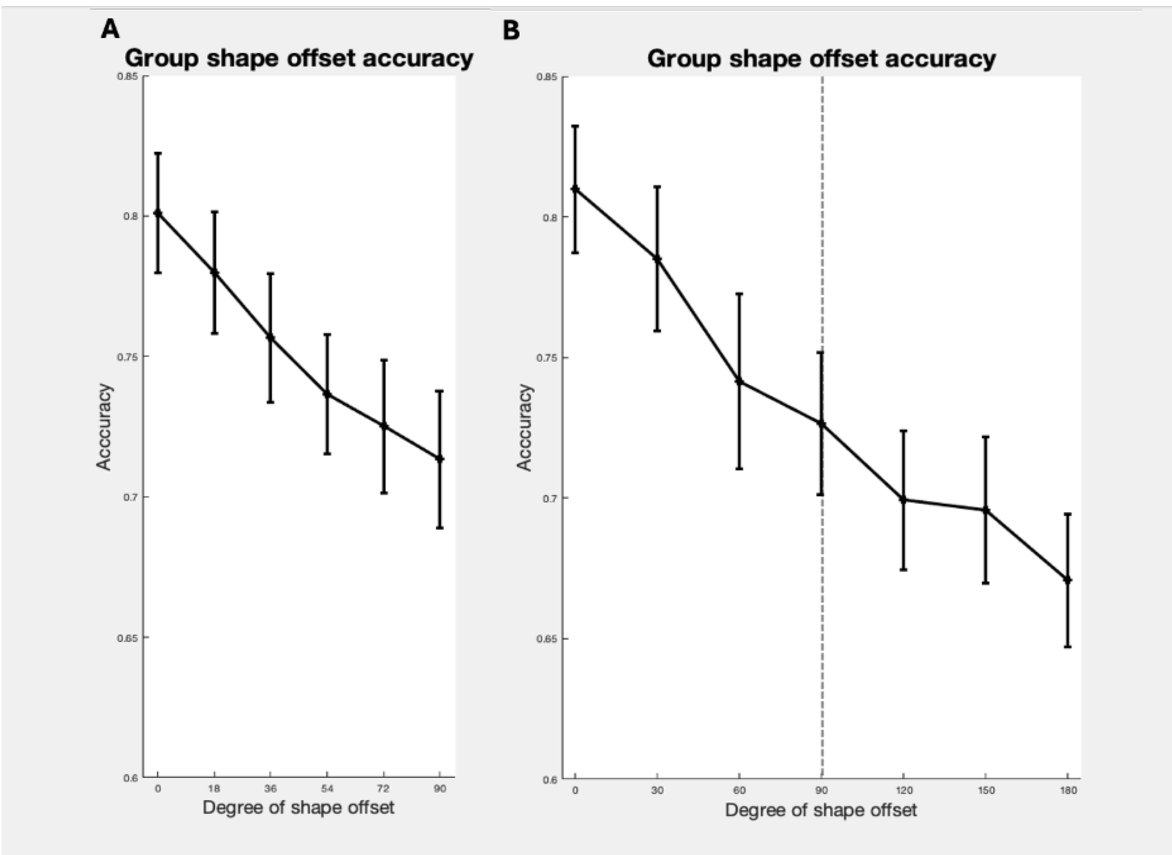

Figure 4 Line graphs of data from both experiments. The line represents group aggregate accuracy data for each target offset. The x-axis represents degree of offset between the two target shapes and the y-axis represents overall task accuracy. Both graphs show the best performance at 0° target offset and a monotonic decline of performance beyond this point. A) Results for Experiment 1 who had a maximum target offset of 90° B) Results for Experiment 2 which had a maximum target offset of 180°. The vertical dotted line is set at 90° to show where the stimulus space stopped overlapping with Experiment 1. The data to the left of the vertical line generally replicates the findings from Experiment 1 in both overall accuracy and slope.

= (0.040, 0.135), conditions. Due to the lack of numerical rebound, no other comparison tests were performed.

Additionally, the data was fit to both a monotonic (Gaussian) and non-monotonic (Ricker Wavelet) model and the Bayesian Information Criteria for both models were calculated and compared to create a Bayes Factor. The Gaussian model (R^2 = .987) was favored over the Ricker Wavelet model (R^2 = .979) by a Bayes Factor of 4.08 which suggests moderate evidence for the monotonic model (Raferty, 1999). For individual subjects, the monotonic model was favored by 8 of the 16 participants.

Discussion

In this experiment, we examined the effect of manipulating the distance between two target shapes on participants' accuracy on a luminance change identification task. The participants' accuracy decreased as the difference between the two target shapes grew and a significant cueing effect when the two targets matched was found. There was no numerical increase in accuracy between any two intervals as the difference between the two shapes grew and the group data better fit a monotonic model than a non-monotonic one. This reinforces that the shapes used differ from each other parametrically so that observers respond in a predictable manner as the shapes become more different, rather than in a way that participant performance level randomly fluctuates for visually distinct shapes.

While these results do suggest a monotonic decline more in line with the feature-similarity gain model, this design does have a significant limitation in the overall space that it covers. Only 50% of the possible difference between the two target shapes is explored. As previously mentioned, some feature spaces do not show maximum suppression until this point (Fang & Liu, 2019), so it is reasonable that the range of possible differences between target shapes was not wide enough to capture the full extent of the enhancement, suppression, and rebound. This leaves open the possibility that an area of suppression exists for this space beyond the range explored in this experiment. Based on the results from Experiment 1 and the expectation of center-surround suppression in object-based attention, a second experiment was conducted, widening the range of possible target differences beyond 90°, to look for a rebound in performance at a larger degree of difference.

EXPERIMENT 2

Methods

Participants

Participants (N = 16, 9 female, 7 male) were collected primarily from the community of undergraduate and graduate students and Michigan State Univeristy and were compensated at a rate of $12 per hour. Informed consent was obtained from every participant. To participate, participants needed to be over the age of 18 and have normal or corrected-to-normal vision. All experimental protocols were approved by the Institutional Review Board at Michigan State University.

Apparatus

The apparatus used was the same as in Experiment 1.

Stimulus

The same shape stimuli from Experiment 1 were used. The two target shapes varied between ±0°-180° difference on the shape wheel in increments of 30°. This created 13 stimulus groups but since only the absolute value of the target offset was visually distinguishable, the trials for the 0° condition were doubled and the other groups were merged based on the absolute value of the target offset, leaving 7 groups of trials. The distractor shapes were always ±45° different from the location on the shape wheel that is maximally different from both target shapes. The distractor that was more different from a particular target appeared overlapping that target.

Procedure

Participants performed the same task and three phase procedure as in Experiment 1: practice, luminance detection thresholding, and main attention task. In the task design practice phase, participants were given the opportunity to practice the task the experimenter has explained to them verbally. Participants ran through a block of 26 trials (2 exemplars of each possible target offset) and were asked if they felt comfortable enough with the task structure to move forward. The participant continued practice blocks until they indicated they were comfortable with the task structure. In the luminance detection threshold blocks, participants performed the same thresholding task as in Experiment 1. Participants ran 3 blocks of 63 trials each and, for each block, 9 trials for each of the 7 target offset conditions was randomly interleaved throughout. The main attention task had the same design as in Experiment 1. Participants completed 4 blocks of 140 trials with a programmed break halfway through each block to allow for rest to limit fatigue. Within each block, 20 trials of each of the 7 target offset conditions were randomly interleaved.

Analysis

To evaluate how shape offset impacts participant performance, participant task accuracy when presented with each of the 7 target offset conditions was compared. The same planned comparisons procedure and model fitting analysis as in Experiment 1 were used.

Results

The trend observed in the data was that, as the difference between the target offset grew, task performance decreased monotonically (Figure 4b). At the group level, there was no numerical rebound in performance between any tested difference; however, there was almost identical performance between the 120° and 150° conditions. A one-way repeated measures ANOVA was conducted to examine the effect of shape offset on task performance. The main effect of target offset was significant, $F(6,90) = 23.19$, $p < .001$. Using follow up, planned comparisons, paired samples t-tests with a Bonferroni correction (at alpha level 0.05) were conducted. All other groups would be compared to the 0° condition to test for a cueing effect expected from both the feature-similarity gain and surround suppression hypotheses. Additional comparison tests would compare any local minimum values to any local maximum values with a larger target offset value to test for the presence of a suppressive surround predicted by the surround suppression hypothesis. The group performed significantly better on the 0° condition than the 60°, $t(15) = 4.93$, $p = 1.8e{-}4$, d = 1.23, CI = (0.039, 0.098), 90°, $t(15) = 6.16$, $p = 1.8e{-}5$, d = 1.54, CI = (0.054, 0.112), 120°, $t(15) = 7.68$, $p = 1.4e{-}6$, d = 1.92, CI = (0.080, 0.141), 150°, $t(15) = 7.25$, $p = 2.8e{-}6$, d = 2.55, CI = (0.080, 0.148), and 180°, $t(15) = 10.21$, $p = 3.8e{-}8$, d = 2.55, CI = (0.110, 0.168), conditions. Due to the lack of numerical rebound, no other comparison tests were performed.

Additionally, the data was fit to both a monotonic (Gaussian) and non-monotonic (Ricker Wavelet) model and the Bayesian Information Criteria for both models were calculated and compared for both models to create a Bayes Factor. The Gaussian model ($R^2 = .967$) was favored over the Ricker Wavelet model ($R^2 = .952$) by a Bayes Factor of 3.57 which suggests moderate/weak evidence for the monotonic model (Raferty, 1999). For individual subjects, the monotonic model was favored by 9 of the 16 participants.

Discussion

In this experiment, we examined the effect of manipulating the distance between two target shapes on participants' accuracy on a luminance change identification task for the whole range of possible differences in the standardized shape space. The participants' accuracy decreased as the difference between the two target shapes grew and a significant cueing effect when the two targets matched was found. Within the range of shape differences tested in Experiment 1, the results appeared to replicate the effect found in Experiment 1 for both overall accuracy level and slope of the differences. Beyond this range, it appeared that the object-similarity gain effect continued as target shape offset grew. There was no numerical increase in accuracy between any two intervals as the difference between the two shapes grew and the group data better fit a monotonic model than a non-monotonic one. These results suggest a monotonic decline in line with an object-similarity gain effect across the entire shape space.

GENERAL DISCUSSION

Throughout both Experiment 1 and 2, a monotonic decline in performance as the two target shapes became more different was evident. This pattern demonstrates that the artificially constructed space that we used has an architecture akin to a naturally occurring circular feature space. While this does not provide evidence for a neural architecture similar to that of features like color and orientation, it does suggest that there is some component of this shape space that exists on a spectrum to which our brains are sensitive. The gradual decline in accuracy as shapes became more different suggests that the neural mechanism of attending to the appropriate shape goes beyond mere holistic shape matching. A simple yes/no matching procedure would likely result in a much more severe drop off in accuracy once the targets retained little visual similarity to each other, leaving only a strong cueing effect and little evidence for extreme difference suppression found in the feature-similarity gain model. This would be shown in a leveling off of task performance rather than a continual decrease. The graded decrease in performance in this task suggests that something graded in the stimuli such as the convexity or concavity of the shape parts or even a general property of the holistic object is represented along a continuum in our object identification system. Bao et al., 2020 found a potential candidate for what dimension our object recognition system is reactive to in the shape space upon finding that macaque inferotemporal cortex shows regions distinctly active for “spikey” and “stubby” inanimate objects respectively. The shape space itself does seem to vary along this spectrum from “spikey” to “stubby” in a general sense. The experimenter and some of the participants noted that an effective strategy to maintain attention on the proper target shape was to label each target with a descriptor like “star” or “blob” which bring about a “spikey” and “stubby” mental image respectively based on these semantic descriptors. While evidence from human fMRI suggests that this “spikey-stubby” dimension is not as extensive in our occipitotemporal cortex as it seems to be in the macaque IT cortex, it does still seem to play a small role in our object identification system (Yargholi & de Beeck, 2023). Further exploration of the shape space, particularly defining which shapes can be classified as “spikey” and which as “stubby”, could lead to insight as to what extent this object dimension plays in object-based attention.

A surprising result from this study was the lack of an area of suppression. A pattern of center surround suppression for object-based attention is predicted by the Selective Tuning Model of attention (Tsotsos, 2011) and is an expected result from contemporary attention researchers (Cavanagh et al., 2023). Previous research by proponents of both theories have found that these two patterns of enhancement and suppression in feature-based attention likely work together to produce both the neural and behavioral patterns seen in human and monkey data on selective attention (Yoo et al., 2021). It is puzzling that only one and not both of these systems is then implemented at the object level. One possible explanation for this is that suppression is found for some individuals and not others. For some individual participants, there does appear, visually, to be suppression and rebound in performance (Figure 5); however, this area of suppression is not consistent, appearing in different places across some participants and is

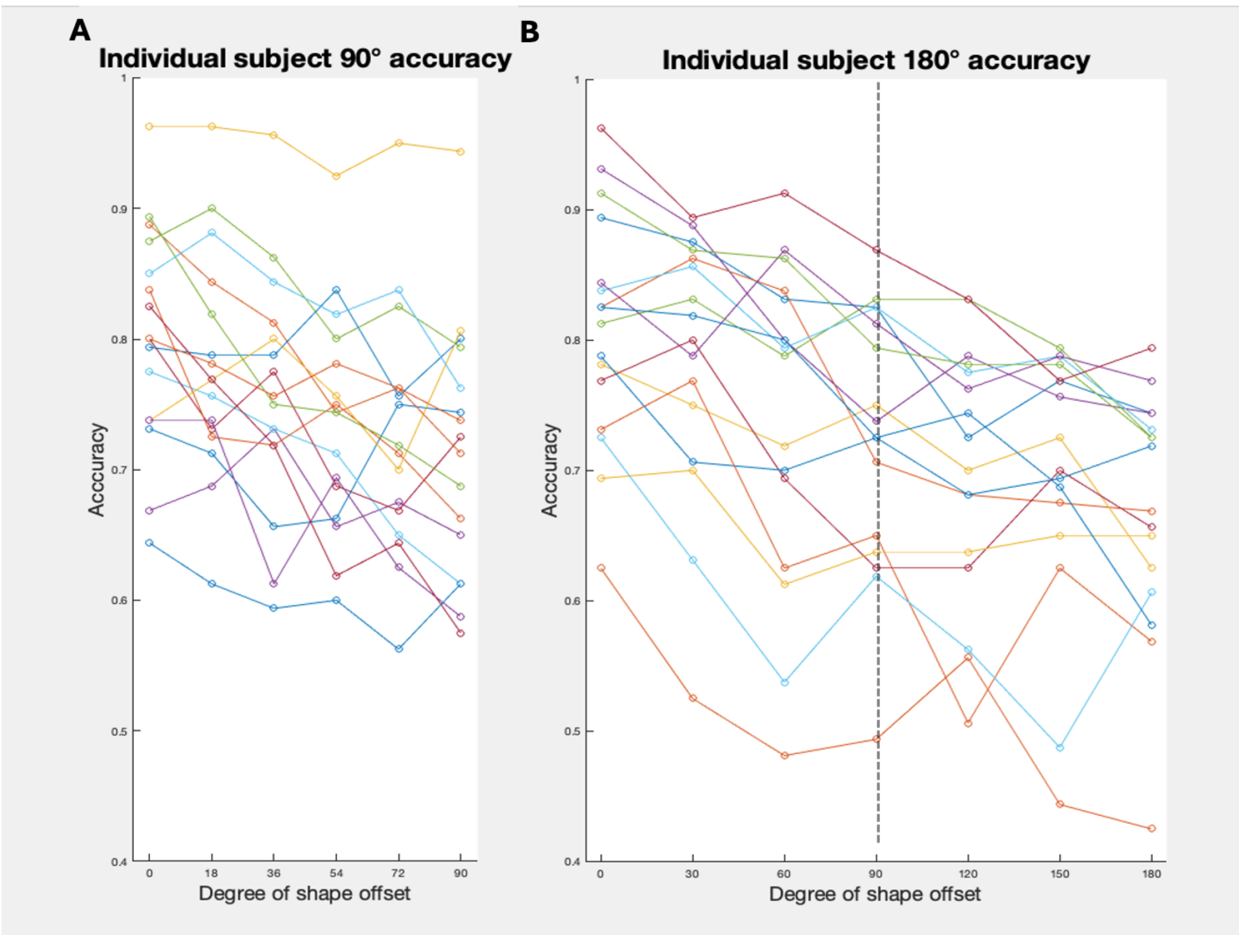

Figure 5 Individual participants data for both Experiments. Each colored line represents an individual participant's data on the main attention task. The x-axis represents the degree of difference between the two target shapes and the y-axis represents task accuracy. A) The individual data for Experiment 1. Some participants show numerical suppression and rebound at various target offsets (ex: at 72° for the dark blue line and 36° for the light purple line) B) The individual data for Experiment 2. The vertical dotted line is set at 90° to show where the stimulus space stopped overlapping with Experiment 1. Some participants show numerical suppression and rebound at various target offsets (ex: at 60° for the bright orange and light blue lines and 90° for the dark purple and light red lines).

completely absent for others. In Experiment 1, for example, some participants had a dip in accuracy at 36° (purple line in Figure 5a), others at 54° (dark red line in Figure 5a), and still others at 72° (dark blue line in Figure 5a). For the Experiment 2, similar patterns can be seen at 60° (dark orange line in Figure 5b), 90° (dark purple line in Figure 5b), and 120° (light orange line in Figure 5b). These instances of suppression and rebound then disappear in the aggregate data and the design of the current experiments does not allow us to dissociate between whether this pattern in individual data is simply noise or is confounded with another factor that changes the exact location of the suppressive surround.

A potential limitation of these experiments is that the shapes shown to participants were fully randomized. It is possible that due to the full randomization of the shape space that possible areas of suppression that differ based on category were hidden by the noise of every possible shape being shown to participants rather than a subset of similar shapes. A possible confound to explain the lack of consistency of the area of suppression is differences in category perception within the shape space. The presence of suppression around category boundary is present in color space and, for different color categories, the area of suppression varied in distance from a category center based on where the category boundary fell (Fang et al.,2019). Categories of shapes could exist within the shape wheel that are relatively consistent between individuals but less consistent than color categories. If these category boundaries were defined for individuals and the task rerun with target shapes focused around an area defined by an individual's category perception, it is possible that a consistent area of suppression would be found. It is unlikely that category boundaries in this artificially constructed shape space, that is novel to participants, are as consistent as color boundaries with which we have extensive real-world experience categorizing and labeling; however, if there is an underlying structural principal within the space that our brains are tuned to, some limited consistency seems reasonable. Additionally, previous research has shown that task difficulty, stimulus salience, and distractor competition are all factors that influence the presence of the suppressive surround (Liu et al., 2023; Yoo et al., 2021). This implies that differences in understanding the task or being challenged by the task could have influenced the presence of center-surround suppression since distractor competition was not incredibly high due to distractors only being two overlapping stimuli.

Finally, a reasonable interpretation of these results is that they support a feature-similarity gain model for selective attention of higher order features, in this case shape, rather than for object-based selective attention. However, this then brings into question where feature-based attention ends, and object-based attention begins, as shape could be considered a feature of an object or a holistic property of an object itself that goes beyond a definition as a feature. Shape could classified as a higher order feature in some instances where shape does not define an object's identity, such as for items like clouds that don't have to fit one general shape pattern to be considered a cloud. However, when shape defines an object, such as for a square or circle whose object identity changes if their general shape is changed, shape seems like an object property rather than a feature. In these experiments, shape seems more like an object defining property than a feature since participants identified targets based on an instance of viewing a specific shape that, if changed, would no longer be identifiable as the target. This supports the idea that something like an object-similarity gain effect is at play in our object identification system that enhances objects similar to a target and suppresses objects very different from that target.

The current study found that for both a smaller range and a more comprehensive range of target shapes, there is evidence of an object-focused similarity gain effect for the artificially constructed shape space. While these findings do not explain what underlying mechanisms create the effect, it does show that a predictable behavioral effect occurs when attending to different shapes within this space. Further research can investigate whether it is also possible to find surround suppression in this space and should continue to test the validity of this stimulus space for studying object-based attention by using it as a continuous stimulus set in established object-based attention task paradigms.

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