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Perception of multi-dimensional regularities is driven by salience

Ru Qi Yu¹ · Yu Luo¹ · Daniel Osherson² · Jiaying Zhao^{1,3}

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Abstract

A challenge for the visual system is to detect regularities from multiple dimensions of the environment. Here we examine how regularities in multiple feature dimensions are distinguished from randomness. Participants viewed a matrix containing a structured half and a random half, and judged whether the boundary between the two halves was horizontal or vertical. In Experiments 1 and 2, the cells in the matrix varied independently in the color dimension (red or blue), the shape dimension (circle or square), or both. We found that boundary discrimination accuracy was higher when regularities were present in the color dimension than in the shape dimension, but the accuracy was the same when regularities were present in the color dimension alone or in both dimensions. By adding a third surface dimension (hollow or filled) in Experiments 3 and 4, we found that discrimination accuracy was higher when regularities were present in the surface dimension than in the color dimension, but was the same when regularities were present in the surface dimension alone or in all three dimensions. Moreover, when there were two conflicting boundaries, participants chose the boundary defined by the surface dimension, followed by the color dimension as more visible than the shape dimension (Experiments 5 and 6). Finally, participants were faster at detecting differences in the surface dimension, followed by the color and the shape dimensions (Experiments 7 and 8). These results suggest that perception of regularities in multiple feature dimensions is driven by the presence of regularities in the most salient feature dimension.

Keywords Attention · Detection · Feature · Randomness · Pattern

Introduction

Regularities are prevalent in the environment. The mind is able to detect many forms of regularities, ranging from repetitions of the same object (Bar-Hillel & Wagenaar, 1991; Thompson & Spencer, 1966), alternations between two different objects (Otto & Eichenbaum, 1992; Yu, Osherson, & Zhao, 2018b), pairings between two distinct objects (Pavlov & Anrep, 2003; Rescorla & Wagner, 1972), co-occurrences of individual objects over space or time (Fiser & Aslin, 2001; Saffran, Aslin, & Newport, 1996), to associations between objects and contexts (Chun & Jiang, 1998; Jiang, Swallow, & Rosenbaum, 2013).

Regularities are often present in multiple dimensions in the environment. For example, the daily cycle between the sun and the moon is reflected by alternations in light intensity, temperature, and colors of the sky. These regularities are highly correlated across feature dimensions. The presence of regularities in multiple feature dimensions can facilitate learning (Turk-Browne, Isola, Scholl, & Treat, 2008). In speech perception, lip movements and vocal sounds are highly correlated, which helps language learning (Patterson & Werker, 2003) and perceptual development in infants (Lewkowicz & Ghazanfar, 2009).

However, regularities are not always correlated across feature dimensions and can in principle exist in each dimension independently. For example, features from the color dimension do not need to correlate with features from the size dimension, and the visual input from the environment does not need to correspond to the auditory input.

Given the presence of regularities in multiple feature dimensions, the challenge for the cognitive system therefore is to detect regularities from these dimensions. It is currently not well understood how the visual system perceives regularities that are present independently in multiple dimensions. The current study addresses this question and tests two hypotheses. The first is the *facilitation hypothesis*, which states that the detection of regularities is improved when regularities are

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present in multiple dimensions of the stimuli compared with when regularities are present in only one dimension. That is, the visual system can readily detect feature conjunctions (Huang & Pashler, 2012) and is able to combine information from multiple sources in order to extract regularities more accurately (Patterson & Werker, 2003; Turk-Browne et al., 2008).

The second is the *dominance hypothesis*, which states that the detection of regularities from multiple feature dimensions is equal to the detection of regularities in the most salient dimension. This hypothesis is based on the assumption that different feature dimensions have varying levels of salience and the most salient dimension captures most attentional resources (Itti, Koch, & Niebur, 1998). Despite the fact that regularities can draw attention themselves (Zhao, Al-Aidroos, & Turk-Browne, 2013; Zhao & Luo, 2017), the dominance hypothesis suggests that regularities in the more salient dimension are prioritized over regularities in the less salient dimension, so the ability to perceive regularities from multiple dimensions is determined by the most salient dimension.

It is important to clarify that we define salience as the perceptual difference between specific feature values within the same dimension, or across different feature dimensions. For example, black circles among white circles differ more than black circles among gray circles, thus black circles among white circles look more salient and may draw more attention. Likewise, black circles among white circles differ more than black circles among black squares (Wolfe & Horowitz, 2017), thus black circles among white circles look more salient and may draw more attention.

A common way to examine the perception of regularities is to test the ability to distinguish regularities (i.e., signals) from randomness (i.e., noise). One method was developed by Zhao, Hahn, and Osherson (2014), where participants viewed a matrix that consisted of a structured half and a random half, and judged whether the division between the two halves was horizontal or vertical. The structured half of the matrix was made from binary bits (e.g., red or blue cells) that alternated more than expected by chance (e.g., red blue red blue red blue), or repeated more than expected by chance (e.g., red red red blue blue blue). The random half of the matrix was made from random bits. Participants were not told anything about how the matrix was generated, or which half was structured; they simply judged the orientation of the boundary. The performance on this task served as a measure for the ability to perceive regularities.

In the current study, we used the same task as in Zhao, Hahn, and Osherson (2014) to examine the ability to detect regularities from multiple feature dimensions. Specifically, we used an algorithm to generate binary bits that deviate from stochastic independence by allowing the previous bit to help determine the next one. Specifically, for each number p in the unit interval (from 0 to 1), let $D(p)$ generate a sequence of bits consisting of zeros and ones as follows:

Sequence generation using the device $D(p)$: An unbiased coin toss determines the first bit. Suppose that the n^{th} bit has been constructed (for $n \geq 1$). Then with probability p the $n + 1^{\text{st}}$ bit is set equal to the opposite of the n^{th} bit (that is, if the n^{th} bit was 0, the $n + 1^{\text{st}}$ bit would be 1, and vice versa); with probability $1 - p$ the $n + 1^{\text{st}}$ bit is set equal to the n^{th} bit. Repeat this process to generate a sequence of any desired length.

The expected proportion of alternation, called the “switch rate” of the sequence, is p . For $p < .5$, $D(p)$ generates a sequence that is more likely to repeat, resulting in long streaks. The repetitions are what we call regularities in the current study. For $p > .5$, $D(p)$ tends to alternate. For $p = .5$, $D(p)$ generates a random sequence. The expected proportion of each bit is 50% for all $p \in [0, 1]$, although, empirically, the output might deviate slightly from 50% (Yu, Gunn, Osherson, & Zhao, 2018a). This algorithm allowed us to manipulate different degrees of repetitions in the sequence while maintaining equal probability of the two outcomes (Yu et al., in press).

The current study used a boundary discrimination task where participants judged the boundary between the two halves in a matrix (Zhao et al., 2014). Specifically, participants viewed a matrix with a random half and a structured half, and judged whether the boundary was horizontal or vertical. Each cell in the matrices could vary independently in three dimensions: color (feature values: red or blue), shape (feature values: circle or square), and surface (feature values: hollow or filled). In each dimension, the two feature values varied according to a binary sequence generated by $D(p)$. The feature values on the three dimensions were determined by three independent binary sequences generated by $D(p)$. In the random half of the matrix, the two feature values were randomly determined with a switch rate $p = 0.5$. In the structured half of the matrix, the two feature values were more likely to repeat with a switch rate $p = 0.2$, and therefore to contain regularities. In other words, regularities (repetitions) could be present in any feature dimension independently. The current study contained seven experiments. In Experiments 1 and 2, the cells in the matrix varied independently in the color dimension, the shape dimension, or both dimensions. We compared the boundary discrimination performance when regularities were present on a single dimension and when regularities were present on both dimensions. In Experiments 3 and 4, the cells in the matrix varied independently in the color, shape, or surface dimension, and we compared the discrimination performance when regularities were present on a single dimension and when regularities were present on all three dimensions. In Experiments 5 and 6, the matrix contained two conflicting boundaries defined by regularities in two different dimensions. In Experiment 7, we measured salience by the accuracy with which participants discriminated differences between the two feature values in each dimension, in order to identify which dimension was more perceptually discriminable.

Finally, in Experiment 8, we used a conventional visual search task to measure salience by the speed with which participants judged whether a target was present or absent among distractors, as a converging method to assess which feature dimension was more perceptually salient.

Experiment 1

The goal of this experiment was to examine how regularities from multiple feature dimensions were perceptually distinguished from randomness.

Participants

Forty-seven undergraduate students (37 female, mean age=20.6 years, $SD=2.3$) from the University of British Columbia (UBC) participated for course credit. Participants in all experiments were undergraduate students at UBC and provided informed consent. All experiments were approved by the UBC Behavioral Research Ethics Board. We conducted a power analysis in G*Power (Faul, Erdfelder, Lang, & Buchner, 2007), using an effect size of $\eta_p^2=0.17$ observed in our prior work using similar methods and analyses (Zhao et al., 2014). Based on the power analysis, 47 participants would be required to have 95% power to detect the effect in our paradigm with an alpha level of 0.05. To keep the power consistent, we recruited 47 participants in all subsequent experiments.

Apparatus

In all experiments, participants seated 50 cm from a computer monitor (refresh rate= 60 Hz). Stimuli in Experiments 1–4 were generated in Java.

Stimuli

The stimuli were 30×30 matrices, each subtending 15.1° of visual angle (Fig. 1a). Every matrix was evenly divided into a structured half and a random half, either horizontally or vertically. The direction of division was randomly determined for each matrix, and each half of the matrix contained 15×30 cells. In the structured half, the cells were tiled from a binary sequence from $D(p)$, with a switch rate of $p=0.2$,¹ and in the random half, the cells were tiled from a random sequence from

¹ The 0.2 switch rate in the structured half was determined from a previous study (Zhao et al., 2014), where the matrices were larger in size and there was only one color dimension. This means that the boundary discrimination task was relatively easier in the previous study than in the current study (with smaller matrices thus less information, and with more feature dimensions thus more complexity). In the previous study, discrimination accuracy started to decline after a switch rate of 0.2, so we chose 0.2 in the current study to avoid possible ceiling or floor effects.

$D(p)$, with a switch rate of $p=0.5$. The direction of tiling in both halves was randomly determined, independent from the boundary orientation, but it was consistent in each half, either both horizontal or both vertical. There were three conditions. In the color condition (Fig. 1b), the cells varied only on the color dimension, and each cell could be red (RGB: 255, 0, 23) or blue (6, 32, 244) determined by a binary sequence of $D(p)$, but all cells were squares. In the shape condition (Fig. 1c), the cells varied only on the shape dimension, and each cell could be a circle or a square determined by a binary sequence of $D(p)$, but all cells were blue. In the combined condition (Fig. 1d), the cells varied on both color and shape dimensions, and each cell could be a red circle, a red square, a blue circle, or a blue square, determined by two independent binary sequences of $D(p)$. The structured half contained a switch rate of $p=0.2$ and the random half contained a switch rate of $p=0.5$ in all three conditions. The tiling direction was the same for both halves of the matrix and for both feature dimensions.

Procedure

There were three conditions: color, shape, and combined. Each condition was a separate block, and each block contained 45 trials, so there were 135 trials in total. The order of the blocks was randomized. In each trial, participants viewed a matrix and were asked to judge the orientation of the boundary between the two halves in the matrix. They were not told anything about how the matrix was made, or which half was structured or random. They were only told that each matrix contained two halves that were separated by a horizontal or vertical boundary, and their task was to judge the orientation of the boundary by pressing the “h” key for horizontal or the “v” key for vertical. Each matrix was presented at the center of the screen for 2.5 s. If participants did not respond within 2.5 s, the screen remained blank. There was no time limit for participants to respond, and they could only proceed to the next trial if they responded in the current trial. Participants took a break of 1–2 min between blocks.

Results and discussion

We used the boundary discrimination accuracy (Fig. 1e) to measure the ability to detect regularities from randomness in each condition. The mean accuracy in the color condition was 0.79 ($SE=0.018$); the mean accuracy in the shape condition was 0.68 ($SE=0.015$); and the mean accuracy in the combined condition was 0.79 ($SE=0.017$). Using a one-way repeated measures ANOVA, we found a significant difference in discrimination accuracy among the conditions [$F(2,92)=49.01$, $p<.001$, $\eta_p^2=0.52$]. *Post hoc* Tukey HSD tests revealed that the accuracy was reliably higher in the color condition than in the shape condition ($p<.001$), it was reliably higher in the combined condition than in the shape condition ($p<.001$),

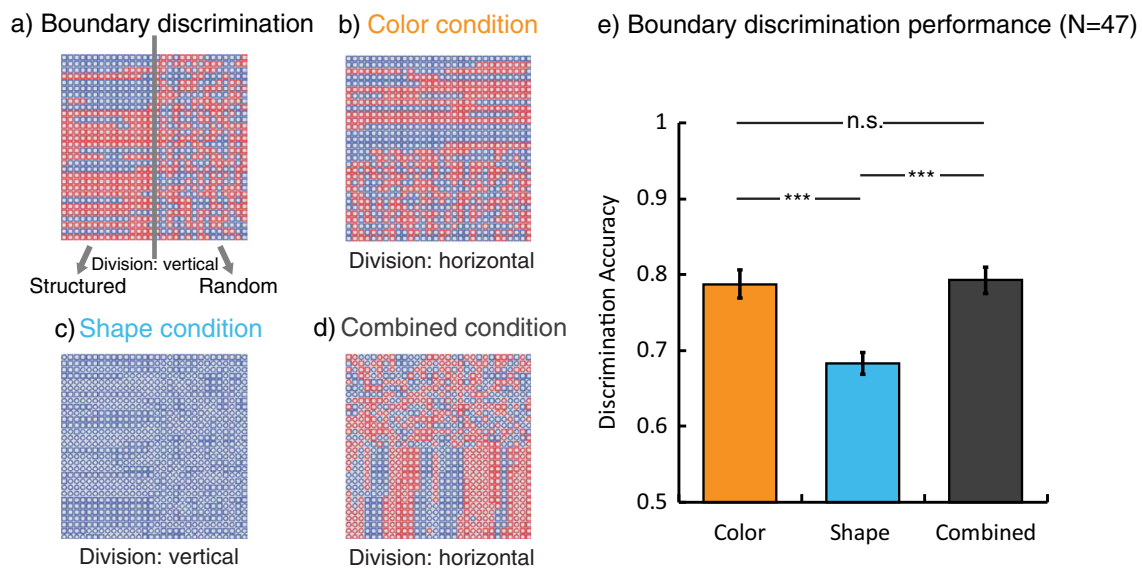


Fig. 1 Stimuli and results in Experiment 1. **(a)** A sample matrix. Each matrix was divided into two halves. The direction of division (vertical or horizontal) was randomly determined. The cells in the matrix were determined by binary sequences. In the structured half, the binary sequence had a switch rate of 0.2, making the cells more likely to repeat. In the random half, the binary sequence had a switch rate of 0.5, making the cells completely random. Participants were asked to judge the

but the accuracy in the color and combined conditions was not different ($p=.88$). This suggests that regularities were more easily detected in the color dimension than in the shape dimension, but there was no additional benefit in discrimination performance when regularities were present in both dimensions. This provides support for the dominance hypothesis rather than the facilitation hypothesis.

Experiment 2

Experiment 1 demonstrated that discrimination accuracy was higher in the color condition than in the shape condition. Importantly, when regularities were present in both dimensions, discrimination accuracy was identical to that when regularities were only present in the color dimension. One explanation for this finding is that participants selectively attended to the regularities in the more salient color dimension and ignored the regularities in the less salient shape dimension. This explanation raises another prediction: The noise (randomness) in the more salient dimension should interfere more strongly with performance than the noise in the less salient dimension. In Experiment 1, the dimension without regularities was uniform (e.g., all blue, or all squares). To test this prediction, we added two more conditions in Experiment 2: In the structured half of the matrix, regularities were present only in the color dimension but the shape dimension was random (condition 4), and both dimensions were random in the random half; and in the structured half of the matrix,

boundary of the two halves in the matrix, without being told which half was structured or random. **(b)** In the color condition, the cells were red or blue, but all cells were squares. **(c)** In the shape condition, the cells were circles or squares, but all cells were blue. **(d)** In the combined condition, the cells were red or blue circles or squares. **(e)** Boundary discrimination accuracy in each condition (error bars indicate ± 1 between-subjects SEM; *** $p < .001$)

regularities were present only in the shape dimension but the color dimension was random (condition 5), and both dimensions were random in the random half.

Due to the randomness in the other dimension, we expect that discrimination accuracy in conditions 4 and 5 will be lower than in color and shape conditions where the feature in the other dimension was uniform. Based on Itti and Koch (1999), we expect that the randomness in the more salient color dimension should capture attention and interfere with regularities detection in the shape dimension more strongly than the randomness in the less salient shape dimension interfering with regularities detection in the more salient color dimension. Thus, we predict an interaction effect where the difference between condition 5 and the shape condition will be greater than the difference between condition 4 and the color condition. Similarly, we expect that the difference between condition 5 and the combined condition will be greater than the difference between condition 4 and the combined condition.

Participants

A new group of 47 undergraduate students (32 female, mean age=19.8 years, $SD=1.4$) participated for course credit.

Stimuli

The stimuli were the same as those in Experiment 1, with the addition of two more conditions (Fig. 2a). Condition 4 (color regular condition) was the same as the color condition in

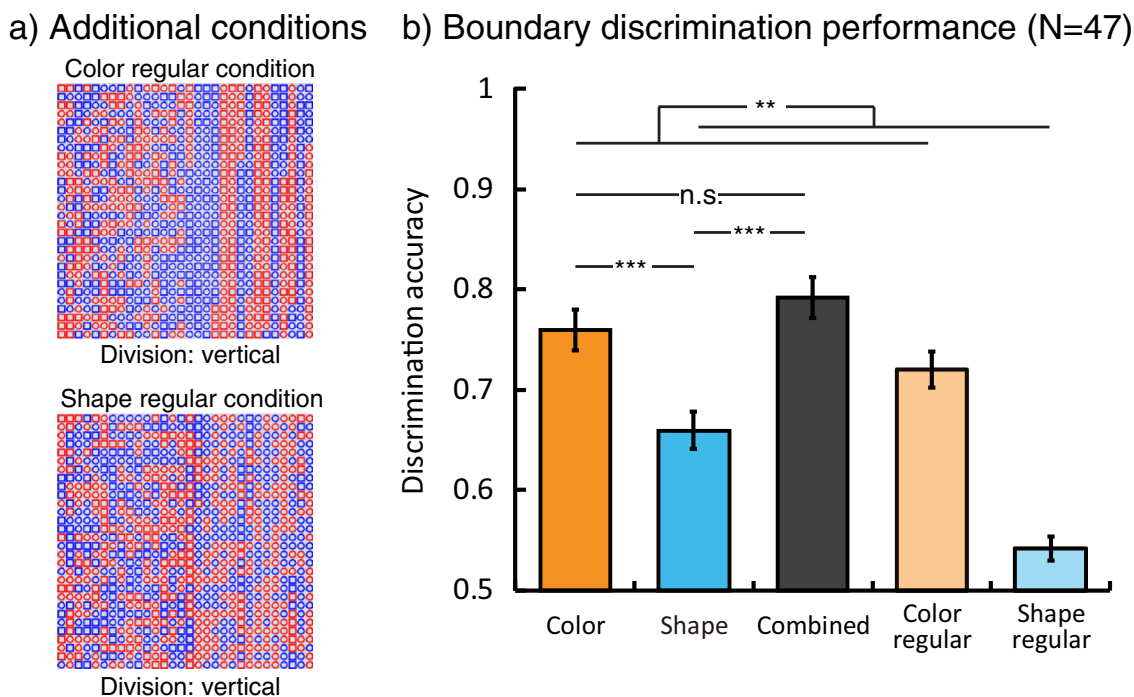


Fig. 2 Stimuli and results in Experiment 2. (a) Two new conditions: the color regular condition was the same as the color condition in Experiment 1, except that for the structured half, the shape dimension was fully random with a switch rate of $p=0.5$; the shape regular condition was the

same as the shape condition in Experiment 1, except that for the structured half, the shape dimension was fully random with a switch rate of $p=0.5$. Condition 5 (shape regular condition) was the same as the shape condition in Experiment 1, except that for the structured half, the color dimension was fully random with a switch rate of $p=0.5$.

Procedure

As in Experiment 1, each condition was a separate block, and each block contained 45 trials, so there were 225 trials in total (45 trials \times 5 blocks). The order of the blocks was randomized. The procedure was the same as that in Experiment 1.

Results and discussion

In the color condition, the mean discrimination accuracy was 0.76 (SE=0.021). In the shape condition, the mean accuracy was 0.66 (SE=0.019). In the combined condition, the mean accuracy was 0.79 (SE=0.021). In the color regular condition, the mean accuracy was 0.72 (SE=0.018). In the shape regular condition, the mean accuracy was 0.54 (SE=0.012).

First, we replicated the results in Experiment 1. Using a one-way repeated measures ANOVA, we found a significant difference in discrimination accuracy among the original three conditions in Experiment 1 [$F(2,92)=25.70, p<.001, \eta_p^2=0.36$]. *Post hoc* Tukey HSD tests showed that the accuracy in the color and combined conditions was reliably higher

same as the shape condition in Experiment 1, except that for the structured half, the color dimension was fully random with a switch rate of $p=0.5$. (b) Boundary discrimination accuracy in each condition (error bars indicate ± 1 between-subjects SEM; *** $p<.001$)

than that in the shape condition ($p<.001$), but not different from each other ($p=.23$).

Next, using a one-way repeated-measures ANOVA, we found a significant difference in discrimination accuracy among the five conditions [$F(4,184)=57.02, p<.001, \eta_p^2=0.55$]. *Post hoc* Tukey HSD tests showed that the accuracy in the color regular condition was reliably higher than that in the shape regular condition ($p<.001$). Moreover, the accuracy in the color regular condition was not lower than that in the color condition ($p=.19$), but the accuracy in the shape regular condition was reliably lower than that in the shape condition ($p<.001$)

We then conducted a two-way 2 (condition: color vs. shape) \times 2 (interference: uniform vs. random) repeated-measures ANOVA, which revealed a main effect of condition [$F(1,46)=86.31, p<.001, \eta_p^2=0.65$] and interference [$F(1,46)=42.84, p<.001, \eta_p^2=0.48$]. Importantly, there was also a reliable two-way interaction [$F(1,46)=8.02, p<.01, \eta_p^2=0.15$], showing that the difference between condition 5 and the shape condition was greater than the difference between condition 4 and the color condition.

The results showed that the randomness in the more salient color dimension interfered with detecting regularities in the shape dimension more strongly than the interference from the randomness in the less salient shape dimension when detecting regularities in the color dimension. This suggests that participants selectively attended to the information in the more salient color dimension, thus providing further support for the dominance hypothesis: the detection of regularities present in two dimensions is determined by the regularities in the more salient dimension.

Experiment 3

To see if the effect observed in Experiments 1 and 2 was specific to the color dimension, we introduced a third dimension in Experiment 3, a surface dimension, and examined how regularities from three feature dimensions were distinguished from randomness.

Participants

A new group of 47 undergraduate students (34 female, mean age=24.5 years, $SD=4.2$) participated in the experiment for course credit.

Stimuli and procedure

The matrices in the color and shape conditions were identical to those in Experiment 1 (Figs. 3a and b), except now there was a third surface condition, and a new combined condition. In the surface condition (Fig. 3c), the cells varied only on the surface dimension, and each cell could be hollow or filled determined by a binary sequence of $D(p)$, but all cells were blue squares. In the combined condition (Fig. 3d), the cells varied on color, shape, and surface dimensions, and each cell could be red or blue, circle or square, or hollow or filled, determined by three independent binary sequences of $D(p)$. As before, the structured half contained a switch rate of $p=0.2$ and the random half contained a switch rate of $p=0.5$ in all four conditions. The procedure was identical to that in Experiment 1, except that each block contained 27 trials, so there were 108 trials in total.

Results and discussion

The boundary discrimination accuracy is shown in Fig. 3e. The mean accuracy in the color condition was 0.85 ($SE=0.019$); the mean accuracy in the shape condition was 0.71 ($SE=0.020$); the mean accuracy in the surface condition was 0.90 ($SE=0.014$); and the mean accuracy in the combined condition was 0.90 ($SE=0.019$). Using a one-way repeated measures ANOVA, we found a significant difference in discrimination accuracy among the conditions [$F(3,138)=74.16$, $p<.001$, $\eta_p^2=0.62$]. *Post hoc* Tukey HSD tests revealed that, as in Experiment 1, the accuracy was reliably higher in the color condition than in the shape condition ($p<.001$), but the accuracy in the surface condition was reliably higher than in the color or shape conditions ($ps<.001$). Moreover, the accuracy in the combined condition was also higher than the color or shape conditions ($ps<.001$). Critically, the accuracy in the combined condition was not different from that in the surface condition ($p=.99$).

These results suggest that regularities were more easily detected in the surface dimension than in the color or shape dimensions, but there was no additional benefit in discrimination performance when regularities were present in all three dimensions than when regularities were present only in the surface dimension. This again provides support for the dominance hypothesis rather than the facilitation hypothesis.

Experiment 4

In Experiment 3, discrimination accuracy in both surface and combined conditions reached 90%. This could be a ceiling effect where any possible further improvement in discrimination

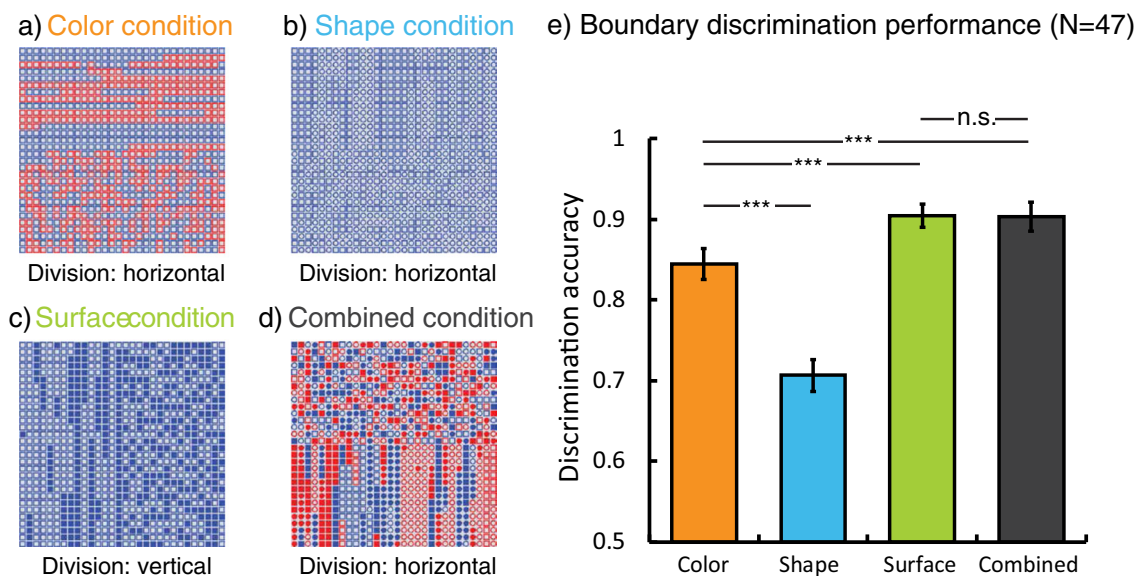


Fig. 3 Stimuli and results in Experiment 3. (a) and (b) The color and shape conditions were identical to those in Experiment 1. (c) In the surface condition, the cells were hollow or filled, but all cells were blue squares.

(d) In the combined condition, the cells were red or blue, circles or squares, or hollow or filled. (e) Boundary discrimination accuracy in all four conditions (error bars indicate ± 1 between-subjects SEM; *** $p<.001$)

accuracy was more difficult given the high accuracy level. To reduce the ceiling effect, we increased the difficulty of the boundary discrimination task by increasing the switch rate in the structured half from 0.20 to 0.22 (i.e., the structured half is now more random).

Participants

A new group of 47 undergraduate students (35 female, mean age=19.8 years, SD=2.8) participated in the experiment for course credit.

Stimuli and procedure

The matrices in Experiment 4 are identical to those in Experiment 3, except for the switch rate p in the structured half of each matrix. To make the boundary discrimination task more difficult, the switch rate p in the structured half was increased from 0.20 to 0.22. This increase made the structured half more similar to the random half (switch rate $p=0.5$).

Results and discussion

The boundary discrimination accuracy is shown in Fig. 4.² The mean accuracy in the color condition was 0.67 (SE=0.014); the mean accuracy in the shape condition was 0.63 (SE=0.012); the mean accuracy in the surface condition was 0.74 (SE=0.012); and the mean accuracy in the combined condition was 0.73 (SE=0.017). The accuracy was lower overall, and the accuracy in both surface and combined conditions just over 70%, reducing the ceiling effect. As in Experiment 3, we found a significant difference in discrimination accuracy among the four conditions [$F(3,138)=20.39$, $p<.001$, $\eta_p^2=0.31$]. *Post hoc* Tukey HSD tests revealed that the accuracy was marginally higher in the color condition than in the shape condition ($p=.07$), and the accuracy in the surface condition was reliably higher than in the color or shape conditions ($ps<.001$). Moreover, the accuracy in the combined condition was also higher than the color or shape conditions ($ps<.001$). Critically, the accuracy in the combined condition was not different from that in the surface condition ($p=.96$). These results replicated the findings in Experiment 3. The marginal difference between the color and shape conditions could be due to a possible floor effect, as the discrimination accuracy in either condition was low (close to 0.6, chance = 0.5).

² We examined whether tiling direction of the matrix influenced boundary discrimination accuracy in this experiment. We found that when tiling direction was consistent with the boundary orientation, discrimination accuracy was overall higher than that when the directions were inconsistent ($p<.001$). Crucially, there was no interaction between tiling direction and conditions ($p=.25$). Thus, tiling direction did not systematically influence the differences between conditions.

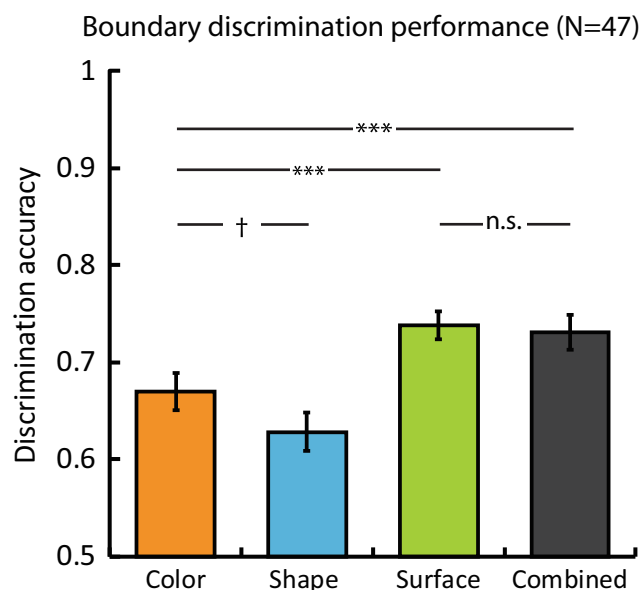


Fig. 4 Results in Experiment 4. Boundary discrimination accuracy in four conditions (error bars indicate ± 1 between-subjects SEM; *** $p<.001$)

To examine whether the improvements in discrimination accuracy were driven by a higher discrimination sensitivity or a shift in decision criterion, we calculated d' and criterion (c) in each condition using signal detection theory. We arbitrarily designated the vertical boundary as “target” and the horizontal boundary as “noise” (although the results would remain the same if the horizontal boundary was designated as “target”). The mean d' and c in each condition was the following: color: $d'=2.56$, $c=-0.51$; shape: $d'=1.88$, $c=-0.54$; surface: $d'=3.61$, $c=-0.50$; and combined: $d'=3.61$, $c=-0.47$. We then performed a repeated-measures ANOVA to compare d' across the four conditions. There was a significant difference in d' among the four conditions [$F(3,138)=20.39$, $p<.001$, $\eta_p^2=0.31$]. *Post hoc* Tukey HSD tests revealed that d' in the surface condition was reliably higher than in the color or shape conditions ($ps<.001$), and d' was marginally higher in the color condition than in the shape condition ($p=.07$). Moreover, d' in the combined condition was higher than in the color or shape conditions ($ps<.001$). Critically, d' in the combined condition was not different from that in the surface condition ($p=.96$).

In addition, we performed the same repeated-measures ANOVA to compare c across the four conditions. There was a significant difference in c among the four conditions [$F(3,138)=4.60$, $p<.01$, $\eta_p^2=0.09$], but *post hoc* Tukey HSD tests revealed that c was not significantly different between any conditions ($ps>.24$), except that c was higher in the combined condition than in the shape condition ($p=.02$).

These results are consistent with the dominance hypothesis and boundary discrimination accuracy, suggesting that discrimination performance was higher for combined and surface conditions than for color or shape conditions, and the changes

in performance were unlikely to have been driven by changes in criterion, except between combined and shape conditions.

Experiment 5

Experiments 1–4 demonstrated that the ability to detect regularities was identical when regularities were present in multiple feature dimensions and when regularities were present in only one dimension with the best discrimination performance. These results support the dominance hypothesis rather than the facilitation hypothesis. However, it remained possible that in the combined condition participants attended to only the more salient dimension and actively ignored the other less salient dimensions, rendering the combined condition equivalent to the single condition where regularities were only present in the most salient dimension.

To address this possibility, we now designed a different type of “combined condition” where regularities were present in two dimensions simultaneously as before, but the regularities in one dimension did not overlap with the regularities in another dimension in the structured half of the matrix. Specifically, the regularities in one dimension defined one boundary in the matrix, whereas the regularities in the other dimension defined the orthogonal boundary. We wanted to see which boundary participants chose as being more visible, as a reflection of which dimension was more salient. For example, the left half of the matrix was structured and the right half was random in the color dimension, but the top half of the matrix was structured and the bottom half was random in the shape dimension, and participants chose the vertical boundary as being more visible. This would suggest that the regularities in the color dimension looked more salient than the regularities in the shape dimension, indicating that the color dimension was more salient or dominant than the shape dimension. Because of this conflict, participants could not ignore a dimension and only focused on one dimension. They had to process the regularities in both dimensions and choose which boundary looked more visible. Importantly, we examined how people choose between the conflicting boundaries in two ways. In Experiment 5, there was one objectively more distinct boundary, which was defined by a larger difference in the switch rates between the structured half and the random half. In Experiment 6, there was no objectively more distinct boundary, because the difference in switch rates between the two halves was the same based on each division.

Participants

A new group of 47 undergraduate students (28 female, mean age=19.6 years, $SD=1.6$) participated for course credit.

Apparatus

In Experiments 5–7, the stimuli were presented using MATLAB and the Psychophysics Toolbox (<http://psycho toolbox.org>).

Stimuli

In each trial, a 30×30 matrix was presented as before, but now each matrix was always divided both horizontally and vertically by two separate dimensions (Fig. 5a). For each division, one half of the matrix was structured and the other half was random. One boundary was more distinct, where the structured half was determined by a binary sequence of $D(0)$ and the random half was determined by a random sequence of $D(0.5)$. The other boundary was less distinct, where the structured half was determined by a binary sequence of $D(0.07)^3$ and the random half was determined by a random sequence of $D(0.5)$. In other words, the difference in switch rates between the two halves was greater with the more distinct boundary (0 vs. 0.5) than with the less distinct boundary (0.07 vs. 0.5). The switch rate of the structured half was lower than that in previous experiments, because we wanted the two boundaries to be simultaneously detectable in the same matrix, and with the previous switch rate of 0.2 the two boundaries were too hard to see at the same time Fig. 6.

Importantly, one boundary was defined by $D(p)$ sequences, which determined the features on one dimension, and the other boundary was defined by $D(p)$ sequences, which determined the features on a different dimension. All $D(p)$ sequences were independently generated. There were three types of conflicts: color versus shape (Fig. 5b), surface versus color (Fig. 5c), and surface versus shape (Fig. 5d). As before, the tiling direction of the sequence in each half was randomly determined, independent from the boundary orientation, but was consistent across the two halves. The location of the structured half was randomly determined, and which boundary was more distinct was counterbalanced across trials.

Procedure

Since there were three types of conflicts, there were three within-subjects conditions. There were 40 trials for each condition, with 120 trials in total. For half of the trials in each condition, the more distinct boundary was defined by one feature dimension, and for the other half of the trials, the more distinct boundary was defined by the other feature dimension. In each trial, one matrix was presented for 2.5 s, and participants were told that there were two boundaries

³ We chose 0.07 based on previous pilot studies where we tried different switch rates ranging from 0.2 to 0.05. To avoid ceiling or floor effects for either dimension, we decided that 0.07 was the optimal level.

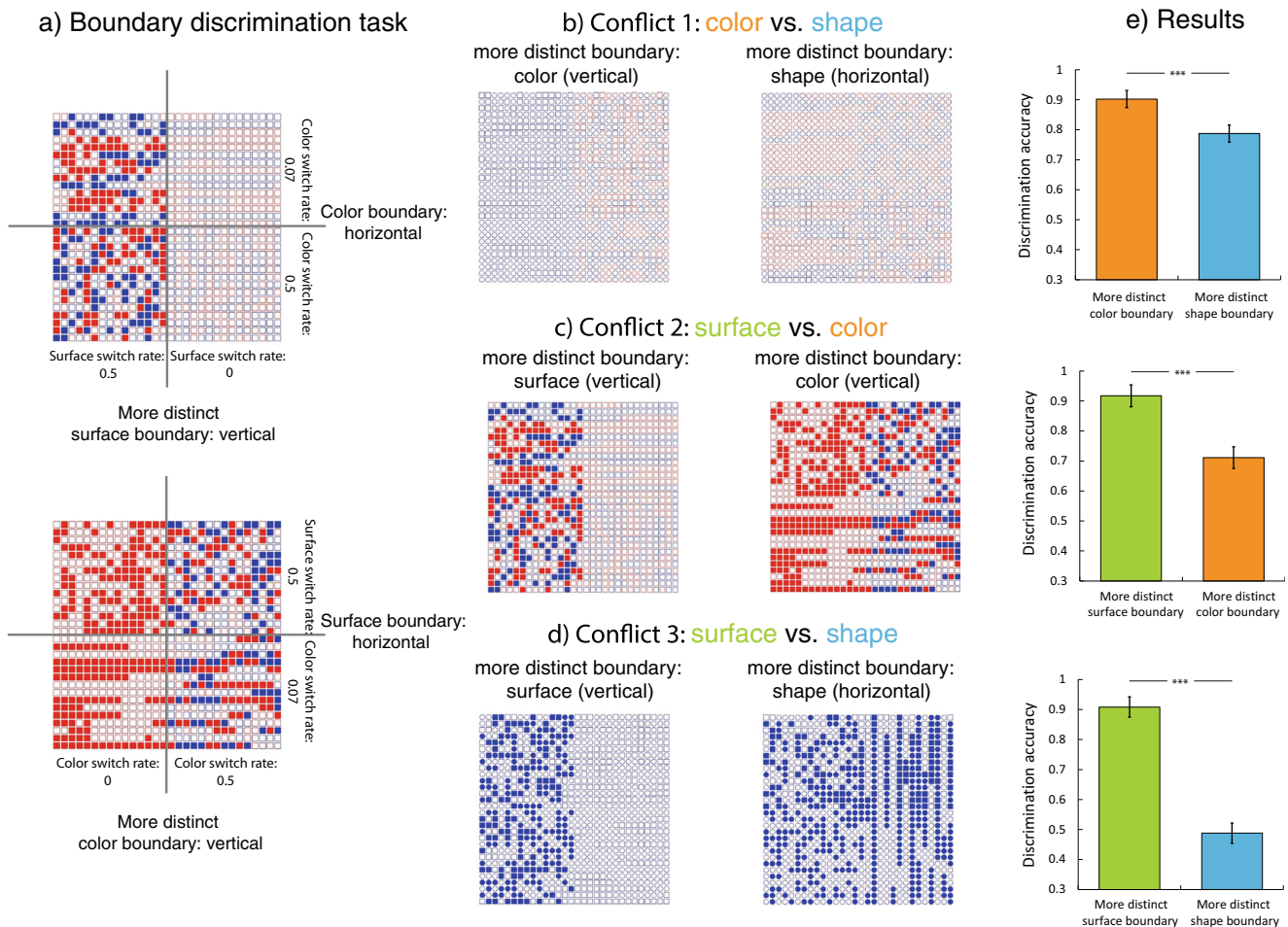


Fig. 5 Stimuli and results in Experiment 5. **(a)** Two sample matrices in the boundary choice task. In each matrix, there were two boundaries. One boundary was more distinct because the structured half was made by a sequence with a switch rate of 0 and the random half was made by a sequence with a switch rate of 0.5. The other boundary was less distinct because the structured half was made by a sequence with a switch rate of 0.07 and the random half had a switch rate of 0.5. Participants were asked to choose which boundary looked more visible to them. The two boundaries were defined by two different feature dimensions. SW stands for switch rate. **(b)** In the first type of conflict, the color dimension and the shape dimension created two conflicting boundaries. For half of the trials, color defined the more distinct boundary, and for the

other half of the trials, shape defined the more distinct boundary. **(c)** In the second type of conflict, the surface and color dimensions created two conflicting boundaries, with surface being the more distinct boundary half of the time and color being the more distinct boundary half of the time. **(d)** In the third type of conflict, the surface and shape dimensions created two conflicting boundaries, with surface being the more distinct boundary half of the time and shape being the more distinct boundary half of the time. **(e)** Accuracy in choosing the objectively more distinct boundary was calculated as the percent of times when participants chose the objectively more distinct boundary as more visible. The choice accuracy was shown for each type of conflict (error bars indicate ± 1 between-subjects SEM; *** $p < .001$)

in the matrix and their task was to choose which boundary (horizontal or vertical) looked more visible to them by pressing the “h” key for horizontal or the “v” key for vertical. Participants were not told anything about how the matrix was made or which half was structured.

Results and discussion

We calculated the accuracy of boundary choice as the percentage of times when participants chose the objectively more distinct boundary as more visible. The reason for using choice accuracy was that the boundary participants chose as being more visible reflects the greater ease with

which regularities were distinguished from randomness in that feature dimension, therefore suggesting that the dimension was more salient. The choice accuracy was presented for each type of conflict in Fig. 5e. We found that when the more distinct boundary was defined by the color dimension, participants were reliably more accurate in choosing the boundary as more visible than when the more distinct boundary was defined by the shape dimension [$t(46)=4.19, p < .001, d=0.62$]. When the more distinct boundary was defined by the surface dimension, participants were reliably more accurate in choosing the boundary as more visible, than when the more distinct boundary was defined by the color dimension [$t(46)=5.66, p < .001,$

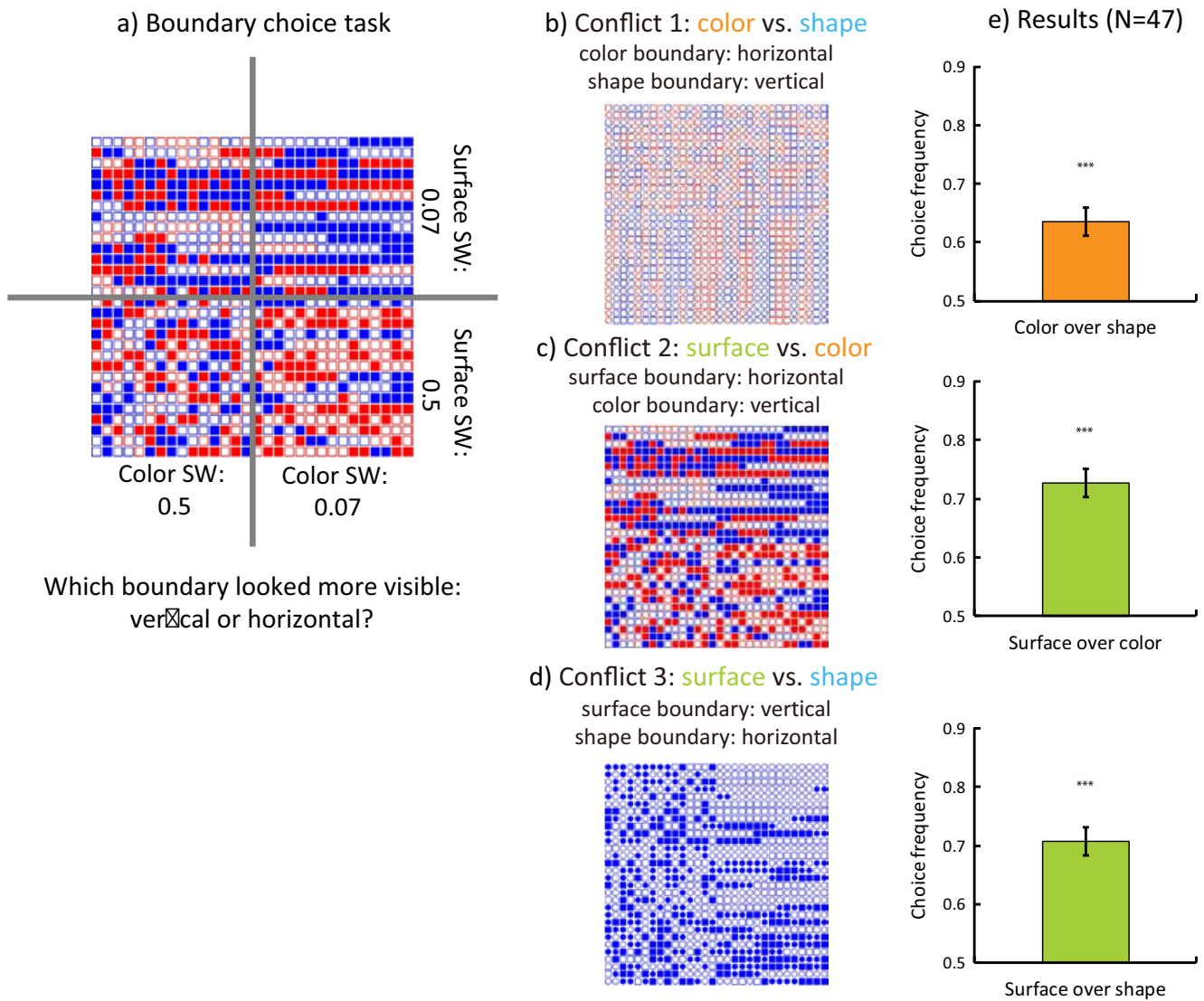


Fig. 6 Stimuli and results in Experiment 6. **(a)** Two sample matrices in the boundary choice task. In each matrix, there were two boundaries. Each boundary was separated by a structured half made by a sequence with a switch rate of 0.07 and the random half made by a sequence with a switch rate of 0.5. Participants were asked to choose which boundary looked more visible to them. The two boundaries were defined by two different feature dimensions. SW stands for switch rate. **(b)** In the first

type of conflict, the color dimension and the shape dimension created two conflicting boundaries. **(c)** In the second type of conflict, the surface and color dimensions created two conflicting boundaries. **(d)** In the third type of conflict, the surface and shape dimensions created two conflicting boundaries. **(e)** Choice frequency was calculated as the percent of times when participants chose one boundary over the other as more visible (error bars indicate ± 1 between-subjects SEM; *** $p < .001$)

$d=1.19$], or when the more distinct boundary was defined by the shape dimension [$t(46)=12.63$, $p < .001$, $d=2.63$].

These results showed that participants were better at detecting regularities in the surface dimension, even when there were competing regularities in the color or shape dimensions. They were also better at detecting regularities in the color dimension when there were competing regularities in the shape dimension. These findings were consistent with those in Experiments 1–4, suggesting that the perception of multi-dimensional regularities was driven by the most salient dimension.

Experiment 6

In Experiment 5, the matrix contained an objectively more distinct boundary that was defined by the greater difference in the switch rates between the two halves in one dimension. To assess the subjective experience of salience, in this experiment both boundaries were defined by the same difference in the switch rates, so there was no objective difference between the two boundaries. Participants were asked to choose the boundary that looked more visible to them.

Participants

A new group of 47 undergraduate students (30 female, mean age=20.4 years, $SD=2.2$) participated for course credit.

Stimuli and procedure

The stimuli and procedure were identical to those in Experiment 5, except that each boundary was separated by a structured half of $D(0.07)$ and a random sequence of $D(0.5)$. As before, participants were asked to choose which boundary (horizontal or vertical) looked more visible to them by pressing the “h” key for horizontal or the “v” key for vertical.

Results and discussion

We calculated choice frequency as the percent of times when participants chose one boundary over the other as being more visible. The reason to use choice frequency was that the boundary participants chose as being more visible reflects the greater subjective ease with which regularities were distinguished from randomness in that feature dimension, therefore suggesting that the dimension looked more salient. In the color versus shape condition, participants chose the boundary defined by the color dimension over shape for 63% of the time, reliably higher than chance [$t(46)=5.51$, $p<.001$, $d=0.80$]. In the color versus surface condition, participants chose surface over color for 72% of the time, again reliably higher than chance [$t(46)=9.16$, $p<.001$, $d=1.42$]. In the shape versus surface condition, participants chose surface over shape for 71% of the time, again reliably higher than chance [$t(46)=8.48$, $p<.001$, $d=1.24$]. These results were consistent with the findings in Experiment 5, suggesting that the surface dimension was the most salient, followed by the color dimension, which was followed by the shape dimension.

Experiment 7

Experiments 1–4 demonstrated that when regularities were present in multiple dimensions the ability to detect regularities was the same as when regularities were present in the most salient dimension. These results support the dominance hypothesis rather than the facilitation hypothesis. The current experiment aimed to offer a more direct measure of salience and a quantitative assessment of the relationship between salience and regularities perception. Specifically, we examined the correlation between perceptual salience (the discriminability of two feature values in a dimension) and boundary discrimination accuracy in that dimension.

Participants

This experiment was conducted with the same group of participants in Experiment 4 ($N=47$, 35 female, mean age=19.8 years, $SD=2.8$). This allowed us to obtain the boundary discrimination accuracy and the salience measure (described below) from the same participant in order to run the correlation analysis. Each participant completed both experiments, with the order of the experiments counter-balanced across participants.

Stimuli and procedure

The stimuli contained two objects per trial. Each object subtended 0.5° of visual angle and were separated by 5° of visual angle (Fig. 7a). For half of the trials, the two objects were either the same in all three dimensions (color, shape, or surface), and for the other half of the trials, the two objects were different in only one of the three dimensions: red or blue in the color dimension, circle or square in the shape dimension, and filled or hollow in the surface dimension (Fig. 7b). The frequency of each feature value was the same. This resulted in four within-subjects conditions: (1) color condition where the two objects only differed in the color dimension, (2) shape condition where the two objects only differed in the shape dimension, (3) surface condition where the two objects only differed in the surface dimension, and (4) the same condition where the two objects were the same. There were 192 trials in total, and the order of the trials was randomized for each participant.

For each trial, there was a fixation cross at the center of the screen and participants were asked to maintain fixation while performing a judgment task: judging whether the two objects were the same or different as quickly and accurately as they could. The two objects were forward and backward masked by a white noise subtending 2° of visual angle. Each mask lasted for 1,000 ms on the screen and immediately preceded or followed the two objects. The objects were presented simultaneously on the screen for 17 ms.

Results and discussion

We calculated the accuracy for each participant on the judgment task. The reason for using accuracy was that it reflects the ease with which different feature values were discriminated in that feature dimension, therefore suggesting that the dimension was more salient. Using a one-way repeated measures ANOVA, we found a significant difference in accuracy across the four conditions [$F(3,138)=55.51$, $p<.001$, $\eta_p^2=0.55$]. *Post hoc* Tukey HSD tests revealed that the accuracy in the surface condition was higher than that in any other conditions ($ps<.01$). The accuracy in the color condition was also higher than that in the shape condition ($p<.001$). These results were consistent with the previous findings that the surface dimension was more salient than

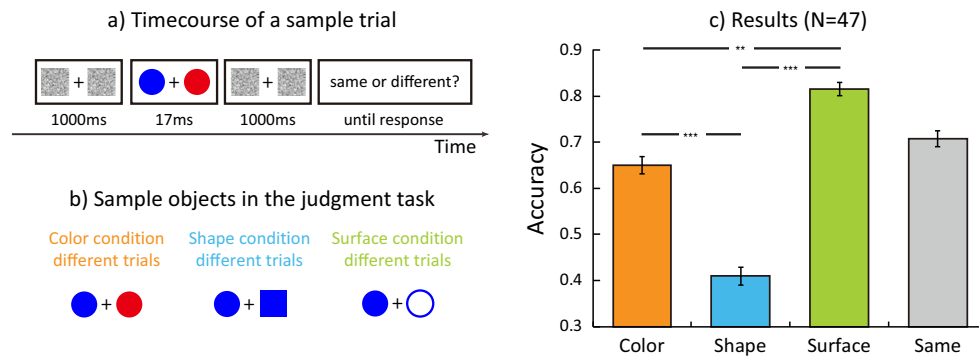


Fig. 7 Stimuli and results in Experiment 7. **(a)** In each trial, two objects were presented on the screen which were either the same or different. Participants were asked judge whether the objects were the same or different as quickly and accurately as they could. **(b)** The two objects were identical in half of the

trials and different in the other half of the trials, where they differed only in one dimension (color, shape, or surface). The objects are not drawn to scale. **(c)** Accuracy was presented in each condition (error bars indicate ± 1 between-subjects SEM; ** $p < .01$, *** $p < .001$)

color or shape dimensions, and the color dimension was more salient than the shape dimension.

Moreover, we correlated the boundary discrimination accuracy in Experiment 4 with the accuracy in the current experiment for each feature dimension. We found a positive correlation between boundary discrimination accuracy and the current accuracy in the surface condition [$r(45) = .26$, $p = .04$]. The discrimination accuracy in the combined condition in Experiment 4 also correlated with the current accuracy in the surface condition [$r(45) = .34$, $p = .01$]. However, no correlations were significant in the color condition [$r(45) = .05$, $p = .37$] or the shape condition [$r(45) = .04$, $p = .39$]. The lack of correlations in the color or shape dimension could be due to the difficulty of the feature discrimination task, since the accuracy in each dimension was relatively low. These findings provide partial support for the relationship between feature discriminability and boundary discrimination performance.

Experiment 8

Since Experiment 7 used a masked discrimination paradigm, the results could be due to differences in the effectiveness of the mask for the three feature dimensions (i.e., the surface dimension may be masked more weakly than the color or shape dimensions). As a more direct test of salience of different feature dimensions, the final experiment used a conventional visual search paradigm where participants searched for a target that differed from the distractors in one of the three feature dimensions (e.g., searching for a blue square among red squares).⁴ We used response time (RT) for each dimension as the measure of salience. We examined the slope of RTs over different set sizes as a measure of salience. We predict that more salient feature dimensions will have shallower RT slopes.

⁴ We thank an anonymous reviewer for suggesting this experiment.

Participants

A new group of 30 undergraduate students from UBC (23 female, mean age = 20.3 years, SD = 1.9) participated in the experiment for course credit.

Stimuli and procedure

We used a visual search paradigm, where participants searched for a target among distractors in each trial and judged whether the target was present or absent as quickly and accurately as possible. The target differed from the distractors only in one feature dimension and the two feature values in a given dimension were the same as in previous experiments (e.g., a blue square among red squares for the color dimension, or a blue circle among blue squares for the shape dimension).

There were 450 trials in total. The number of objects in each trial (set size) was 10, 20, or 30 (150 trials per set size). For each set size, there were three conditions (50 trials per condition). In the color condition, the objects in the search array were blue or red squares as in Experiments 1–4. For target-present trials (25 trials), the target differed from the distractors only in the color dimension (e.g., a blue square among red squares). For target-absent trials (25 trials), all objects were identical (e.g., all red squares). Likewise in the shape condition, the objects were circles and squares of the same color as in Experiments 1–4, and the target differed from the distractors only in the shape dimension (e.g., a blue circle among blue squares). In the surface condition, the objects were hollow or filled objects in Experiments 1–4, and the target differed from the distractors only in the surface dimension (e.g., a red hollow circle among red filled circles).

Participants were told the target was an oddball that differed from the rest of the objects. For each trial, they judged whether the target was present or absent as quickly and accurately as possible. If the target was present, participants pressed the “p” key; if the target was absent (all objects were

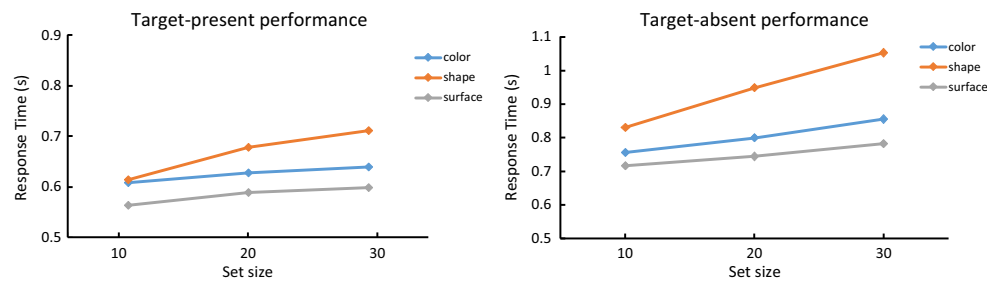


Fig. 8 Target search performance. The average response times across the three set sizes were shown for target-present trials (left) and target-absent trials (right)

identical), participants pressed the “a” key. The search array remained on the screen until response.

Results and discussion

The overall accuracy in the search task was 0.99. Therefore, we used RT of correct trials to measure the salience of different feature dimensions. The average RT in each condition for target-present and target-absent trials across set sizes were plotted in Fig. 8.

A 3 (condition: color, shape, and surface) \times 2 (target presence: present and absent) \times 3 (set size: 10, 20, and 30) repeated-measures ANOVA revealed that there was a main effect of set size [$F(2,58)=32.81, p<.001, \eta_p^2=0.53$], suggesting that RT was higher for larger set sizes. There was a main effect of target presence [$F(1,29)=22.91, p<.001, \eta_p^2=0.44$], suggesting RT was higher for target-absent trials. There was a marginal main effect of condition [$F(1,29)=2.88, p=.06, \eta_p^2=0.09$], suggesting RT was marginally lower in the surface condition. There was no significant three-way interaction among condition, target presence, and set size [$F(2,58)=0.804, p=.452, \eta_p^2=0.027$].

To separately examine target-present and target-absent trials, we conducted a 3 (condition) \times 3 (set size) repeated-measures ANOVA for each trial type. For target-present trials, there was a significant two-way interaction between condition and set size [$F(2,58)=6.89, p<.01, \eta_p^2=0.19$], suggesting that RT increased more with set size for the shape dimension than other dimensions. *Post hoc* Tukey HSD tests revealed that RT was reliably lower in the surface condition than in the shape condition ($p=.03$), and other pair-wise comparisons were not reliable ($ps>.4$). For target-absent trials, there was also a significant two-way interaction between condition and set size [$F(2,58)=3.26, p<.05, \eta_p^2=0.10$]. *Post hoc* Tukey HSD tests revealed that RT was reliably lower in the surface condition than in the shape condition ($p=.04$), and other pair-wise comparisons were not reliable ($ps>.1$).

We computed the slope of RT as a function of set size. For target-present trials, the slope was 1.56 ms/item for the color condition, 4.80 ms/item for the shape condition, and 1.80 ms/item for the surface condition. For target-absent trials, the slope was 5.04 ms/item for the color condition, 11.10 ms/item for the shape condition, and 3.29 ms/item for the surface condition.

Across all trials, the slope was 3.30 ms/item for the color condition, 7.95 ms/item for the shape condition, and 2.54 ms/item for the surface condition. These results suggested that RT in the surface condition slowed the least with increasing set sizes, and RT in the shape condition slowed the most with increasing set sizes. Taken together, these results suggested that the surface dimension was the most salient among other feature dimensions, consistent with the findings in previous experiments.

General discussion

The current study aimed to examine the perception of regularities in multiple feature dimensions. We found that discrimination accuracy between the structured half and the random half of the matrix was higher when regularities were present in the color dimension than in the shape dimension, but the accuracy was the same when regularities were present in the color dimension alone or in both dimensions (Experiment 1). This result can be explained by the selective processing of regularities in the color dimension over the shape dimension (Experiment 2). By adding a third surface dimension, we found that discrimination accuracy was higher when regularities were present in the surface dimension than in the color dimension, but the accuracy was the same when regularities were present in the surface dimension alone or in all three dimensions (Experiments 3 and 4). Moreover, when there were two conflicting boundaries separately defined by two different dimensions, participants chose the boundary defined by the surface dimension, followed by the color dimension, as more visible than the shape dimension (Experiments 5 and 6). Moreover, participants were better at discriminating differences in the surface dimension, followed by the color dimension, than in the shape dimension (Experiment 7), which can partially explain the findings in Experiments 1–4. Finally, participants were faster in the visual search task when the target differed from the distractors in the surface dimension, followed by color or shape dimensions (Experiment 8). These results collectively suggest that the perception of regularities in multiple dimensions is driven by the presence of regularities in the most salient feature dimension.

It is important to note that in Experiments 1 and 3, each dimension contained the same number of regularities. That is, for all matrices, the structured half contained a sequence with a

switch rate of 0.2 and the random half contained a random sequence with a switch rate of 0.5. This was true for the color, the shape, and the surface dimensions. Thus, there was no objective difference in the amount of information available between the dimensions, and yet participants were better at detecting regularities from randomness in the color dimension than in the shape dimension, and better in the surface dimension than in the color or shape dimension. Furthermore, when both feature dimensions contained the same number of regularities, participants chose the boundary in the more salient dimension as more visible (Experiment 6). This suggests that the perception of regularities depends on not only the information available in each dimension, but also the perceptual salience of the features in that dimension.

The current findings support the dominance hypothesis over the facilitation hypothesis. That is, the detection of regularities from multiple dimensions is dominated by the presence of regularities in the most salient dimension, rather than facilitated by the presence of regularities in all dimensions. In other words, the presence of regularities in other less salient dimensions does not seem to further help with the detection of regularities. It is worth noting that in the combined condition in Experiment 1, the structured half contained twice as many regularities as that in the color or shape conditions. In the combined condition in Experiment 3, the structured half contained three times as many regularities as that in the color, shape, or surface conditions. This is because the cells in the combined condition was determined by two or three independent binary sequences of $D(0.2)$ on separate feature dimensions. This means that cells in the structured half contained regularities independently in multiple feature dimensions. The fact that the sequences were independent means that features in one dimension could not predict features in a different dimension. For an ideal observer, performance in the combined condition should be, in principle, higher than that in the color, shape, or surface conditions alone. However, for human observers, despite the greater number of regularities in the combined condition, they still performed at the same level as when regularities were present in one dimension only. This suggests a bottleneck in the perceptual integration of regularities from multiple feature dimensions. This integration bottleneck could be due to the presence of regularities in the most salient dimension. These experiments suggest that people prioritized regularities in the most salient dimension when multiple dimensions contained regularities. This raises the possibility that people may not be able to attend to or process the regularities in other less salient dimensions.

Our manipulation of regularities results in longer streaks in the structured half of the matrix. In fact, the structured half often looks more chunky than the random half, which leads to stronger contrasts between the features in one dimension (Itti et al., 1998; Itti & Koch, 1999; Li, Levine, An, Xu, & He, 2013). Moreover, the visual contrast of hollow and solid cells in the surface dimension seemed greater than that in the color or shape dimension, which may have contributed to the greater salience of the surface dimension, resulting in the

prioritization of that feature dimension (Maunsell & Treue, 2006; Saenz, Buracas, & Boynton, 2002).

One limitation of the current study is that we used only two feature values in each dimension (e.g., red and blue in the color dimension). In future extensions of this work, the paradigm can contain other feature values (e.g., yellow vs. blue, square vs. diamond) to test whether the effects would hold with other contrast features. Based on the current experiments, we predict that the more discriminable the two features are in a given dimension, the more salient the regularities are, therefore the easier it is to detect the regularities in that dimension. For example, if the color dimension contained pink and red, which may be less discriminable than blue and red, the color dominance over shape may diminish. Future studies can investigate how discriminability of features determines the ability to detect regularities in a given dimension. By systematically varying the level of discriminability between features (e.g., a matrix with black and white cells vs. a matrix with black and gray cells). Finally, salience was measured as the perceptual discriminability between two objects in Experiment 7, and as the search time for an oddball target in Experiment 8. Alternative measures could use other feature-based attention tasks (e.g., Nothelfer, Gleicher & Franconeri, 2017) to measure salience.

In conclusion, the current study suggests that the perception of regularities from multiple feature dimensions is driven by the presence of regularities in the most salient dimension.

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