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Perceptual Organization in Vision: Emergent Features in Two-Line Space

by

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Abstract

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What exactly are the "parts" that make up the whole object, and how and when do they group? The answer that is proposed hinges on Emergent Features: features that materialize from the configuration which make the object more discriminable from other objects. EFs are not possessed by any individual part and are processed as or more quickly than are the properties of the parts. The present experiments focus on visual discrimination of two-line configurations in an odd-quadrant task. RT data were obtained and compared with a prediction based on the number of EF differences in the odd quadrant (the higher the number of EF differences, the faster the discrimination was predicted). The results suggest that the EFs most responsible for the variations in RT might be lateral endpoint offset, intersections, parallelism, connectivity, number of terminators, and pixel count. Future directions include investigating the individual contributions and salience of EFs.

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Introduction

Gestalt psychologists have tried to understand how things humans see in the world are translated into perceptually-organized objects. Just thinking about the vast number of objects and their parts present in the visual environment, it is a wonder that our perceptual systems can accurately parse the relevant from the irrelevant in order to make sense of the world. It has been proposed that this process happens by the analysis of different parts or features which group together to make up the objects. For instance, Neisser (1967) proposed a two-stage system of perception: first, a pre-attentive process registers the basic features of an object; second, an attention-demanding process integrates the basic features into objects. Another example is Treisman's Feature Integration theory (Treisman & Gelade, 1980), which states that individual features, or parts, of an object are massed together during a task of visual search. However, these approaches have been vague or inconsistent in defining exactly what makes a "part."

One way to define the relationship between different parts of an object is to look at the Emergent Features (EFs) of that shape. EFs are features that result from the nonadditive combination of simple elements, and it is hypothesized that the presence of an EF diagnoses grouping. More specifically, an EF is defined as a salient property of an object, that does not appear in any of the individual elements but materializes only as the elements come together to form the new object. Moreover, EFs are processed as or even more quickly than are the properties of the individual parts.

Non-additivity refers simply to the fact that stimulus A, when presented together with stimulus B, does not simply make up a stimulus of A+B, but a completely or at least partly new stimulus, C. Some examples of such EFs are orientation, symmetry, closure, parallelism, and number of terminators (or end points).

Presumably, a cluster of elements is more likely to form an object if salient features (EFs) emerge from the configuration. An object possessing many EFs is, therefore, more salient in a field of other objects lacking those EFs. Moreover, certain EFs might be more salient to the visual system than others. For example, it has been shown that proximity seems to be a particularly salient EF, while there was inconsistent support for symmetry as an EF (Portillo, 2006). Evidence for these results can be obtained by studying Configural Superiority Effects (CSEs) and Configural Inferiority Effects (CIEs). The phenomenon of these effects becomes evident during a task of visual discrimination. For example, the task involves making a discrimination between base images A and B. Then, a third image (context) C is added to both A and B, producing novel stimuli AC and BC. In most cases, adding the third image dilutes the differences between both images A and B, making the discrimination between the composite stimuli AC and BC harder than between A and B alone. Adding a context also increases total processing load, increases the chances that perceivers will attend to the wrong element, and increases the chances that the context will either mask or crowd the target. This is termed a Configural Inferiority Effect (CIE), because the composite stimuli are significantly harder to discriminate in comparison to the base images. However, in certain cases the stimuli will group together to form an EF which is highly salient to the visual system, thus producing a CSE. When this effect is present, the discrimination task on the novel, composite stimuli will become significantly easier as evidenced by reaction time to make the discrimination.

Treisman and Paterson (1984) studied the CSE of arrows and triangles, which is a very powerful effect (Figure 1). Some other stimuli producing CSEs and CIEs were identified and studied also by Pomerantz et al. (1977) (for selected examples, see Figure 2). The question with stimuli producing CSEs is always what makes the odd quadrant so easy to tell apart from the other three? In essence, this boils down to the question of what are the feature differences between the quadrants? In the example of the arrow and triangle, it could be said that the arrow has just a single fork intersection, whereas the triangle has three V-intersections, and the triangle in turn has closure which is lacking in the arrow. Alternatively, it could be a terminator difference (the arrow has 3 end-points, while the triangle has none), or even pointing (the arrow indicates direction and the triangle doesn't, or, at least, not as well). However, these questions require a more principled approach with simpler stimuli to un-confound the multiple differences; apparently, stimuli such as arrows and triangles are already too complex.

More recently, Portillo (2006) studied the EFs of dot patterns. Studying dots has the great advantage that dots seem to be the simplest stimuli that can be created or perceived. They can also be manipulated by changing the position of a single

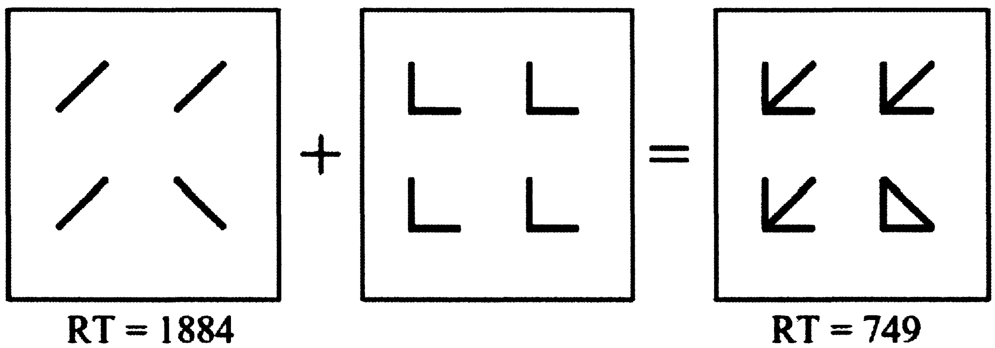


Figure 1 : Triangle and arrow CSE

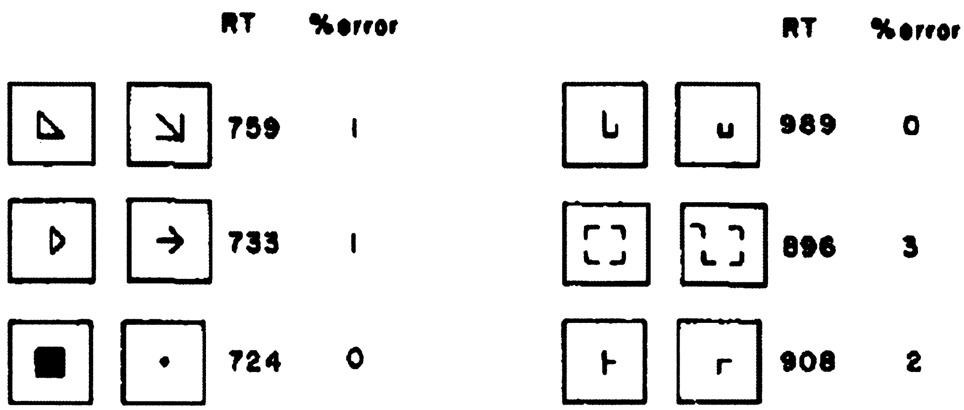


Figure 2 : Examples of other CSEs

dot while minimizing the number of unintended, confounded changes in the stimulus. However, the features that can be studied with dots are limited. For instance, Portillo studied properties such as proximity (the distance between two dots), orientation (the angle of one dot in relation to the other), linearity (whether three or more dots fall on a straight line), and surroundedness (whether one dot appears to be "surrounded" by three or more others in the sense of falling with their convex hull). In order to study more possible Emergent Features, it is necessary to move to the next most simple stimulus than a dot: a straight line segment.

With lines it is also possible to study proximity and orientation, but now there appear to be also new features: number of terminators (how many endpoints the figure has), collinearity (the degree to which two lines appear to be, or actually are in line with each other), symmetry, parallelism, lateral endpoint offset (the extent to which the end-points of two parallel lines are in line with each other) and number of intersections in the figure. With three or more lines, the additional features of closure (closed figure or open), area, zigzag, and inside/outside (whether a line is inside of a closed figure or outside when there are four or more lines) can be seen. Figure 3 enumerates these properties of dots and lines. Some preliminary work has been done with lines (Portillo, 2006), but since then simple stimuli have not been well-studied.

The following experiments represent an attempt to study and define the relationship between the different elements of an object by focusing on the EFs of that object. In order to make sure that only those features which are studied are present (i.e. no confounded variables are present), and also to make the experiments manageable, the focus of these experiments is on stimuli made up of just two line segments. Thus, by being systematic and adequately sampling the stimulus space, empirical support can be shown for Emergent Features such as parallelism, symmetry, collinearity, number of terminators, and others.

In Experiment 1, eight EFs were investigated. A model for predicting effective grouping via EFs was developed. Experiment 2 served as a replication of Experiment

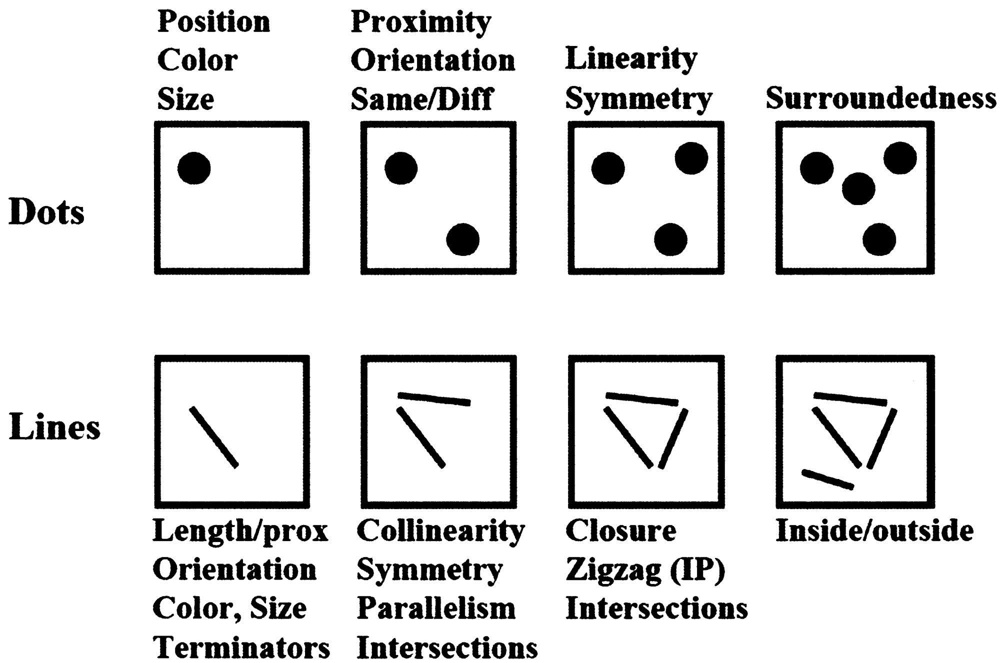


Figure 3 : EF Properties of Dot and Line Patterns

1, and a validation for the predictive model. In addition, Experiment 2 addressed many limitations of Experiment 1, as well as was able to inform the discussion of CSE/CIE effects.

Experiment 1

Participants

41 undergraduates (29 female; mean age 18.78) from Rice University took part in the experiment. They were compensated with participation credit, which partially fulfills course requirements.

Materials and Methods

Odd Quadrant Task

Visual discriminations were made in the context of an odd-quad task. This task consists of a display that is divided into four quadrants, each of which contains one of two images: three of these images will be identical, with the odd image being the target (Figure 4 shows an example of an arrangement that the participants saw). Participants then judged which of the four quadrants contained the odd image by touching the appropriate image on a touch-screen computer monitor as quickly and accurately as possible. Reaction time (RT) and accuracy were measured.

Test Setup

Stimuli were generated by a computer drawing package (Corel Draw or Photoshop), and then converted to bitmap files. A programming package developed for psychological experimentation (E-Prime) was used to generate and run the experiment, as

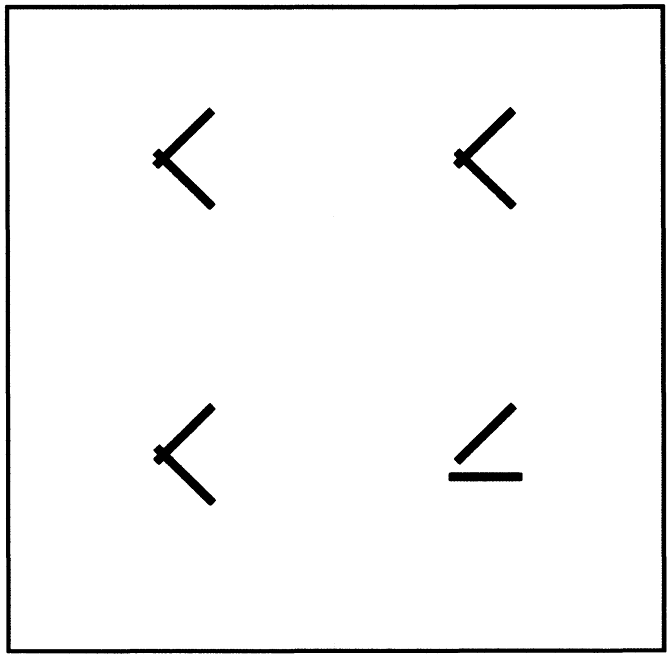


Figure 4 : Screenshot of Display in Odd-Quadrant Task

well as to collect RT, and other, data. The measurement accuracy obtained was to the millisecond level.

The size of the touch-screen monitor was $15''$ diagonally. Participants viewed the screen from a distance of approximately $15''$. They were allowed to move around during the experiment, so it is possible that the viewing distance varied for all participants (most likely between $12''$ and $17''$). The size of each individual image in each quadrant was between $1''$ and $3''$ in size diagonally (depending on the particular configuration of the line segments).

Stimuli

The procedure for mapping out a stimulus space has been hinted at by Shepard and Cermak (1973). A context, which does not add any extra information because it is the same for all four quadrants, was added to the stimuli (Figure 5). A space of composite stimuli is then created by systematically moving the context horizontally and vertically so as to sample uniformly a portion of the possible space of this type of stimulus (Figure 6).

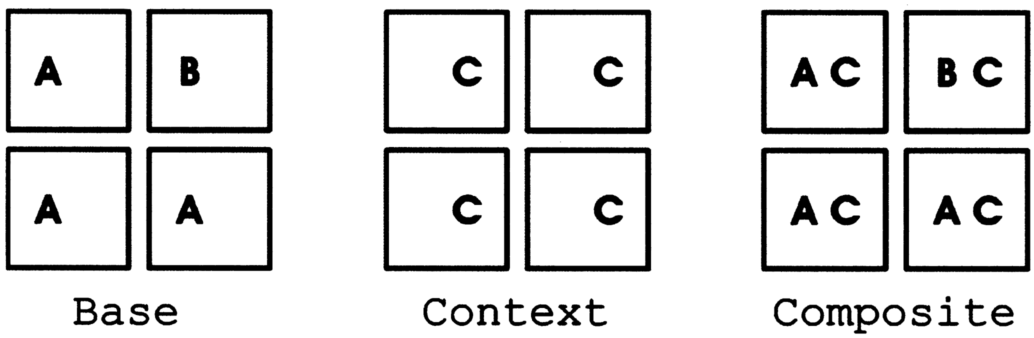


Figure 5 : Generation of Stimuli in an Odd-Quadrant Task

Using this technique, 48 such stimulus spaces were mapped out, using 2 line segments in varying orientations: horizontal, vertical, positively-sloped and negatively-sloped diagonals. Each stimulus space consisted of 169 stimuli in a 13x13 grid. Each stimulus is denoted by its x and y coordinates within the space. Figure 7 shows all the possible combinations using varying orientations of 2 line segments.

In Experiment 1, the focus was limited to the study of the combinations produced by combining Bases 1 and 2 with Contexts A, B, and C, thus generating six stimulus spaces. Search asymmetry (Treisman & Souther, 1985) was included as a factor by

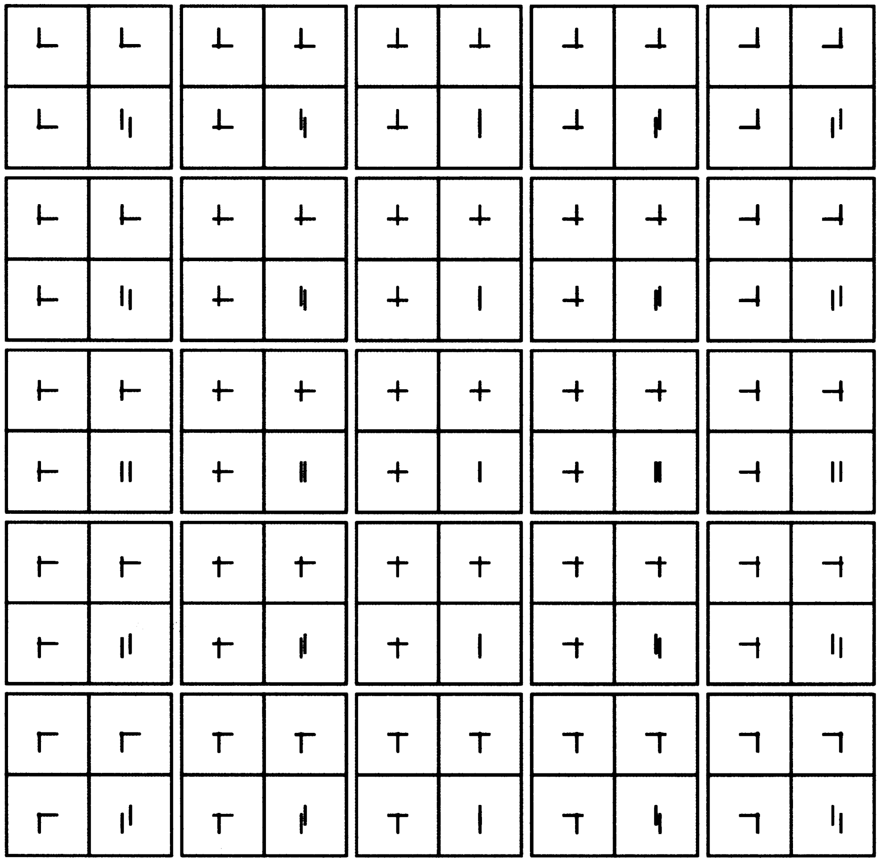


Figure 6 : A Sample of 2-line Space

including both Base 1 and Base 2 (horizontal line in a field of verticals, and vice versa). Table 1 shows a graphic representation of the stimulus spaces investigated in Experiment 1, and the entire spaces can be found in Appendix A (Figures 33-44).

Due to the large amount of time it would take for a participant to be run through all (169 x 6 = 1014) stimuli, the six spaces were each divided into 4 regions. Spaces 1A, 2A, 1B and 2B were each divided into four regions. Spaces 1C and 2C were each divided in half. These divisions produced 4 versions of the experiment, and they are

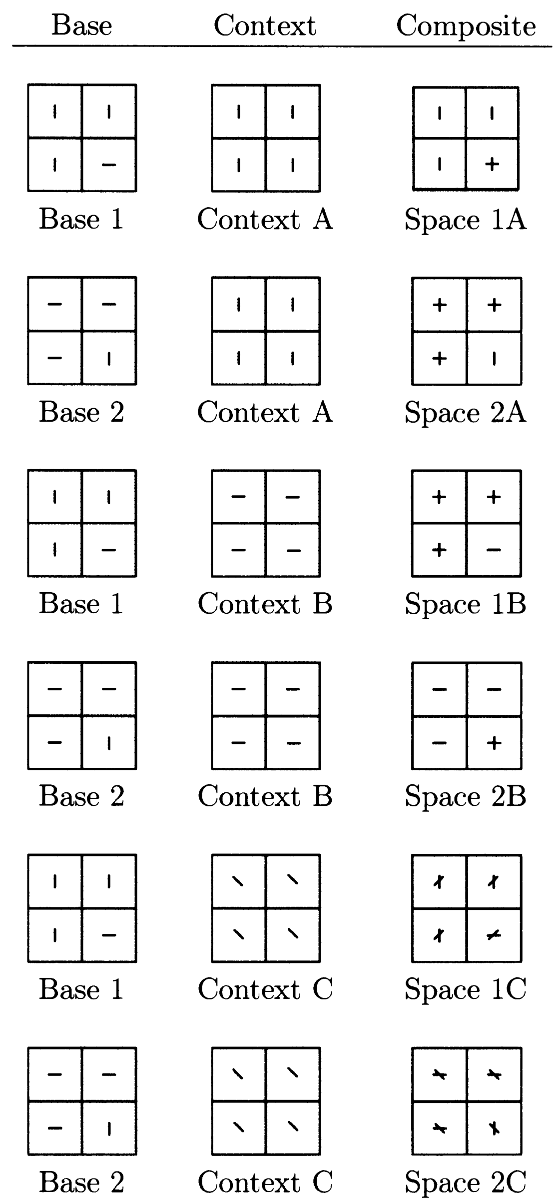


Table 1 : Stimulus Spaces - Experiment 1

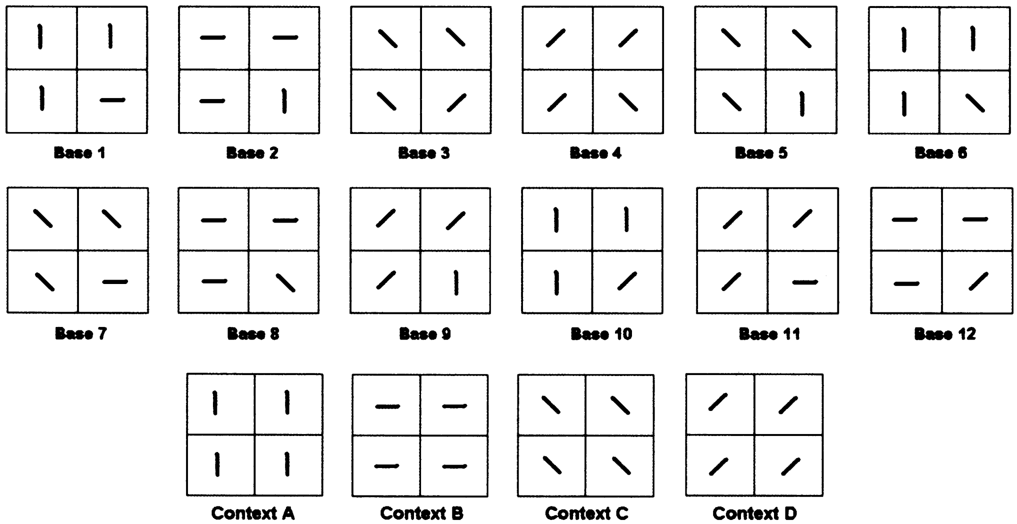


Figure 7 : Combinations of Possible Bases and Contexts

graphically represented in Figure 8. Versions were counterbalanced between subjects. This division was based on the fact that the grid of stimuli is symmetrical along the horizontal and vertical axes in the case of Spaces 1A, 2A, 1B and 2B, and along the vertical axis for Spaces 1C and 2C. It is expected that the symmetrical groups of stimuli would have comparable features and feature differences, and thus similar RTs for the discrimination. Therefore, it would be unnecessary for any one subject to be tested with the full stimulus space.

Prediction Maps

Prediction maps were generated for each stimulus space, based on the differential absence or presence of the features of interest. These predictions assumed that the relationship between EFs and RT was inversely proportional: that is, the greater the

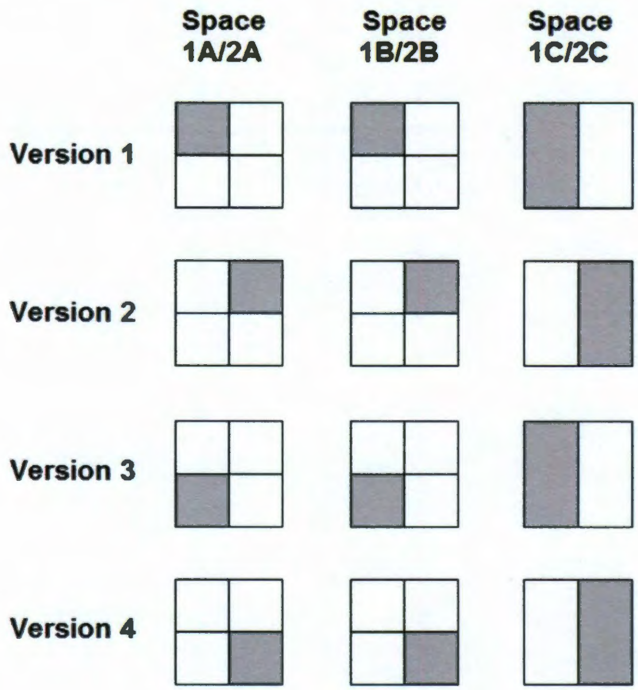


Figure 8 : Versions of Experiment 1

number of EF differences between the odd quadrant and the other three quadrants, the better performance should be (as evidenced by lower RTs). Prediction maps were used to test whether any or all of the features listed above contributed significantly to any changes in RT among the stimuli by means of correlation analysis.

The included EFs are described in Appendix B, and are: number of terminators (or endpoints) on the image, collinearity (whether two line segments fall in a straight line), symmetry (in this case only axial symmetry is taken into account), parallelism (whether two lines are parallel or not), lateral endpoint offset (the extent to which the endpoints of two parallel line segments begin and end together – more specifically, the position in space of the two sets of terminators on the segments of parallel lines is compared), intersections (whether the two line segments intersect or not), connectivity (whether the two line segments are touching or not), and pixel count (the number of black pixels making up the image). In addition, all spaces were scored on spatial proximity. This score is a direct manifestation of the method of generating stimulus spaces (described earlier), and it reflects the distance between the midpoints of the two line segments according to their position (the x and y coordinates) in the stimulus space. Proximity scoring was identical for all spaces and served as a multiplier for the EFs of parallelism and symmetry. Proximity is one of the primary Gestalt grouping principles (e.g., Hochberg et al. (1956), Kubovy (1994), Pomerantz and Schwaitzberg (1975)), and thus it follows that the spatial distance between two line segments would influence their grouping, and, as an extension, the EF difference scores in the prediction model.

Prediction map scoring for this experiment was assigned post-hoc. The scoring criteria for each EF were assigned in such a way so that the relationship between the EF scoring and the RT data was negative. For example, it was hypothesized that the greater the number of terminator differences between the odd and the other three quadrants, the higher the EF prediction score, and the lower the RT. For the sake of parsimony, scoring was based on a three-tier system: the display was scored as "0" if there were no feature differences between the target quadrant and the other three, or if the feature was not present in any quadrant; it was scored as "0.5" if the

EF was absent in the odd quadrant but present in the other three; finally, a score of "1" was awarded if the target (odd) quadrant differed from the other three on a particular Emergent Feature. The exception to this system was lateral endpoint offset, which was scored on a continuum from "0" to "1" in "0.2" increments based on the amount of overlap between the line segments. For full instructions on scoring, see Appendix C. Total scores for each display were computed by adding across all individual Emergent Feature scores. For the sake of parsimony, all EFs were assigned a weight of 1. The final score was then subtracted from a total possible score (in this case, if all the EFs received a score of 1, the total score would be 8). This was done to reverse the relationship between the EF scores and RT, so that it now became positive. Looking at the positive instead of the negative relationship facilitates presentation of the data, and the data will be referred to in this manner for the rest of this paper. The prediction maps were linearly transformed to match the RT data mean and standard deviation for the purposes of representing the EF difference scores in meaningful units (ms), and also facilitate graphical representation of the two maps.

Results

The means, standard deviations, and accuracy data are presented in Table 2. Spaces 1A, 2A, 1B and 2B were similar in difficulty, and Spaces 1C and 2C were harder, as evidenced by the higher mean reaction time and lower average accuracy.

The surface plots of mean RT for all stimuli, by space, are presented in Figures 9 -

Space	Mean (ms)	SD (ms)	Mean Accuracy
1A	915	278	0.97
2A	1061	309	0.94
1B	1048	318	0.95
2B	924	280	0.97
1C	1349	429	0.92
2C	1334	421	0.91

Table 2 : Means, Standard Deviations, and Mean Accuracy - Experiment 1

14. The x and y axes, labeled "X-Coordinate" and "Y-Coordinate" refer to the stimulus position in the space (see Appendix A). RT is presented on the z-axis, in ms. In addition to the RT data and the prediction map, a "difference" map is also presented. This difference graph is the subtraction of the predicted RTs from the obtained RTs. In other words, the difference map is a graphical representation of the variance in RT that was not accounted for by the prediction model.

Repeated measures ANOVA analyses were performed on the RT data "surfaces" to determine whether RT differed based on the position of the stimulus within the space (x- and y-coordinate interaction effect is reported). Because of the experimental design, any given participant was tested on only 1/4th of spaces 1A, 2A, 1B and 2B, and 1/2 of spaces 1C and 2C. Therefore, the repeated measures ANOVA analysis was conducted by 1/4-space at a time for spaces 1A, 2A, 1B, and 2B, and 1/2-space at a time for spaces 1C and 2C. In the cases where fractional degrees of freedom are reported, the F and p values were corrected for violations of sphericity using the Greenhouse-Geisser correction.

A multiple regression analysis was performed on the RTs averaged across subjects for each space, correlating the RT data with prediction scores using the 8 individual EF scores as predictors.

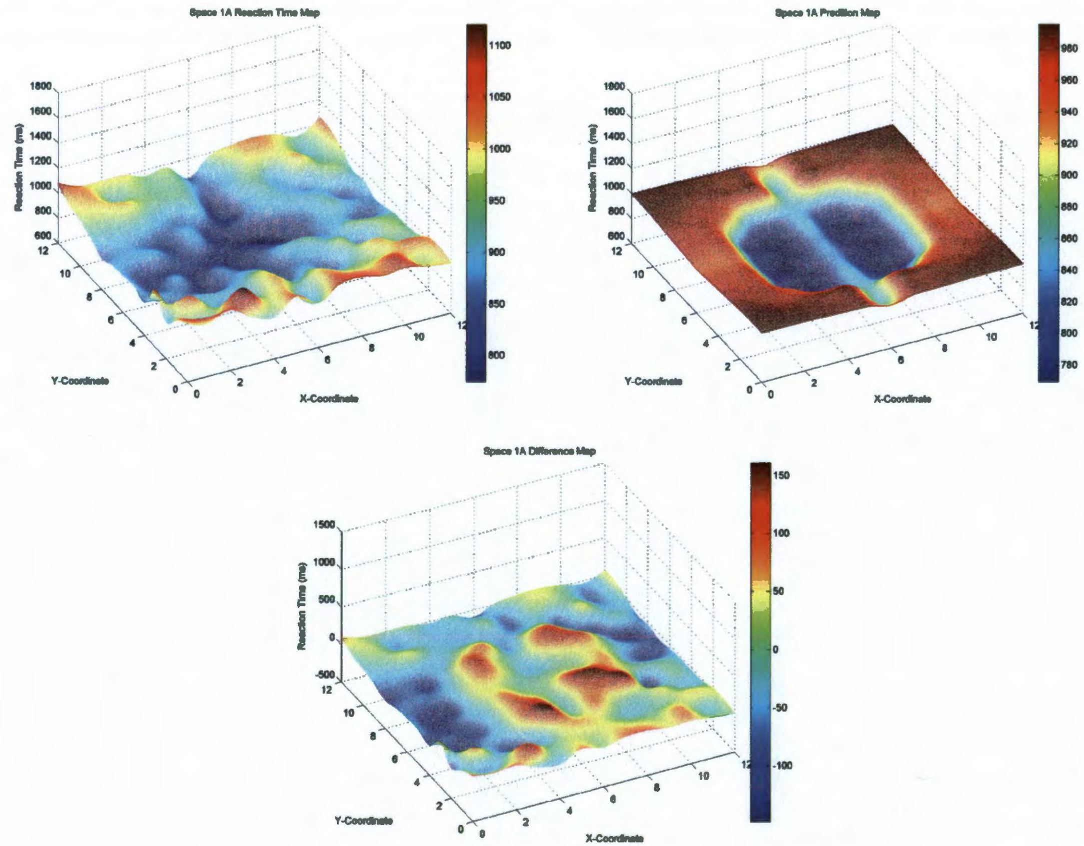


Figure 9 : Reaction Times, Prediction Map and Difference Map - Space 1A
ANOVA analysis on the RT data map did not reach significance ($F(9.49, 151.79) = 1.82$, $p = 0.07$; $F(7.19, 64.67) = 1.05$, $p = 0.41$; $F(3.42, 13.68) = 1.28$, $p = 0.32$; $F(4.75, 28.50) = 1.48$, $p = 0.23$ for versions 1, 2, 3, and 4 of the experiment, respectively). The prediction map for Space 1A correlated strongly with the data ($R = .80$, $R^2 = .64$, $F(8, 160) = 35.88$, $p < .01$).

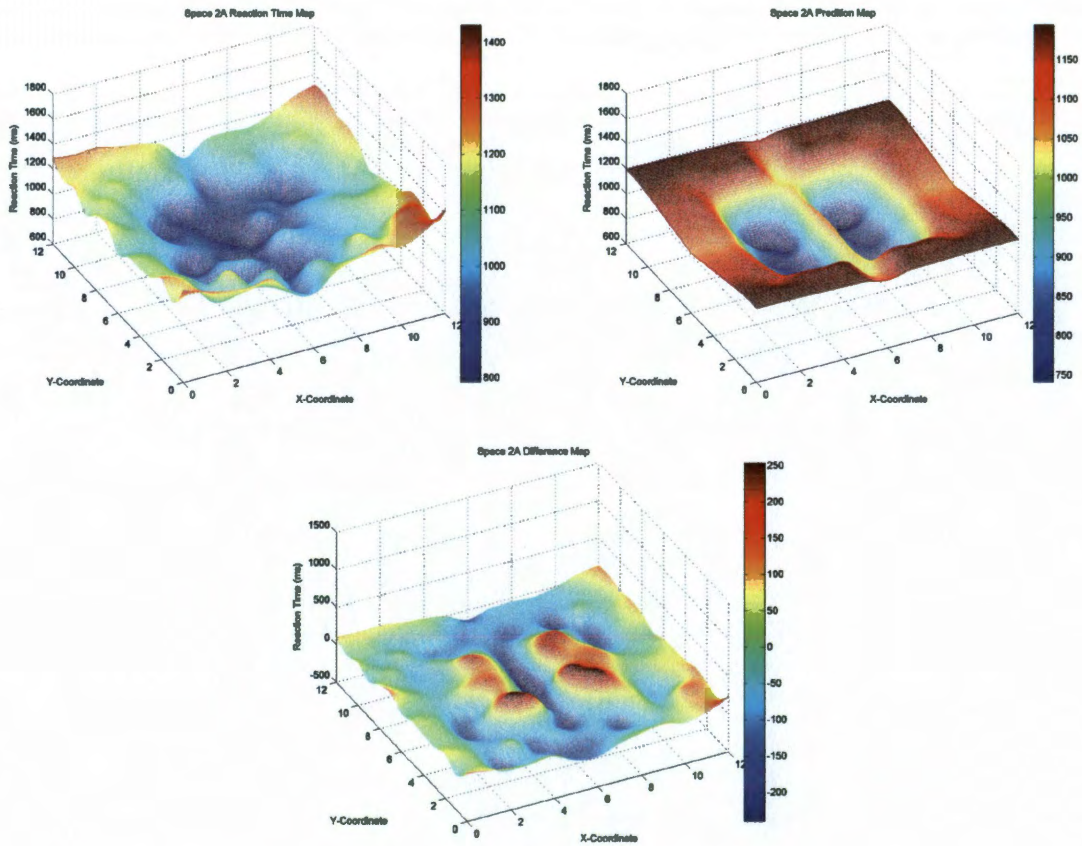


Figure 10 : Reaction Times, Prediction Map and Difference Map - Space 2A
ANOVA analysis on the RT data map did not reach significance ($F(9.49, 151.79) = 1.82$, $p = 0.07$; $F(7.19, 64.67) = 1.05$, $p = 0.41$; $F(3.42, 13.68) = 1.28$, $p = 0.32$; $F(4.75, 28.50) = 1.48$, $p = 0.23$ for versions 1, 2, 3, and 4 of the experiment, respectively). The prediction map for Space 2A correlated strongly with the data ($R = .78$, $R^2 = .61$, $F(8, 160) = 31.68$, $p < .01$).

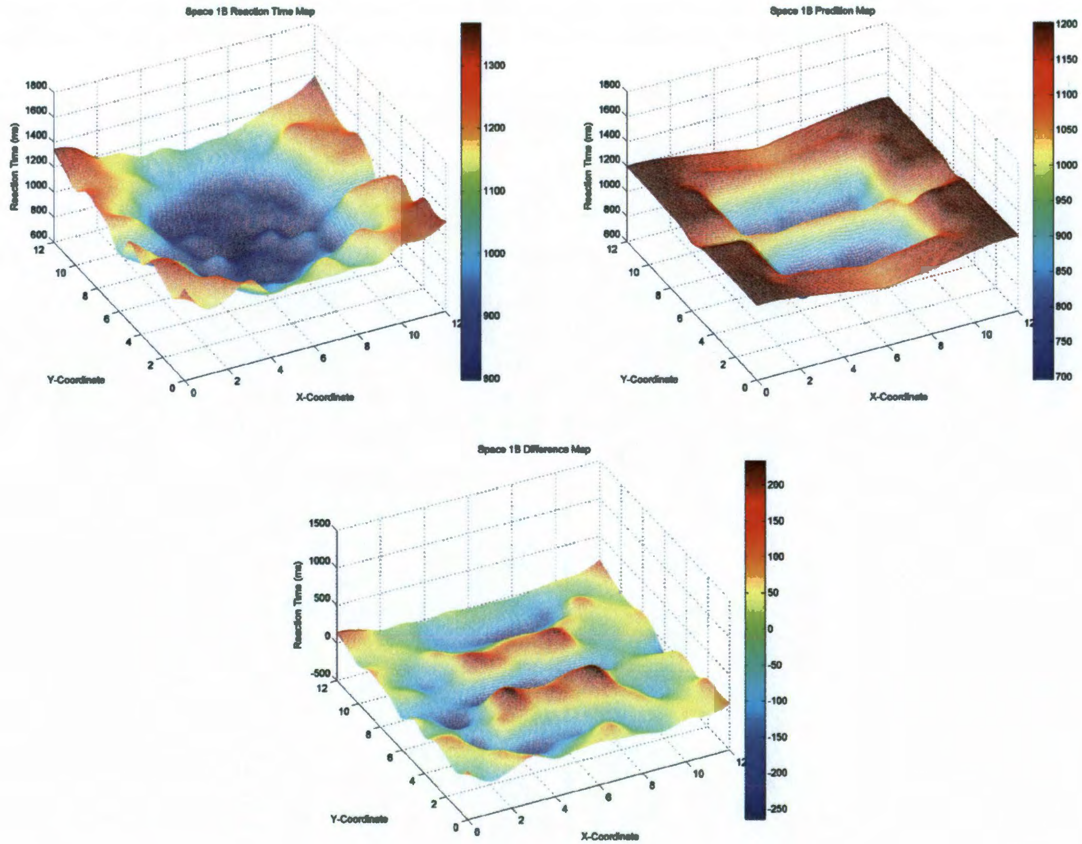


Figure 11 : Reaction Times, Prediction Map and Difference Map - Space 1B
ANOVA analysis on the RT data map reached significance only in version 1 ($F(10.96, 186.24) = 2.82$, $p < .01$; $F(6.85, 61.60) = 1.94$, $p = 0.08$; $F(3.75, 15.01) = 1.05$, $p = 0.41$; $F(4.86, 29.15) = 1.93$, $p = 0.12$, for versions 1, 2, 3, and 4 of the experiment, respectively). The prediction map for Space 1B correlated strongly with the data ($R = .86$, $R^2 = .75$, $F(8, 160) = 58.71$, $p < .01$).

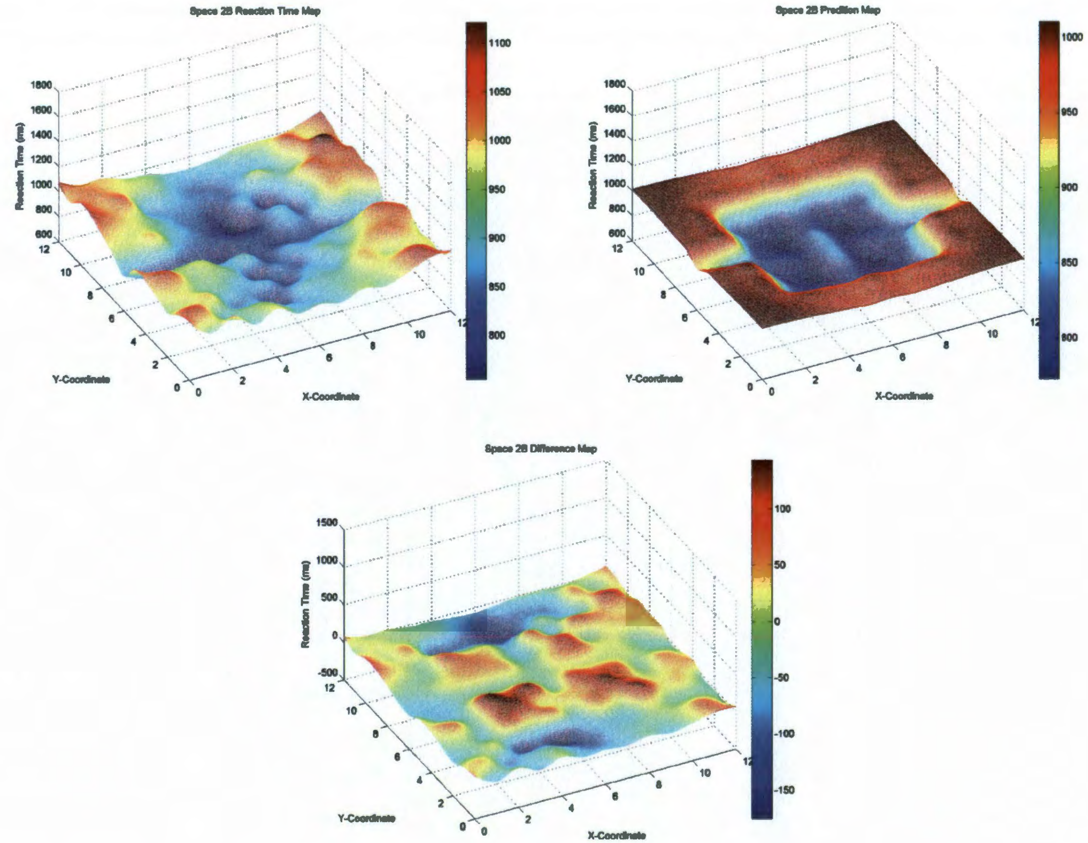


Figure 12 : Reaction Times, Prediction Map and Difference Map - Space 2B

ANOVA analysis on the RT data map reached significance only in version 1 ($F(10.96, 186.24) = 2.82$, $p < .01$; $F(6.85, 61.60) = 1.94$, $p = 0.08$; $F(3.75, 15.01) = 1.05$, $p = 0.41$; $F(4.86, 29.15) = 1.93$, $p = 0.12$, for versions 1, 2, 3, and 4 of the experiment, respectively). The prediction map for Space 2B correlated strongly with the data ($R = .87$, $R^2 = .77$, $F(8, 160) = 66.25$, $p < .01$).

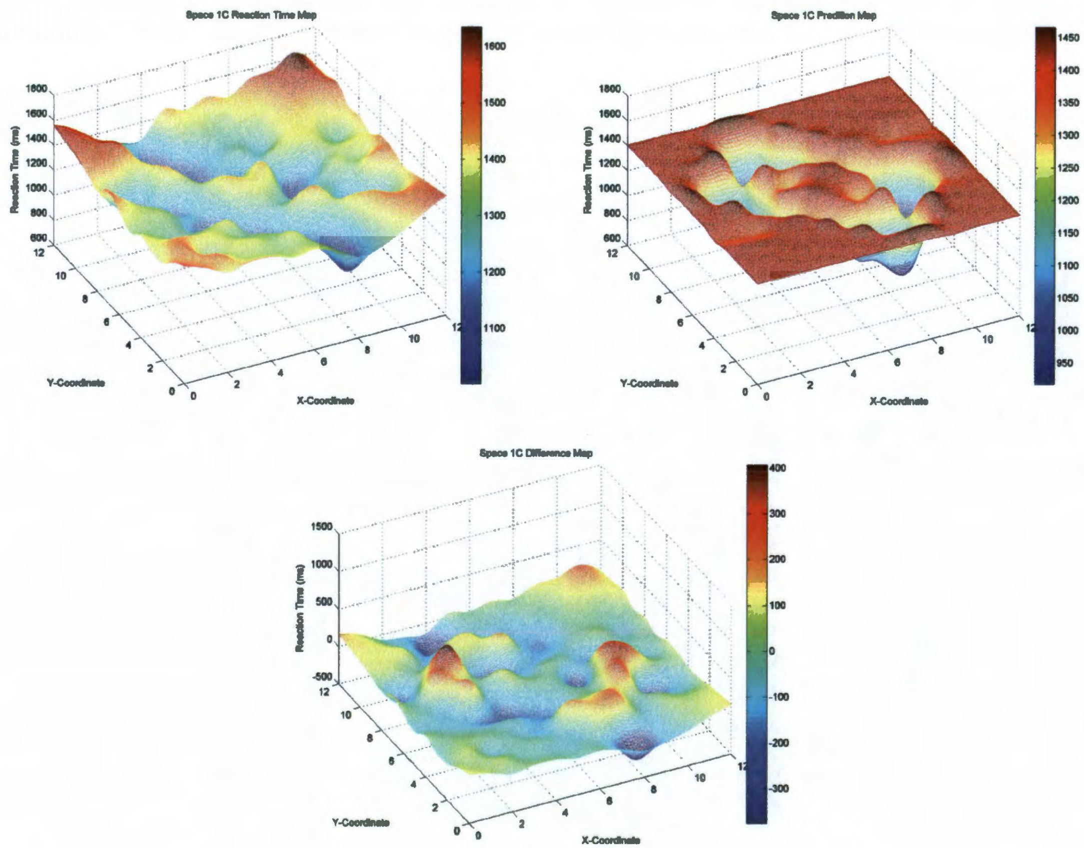


Figure 13 : Reaction Times, Prediction Map and Difference Map - Space 1C
ANOVA analysis on the RT data map reached significance in both versions ($F(14.88, 312.44) = 7.01$, $p < .01$; $F(11.74, 176.13) = 4.54$, $p < .01$, for versions 1 and 2, respectively). The prediction map for Space 1C correlated moderately with the data ($R = .66$, $R^2 = .44$, $F(4, 164) = 31.65$, $p < .01$).

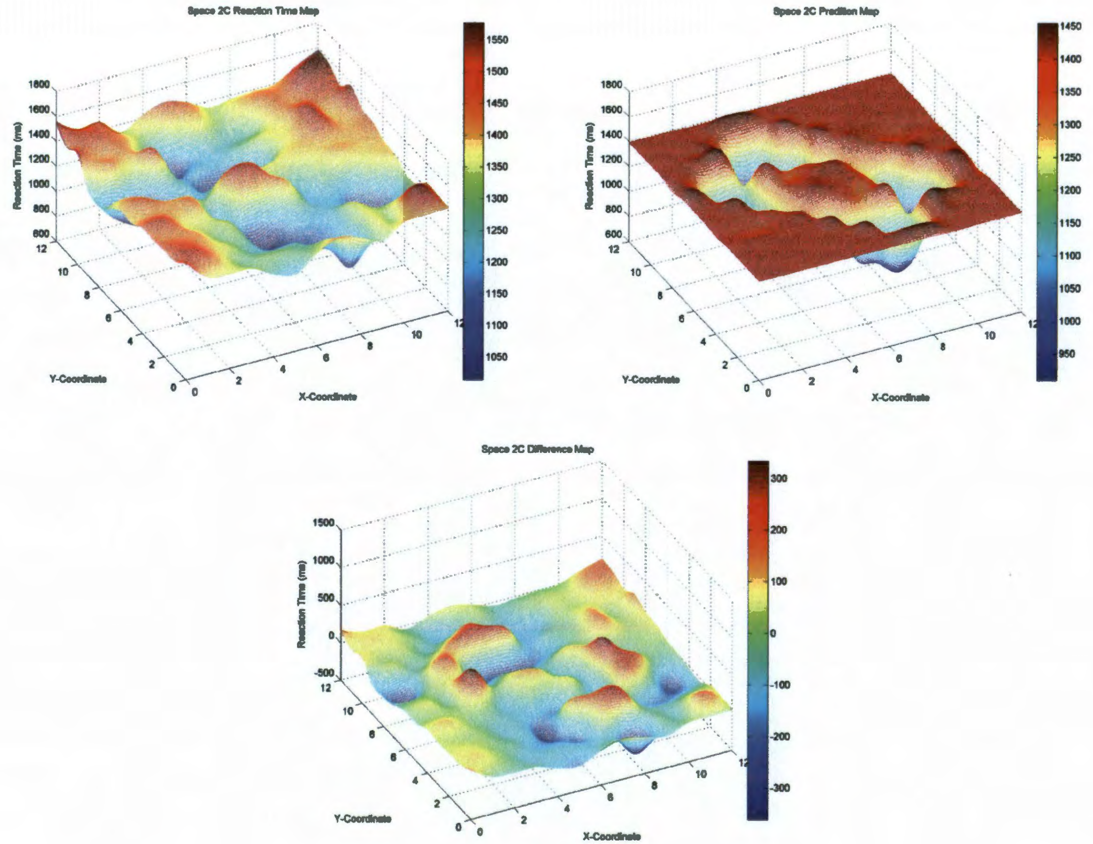


Figure 14 : Reaction Times, Prediction Map and Difference Map - Space 2C
ANOVA analysis on the RT data map reached significance in both versions ($F(14.88, 312.44) = 7.01$, $p < .01$; $F(11.74, 176.13) = 4.54$, $p < .01$, for versions 1 and 2, respectively). The prediction map for Space 2C correlated moderately with the data ($R = .65$, $R^2 = .43$, $F(4, 164) = 31.01$, $p < .01$).

It is of note to mention that in Spaces 1A, 2A, 1B, and 2B the ANOVA analyses investigating the variability of RT across the stimulus space failed to reach statistical significance. This might be because of the way the conditions for the analysis were set up – i.e., when only a fourth of the stimulus space is considered for analysis at a time, the variability in RTs may, indeed, not be high in that quadrant of space by itself. In those cases when the stimulus spaces were split up into only 2 conditions, the ANOVA analyses for the variability of RT were highly significant. The significance of this analysis points to the fact that RT varied reliably within the entire stimulus space but less so in local regions of the space.

In order to look at the individual contributions of EFs to the overall prediction score, correlations were calculated between the individual EFs and RT (Tables 3 & 4). Table 5 presents the overall correlations between the overall prediction score and RT data. The R^2 values represent the percentage of variance accounted for by the particular correlations.

Space	1A	2A	1B	2B	1C	2C
Terminators	$r = 0.49$ $R^2 = 0.24$ $F(1, 167) =$ 53.39 $p < .01$	$r = 0.62$ $R^2 = 0.39$ $F(1, 167) =$ 107.94 $p < .01$	$r = 0.64$ $R^2 = 0.42$ $F(1, 167) =$ 120.28 $p < .01$	$r = 0.60$ $R^2 = 0.36$ $F(1, 167) =$ 94.98 $p < .01$	$r = 0.61$ $R^2 = 0.38$ $F(1, 167) =$ 100.59 $p < .01$	$r = 0.59$ $R^2 = 0.36$ $F(1, 167) =$ 92.86 $p < .01$
Collinearity	$r = 0.03$ $R^2 = 0.00$ $F(1, 167) =$ 0.19 $p = 0.66$	$r = 0.05$ $R^2 = 0.00$ $F(1, 167) =$ 0.48 $p = 0.49$	$r = 0.02$ $R^2 = 0.00$ $F(1, 167) =$ 0.14 $p = 0.7$	$r = 0.06$ $R^2 = 0.00$ $F(1, 167) =$ 0.70 $p = 0.4$	N/A	N/A
Symmetry	$r = 0.21$ $R^2 = 0.04$ $F(1, 167) =$ 7.75 $p < .01$	$r = 0.26$ $R^2 = 0.07$ $F(1, 167) =$ 13.07 $p < .01$	$r = 0.30$ $R^2 = 0.09$ $F(1, 167) =$ 17.43 $p < .01$	$r = 0.13$ $R^2 = 0.02$ $F(1, 167) =$ 3.31 $p = .07$	$r = 0.34$ $R^2 = 0.12$ $F(1, 167) =$ 23.08 $p < .01$	$r = 0.28$ $R^2 = 0.08$ $F(1, 167) =$ 14.53 $p < .01$
Parallelism	$r = 0.53$ $R^2 = 0.28$ $F(1, 167) =$ 65.26 $p < .01$	$r = 0.62$ $R^2 = 0.39$ $F(1, 167) =$ 104.95 $p < .01$	$r = 0.65$ $R^2 = 0.43$ $F(1, 167) =$ 126.24 $p < .01$	$r = 0.55$ $R^2 = 0.31$ $F(1, 167) =$ 73.37 $p < .01$	N/A	N/A

Table 3 : Individual Correlations for EFs - Experiment 1

Space	1A	2A	1B	2B	1C	2C
Intersections	$r = 0.56$ $R^2 = 0.71$ $F(1,167) =$ 178.02 $p < .01$	$r = 0.71$ $R^2 = 0.52$ $F(1,167) =$ 178.02 $p < .01$	$r = 0.78$ $R^2 = 0.61$ $F(1,167) =$ 263.36 $p < .01$	$r = 0.61$ $R^2 = 0.38$ $F(1,167) =$ 102.15 $p < .01$	$r = 0.35$ $R^2 = 0.13$ $F(1,167) =$ 24.16 $p < .01$	$r = 0.46$ $R^2 = 0.22$ $F(1,167) =$ 46.85 $p < .01$
Lateral Endpoint Offset	$r = 0.60$ $R^2 = 0.36$ $F(1,167) =$ 95.85 $p < .01$	$r = 0.41$ $R^2 = 0.17$ $F(1,167) =$ 35.21 $p < .01$	$r = 0.59$ $R^2 = 0.35$ $F(1,167) =$ 91.19 $p < .01$	$r = 0.60$ $R^2 = 0.37$ $F(1,167) =$ 98.45 $p < .01$	N/A	N/A
Connectivity	$r = 0.48$ $R^2 = 0.24$ $F(1,167) =$ 51.60 $p < .01$	$r = 0.60$ $R^2 = 0.37$ $F(1,167) =$ 98.62 $p < .01$	$r = 0.65$ $R^2 = 0.42$ $F(1,167) =$ 123.29 $p < .01$	$r = 0.53$ $R^2 = 0.28$ $F(1,167) =$ 66.41 $p < .01$	$r = 0.35$ $R^2 = 0.13$ $F(1,167) =$ 24.16 $p < .01$	$r = 0.46$ $R^2 = 0.22$ $F(1,167) =$ 46.85 $p < .01$
Pixel Count	$r = 0.46$ $R^2 = 0.22$ $F(1,167) =$ 46.28 $p < .01$	$r = 0.52$ $R^2 = 0.28$ $F(1,167) =$ 63.72 $p < .01$	$r = 0.56$ $R^2 = 0.32$ $F(1,167) =$ 78.44 $p < .01$	$r = 0.54$ $R^2 = 0.29$ $F(1,167) =$ 69.42 $p < .01$	$r = 0.48$ $R^2 = 0.23$ $F(1,167) =$ 50.21 $p < .01$	$r = 0.44$ $R^2 = 0.20$ $F(1,167) =$ 42.00 $p < .01$

Table 4 : Individual Correlations for EFs - Experiment 1 (cont'd)

Space	1A	2A	1B	2B	1C	2C
Overall	$R = 0.80$ $R^2 = 0.64$ $F(8, 160) = 35.88$ $p < .01$	$R = 0.78$ $R^2 = 0.61$ $F(8, 160) = 31.68$ $p < .01$	$R = 0.86$ $R^2 = 0.75$ $F(8, 160) = 58.71$ $p < .01$	$R = 0.87$ $R^2 = 0.77$ $F(8, 160) = 66.25$ $p < .01$	$R = 0.66$ $R^2 = 0.44$ $F(4, 164) = 31.65$ $p < .01$	$R = 0.65$ $R^2 = 0.43$ $F(4, 164) = 31.01$ $p < .01$

Table 5 : Overall Correlations for EFs - Experiment 1

As can be seen from Table 5, overall multiple regression values ranged from .65 to .87, and intersections, terminators, lateral endpoint offset and connectivity seem to consistently account for a big portion of the variance in the RT data (the variance between data and prediction represents the error in the model). It is worth noting here that due to the nature of the stimuli in Spaces 3A and 3B (the context line segment was always a diagonal), it was impossible to obtain the EF of parallelism or lateral endpoint offset in the physical stimuli and so these EFs could not be tested there.

Conclusions

This experiment showed that when people are asked to find the vertical line in a field of horizontals (or vice versa), their performance depends significantly on the orientation and placement of irrelevant, identical contextual lines that are added to the to-be-discriminated lines. This result is interpreted to show that when context lines are placed near target lines, they form perceptual groups. Specifically, it is interpreted to mean that novel Emergent Eeatures result from placing lines near one another, and that these highly salient EFs drive discrimination performance. Thus, this experiment provides continued support for Emergent Features and demonstrates the specific EFs that appear when the stimuli consist of just two line segments. Reaction times differed within the stimulus space based on the position of the context, which hints at grouping as being the likely mechanism driving perception of these stimuli. In this experiment, eight of these possible EFs were investigated.

Using multiple regression analysis, support was shown for the prediction scoring paradigm, with correlations ranging from .65 to .87, with the percentage of variance accounted for (as evidenced by the R^2 values) ranging from 43% to 77%.

Given the data that was obtained in this experiment, it seems that lateral endpoint offset, intersections, parallelism, connectivity, number of terminators, and pixel count accounted for a lot of the variance between the data and the prediction. Collinearity failed to reach statistical significance possibly due to the small sample size of stimuli which contained this EF difference (only 2 stimuli per space).

Limitations

Despite strong support for the investigated EFs in Experiment 1, there were some limitations of this experiment.

First, it is very likely that the EFs vary in their importance to the visual system. The property of parallelism, for example, might not be as salient as are intersections. It would be necessary to adjust the weights given to these features on the prediction map to better account for the remaining variance.

Second, EF differences might be correlated amongst themselves in the same stimulus space. For instance, if an image has the EF of connectivity, it likely also has the property of intersections, whereas if two lines have the EF of parallelism, they cannot then have intersections. Therefore, while this issue does not directly impact the multivariate analysis, it is not possible to infer any one EF's contribution due to multi-collinearity.

Third, comparing the same EF differences across the spaces might change the salience of those particular EFs. For example, spaces 1C and 2C did not have some of the EF differences that spaces 1A, 2A, 1B and 2B had, and this, along with the possibility of EF inter-correlations, might have influenced the salience of some, or maybe even most, of the EFs in a way that was not uniform across all the spaces.

Fourth, in order to investigate Configural Superiority (CSE) and Configural Inferiority (CIE) effects, a baseline measurement (RT for the discrimination of the odd quadrant in a base-only condition) is needed.

Lastly, it is also necessary to validate the present prediction maps *a priori*.

Experiment 2a

Introduction

Experiment 2a was designed to improve prediction coding for the EFs of symmetry and connectivity. Some of the image displays used throughout this series of experiments were difficult to determine, objectively, as containing symmetry or connectivity, or not. For instance, there were cases where the two line segments were extremely close to each other (1 or 2 pixels apart), and inter-rater agreement on those displays regarding connectivity was low. In the case of symmetry, Palmer and Hemenway (1978) showed that symmetry along the vertical axis is perceptually more salient than symmetry along the horizontal, diagonal, or oblique axes, as had been noted informally by Mach in the 1800s. Therefore, it was more beneficial to allow participants to code these two features, in a task which closely approximated the odd-quadrant discrimination task, and to use those scores in the prediction maps.

Participants

10 Rice University undergraduates (4 females; mean age 19.1) took part in this experiment. They were screened to make sure they have not participated in Experiment 1, or other similar experiments. They were compensated with experiment participation credit, which partially fulfills course requirements.

Materials and Methods

Task

The stimuli were presented on a computer display identical to that used in Experiment 1. On any given trial, a pre-generated configuration of two line segments was shown for 125ms in one of the 4 corners of the touch-screen. A blank screen was then provided for participants to make their judgment as to whether the image possesses the property of symmetry or connectivity. When the participants perceived the image as containing the property, they were required to press the "1" number key on a standard QWERTY keyboard. If they did not perceive the image as containing the property, they were required to press the "3" number key on the keyboard. Each participant was randomly selected to code for either symmetry or connectivity.

Test Set-Up

Test setup (stimulus generation, experiment programming, screen size, image size, and viewing distance) were identical to that used in Experiment 1.

Stimuli

Stimuli consisted of single configurations of two line segments. The configuration of the two lines was identical to the ones that were to be tested in Experiment 2b; that is, participants coded the stimuli that were going to be used in the subsequent experiment.

Analysis

To analyze the data, the scores were averaged for each individual image. Inter-rater disagreement was resolved by the following sequence of methods: first, the coding assigned to the image by the majority of participants was kept. If there was a "tie" (an equal number of participants coded a given image both ways), or a missing cell, the coding was replaced by that given to the same image on the other (symmetric) side of the two-line stimulus space. For example, an image located at coordinates (0,12) is symmetric to the image at coordinates (12,0), and (1,2) is symmetric to (11,10). Since each image in this experiment was only one quadrant out of the full displays used in Experiment 2b, the corresponding pair of image codings was combined (one was subtracted from the other to form the difference in EF score) to form the score for the whole display. The ratings obtained from this experiment were used as the symmetry and connectivity scores in prediction maps for Experiment 2b.

Experiment 2b

Introduction

Experiment 2 was designed to be a replication and direct extension of Experiment 1. First, the study and definition of the relationship between different elements of an object was continued by focusing on the Emergent Features (EFs) of that object. Second, Experiment 2 served as a replication of the results obtained in the previous experiment. Last, this experiment addressed many of the limitations of Experiment 1.

Participants

22 Rice University undergraduates (11 females; mean age 18.9) took part in this experiment. They were screened to make sure they have not participated in Experiment 1, 2a, or other similar experiments. They were compensated with experiment participation credit, which partially fulfills course requirements.

Materials and Methods

The method of this experiment was almost identical to that outlined earlier in Experiment 1. Visual discriminations were made in the context of an odd-quadrant task. The display consisted of four quadrants, three of which contained an identical image, with the odd image being the target. Participants judged which quadrant contained

Alpha	Beta	Gamma	Delta
Intersections Symmetry	Intersections Symmetry Parallelism	Collinearity Lateral Endpoint Offset	Collinearity Lateral Endpoint Offset Symmetry

Table 6 : Patterns of EFs

the odd image, and then selected it by touching it via a touch-screen monitor as quickly and accurately as possible. Reaction time (RT) and accuracy were measured. Test setup (stimulus generation, presentation, experiment programming, screen size, image size, and viewing distance) was identical to that used in Experiment 1.

Stimuli

Stimulus spaces were mapped out in a manner identical to that stated above. They were generated by combining two line segments in varying orientations. The orientations were again limited to horizontal, vertical, positively-sloped, and negatively-sloped diagonals.

In an effort to be systematic and include spaces containing the most variety of grouping variations between two line segments, the 48 possible spaces (earlier presented in Figure 7) were classified based on the EFs present in the stimuli belonging to each space. Four distinct patterns emerged as a result of this grouping, and they are presented in Table 6. (Note: the EFs presented in this table are only those that manifest themselves in the odd quadrant. Terminators, connectivity, and pixel count are always present in all the patterns, and are coded in all the spaces.)

These patterns were used as a basis to decide which stimulus spaces were included in the experiment, with at least one space corresponding to each EF pattern. In addition to sampling from each EF pattern, the shape prototypes included in each space were also considered, with those prototypes not previously tested in Experiment 1 included in Experiment 2. Figure 15 shows these prototypes (those already tested in Experiment 1 are underlined).

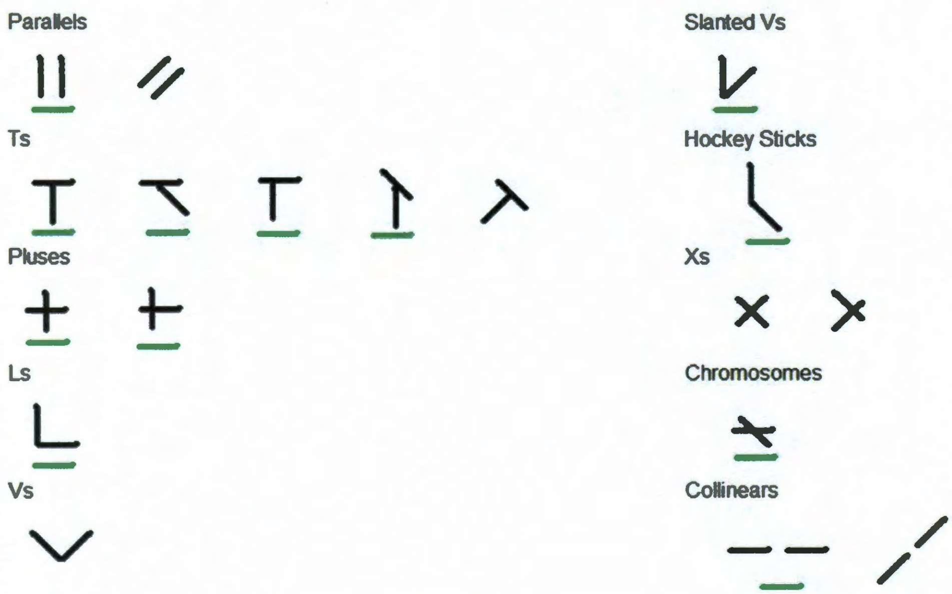


Figure 15 : Shape Prototypes Resulting from Grouping

Table 7 presents the stimulus spaces that were selected to be tested in this experiment. The full stimulus spaces can be found in Appendix A, Figures 39 - 44.

Due to time constraints and large number of stimuli to be tested, the spaces were again divided into regions, based on the axis of symmetry of the whole stimulus space, for the same reasons as stated in Experiment 1. In all the stimulus spaces

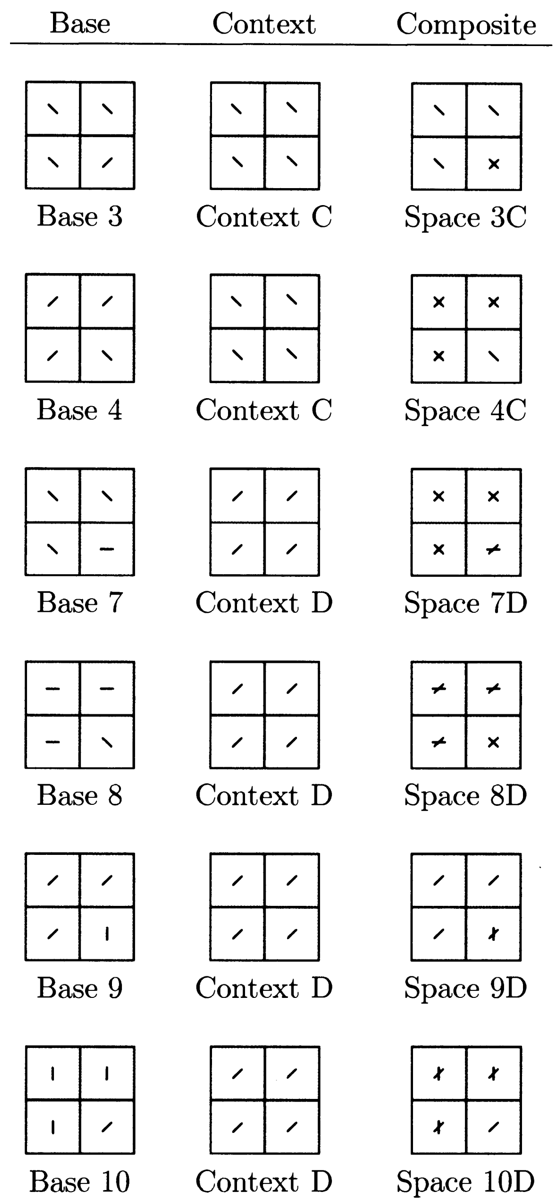


Table 7 : Stimulus Spaces - Experiment 2

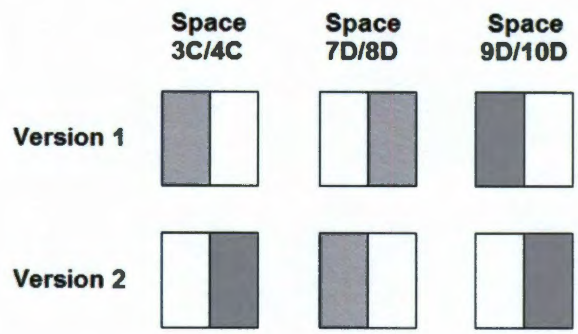


Figure 16 : Versions of Experiment 2

selected for Experiment 2, the symmetry of the space was diagonal. Therefore, each participant was tested on half of each of the six spaces. This method resulted in 2 experimental versions, and they are presented graphically in Figure 16. Versions were counter-balanced between subjects.

In addition to the stimulus spaces, which were tested as described in Experiment 1, "baseline" measurements were also taken. RT and accuracy data was recorded for displays which consisted of only the base image, without the context. This baseline measurement served as a basis for informing the discussion of Configural Superiority Effects (CSEs) and Configural Inferiority Effects (CIEs). If, for example, grouping greatly facilitates discrimination (as evidenced by lower RT in the composite condition than in the base-only condition, signifying a CSE), a stronger case can be made for EFs as a method for that grouping.

Space	Mean (ms)	SD (ms)	Mean Accuracy
3C	1012	121	0.93
4C	1185	183	0.93
7D	1231	183	0.98
8D	1257	139	0.96
9D	883	100	0.98
10D	1084	171	0.95

Table 8 : Means, Standard Deviations, and Mean Accuracy - Experiment 2

Prediction Maps

Prediction maps were generated, prior to data collection, in the same manner as in Experiment 1. The coding for lateral endpoint offset was adapted to accommodate diagonal line segments. Scores for symmetry and connectivity were obtained from Experiment 2a, described above. As in Experiment 1, all EFs were assigned a weight of 1, and the prediction maps were linearly transformed in the manner described earlier.

Results

Means, standard deviations, and accuracy data are presented in Table 8.

Figures 17 - 22 show graphical representations of the RT data, prediction map, and the difference map. The x and y axes, labeled "X-Coordinate" and "Y-Coordinate" refer to the stimulus position in the space (see Appendix A). RT is presented on the z-axis, in ms. The difference map is the unaccounted variance in the model, left over after the predicted RT was subtracted from the RT data.

Repeated measures analysis of variance (ANOVA) was conducted on the RT data for each space to test whether RT varied across the space (the x and y coordinate interaction effect is reported). Because of the experimental design, any given participant was tested on only half of each space. Therefore, the analysis was conducted by versions (that is, by half-space at a time). ANOVA analysis on the RT data maps showed that none of the surfaces were flat, that is, RT did vary reliably across the space (statistics are provided in the figures below).

Multivariate regression was performed to assess the fit of the prediction model to the RT data. The eight EFs (terminators, (collinearity*proximity), (symmetry*proximity), (parallelism*proximity), intersections, lateral endpoint offset, connectivity, and pixel count) served as predictors.

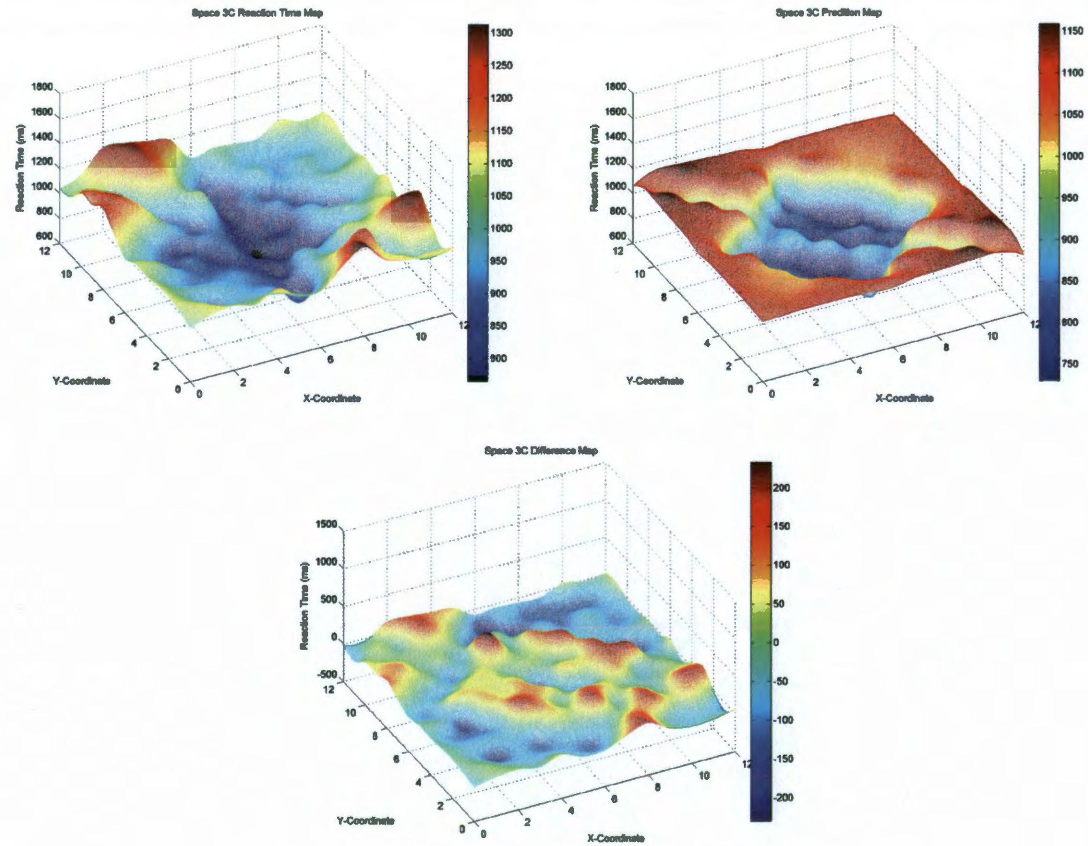


Figure 17 : Reaction Times, Prediction Map and Difference Map - Space 3C
ANOVA analysis on the RT data map reached significance in both versions of the experiment ($F(6.18, 43.26) = 3.52$, $p < .01$; $F(9.49, 113.84) = 7.62$, $p < .01$, for version 1 and 2, respectively). The prediction map for Space 3C correlated strongly with the data ($R = .84$, $R^2 = .71$, $F(8, 160) = 48.87$, $p < .01$).

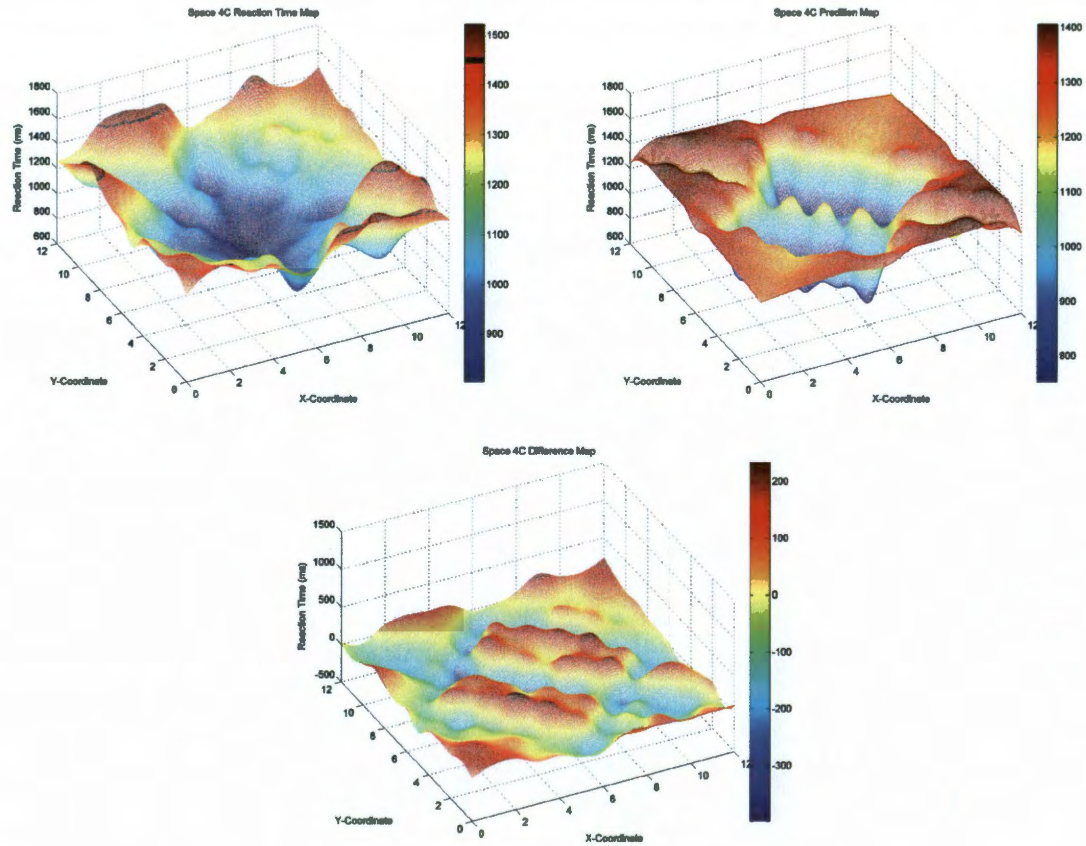


Figure 18 : Reaction Times, Prediction Map and Difference Map - Space 4C
ANOVA analysis on the RT data map reached significance in both versions of the experiment ($F(6.18, 43.26) = 3.52$, $p < .01$; $F(9.49, 113.84) = 7.62$, $p < .01$, for version 1 and 2, respectively). The prediction map for Space 4C correlated strongly with the data ($R = .85$, $R^2 = .73$, $F(8, 160) = 53.79$, $p < .01$).

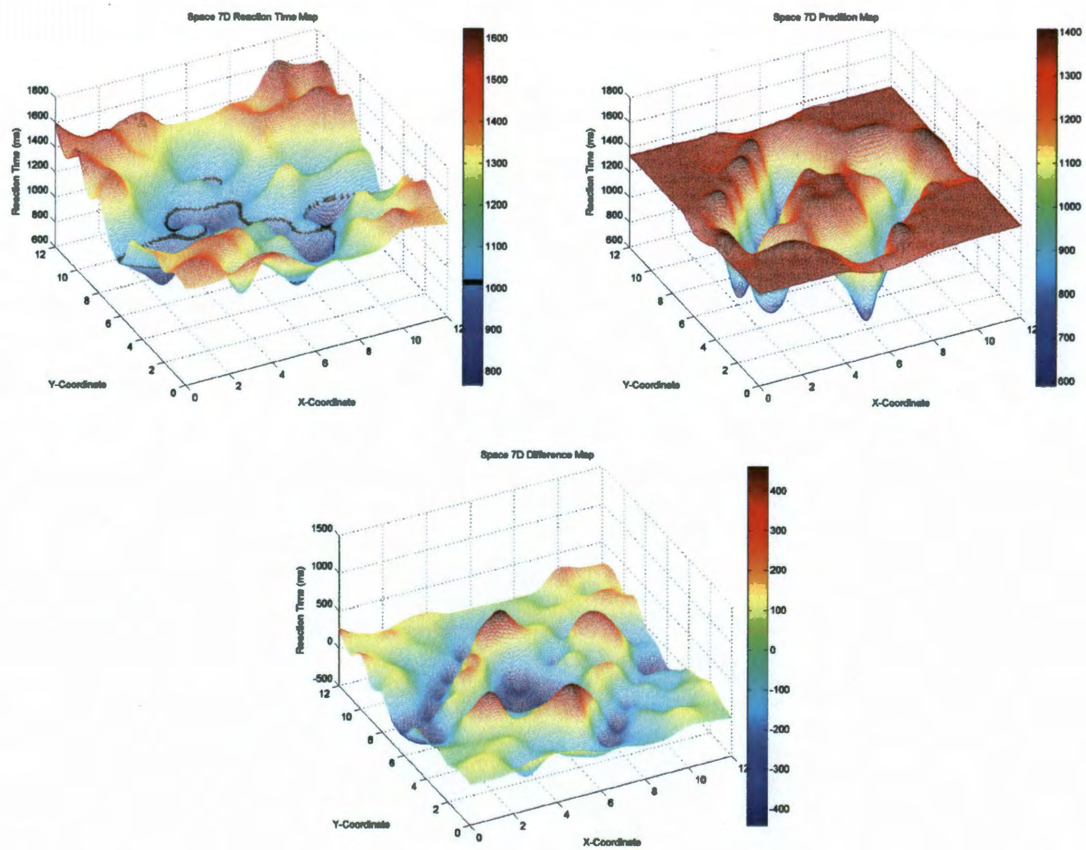


Figure 19 : Reaction Times, Prediction Map and Difference Map - Space 7D
ANOVA analysis on the RT data map reached significance in both versions of the experiment ($F(5.85, 40.96) = 3.62$, $p < .01$; $F(8.30, 82.95) = 3.69$, $p < .01$, for version 1 and 2, respectively). The prediction map for Space 7D correlated strongly with the data ($R = .60$, $R^2 = .37$, $F(5, 163) = 19.23$, $p < .01$).

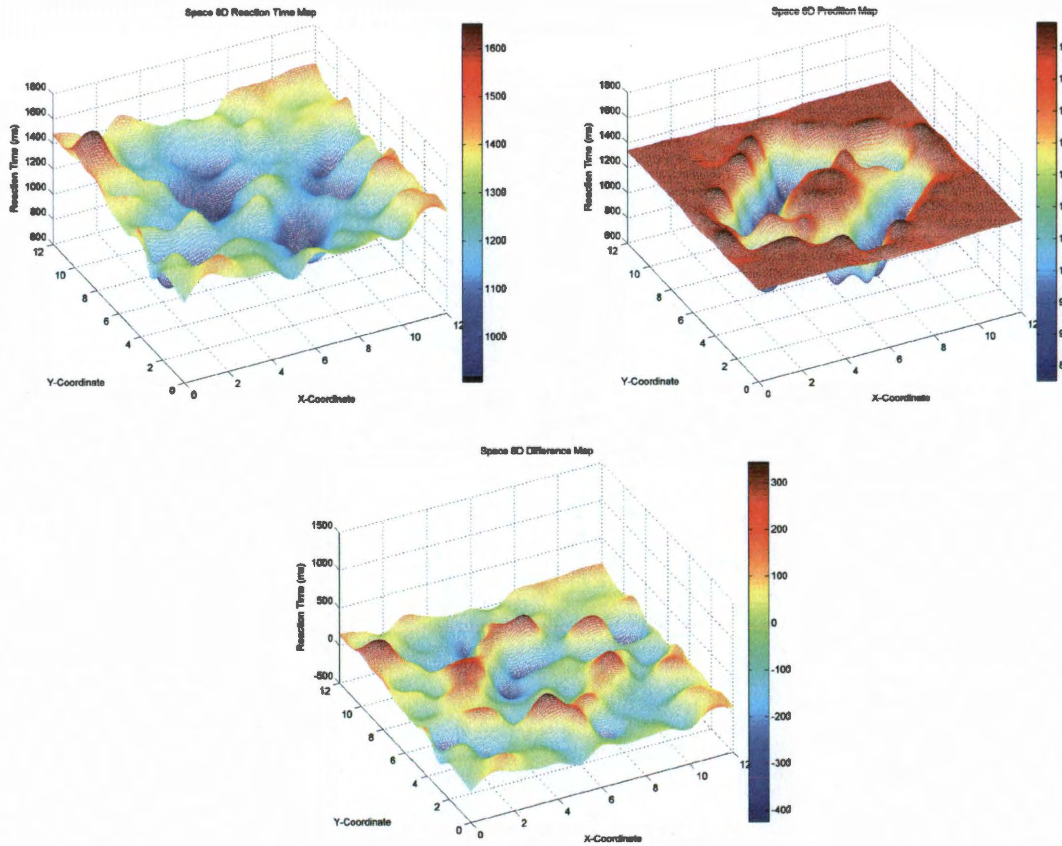


Figure 20 : Reaction Times, Prediction Map and Difference Map - Space 8D
ANOVA analysis on the RT data map reached significance in both versions of the experiment ($F(5.85, 40.96) = 3.62$, $p < .01$; $F(8.30, 82.95) = 3.69$, $p < .01$, for version 1 and 2, respectively). The prediction map for Space 8D correlated strongly with the data ($R = .67$, $R^2 = .45$, $F(5, 163) = 27.05$, $p < .01$).

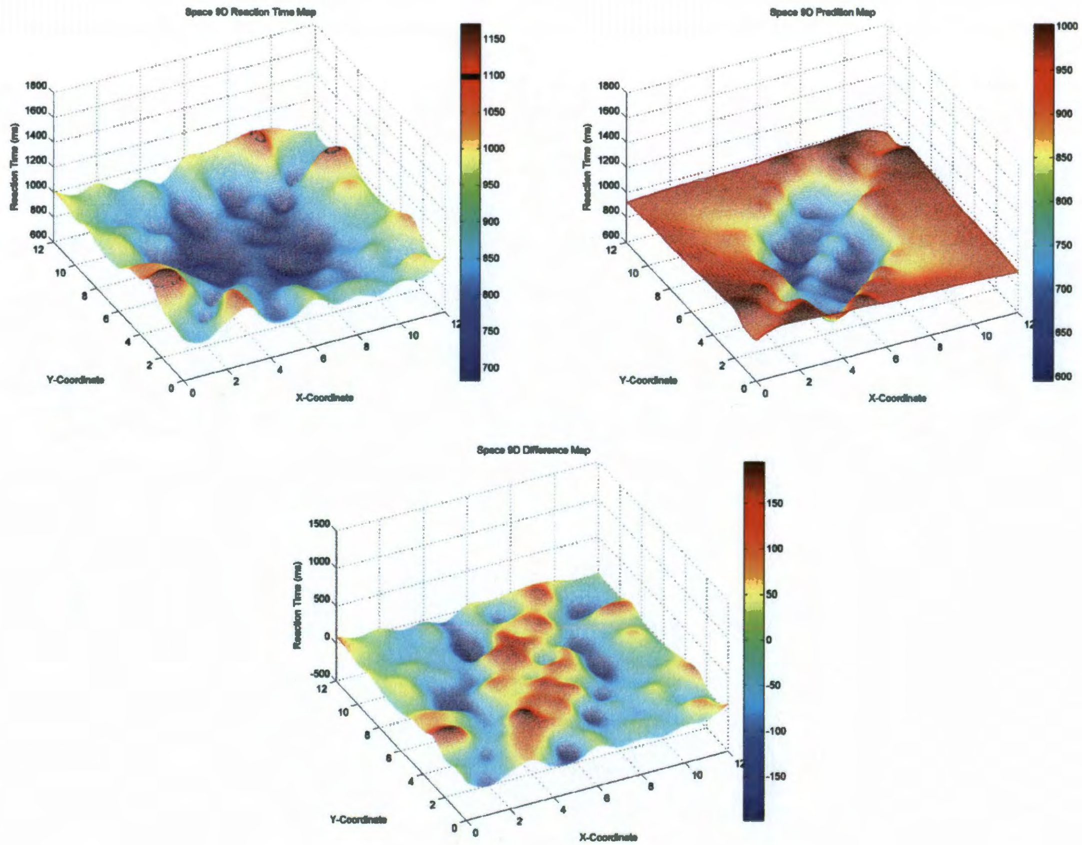


Figure 21 : Reaction Times, Prediction Map and Difference Map - Space 9D
ANOVA analysis on the RT data map reached significance in both versions of the experiment ($F(5.42, 37.94) = 4.664$, $p < .01$; $F(9.08, 108.95) = 6.66$, $p < .01$, for version 1 and 2, respectively). The prediction map for Space 9D correlated strongly with the data ($R = .82$, $R^2 = .67$, $F(8, 160) = 41.05$, $p < .01$).

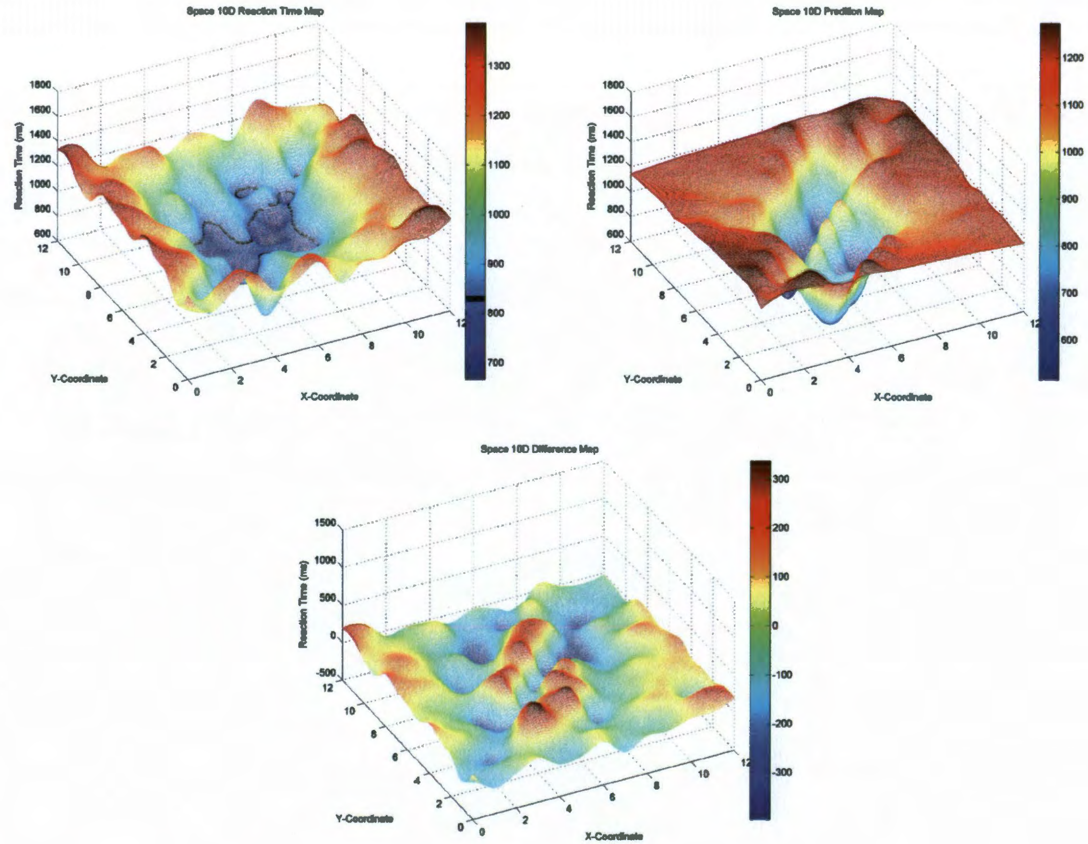


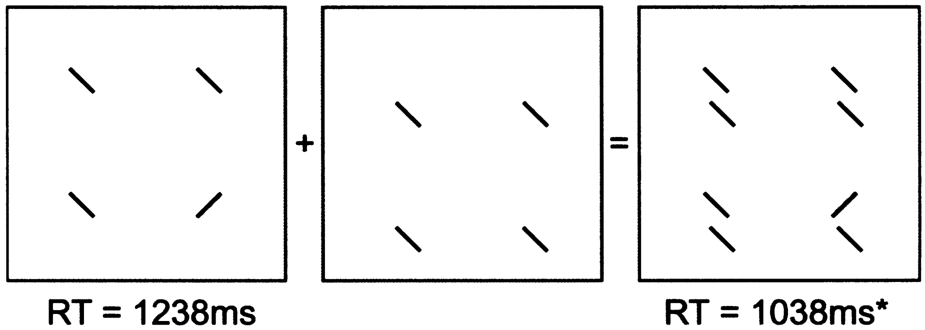
Figure 22 : Reaction Times, Prediction Map and Difference Map - Space 10D
ANOVA analysis on the RT data map reached significance in both versions of the experiment ($F(5.42, 37.94) = 4.66$, $p < .01$; $F(9.08, 108.95) = 6.66$, $p < .01$, for version 1 and 2, respectively). The prediction map for Space 10D correlated strongly with the data ($R = .76$, $R^2 = .59$, $F(8, 160) = 28.83$, $p < .01$).

T-tests were performed on each base-only/composite pair within each space (for a total of 169 comparisons in each stimulus space). Since these comparisons were planned, a correction for multiple comparisons was not necessary. The results are presented graphically in Figures 17 - 22 via the black contours, which show the average RT for discrimination made in the base-only display. All the points lying above that RT represent Configural Inferiority Effects (CIEs), where the discrimination without the context images was considerably faster than in the composite image. Conversely, all points lying below the baseline RT correspond to displays in which the context images greatly facilitated the discrimination, producing Configural Superiority Effects (CSEs).

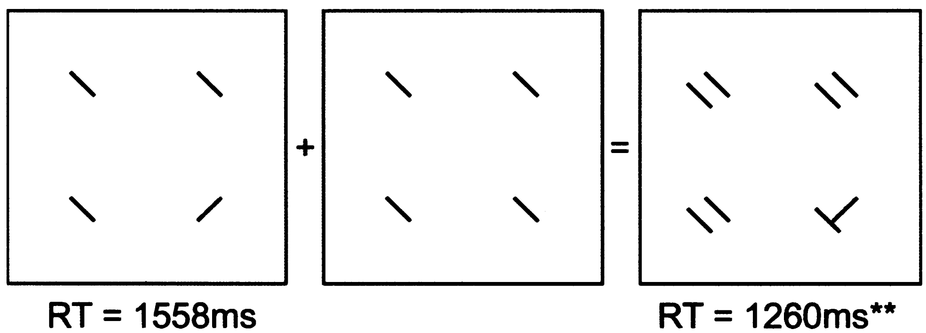
In the following Figures (23 - 32), selected CSEs and CIEs are presented. In each case, first, the base image is presented, along with the baseline RT (the RT is an average of all subjects' measurements). Then, the context image is presented. Finally, the composite image is presented, along with its recorded RT. It is worth noting here that, for certain stimuli within the same space, the baseline RTs vary slightly for the same display. This is an artifact of the experimental design (i.e., different subjects were tested on different regions of the same space) and possible missing data for certain subjects. For each space, CSEs and CIEs are presented along with the EF difference prediction ratings of the composite stimuli for each one. Stimuli falling into 3 ranges were included: those which had a high prediction rating (predicted RT was slow), a moderate prediction rating, and a low prediction rating (predicted RT was fast). 2 of the spaces only produced one of the effects: space 3C did not produce any CIEs, and space 8D did not produce any CSEs.

It is also worth noting that not all CSEs contained a great number of EF differences (i.e., a fast RT prediction). Conversely, not all CIEs contained few EF differences (i.e., slow RT prediction). These results will be revisited again in the conclusion.

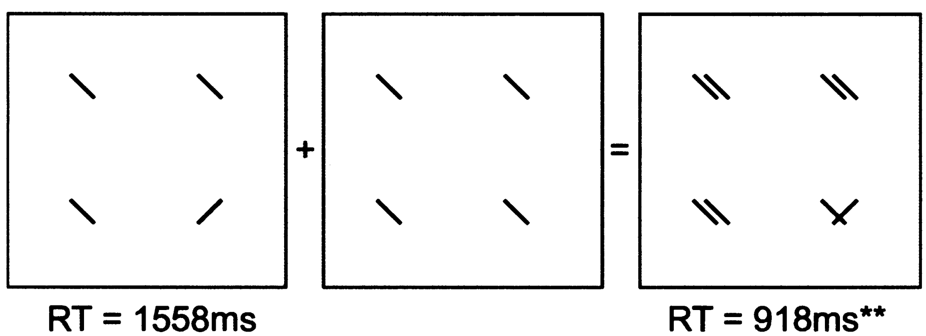
The correlations between individual EFs and RT data, as well as the overall (multivariate) model fit, are presented in Tables 9 - 11.



(a) **CSE** $t(7) = 3.11,\ p = .02$
Stimulus prediction rating = ***7.7*** *(RT predicted slow, least EF differences)*

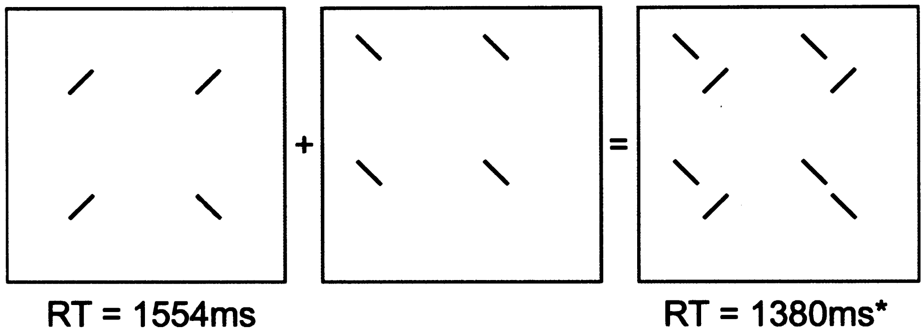


(b) **CSE** $t(12) = 3.46,\ p < .01$
Stimulus prediction rating = ***5.9*** *(RT predicted moderate, some EF differences)*

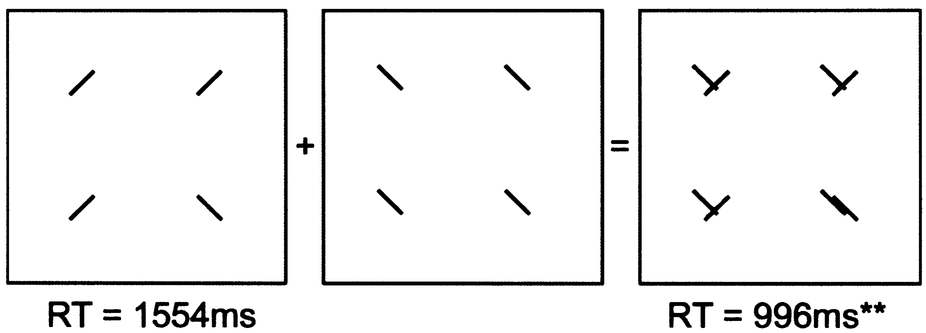


(c) **CSE** $t(12) = 12.35,\ p < .01$
Stimulus prediction rating = ***3.8*** *(RT predicted fast, most EF differences)*

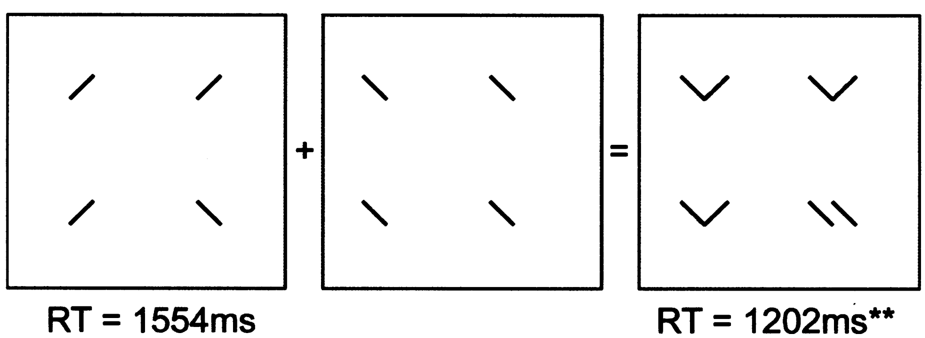
Figure 23 : Space 3C - CSEs



(a) **CSE** $t(12) = 2.45,\ p = .03$
Stimulus prediction rating = ***8.0*** *(RT predicted slow, least EF differences)*

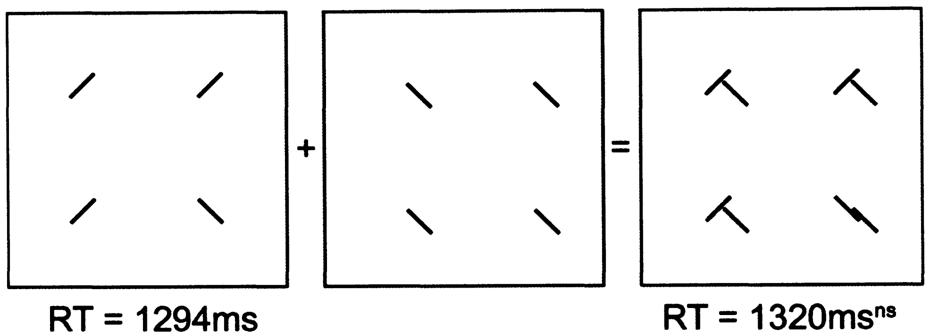


(b) **CSE** $t(12) = 13.14,\ p < .01$
Stimulus prediction rating = ***5.1*** *(RT predicted moderate, some EF differences)*



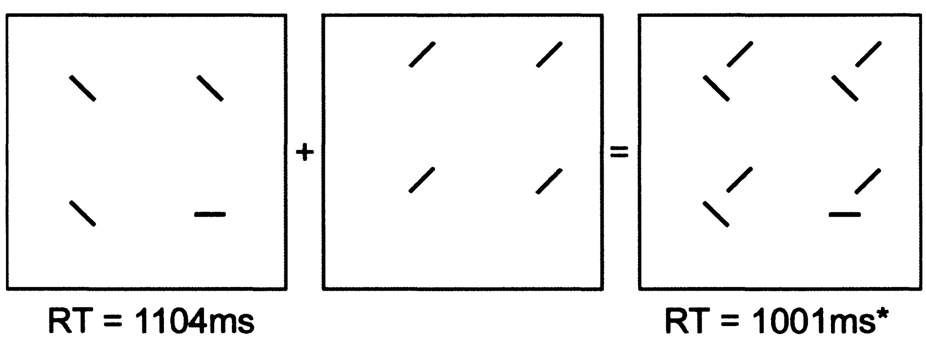
(c) **CSE** $t(12) = 5.79,\ p < .01$
Stimulus prediction rating = ***3.7*** *(RT predicted fast, most EF differences)*

Figure 24 : Space 4C - CSEs



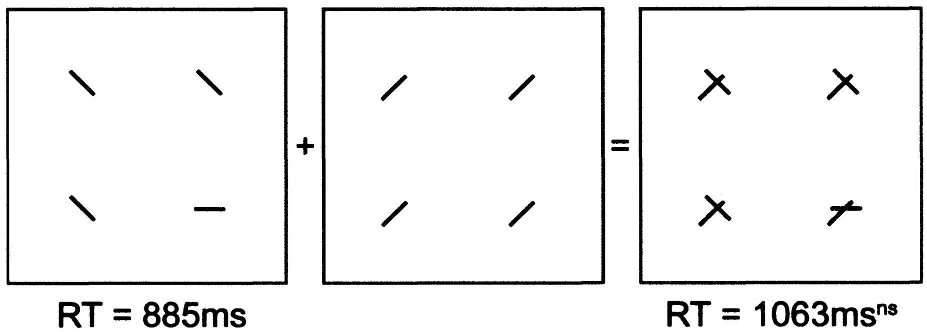
(a) **CIE** $t(8) = -.45,\ p = .67$
Stimulus prediction rating = ***7.5*** *(RT predicted slow, least EF differences)*

Figure 25 : Space 4C - CIEs

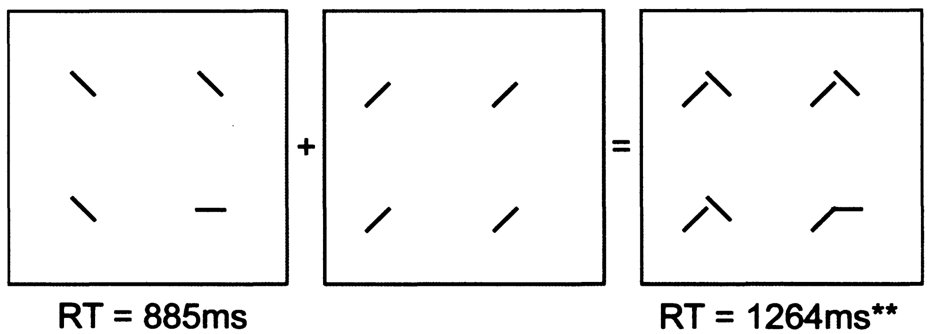


(a) **CSE** $t(12) = 2.21,\ p = .048$
Stimulus prediction rating = ***8.0*** *(RT predicted slow, least EF differences)*

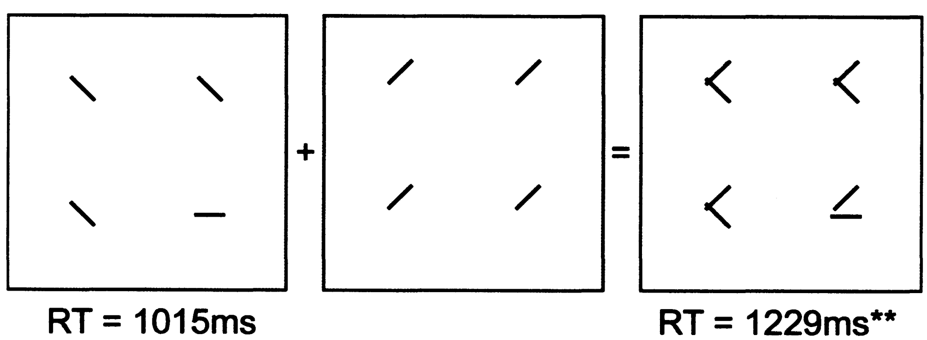
Figure 26 : Space 7D - CSEs



(a) **CIE** $t(8) = -2.09,\ p = .07$
Stimulus prediction rating = ***8.0*** *(RT predicted slow, least EF differences)*

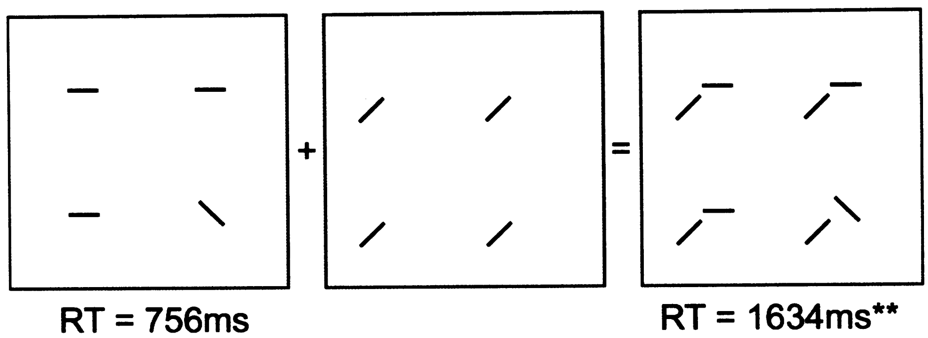


(b) **CIE** $t(8) = -5.02,\ p < .01$
Stimulus prediction rating = ***5.1*** *(RT predicted moderate, some EF differences)*

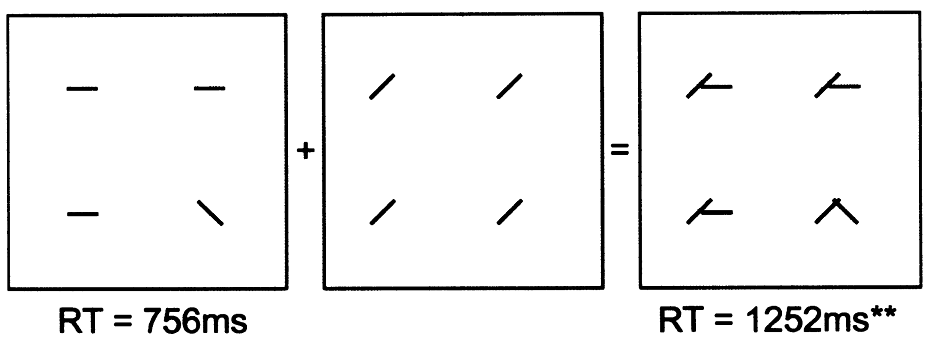


(c) **CIE** $t(21) = -3.71,\ p < .01$
Stimulus prediction rating = ***4.3*** *(RT predicted fast, most EF differences)*

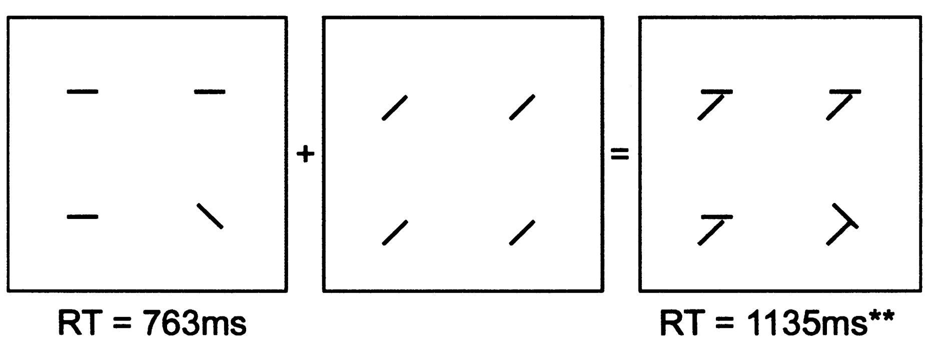
Figure 27 : Space 7D - CIEs



(a) **CIE** $t(8) = -7.52,\ p < .01$
*Stimulus prediction rating = **8.0** (RT predicted slow, least EF differences)*

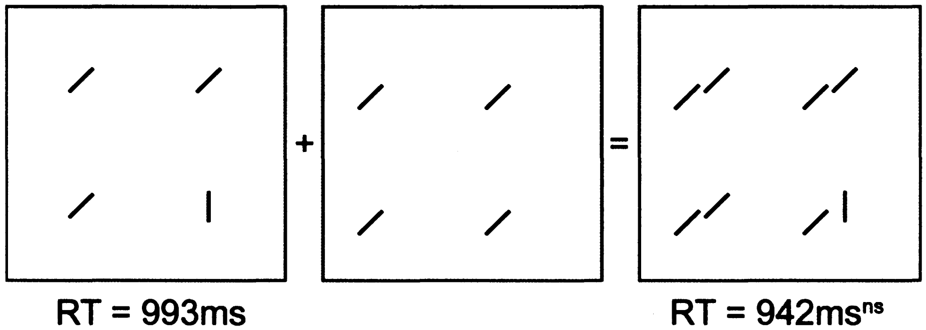


(b) **CIE** $t(8) = -7.21,\ p < .01$
*Stimulus prediction rating = **5.7** (RT predicted moderate, some EF differences)*

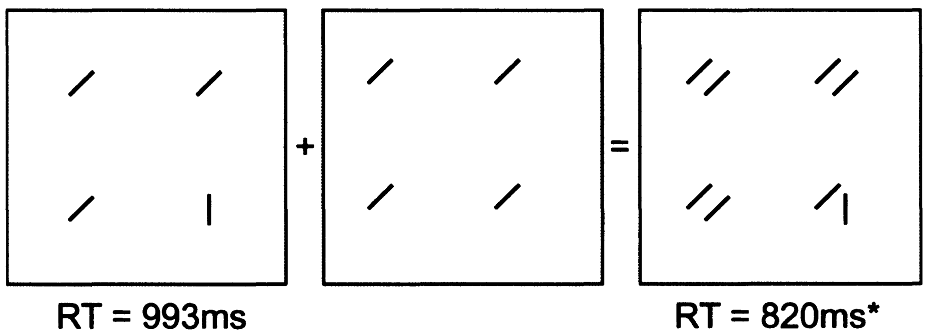


(c) **CIE** $t(7) = -5.26,\ p < .01$
*Stimulus prediction rating = **4.5** (RT predicted fast, most EF differences)*

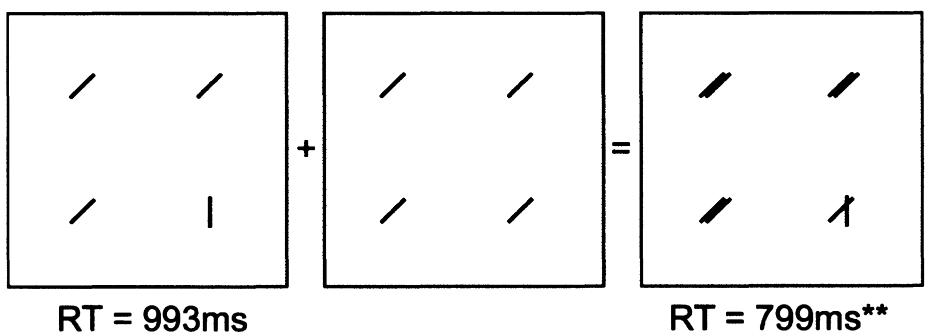
Figure 28 : Space 8D - CIEs



(a) **CSE** $t(8) = .66,\ p = .53$
Stimulus prediction rating = ***7.8*** *(RT predicted slow, least EF differences)*

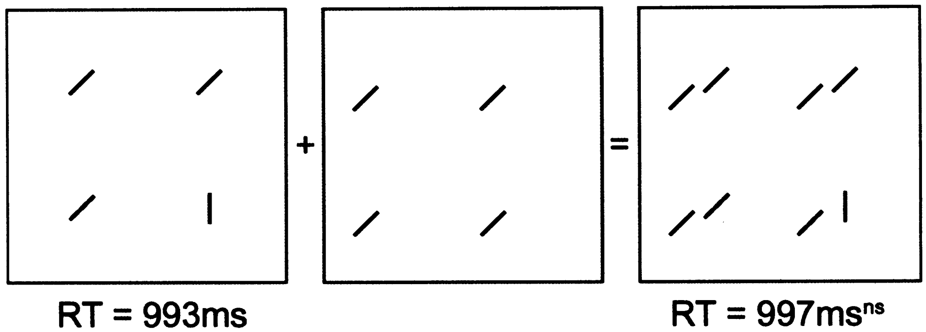


(b) **CSE** $t(8) = 2.58,\ p = .03$
Stimulus prediction rating = ***6.6*** *(RT predicted moderate, some EF differences)*



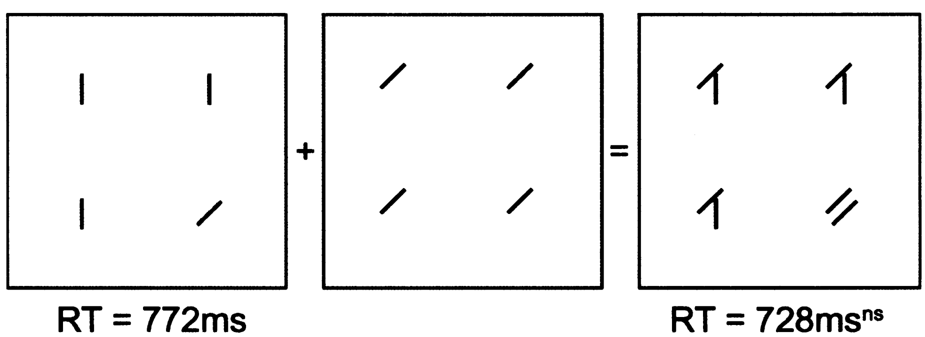
(c) **CSE** $t(8) = 3.59,\ p < .01$
Stimulus prediction rating = ***3.3*** *(RT predicted fast, most EF differences)*

Figure 29 : Space 9D - CSEs



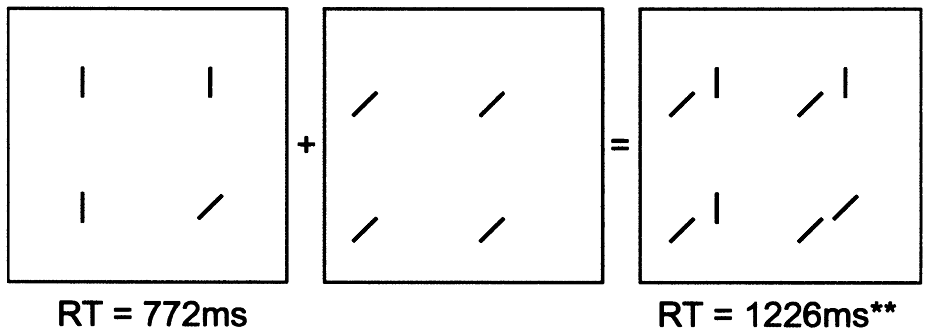
(a) **CIE** $t(8) = -.06,\ p = .96$
Stimulus prediction rating = ***8.0*** *(RT predicted slow, least EF differences)*

Figure 30 : Space 9D - CIEs

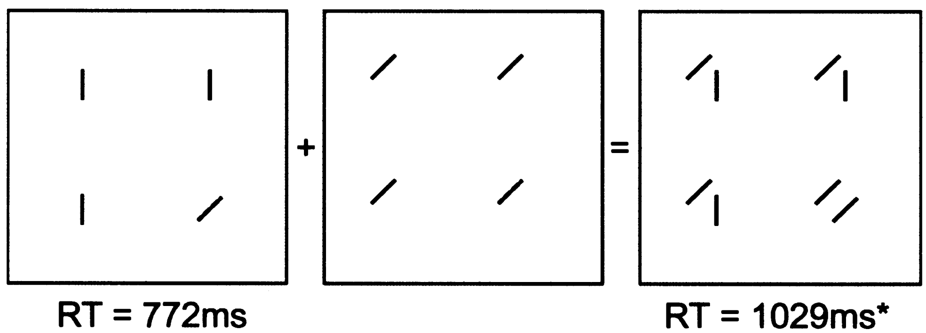


(a) **CSE** $t(8) = 1.61,\ p = .15$
Stimulus prediction rating = ***4.95*** *(RT predicted slow, least EF differences)*

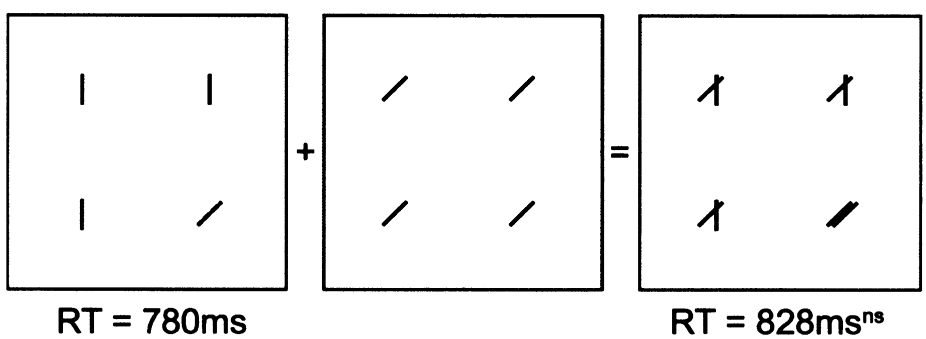
Figure 31 : Space 10D - CSEs



(a) **CIE** $t(8) = -12.22$, $p < .01$
Stimulus prediction rating = ***8.0*** *(RT predicted slow, least EF differences)*



(b) **CIE** $t(8) = -2.77$, $p = .02$
Stimulus prediction rating = ***6.9*** *(RT predicted moderate, some EF differences)*



(c) **CIE** $t(7) = -1.17$, $p = .28$
Stimulus prediction rating = ***4.1*** *(RT predicted fast, most EF differences)*

Figure 32 : Space 10D - CIEs

Space	3C	4C	7D	8D	9D	10D
Terminators	$r = 0.31$ $R^2 = 0.10$ $F(1,167) =$ 18.36 $p < .01$	$r = 0.42$ $R^2 = 0.18$ $F(1,167) =$ 37.44 $p < .01$	$r = 0.52$ $R^2 = 0.27$ $F(1,167) =$ 62.84 $p < .01$	$r = 0.59$ $R^2 = 0.36$ $F(1,167) =$ 92.64 $p < .01$	$r = 0.47$ $R^2 = 0.23$ $F(1,167) =$ 49.00 $p < .01$	$r = 0.59$ $R^2 = 0.35$ $F(1,167) =$ 91.08 $p < .01$
Collinearity	$r = 0.06$ $R^2 = 0.00$ $F(1,167) =$ 0.71 $p = 0.40$	$r = 0.05$ $R^2 = 0.00$ $F(1,167) =$ 0.30 $p = 0.58$	N/A	N/A	$r = 0.04$ $R^2 = 0.00$ $F(1,167) =$ 0.30 $p = 0.58$	$r = 0.04$ $R^2 = 0.00$ $F(1,167) =$ 0.31 $p = 0.58$
Symmetry	$r = 0.51$ $R^2 = 0.27$ $F(1,167) =$ 60.63 $p < .01$	$r = 0.54$ $R^2 = 0.30$ $F(1,167) =$ 71.80 $p < .01$	$r = 0.46$ $R^2 = 0.21$ $F(1,167) =$ 45.32 $p < .01$	$r = 0.46$ $R^2 = 0.22$ $F(1,167) =$ 47.11 $p < .01$	$r = 0.47$ $R^2 = 0.23$ $F(1,167) =$ 49.00 $p < .01$	$r = 0.45$ $R^2 = 0.20$ $F(1,167) =$ 42.68 $p < .01$
Parallelism	$r = 0.58$ $R^2 = 0.34$ $F(1,167) =$ 85.76 $p < .01$	$r = 0.68$ $R^2 = 0.47$ $F(1,167) =$ 145.70 $p < .01$	N/A	N/A	$r = 0.53$ $R^2 = 0.29$ $F(1,167) =$ 68.34 $p < .01$	$r = 0.50$ $R^2 = 0.25$ $F(1,167) =$ 56.65 $p < .01$

Table 9 : Individual Correlations for EFs - Experiment 2

Space	3C	4C	7D	8D	9D	10D
Intersections	$r = 0.63$ $R^2 = 0.40$ $F(1,167) =$ 111.24 $p < .01$	$r = 0.73$ $R^2 = 0.54$ $F(1,167) =$ 193.56 $p < .01$	$r = 0.34$ $R^2 = 0.12$ $F(1,167) =$ 21.77 $p < .01$	$r = 0.48$ $R^2 = 0.23$ $F(1,167) =$ 51.28 $p < .01$	$r = 0.52$ $R^2 = 0.28$ $F(1,167) =$ 64.85 $p < .01$	$r = 0.70$ $R^2 = 0.50$ $F(1,167) =$ 165.06 $p < .01$
Lateral Endpoint Offset	$r = 0.54$ $R^2 = 0.30$ $F(1,167) =$ 70.50 $p < .01$	$r = 0.26$ $R^2 = 0.07$ $F(1,167) =$ 12.62 $p < .01$	N/A	N/A	$r = 0.39$ $R^2 = 0.15$ $F(1,167) =$ 29.91 $p < .01$	$r = 0.12$ $R^2 = 0.01$ $F(1,167) =$ 2.45 $p = .11$
Connectivity	$r = 0.61$ $R^2 = 0.37$ $F(1,167) =$ 98.84 $p < .01$	$r = 0.67$ $R^2 = 0.45$ $F(1,167) =$ 136.52 $p < .01$	$r = 0.36$ $R^2 = 0.13$ $F(1,167) =$ 25.30 $p < .01$	$r = 0.39$ $R^2 = 0.15$ $F(1,167) =$ 30.04 $p < .01$	$r = 0.47$ $R^2 = 0.23$ $F(1,167) =$ 48.90 $p < .01$	$r = 0.57$ $R^2 = 0.33$ $F(1,167) =$ 81.25 $p < .01$
Pixel Count	$r = 0.58$ $R^2 = 0.34$ $F(1,167) =$ 85.89 $p < .01$	$r = 0.74$ $R^2 = 0.55$ $F(1,167) =$ 205.23 $p < .01$	$r = 0.50$ $R^2 = 0.25$ $F(1,167) =$ 56.23 $p < .01$	$r = 0.45$ $R^2 = 0.21$ $F(1,167) =$ 43.26 $p < .01$	$r = 0.49$ $R^2 = 0.25$ $F(1,167) =$ 54.88 $p < .01$	$r = 0.53$ $R^2 = 0.28$ $F(1,167) =$ 65.26 $p < .01$

Table 10 : Individual Correlations for EFs - Experiment 2 (cont'd)

Space	3C	4C	7D	8D	9D	10D
Overall	$R = 0.84$ $R^2 = 0.71$ $F(8, 160) =$ 48.87 $p < .01$	$R = 0.85$ $R^2 = 0.73$ $F(8, 160) =$ 53.79 $p < .01$	$R = 0.60$ $R^2 = 0.37$ $F(5, 163) =$ 19.23 $p < .01$	$R = 0.67$ $R^2 = 0.45$ $F(5, 163) =$ 27.05 $p < .01$	$R = 0.82$ $R^2 = 0.67$ $F(8, 160) =$ 41.05 $p < .01$	$R = 0.76$ $R^2 = 0.59$ $F(8, 160) =$ 28.83 $p < .01$

Table 11 : Overall Correlations for EFs - Experiment 2

As can be seen from Table 11, overall multiple correlation values ranged from .60 to .85, and the EFs of terminators, symmetry, parallelism, intersections, connectivity, pixel count and lateral endpoint offset accounted for the majority of the variance. Due to the nature of the stimuli in Spaces 7D and 8D (horizontal and diagonal line segments), it was not possible to have the EFs of collinearity, parallelism, and lateral endpoint offset present in the physical stimuli, and thus it was not possible to test these EFs here.

It is worth noting that the individual correlations between symmetry and RT data in this experiment are higher than those observed in Experiment 1 (a range of $0.21 - 0.30$ in Experiment 1, and $0.46 - 0.54$ in Experiment 2). Interestingly, the same pattern is not observed with connectivity (range of $0.35 - 0.60$ in Experiment 1, and $0.36 - 0.67$ in Experiment 2). Both symmetry and connectivity were scored using an experimental, subjective, design in Experiment 2, but only the ratings for symmetry improved as a result of this procedure. This finding will be revisited in the following section.

Conclusions

Experiment 2 replicated and extended the results of Experiment 1, showing that performance significantly varies with the orientation and placement of irrelevant, identical contextual lines near the target lines. This suggests that the targets and the contexts form perceptual groups, and that highly salient EFs drive this grouping. In this particular experiment, support was shown for the EFs of terminators, symmetry, parallelism, intersections, connectivity, pixel count and lateral endpoint offset. Overall multiple regression values ranged from .60 to .85, with the percentage of variance accounted for (as evidenced by R^2 values) ranging from 37% to 73%.

Stronger support was shown for the EF of symmetry across all stimulus spaces in Experiment 2 than in Experiment 1. This might be due to the different strategies used to obtain the scores (objective in Experiment 1, and subjective in Experiment 2). Perhaps the objective scoring system used in the present experiment (according to the coding criteria in Appendix C) to code for symmetry was not sensitive enough to the perception of this EF. Using participants' subjective scores for this EF was perhaps a more true representation of the perception of symmetry. It is interesting to note that connectivity, also scored subjectively by participants, did not experience such a benefit in its correlation with RT in Experiment 2 compared with Experiment 1. It is possible that the differences among symmetric stimuli (i.e., those stimuli which vary in their axis of symmetry) are greater than those among stimuli which vary in their degree of connectedness. Thus, it might be possible that axis of symmetry is a stronger predictor of grouping than is connectivity, although further research will be needed to support this hypothesis.

Support has been shown for strong CSEs. Due to the nature of the stimuli used, some spaces (7D, 8D, 10D) had a majority of, and sometimes exclusively, CIE effects (e.g., the discrimination between a vertical line segment and a diagonal was already very fast, so most of the composite stimuli produced an inferiority effect because the context made the quadrants more similar than they were. However, it is important to note that it was not simply the addition of a context which diluted the dissimilarity of the quadrants which led to a CIE. Dilution of dissimilarity is presumably also operating in those cases where a CSE is obtained, but in the cases of CSEs the beneficial grouping effects from EFs trump other effects which work against grouping. These factors will be further discussed later on). Other spaces (3C, 4C, 9D) produced mostly CSEs (e.g., the initial discrimination was very hard, so any kind of context helped). However, it is interesting to note that there were 2 kinds of CIEs that were obtained in this experiment: those which arose from stimuli containing EF differences between the odd quadrant and the other 3, and those from stimuli without EF differences. Moreover, the CIE effects which arose from stimuli with EF differences were weaker than those without EF differences. So why weren't the CIEs with EF differences CSEs? It is possible that, just as EF differences help discrimination, other properties of the stimulus work to hinder it. One such property might be "crowding", or the effect which occurs when features from nearby objects combine together to form a jumble (Levi, 2008). Other such factors may include masking, additional processing load, and distraction from the target elements of the display. Thus, the observed RTs might be the the net difference of these two forces. In the case that crowding might be coded and accounted for, some CIEs with EF differences would become CSEs, providing stronger support for EFs.

Experiment 2 was an improvement over Experiment 1 in three ways. First, to address the concern that EFs behaved differently in combinations with different EFs, Experiment 2 sampled from 4 different patterns of EF presence in the odd quadrant (Alpha, Beta, Gamma, and Delta). This procedure did not affect the overall results as they were observed in Experiment 1. Second, Experiment 2 included baseline (base image discrimination only) RT measurements to inform the discussion of CSE/CIEs. Third, prediction scoring in Experiment 2 was *a priori*, and thus validated the prediction method developed and employed in Experiment 1.

Limitations

Some limitations of Experiment 2 included 1) possibility of unequal salience of EFs, 2) inability to tease apart the individual salience of EFs, and 3) insufficient data for some of the patterns.

First, the possibility of unequal salience of EFs has not fully been addressed. This limitation is reflected in the present model, which does not account for this possibility given the equal weights assigned to all EFs. However, very strong correlations have been obtained between the equal-weight predictions and the data despite this limitation. In fact, having fewer parameters and still accounting for 40-60% of the overall variance increases the parsimony of the model.

Second, the problem of multi-collinearity has also not been addressed, and it is not possible in the present model to tease apart the individual salience of EFs. It is not clear, for example, whether the EF of connectivity is as important as the EF of terminators. This limitation might be addressed by having fewer predictors, but the preferred method would be to collect more data (preferably on different stimulus spaces, as described below).

Third, there was insufficient data for analyzing individual EFs in each of the patterns. Given this limitation, it is not possible to investigate EF contributions in the context of other EFs at present.

General Discussion

Both of the present experiments showed that performance during visual discrimination tasks depends significantly on the identical "context" lines which are placed near the target line segments in all 4 quadrants. The target always remained the same, and in the same spatial position. This result is interpreted to signify that the target lines and context lines form perceptual groups. This can be shown by studying CSEs and CIEs. What makes CSEs and CIEs work? An object which has more Emergent Features in its configuration will be more salient in its contrast with objects lacking such features. In the present experiments, eight such EFs have been identified. Support has been shown for such EFs as number of terminators, connectivity, intersections, parallelism, lateral endpoint offset, and pixel count. It follows from this argument that a cluster of elements is more likely to form a coherent object, or group, if it possesses these features. Thus, "parts" and "objects" can be defined using the relationship between elements based on Emergent Features.

Future Research

The methods for teasing apart the contributions of individual EFs are worth pursuing further. For instance, obtaining more data with stimulus sets which fall into the four patterns might lead to insights about EF salience when paired with other EFs within the same stimulus space. Conversely, it might be possible to devise new stimulus spaces where the displays vary only on one particular EF.

CSEs and CIEs might be possible to study further as the products of the differences between EF and crowding effects. This might be accomplished by finding properties of objects which would produce "clutter" and coding them in much the same manner as was presented here with EFs.

Lastly, further study will be needed to determine the correct relationship of the EF of symmetry to the perception of this EF with a scoring system which is more sensitive to this relationship.

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Appendix A - Stimulus Spaces

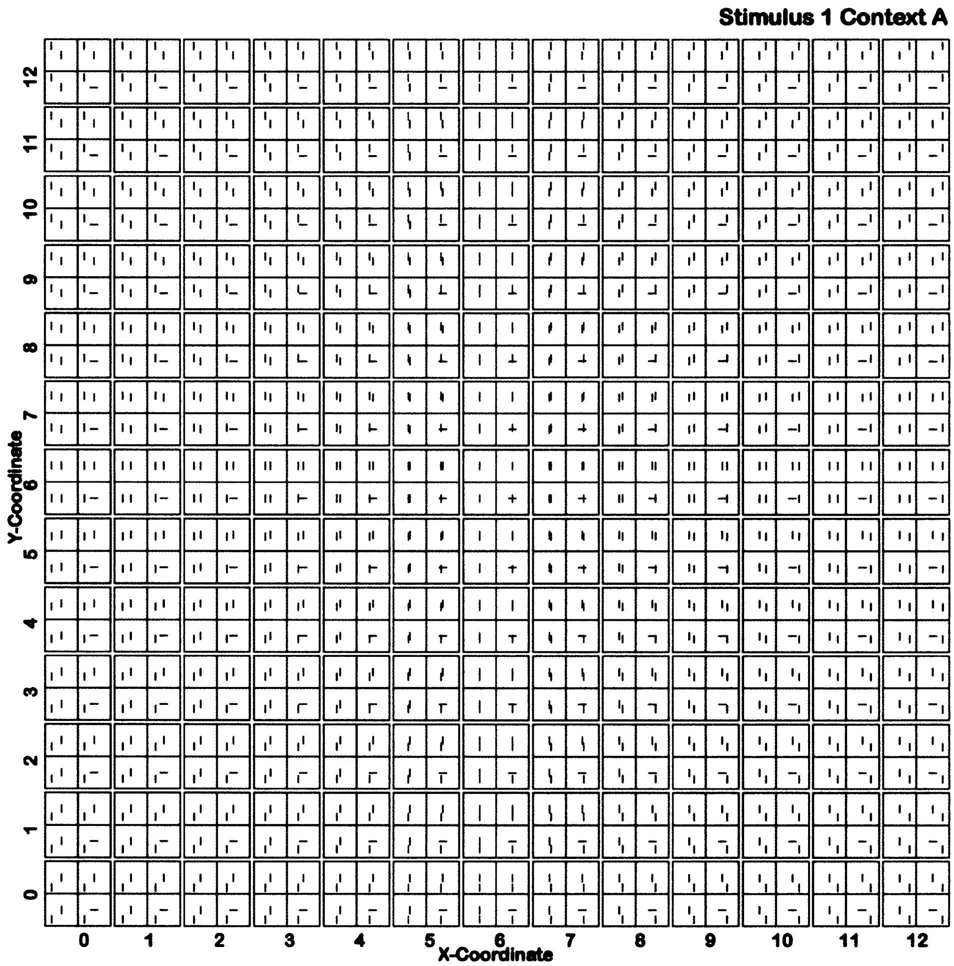


Figure 33 : Space 1A

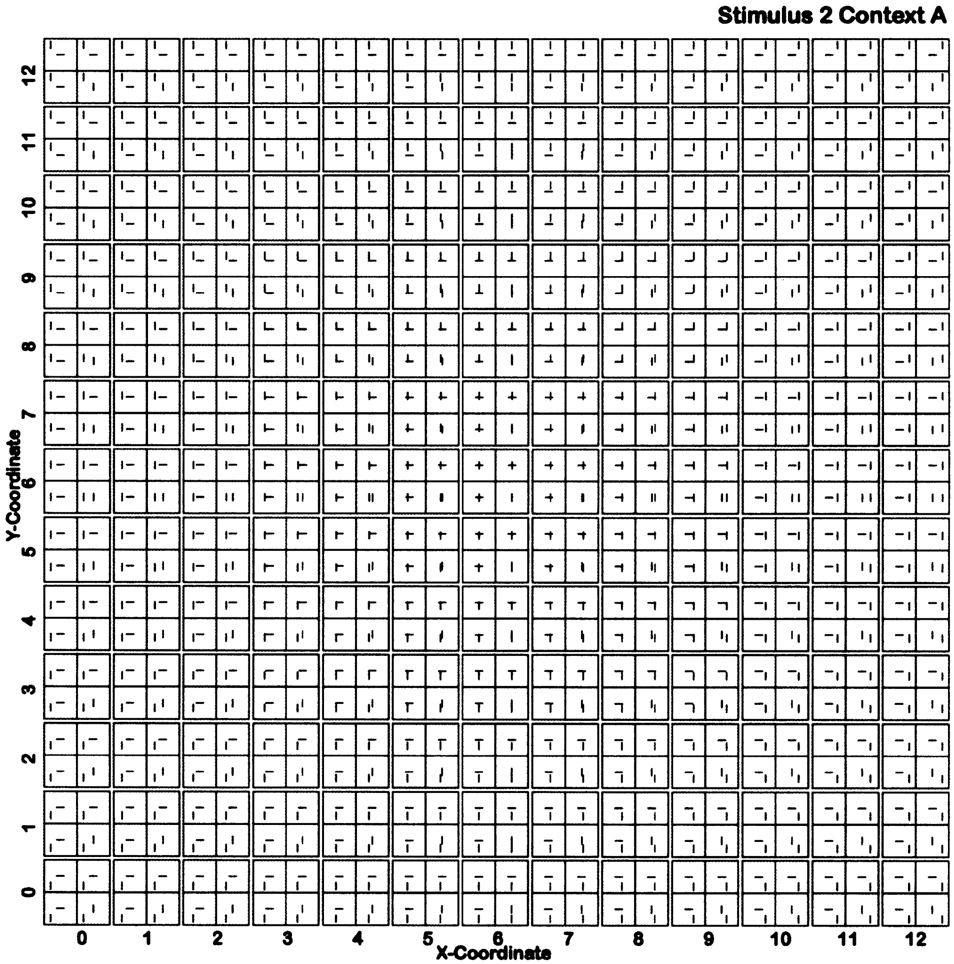


Figure 34 : Space 2A

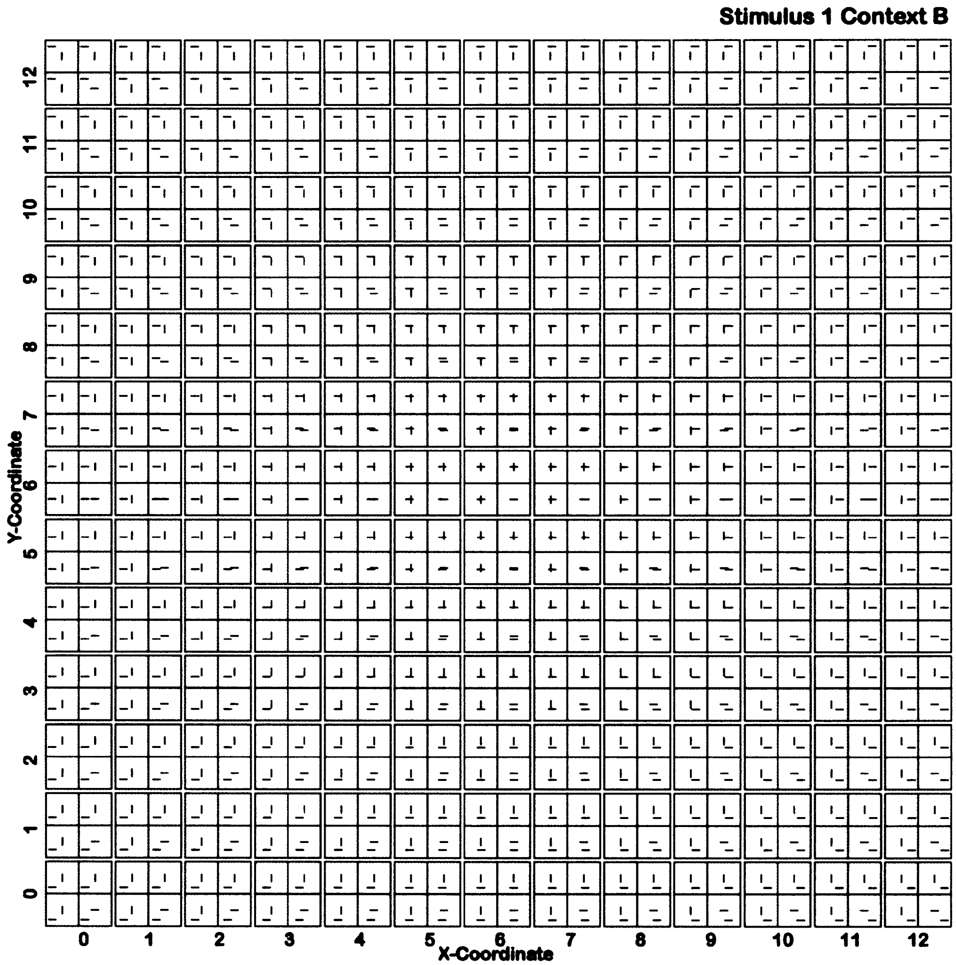


Figure 35 : Space 1B

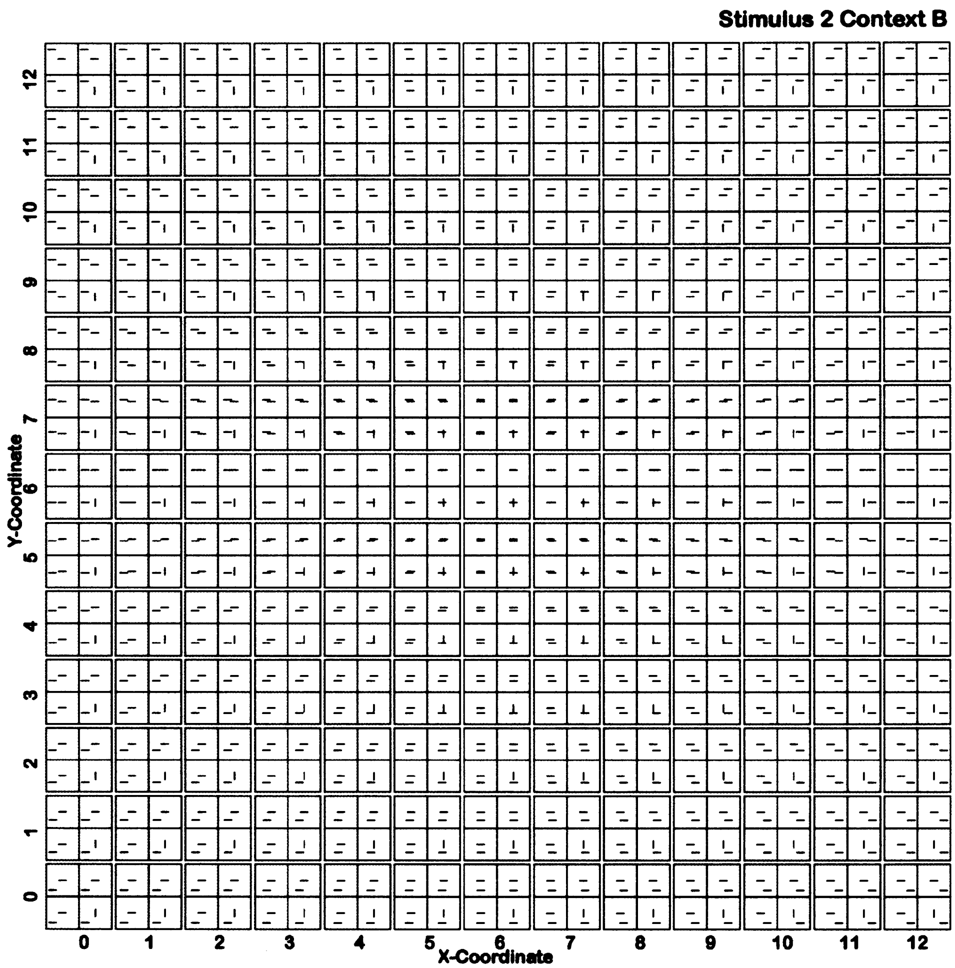


Figure 36 : Space 2B

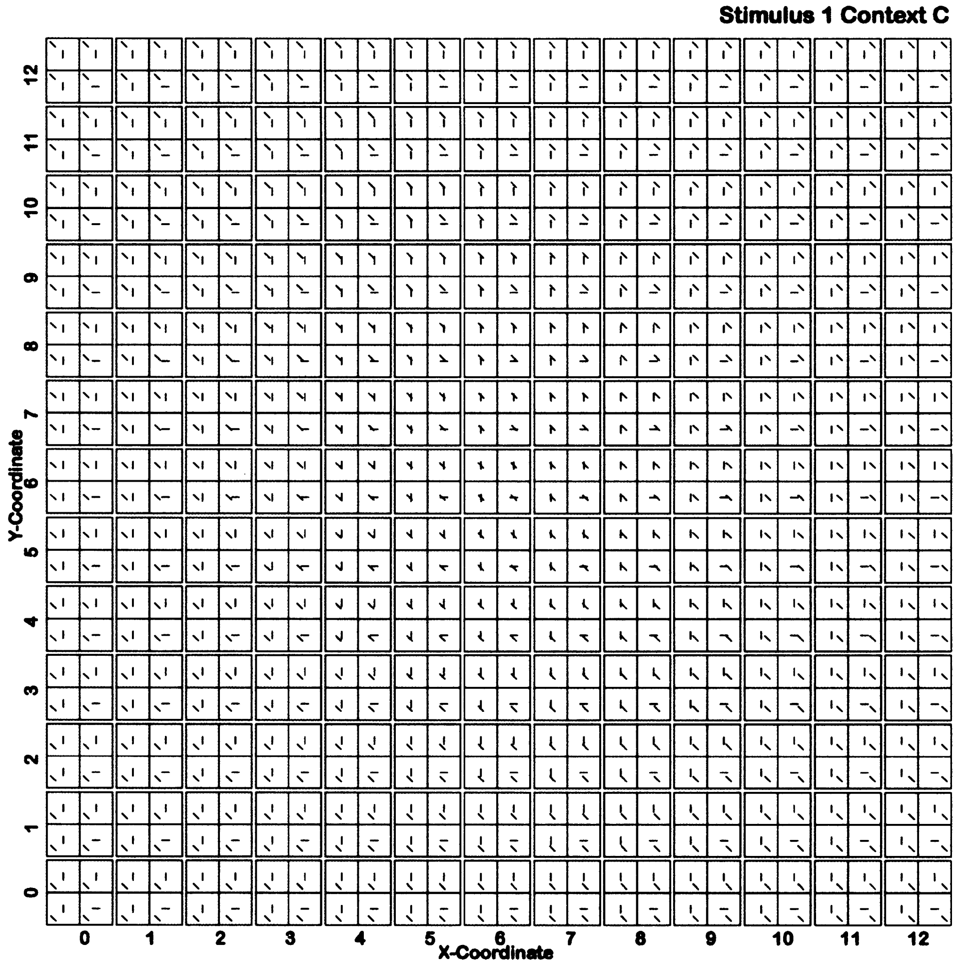


Figure 37 : Space 1C

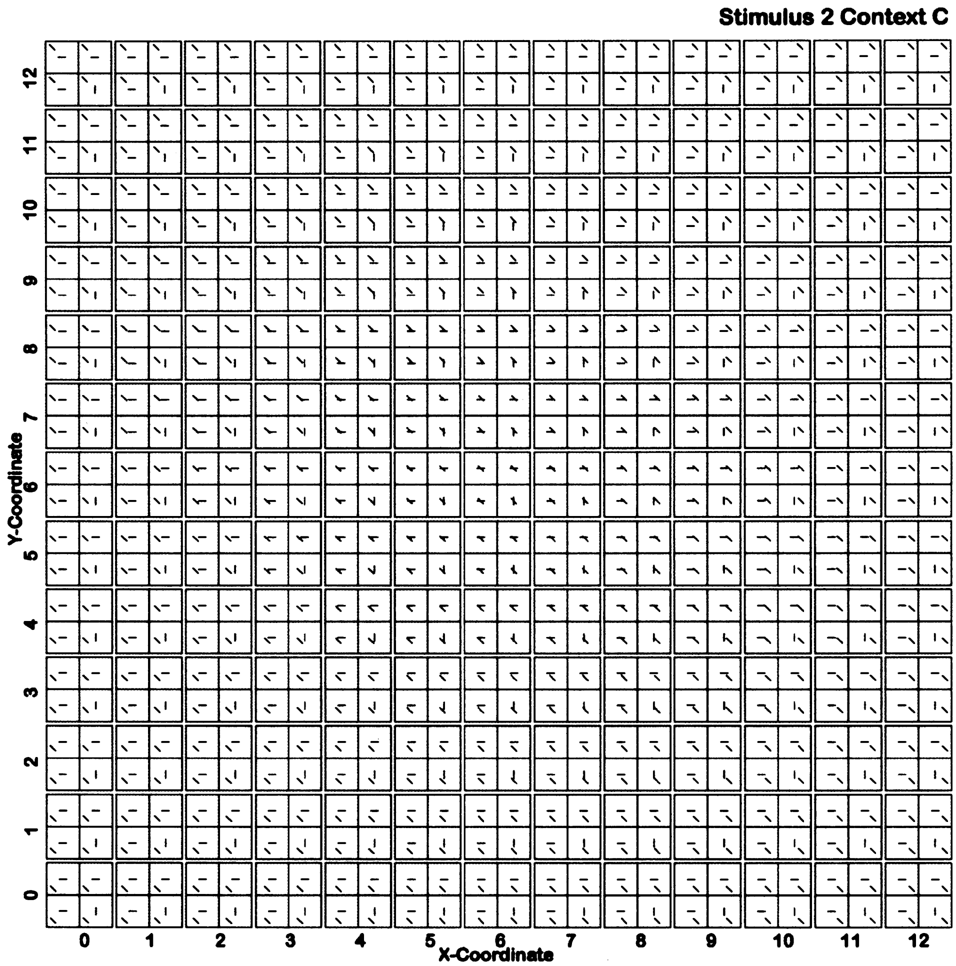


Figure 38 : Space 2C

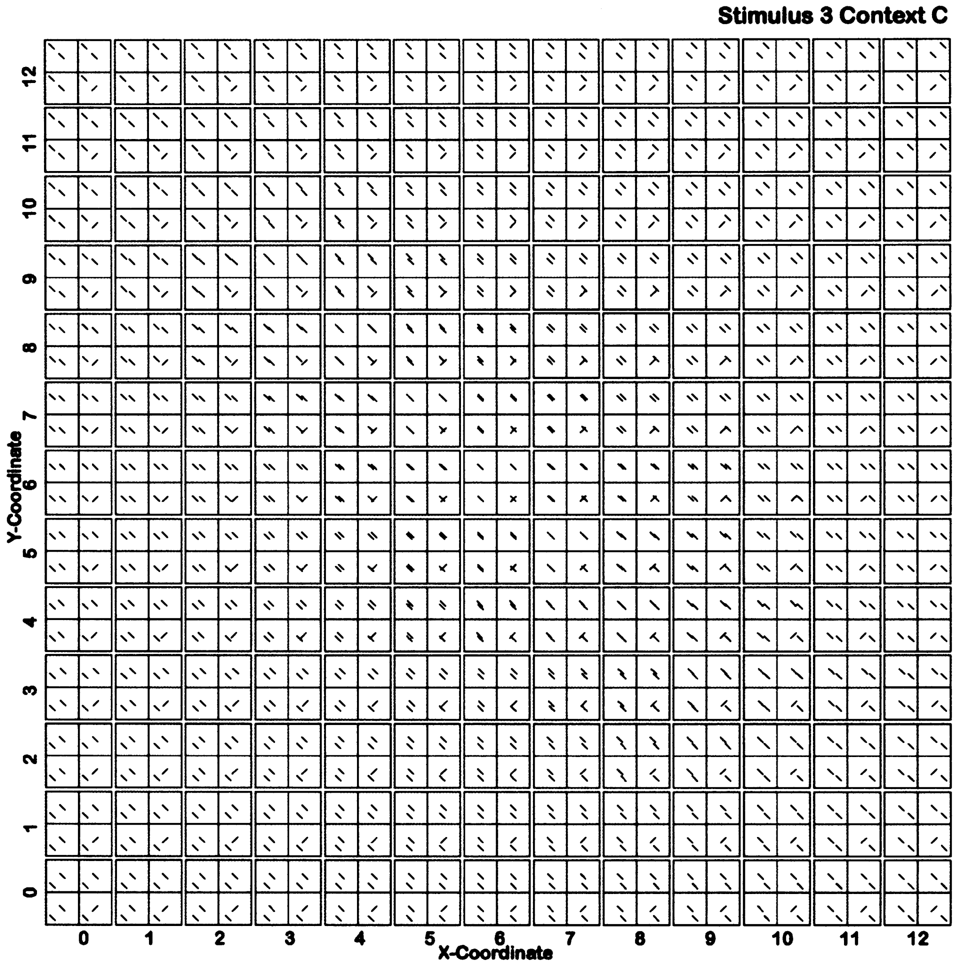


Figure 39 : Space 3C

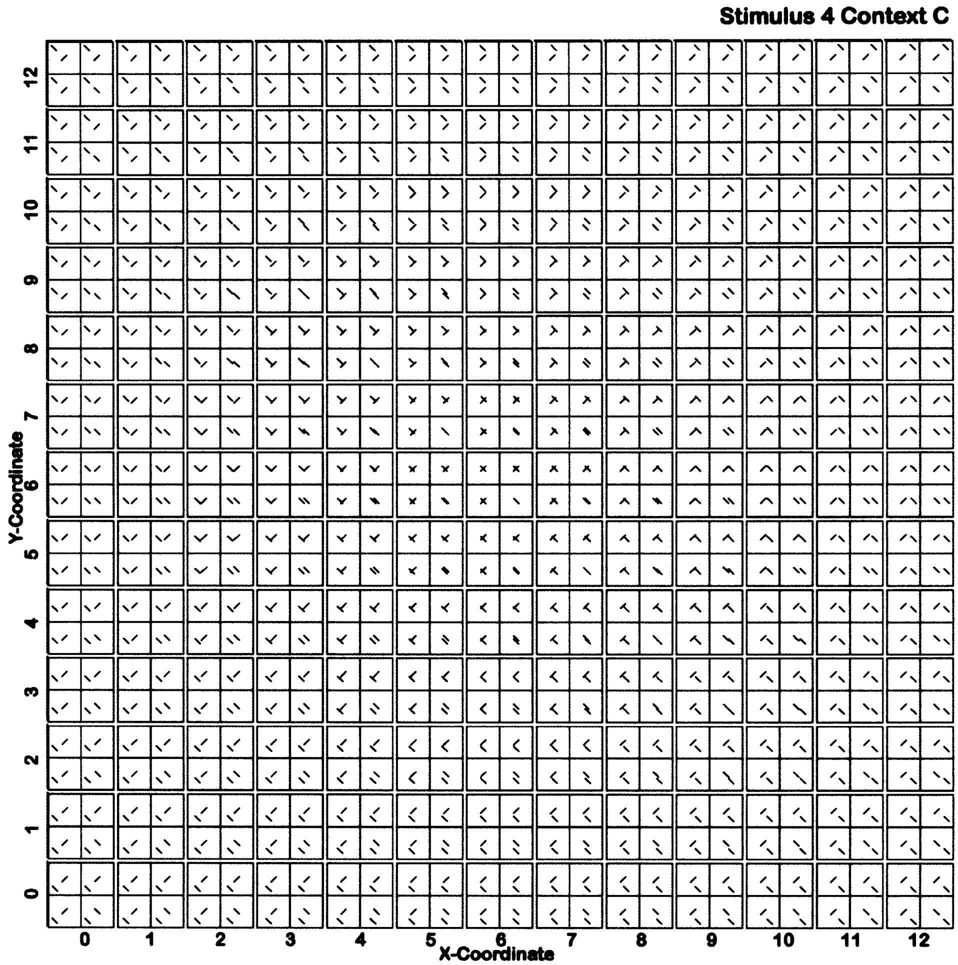


Figure 40 : Space 4C

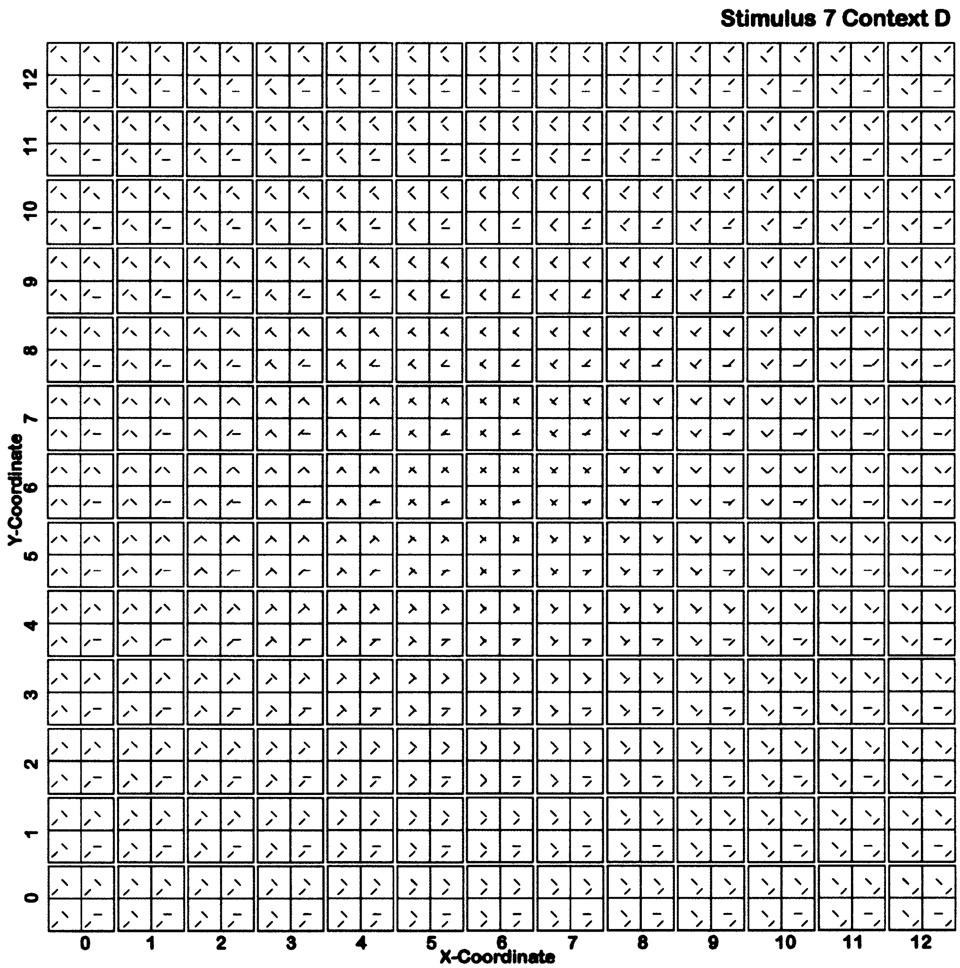


Figure 41 : Space 7D

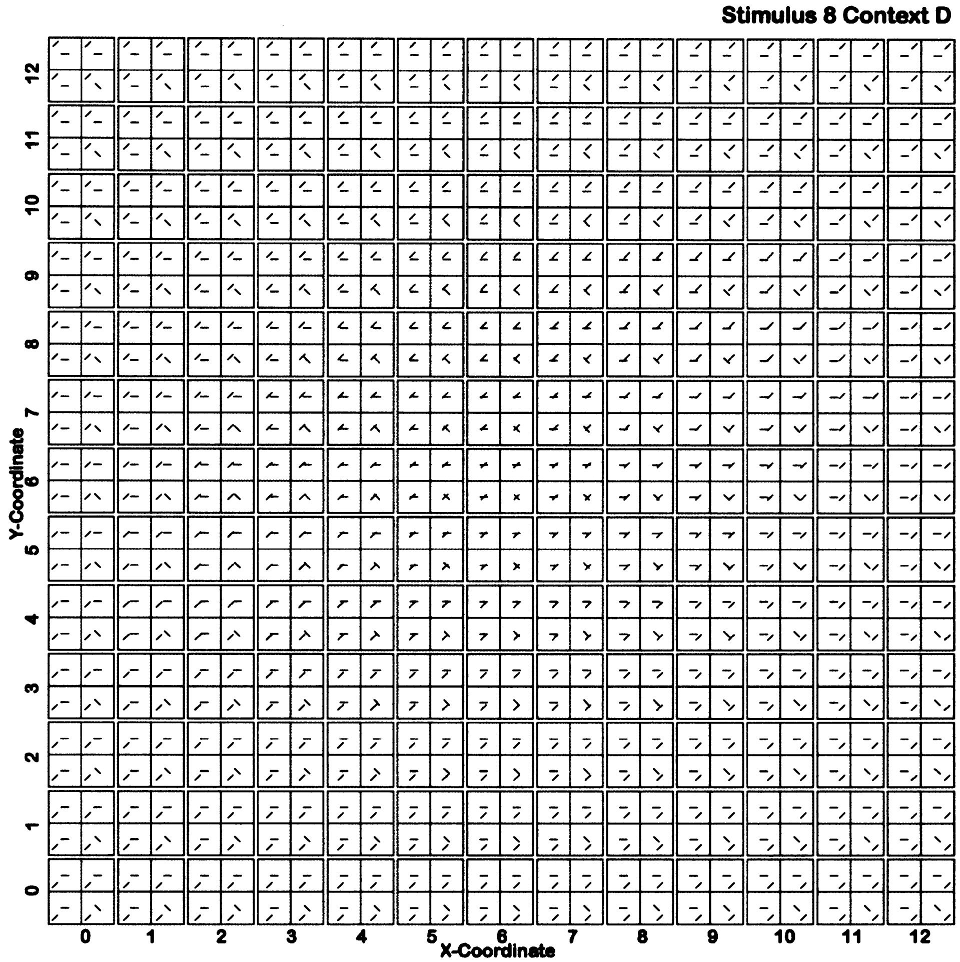


Figure 42 : Space 8D

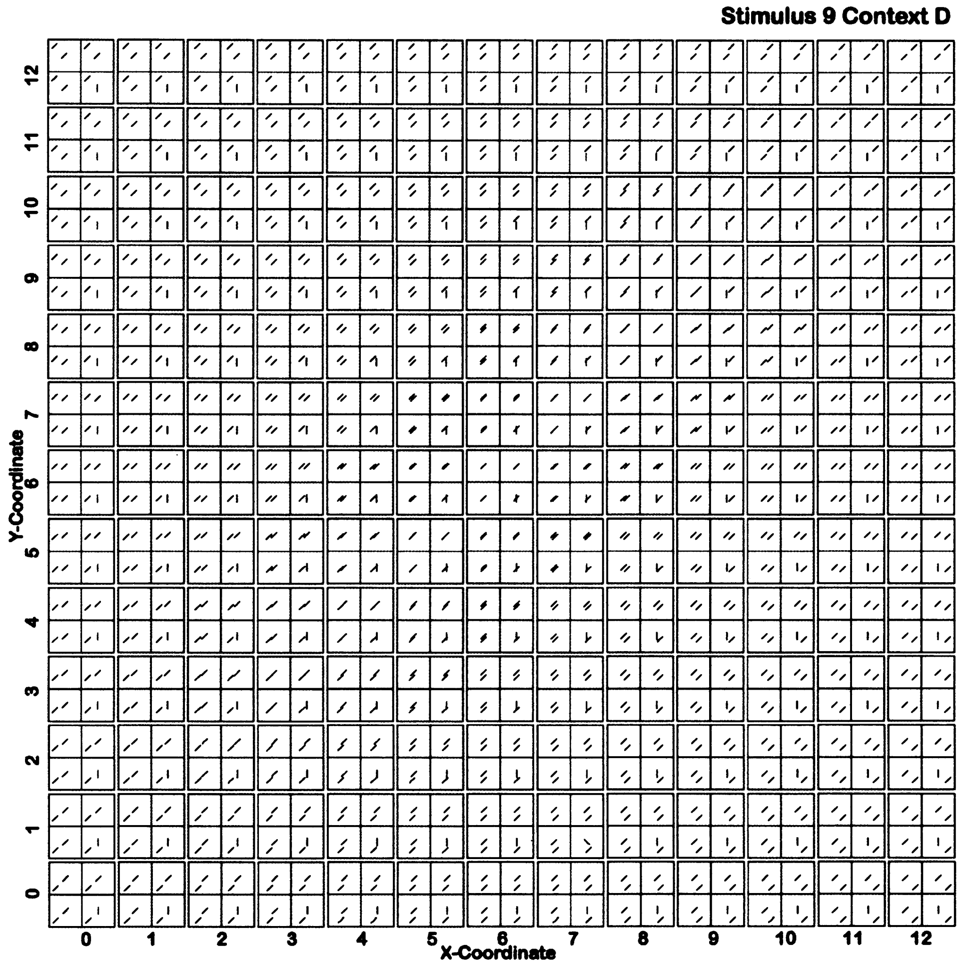


Figure 43 : Space 9D

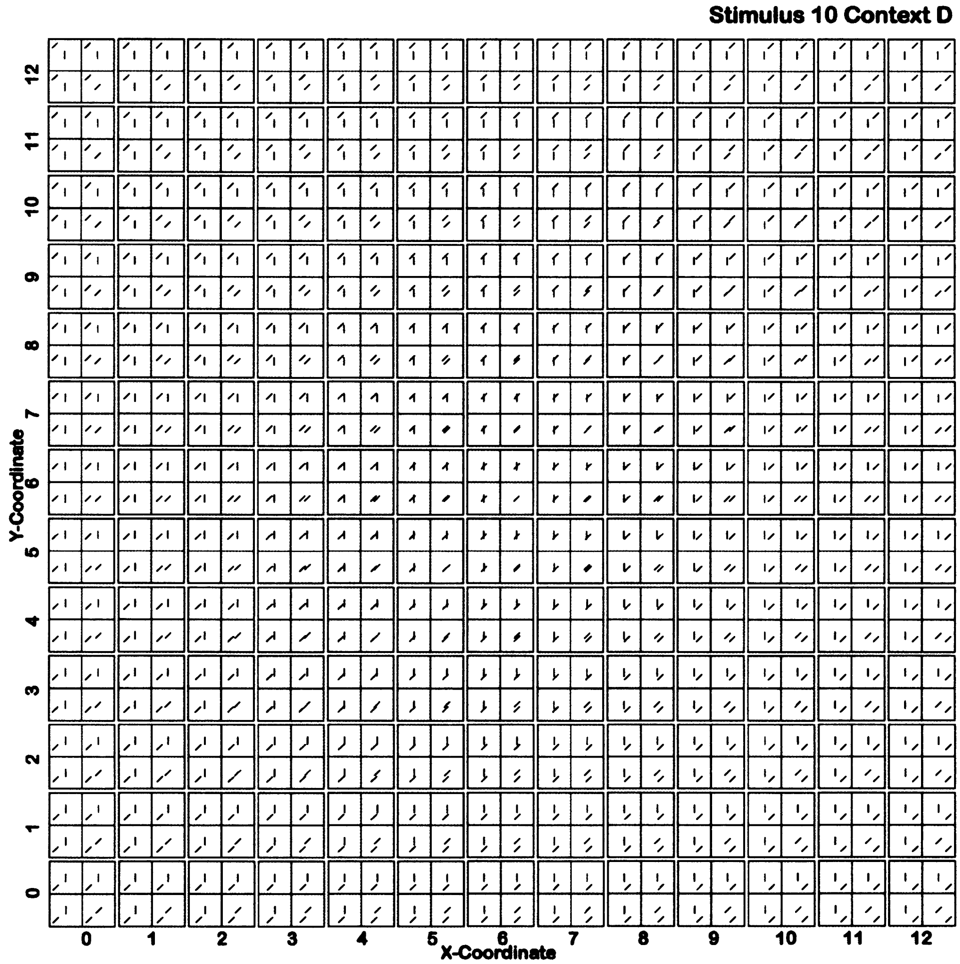
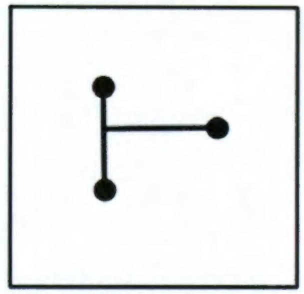
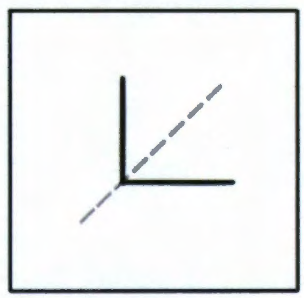
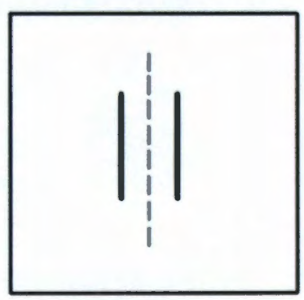
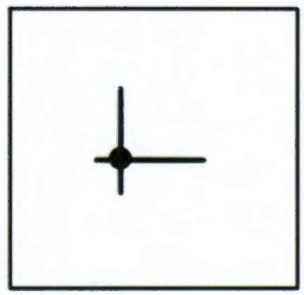
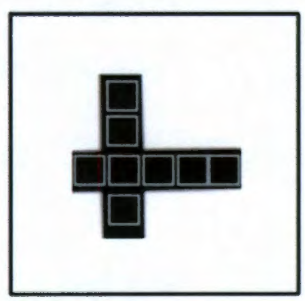


Figure 44 : Space 10D

Appendix B - Descriptions of Emergent Features

Emergent Feature	Description	
Terminators	The number of end-points on an image	
Collinearity	The extent to which two line segments fall in a straight line	
Symmetry	The property that allows the recreation of an image when rotated around an axis	
Parallelism	Two line segments that never intersect	

Emergent Feature	Description	
Lateral Endpoint Offset	The extent to which two parallel line segments begin and end together in the same plane	
Intersections	Whether two line segments cross each other	
Connectivity	Whether two line segments are in contact with one another, making for a continuous line or shape	
Pixel Count	The amount of black (figure) pixels present in the image	

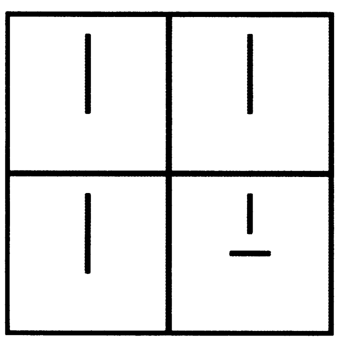
Appendix C - Scoring Criteria and Instructions

1. Terminators

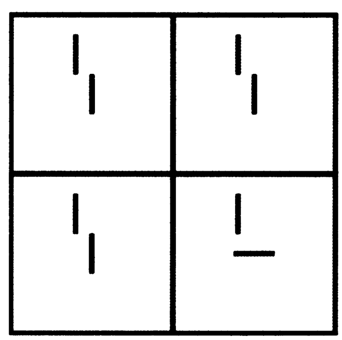
The number of "end points" in the image.

Scoring is determined by counting the number of end-points in the odd image as well as in the distractor image. Scoring is then assigned according to the table below.

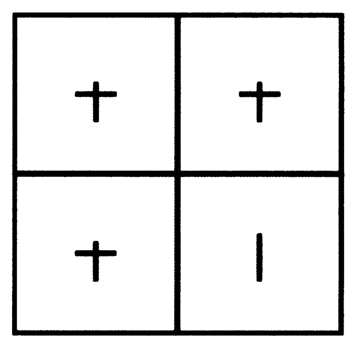
		# of Terminators in Odd Quadrant		
		4	**3**	**2**
# of Terminators in other 3 quadrants	**4**	0	0.5	0.25
	3	0.75	0	0.5
	2	1	0.75	0



Terminator difference (1)



No terminator difference (0)



Less terminators in odd quad (.25)

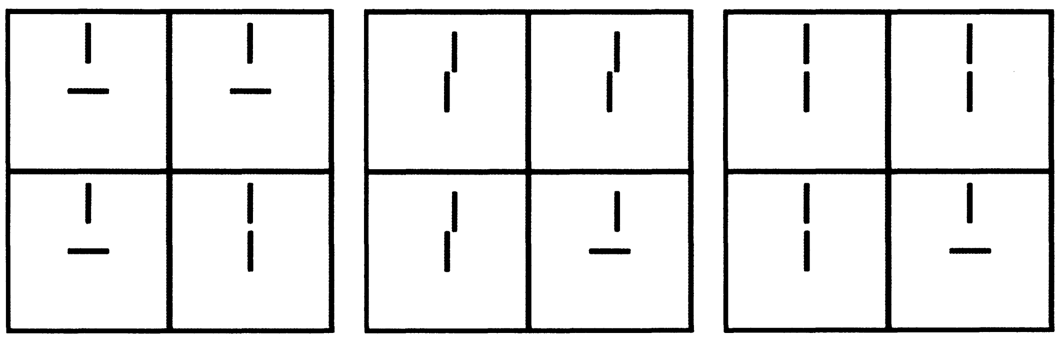
2. Collinearity

When the two line segments are in line with each other (valid only for 2 separate line segments).

Code .5 for presence of collinearity in odd quadrant.

Code 1 for absence of collinearity in odd quadrant, but presence in the other 3.

Multiplied by Proximity for final score.



Collinearity difference (.5)	No collinearity difference (0)	No collinearity in odd quad (1)

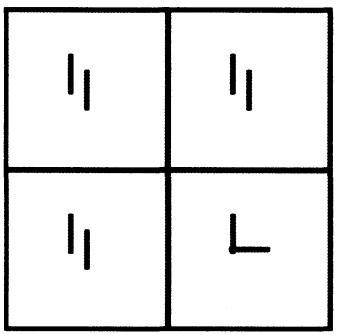
3. Symmetry

Symmetrical regardless of axis. If stimuli have symmetry along any axis, symmetry is coded. For this variable, it doesn't make a difference in the scoring whether the odd quadrant is symmetrical over a different axis from the other 3.

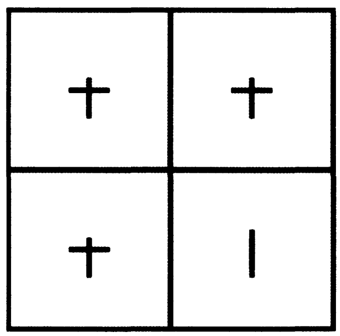
Code .5 for presence of summetry in odd quadrant.

Code 1 for absence of symmetry in odd quadrant, but presence in the other 3.

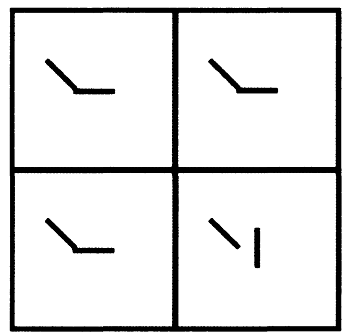
Multiplied by Proximity for final score.



Symmetry difference (.5)



No symmetry difference (0)



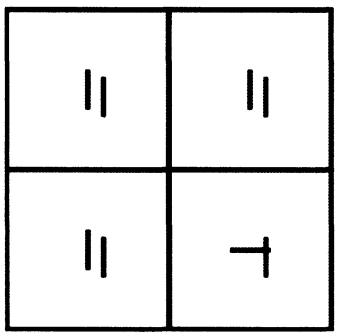
No symmetry in odd quad (1)

4. Parallelism

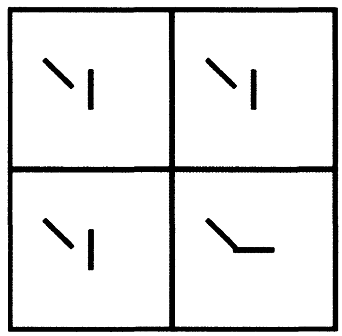
Code 1 for absence of parallelism in odd quadrant.

Code .5 for presence of parallelism in odd quadrant, but not other 3.

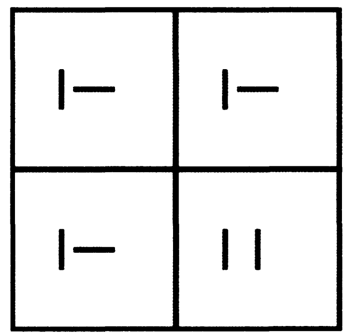
Multiplied by Proximity for final score.



Parallelism absence in odd quad (1)



No parallelism (0)



Parallelism presence in odd quad (.5)

5. Lateral Endpoint Offset (horizontally and vertically)

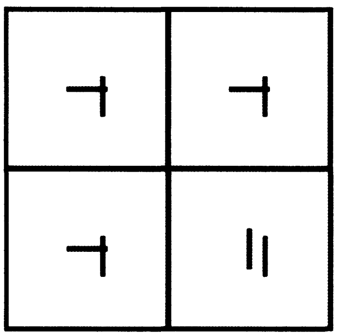
The extent to which two lines begin and end together. The range is from 0-1 in 0.2 increments.

For lateral endpoint offset in odd quadrant:

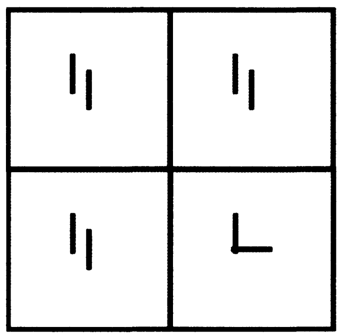
Possible values: 0, 0.2, 0.4, 0.6, 0.8, 1 (arranged symmetrically along the grid)

For lateral endpoint offset in the other 3 quadrants:

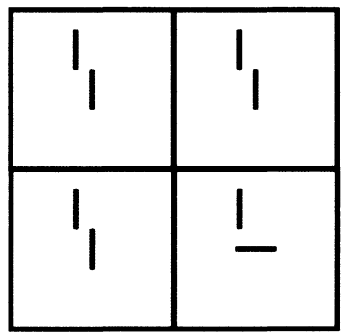
Possible values: 0, 0.1, 0.3, 0.5, 0.7, 0.9 (arranged symmetrically along the grid)



L.E.O. in odd quadrant (.8)



L.E.O. in other 3 quadrants (.5)



L.E.O. in other 3 quadrants (0)

Lateral Endpoint Offset (diagonally)

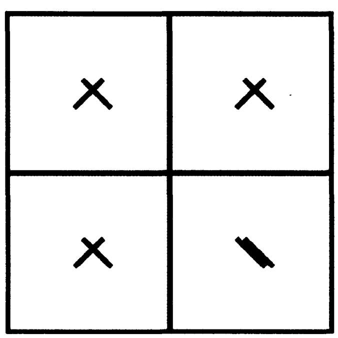
The extent to which two lines begin and end together. The range is from 0-1 in 1/7 increments.

For L.E.O. in odd quadrant:

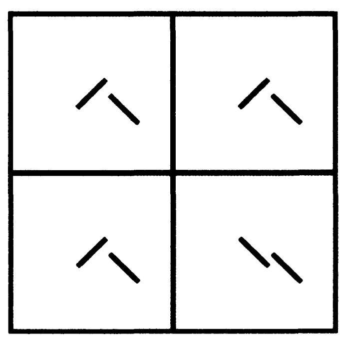
Possible values: 0, 1/7, 2/7, 3/7, 4/7, 5/7, 6/7, 1 (arranged symmetrically along grid)

For L.E.O. in other three quadrants:

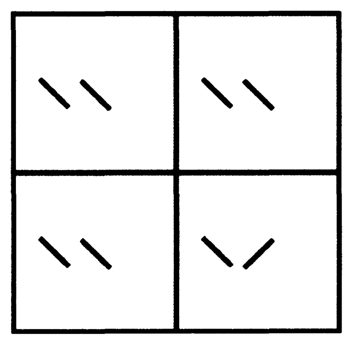
Possible values: 0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7 (arranged symmetrically along grid)



L.E.O. in odd quadrant (6/7)



L.E.O. in odd quadrant (1/7)

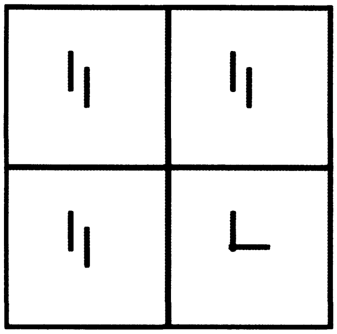


L.E.O. in other 3 quadrants (.2)

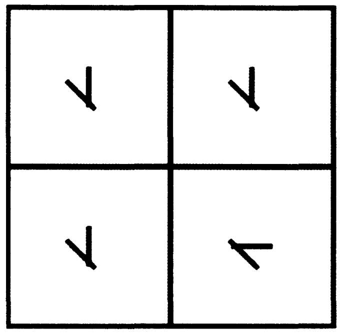
6. Intersections

Code 1 for intersections in odd quadrant.

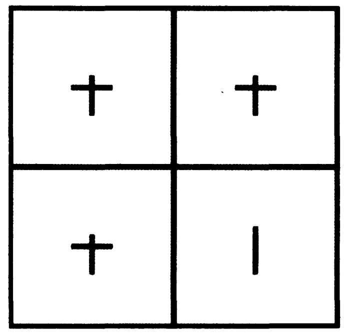
Code 0.5 for intersections in other 3 quadrants, but not in odd quadrant.



Intersection difference (1)



No intersection difference (0)



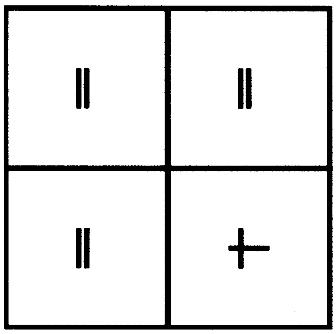
No intersection in odd quad (.5)

7. Connectivity

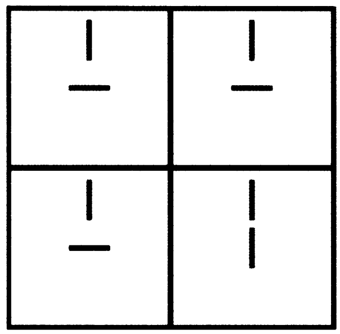
When the context and base are connected (touching) versus when they are not.

Code 1 for connectivity in odd quadrant.

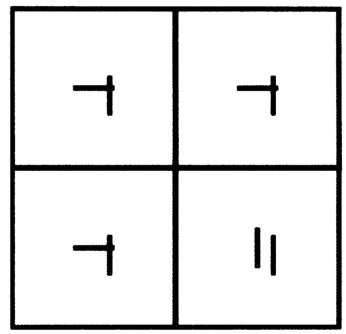
Code 0.5 for connectivity in other three quadrants, but not in the odd quadrant.



Connectivity difference (1)



No connectivity difference (0)



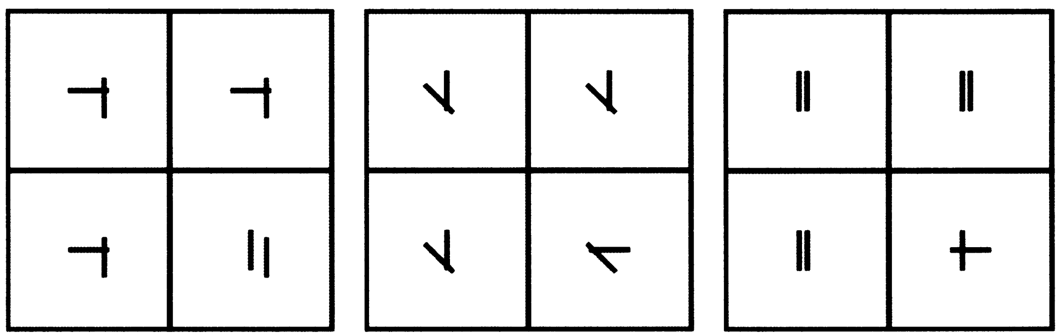
No connectivity in odd quad (.5)

8. Pixel Count

Difference between the number of black (image) pixels between the odd quadrant and the other three.

Code 1 for more pixels in odd quadrant.

Code 0.5 for more pixels in the other three quadrants.



More pixels in odd quad	No pixel count difference	Less pixels in odd quad
(1)	(0)	(.5)

9. Proximity

The center-to-center distance between the two line segments in the image. Based on the movement of the context across the grid.

The coding shown below was used for all the spaces. The bold "coordinates" are the identifiers for each display.

	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
12	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0
10	0	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0
9	0	0.1	0.2	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.2	0.1	0
8	0	0.1	0.2	0.4	0.6	0.6	0.6	0.6	0.6	0.4	0.2	0.1	0
7	0	0.1	0.2	0.4	0.6	0.8	0.8	0.8	0.6	0.4	0.2	0.1	0
6	0	0.1	0.2	0.4	0.6	0.8	1	0.8	0.6	0.4	0.2	0.1	0
5	0	0.1	0.2	0.4	0.6	0.8	0.8	0.8	0.6	0.4	0.2	0.1	0
4	0	0.1	0.2	0.4	0.6	0.6	0.6	0.6	0.6	0.4	0.2	0.1	0
3	0	0.1	0.2	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.2	0.1	0
2	0	0.1	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.1	0
1	0	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0