Feature binding in visual short term memory: A General Recognition Theory analysis

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Published online: 23 May 2017
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Abstract Creating and maintaining accurate bindings of elementary features (e.g., color and shape) in visual short-term memory (VSTM) is fundamental for veridical perception. How are low-level features bound in memory? The present work harnessed a multivariate model of perception – the General Recognition Theory (GRT) – to unravel the internal representations underlying feature binding in VSTM. On each trial, preview and target colored shapes were presented in succession, appearing in either repeated or altered spatial locations. Participants gave two same/different responses: one with respect to color and one with respect to shape. Converging GRT analyses on the accuracy confusion matrices provided substantial evidence for binding in the form of violations of *perceptual independence* at the level of the individual stimulus, such that positive correlations were obtained when both features repeated or alternated together, while negative correlations were obtained when one feature repeated and the other alternated. This “cloverleaf” GRT pattern of binding was similar whether the spatial location of the preview and target repeated or altered. The current results are consistent with: (a) the discrete memory “slots” model of VSTM, and (b) the notion that spatial location is not necessary for the formation of “object files.” The GRT approach presented here offers a viable quantitative model for testing various questions regarding feature binding in VSTM.

Keywords Visual short-term memory · Feature binding

Electronic supplementary material The online version of this article (doi:10.3758/s13423-017-1303-y) contains supplementary material, which is available to authorized users.

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Introduction

The objects of perception are multidimensional, yet they are perceived as unitary wholes. Looking at a plate of fruit, we integrate the red color of the apple with its round shape, and the yellow color of the banana with its curved shape. Fortunately, we do not mix the colors or the shapes of the two objects. This accurate and rapid binding documents a remarkable achievement of our visual system. The reason is that although features (e.g., color, shape, or size) are encoded in a distributed manner across different locations in the brain (Hubel & Wiesel, 1977), they are integrated into their veridical configuration. The computational challenge involved in such an endeavor has been often dubbed the *binding problem* (Singer & Gray, 1995; Treisman, 1996; von der Malsburg, 1999; see also Fitousi, 2017a, b). A major question in the study of binding concerns the nature of the internal representation underlying the bound features (Luck & Vogel, 1997), as well as the role of attention to location in generating these bindings (Wheeler & Treisman, 2002). The present study harnessed a powerful methodology known as the General Recognition Theory (GRT; Ashby & Townsend, 1986) to address these questions.

Evidence for feature binding in visual memory comes from various sources. Kahneman, Treisman, and Gibbs (1992) have used a preview task in which a letter appeared in a prime display, and then the same letter or different letters were presented in a probe display. Naming latencies for the probe letter were faster if the letter’s identity was repeated within the same location/object. This result was taken as evidence for the creation of “object files” – temporary, episodic structures that are capable of overcoming spatiotemporal discontinuities. Using a similar preview task, Hommel (1998) asked observers to judge the color of a probe letter preceded by a preview letter. The color, shape, or location of the probe letter could repeat or

alternate from the preview letter. Hommel found that repeating two given features (e.g., a red “x” followed by a red “x”) or alternating them altogether (e.g., a red “x” followed by a green “o”) yielded superior performance to that observed in conditions in which one of the features was repeated and the other was alternated (e.g., a red “x” followed by a red “o”). The pattern – *partial-repetition costs* (Hommel, 1998; Fitousi, 2017a, b) – was taken as evidence for the creation of “object files.” According to Hommel, “object files” do not consist of the entire list of features, but rather include a set of pairwise bindings (e.g., shape + color, shape + location). Partial repetition costs may reflect the difficulty of retrieving an “object file” when one of its features overlaps with a previously seen “object file.” According to Hommel (1998), attention to location is not necessary for binding, because partial repetition costs are found even when the probe and preview letters appear in different spatial locations.

Another source of evidence for the presence of feature bindings in visual short-term memory (VSTM) comes from a *change-detection* paradigm (Luck & Vogel, 1997; Wheeler & Treisman, 2002), in which observers indicate whether a display consisting of several colored shapes is the “same” or “different” from a preview display. Binding in this paradigm is often measured by comparing levels of accuracy for single feature (e.g., shape) and conjunctions (e.g., color and shape) (Allen, Baddeley, & Hitch, 2006).

In most of the reviewed paradigms (Hommel, 1998; Kahneman et al., 1992; Makovski & Jiang, 2009; Luck & Vogel, 1997) the internal representation underlying the bound features is not well specified. Inferences regarding feature binding are made based on comparisons of performance levels (i.e., reaction time (RT), accuracy) across experimental conditions (but see Ashby, Prinzmetal, Ivry & Maddox, 1996; Bays et al., 2011). Note that performance differences might or might not reflect a true binding process. There is always the possibility that the observed differences were generated by differences in task difficulty, or by decisional rather than perceptual influences (Green & Swets, 1966). Arguably, such factors are only remotely, if at all, related to binding. What is needed is a model that is capable of defining a priori and quantitatively the internal representations underlying feature bindings. This model should also be capable of dissociating perceptual and decisional factors. With such a model at hand, predictions can be made and tested with increased confidence that dependent variables truly reflect the presence or absence of binding. Such a model is introduced next.

General Recognition Theory (GRT)

The GRT (Ashby & Townsend, 1986) is one of the most powerful tools available for modeling featural interaction.

It has been applied successfully to numerous research questions (see e.g., Algom, 2016; Algom & Fitousi, 2016; Silbert & Hawkins, 2016). The GRT is a two-stage model of encoding and response selection. It is often considered to be a multidimensional extension of signal detection theory (SDT; Green & Swets, 1966). A fundamental assumption in GRT is that perception is noisy, and consequently leads to random variability in the encoding of features. The noisy perception implies that encoding of each stimulus (a conjunction of two features) engenders stochastic trial-by-trial perceptual effect. The effect for a particular stimulus $A_i B_j$ is represented as a joint density function $f_{A_i B_j}(x, y)$. A 2×2 GRT model with four stimuli leads to a perceptual space with four multidimensional distributions. When cut horizontally at a fixed probability level, four equal-likelihood contours are created. Observers assign a decisional bound with each perceptual region, and partition the perceptual space into four response regions (see Fig. 1).

GRT and binding

Consider the following change-detection paradigm. On each trial, a colored letter is presented (i.e., preview display), disappears, and then after a long enough interval that allows VSTM to operate, is followed by another letter (i.e., target display) (Fig. 2). The target’s color and/or shape and/or location can either repeat or alternate from the preview (as in Hommel, 1998). Observers are asked to indicate whether the target and preview letter were *same* or *different* with respect to: (a) shape and (b) color. Four types of stimuli/responses are thus possible in such a setting: (1) same shape, same color, (2) same shape, different color, (3) different shape, same color, and (4) different shape, different color. With a considerable number of trials, confusion matrices are generated, to which GRT analyses for change-detection task are applicable (Wenger & Ingvalson, 2002).¹

Feature binding in GRT may reflect one or several types of deviations from independence between the encoded features (shape and color). A similar set of assumptions regarding uncertainty in perception and deviance from independence as markers of binding has been adopted by Ashby et al. (1996) in a stochastic model of illusory conjunction. That model is closely related to the GRT approach advanced here. In the GRT, there are three ways by which independence may hold or fail.

¹ Thomas (1996) has developed a GRT extension for a same/different task in which only a single response is given with respect to a multidimensional stimulus. But this development does not apply to the current task because here two responses are generated by the observer.

Fig. 1 An example of General Recognition Theory space in a same-different task with shape and color as dimensions

These are mapped onto three ways by which binding may fail or succeed: (a) *Perceptual independence* occurs *if and only if* the perceptual effects of shape and color are stochastically independent. When perceptual independence holds (and binding fails), the equal-likelihood contours will appear as either circles or ellipses, with the major and minor axes parallel to the coordinate axes in the perceptual space. When perceptual independence is violated, the ellipses will be tilted with respect to the horizontal and vertical axes. (b) *Perceptual Separability* holds *if and only if* the marginal perception of shape (color) dimension does not vary as a function of the color (shape) levels. When perceptual separability holds on both shape and color, the

Fig. 2 A typical trial in the experiment

centroids of the equal likelihood contours take the form of a rectangle. When perceptual separability is violated (and binding occurs), the distances between the distributions for shape (color) are not equal across levels (e.g., same vs. different) of color (shape). (c) *Decisional Separability* holds *if and only if* the decision bound for shape (color) remains invariant across levels color (shape). Decisional separability is violated when the decision bound for shape (color) varies at the levels of color (shape).

Theoretical notions of binding (Ashby et al., 1996; Bays et al., 2011; Treisman & Gelade, 1980; Treisman & Schmidt, 1982) have often assumed that binding involves some degree of interactive processing between features. If the features are not bound together, then they should not exhibit any form of interaction and appear as strictly independent. Thus, any violation of one of the three constructs of GRT that signals independence might serve as an indicator of binding.

Methods

Participants

Twenty-six undergraduate students from Ariel University participated. They received course credit for their participation. All observers reported normal or corrected-to-normal vision.

Stimuli

The experiment was controlled by a desktop computer. From a viewing distance of 76 cm the participants saw three $3.16^\circ \times 2.7^\circ$ black square outlines arranged vertically from the top to the bottom (see Fig. 2). The letters “O” and “X” presented at $0.4^\circ \times 0.4^\circ$ visual angle could appear either in red or green. The stimuli set consisted therefore of: a red “O,” a green “O,” a red “X,” or a green “X.” Each stimulus could appear in the upper or lower box. Responses were made by pressing one of four keys (“V,” “B,” “N,” “M”) on the keyboard.

Procedure and design

Each experimental trial started with the presentation of the preview letter (e.g., red “O”), for 500 ms either on the top or bottom square. Then an empty square outline was presented for 2,000 ms, followed by a target letter. The observer was instructed to press one of four response keys according to the following: (1) “V” if both shape and color in the preview and target were “same”, (2) “B” if shape was “same” and color was “different”, (3) “N” if shape was “different” and color was “same”, and (4) “M”

if both were “different.” Extensive practice was held prior to the experiment to guarantee that participants remembered the response mapping. Each experimental block consisted of the factorial combination of all possible levels of color (red, green), shape (x, o), location (top, bottom), and preview-target relationship (repeat, alternate). All types of stimuli were presented with equal frequency. Each block consisted of 192 trials. Participants completed three blocks, which amounted to 576 trials. Accuracy was kept at 60–70% correct using a simple staircase algorithm in which the target’s presentation duration on trial n was increased or decreased by 5 ms depending on whether the participant was correct or incorrect on trial $n-1$.

Results

Confusion matrices for conditions in which the spatial location of the preview and target letters repeated or alternated were derived separately for each of the 26 participants. All of the analyses were performed twice: once on each of the individual confusion matrices and once on the aggregate matrices. The degree of correspondence between the individual-by-individual and the aggregate analyses was very high (see [Supplementary Material](#)).

Table 1 presents the aggregate confusion matrices. These were created by summing up the individual matrices. The four possible stimuli are designated as: A_1B_1 , A_1B_2 , A_2B_1 , and A_2B_2 , respectively, with “A” referring to shape and “B” to color. The subscript “1” denotes “same” and “2” denotes “different.” Two complementary statistical approaches to analyzing the GRT data have been used (Ashby & Lee, 1991; Fitousi, 2014; Silbert & Hawkins, 2016). The first method consisted of a set of nonparametric tests, originally developed by Ashby and Townsend (1986). The second method relied on fitting a set of parametric models (Ashby & Lee, 1991; Fitousi, 2014; Thomas, 2001). Recent work on GRT (Silbert & Thomas, 2013; Silbert & Hawkins, 2016) has shown that

decisional separability in Gaussian GRT models is not identifiable (but see, Soto et al., 2014). Silbert and Thomas (2016) have recommended making the simplifying assumption that decisional separability holds (see also Silbert & Hawkins, 2016). In agreement with this recommendation, decisional separability has been assumed throughout.

Nonparametric tests

The *sampling independence* test (Ashby & Townsend, 1986; Townsend, Hu, & Ashby, 1981) confirms *perceptual independence* and *decisional separability*, which may hold or fail for each stimulus. Sampling independence holds for a given stimulus if the probability of correctly identifying a given stimulus is equal to the product of the marginal probabilities of accurately identifying the level of each component of that stimulus. In the present case, this means that the probability of correct change-detection for *both* color and shape in a given stimulus (e.g., same shape, same color) should be equal to the product of the probability of correct change-detection for shape AND the correct change-detection for color for this stimulus. Sampling independence in A_iB_j holds if and only if:

$$\begin{aligned} p(a_i b_j | A_i B_j) &= p(a_i | A_i B_j) \times p(b_j | A_i B_j) \\ &= [p(a_i b_1 | A_i B_j) + p(a_i b_2 | A_i B_j)] \times [p(a_1 b_j | A_i B_j) \\ &\quad + p(a_2 b_j | A_i B_j)] \end{aligned}$$

Failures of sampling independence imply violations of perceptual independence and/or decisional separability (see Ashby & Townsend, 1986, *Theorem 1*). Because decisional separability is assumed, failure of sampling independence implicates perceptual interdependency. The sampling independence test was modeled after Thomas (2001), who proposed a compact version, using a Chi-square test. Table 2 gives the sampling independence results for each observer, in each stimulus and location condition. As can be noted, failures of sampling independence were numerous across all stimuli and conditions. These results support a failure of perceptual independence, and therefore provide positive evidence for feature binding at the level of each stimulus.

Perceptual separability can be assessed with the *Marginal response invariance* (MRI) test (Ashby & Townsend, 1986; Silbert & Thomas, 2013). MRI in a discrimination confusion matrix holds when the probability of correctly detecting a change at one level of the shape feature (e.g.,

Table 1 Observed confusion tables for the aggregate

Stimulus	Location repeats				Location alternates			
	Response							
	$a_1 b_1$	$a_1 b_2$	$a_2 b_1$	$a_2 b_2$	$a_1 b_1$	$a_1 b_2$	$a_2 b_1$	$a_2 b_2$
$A_1 B_1$	1,133	312	268	183	1,167	295	246	174
$A_1 B_2$	251	1,132	263	240	234	1,104	283	271
$A_2 B_1$	369	333	973	207	293	307	964	204
$A_2 B_2$	236	363	206	1,067	232	333	221	1,112

A = Shape, B = Color, “1” = Same, “2” = Different

Table 2 Chi-square values of the sampling independence tests. Significant values ($p < 0.05$) are highlighted in bold type

Stimulus	Location repeats				Location alternates			
	A ₁ B ₁	A ₁ B ₂	A ₂ B ₁	A ₂ B ₂	A ₁ B ₁	A ₁ B ₂	A ₂ B ₁	A ₂ B ₂
Obs.	A ₁ B ₁	A ₁ B ₂	A ₂ B ₁	A ₂ B ₂	A ₁ B ₁	A ₁ B ₂	A ₂ B ₁	A ₂ B ₂
1	6.30	16.02	4.09	2.61	8.71	9.81	4.30	5.78
2	21.82	0.06	13.78	22.49	13.42	0	1.83	27.42
3	21.60	0	5.79	12.34	3.04	0.02	5.80	29.51
4	4.10	24.74	10.88	11.03	5.59	15.95	6.53	1.93
5	5.11	6.77	11.56	6.36	0.49	4.16	1.27	19.50
6	0.75	6.52	5.70	7.21	0.91	6.50	5.75	13.52
7	0.06	3.76	0.57	13.24	3.78	10.08	0.01	6.20
8	0.02	23.58	25.38	0.08	2.30	32.95	30.17	0.28
9	26.44	0.08	0.63	43.09	36.05	1.77	1.69	25.80
10	2.79	27.95	7.89	1.85	7.99	12.72	8.30	0.01
11	3.41	2.43	23.38	0.95	18.12	5.90	9.81	3.15
12	2.17	24.75	2.85	1.85	1.94	14.73	15.21	8.57
13	0.16	4.89	1.86	0	10.19	9.13	22.18	1.29
14	0	34.57	23.58	0	0.27	31.67	10.25	0.08
15	1.16	6.16	11.89	2.34	1.65	14.51	9.32	0.72
16	0	1.21	1.87	7.38	1.81	0.77	2.95	27.35
17	0	0	1.09	72.00	33.49	1.79	1.17	71.10
18	1.49	3.08	0.76	5.72	1.37	2.91	11.05	3.50
19	8.81	2.82	0.85	9.20	7.32	11.11	12.78	6.35
20	15.65	32.03	11.58	7.23	16.79	20.54	6.73	1.68
21	2.42	12.00	1.06	0.23	3.19	10.45	6.56	0.08
22	2.09	2.69	6.77	0.01	1.74	25.22	3.76	0.07
23	14.66	5.55	0.01	1.34	6.63	2.82	9.21	10.06
24	0.14	17.94	13.29	4.62	0.03	20.30	5.40	1.98
25	0	46.27	52.33	0	0.04	35.65	67.00	0
26	0.01	43.14	59.0	5.60	2.66	45.98	42.62	1.90

Obs. Observer

same) does not depend on the level of color (i.e., same or different). That is:

$$p(a_i | A_i B_1) = p(a_i b_1 | A_i B_1) + p(a_i b_2 | A_i B_1) \\ = p(a_i b_1 | A_i B_2) + p(a_i b_2 | A_i B_2) = p(a_i | A_i B_2)$$

Analogous parity exists for color (B):

$$p(b_j | A_i B_j) = p(a_1 b_j | A_1 B_j) + p(a_2 b_j | A_1 B_j) \\ = p(a_1 b_j | A_2 B_j) + p(a_2 b_j | A_2 B_j) = p(b_j | A_2 B_j)$$

When perceptual separability and decisional separability hold for both shape (A) and color (B), MRI holds. To test this hypothesis, the statistic Z was carefully

constructed (cf. Silbert & Hawkins, 2016; Thomas, 2001). Tables 3 and 4 present the results of these analyses. As can be noted, violations of MRI were sparse, suggesting that perceptual separability held whether the target's location repeated or alternated.

Taken together, the results of the non-parametric tests reveal one way by which features are bound in VSTM – violations of *perceptual independence*. This entails binding at the level of the individual stimulus (e.g., red X). The next section deploys a parametric approach to validate the conclusions drawn from the non-parametric tests.

Fitting parametric GRT models

A hierarchical model fitting procedure has been performed (Ashby, & Lee, 1991; Fitousi, 2014; Thomas, 2001) on each of the observers' confusion matrices as well as on the aggregate. In brief, it is customary to assume that the GRT distributions are bivariate-Gaussian (Ashby & Lee, 1991; Fitousi, 2013, 2014). In a 2×2 Gaussian model, there are 12 parameters to estimate. Under the assumption of decisional separability, the decision bounds are set to $x = y = 0$, and the marginal variances are fixed at unity (see Silbert & Thomas, 2013). The hierarchical model-fitting procedure starts by defining a null model in which perceptual independence, perceptual separability, and decisional separability hold. In this null (constrained) model the number of free parameters is minimal (i.e., 4). Next, the researcher defines new models (general) with an increasing number of free parameters, and compares them to the older models. If a general model is found to have better fit than its predecessor constrained model, the researcher constructs a new model with a larger number of free parameters. The degree of fit for each model is measured with the (-) *log-likelihood*. General models may produce better absolute fit either due to their larger number of parameters, or due to their success at capturing real aspects of the data. To decide between two models, a *likelihood ratio test* has been used (Thomas, 2001). Consider two models, M_1 and M_2 , where M_1 is the constrained model and M_2 is the general model and their respective likelihoods L_1 and L_2 . The null hypothesis for this test is that the constrained model is correct. The test statistic χ^2 is defined from the likelihood ratio L_1/L_2 to be:

$$\chi^2 = -2 \ln \left(\frac{L_1}{L_2} \right)$$

Also, the Akaike Information Criterion (AIC; Akaike, 1983), adjusted for the number of free parameters, has been

Table 3 Marginal response invariance (MRI) test values. Significant Z values ($p < 0.05$) are highlighted in bold type

Location repeats												
Stimulus												
Obs.	$A_1B_1 - A_1B_2$		z	$A_2B_1 - A_2B_2$		z	$A_1B_1 - A_2B_1$		z	$A_1B_2 - A_2B_2$		z
1	0.69	0.59	1.21	0.27	0.27	0	0.62	0.72	-1.24	0.34	0.22	1.66
2	0.75	0.68	9.97	0.44	0.32	1.43	0.67	0.55	1.43	0.23	0.16	1.07
3	0.85	0.88	-0.56	0.46	0.40	0.80	0.77	0.70	0.88	0.23	0.30	-0.85
4	0.71	0.72	-0.13	0.29	0.23	0.21	0.80	0.72	1.17	0.37	0.29	0.96
5	0.80	0.67	1.76	0.31	0.31	0	0.79	0.73	0.78	0.35	0.31	0.41
6	0.71	0.79	-1.19	0.41	0.30	1.32	0.90	0.87	0.52	0.32	0.30	0.40
7	0.77	0.62	2.05	0.52	0.40	1.45	0.83	0.82	0.18	0.17	0.18	-0.15
8	0.71	0.61	1.31	0.40	0.28	1.52	0.78	0.73	0.78	0.48	0.35	1.56
9	0.78	0.61	2.27	0.29	0.26	0.32	0.70	0.69	0.16	0.20	0.23	-0.42
10	0.72	0.65	0.98	0.33	0.19	1.92	0.75	0.62	1.69	0.29	0.16	1.82
11	0.74	0.63	1.33	0.30	0.27	0.32	0.75	0.65	1.27	0.20	0.18	0.29
12	0.75	0.73	0.28	0.50	0.31	2.29	0.74	0.78	-0.66	0.29	0.24	0.61
13	0.76	0.82	-0.90	0.44	0.39	0.62	0.72	0.71	0.13	0.17	0.18	-0.15
14	0.77	0.79	-0.27	0.39	0.30	1.15	0.88	0.72	2.43	0.22	0.36	-1.74
15	0.72	0.69	0.42	0.24	0.24	0	0.69	0.64	0.65	0.22	0.16	0.96
16	0.68	0.75	-0.91	0.28	0.25	0.43	0.70	0.67	0.40	0.18	0.14	0.78
17	1.00	1.00	0	0.52	0.63	-1.45	0.98	0.98	0	0.44	0.63	-2.34
18	0.69	0.67	0.18	0.28	0.27	0.23	0.73	0.78	-0.67	0.28	0.10	2.69
19	0.65	0.60	0.64	0.28	0.19	1.36	0.79	0.68	1.53	0.28	0.20	1.06
20	0.74	0.65	1.13	0.38	0.19	2.46	0.75	0.75	0	0.32	0.28	0.61
21	0.67	0.66	0.11	0.22	0.26	-0.52	0.70	0.74	-0.55	0.33	0.32	0.12
22	0.70	0.78	-1.10	0.31	0.34	-0.29	0.73	0.72	0.18	0.23	0.18	0.82
23	0.67	0.73	-0.85	0.31	0.23	1.16	0.77	0.79	-0.31	0.35	0.24	1.44
24	0.82	0.76	0.92	0.25	0.32	-1.03	0.72	0.72	0.05	0.36	0.27	1.14
25	0.97	0.89	1.87	0.60	0.48	1.43	0.47	0.43	0.42	0.09	0	2.63
26	0.88	0.93	-1.03	0.52	0.56	-0.51	0.35	0.50	-1.76	0.04	0.05	-0.42

Obs. Observer

used to adjudicate between goodness of fit and number of free parameters.

Table 5 presents the results of the hierarchical model fitting for the aggregate in a decreasing order of fit, with the best fitting model appearing on top. It should be noted that the level of correspondence between the individual-by-individual and the aggregate analyses was very high (see [Supplementary Material](#)). The two best-fitting models were: (a) a model in which *perceptual independence* was violated in all four stimuli and *perceptual separability* was violated on both dimensions, and (b) a model in which only *perceptual independence* was violated in all four stimuli. Note that the former model has more free parameters (12) than the latter (eight). To trade off improvement in fit against increase in number of free parameters, likelihood ratio tests were conducted (see Table 6).

All individual-by-individual likelihood ratio tests (see [Supplementary Material](#)) pointed to the model in which *perceptual independence* was violated in all four stimuli and *perceptual separability* held. The aggregate and the individual analyses were consistent with respect to this model in the location alternated condition. However, in the location repeated condition the aggregate analysis favored a model in which both *perceptual independence* and *perceptual separability* were violated. A closer look at this model showed that the degree of violation of perceptual separability was minimal. The large statistical power of the aggregate might be responsible for this deviation. So, given that both the individual-by-individual parametric and non-parametric analyses exhibited clear evidence for perceptual separability and violations of perceptual independence, the winning model was chosen to

Table 4 Marginal response invariance (MRI) test values. Significant Z values ($p < 0.05$) are highlighted in bold type

Location alternates												
Stimulus												
Obs.	$A_1B_1 - A_1B_2$		z	$A_2B_1 - A_2B_2$		z	$A_1B_1 - A_2B_1$		z	$A_1B_2 - A_2B_2$		z
1	0.73	0.75	-0.23	0.27	0.19	1.13	0.80	0.71	1.36	0.22	0.30	-1.03
2	0.78	0.70	1.19	0.34	0.25	1.26	0.64	0.72	-1.08	0.18	0.22	-0.53
3	0.84	0.79	0.86	0.54	0.36	2.07	0.82	0.70	1.71	0.31	0.19	1.71
4	0.77	0.68	1.33	0.33	0.23	1.28	0.68	0.68	0	0.34	0.26	1.11
5	0.76	0.69	1.01	0.36	0.27	1.19	0.82	0.72	1.43	0.24	0.17	0.92
6	0.81	0.76	0.77	0.40	0.34	0.66	0.83	0.83	0	0.38	0.30	0.99
7	0.79	0.70	1.20	0.40	0.18	2.93	0.83	0.68	2.13	0.19	0.11	1.42
8	0.73	0.55	2.32	0.28	0.25	0.32	0.91	0.71	3.11	0.54	0.38	1.93
9	0.79	0.74	0.69	0.37	0.32	0.55	0.73	0.73	0.11	0.21	0.32	-1.59
10	0.68	0.58	1.15	0.22	0.29	-0.91	0.73	0.73	0	0.28	0.18	1.46
11	0.67	0.47	2.36	0.30	0.12	2.60	0.68	0.69	0	0.20	0.14	1.02
12	0.85	0.68	2.41	0.27	0.27	0	0.77	0.75	0.29	0.35	0.21	1.82
13	0.78	0.75	0.33	0.30	0.32	-0.15	0.69	0.76	-0.93	0.17	0.21	-0.63
14	0.77	0.63	1.82	0.40	0.30	1.18	0.89	0.68	3.09	0.31	0.29	0.30
15	0.68	0.69	-0.19	0.25	0.21	0.48	0.68	0.65	0.34	0.21	0.23	-0.19
16	0.78	0.67	1.43	0.24	0.27	-0.37	0.75	0.56	2.39	0.22	0.22	0
17	0.98	0.97	0.52	0.63	0.48	1.90	0.97	0.97	0.53	0.49	0.49	0
18	0.67	0.67	0	0.28	0.35	-0.91	0.81	0.67	1.96	0.15	0.19	-0.58
19	0.68	0.56	1.56	0.23	0.22	0.11	0.72	0.76	-0.52	0.28	0.19	1.19
20	0.71	0.63	0.95	0.25	0.29	-0.52	0.73	0.76	-0.29	0.33	0.38	-0.62
21	0.73	0.64	1.14	0.20	0.18	0.17	0.81	0.85	-0.60	0.25	0.27	-0.29
22	0.75	0.71	0.52	0.20	0.25	-0.71	0.71	0.71	0.05	0.30	0.24	0.94
23	0.69	0.71	-0.15	0.20	0.22	-0.34	0.78	0.69	1.20	0.30	0.28	0.26
24	0.78	0.73	0.71	0.29	0.37	-0.97	0.70	0.84	-1.96	0.30	0.28	0.22
25	0.95	0.86	1.98	0.52	0.50	0.26	0.60	0.47	1.50	0.12	0	3.11
26	0.92	0.95	-0.92	0.62	0.58	0.51	0.36	0.39	-0.38	0.02	0.05	-0.76

Obs. Observer

Table 5 Summary of the fit statistics for the General Recognition Theory (GRT) hierarchical models

Location repeats				Location alternates			
Model	Par.	-lnL	AIC	Model	Par.	-lnL	AIC
~PI ₄ , ~PS, DS	12	8,614	17,252	~PI ₄ , ~PS, DS	12	8,408	16,840
~PI ₄ , PS, DS	8	8,621	17,258	~PI ₄ , PS, DS	8	8,411	16,838
~PI ₁ , PS, DS	5	8,893	17,796	PI, ~PS, DS	8	8,703	17,422
PI, ~PS, DS	8	8,895	17,806	~PI ₁ , PS, DS	5	8,710	17,430
PI, ~PS _{shape} , DS	6	8,900	17,812	PI, ~PS _a , DS	6	8,710	17,432
PI, ~PS _{color} , DS	6	8,903	17,818	PI, ~PS _b , DS	6	8,719	17,450
PI, PS, DS	4	8,907	17,822	PI, PS, DS	4	8,726	17,460

PI Perceptual Independence, PS Perceptual Separability, DS Decisional Separability, Par. Parameters, ~ Violation, PI₄ each of the four coefficient correlation parameters (ρ), one per distribution, was allowed to vary freely, PI₁ only one coefficient correlation parameter (ρ) was allowed to vary in the four distributions

Table 6 Likelihood ratio tests for nested models

Location repeats					Location alternates				
Restricted	General	χ^2	df	p	Restricted	General	χ^2	df	p
PI,PS,DS	PI,~PS_a,DS	14	2	**	PI,PS,DS	PI,~PS_a,DS	32	2	**
PI,PS,DS	PI,~PS_b,DS	8	2	*	PI,PS,DS	PI,~PS_b,DS	14	2	**
PI,~PS_shape,DS	PI,~PS,DS	10	2	*	PI,~PS_shape,DS	PI,~PS,DS	14	2	**
PI,~PS_color,DS	PI,~PS,DS	16	2	**	PI,~PS_color,DS	PI,~PS,DS	32	2	**
PI,PS,DS	~PI_1,PS,DS	28	1	**	PI,PS,DS	~PI_1,PS,DS	32	1	**
PI,PS,DS	~PI_4,PS,DS	572	4	**	PI,PS,DS	~PI_4,PS,DS	630	4	**
~PI_4,PS,DS	~PI_4,~PS,DS	14	4	*	~PI_4,PS,DS	~PI_4,~PS,DS	6	4	n.s

$p < 0.05^*$, $p < 0.01^{**}$, $p < 0.001^{***}$

H_0 restricted model is correct, *PI* Perceptual Independence, *PS* Perceptual Separability, *DS* Decisional Separability, *Par*: Parameters, ~ Violation, *PI_4* each of the four coefficient correlation parameters (ρ), one per distribution, was allowed to freely vary, *PI_1* only one coefficient correlation parameter (ρ) was allowed to vary in the four distributions

be the one in which only *perceptual independence* is violated in all four stimuli.

Figure 3 depicts the derived GRT spaces for the winning models. The emerging pattern for most observers (25/26 in the location repeat and 24/26 in the location altered condition) was found to be a “cloverleaf” (Silbert & Thomas, 2014). In this pattern, violations of *perceptual independence*, as indicated by the coefficient correlation (ρ), entail the presence of positive correlations between shape and color for stimuli in which the two features repeated or alternated together (e.g., the ellipses are tilted to the right), and a negative correlation for stimuli in which one feature repeats, but the other alternates (e.g., the ellipses are tilted to the left). Silbert and Thomas (2014) have recently shown that in Gaussian GRT models, optimal (Bayesian) response selection rule and mimicry of decisional separability imply either a

constrained rectangular arrangement of means with zero perceptual correlation or the cloverleaf pattern observed here. Thus, it might be the case that an optimal response rule in the change detection task used here mimics decisional separability due to the pattern of perceptual interactions induced by feature binding.

Conclusions

The present work harnessed a multivariate model of perception – the GRT (Ashby & Townsend, 1986) – to investigate binding in VSTM. Converging GRT analyses provided positive evidence for binding between encoded features of shape and color. Binding was indicated by violations of *perceptual independence* at the level of each of the four possible stimuli,

Fig. 3 Best fitting General Recognition Theory models of the hierarchical modeling fit procedure for the aggregate and for the individual data in: (a) conditions in which spatial location of the

preview repeated in the target, and (b) conditions in which the spatial location alternated from preview to target

giving rise to a cloverleaf pattern (Silbert & Thomas, 2014). Color and shape were positively correlated when they repeated or alternated together, but negatively correlated when only one of them repeated and the other alternated (e.g., partial repetition). Comparable patterns have been observed whether the target and preview locations repeated or alternated. The current results are consistent with the discrete memory "slots" model of VSTM (Cowan, 2001). According to this model, each slot is storing an integrated representation of a single visual object. The "slots" model predicts that errors in recalling multiple features of the same object will be correlated (see also Bays et al., 2011). The results also support the notion of "object files" advanced by Hommel (1998), who has argued that spatial location is not necessary for the creation of an "object file." Finally, the current work offers a novel quantitative model of feature binding in VSTM that is capable of accounting for various binding phenomena, including that of "illusory conjunction" (Treisman & Schmidt, 1982). Future work should test the assumption of decisional separability made here (Soto et al., 2014), extend the investigation to GRT reaction time measures (Ashby, 2000; Townsend, Houpt, & Silbert, 2012), and make contact with other computational approaches to binding and memory (Ashby et al., 1996; Bays et al., 2011; Fitousi, 2013).

Acknowledgments I would like to thank Dr. Noah Silbert and an Anonymous Reviewer for their insightful comments on an earlier version of this article.

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