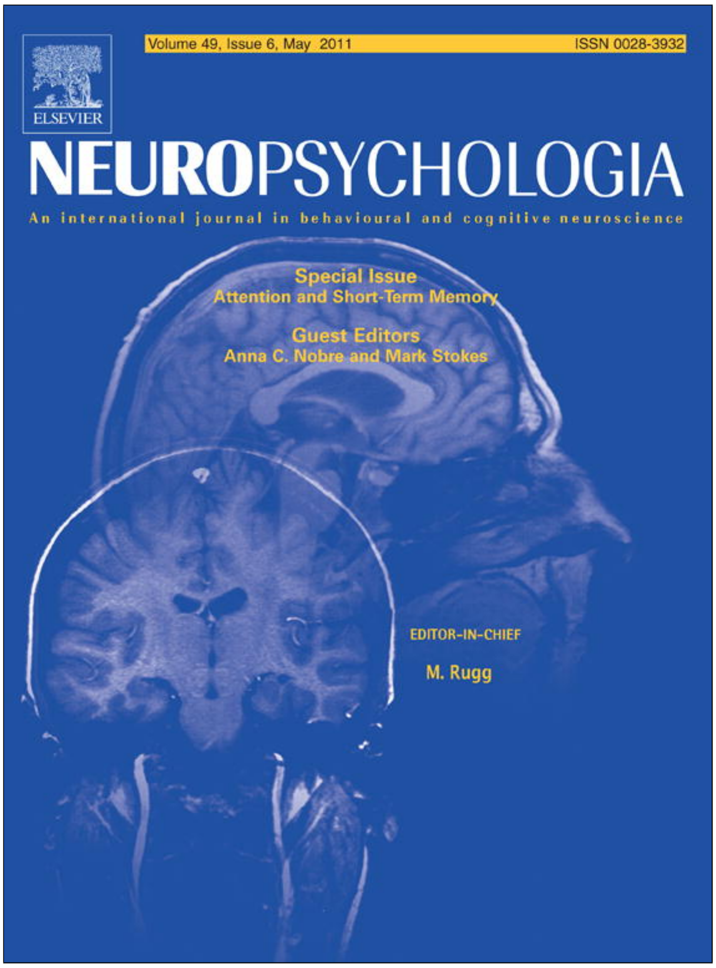
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Shape and color conjunction stimuli are represented as bound objects in visual working memory

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ABSTRACT

The integrated object view of visual working memory (WM) argues that objects (rather than features) are the building block of visual WM, so that adding an extra feature to an object does not result in any extra cost to WM capacity. Alternative views have shown that complex objects consume additional WM storage capacity so that it may not be represented as bound objects. Additionally, it was argued that two features from the same dimension (i.e., color–color) do not form an integrated object in visual WM. This led some to argue for a "weak" object view of visual WM. We used the contralateral delay activity (the CDA) as an electrophysiological marker of WM capacity, to test those alternative hypotheses to the integrated object account. In two experiments we presented complex stimuli and color–color conjunction stimuli, and compared performance in displays that had one object but varying degrees of feature complexity. The results supported the integrated object account by showing that the CDA amplitude corresponded to the number of objects regardless of the number of features within each object, even for complex objects or color–color conjunction stimuli.

1. Introduction

Visual working memory (WM) is a temporary buffer that can maintain a limited set of items in an "online" state. Although visual WM capacity is limited to 3–4 objects, there are robust individual differences in its capacity that correlate with attentional control, fluid intelligence and scholastic aptitude (Cowan et al., 2005; Vogel, McCollough, & Machizawa, 2005) indicating that WM plays an important role in guiding behavior. Thus, understanding how WM works and how it interacts with attentional mechanisms reflects a fundamental and important question in cognitive neuroscience. In the present study, we will be examining visual WM for objects that possess a conjunction of multiple features. Such objects require active bindings between the features of the object, and this binding process has been proposed to be attentionally demanding and highly capacity limited (Treisman, 1998; Wheeler & Treisman, 2002).

A common paradigm used to study visual WM is the change detection paradigm (e.g., Luck & Vogel, 1997). This paradigm involves a brief presentation of a memory array (consisting of a set of objects), followed by a retention interval (often about 1 s), and then a test array. Participants indicate whether the test array is identical or different to the remembered memory array. Performance in the change detection task is typically very high when up to 3–4 items are remembered, and then declines as more items are added to the memory array.

Accuracy in this task is frequently transformed to an index (i.e., K) that reflects how many items are represented in visual WM based on formulas developed by Pashler (1988) and Cowan (2001). The underlying assumption is that accuracy in the change detection task reflects WM capacity during the maintenance stage. Note, however, that the paradigm also involves a perceptual encoding stage and a comparison stage. Consequently, poor behavioral performance could be the result of insufficient encoding or errors that arise at the comparison stage, and not exclusively the maintenance stage. Luck and Vogel (1997) argued that performance during their change detection task was primarily determined by limitations arising during the maintenance stage because they used perceptually simple stimuli, limited the number decisions at test, and conducted several control experiments aimed at ruling out limits at stages other than maintenance.

1.1. Object-based WM

Using the change detection paradigm, Luck and Vogel (1997) demonstrated that performance was identical for objects that had only a single feature (e.g., a color) relative to objects that had multiple features (e.g., color and orientation). They argued that objects, and not features, are the building blocks of visual WM. Subsequently, this integrated object account has also been sup-

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ported by studies using other paradigms that have found memory advantage for features when they are presented within an object (Awh, Dhaliwal, Christensen, & Matsukura, 2001; Duncan, 1984; see also Xu, 2006). For example, Gajewski and Brockmole (2006) showed that forgetting in a WM recall task was also object based: subjects could recall all features of an object or none. However, the integrated object account has been challenged on the basis of two primary grounds. First, it was argued that this view could not explain how binding of features in visual WM could scale up to maintain much more complex objects (Alvarez & Cavanagh, 2004). Second, a number of studies have argued that objects that are composed of features from the same dimension (e.g., two colors) are not bound as one object in WM.

At first blush, it seems that Luck and Vogel (1997) have provided compelling evidence confirming that visual WM is object based. Namely, an increase in "information" load of each object did not further deteriorate performance. However, this study used very basic features (such as color and orientation) and it might still be the case that conjunctions are cost-free in memory only across different types of basic features, but not for much more complex objects such as random polygons. By complexity we mean the amount of visual detail that is being stored in WM for each object. That is, the features and other details that are encoded and maintained in WM for a particular object or set of objects.

Alvarez and Cavanagh (2004) measured WM capacity for various complex stimuli and found a monotonic decrease in change detection performance as the object's complexity (quantified by visual search efficiency) increased. For example, while WM was able to maintain four colors, its capacity was reduced to two when representing random polygons. Similarly, using ovals with varying aspect ratios and color mixtures, Olsson and Poom (2005) showed that WM capacity can be reduced to just one object. Together, those studies have suggested that the information load (the amount of perceptual details for a given object that are stored in WM) engendered by the to-be-remembered material is an important factor that determines WM capacity. Specifically, in order to remember a complex object, a larger proportion of capacity must be allocated as compared to a simple object with less information content (as indicated by a larger CDA amplitude, see below). Note that these findings are inline with the object-based view of WM because this view only argues that once an object is encoded, there is no additional cost at encoding multiple features from that same object.

Alvarez and Cavanagh (2004) and Olsson and Poom (2005) assumed that poor performance in the change detection paradigm reflects errors during the WM maintenance stage, and thus indicates poor WM capacity. However, as noted above, this assumption that seemed reasonable for simple (single featured) objects, may not necessarily hold for more complex objects. For example, Awh, Barton, and Vogel (2007) provided evidence that for highly complex stimuli, accuracy in the change detection paradigm might primarily reflect task-related processes other than WM storage capacity. Specifically, they argued that the comparison process responsible for deciding whether an item in the test array was remembered (by comparing the contents of the memory and the test array) is prone to errors, especially when complex stimuli are evaluated. The reason is that these items are more similar to one another than simple objects resulting in a much smaller change magnitude. Awh et al. replicated the findings that fewer complex objects were maintained in WM, however, when they decreased the test to memory array similarity, WM successfully represented 3–4 *complex* objects.

1.2. Weak object-based representation in WM

In their final experiment, Luck and Vogel (1997) addressed the issue of separate WM limitations for different visual features. Specifically, the finding of no performance cost of adding another feature (e.g., color and orientation) may simply be due to separate WM stores for each of the to-be-remembered features rather than due to object binding (e.g., Jiang, Makovski, & Shim, 2009; Magnussen, Greenlee, & Thomas, 1996). To examine this, they tested a condition with color–color conjunction stimuli, so that each object included a small colored square and a colored "frame". Even in this condition, when an object was composed of two features from the same dimension, performance still benefited from being "object based". Namely, when comparing the same number of objects, accuracy for color–color conjunction stimuli was identical to one-feature stimuli. Luck and Vogel argued that this ruled out any independent memory representation as an explanation for their results, however, several subsequent studies have tried and failed to replicate this particular result (Delvenne & Bruyer, 2004; Olson & Jiang, 2002; Parra, Abrahams, Logie, & Della Sala, 2009; Wheeler & Treisman, 2002). This failure to replicate casts doubts regarding visual WM as being strictly object based (Jiang et al., 2009), and led some to argue for a "weak" object based WM representations (Olson & Jiang, 2002). That is, although these studies have found that representing information within an object is still superior to representing the same amount of information in separate objects, there is also a cost when multiple feature objects are compared to single feature objects as long as the features are from the same dimension.

The main problem with accepting the weak object hypothesis is that poor performance for multiple-feature objects, especially if the features are from the same dimension (e.g., color–color conjunction stimuli) could also be attributed to failures at other stages of processing of the change detection task rather than WM storage capacity. Note that when evaluating conjunction stimuli there are (at least) two decisions that need to be made in order to detect a change, while for a one-feature object only one decision is made. For example, when a tilted bar is presented, participants only need to decide whether its orientation is the same, while for a colored tilted bar a decision needs to be made regarding both its orientation and its color. Thus, poorer performance for conjunction stimuli may be the result of an increased number of decisions rather than a reduced storage capacity. Another option along the same line is that participants simply confuse the features they need to compare (Bays, Catalao & Husain, 2009), so that increasing the number of features raises the possibility of confusing them.

1.3. The present study

In the present study, we will address these challenges to the integrated object hypothesis using an electrophysiological marker for the allocation of WM resources that is measured exclusively during the maintenance stage: the contralateral delay activity (CDA). The CDA is a negative slow wave found at posterior sites contralateral to the memorized visual field, and it has been shown to be an excellent marker for visual WM capacity allocation (Jolicœur, Brisson, & Robitaille, 2008; Luria, Sessa, Gotler, Jolicoeur, & Dell'Acqua, 2010; McCollough, Machizawa, & Vogel, 2007; Vogel & Machizawa, 2004; Vogel et al., 2005). Important for the present purpose, while the CDA amplitude is sensitive to both the number of memorized objects and their complexity, it is not affected by the number of spatial positions or by the perceptual difficulty of the task (Ikkai, McCollough, & Vogel, 2010; Luria et al., 2010).

Recently, Ikkai et al. (2010) have presented different objects in the *same* spatial positions (one after the other), and found that the resultant CDA amplitude was identical to a condition in which the two objects were presented at different locations. This result is strong evidence that the CDA is not sensitive to the number of locations per se. In another experiment, Ikkai et al. (2010) manipulated the contrast of the remembered color stimuli. Low contrast stimuli led to low accuracy relative to high contrast stimuli but the

CDA was identical for both contrast conditions. In the same vein, Luria et al. (2010) found low accuracy for arrays including similar colors (shades between blue and green). Again, the CDA amplitude was similar to a condition with dissimilar colors, suggesting that WM capacity allocation was the same when comparing similar and dissimilar colors. Importantly, those studies report that there can be dissociations between accuracy measures and WM capacity (as indicated by the CDA amplitude). Thus, for the purpose of measuring capacity, accuracy data should often be interpreted with caution. The advantage of using the CDA as an index of WM capacity is that it is specific to the neural activity during the maintenance stage of WM, corresponding to the amount of capacity that is allocated at any given moment. Unlike behavioral performance, it is not susceptible to the errors that arise during the comparison process at the end of the trial (see Awh et al., 2007).

The goal of the present research was to use the CDA in order to test challenges to the strong object based view of visual WM. If poor accuracy for conjunction objects that was found in former studies can be attributed to processes that are not related to visual WM capacity, then the CDA should be sensitive only to the number of integrated objects, and not to the number of features each object has. Experiment 1 asked whether complex stimuli (random polygons) are treated as bound objects during visual WM maintenance stage. Experiment 2 asked the same question for objects that have two features along the same dimension (color–color conjunction stimuli).

2. Experiment 1

In Experiment 1, participants had to remember the orientation of a bar or the identity of a randomly shaped polygon. Critically, we compared performance across 3 conditions: one object with a single feature (e.g., a tilted bar or a random polygon), one conjunction object with two features (e.g., a blue tilted bar or a red polygon), and two separate one-feature objects (e.g., a tilted bar and a blue square or a random polygon and a red square). Previous research has shown that random polygons consume more capacity relative to simple (single-feature) objects (Gao et al., 2009; Luria et al., 2010). This observation seems to be at odds with the discrete slot view of WM capacity (see below), however, it does not necessarily contradict the integrated object view. The reason is that random polygons may initially consume more WM resources, but then are still treated as bound objects.

In order to test this idea, we increased the information load by adding a color feature to the random polygon. If polygons are represented as integrated objects, adding an extra feature should be "cost free" in terms of WM capacity as indicated by the CDA amplitude. Thus, the goal of Experiment 1 was to test the integrated object account using the CDA as an unbiased measure of WM capacity.

Experiment 1 also included conjunction conditions with simple objects (titled bars and colors). Our objective was to replicate previous results supporting the integrated objects account (Woodman & Vogel, 2008) in a condition that included only one object – when capacity is clearly below its maximum.

According to the weak object view capacity is not always allocated to objects. This account highlights that information load is important in determining WM capacity allocation. For example, Alvarez and Cavanagh (2004) have argued that capacity is allocated also according to the feature complexity of the represented memoranda and is not sensitive exclusively to the number of maintained objects (see also Olson & Jiang, 2002). This weak object view can naturally account for the increased capacity consumption for complex stimuli, but it makes complete different prediction in respect to the conjunction condition. Since adding a color feature to a titled bar increases the information load, the weak object view posits that it should result in a parallel increase in capacity allocation.

The integrated object view of visual WM assumes that it is the object (and not its features) that consumes capacity (although not all objects are identical in their initial capacity consumption, see below). It predicts that more capacity should be allocated when the number of objects is increased, even when the amount of perceptual information is kept constant. Accordingly, this model predicts that capacity consumption should be equal when comparing one object with a single feature to one object with two features (e.g., a random polygon and a colored random polygon), and both should consume less capacity than the two objects condition. Note that the integrated object is inline with the complexity notion in the sense that different objects may consume different amounts of capacity (i.e., polygons and colors), and this would be evident in the CDA amplitude. However, it strongly argues that any increase in the object's encoded information would not further increase WM capacity consumption. For this reason, we were particularly interested in the color–polygon conjunction condition. Since random polygons consume more capacity than colors, further increasing the polygons' complexity by adding a color feature to it, should be a direct test for the predictions made by the weak and integrated object views.

2.1. Method

2.1.1. Participants

All participants gave informed consent after the procedures of a protocol approved by the Human Subjects Committee at the University of Oregon. All subjects were members of the University of Oregon community and were paid $10 per hour for participation. 19 participants took part in the experiment. Subjects with more than 25% rejection rate due to eye-blink or eye-movement were rejected from further analysis (1 subject).

2.1.2. Electroencephalography recording

ERPs were recorded in each experiment using our standard recording and analysis procedures (McCollough et al., 2007), including rejection of trials contaminated by blinks or large (>1°) eye movements (the criterions for eye movements rejection was 30 μV and 250 μV for blinks). We recorded from 22 standard electrode sites spanning the scalp, including international 10/20 sites F3, F4, C3, C4, P3, P4, O1, O2, PO3, PO4, P7, P8, as well as nonstandard sites occipital left (OL) and occipital right (OR) (midway between O1/2 and P7/8). The horizontal electrooculogram (EOG) was recorded from electrodes placed 1 cm to the left and right of the external canthi to measure horizontal eye movement, and the vertical EOG was recorded from an electrode beneath the right eye referenced to the left mastoid to detect blinks and vertical eye movements. Trials containing ocular artifacts, movement artifacts, or amplifier saturation were excluded from the averaged ERP waveforms. The electroencephalography and EOG were amplified by an SA Instrumentation amplifier with a bandpass of 0.01–80 Hz (half-power cutoff, Butterworth filters) and were digitized at 250 Hz by a personal computer compatible microcomputer.

2.1.3. Stimuli and procedure

Each trial started with the presentation of a fixation point ("+") in the middle of the screen for 500 ms. Then, two arrow-cues were presented for 200 ms above and below fixation, indicating the to-be-attended side for the upcoming trial. After a random interval (400, 500 or 600 ms, from the cues offset), the memory array was presented for 200 ms, followed by a retention interval (when only the fixation cross was presented) of 900 ms and then the test array (see Fig. 1). The test array remained visible until a response was emitted. The memory array included 7 possible conditions that were randomly intermixed within each block: a colored square, a tilted bar, a black polygon, a colored bar, a colored polygon, 1 colored square and 1 tilted bar, 1 colored square and one polygon (see Fig. 2A). Participants were instructed to remember the stimuli for a change detection task. They were informed that a black-bar or a black polygon never change their color, so they could only change orientation or shape (respectively), while a change for a colored-bar or a colored-polygon might occur for either the color or the orientation/shape (but never on both). Overall, participants performed 16 trials of practice followed by 22 blocks that included 60 trials each.

2.1.4. CDA analysis

The raw EEG wave was segmented into 1200 ms epochs starting 200 ms before the target array onset. Only correct trials were included in the analysis. Separate average waveforms for each condition were then generated, and difference waves were constructed by subtracting the average activity recorded from the electrodes ipsilateral to the memorized array from the average activity recorded from elec-

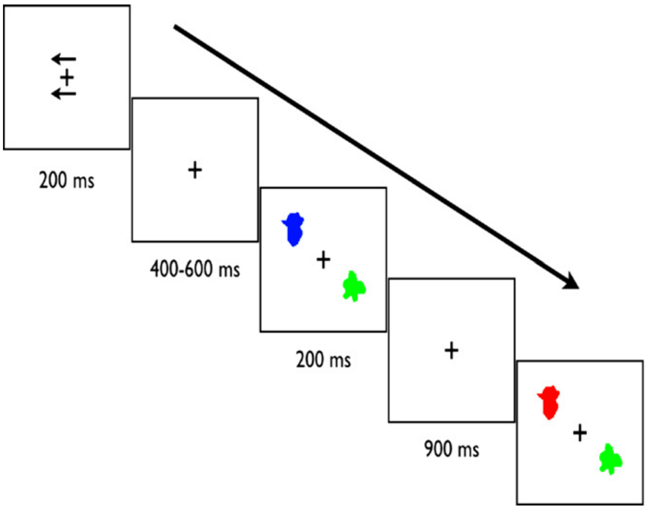

Fig. 1. An example of a trial: the arrow cues indicate the relevant side for the up coming trial, followed by the memory array (presented for 200 ms) and a retention interval of 900 ms.

trodes contralateral to the memorized array. The time range for measuring the CDA was 400–1000 ms time locked to the memory array. The analysis included at least 120 trials per condition per subject.

For the ease of description purposes, we will only present the results from the OL/OR electrodes because that is where the CDA amplitude is most evident. However, similar patterns of activations were observed over neighboring electrode positions (O1/O2, P7/P8 and PO3/PO4).

2.2. Results

2.2.1. Behavioral

The accuracy for the different conditions is presented in Table 1. We first analyzed the tilted bar-conjunction accuracy, followed by the polygon data. Importantly, we found no cost in accuracy for colored-bars conjunction stimuli relative to (black) tilted bars, $F < 1$. In addition, accuracy for a conjunction colored-bar (one object) was better than accuracy for the same perceptual information presented as separate objects (i.e., a color and a black-bar), $F(1,17) = 11.99$, $p < .005$, MSE = .0004. Similar to the bar data, random polygon accuracy showed no sign for a conjunction cost: accuracy for a colored polygon was actually better than a black polygon, $F(1,17) = 15.80$, MSE = .001, $p < .005$ and better than a colored-square and a black polygon (presented separately), $F(1,17) = 19.25$, MSE = .002, $p < .0005$.

2.2.2. Electrophysiology

The CDA waveforms for all the different conditions are presented in Fig. 3. We first compared the CDA amplitude for one color and one polygon. Replicating previous findings, the CDA amplitude for a single polygon was higher than one color, $F(1,17) = 18.42$, MSE = .14, $p < .0005$. This is important in further demonstrating that the CDA is sensitive to the object complexity (at least for polygons).

Mirroring the accuracy data, WM showed no cost for conjunction stimuli (colored-polygon or a colored-bar) relative to single feature items (a black polygon or a black bar). As can be seen in Fig. 3, the CDA amplitude for a black bar was identical to the CDA amplitude for a colored-bar, $F = 1.09$. Furthermore, the CDA amplitude for a black bar and a colored square (as separate items) was higher than the amplitude for a conjunction colored-bar even though they both contain the same amount of information, $F(1,17) = 8.38$, MSE = .35, $p < .05$. Polygons showed the exact same pattern: the CDA amplitude for a black polygon was identical to the amplitude of a colored-polygon, $F < 1$, but the amplitude for a black polygon and a colored square presented separately was larger than that for a colored-polygon[1], $F(1,17) = 4.84$, MSE = .09, $p < .05$.

2.3. Discussion

Experiment 1 provided further supporting evidence that WM capacity is object based by demonstrating that maintaining a complex conjunction stimulus is cost-free: a polygon consumed the same amount of capacity relative to a colored polygon, indicating that WM represented the polygon as a single bound object (even though it consumed more capacity to begin with). Similarly, a colored tilted bar showed no conjunction cost relative to a condition in which only the orientation was relevant (see also Woodman & Vogel, 2008). Moreover, more WM resources were needed in order to maintain a polygon and a color presented as separate objects relative to a condition in which the same information is presented as a single conjunction object, confirming the prediction made by the integrated object view. These results were obtained with just one object maintained in memory, a condition that is well below the maximum capacity for both bars and polygons (as indicated also by the relative high accuracy).

One objection that might be raised is that perhaps participants cannot encode just a single feature from an object and ignore others. This alternative explanation would argue that when we encode a polygon, we also automatically encode its colors, even when color is a task-irrelevant property. This could explain why performance was similar for colored polygons (when both color and shape were encoded) and black polygons (when only shape was encoded), by arguing that in both cases a color was maintained in visual WM. However, there are several convincing pieces of evidence demonstrating that we can voluntarily store a single attribute of an object without necessarily storing all of its remaining features. Woodman and Vogel (2008) compared conditions in which only color was relevant, only orientation was relevant and a condition in which both color and orientations were relevant. Despite of identical physical

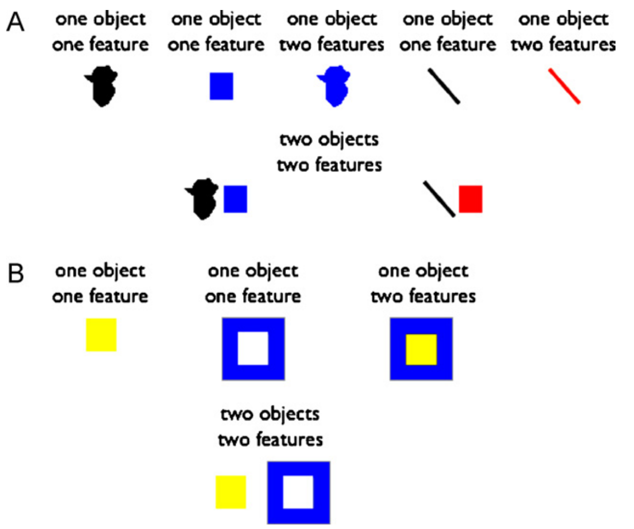

Fig. 2. Examples of the stimuli set used in Experiment 1 (top panel) and Experiment 2 (bottom panel).

[1] If we assume that the WM (and hence the CDA) encodes relational information in addition of the objects' identity, then presenting information within one object should result in a drop in the CDA amplitude (relative to a condition in which the same information is presented in two separate objects). However, the relational information account cannot explain the results of Experiment 2, in which the conjunction condition retained the relational information between the two objects and yet the CDA amplitude was lower than the two separate object condition throughout the retention interval.

Table 1
Accuracy and standard deviation (in parenthesis) for Experiments 1 and 2 across the different conditions.

Experiment 1						
Color	Polygon	Color + polygon	Colored polygon	Bar	Bar + color	Colored bar
.97 (.03)	.89 (.06)	.87 (.06)	.90 (.06)	.96 (.04)	.93 (.06)	.95 (.05)

Experiment 2				
Color	Bicolor	2 colors	2 bicolor	4 colors
.98 (.01)	.97 (.03)	.96 (.03)	.86 (.06)	.83 (.06)

stimuli between these conditions, the color relevant trials showed a steeper consolidation slope and a less of WM capacity demand relative to conjunction stimuli. Luria et al. (2010) have found an identical pattern of results for colored polygons. Moreover, the current data can also speak against an obligatory storage explanation. Accuracy to detect a polygon change (Hit rate for polygons) was better in a condition when color was irrelevant relative to a condition in which both color and shape were encoded (.87 vs. .78 for only polygon and conjunction polygon respectively, $t(17) = 2.73$, $p < .05$).

3. Experiment 2

In Experiment 2 we measured WM capacity consumption for color–color conjunction stimuli. As in Experiment 1, we were particularly interested in comparing the conditions in which we increased the amount of information (by adding a color feature) but without increasing the number of the to-be-remembered objects (e.g., comparing a bicolored square to a display that contains just one color, see Fig. 2b). While Luck and Vogel (1997) did not find any cost for color–color conjunction stimuli, others have failed to replicate this result (Delvenne & Bruyer, 2004; Olson & Jiang, 2002; Parra et al., 2009; Wheeler & Treisman, 2002), and found lower accuracy for color–color conjunction stimuli relative to the same number of one-color items. This failure to replicate was taken as evidence supporting the weak object based account, because WM does not treat a bicolored square as one object. It was also taken as support for the separate independent memory representations view (Jiang et al., 2009; Magnussen et al., 1996).

However, one possible reason for the failure to replicate may have been that color–color conjunction objects involve a more difficult comparison process. Namely, when one colored object is presented, participants need to make one decision regarding a change in its color. However, when one color–color conjunction stimulus is presented, two decisions are required regarding each color. Thus, errors during the comparison process might account for the low accuracy in the color–color conjunction condition (e.g., Awh et al., 2007). The interrelated object account makes a clear prediction regarding color–color conjunction stimuli – they should consume the same amount of capacity as one color. This should be reflected in the CDA amplitude as a measure of the WM storage demands during maintenance.

3.1. Method

Except as noted below, all details are identical to Experiment 1.

3.1.1. Participants

19 fresh subjects participated in Experiment 2. Subjects with more than 25% rejection rate due to eye-blink or eye-movement were rejected from further analysis (3 subjects).

3.1.2. Stimuli and procedure

There were 8 different conditions that were randomly intermixed within each block: one small color, one “frame”, one conjunction color (that was composed of one small color and one colored “frame”), one small color and one frame, 2 conjunction color–color stimuli, 2 small colors, 2 frames, and 4 separate colors (2 small + 2 frames). Subject performed a 16 trials practice followed by 27 blocks, 60 trials each.

3.2. Results

3.2.1. Behavioral

The accuracy for the different conditions is presented in Table 1. Accuracy for one object single-feature stimuli (i.e., one small square

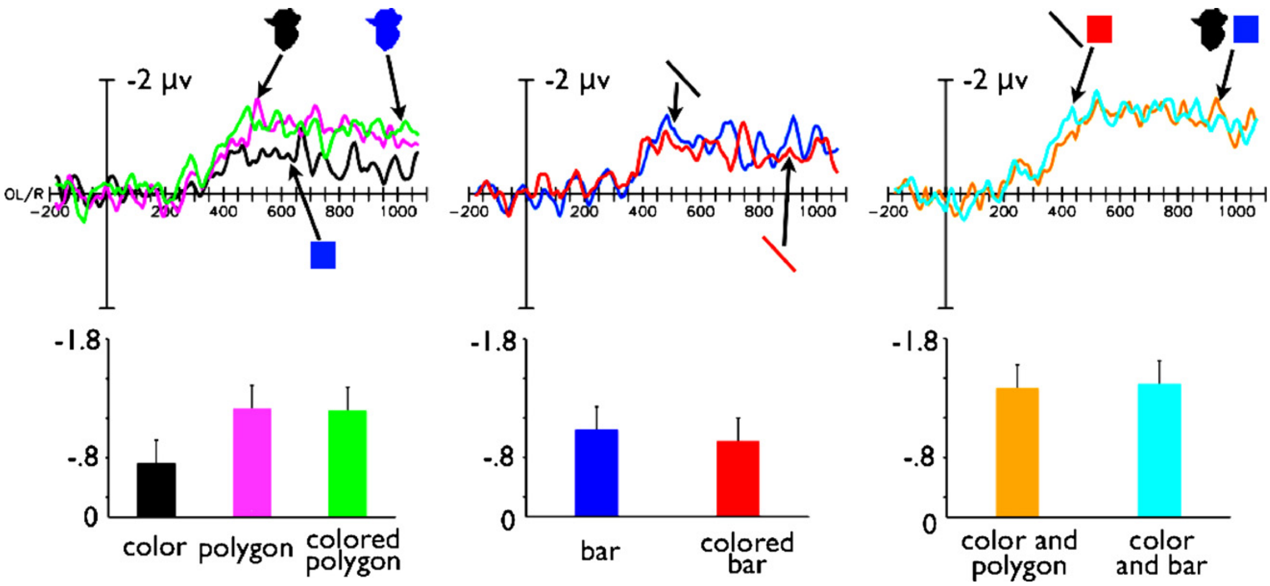

Fig. 3. The CDA wave for the different conditions in Experiment 1.

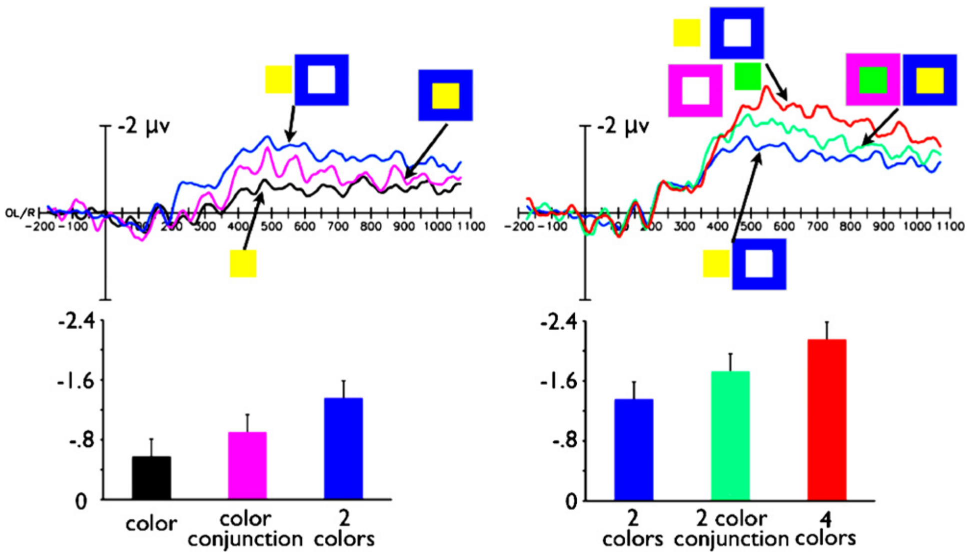

Fig. 4. The CDA wave for the different conditions in Experiment 2.

and one frame) and two objects single-feature each stimuli (i.e., 2 small squares, 2 frames and one sqaure + one frame) did not differ between themselves, $F < 1$, $F = 1.63$ ($p > .2$), for one object and two objects, respectively. Since this result was reflected in the CDA analysis as well (see below), we averaged together all the single-featured one object conditions and all single-featured two objects for any further analysis.

Accuracy for one object was better in the single feature condition relative to the color–color conjunction condition, F (1, 15) = 7.56, MSE = .0002, $p < .05$. Accuracy for one color–color conjunction stimulus was the same as 2 objects, $F < 1$. Accuracy for single feature 2 objects was better then 2 color–color conjunction stimuli, F (1,15) = 96.23, MSE = .001, $p < .0001$. Accuracy for 2 color–color conjunction stimuli was marginally better than 4 objects, F (1,15) = 4.24, $p = .057$. Overall, we found large and significant costs for color–color conjunction stimuli, replicating previous results (Delvenne & Bruyer, 2004; Olson & Jiang, 2002; Parra et al., 2009; Wheeler & Treisman, 2002).

3.2.2. Electrophysiology

The CDA waveforms for all the different conditions are presented in Fig. 4. CDA amplitudes for one object single-feature stimuli (i.e., one small square; one frame) did not significantly differ from one another ($F < 1$). Similarly, CDA amplitudes for single-feature arrays with two objects (i.e., 2 small squares, 2 frames and one sqaure + one frame) also did not differ, $F = 2.13$ ($p > .13$). For this reason, we averaged together the one object single-feature conditions and the two objects single-feature conditions for all subsequent analyses.

The CDA analysis revealed that there was a conjunction cost for both one and two items. CDA amplitude for one single-feature object was lower than 1 color–color conjunction object, F (1,15) = 10.56, MSE = .01, $p < .01$, and the 2 single-feature objects CDA amplitude was lower than 2 color–color conjunction objects, F (1,15) = 6.11, MSE = .26, $p < .05$. An inspection of Fig. 4 revealed that for both one and two item arrays, the CDA for color–color conjunctions differs from the single-featured condition during the initial portion of the maintenance period and then declines to the level of the single-feature condition near the end of the trial. This was supported by a separate analysis for the early vs. late maintenance period. While the CDA amplitude was higher for color–color conjunction stimuli in the initial CDA period (450–600 ms post memory array), F (1,15) = 16.72, MSE = .15, $p < .005$, for one object, F (1,15) = 9.06, MSE = 30, $p < .01$, for two objects, the same differences were not significant in the late maintenance period (750–1000 ms), $F = 2.10$, $p = .2$, for one object, and $F = 1.87$, $p = .37$, for two objects.

In addition, the CDA amplitude for one color–color conjunction object was significantly lower than 2 objects, F (1,15) = 14.43, MSE = .20, $p < .005$ indicating that more WM resources are consumed to maintain 2 objects relative to 1 object, even when both conditions have the same amount of featural information. The same trend was evident for 2 objects: the CDA amplitude for 2 color–color conjunction stimuli was lower than 4 objects, F (1,15) = 7.63, MSE = .13, $p < .05$. Finding lower CDA amplitudes for color–color conjunction stimuli relative to single objects conditions even though they have the exact "information" load is consistent with the prediction made by integrated object view of WM capacity.

3.3. Discussion

Although we found large accuracy costs for color–color conjunction stimuli (comparing a bicolor object to a single color object), the CDA revealed only a small conjunction cost, which appeared to dissipate as the retention interval progresses. Overall, this pattern of result is inline with the integrated object account of WM capacity. The discrepancy between the large behavioral cost, and the dissipating CDA cost may potentially explain why some behavioral studies have failed to replicate the original Luck and Vogel (1997) data that showed no color–color conjunction cost. Furthermore, the results strongly support the integrated object view: the CDA amplitude for color–color conjunction objects was lower than a condition displaying identical perceptual information across separate objects. Thus, WM capacity, as measured by the CDA amplitude, is primarily sensitive to the number of objects and not simply the total amount of the maintained information.

4. General discussion

The purpose of the current work was to test alternative explanations for the integrated object account of WM capacity. To this end, we asked participants to remember single objects (e.g., a tilted bar, a polygon, or a color), and compared performance to displays that contained higher perceptual information, that were still presented in single objects (e.g., a colored tilted bar, a colored polygon, or a bicolor stimulus). Thus, we increased the amount of information that was remembered, without increasing the number of the to-be-remembered objects. For the polygon and bar conjunction stimuli, adding an extra color feature was cost-free in terms of WM capacity as indicated by both accuracy and the CDA data. The polygon data is especially informative, since representing a polygon consumes more capacity relative to simpler stimuli. Yet, once a polygon is represented, it is maintained as a bound object and not as separate features.

The bicolor condition of Experiment 2 showed large conjunction cost in accuracy but only a small (yet significant) conjunction cost in the CDA amplitude that was restricted to the initial part of the retention interval. These results are important in highlighting several points: first, the dissipating CDA cost supports the "strong" object account of WM capacity since WM maintenance treated a bicolor object as a single feature object (after an initial cost). Second, the large accuracy cost might be due to an overloaded comparison process (Awh et al., 2007) or other processes that do not exclusively reflect WM storage capacity. Third, because the CDA amplitude for color–color conjunction stimuli was lower relative to the condition in which the same amount of color information was presented as separate objects, it challenges the predictions made by the weak object WM account (Jiang et al., 2009; Olson & Jiang, 2002), and the separate WM systems hypothesis (Magnussen et al., 1996).

The small color–color conjunction cost that we observed is an intriguing result, as it may reflect an evolving WM representation in which the features are initially only partially bound but become fully bound over the first several hundred milliseconds of the retention period. This observation is inline with models that emphasize the role of attention in a two-stage account of binding. At the first stage, visual features are only weakly bound, and binding may dissipate unless a second stage that acts to consolidate the bindings reinforces the initial noisy process (Braet & Humphreys, 2009). At this point, more data is needed in order to evaluate this idea and other alternative accounts.

The present results shed light on the role of attention in bindings. While feature integration theory argued that binding is an attentional demanding process with an apparent behavioral cost (Treisman, 1998; Wheeler & Treisman, 2002) others have argued that attention is not required for feature integration to occur (Mordkoff & Halterman, 2008). The result of Experiment 1 did not find any behavioral or electrophysiological binding cost in WM when binding features from dimensions. Thus, even though WM has strictly limited its attentional capacity, it did not exhibit any binding cost (which does not rule out the involvement of attention in earlier binding related processes). Experiment 2 did find significant binding cost in behavior for same dimension bindings, however, this evidence in not conclusive since accuracy cost may not necessarily indicate the involvement of an attentional demanding process during binding (Awh et al., 2007; Mordkoff & Halterman, 2008). The CDA result (at the initial maintenance stage) is relevant evidence that demonstrates bindings cost within WM capacity. This is inline with previous evidence for the involvement of early spatial attention in the binding process (Hyun, Woodman, & Luck, 2009).

Another important aspect of the current design is that we purposefully focused on adding an extra feature to only one object, while other studies (e.g., Luck & Vogel, 1997; Olson & Jiang, 2002; Parra et al., 2009; Xu, 2002) mostly presented arrays that exceeded capacity. For our current goal, we consider the data from one object (and sometimes two objects) to be the most informative, because we can be certain they are below the maximum capacity level. Using super-capacity arrays probably involves selection (bottom-up or top-down) regarding which objects (or features) from the display will be stored in memory, and this might interact with the binding mechanisms, adding a confounding factor that might obscure differences between the predictions the two models make. Importantly, the current results indicate that complex stimuli are stored as bound objects in the sense that increasing the information load by adding a color feature does not increase any WM capacity consumption. This pattern held for both complex stimuli and bicolor conjunction stimuli, so that we found no support for the weak object based view of WM capacity.

There are two presently active debates regarding visual WM: the strong vs. weak object viewpoints (as discussed throughout the ms), which debate the nature of the representations held in visual WM; and the discrete vs. flexible resource viewpoints, which debate the nature of the capacity limitations of visual WM. While these two debates are highly similar and share overlapping concerns, they are not identical. The discrete view proposes that capacity limitations are defined by a maximal number of slots (or pointers) that each can represent one object (Luck & Vogel, 1997; Zhang & Luck, 2008). The discrete model indorses an object view of WM, but will face difficulties explaining why polygons consume more capacity than colors, if we adopt a one slot per object assumption. Note that this assumption is not shared by the integrated object view (and even not necessarily by the discrete model, see Luck, 2008). On the other hand, the flexible resource model suggests that capacity can be divided in a graded and continuous fashion according to the object's complexity (Bays & Husain, 2008; Wilken & Ma, 2004). As more items are presented, the capacity that is devoted to each item drops, causing performance to gradually deteriorate. Importantly, this drop in performance is associated with an increase in the represented information load rather than an increase in the number of items being represented. While the integrated object viewpoint is most readily consistent with discrete models of capacity, evidence for object integration could be accommodated by flexible resource models that argue that the allocation of visual WM resources is distributed in units of objects with simply less precision dedicated to each object as more items must be remembered. Presently, we know of no flexible resource models that explicitly make this stipulation, yet we could imagine that this attribute could be added to existing models.

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