Research Article

Visual Working Memory Represents a Fixed Number of Items Regardless of Complexity

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ABSTRACT—*Does visual working memory represent a fixed number of objects, or is capacity reduced as object complexity increases? We measured accuracy in detecting changes between sample and test displays and found that capacity estimates dropped as complexity increased. However, these apparent capacity reductions were strongly correlated with increases in sample-test similarity (*r *= .97), raising the possibility that change detection was limited by errors in comparing the sample and test, rather than by the number of items that were maintained in working memory. Accordingly, when sample-test similarity was low, capacity estimates for even the most complex objects were equivalent to the estimate for the simplest objects (*r *= .88), suggesting that visual working memory represents a fixed number of items regardless of complexity. Finally, a correlational analysis suggested a two-factor model of working memory ability, in which the number and resolution of representations in working memory correspond to distinct dimensions of memory ability.*

Working memory enables a limited amount of information to be maintained in an "on-line" or readily accessible state. Several different paradigms have converged on the conclusion that visual working memory has a capacity limit of only about three to four simple objects (e.g., Luck & Vogel, 1997; Pashler, 1988; Sperling, 1960). Moreover, individual differences in working memory capacity exhibit robust positive correlations with general intelligence and scholastic aptitude (Cowan et al., in press). Thus, there is strong motivation to understand the basic determinants of this item limit.

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Some researchers have suggested that capacity is set by the number of objects that can be stored (e.g., Irwin, 1992; Luck & Vogel, 1997; Vogel, Woodman, & Luck, 2001) and is independent of the number of features within each object. Luck and Vogel (1997) used a change-detection paradigm that required subjects to remember a sample array of objects over a brief retention interval and then indicate whether any item in a subsequent test array had changed. They found that memory capacity for objects defined by a single feature (e.g., color or orientation) was equivalent to capacity for multifeature objects (e.g., colored lines of varying orientations). They concluded that capacity is determined by the number of objects, and not by the number of features that are stored. By contrast, other researchers have reported marked reductions in capacity as object complexity increases (Alvarez & Cavanagh, 2004; Eng, Chen, & Jiang, 2005). Using a clear operational definition of complexity or "information load" (the efficiency of search for a target among distractors from the same category), Alvarez and Cavanagh (2004) observed monotonic reductions in capacity estimates as complexity increased. In the present research, we attempted to resolve this apparent contradiction.

One key assumption of these studies is that change detection is limited solely by the number of items that are maintained in memory, without the contribution of errors during the encoding of the sample array or during the comparison of the test array with the items in memory. Encoding was probably not a limiting factor for either Luck and Vogel's (1997) or Alvarez and Cavanagh's (2004) study. In both cases, change-detection accuracy was insensitive to relatively large changes in the exposure duration of the sample array. This does not necessarily mean that every object in the sample array was encoded, but it does suggest that encoding was not the limiting factor for change detection. Alvarez and Cavanagh (2004) also examined whether increased sample-test similarity elicited errors during the comparison stage of the task. They measured change-detection accuracy

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with upright or rotated versions of block 2s and 5s. Although the physical similarity between 2s and 5s did not change when both were rotated, rotation did lead to steeper search slopes and higher estimates of information load. Moreover, capacity estimates declined for the rotated stimuli, confirming Alvarez and Cavanagh's initial observation that information load impairs change detection. Given that rotation did not change the physical similarity of the stimuli, they concluded that information load influenced the number of objects that were stored rather than the probability of comparison errors.

In the present work, we reexamined whether comparison errors play a role in the inverse relation between capacity and complexity. Although physical similarity was perfectly controlled during rotations of the 2s and 5s in Alvarez and Cavanagh's (2004) experiment, it is likely that subjective similarity increased when the digits were rotated to less familiar orientations. In the same way, inverted faces are harder to discriminate than upright faces, even though physical similarity is held constant (Yin, 1969). This leaves open the possibility that increases in subjective similarity caused comparison errors when the digits were rotated even though the same number of items were stored as when the digits were upright. Thus, our goal was to test whether object complexity influences the number of active representations, or "slots," that are maintained in working memory, or whether complexity influences the probability of comparison errors.

In our first set of experiments (1a and 1b), we sought to replicate Alvarez and Cavanagh's (2004) finding of reduced change-detection performance for complex objects and to also test whether the subjective similarity of the objects increases along with complexity. A strong relation between similarity and complexity would increase the likelihood that poorer change-detection performance for more complex items is due to errors made when the subject compares the representations in memory with the items presented in the test array. To further test this hypothesis, in the second experiment, we reduced the similarity of the complex objects to determine whether performance would increase to the level observed for the simple objects. Such an increase would further implicate the role of comparison errors in reducing change-detection performance for complex objects and, more important, would demonstrate that a fixed number of items are represented regardless of their complexity.

EXPERIMENTS 1A AND 1B

Experiment 1a assessed change-detection performance for four categories of objects that spanned the full range of complexity tested by Alvarez and Cavanagh (2004). This study replicated their finding that capacity estimates drop as object complexity increases. Experiment 1b measured reaction times (RT) during a one-item change-detection task. High levels of accuracy with one-item arrays suggested that performance was not limited by encoding or maintenance of the objects in working memory. However, if an item presented at test is very similar to the item held in memory, then additional time will be necessary to compare them. Thus, we used RT as an operational definition of similarity within each category and examined whether similarity increases with object complexity.

Method

Subjects

Two different groups of 16 subjects received course credit for 1 hr of participation in Experiment 1a or 1b. The subjects ranged from 18 to 30 years of age and had normal or corrected-to-normal vision.

Stimuli

The stimuli (adapted from Alvarez & Cavanagh, 2004) included colored squares, Chinese characters, random polygons, and shaded cubes (see Fig. 1). The widest aspect of each object touched the borders of a square region that subtended approximately 3.3° × 3.3° of visual angle. During Experiment 1a, four or eight objects were presented in randomly selected positions within a square region (30° per side), with the constraint that all quadrants contained an equal number of objects, and no object could appear within 3.3 object widths of another object. The displays were the same for Experiment 1b, except that only one item was presented.

Procedure

During Experiment 1a, the first trial event was the onset of a light-gray region that demarcated the possible stimulus positions and contained a central fixation point. After 1,092 ms, four or eight objects (randomly selected with replacement, with the constraint that no object appeared more than twice) from one of the four categories appeared for 500 ms, followed by a 1,000-ms delay period. Finally, a test array of objects appeared and remained visible until the subject pressed the "z" key to indicate "same" or the "/" key to indicate "different." In half of the test arrays, one item was replaced with another item randomly

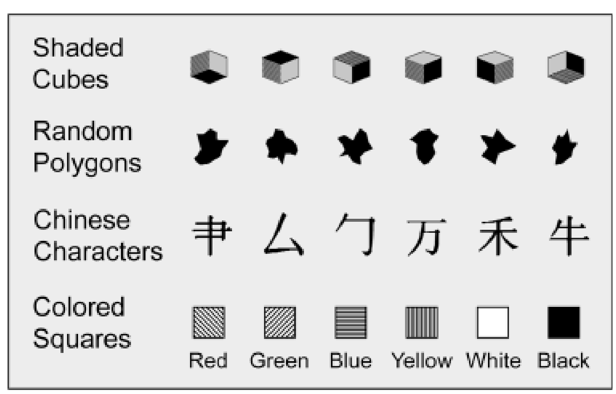

Fig. 1. Possible objects in Experiments 1a and 1b (adapted from Alvarez & Cavanagh, 2004).

selected from the same category. Subjects in Experiment 1a were instructed to place highest priority on accuracy, without regard for speed.

The procedure was the same in Experiment 1b, except that only one-item displays were presented, and subjects were instructed to respond as quickly as possible while maintaining high accuracy. In addition, subjects were instructed to maintain fixation so that viewing eccentricity would be roughly equated with that in Experiment 1a (subjects did not have time to fixate all four or eight items within the 500-ms sample display).

In Experiments 1a and 1b, each subject completed eight blocks of 64 trials. Each block included 16 instances of each category (8 *no-change* and 8 *change* trials). Trial order was randomized within each block.

Results and Discussion

Accuracy during Experiment 1a declined as object complexity (as estimated by Alvarez & Cavanagh, 2004) and array size increased (see Fig. 2). A two-way analysis of variance with factors of object type (colored squares, characters, polygons, or cubes) and array size (four or eight) found significant main effects for object type, $F(3, 45) = 123.2$, $p < .001$, $\eta_p^2 = .99$, and array size, $F(1, 15) = 104.4$, $p < .001$, $\eta_p^2 = .99$, as well as a significant interaction of these factors, $F(3, 45) = 4.1$, $p < .02$, $\eta_p^2 = .8$, driven by near-floor accuracy in the polygon and cube conditions. Memory capacity (based on the eight-item condition because of ceiling effects with four items) for each object category was estimated using the formula developed by Pashler (1988) and refined by Cowan (2001). As Alvarez and Cavanagh (2004) found, capacity estimates (k) ranged widely across the four categories, from 4.9 for colored squares to 0.9 for shaded cubes, with monotonic declines in accuracy as complexity increased.

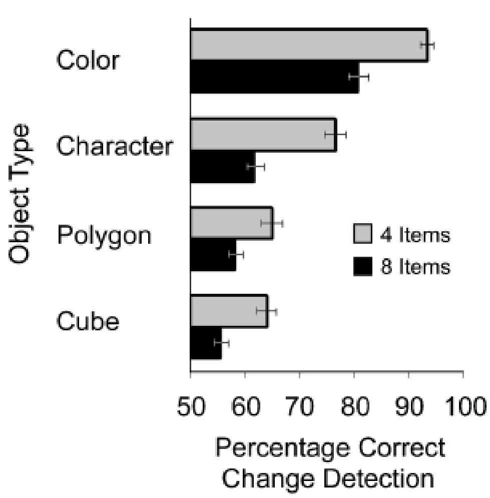

Fig. 2. Change-detection accuracy in Experiment 1a as a function of object type and set size.

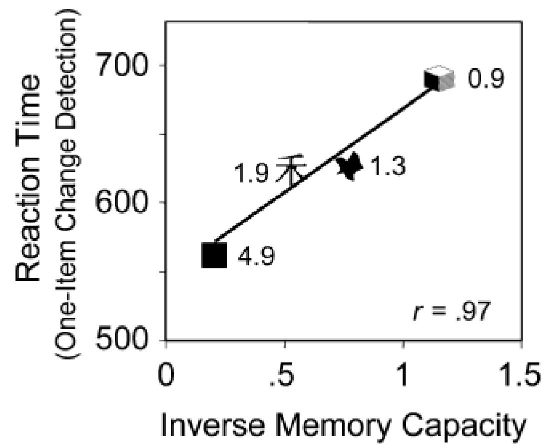

Fig. 3. Reaction time (in milliseconds) in the one-item change-detection task of Experiment 1b as a function of inverse memory capacity estimated using eight-item displays. Symbols indicate the different object types (colored squares, Chinese characters, random polygons, and shaded cubes). Capacity, calculated using Cowan's (2001) k, is shown next to each symbol.

RTs from Experiment 1b were trimmed by removing trials in which RT was greater than 2 standard deviations from the mean (3%) and trials with incorrect responses (7% error rate). The RT to detect changes in the one-item displays varied strongly across different object types, with monotonic increases in RT as complexity increased, $F(3, 45) = 36.2$, $p < .001$, $\eta_p^2 = .97$. Mirroring this effect, there were small but reliable reductions in accuracy ($M = 93\%$) as complexity increased, $F(3, 45) = 15.0$, $p < .001$, $\eta_p^2 = .93$. Mean accuracy was 96%, 95%, 92%, and 91% for colored squares, characters, polygons, and cubes, respectively, showing that the RT differences across object types in one-item change detection were not due to a speed-accuracy trade-off. These accuracy differences raise the possibility that encoding and maintenance were limiting factors in this task. However, given the small size (5%) of these effects, we argue that RT was primarily determined by the difficulty of discriminating the sample and test items. Thus, when similarity was operationalized by RT in the one-item task, we found that increases in complexity were associated with strong increases in the similarity between items in that category. Note that this RT measure of similarity was strongly predictive of inverse memory capacity from Experiment 1a (see Fig. 3), yielding a significant linear correlation between RT and inverse capacity, $r(2) = .97$, $p < .05$, $p_{rep} = .938$, $d = 8.0$.[1]

Experiments 1a and 1b replicated the observation that capacity estimates go down as object complexity increases (Alvarez & Cavanagh, 2004; Eng et al., 2005). However, given the strong association between object complexity and sample-test similarity, reduced capacity estimates for complex objects may have been caused by a higher incidence of comparison errors. Experiment 2 tested whether object complexity influences the

[1]Using inverse capacity (1 divided by k) allowed a straightforward linear analysis, even though differences in k were compressed as similarity increased.

number of items held in working memory or the probability of comparison errors.

EXPERIMENT 2

If the higher information load associated with complex objects leads to a smaller number of items stored in working memory, then change-detection performance should be impaired even if sample-test similarity is low. Consider the case of the shaded cubes. Experiment 1a produced a capacity estimate of 0.9 items for these stimuli. If only one object is represented during trials in this condition, then even large changes in any additional memory items should be missed. The same logic explains why subjects fail to detect salient color changes or large changes in visual scenes when memory capacity has been exceeded (Luck & Vogel, 1997; Simons, 1996; Simons & Levin, 1997). By contrast, if increased complexity causes comparison errors because of increased sample-test similarity, then the discriminability of the sample and test items should affect accuracy more than the complexity of the sample array alone.

Experiment 2 employed a single set of potential memory objects that included 6 Chinese characters and 6 shaded cubes. Sample arrays contained randomly selected objects from this set of 12. During change trials, one object in the array was replaced with an item that was randomly selected from the 11 remaining objects in the set. Thus, in 6 out of every 11 change trials, the changed item was replaced with an item from a different category (i.e., a cube replaced a character or a character replaced a cube; hereafter referred to as a *cross-category* change). In the remaining 5 out of every 11 change trials, the changed item was replaced with an item from the same category (i.e., a cube replaced a cube or a character replaced a character; hereafter referred to as a *within-category* change). We reasoned that sample-test similarity was lower in the cross-category-change condition than in the within-category-change condition, and that comparison errors would be minimized in the cross-category-change condition. Thus, if complexity influences the number of items held in working memory, then reductions in sample-test similarity should not improve change-detection performance, and performance should not differ between the cross-category-change and within-category-change conditions. But if complexity has its influence during the comparison stage, then performance should be better in the cross-category condition than in the within-category condition, and comparable capacity estimates should be obtained for simple and complex objects.

Method

All aspects of Experiment 2 were the same as in Experiment 1a with the following exceptions. The potential memory items were taken from a combined set of six cubes and six Chinese characters. In addition, we included trials with simple colors that served as a measure of the approximate upper limit in visual memory capacity.

So that subjects could not simply count the number of cubes and characters in the sample array and respond "different" if these totals were changed in the test array, the test array contained only one object (regardless of whether four or eight objects had been presented in the sample array). Half of the time the test object was the same as the sample item that had appeared in exactly the same position, and half of the time it was different. Subjects indicated "change" or "no change" with an unspeeded key press.

Subjects

Twenty-two subjects from the same community as in Experiments 1a and 1b participated in a 1-hr session for course credit.

Procedure

There were eight blocks of 48 trials (16 color trials and 32 trials using the mixed arrays of cubes and characters). Trial order was randomized within each block.

Results and Discussion

Once again, object type had a strong influence on change-detection accuracy. An analysis that excluded the cross-category-change trials showed that accuracy was lower for cubes (k = 1.4) than for characters (k = 1.7), $t(21) = 2.1$, $p < .05$, $p_{\text{rep}} = .878$, $d = 0.33$, and lower for characters than for colors (k = 3.6), $t(21) = 2.7$, $p < .05$, $p_{\text{rep}} = .94$, $d = 0.42$. We considered whether the mere presence of cross-category changes might have encouraged subjects to adopt a "low-resolution" strategy for encoding sample arrays (e.g., encoding only category-level information). However, we note that capacity estimates in the within-category-change condition of Experiment 2 were statistically indistinguishable from those in Experiment 1a (for cubes, $p = .19$; for characters, $p = .70$), suggesting that a similar level of detail was encoded in the two cases.

Figure 4 shows accuracy for trials in which a change occurred. For within-category changes, there were monotonic decreases in accuracy as complexity increased. However, when a cross-category change occurred (and sample-test similarity was therefore low), accuracy for even the most complex objects was equivalent to that for simple colors. Capacity estimates (using only no-change trials and cross-category-change trials) for cubes (k = 4.2) and Chinese characters (k = 3.5) were as high as the estimate for colors (k = 3.6).[2] These data suggest that the number of slots active in visual working memory was the same even for the most complex objects as for simple colors. Otherwise, change-detection accuracy could not have reached the same level in the cross-category-change condition as in the simple color condi-

[2]Cube-to-character changes led to higher capacity estimates than character-to-cube changes, $t(21) = 2.7$, $p < .01$. All other paired comparisons were nonsignificant.

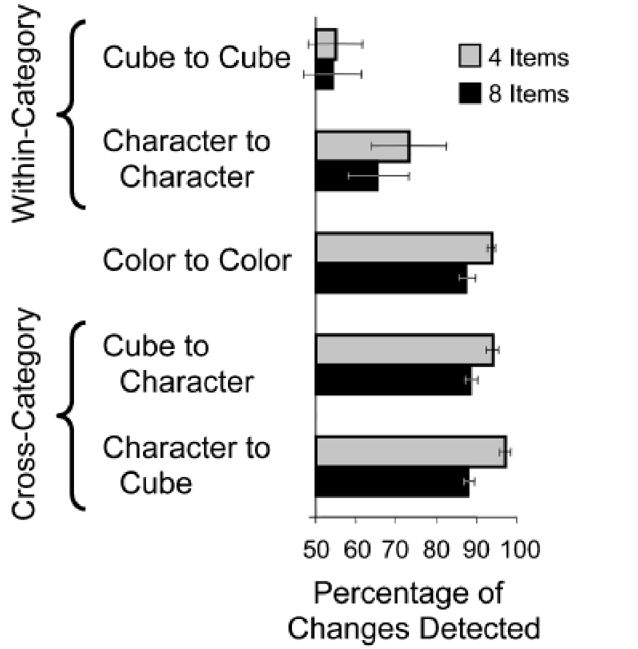

Fig. 4. Accuracy during change trials in Experiment 2 as a function of the type of change and set size. Accuracy for detecting simple color changes provided a benchmark for performance when sample-test similarity was low.

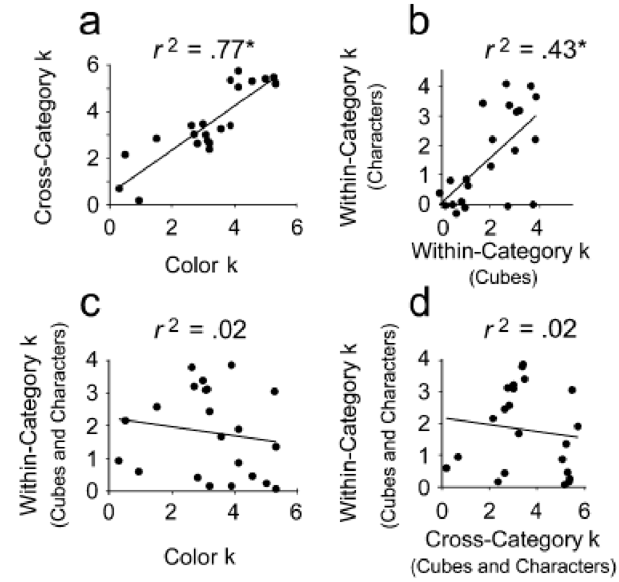

Fig. 5. Correlations between individual capacity estimates in the main conditions of Experiment 2: correlation between (a) the two conditions with low sample-test similarity (i.e., the color and cross-category-change conditions), (b) the two conditions with high sample-test similarity (i.e., within-category-change conditions), (c) the color condition and the within-category-change condition, and (d) the cross-category-change conditions and the within-category-change condition. Asterisks denote significant correlations, $p < .001$. Capacity was calculated using Cowan's (2001) k.

tion. Thus, difficulties in detecting within-category changes of complex objects could be accounted for entirely by comparison errors, even if the number of stored items is the same for complex and simple objects.

Essentially, we are suggesting that as object complexity increases, the limiting factor for performance shifts from the number of items that can be maintained in working memory to the probability of comparison errors. This shift is driven not by increases in object complexity per se, but by the associated increases in sample-test similarity. Thus, for simple colors or cross-category changes, the limiting factor is the number of items that can be held in visual working memory. By contrast, within-category changes with complex objects entail high sample-test similarity, so the limiting factor is the probability of errors during the comparison stage of the task. In this case, performance may be determined by the resolution, rather than the number, of representations in working memory.

This hypothesis can be tested further by examining individual differences in performance across the conditions. If change detection with simple and complex objects measures a common storage capacity, then an individual's performance with simple objects should be strongly predictive of his or her performance with complex objects. That is, individuals who have a high capacity for simple objects should also have a relatively high capacity for complex objects. By contrast, if performance for complex objects is limited by a factor other than storage capacity (e.g., comparison errors), then there may be little or no relation between an individual's capacity estimates for simple and complex objects.

Figure 5 shows correlations between individual capacity estimates obtained from different conditions in Experiment 2. Table 1 shows the full correlation matrix.[3] The within-category-change and cross-category-change conditions were distinguished only during change trials, even though capacity estimates are calculated using both change and no-change trials. Thus, when capacity estimates were calculated for the within-category-change and cross-category-change conditions, a common set of no-change trials was used for these estimates (averaged across the four- and eight-item trials). This enabled a shared metric (k) for all conditions. Three results are of primary interest. First, there was a strong positive correlation between capacity estimates from the cross-category-change condition and the color condition (Fig. 5a), $r(20) = .88$, $p < .01$, $p_{rep} > .995$, two conditions in which sample-test similarity was low. This correlation suggests that these two measures tap into a common on-line memory capacity. Second, there was also a clear correlation between capacity estimates from within-category-change trials with the shaded cubes and within-category-change trials with the Chinese characters (Fig. 5b), $r(20) = .65$, $p < .01$, $p_{rep} = .990$, two conditions in which sample-test similarity was relatively high. Finally, there was no trace of a correlation between

[3]A further split-half analysis showed that all significant and nonsignificant correlations were replicated within the first and second halves of this experiment.

TABLE 1

Correlations Between Capacity in the Four Main Conditions of Experiment 2

Condition	Condition: Color	C-C change	W-C change: Chinese
Color	—		
C-C change	.88*	—	
W-C change: Chinese	.07	.07	—
W-C change: cubes	−.32	−.28	.65*

Note. Asterisks denote significance at a threshold of $p < .01$. No other correlations were significant. C-C = cross-category; W-C = within-category.

estimates based on the conditions in which sample-test similarity was low and the conditions in which it was high (Figs. 5c and 5d). For example, although capacity estimates from the color condition were an excellent predictor of performance in the cross-category-change condition, there was no significant correlation between capacity in the color condition and capacity in the within-category-change condition ($r = -.14$, $p = .53$). Finally, a test of differences between within-sample correlations revealed that the correlation between capacity estimates in the color condition and in the cross-category-change condition was significantly larger than the correlation between capacity estimates in the color condition and in the within-category-change condition ($Z = 4.76$).

The absence of any correlation between capacity estimates for colors and complex objects (in the within-category-change condition) is striking given the natural assumption that change-detection tasks with colors and complex objects measure the same cognitive ability. Capacity estimates for simple colors correlate with a variety of cognitive measures, including scores on wide-ranging tests like the Stanford-Binet Intelligence Scale and Raven's Progressive Matrices (Cowan et al., 2005). Thus, it seems plausible that memory capacity for simple colors should predict capacity for complex visual stimuli. Nevertheless, these results suggest that change-detection tasks with simple and complex objects measure two relatively distinct abilities. Thus, individual differences in the number of representations that can be held in working memory appear to be independent of individual differences in the resolution of those representations.

GENERAL DISCUSSION

Our primary conclusion is that a fixed number of items are represented in visual working memory, regardless of the complexity of those items. Although previous research has reported reductions in the number of stored objects as complexity increases (Alvarez & Cavanagh, 2004; Eng et al., 2005), our results suggest that errors in comparing the test array with the remembered information led to underestimates of the number of items in working memory. This conclusion is supported by our finding that change-detection performance was equivalent with simple colors and complex objects when low sample-test similarity minimized comparison errors.

We propose that as the similarity between the sample and test arrays increases, there is a qualitative shift in the ability that is measured by the change-detection procedure. When sample-test similarity is low, performance is limited by the number of representations that can be simultaneously maintained in working memory. The simple colored stimuli employed by Luck and Vogel (1997) fall into this category. However, more complex objects entail high sample-test similarity, so that performance is limited during the comparison stage of the task. Although there are stable individual differences in the ability to make fine discriminations between complex objects (as shown by the significant correlation between change detection with cubes and with Chinese characters), this ability is apparently independent of the number of items that an individual can hold in working memory. This raises an intriguing empirical question. Although previous studies have found robust correlations between various measures of intelligence and the number of items that an individual can maintain in working memory (i.e., change detection with low sample-test similarity), it remains to be seen whether a similar relation holds between intelligence and the resolution of representations in working memory.

This two-factor model is consistent with Xu and Chun's (2005) suggestion that two dissociable neural mechanisms mediate visual working memory. They reported that neural activity within the inferior intraparietal sulcus represented about four items regardless of complexity, whereas the number of items represented within the superior parietal and lateral occipital regions was reduced for complex objects. It is possible that activity within the inferior intraparietal sulcus determines the number of representations an individual can hold (Todd & Marois, 2004; Vogel & Machizawa, 2004), and activity within the superior parietal and lateral occipital regions determines the resolution of these representations.

These results do not contradict the basic insight that information load influences change-detection performance. Indeed, our measure of similarity probably taps into the same thing as the information-load measure introduced by Alvarez and Cavanagh (2004), who defined information load as the "amount of visual detail" (p. 106) that is stored for an object. Clearly, higher sample-test similarity means that more visual detail must be maintained to detect potential changes. Moreover, it is known that search slopes increase as target-distractor similarity increases (Duncan & Humphreys, 1989), which leaves open the possibility that changes in similarity were the cause of the variations in information load in Alvarez and Cavanagh's experiments. Our focus on similarity places more emphasis on the discriminability of the sample and test, whereas the information-load construct emphasizes the intrinsic complexity of the sample array. But the predictive power of both measures draws from the fact that a representation of higher resolution is required to detect changes between similar objects than to detect changes between dissimilar objects. Thus, the key insight that our work may offer is to show that the relation between change-detection performance and complexity is determined by the resolution, rather than the number, of representations that can be held in working memory.

On the basis of the finding that change detection with one-item displays was nearly perfect for both simple and complex objects, Alvarez and Cavanagh (2004) argued that complexity effects cannot be explained by positing a fixed number of slots with limited resolution. We agree that near-perfect performance with one complex object suggests a higher-resolution representation than is found with multiple-item displays. Perhaps resolution is determined by the total number of items maintained in working memory, such that resolution increases as the number of items goes down. But the finding that capacity estimates for simple and complex objects are equated when sample-test similarity is low may be best explained by a fixed number of active slots with limited resolution.

We conclude that visual working memory holds a fixed number of items, regardless of the complexity of those items. These slots have limited resolving power, however, such that high similarity between sample and test items will elicit errors during the comparison stage of a change-detection task. Thus, complexity can have a strong influence on change-detection performance, but it does not do so by influencing the number of items that are represented. When low similarity prevents comparison errors, capacity estimates for complex and simple objects are equivalent.

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