Superfamiliarity affects perceptual grouping but not the capacity of visual working memory

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Abstract

Visual working memory (VWM) can represent information from approximately three objects in parallel, but the capacity of long-term memory appears almost limitless. If VWM is so limited, can familiarity with a scene or object increase the capacity of VWM for that object? Some evidence from change detection suggests not: providing additional exposure to a visual scene before introducing a change to it does not enhance change detection performance (Rensink, O'Regan, & Clark, 2000). But other evidence suggests that some information from the pre-change display can be encoded into long-term memory (e.g., Simons, Chabris, Schnur, & Levin, 2002) and that long-term memory may contribute to change detection (e.g, Hollingworth, Williams, & Henderson, 2001). Here we examine the role of familiarity in change detection by estimating the capacity of VWM under conditions of acquired "superfamiliarity" with the stimuli. Such superfamiliarity had no significant effect on the estimated item-based capacity of VWM, suggesting that the three-item limit is a fixed structural limit. Furthermore, an algorithmic analysis of the ease of perceptual grouping of items within the displays suggested that any apparent increases in capacity beyond 3 items could be attributed to grouping of elements into larger chunks; perceptual grouping changes what counts as an "item" for VWM, but the three-item limit of VWM appears impenetrable to the ameliorating effects of superfamiliarity.

Introduction

In order to perceive and encode a scene, observers must shift attention from one region to another, registering attended aspects of the scene into visual working memory (VWM). Converging evidence from a variety of tasks reveals a capacity limit of approximately 3-4 items both for visual attention and VWM (Luck & Vogel, 1997; Pashler, 1988; Phillips, 1974; Pylyshyn & Storm, 1988; Scholl & Xu, 2001; Sperling, 1960; Vogel, Woodman & Luck, 2001). For example, human infants, adults, and even non-human primates can use attention and memory to keep track of 3-4 moving items (Pylyshyn & Storm, 1988; Scholl & Pylyshyn, 1999; Feigenson, Carey & Hauser, 2002; Feigenson & Carey, 2003; Hauser, Carey & Hauser, 2000; Hauser & Carey, 2003). Similarly, transsaccadic memory is limited to about four items (Irwin & Gordon, 1998), adults can detect changes to the properties of 3-4 objects in parallel (Luck & Vogel, 1997), and approximately four items can capture attention in a visual search task (Yantis & Johnson, 1990; but evidence from visual marking tasks might suggest a higher number, see Belopolksy, Theeuwes, & Kramer, 2005).

Despite the consistency of this 3-4 item limit, a few tasks suggest different limits. For example, the measured capacity for complex stimuli in VWM is often fewer than three items (Phillips & Christie, 1977; Alvarez & Cavanagh, 2003), suggesting that an information limit can be exceeded before the limit of 3-4 objects is reached (Alvarez & Cavanagh, 2003). In contrast, with arrays of simple objects, capacity estimates can be substantially higher than 3-4 objects (Rensink, 2000a). These higher capacity estimates might well result from grouping or chunking processes that allow information from more than one item to be encoded into a single higher-order individual. For example, three adjacent, similar items might be treated as a single object, resulting in a capacity limit greater than four individual items, but not necessarily more than four "objects" in memory. An important open question is whether the purported item-based limit of VWM is malleable. For example, can additional "slots" be made available through practice or training?

Some evidence from the change detection literature suggests that such expansion does not occur — increasing the initial exposure time for natural scenes does not greatly facilitate change detection (Rensink, O'Regan, & Clark, 2000). But other evidence suggests that some information from the pre-change display can be encoded into long-term memory (Simons, Chabris, Schnur, & Levin, 2002) and that long-term memory may contribute to change detection (Hollingworth, Williams, & Henderson, 2001). However, none of these studies directly measured VWM capacity and they did not control for alternative routes to change detection that could affect estimates of the capacity of VWM.

In this paper, we explore whether familiarity with a stimulus influences estimates of VWM capacity. To determine whether familiarity allows more "slots" in a VWM capacity, we must first control for the following alternative ways in which long-term memory processes could influence VWM performance:

1) Attention: Knowledge of the task or of the display can facilitate guidance of attention to the relevant information thereby artificially inflating an estimate of capacity (e.g., Chun & Jiang, 1998; Jiang & Chun, 2001). For instance, knowing that the changing object in a scene will be a toaster allows subjects to search first on counters in a kitchen scene (Biederman, Mezzanotte & Rabinowitz, 1982; Palmer, 1975). In this case, longer-term semantic knowledge would allow faster change detection by eliminating the need to search the entire display. In essence, subjects are better able to choose what information to place in VWM, but they do not necessarily store more information; i.e. they have better information in VWM, not necessarily more information.
2) Recoding: Subjects might recode display items using a system other than VWM, for example categorical or verbal encoding. Familiarity might enhance such recoding, leading to even better performance. Again, enhanced performance due to recoding does not reflect a change to the capacity of VWM. Instead, it involves offloading information to other memory systems.
3) Grouping: Familiarity might allow enhanced grouping of elements into larger units based on their similarity, just as we can treat a multi-part object as a single unit. Grouping allows

more efficient encoding of the input by removing redundancies. But increased efficiency does not necessarily change the number of "slots" in VWM – it just allows more efficient packaging of information into each slot.

4) Comparison: Change detection occurs when subjects successfully compare a representation of the initial item to the changed item. If this representation is in long-term memory rather than VWM, observers might be able to detect the change via a comparison to LTM, but the mechanism would be different than actually seeing the change happen (see Simons & Rensink, 2005 for discussion). In essence, such detection amounts to "finding the item that is wrong or missing" in the second display rather than seeing the item change from one display to another. For example, if you have representations of thousands of faces, noticing that one of them has changed a feature (e.g. a new haircut) does not mean that VWM stores thousands of faces. Comparison of VWM information to longer-term representations is not evidence of an increase in the capacity of VWM, even if it can lead to enhanced change detection.

To our knowledge, all existing evidence for the positive effects of long-term memory on VWM capacity can be attributed to one of these four mechanisms, and most have not claimed otherwise. Only a few studies have directly addressed whether or not familiarity with a display can increase the capacity of VWM after controlling for these mechanisms. Here we attempt to do so by modifying the traditional tasks used to measure VWM capacity in several ways. We minimized the impact of attentional guidance by familiarizing subjects with an array, but using a different target item within that array on each trial. Thus, familiarity with the array cannot guide attention to the change location either implicitly or explicitly. We minimized the contribution of recoding by using stimulus arrays of simple objects (gray-scale dots with 30 possible luminance values), making verbal or categorical recoding difficult. We reduced the impact of grouping by randomly assigning the dots to positions in a uniform 6x6 grid. Furthermore, we directly analyzed the contributions of perceptual grouping to estimates of the capacity of VWM by correlating models of the perceptual groups in an array with performance for that array. Finally, we tried to minimize the effect of comparison to long-term representations (i.e., finding the *changed* dot rather than seeing the *changing* dot) by controlling presentation time to make a VWM search possible while discouraging an LTM search.

Broadly construed, there are at least two kinds of familiarity that might be represented in long-term memory for any visual array: 1) familiarity with the items that make up the array regardless of their arrangement within the array and 2) familiarity with the array as a whole. Early studies suggest that familiarity of the first type does not increase the capacity of VWM. For instance, VWM for highly familiar alphanumeric characters (e.g. the letter "E") is limited to approximately 3-4 characters (Pashler, 1988). But, it remains unclear whether the representation of a single grapheme (e.g. "E") functions as an individual for visual processing (Pelli, Farell & Moore, 2003), so it is possible that familiarity <u>did</u> increase VWM capacity for letters but only up to the 3-slot limit. Eliminating this possibility requires a comparison of VWM capacity for familiar alphanumeric characters to capacity for unfamiliar, but similarly complex, characters.

In a recent study along these lines, subjects memorized a set of eight complex polygons (Chen, Eng & Jiang, 2006), and VWM capacity for these familiar polygons was compared to that for visually similar, but unfamiliar polygons. In each case, the items were randomly assigned to positions, providing a test of the first type of familiarity. Three experiments revealed no evidence for an increase in capacity for familiar polygons suggesting again that familiarity with items does not increase the capacity of VWM for those items.

Although subjects showed no increase in capacity for familiar polygons, these studies admittedly did not directly assess the fidelity of the LTM representations formed during memorization. And, LTM representations for polygons following familiarization likely were less precise than those for "superfamiliar" items such as alphanumeric characters (Chen et al, 2006).

Whether "superfamiliarity" allows for a genuine increase in the item-based limit of VWM remains an open question.

In the present study, two subjects developed "superfamiliarity" for an array of subtly different gray-scale dots through 3 weeks of training. Their acquired superfamiliarity for both the individual items in the array (Type 1 familiarity) and for the array as a whole (Type 2 familiarity) was assessed prior to testing VWM capacity. Following this assessment, we used a change-detection task to compare VWM capacity for items in this familiar array to capacity for similar items in randomized arrays. Finally, we examined the extent to which perceptual grouping contributed to capacity estimates, both with and without superfamiliarity. In sum, this paper examines whether superfamiliarity with a display can increase the capacity of VWM beyond 3-4 items.

Experiment

The purpose of the experiment was to provide the strongest test possible of the potential benefits of familiarity on estimates of VWM capacity, using a change detection task that controls for the alternative mechanisms for improved performance discussed in the introduction. The use of gray-scale dots in a grid as our stimuli has the benefit that they are visually simple, difficult to encode verbally or categorically, and allow for an assessment of the contributions of perceptual grouping to capacity estimates.

The experiment included three phases: (1) a memorization phase, (2) a memory test phase, and (3) a capacity measurement phase. Each is described in turn below. Methods and results are grouped within each phase for expository purposes. Two participants, author J.H. and an undergraduate participant G.P. who was naïve to the hypotheses of the experiment, undertook the task of memorizing an entire grid of 36 gray-scale dots to a level of specificity that far exceeded that required for the change detection task. Successful memorization of the display constitutes an existence proof that the stimuli could be encoded into long-term memory. Presumably, complete memorization also constitutes evidence that the display is familiar.

All phases were performed using Macintosh iMac computers (CRT monitors with viewable area measuring 29.5 X 22.5 cm). Viewing distance was unconstrained, but averaged approximately 50 cm. (All visual angle measurements below are based on a 50cm viewing distance). Except when noted, stimuli consisted of an original and modified array of 36 grayscale dots arranged into a 6x6 grid against a black background (see Figure 1). The diameter of each dot subtended approximately 1 degree of visual angle and the centers of adjacent dots were separated by 2.66 degrees. Each dot was randomly assigned one of 30 equally-spaced luminance values ranging from 4.65 to 61.51 cd/m2 (possible values ranged from 55 to 200 in 5 volt intervals).

<u>Memorization Study Phase</u>

Each subject completed 24 memorization sessions (approximately 10 hours total) over the course of 3 weeks in which they attempted to memorize the location and luminance of each dot in the 36-dot grid displayed in Figure 1 (Mean grid luminance = 117.4 volts, SD = 43.8 volts).

INSERT FIGURE 1 ABOUT HERE

At the start of each session, subjects viewed the entire grid until they felt prepared to begin the memorization testing (Mean free viewing per session was approximately 2 minutes). Subjects then pressed the space bar and all of the dots in the grid were replaced by white plus signs (+). On each of 100 trials in each session, a dot appeared in one randomly chosen grid location and subjects indicated by key press whether or not this dot had the correct luminance for that grid location. For the first 12 sessions, a liberal criterion was adopted: a “yes” response was coded as correct if the probed luminance was within ±3 luminance values of the actual luminance of that dot in the memorized grid. The probe’s luminance was selected at random from 30 possible luminance values with the constraint that half of the trials should yield a correct by our liberal criterion. Thus, 7 of the 30 luminance values were considered to be correct (i.e. actual value ± 3). In the change detection task used to assess the item-based capacity of VWM, the target dot was changed by ±14 luminance values (see below). Thus, success in the first 12 sessions required a long-term memory representation that was more precise than that required by the change detection task. Response time and accuracy were recorded for each trial.

Both subjects responded faster with increasing exposure to the grid over the first 12 sessions (approximately 1 week) of memorizing: for G.P., response times decreased by 25.44ms/session on average as demonstrated by a linear regression of mean RT by session (t-test of the slope of the regression line compared to a test value of zero-slope, t (10) = 2.427, p < .05); for J.H., response times decreased 45.78 ms/session, t (10) = 5.705, p < .001. Accuracy increased for both subjects: for G.P., by 1.46%/session, t (10) = 4.504, p < .005; for J.H., by 0.71%/session, t (10) = 2.235, p < .05 (see Figure 2). In sum, both subjects improved over the course of the first 12 sessions when using a relatively lenient criterion for correct judgments.

INSERT FIGURE 2 ABOUT HERE

In the remaining 12 sessions (Difficult Sessions), the criterion for a correct response and the selection of probes was altered to require more precise memory. The luminance of the probe dot was always within ±7 luminance values of the actual value, and only the actual luminance value ±2 values were considered correct. Thus, successful performance required subjects to discriminate between a ‘correct’ value (-2, -1, actual, +1, +2) and an ‘incorrect’ value (-7, -6, -5, -4, -3, +3, +4, +5, +6, +7). As in the first 12 sessions, the probe luminance varied randomly within this range with the constraint that half of the trials were ‘correct’. As with the first 12 sessions, the level of specificity in long-term memory required to perform this task far exceeded the precision needed for the change detection task (see Figure 3).

INSERT FIGURE 3 ABOUT HERE

The criterion chosen for the Difficult Sessions was quite stringent. Both subjects showed nonsignificant improvements in response time and accuracy over the course of the 12 Difficult Sessions: GP, RT, $t(10) = .773$, $p = .46$, accuracy, $t(10) = .833$, $p = .42$; JH, RT $t(10) = .576$, $p = .58$, accuracy, $t(10) = .968$, $p = .36$. Despite their lack of improvement across these difficult sessions, subjects were able to perform the task. Both subjects successfully discriminated correct and incorrect probe dots at better than chance levels, where chance is 50% (see Figure 2): for GP, $t(11) = 11.02$, $p < .001$; for JH, $t(11) = 13.12$, $p < .001$, demonstrating that they had memorized the location and luminance of every dot in the 36-dot grid to a level of specificity that far exceeded that required by the change detection task.

Upon completion of all 24 sessions, both subjects wrote descriptions of how they performed the memorization task (subjects were not allowed to discuss their strategies with one another throughout the experiment). Subject J.H. reported attempting to form figures from adjacent dots and assigning labels to the figures (e.g., "the bright dots on the left and top of the grid with the black dots inside are an upside-down ‘L’, the gray dots in the center form a counter-clockwise spiral of decreasing luminance,” etc). J.H. drew the grid and circled these groups. The majority of the groups in this drawing were formed from adjacent dots of similar luminance. Subject G.P. chose a different strategy: "I saw each row as a unit. I would think of it as a stick from left to right where each dot contrasted with the ones beside it by some specified degree. I gave labels to these contrasts like 'early autumn', 'late autumn' etc.” Thus, both subjects attempted to chunk the display items into larger units, J.H. defining units based on proximity and similarity and G.P. defining units based on relative changes in luminance within a row.

Memorization Testing Phase

After the 24 memorization sessions and a delay of one week, both subjects completed three test sessions, on three separate days, without being allowed to view the complete grid. In each trial of each test session, subjects viewed a grid of plus signs followed by a probe dot at one of the plus locations. This dot was either the correct dot for that location or differed from that dot by ± 14 luminance values. Subjects pressed keys to indicate whether the probe dot was correct or incorrect.

Both subjects performed this task well (for G.P., M = 96% correct and 1754ms response latency; for J.H., M=100% correct and 1289ms response latency). Together, the Memorization Study Phase and the Memorization Testing Phase show that both subjects successfully committed the 36-dot array to long-term memory with a level of specificity that could potentially aid change detection performance. As further evidence of the robustness of this representation, J.H. completed 3 additional test sessions of 100 trials each after not having viewed the array for one year (G.P. was no longer available for this test). In these sessions, J.H. averaged 93% correct (average RT = 1432ms) demonstrating both superfamiliarity and robust long-term memory for the array.

Capacity Measurement Phase

Subjects were asked to find the changing dot in a 36-dot grid using a flicker change-detection paradigm (Rensink et al, 1997). On each trial, participants viewed the first array of dots for 700ms, followed by a 120ms black-screen, and then by a second array that was identical to the first except that one dot changed luminance by ±14 shades (70 volts) (Figure 4). The two screens alternated continuously, separated by black screens. When participants detected the change, they pressed the space bar to stop the alternation and then used the mouse to click on the changing dot. Response times were recorded from the onset of the first display until the participant pressed the space bar. Participants responded as quickly as possible while prioritizing accuracy.

INSERT FIGURE 4 ABOUT HERE

The flicker task is optimal for our purposes as it returns an estimate of the capacity of VWM (derived from RT) for displays that contain many more than 3-4 objects (See Rensink, 2000a; Halberda et al, submitted). Our previous work employing this task demonstrates that human adults show a capacity of approximately 3 dots held in VWM over a wide range of display on-times, off-times, and array sizes (Halberda et al, submitted). Response times on each trial were converted into an estimate of the item-based capacity of VWM using Equation 1[1].

$$\textbf{1)} \quad \text{Capacity} = \frac{[(\text{array size} + 1)/2] * (\text{display duration} + \text{blank duration})}{\text{RT} - (\text{display duration} + \text{blank duration})}$$

This equation assumes that participants can compare information currently on the screen to information stored in VWM, reach a decision that no change has occurred for the remembered items, shift attention to new items without replacement and load information from these items into VWM all during a single display on-time. Our previous work demonstrates that an on-time of 700ms is sufficient for these processes to occur (Halberda et al, submitted). It is important that we not provide subjects with more than 700ms as they could search for the 'wrong' dot during any additional on-time resulting in a contaminated estimate of the capacity of VWM (contaminated by the comparison of what is currently on the screen directly to a LTM representation). It is critical to our test of the effects of superfamiliarity on VWM to minimize the impact of such comparisons of information currently on the screen directly to LTM representations.

G.P and J.H. participated in 8 sessions of 100 trials each, with each session completed on a different day. Each session consisted of ten blocks, with ten trials per block. On the odd numbered blocks of each session, subjects performed the change detection task on the memorized grid. On even numbered blocks, subjects performed the change detection task on randomized grids that were matched to the memorized grid in terms of the mean and standard deviation of the overall luminance. Thus, each session had 50 trials with the memorized grid and 50 with randomized grids, and the trials were yoked for analysis such that the first memorized grid trial was analyzed with respect to the first randomized grid trial for each session. Across the 8 sessions, each subject

[1] For details supporting the derivation of this equation see Halberda et al (submitted).

had a total of 400 yoked trial pairs. G.P. selected the incorrect change item on 3 trials and had unusually long response times on 5 additional trials. These trials and their paired trials were eliminated from the analyses, leaving a total of 392 trial pairs. J.H. selected the incorrect item on 3 trials, leaving 397 trial pairs for analysis.

For memorized grid trials, some trials started with the memorized grid and some started with the changed grid. For these trials, once subjects pressed the space bar to indicate change detection, the memorized grid was re-displayed and subjects indicated the change location with the mouse. For the randomized grid trials, the first display of the trial was shown during change localization.

On memorized grid trials, because the initial display varied, subjects were unable to limit their search to the changed array (e.g. by focusing only on every other display and comparing that display to a long-term memory representation). Neither subject reported using this strategy. In principle, subjects could still detect a change via comparison to a long-term memory representation even without using such a strategy. For example, if the subject's attention happened to fall on the changed item when its luminance was different from its memorized value, they might detect a discrepancy from their long-term memory representation rather than from the previous display of the memorized grid. Such change detection would amount to finding the "changed dot" rather than finding the "changing dot." After each session, subjects reported whether they had detected the change by happening to notice a dot that was the 'wrong' luminance for that location in the memorized grid. Both G.P. and J.H. reported discovering the 'changing' dot by noticing a 'wrong' luminance on approximately 10% of trials with the memorized grid. Consequently, the capacity estimate for the memorized grid might be slightly inflated by this alternative means of change detection, and any advantage for the memorized grid blocks should be interpreted with caution.

Note, however, that this means of change detection also appears to be limited in scope. If subjects could successfully compare the entire visual scene to a long-term memory representation, then they should have been able to detect the 'changed' dot during the first alternation on every trial. Instead, information from long-term memory might be subject to the same comparison constraints as VWM and it is possible that information from long-term memory might need to be downloaded into VWM in order to be compared to an incoming stimulus.

Results: Capacity Measurement Phase

Despite the concern that capacity estimates might be inflated by the detection of the 'wrong' dot, G.P. had an average capacity of approximately 4 dots for both the memorized and randomized grids across sessions (see Figure 5). Prior to the experiment, G.P. had no experience with the change detection task, and in the first change detection session, G.P.'s capacity was approximately 3 items for both types of grids. A 2 (memorized grid vs. randomized grid) X 8 (session) repeated measures ANOVA on G.P.'s performance revealed a significant effect of Grid Type: $F(1, 384) = 8.24$, $p < .005$. Collapsing across sessions, G.P. had a slightly higher capacity for the memorized grid (M=4.74 items) than for the randomized grids (M=3.91 items). Again, this result must be interpreted cautiously given that G.P. reported noticing a 'wrong' dot on approximately 10% of memorized grid trials. Planned comparison t-tests on each session revealed a significant effect of Grid Type in session 3: $t(47) = 2.17$, $p < .05$, and in session 6: $t(48) = 2.34$, $p < .05$, as well as a marginal effect in session 7: $t(49) = 1.94$, $p = .058$. Interestingly, G.P.'s capacity also increased with practice as revealed by a significant effect of Session: $F(7, 384) = 4.16$, $p < .001$. By session 8, G.P.'s capacity was approximately 6 dots for the memorized grid *and* the randomized grids! Although superfamiliarity with the memorized grid had a minimal effect on capacity estimates relative to randomized grids, it appears that measured capacity can increase through practice. This increase could result either from an expansion of VWM capacity or by encoding more information into the same number of slots in VWM, an alternative we address below.

INSERT FIGURE 5 ABOUT HERE

J.H. also had an average capacity of approximately 4 dots for both the memorized and randomized grids across sessions. Collapsing across sessions, J.H. showed a slightly higher capacity for the memorized grid (M=4.85 items) than for the randomized grids (M=4.17 items): $F(1, 389) = 6.80$, $p < .01$ (see Figure 6). J.H.'s capacity also increased for both grid types across the 8 sessions: $F(7, 389) = 5.25$, $p < .001$. And, importantly, J.H.'s capacity in session 1 was approximately 3 items for both grid types (Memorized grid = 3.7, Randomized grids = 2.8). Planned t-tests revealed that J.H. had a significantly higher capacity for the memorized grid than the randomized grids in session 4: $t(48) = 2.52$, $p < .05$, and it was marginally higher in session 3: $t(49) = 1.91$, $p = .062$. By session 5 the advantage for the memorized grid disappeared as capacity for the randomized grids improved to the same level as for the memorized grid.

INSERT FIGURE 6 ABOUT HERE

Estimated capacity increased for both G.P. and J.H. to more than 3 items demonstrating that the parameters used in this experiment (e.g. display on-time = 700ms, ISI = 120ms) were sufficient to allow subjects to show "super-capacity". At the same time, the results provide no conclusive evidence that change detection in familiar displays is any easier than in novel displays when the usefulness of alternative mechanisms for change detection are minimized. Both G.P. and J.H. had estimated capacities in excess of the 3 items found in earlier studies, but this super-capacity was not restricted to the memorized grid. Rather, by session 8, both G.P. and J.H. had estimated capacities of approximately 6 items for both the memorized and randomized grids. This finding suggests that improvements in capacity were not caused by familiarity with a particular display. Rather, they resulted from experience with this *type* of display, with these types of items, and with the nature of the change detection task. But what is the source of this super-capacity? Did subjects G.P. and J.H. add additional slots to VWM over the course of the experiment, or could it be explained by perceptual grouping? We performed an analysis of the contribution of perceptual grouping to capacity estimates in both randomized and memorized grids.

Analyzing the contribution of perceptual grouping

Just as capacity estimates for verbal working memory increase when subjects can group more items into the same number of memory slots (Cowan, 2000, Ericsson, Chase & Faloon, 1980), visual working memory might be limited to approximately three items, but what counts as an item might change. That is, subjects might be able to group multiple dots into single memory slots, thereby increasing an estimate of capacity without fundamentally increasing the number of "items" that can be stored in VWM. Did G.P. and J.H. really increase the capacity of VWM itself or did these higher capacity estimates result from perceptual grouping?

To test for the possible contributions of perceptual grouping to estimates of capacity, we analyzed the memorized and randomized grid blocks based on two simple predictions: (1) J.H. and G.P. used explicit grouping strategies to memorize the memorized grid. When these strategies were not effective for a particular dot in the memorized grid (because of the relative luminance of the surrounding dots), capacity should be approximately 3 items. And (2) for both the memorized and randomized grids, change detection capacity should vary as a function of the size of the perceptual group that includes the changing target (e.g. the bigger and more salient the group, the easier it should be to find the target).

To identify perceptual groups within a display, we developed a simple algorithm based on the Gestalt principles of similarity (in luminance) and proximity (Palmer & Rock, 1994; Wertheimer, 1923/1955). The luminance and location of each dot in each display was recorded throughout the experiment, and for each display, we calculated the similarity (in luminance) of all of the dots that surrounded the target item. We then devised a cluster rating for each dot that consisted of the number of dots "connected to" it that were within ±4 luminance values of the target, divided by 35 (the total number of distractor dots). In order to calculate proximity, or "connectedness", the similarity calculation was first performed on dots immediately adjacent to the target dot (the first layer) and then for dots surrounding the immediately adjacent dots (the second layer) and so on throughout the entire grid. In order for a dot in the second layer to be counted as similar, it had to be connected to a dot in the first layer that was also similar (and so on for all possible layers in the grid).[2]

<u>The Memorized Grid</u>

Figure 7 shows the cluster rating for each dot in the Memorized grid. The results of the cluster analysis effectively distinguished dots that were similar to their surroundings from those that were singletons. This analysis gave each dot a cluster rating, such that for the 36 item grid, having 1 similar neighbor translated into approximately a .03 cluster rating, 2 neighbors was approximately a .06 cluster rating and so on. Note that cluster rating did not correlate significantly with luminance in the Memorized Grid ($p > .18$).

INSERT FIGURES 7, 8, and 9 ABOUT HERE

We computed subject J.H.'s estimated capacity for each target location in the memorized grid using the 397 memorized grid trials (Figure 8). Cluster rating and capacity were positively correlated, r = .424, t (394) = 9.307, p < .0001(see Figure 9) — J.H. found the changing item faster when it was part of a cluster of similar items. Moreover, when the target was a single dot with no similar dots connected to it (i.e. cluster rating = 0), J.H.'s capacity was 3 items. Capacity estimates increased noticeably as the size of the cluster increased, suggesting that J.H. had segmented the

[2] Preliminary analyses suggested that this algorithm formed clusters which correlated with change-detection performance as well or better than the following alternative algorithms: 1) conditionalizing similarity in luminance to the connected dots in the intermediate layers rather than conditionalizing similarity to the target dot itself as we did, 2) increasing or decreasing the similarity range above or below ±4 luminance values, 3) restricting the algorithm to only the first 1, 2, 3, or 4 layers away from the target dot rather than allowing it to range over the entire grid as we did, 4) weighting similar dots close to the target more heavily than similar dots connected to but further away from the target, 5) removing the requirement of "connectedness" from the similarity analysis, and 6) computing a ratio of the size of the

memorized grid into perceptual units larger than a single dot on the basis of their proximity and similarity in luminance. This finding is consistent with J.H.'s reported strategy for encoding the memorized grid. Note, of course, that grouping strategies other than luminance- and proximity-based similarity might also contribute to and account for increased capacity estimates.

G.P. reported using a different strategy than J.H. for memorizing the grid. He attempted to form an image in his mind of each row of dots and used the contrasts within the row to remember the luminance for each individual dot. Thus, G.P. attempted to form perceptual groups of each individual row, irrespective of the similarity of adjacent dots that cut across rows. If perceptual grouping based on similarity and proximity is at least partially a default grouping principle for the visual system (Rock & Brosgole, 1964; Rock, Nijhawan, Palmer & Tudor, 1992a; Rock, Nijhawan, Palmer & Tudor, 1992b), then such Gestalt grouping mechanisms should interfere with the chunks that G.P. attempted to form. Given that G.P. focused on contrasts between dots rather than similarities among dots, our cluster rating might be negatively correlated with estimates of his capacity. In other words, given his memorization strategy, G.P. might find changes more efficiently when the target dot is dissimilar to adjacent dots. With high dissimilarity, interference from similarity-based grouping would be reduced and G.P.'s strategy would be maximally effective.

INSERT FIGURE 10 ABOUT HERE

For G.P., our cluster rating was negatively correlated with estimates of his capacity, $r = -.224$, $t\ (391) = -4.558$, $p < .0001$ (see Figure 10). This negative correlation suggests that the natural grouping of items based on similarity and proximity (as estimated by cluster rating) interfered with his strategy of row-based grouping. G.P. detected changes faster for target items that were dissimilar to all surrounding items (cluster rating = 0) than for targets that were part of a cluster of

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cluster that included the target dot divided by the average sized cluster for the entire grid (i.e. is this dot in a big cluster similar items (e.g., cluster rating > .2). Moreover, when G.P.'s grouping strategy was ineffective, i.e. when the target was surrounded by a large group of similar dots (cluster rating = .26), G.P.'s estimated capacity was approximately 3 items.

For both subjects, when the target location coincided with an optimal group according to their memorization strategy, they showed increased capacity. However, when the target location was poorly grouped based on their strategy, their capacity was 3 items. This suggests that capacity estimates for the memorized grid were inflated by grouping mechanisms. Grouping allowed the subjects to change what counted as an item, clustering several dots into a single memory slot. For J.H., these perceptual groups were consistent with the Gestalt principles of similarity and proximity. For G.P., these groups were the rows themselves. Importantly, when these grouping strategies failed (J.H. cluster rating = 0, G.P. cluster rating = .26), both subjects showed the predicted capacity of approximately 3 items. Furthermore, reorganizing the array into higher-order perceptual groups for the purposes of the change detection task took time and practice. Both subjects showed significant gains in estimated capacity for the memorized grid across sessions suggesting that, initially, they performed the change detection task by storing individual dots and only gradually did they become able to search higher-order chunks.

<u>The Randomized Grids</u>

Perceptual grouping contributed to performance with the memorized grid for both subjects and explains how capacity estimates sometimes exceeded 3 items. J.H. and G.P. had memorized this grid, so they had sufficient time and exposure to form optimal perceptual groups. However, in sessions 5-8, they also showed capacities greater than 3 items for the randomized grids, suggesting that superfamiliarity with the display was unnecessary for perceptual grouping to affect capacity estimates. Did grouping strategies contribute to capacity estimates even for these novel grids?

We calculated our cluster rating for the target in the first display for each of the randomized grids in sessions 5-8 (where subjects showed greater capacity). For J.H., cluster rating was

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or a small cluster for this particular grid).

positively correlated with change detection performance (Figure 11), r = .221, t (198) = 3.194, $p <$ .002, r-squared = .04901, suggesting that J.H. increased his change detection capacity by chunking elements of the randomized grids according to proximity and similarity of luminance. Because of the relatively limited number of trials within any one session it was not possible to assess whether this correlation increased gradually across sessions, but the increase in capacity across sessions displayed in Figure 6 for randomized grid trials suggests that it did. J.H. reported that he had not used an explicit strategy on randomized grid trials, so this effect of similarity and proximity apparently did not require intentional control. Interestingly, the correlation for J.H.'s sessions 1-4 was not significant (r = .07, p = .3, r-squared = .005), suggesting that the grouping was not yet effective and that practice with the task was necessary for grouping to contribute to change detection for novel displays.

For the randomized grids in sessions 5-8, G.P. showed a non-significant positive correlation between the cluster rating and capacity, r = .125, p = .16, r-squared = .016 (see Figure 12). Evidently, although G.P. organized the memorized grid by rows resulting in a significant negative slope, the more natural grouping based on similarity and proximity contributed to his performance on randomized grids for which he reported using no explicit grouping strategy. Interestingly, for G.P.'s randomized grids in sessions 1-4, the correlation between cluster rating and capacity showed a marginally significant negative slope suggesting that, initially, G.P. attempted to search randomized grids using the same grouping strategy that he used on memorized grid trials, r = .134, p = .068, r-squared = .018.

INSERT FIGURES 11 & 12 ABOUT HERE

Conclusions on Perceptual Grouping

Together, the analyses of the memorized and randomized grids suggest that perceptual grouping contributed to change detection performance, leading to increased estimates of capacity.

However, when grouping strategies were ineffective, capacity remained at 3 items. Our analysis of perceptual grouping suggests that long-term familiarity, even superfamiliarity, does not expand the item-based capacity limit of VWM. Rather, information in long-term memory might enhance the ability to chunk a display into larger perceptual units, thereby enhancing change detection. However, much of the improvement in grouping results from practice with the items and tasks, and it does not depend on extreme familiarity with a particular display. Given experience with the task and with the items composing the arrays, subjects learn to group elements even when the arrays are novel on each trial. Interestingly, the particular grouping strategy that subjects adopted had systematic effects on their later processing of the memorized grid; prior experience with a stimulus and top-down construal can affect subsequent perceptual grouping of the items in the array (for other examples, see Beck & Palmer, 2002; Kimchi & Hadad, 2002; Wertheimer, 1923/1955).

General Discussion

The experiment showed that superfamiliarity with both the items in an array and the array as a whole did not increase the capacity of VWM above a 3-item limit. Even when subjects memorized an entire array of items to a level of specificity that far exceeded the demands of the change detection task used to measure capacity, performance did not improve substantially. Although the capacity for change detection is apparently limited to 3 items, what counts as an item for change detection can change. Superfamiliarity and experience with the task <u>did</u> improve grouping of display elements, and these groupings facilitated change detection when the target was part of such a cluster; using a simple estimate of perceptual grouping, we found that clustering predicted performance for both memorized and randomized displays, and in the absence of a larger perceptual cluster, change detection capacity was again limited to 3 items. Thus, when the items in a display are clustered into larger perceptual groups, more of them can be stored and compared across a delay without exceeding the 3-item limit of VWM.

This finding parallels similar results from the verbal working memory literature, where estimates of capacity occasionally exceed a 3-item limit (Cowan, 2000). Capacity estimates for other simple visual features such as orientation and polarity (Rensink, 2000a) might similarly be inflated due to grouping, categorical encoding, or even verbal labeling. If such grouping options were eliminated or reduced, the capacity for polarity and orientation could well revert to a more typical 3-item capacity for VWM.

In contrast to our findings using a change detection task (see also Chen et al, 2006; Pashler, 1988), in standard visual search tasks, search for a highly familiar target can become highly efficient (Suzuki & Cavanagh, 1995; Wang, Cavanagh, & Green, 1994) suggesting that familiarity does reduce the requirements of focal attention for processing superfamiliar targets. One way to account for the discrepancy between these methods is that change detection requires attention to an item both before and after a change in order to detect it (Rensink, 1997, 2000a, 2000b; Simons, 2000) and, typically, the subject has no way of knowing which item might be the changing target. In contrast, the effects of familiarity on classic visual search appear to operate without a need for focused attention to the distractor items (Wang, Cavanagh & Green, 1994), and they do not require a comparison to an episodic representation in memory.

Some recent evidence suggests that although the maximum capacity of VWM might be 3 items, VWM might also be information-limited (Alvarez & Cavanagh, 2003). If the features to be encoded are categorical (e.g., red vs. blue) and/or easily distinguished, then capacity might reach its maximum of approximately 3 items (Luck & Vogel, 1997). However, the information limit could be reached before the 3-item limit when the items to be stored are complicated or require fine discriminations (Alvarez & Cavanagh, 2003). Conceivably, the information required by complex items could be reduced with experience or superfamiliarity such that the capacity for complex items could be increased. However, as shown here, this capacity is unlikely to exceed the 3-item limit even with superfamiliarity.

Given our use of simple, superfamiliar, non-categorically defined stimuli, and our demonstration of the effects of perceptual grouping, our results suggest that VWM capacity estimates in excess of 3-items likely involve perceptual grouping or other processes (e.g. routes 1-4 in the Introduction) that artificially inflate capacity estimates. Although perceptual grouping allows information from multiple objects to be combined into a single slot in VWM, the 3-item limit of VWM might be immutable.

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Figure Captions

Figure 1. The memorized grid used throughout the experiment. During memorization, G.P. and J.H. spent a total of approximately 30 min. viewing the complete array and approximately 10 hours viewing the array one dot at a time, arranged by position.

Figure 2. Memorization accuracy for subjects G.P. and J.H. for the 24 memorization sessions (±SE). Accuracy increased for both subjects throughout the Easy Sessions. Accuracy was above chance for both subjects throughout the Difficult Sessions (chance = 50%).

Figure 3. The change in luminance used for the Difficult Sessions (+2) and the change detection task (+14). The top grid is the one that G.P. and J.H. memorized (memorized grid). On the bottom-left, this same grid is shown with one dot changed by +2 luminance values (the level of specificity required in the Difficult Sessions). On the bottom-right this same dot is shown changed by +14 luminance values (the level of specificity required by the change detection task). The changed dot is in the fourth column from the left and the second row from the bottom.

Figure 4. The trial structure for the change detection flicker task. The cycle of the displays repeated until the subject found the changing dot. In this figure, the changing dot is located in the fourth column from the left and in the third row from the bottom.

Figure 5. Subject G.P.'s estimated capacity for the memorized grid and randomized grids (±SE) for the 8 successive change detection sessions.

Figure 6. Subject J.H.'s estimated capacity for both the memorized grid and randomized grids (±SE) for the 8 successive change detection sessions.

Figure 7. The cluster analysis for each position in the memorized grid. Cluster rating equals the number of dots that are "connected" to the target dot and are similar in luminance to the target dot divided by 35 (the total number of distractors). The resulting cluster for a sample dot is outlined in white. For a grid with 36 dots, having 1 similar neighbor resulted in a cluster rating of .03, two similar neighbors in a rating of .06, etc.

Figure 8. Subject J.H.'s estimated capacity for detecting a changing dot in the memorized grid. Overlaid on top of each location in the memorized grid is the estimated capacity for change detection when that location was the changing target.

Figure 9. Subject J.H.'s estimated capacity for detecting a changing dot in the memorized grid in Sessions 1-8 displayed as a function of the cluster rating of the changing target. The significant positive linear regression suggests that subject J.H. had chunked the memorized grid into perceptual units that were each larger than a single dot. For dots that were singletons (cluster rating = 0), J.H. had an estimated capacity of approximately 3 items.

Figure 10. Subject G.P.'s estimated capacity for detecting a changing dot in the memorized grid in Sessions 1-8 of displayed as a function of the cluster rating of the changing target. The significant linear regression is consistent with G.P.'s chosen grouping strategy of focusing on contrasts within a row. G.P. was faster to detect targets that were dissimilar with their surroundings (cluster rating = 0). Importantly, when this grouping strategy was sub-optimal (cluster rating = .26), G.P. showed the predicted limit of 3 items.

Figure 11. Subject J.H.'s estimated capacity for detecting a changing dot in randomized grids in Sessions 5-8 displayed as a function of the cluster rating of the changing target.

Figure 12. Subject G.P.'s estimated capacity for detecting a changing dot in randomized grids in Sessions 5-8 displayed as a function of the cluster rating of the changing target.

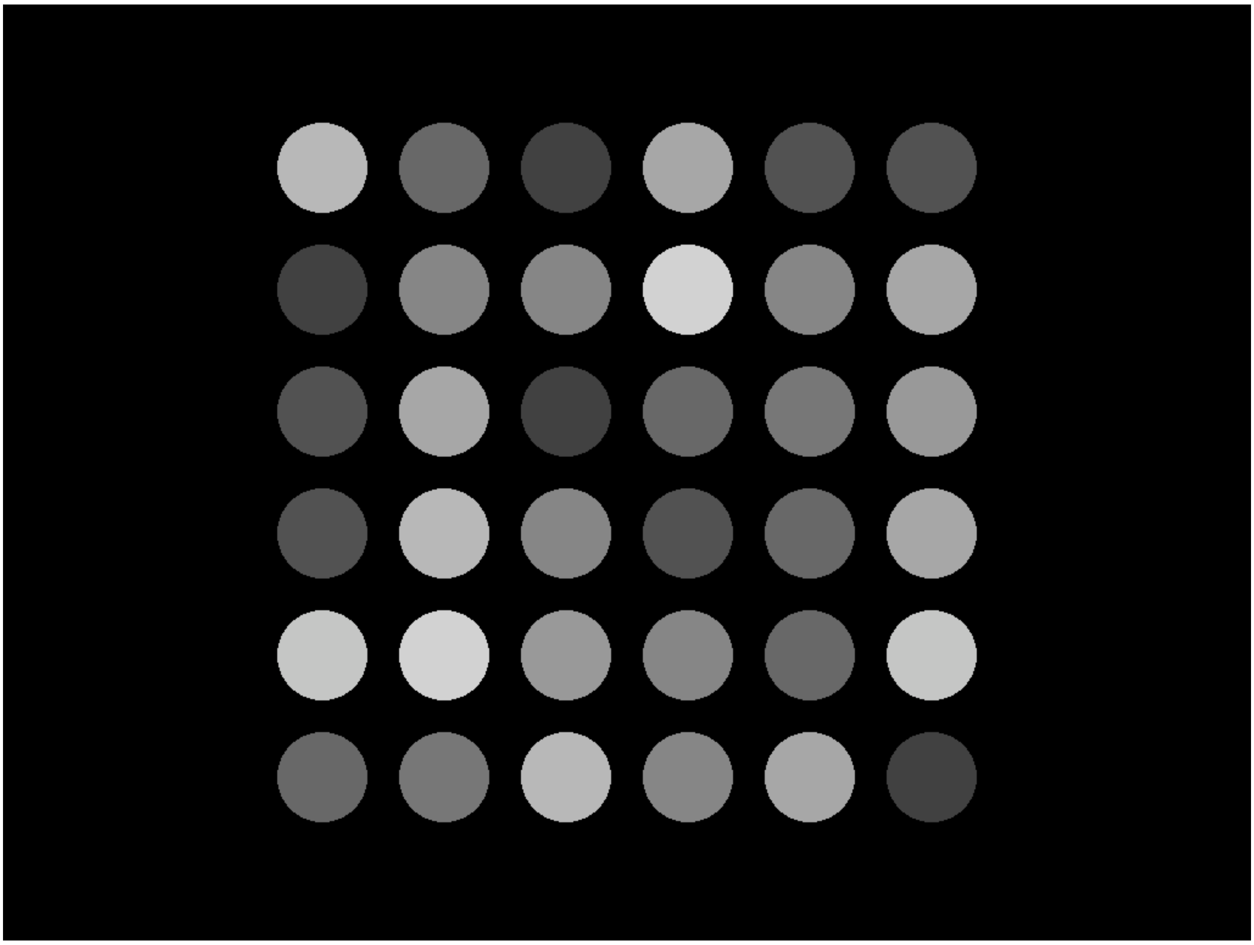


Figure 1

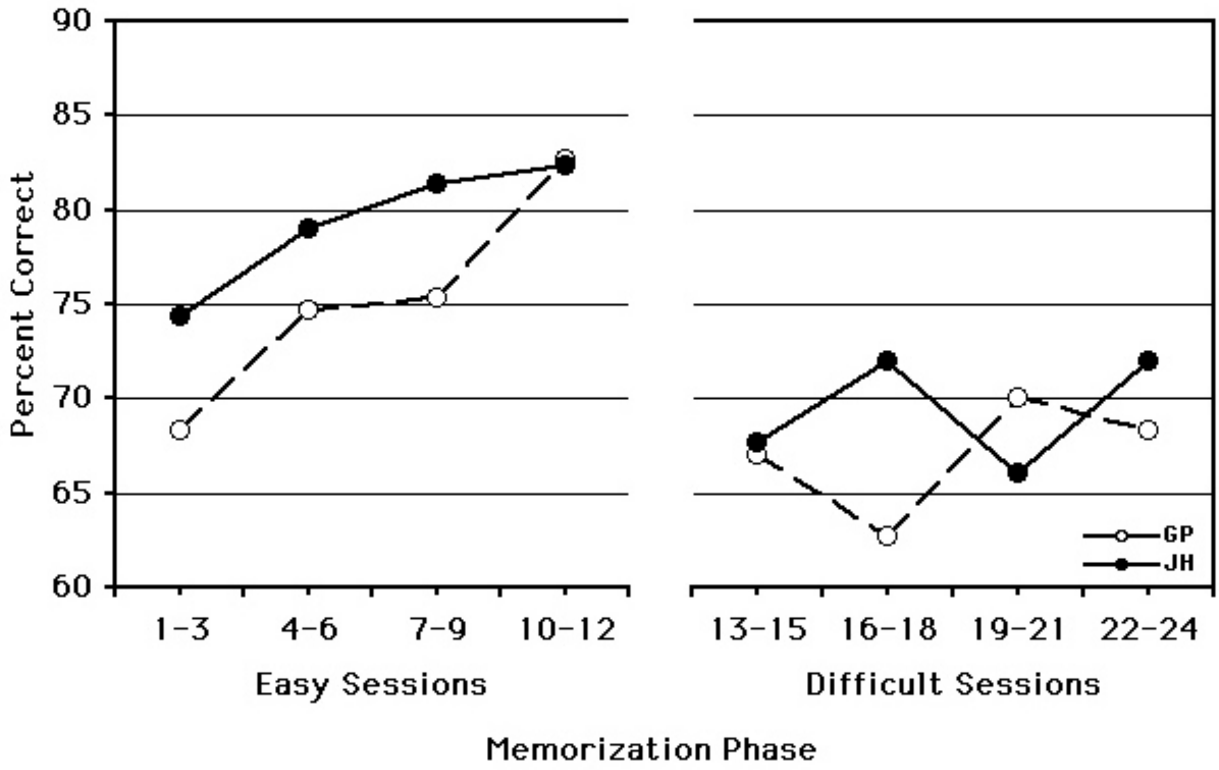

90
85
80
75
70
65
60
Percent Correct
1-3
4-6
7-9
10-12
13-15
16-18
19-21
22-24
GP
JH
Easy Sessions
Difficult Sessions
Memorization Phase

Figure 2

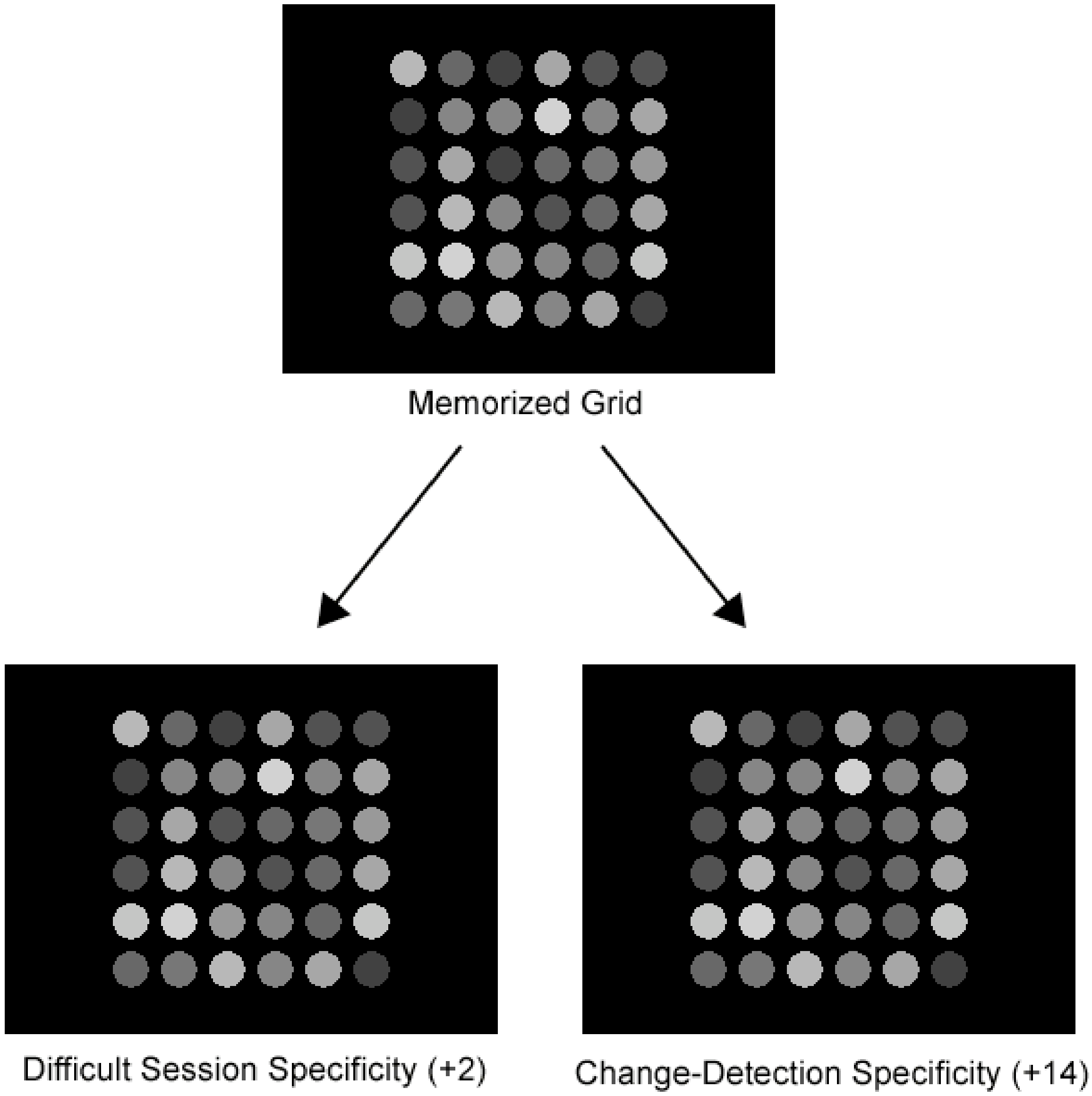
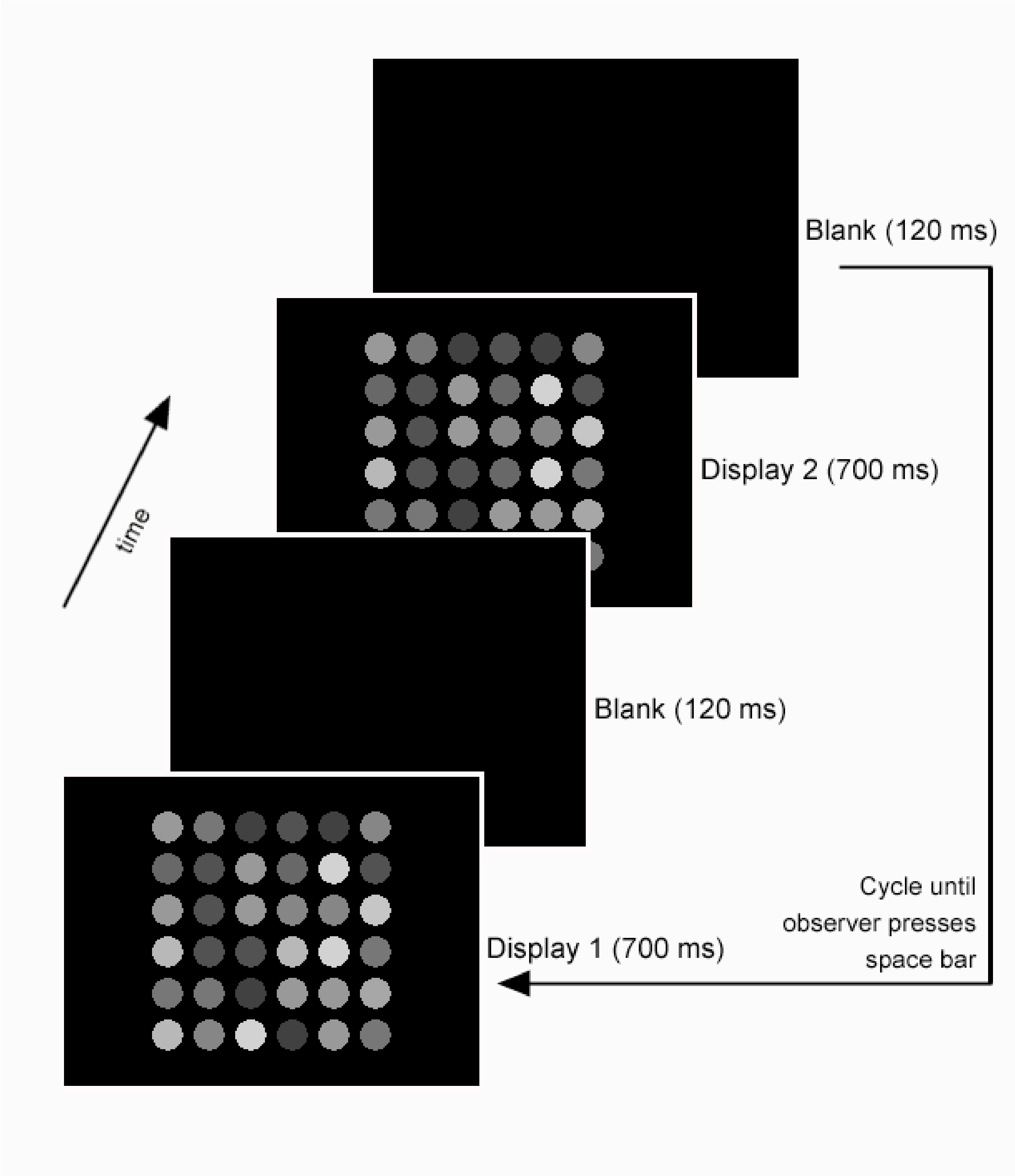
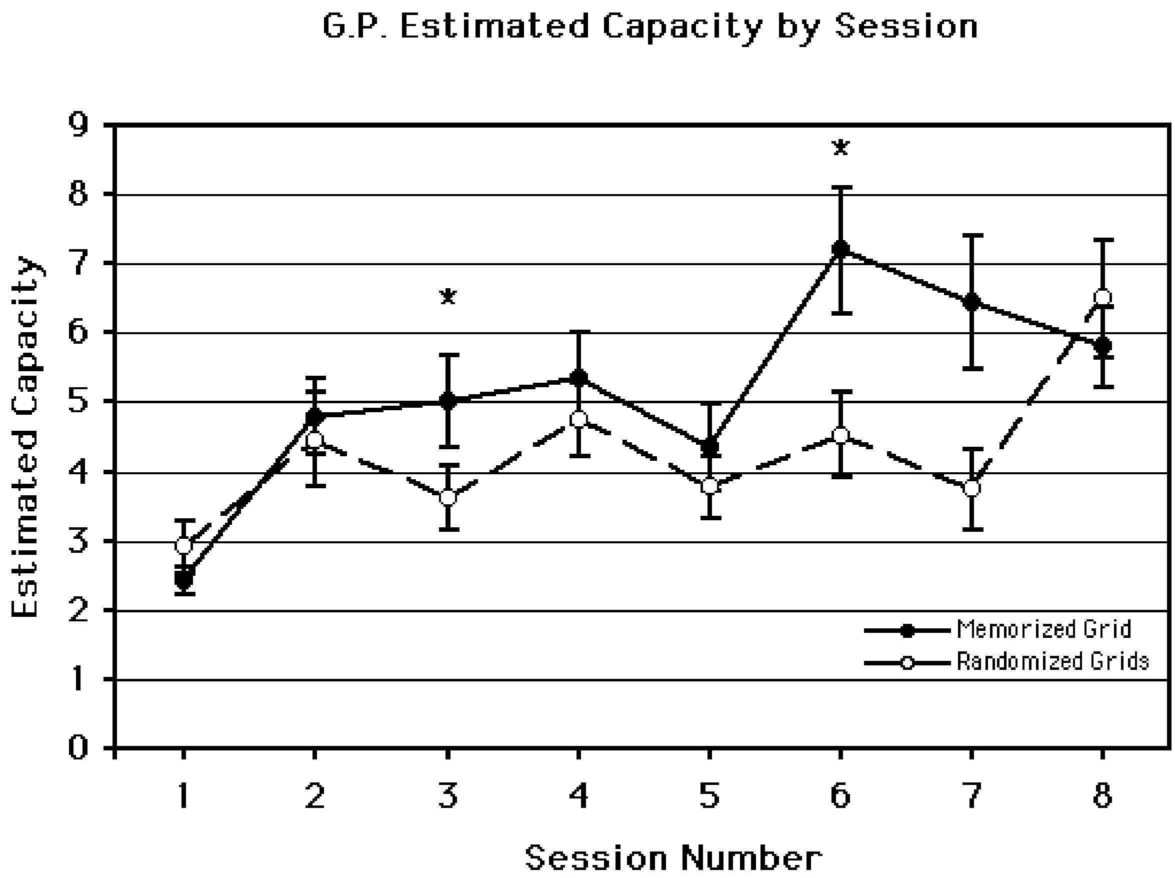

Memorized Grid
Difficult Session Specificity (+2)
Change-Detection Specificity (+14)

Figure 3



Blank (120 ms)
Display 2 (700 ms)
time
Blank (120 ms)
Cycle until
observer presses
space bar
Display 1 (700 ms)

Figure 4


G.P. Estimated Capacity by Session
Estimated Capacity
Session Number
Memorized Grid
Randomized Grids
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*
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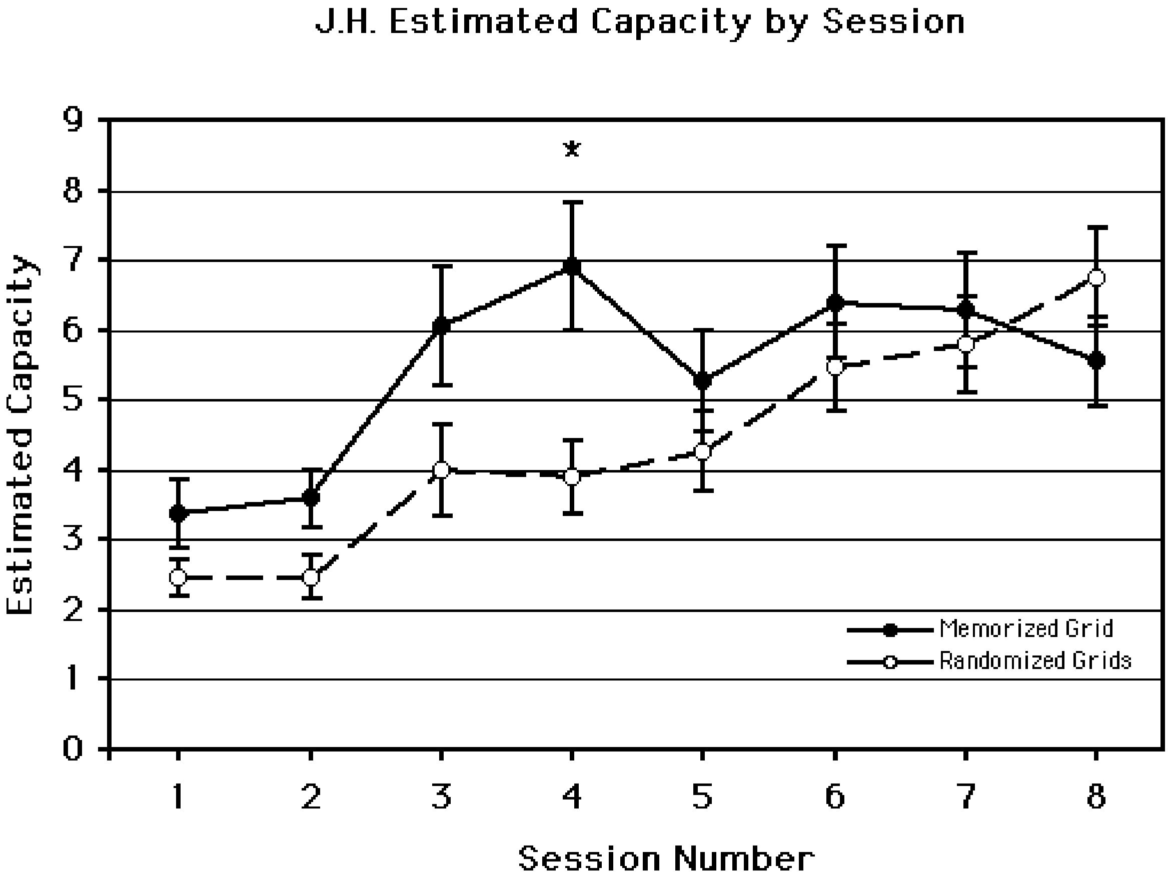
Figure 5


J.H. Estimated Capacity by Session
Estimated Capacity
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Session Number
Memorized Grid
Randomized Grids

Figure 6

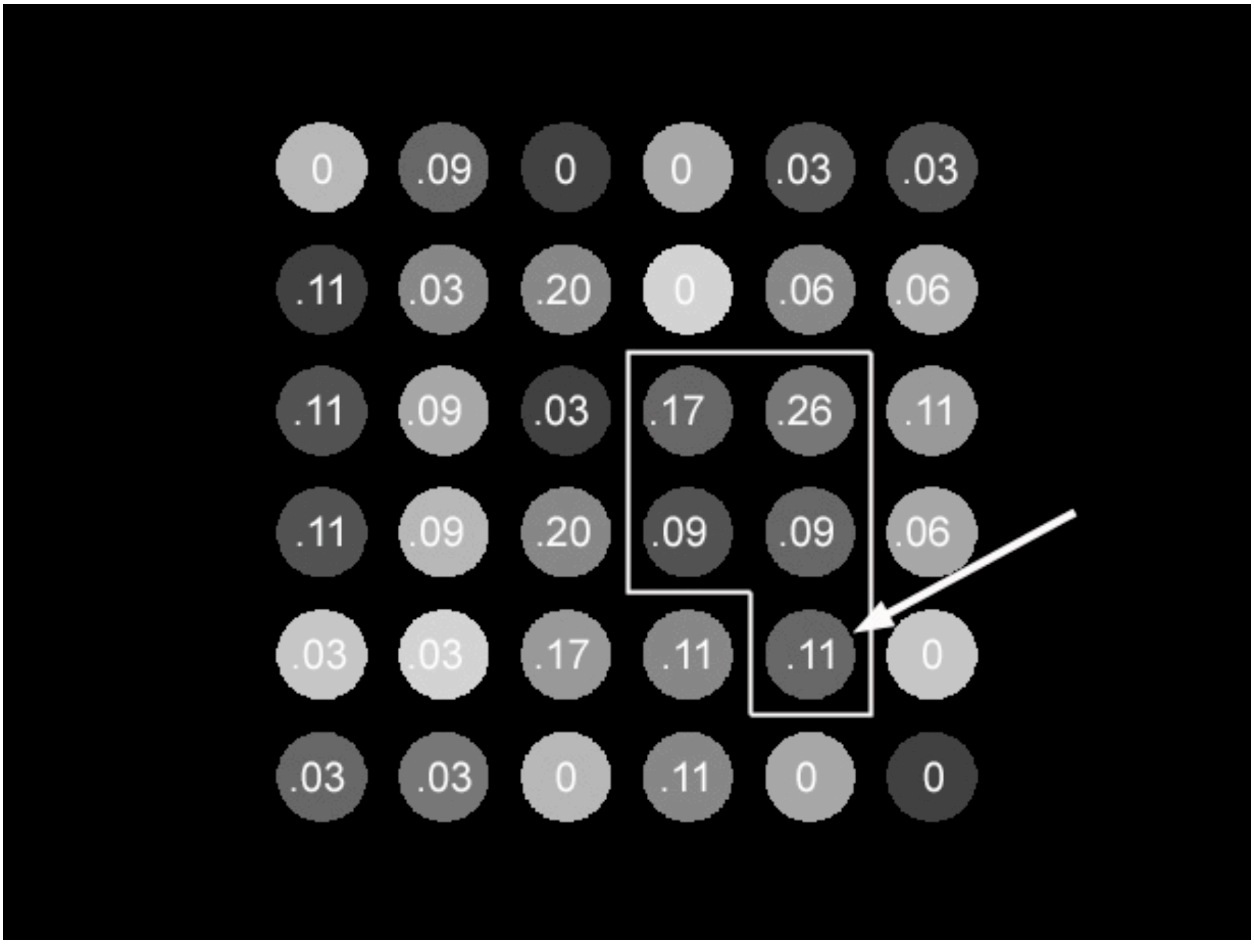
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Figure 7

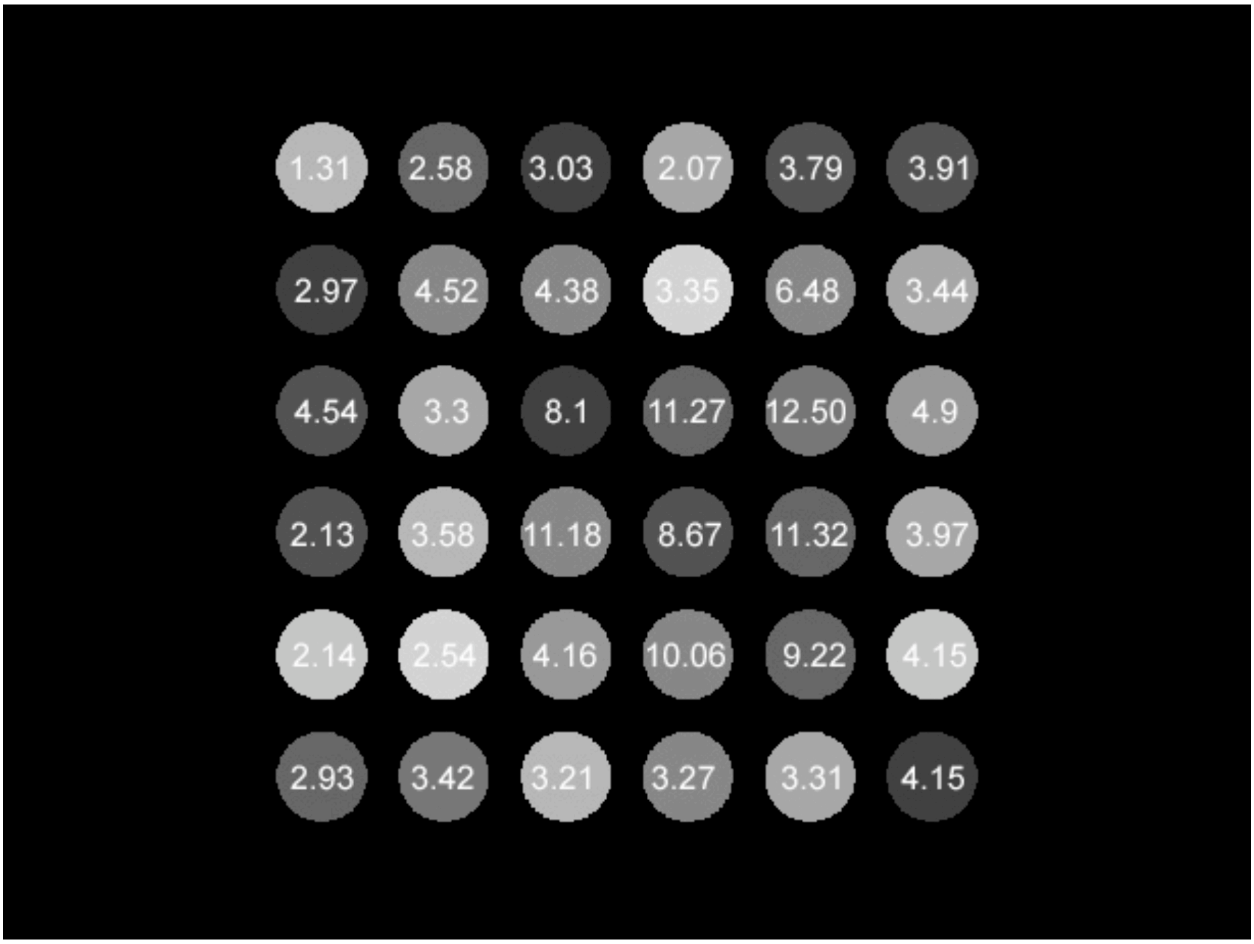

1.31 2.58 3.03 2.07 3.79 3.91
2.97 4.52 4.38 3.35 6.48 3.44
4.54 3.3 8.1 11.27 12.50 4.9
2.13 3.58 11.18 8.67 11.32 3.97
2.14 2.54 4.16 10.06 9.22 4.15
2.93 3.42 3.21 3.27 3.31 4.15

Figure 8

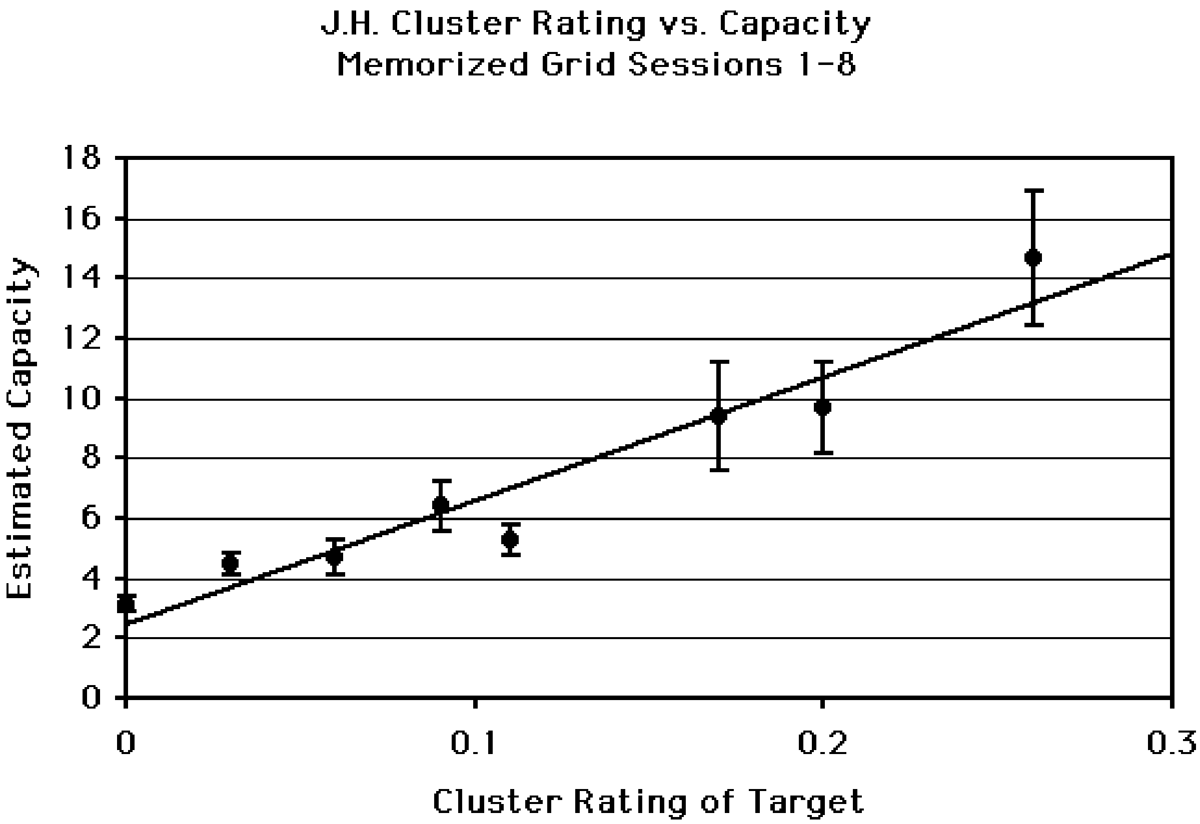
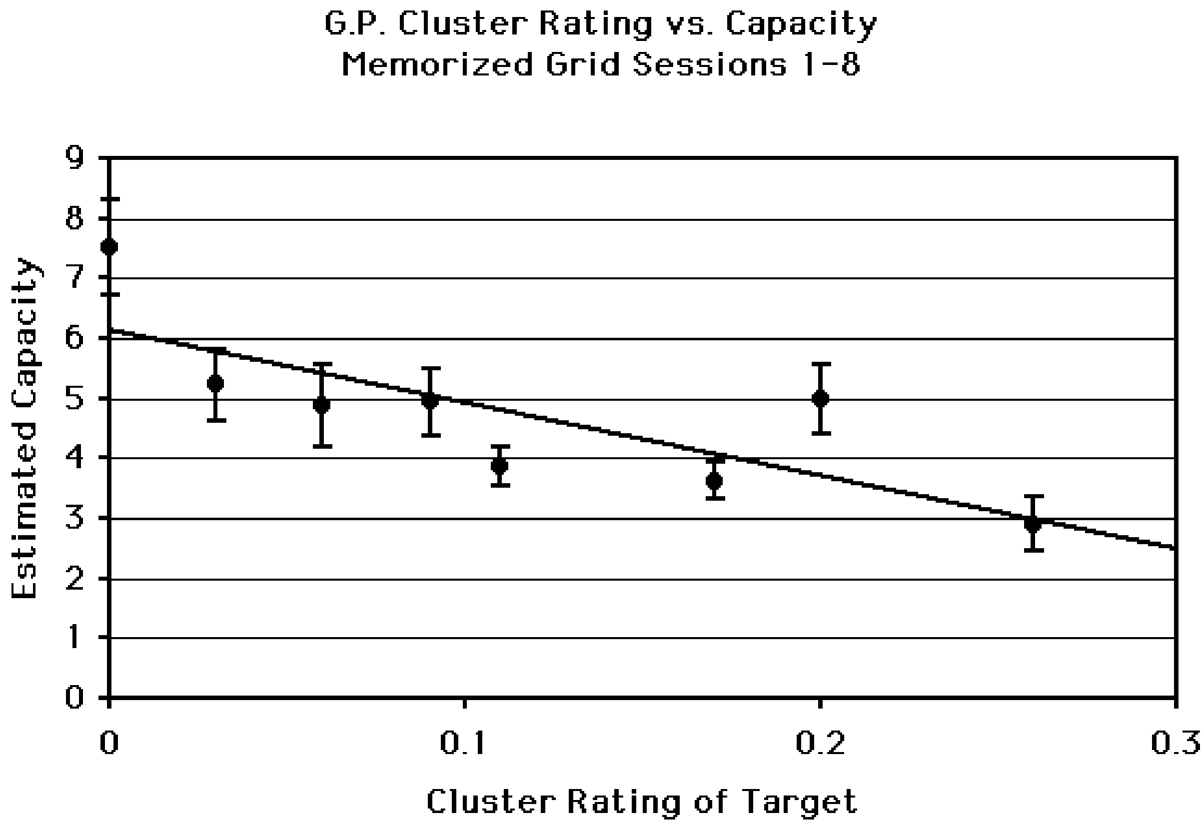

J.H. Cluster Rating vs. Capacity
Memorized Grid Sessions 1-8
Estimated Capacity
0
2
4
6
8
10
12
14
16
18
0
0.1
0.2
0.3
Cluster Rating of Target

Figure 9


G.P. Cluster Rating vs. Capacity
Memorized Grid Sessions 1-8
Estimated Capacity
9
8
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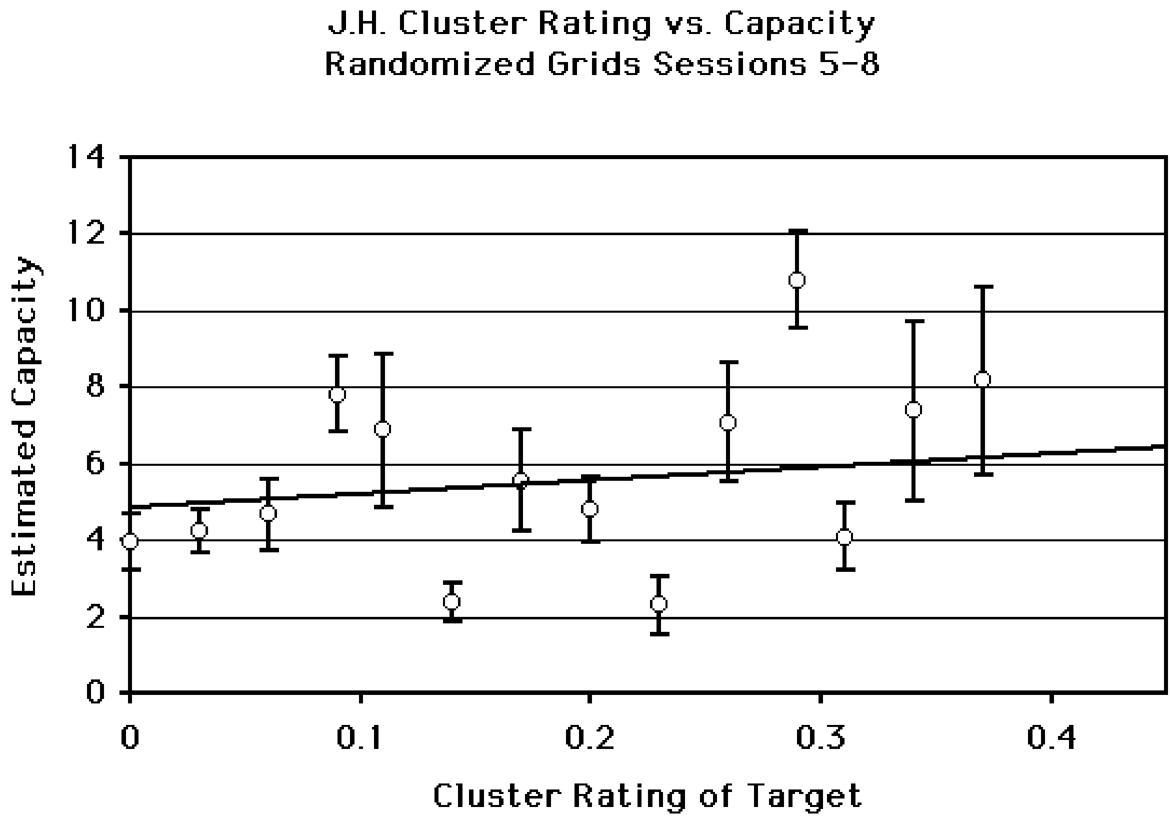
4
3
2
1
0
0
0.1
0.2
0.3
Cluster Rating of Target

Figure 10


J.H. Cluster Rating vs. Capacity
Randomized Grids Sessions 5-8
Estimated Capacity
Cluster Rating of Target
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14
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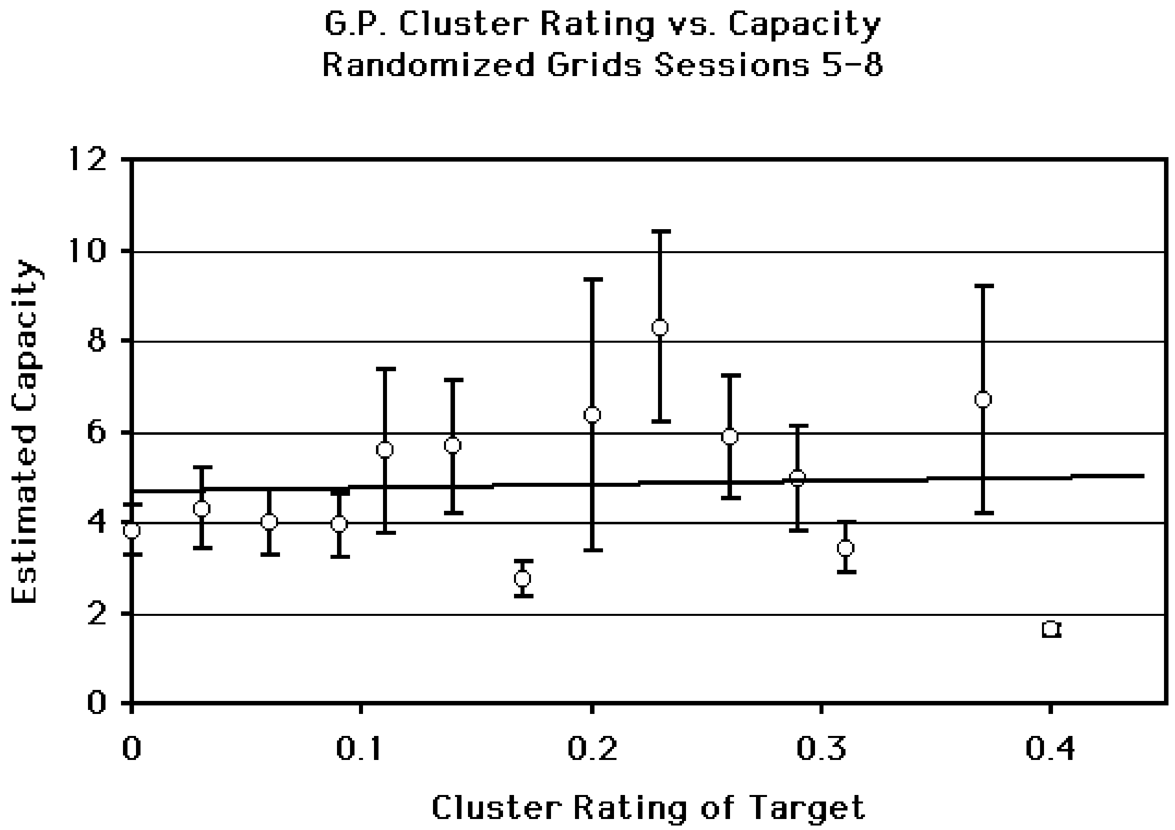
0.1
0.2
0.3
0.4

Figure 11


G.P. Cluster Rating vs. Capacity
Randomized Grids Sessions 5-8
Estimated Capacity
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2
4
6
8
10
12
0
0.1
0.2
0.3
0.4
Cluster Rating of Target

Figure 12