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Integrated Object Representations in Visual Working Memory Examined by Change Detection and Recall Task Performance*

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This study investigates the characteristics of visual working memory (VWM) representations by examining two theoretical models: the integrated-object and the parallel-independent feature storage models. Experiment I involved a change detection task where participants memorized arrays of either orientation bars, colored squares, or both. In the one-feature condition, the memory array consisted of one feature (either orientations or colors), whereas the two-feature condition included both. We found no differences in change detection performance between the conditions, favoring the integrated object model over the parallel-independent feature storage model. Experiment II employed a recall task with memory arrays of isosceles triangles' orientations, colored squares, or both, and one-feature and two-feature conditions were compared for their recall performance. We found again no clear difference in recall accuracy between the conditions, but the results of analyses for memory precision and guessing responses indicated the weak object model over the strong object model. For ongoing debates surrounding VWM's representational characteristics, these findings highlight the dominance of the integrated object model over the parallel independent feature storage model.

Key words : Visual working memory, representation, integrated object model, parallel-independent feature storage model

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Introduction

Visual working memory (VWM) is crucial for temporary information retention and manipulation in pursuit of goals, involving the creation of stable internal representations (Baddeley & Hitch, 1994; Luck & Vogel, 1997; Murray et al., 2013). Despite its importance, VWM has a limited capacity, storing only 3-4 items at a time (Luck & Vogel, 1997), leading to performance decline with more items. Numerous studies have explored the nature of VWM representations, but consensus remains elusive, resulting in various explanatory models (Bays, 2015; Brady et al., 2011; Donkin et al., 2013; Luck & Vogel, 2013; Suchow et al., 2014). Among these, two contrasting models stand out: the integrated object model and the parallel-independent feature storage model (Zhang & Luck. 2008; Vogel et al., 2001; Fougnie & Alvarez, 2011; Bays et al., 2009).

The integrated object model proposes that objects are fundamental units of representations within the cognitive system (Awh et al., 2001; Jiang et al., 2000; Vogel et al., 2001; Xu, 2010; Zhang & Luck, 2008). This model suggests that VWM encodes visual information by organizing features like color, orientation, and shape into integrated object representations, which serve as the primary memory units; forgetting occurs in item-based units (Gajewski & Brockmole, 2006). The integrated objects are automatically formed, facilitating efficient storage and manipulation of visual information. The model aligns with the limited VWM capacity of approximately 3-4 objects, each composed of combined features (Cowan, 2001; Luck & Vogel, 1997).

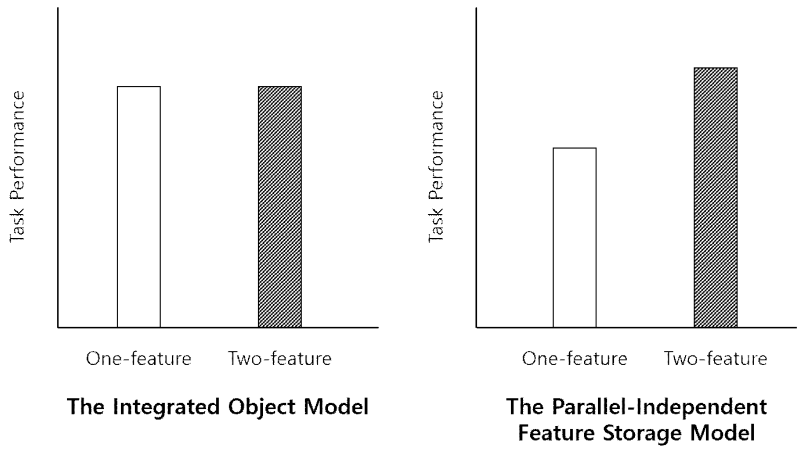
The parallel-independent feature storage model offers an alternative perspective on visual stimuli processing in VWM, in contrast to the integrated object model. This model suggests that individual features of visual stimuli are stored independently and concurrently, without feature binding (Bays et al., 2009; Magnussen et al., 1996; Wilken & Ma, 2004). Memory load is, therefore, linked to the quantity and complexity of features, indicating that memory items consist of separate features rather than integrated objects (Fougnie & Alvarez, 2011). Thus, a trade-off mechanism may exist between the quantity of stored items and their degree of detail.

Much research have been already conducted, and several previous studies have supported the fixed-resolution slot model, a key hypothesis of the integrated object model (Zhang & Luck, 2008). The fixed-resolution slot model suggests VWM stores object representations in 3-4 individual slots, each with a fixed high resolution, regardless of the complexity. According to this model, it is impossible to take a trade-off strategy to enhance the resolution of one representation by sacrificing the resolution of another. However, when memory items are fewer than the available slots, certain representations can exhibit slightly higher resolution by benefiting from storing one representation across multiple slots. This model also states VWM representation formation follows an all-or-none process that when the set size exceeds the VWM capacity, only 3-4 items can be stored, and taking a trade-off strategy of lowering the resolution of individual items in order to store more items is impossible.

On the other hand, other research have provided support for the flexible-resource model, which aligns with the parallel-independent feature storage model (Bays et al., 2009). According to this model, VWM representations are based on independently stored features, and the limited resource is shared collectively within VWM. Consequently, memory load increases in proportion to the visual complexity of each item. Here, resources can be allocated flexibly to each feature, allowing to form representations with higher resolution compared to others by focusing resources on specific representations. Furthermore, a trade-off strategy between the number of stored representations and the precision of those representations is also possible.

Although these two models, the fixed-resolution model and the flexible-resource model are derived from the integrated object model and the parallel-independent feature storage model, they tend to focus more on qualitative aspects of differences in resolution of VWM representations rather than the quantitative aspects, and therefore, it would be challenging to show differences between the integrated object model and the parallel-independent feature storage model which focus on quantitative differences of VWM representations by using the fixed-resolution model and the flexible-resource model. Moreover, although recent studies have yielded results which either support one model or introduce new hybrid models (Adam et al., 2017; Sone et al., 2021; Dube, 2017; Markov et al., 2019), more studies are required to fully understand the nature of VWM representations (Ye et al., 2020).

In this study, thus, our aim was to assess the validity of two opposing models: the integrated object model and the parallel-independent feature storage model. To achieve this, we employed two commonly used tasks: a change detection task, a common short-term recognition task, and a recall task designed to address the limitations of the change detection task. In both experiments, there were two conditions: the one-feature condition and the two-feature condition. In the one-feature condition, the memory array included either orientations or colors, while in the two-feature condition, both orientations and colors were included in the memory array. This study used these two different conditions because the two models we are trying to compare make different predictions for change detection task performance and recall task performance (see Figure 1). The integrated object model, expecting only item-based effects, predicts no differences in change detection and recall performance between the two conditions. In contrast, the parallel-independent feature storage model anticipates differences between the two conditions because interference among memory items is reduced when two different features are spatially segregated compared to features within the same dimension.



(Fig. 1) Different Predictions of Experiments according to Each Model

Experiment Ⅰ

Experiment I investigated the possible impact of different storage demands resulting from various features distributed among multiple memory items on the efficacy of VWM. Kim & Hyun (2012) explored the impact of spatial feature segregation on the efficiency of VWM. In their study, the memory array used in the separate memory condition applied spatial feature segregation by partitioning the display into left and right sections centered around the midpoint. However, this approach might unintentionally facilitate grouping by different individual features, in contrast to the segregated feature condition where memory items consist of a singular feature (Kim, 2012), and this cannot be ignored, as this may give potential advantages of grouping, enhancing memory retention by facilitating the encoding of memory items (Woodman et al., 2003; Jiang et al., 2004). Therefore, to minimize possible grouping effects, this experiment applied spatial feature segregation by randomly positioning orientation bars and colored squares across a range of possible positions, as opposed to the strict segregation of features onto distinct sides of the visual fields. By minimizing potential grouping effects, this experiment may yield more valid results and thus allows to better investigate the impact of spatial feature segregation on the efficiency of VWM.

According to the integrated object model, where the emphasis lies on item-based effects, spatially distinguishing various features does not necessarily lead to an improved change detection performance. In contrast, the parallel-independent feature storage model predicts an enhanced change detection performance in the two-feature condition. This expectation stems from the assumption of the model that features within the same dimension would cause more interference, competing for limited capacity, while features from different dimensions can be processed and stored in parallel. This parallel processing potentially enhances change detection performance in the two-feature condition.

Methods

Participants

Fifteen participants (6 males and 9 females, mean age = 24.3) voluntarily participated in Experiment I. All participants reported to have normal or corrected-to-normal vision, and none were color-blind. Before the experiment, participants were provided with detailed information about the study and were asked to sign an informed consent form, which had been approved by the Research Ethics Board at Chung-Ang University (Approval Number: 1041078-202004-HRSB-087-01). Upon completion of their participation, participants received approximately $10 as monetary compensation.

Apparatus

Experiment I was carried out using the Psychophysics Toolbox built upon the MATLAB (Brainard, 1997; The MathWorks, Natick, MA) program using a 24-inch LCD monitor with a 60Hz refresh rate. All stimuli were presented on a gray [125, 125, 125] background and viewed from a distance of 60cm.

Stimuli

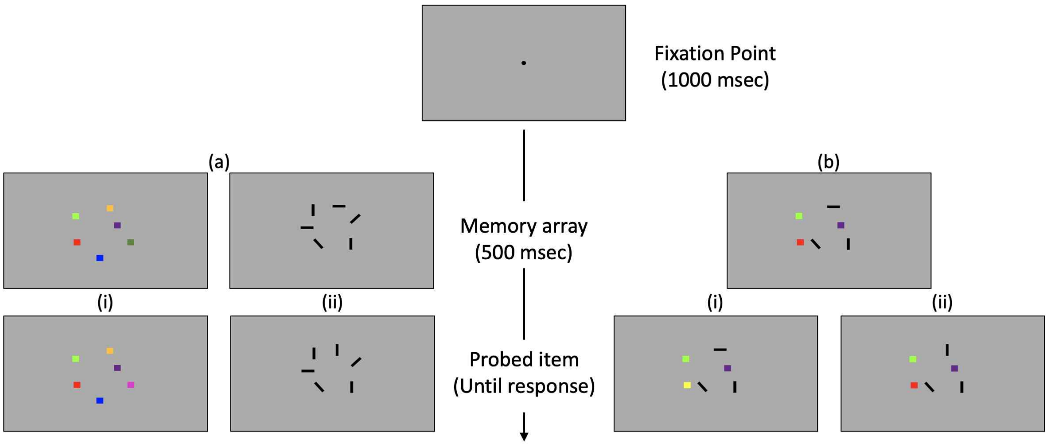
Same with the study by Kim and Hyun (2012), four types of orientation bars (horizontal at 0°, vertical at 90°, and diagonal at ±45°) and six colored squares as stimuli. Colors used were red [255, 0, 0], green [0, 255, 0], blue [0, 0, 255], cyan [0, 255, 255], yellow [255, 255, 0], and purple [255, 71, 222]. The colors or the orientations for the items in the arrays of the experiment were randomly selected from the given set of orientations and colors, and for a set size greater than 6, the orientations and the colors were repeated with replacement. Stimuli (1.2° x 1.2° in visual angle) were evenly distributed within the area of 16.1° x 13.8° on the screen, maintaining balance between left and right sides relative to the central fixation point.

Procedure

Figure 2 illustrates the experimental design of Experiment I. There were two conditions, the one-feature condition and the two-feature condition, and all participants engaged in both conditions with the order of conditions being counter-balanced across the participants. Two conditions were the same except for the number of features each memory array contains. In each trial of the one-feature condition, both the memory and test items were made exclusively of either orientation bars or colored squares. However, in each trial of the two-feature condition, half of the items in the arrays were orientation bars and the remaining half were colored squares. When the test array had a change (50% of the trials), one of the test items changed its orientation or color from the corresponding memory item. In the one-feature condition, the number of trials for the arrays of orientation bars was the same as the number of trials for the colored squares (50%), and also the likelihood of either an orientation or a color change in the test of the two-feature condition was equiprobable (50%). In both conditions, participants were asked to remember all stimuli displayed on the screen.

A black [255, 255, 255] fixation point (0.4° x 0.4° in visual angle) was presented for 1000ms in the beginning of each trial. A 50ms blinking of the fixation point occurred 100ms before the memory array, signaling the start of the trial. Then, the memory array was displayed for 500ms, followed by a 1000ms memory delay before the test array. The test array remained until participants respond, and the participants responded using either the “z” or “/” keys to indicate whether or not one of the orientation bars or the colored squares in the test array had a change either in its orientation, or otherwise in its color, compared to the corresponding item in the memory array. Specifically for an orientation change, an orientation bar in the test array was replaced with another bar having an angle difference of 90° clockwise or counterclockwise. Participants were provided with auditory feedback for the correctness of their responses.

The number of trials in the experiment was 256 in total. Each one- and two-feature condition had 128 trials respectively. When running the trials, they were partitioned into four trial blocks, each consisting of 32 trials. A 10-second short break was provided between each trial block. Set size of the memory array in each condition varied across 2, 4, 6 or 8 items, each having the same number of 32 trials.



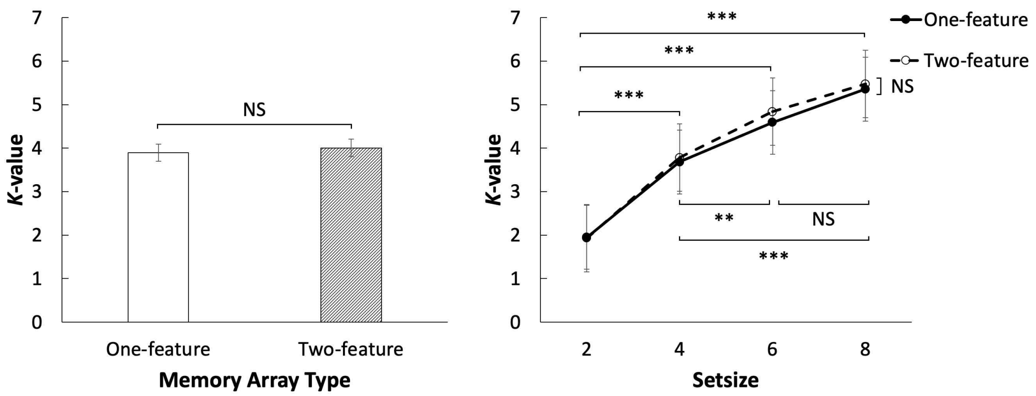
(Fig. 2) Example of Sequence of a Single Trial (set size: 6) in Experiment I. (a) One-feature condition (i) a Color trial (ii) an Orientation trial. (b) Two-feature condition (i) a Color trial (ii) an Orientation trial

Results and Discussion

To assess the participants' performance in the change detection task, K-values[1] were calculated, and a repeated-measures two-way analysis of variance (ANOVA) was conducted with those, considering two factors: type of the memory array (one-feature vs. two-feature) and set size (2, 4, 6, and 8). In this experiment, K-values were used instead of general accuracy to evaluate performance in the change

1) K = {(Hit rate) - (False alarm rate)} / {1 - (False alarm rate)} * (set size)

detection task. Generally, independent variables are assumed to influence VWM capacity when investigating characteristics of VWM using change detection tasks (Rouder et al., 2011). However, task performance is actually affected by not only independent variables but also other factors like guessing response due to the nature of tasks using recognition memory. Therefore, *K*-values which account for the possibility of participants' guessing responses were used for more accurate assessment of performance in the change detection task. The average of *K*-values are illustrated in Figure 3.



(Fig. 3) The Average *K*-value for Each Memory Type (Left). The Average *K*-value for Each Setsize (Right). *Error bars* represent standard error of the mean. ** $p < .01$, $p < .001$, *NS*: not significant

In congruence with preceding research (Kim & Hyun, 2012), the pattern of participants' performance, as measured by *K*-values, did not show any statistically significant differences between two conditions, $F(1, 14) = 1.37$, $p > .05$, $\eta^2 = .09$[2]. However, there was a significant difference in the *K*-values with respect to set size, $F(3, 42) = 90.36$, $p < .001$, $\eta^2 = .87$. The effect of set size could be explained by the limited capacity of VWM, known to be approximately 3-4 objects at a time. A *t*-test, conducted to check for the null effect of the memory array type yielded the same results. No significant differences in *K*-values were found between one-feature condition ($M = 3.92$, $SD = .44$) and two-feature condition ($M = 4.00$, $SD = .43$), $t(15) = -.82$, $p > 0.05$. Hence, we could conclude the absence of significant differences in change detection task performance between the two conditions. This contradicts the idea of the parallel-independent feature storage model which predicts a better change detection task performance in the two-feature condition due to less

2) Additional equivalence tests were conducted to confirm the null effect, and the results indicated equivalence between two conditions, 90% Confidence interval: (-0.227, 0.374).

interference among items.

Experiment Ⅱ

While the change detection task has been a common choice for investigating VWM, some research have highlighted its significant limitations in accurately assessing the nature of VWM representations (Awh et al., 2007; Hollingworth, 2003; Hyun et al., 2009; Kahana & Sekuler, 2002). Consequently, change detection tasks have been deemed less suitable for investigating the nature of VWM representations (Barton et al., 2009). As an alternative, recent studies have turned to the recall task to explore VWM representations. Therefore, Experiment II aimed to explore VWM representations using a recall task, yielding three recall indices (P_m, *s.d.*, and *AUC*) as results. By doing so, the two models could be more accurately compared and results could provide a better explanation of VWM representations.

The results each model expects from Experiment II are similar to Experiment I. The integrated object model predicts that change detection task performance would not show significant differences irrespective of spatial separation of different features. On the other hand, the parallel-independent feature storage model expects an improvement in change detection task performance under the two-feature condition because features within the same dimension cause more interference due to limited capacity compared to features from different dimensions which could be processed independently and concurrently.

Methods

Participants

Another group of sixteen participants (7 males and 9 females, mean age = 26.2) participated in Experiment II on a voluntary basis. All participants reported to have normal or corrected-to-normal vision, and none were color-blind. They all signed the same informed consent form that was used in Experiment I and received monetary compensation of $10.

Apparatus

Same as Experiment I.

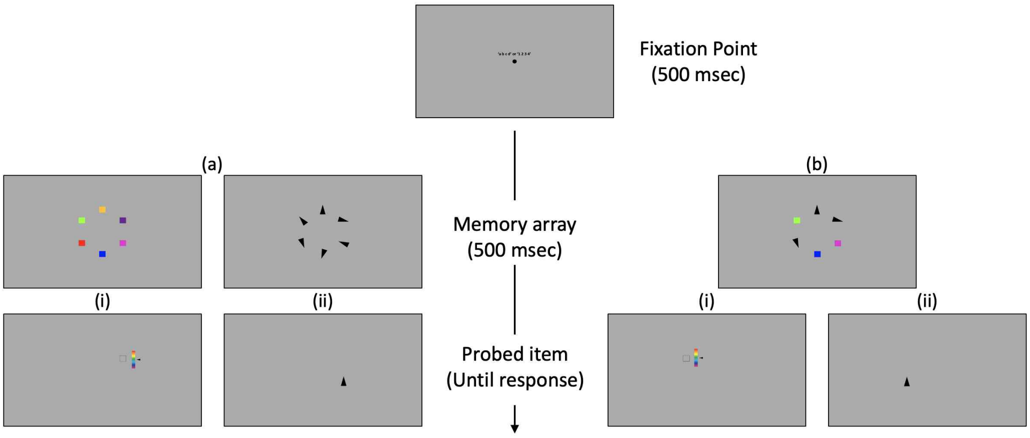
Stimuli

Experiment II used similar stimuli to Experiment I but with some modifications. Unlike Experiment I, which randomly selected stimuli from four orientation types and eight colors, Experiment II used orientations of isosceles triangles and colors of squares from a 360-degree pool and the color wheel (Zhang & Luck, 2008), respectively. Stimuli (1.2° x 1.2° in visual angle) were evenly distributed in a hexagonal pattern on the screen (16.1° x 13.8° area).

Procedure

Figure 4 illustrates the experimental structure in Experiment II. Unlike Experiment I, each trial started with a black fixation point (0.4° x 0.4°) and included an articulatory suppression task which required participants to silently repeat 'a b c d' or '1 2 3 4.' The researcher continuously monitored whether participants were continuously performing the articulatory suppression task from outside the experiment booth. The memory array appeared for 500ms, followed by a 200ms masking stimuli before the test array. During the test, one item among memory items was randomly selected and presented. Participants were then asked to recall either the orientation or the color of that specific item. In the two-feature condition, half of the trials asked participants to recall the orientation of the isosceles triangle, while the other half trials asked participants to recall the color of the colored square. Participants recalled a randomly selected stimulus in the test array, using keys "q", "w", "e", "r" for orientations and "3", "6", "9", "*" for colors. "q" and "r" adjusted orientations by 10-degree, "w" and "e" by 1-degree. "3" and "9" modified colors by 10-degree, "6" and "*" by 1-degree within a 360-degree circular spectrum. Participants proceeded to the next trial by pressing the spacebar.

The experiment comprised a total of 240 trials, evenly distributed between the one-feature and two-feature conditions, each containing 120 trials. They were organized into four blocks, with each block containing 30 trials. A brief 60-second break was given between each block. Within each condition, set size of the memory array was manipulated across three levels: 2, 4, and 6 items, with each set size consisting of 40 trials.



(Fig. 4) Example of sequence of a single trial (set size: 6) in Experiment Ⅱ. (a) One-feature condition (i) a Color trial (ii) an Orientation trial. (b) Two-feature condition (i) a Color trial (ii) an Orientation trial

Data Analysis

Mixed Model

To analyze recall task results effectively, we followed the mixed model analysis originally proposed by Zhang & Luck (2008). It predicts responses in recall tasks by combining memory and guessing responses. Memory responses occur when items are successfully recalled and follow a Gaussian distribution centered on the cued memory item's actual color location. Guessing responses, on the other hand, occur when memory storage fails, resulting in random responses uniformly distributed across the color wheel. The mixed model combines these components to form the final response probability distribution in a color wheel recall task. It's worth noting that circular stimulus distributions have led to the exploration of specialized models like von Mises functions for memory response probability distributions (Bays & Taylor, 2018).

P_m and *s.d.*

Analyzing recall task responses within the mixed model involves assessing the *"d"* distribution, representing the difference between participants' chosen orientation and color location on the wheel and the actual orientation and color of the memory item. Key measurements obtained through this process include the probability of successful recall (P_m), indicating accuracy; guessing response probability (P_u), indicating memory failure; and the standard deviation (*s.d.*) of the von Mises function, reflecting memory precision or resolution (Bays & Taylor, 2018). Data collection and calculations for P_m and *s.d.* were conducted using the MATLAB toolbox MemToolbox[3] (Suchow et al., 2013).

AUC

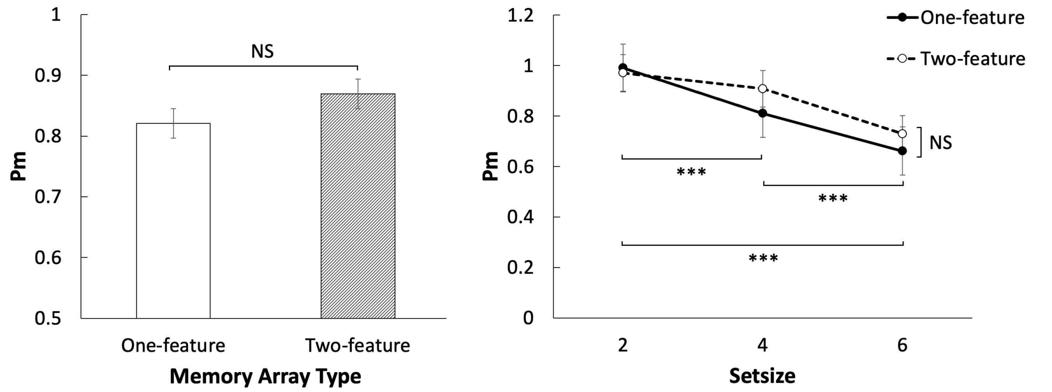
In addition to P_m and *s.d.*, Sone *et al.* (2021) introduced the Area Under the Cumulative Distribution Function (*AUC*) as another measure to investigate VWM representations. According to Sone and colleagues, *AUC* values near 0.5 indicate primarily guessing behavior, as the cumulative distribution linearly increases. Conversely, an *AUC* of 1 reflects perfect responses. In essence, *AUC* increases as the proportion of 0-degree offset responses increases, indicating more precise responses (Sone et al., 2021).

Calculation of *AUC* was done following several steps. First, the absolute values of all "*d*" values were computed. Next, the cumulative distribution for these absolute "*d*" values was plotted. Finally, the area under the resulting cumulative distribution function (*AUC*) was determined.

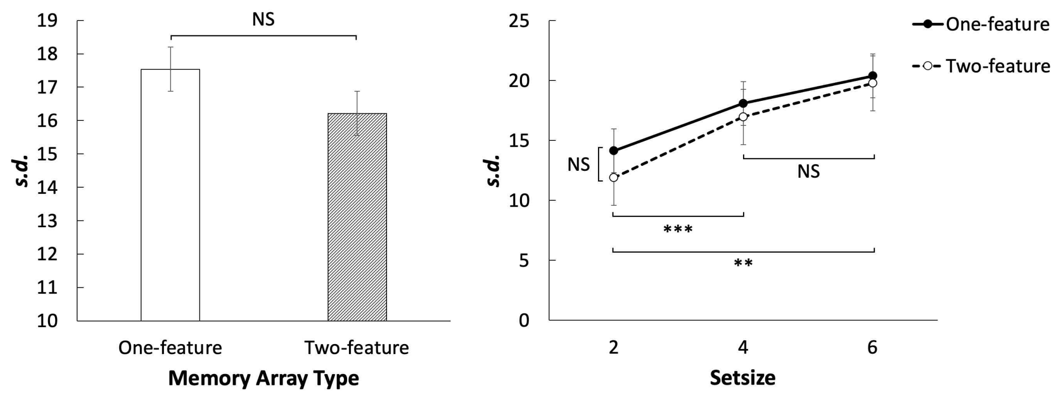
Results and Discussion

In line with Experiment I, a two-way repeated-measures ANOVA was conducted, examining the effects of memory array type (one-feature vs. two-feature) and set size (2, 4, 6) on P_m, *s.d.*, and *AUC*. Figure 5, 6 and 7 depict the average P_m, *s.d.*, and *AUC* for each condition and set size. As expected from the results of Experiment I, the results showed no effects of the memory array type on

3) See The MemToolbox in Suchow et al. (2013) for the equations/principles to calculate P_m and P_u in the present study.



(Fig. 5) The Average P_m for Each Memory Type (Left). The Average P_m for Each Set Size (Right). *Error bars* represent standard error of the mean. *** p < .001, *NS*: not significant

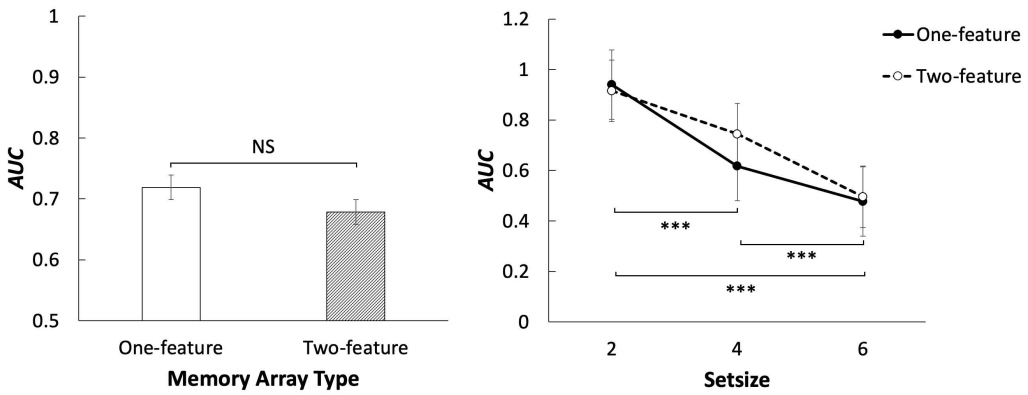


(Fig. 6) The Average *s.d.* for Each Memory Type (Left). The Average *s.d.* for Each Set Size (Right). *Error bars* represent standard error of the mean. ** p < .01, *** p < .001, *NS*: not significant

any of P_m, *s.d.*, or *AUC*, suggesting comparable recall performance between the one- and two-feature conditions, $F(1, 15) = 2.10$, $p > .05$, $\eta^2 = .12$, $F(1, 15) = 1.13$, $p > .05$, $\eta^2 = .07$, and $F(1, 15) = 2.77$, $p > .05$, $\eta^2 = .16$, respectively[4]. P_m also decreased as the set size increased, just as the change detection accuracy decreased in Experiment I, $F(2, 30) = 68.12$, $p < .001$, $\eta^2 = .82$.

Additionally, two distinct patterns of set size effects were revealed for *s.d.* and *AUC*: the increase of *s.d.* along the set size and decrease of *AUC* as the set size increased, $F(2, 30) = 8.49$, $p < .05$,

4) Equivalence tests were also conducted here to confirm the null effect, and the results indicated equivalence between two conditions, 90% Confidence interval: (-0.439, 0.037), (-0.355, 0.12), and (-0.243, 0.429) for P_m, *s.d.*, and *AUC*, respectively.



(Fig. 7) The Average *AUC* for Each Memory Type (Left). The Average AUC for Each Set Size (Right). *Error bars* represent standard error of the mean. *** p < .001, *NS*: not significant

η^2 = .36 and $F(2, 30) = 166.92$, $p < .001$, η^2 = .92, respectively. These set size effects in Experiment II indicate the precision of items in VWM somewhat varied as the number of memory items increased when participants performed both the two different recall tasks requiring the one-feature or two-feature memory. No interaction effects on P_m and *s.d.* were observed between the memory array type and the set size, $F(2, 30) = 1.30$, $p > .05$, $\eta^2 = .08$, $F(2, 30) = 0.04$, $p > .05$, $\eta^2 = .003$, respectively, but an interaction effect on *AUC* was found, $F(2, 30) = 5.33$, $p < .05$, $\eta^2 = .26$. Like Experiment I, a *t*-test was also conducted to assess the null effect of two conditions. Consequently, no significant differences were found in P_m and *s.d.* between the one-feature condition (M = .82, SD = .06 and M = 17.29, SD = 5.58, respectively) and the two-feature condition (M = .86, SD = .06 and M = 16.02, SD = 2.65, respectively), $t(15) = -1.99$, $p > 0.05$ and $t(15) = .82$, $p > 0.05$, respectively. Regarding the *AUC*, like P_m and *s.d.*, no differences were observed between two conditions (M = .67, SD = .05 and M = .69, SD = .06, respectively), $t(15) = -1.13$, $p > 0.05$.

General Discussion

This research aimed to confirm controversial models related to VWM representations, specifically focusing on two models: the integrated object model and the parallel-independent feature storage model.

The integrated object model posits that VWM represents information as integrated objects, not individual features (Awh et al., 2001; Jiang et al., 2000; Vogel et al., 2001; Xu, 2006; Zhang & Luck, 2008). Conversely, the parallel-independent feature storage model suggests that VWM relies on feature-based units (Bays et al., 2009; Magnussen et al., 1996; Wilken & Ma, 2004).

Although not conclusive, the results from this study indirectly support the integrated object model over the parallel-independent feature storage model by presenting findings that contradict the idea of the parallel-independent storage model, as the model predicts better task performance when two different features are spatially segregated in the two-feature condition compared to the one-feature condition. Experiment I, similar with Kim and Hyun's (2012) study, confirms that VWM operates at the integrated object level, not individual features. Set size significantly affected change detection task performance, especially with set sizes which exceeded four items, in line with 3-4 item limit of VWM (Cowan, 2001; Luck & Vogel, 1997). Surprisingly, the memory array type, one- versus two-feature, did not influence participants' accuracy and *K*-values that participants performed the change detection task consistently with the same number of items in VWM regardless of the number of features included. These findings provide the evidence that opposes to the parallel-independent feature storage model, as the model predicts different performances depending on the number of features included when different features are displayed spatially separated from one another.

Experiment II, consistent with Experiment I, yielded results contradicting the parallel-independent feature storage model that no performance differences were found between two memory array types, whereas the parallel-independent feature storage model expects to see a significant diffference between them. However, the indicator of memory precision, *s.d.*, apparently increased as the set size increased regardless of whether the recall was necessary for either the one- or two-feature memory items. This additional finding can be explained as follows:

On one hand, this result alone does not prove resolutions of VWM representations decreased; this may be attributed to similarity among items within each memory array. Awh et al. (2007) have demonstrated that precise recall of probed items becomes more challenging as the set size increases. This is due to the substantial similarities among items within the memory array, making it difficult to detect subtle differences among stimuli. Thus, the increase of *s.d.* along the increasing set size in a recall task may not be attributable to a gradual drop of item precision but to the increasing demand for general cognitive resources (Awh et al., 2007).

This could explain the results of Experiment II, wherein the presence of a larger number of items in each memory array resulted in less distinctiveness among items; the lack of distinctiveness made it difficult to recall probed items precisely. Notably, previous research conducted by Barton et al. (2009) similarly demonstrated a decrease in mnemonic resolution as the set size increased. Importantly, however, the resolution of a specific item remained consistent, even when other items varied in complexity, as long as the set size remained constant. This suggests that it is the set size rather than the complexity of information, such as the number of features included in each memory array, that influences the resolution of memory representations (Barton et al., 2009).

On the other hand, an ongoing significant debate revolves around the determination of which model better explains VWM representations: the strong object model or the weak object model. The strong object model aligns with the integrated object model, while the weak object model serves as a compromise between the integrated object model and the parallel-independent feature storage model by suggesting integrated representations in VWM are formed conditionally only when features successfully combine within a memory item (Xu, 2001; Olson & Jiang, 2002). The results of Experiment II can be interpreted using these models. As the set size increases, there is a greater potential for interference among memory items compared to smaller set sizes. The presence of increased interference with larger set sizes hinders the successful feature integration required for integrated representations in VWM. The results of Experiment II favor the weak object model, underscoring the role of feature integration within VWM and suggesting the parallel-independent feature storage alone may not account for the observed phenomena. The findings from Experiment II provide support for the weak object model as it offers a more detailed explanation of VWM representations in the context of the set size variations and interference among memory items.

Furthermore, the observed interaction effects between the memory array type and the set size on *AUC* can be attributed to the presence of guessing. Notably, a significant difference in *AUC* was found between two conditions only when the set size was 4, with no substantial differences observed when the set size was 2 or 6. In this context, the influence of guessing cannot be ignored. When set size is two, there is no doubt that all two items would be encoded and stored in VWM because two items fall below VWM capacity limit. Conversely, when set size is six, it is evident that six items exceed VWM capacity limit. However, when set size is four, it becomes ambiguous whether all four items would be successfully encoded and stored in VWM since four items are situated on the border of VWM capacity limit. What is clear, though, is that the guessing effect is more significant when set size is four compared to two and less significant when set size is four compared to six. Therefore, these results present challenges when attempting to explain them solely through the integrated object model. Instead, it is possible that the nature of features used played a role in influencing participants' performance. Specifically, the inclusion of non-canonical orientations and the random selection of colors from an ambiguous color wheel may have had an impact.

Likewise, the results of Experiment II do not support the prediction from the perspective of the strong object model, which is not exactly identical to but has been inherited to the idea of fixed-resolution slot hypothesis (Zhang & Luck, 2008). However, at the very least, there was evidence of some forms of integrated object-based representations that maintained the efficiency of multi-feature item storage. This is supported by the absence of an interaction between the memory array type and the set size in the *s.d.* observed in Experiment II.

Consequently, this study, as a whole, aligns with the integrated object model but suggests a modified interpretation in line with the weak object model, proposing that items are represented in VWM as integrated objects conditionally, only when successful integration is necessary. Nevertheless, additional considerations must be necessary to fully address the nature of VWM representations.

Firstly, instead of randomly positioning individual stimuli in the two-feature condition of Experiment II, the memory array configuration of Kim & Hyun (2012) could be considered. In other words, spatial segregation of features could be done by dividing the memory and test arrays into two separate regions with a single feature, each.

Secondly, as previously mentioned, in Experiment II, both orientations and colors were randomly selected from a continuous pool of 360° and a wider range of neighboring colors on a color wheel, respectively. This stimuli selection led items within each memory array to categorical confusion in terms of their orientations or colors as set size increases. This can result in increased similarity among items and reduced perceptual differences among them, making precise recall more difficult. To address this, there must be a way to ensure comparable categorical differences among items within each memory array regardless of varying set sizes.

Thirdly, due to the nature of the task, as set size increases, there are trials where participants may not be able to attend to every single item in each memory array, and these trials cannot be considered as true tests of participants' memory. Thus, it is necessary to conduct an experiment that uses experimental methods which reduce or eliminate such trials, for example, by tracking participants' eye movements (Ye et al., 2020).

Lastly, orientations and colors are the only features used in this research. However, replicating experiments using other types of features would help us better understand VWM representations, as some research demonstrated each feature has different characteristics (Alvarez & Cavanagh, 2004). Therefore, by using different types of stimulus features such as shapes or lengths, research whether different features lead the same results with orientations and colors would be possible, and thereby our understanding of VWM representations would be deepened.

While this study advanced our knowledge of characteristics of VWM representations, it highlights the crucial necessity for future research in this field.

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(요 약)

변화탐지와 회상 과제에 기초한 시각작업기억의 통합적 객체 표상 검증*

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본 연구는 두 가지 이론적 모델인 통합된 객체 모형과 특장 병렬-독립 저장 모형을 검증함으로써 시각작업기억 표상의 특성을 조사하였다. 실험 Ⅰ에서 참가자들은 색상 사각형, 방위 막대 또는 두 가지 모두로 구성된 배열을 기억한 뒤 이를 토대로 변화탐지과제를 수행했다. 단일 특징 조건에서 기억배열은 하나의 특징(방위 또는 색상)으로만 구성된 반면, 두 가지 특징 조건은 둘 모두를 포함했다. 두 조건간 변화탐지 수행의 차이는 없었으며 이는 병렬-독립 저장 모형보다는 통합된 객체 모형을 지지한다. 실험 Ⅱ에서는 이등변삼각형의 방위, 색상 사각형 또는 두 특징 모두로 구성된 기억배열을 대상으로 회상과제가 실시되었으며, 단일 특징과 두 가지 특징 조건 간 회상 수행이 비교되었다. 두 조건 간 회상 정확도에는 차이가 없었으나 표상 선명도와 추측반응에 대한 분석 결과는 강한 객체 모형보다는 약한 객체 모형을 시사했다. 본 연구의 결과는 시각작업기억의 표상 특성을 둘러싼 현시점의 논쟁에 있어서 병렬-독립 저장 모형이 아닌 통합된 객체 모형의 우세를 지지한다.

주제어 : 시각작업기억, 표상, 통합된 객체 모형, 특징 병렬-독립 저장 모형

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