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A two-phase model of resource allocation in visual working memory

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Abstract

Two broad theories of visual working memory (VWM) storage have emerged from current research, a discrete slot-based theory and a continuous resource theory. However, neither the discrete slot-based theory or continuous resource theory clearly stipulates how the mental commodity for VWM (discrete slot or continuous resource) is allocated. Allocation may be based on the number of items via stimulus-driven factors, or it may be based on task demands via voluntary control. Previous studies have obtained conflicting results regarding the automaticity vs. controllability of such allocation. In the current study, we propose a two-phase allocation model, in which the mental commodity could be allocated only by stimulus-driven factors in the early consolidation phase. However, when there is sufficient time to complete the early phase, allocation can enter the late consolidation phase, where it can be flexibly and voluntarily controlled according to task demands. In an orientation recall task, we instructed participants to store either fewer items at high-precision or more items at low-precision. In three experiments, we systematically manipulated memory set size and exposure duration. We did not find an effect of task demands when the set size was high and exposure duration was short. However, when we either decreased the set size or increased the exposure duration, we found a trade-off between the number and precision of VWM representations. These results can be explained by a two-phase model, which can also account for previous conflicting findings in the literature.

Keywords: visual working memory; mental commodity allocation; voluntary; involuntary.

Introduction

Visual working memory (VWM), which could be generally defined as "the active maintenance of visual information to serve the needs of ongoing tasks" (Luck & Vogel, 2013), has been proposed to be a cognitive system that holds a limited amount of visual information in a temporary storage buffer so that it may be quickly accessed, integrated with other information, or otherwise manipulated (Drew & Vogel, 2009). VWM capacity exhibits a stable individual difference and is correlated with measures of higher cognitive function, accounting for 43% of individual differences in global fluid intelligence (Fukuda, Vogel, Mayr, & Awh, 2010), 46% of individual differences in overall performance on a broad battery of cognitive tasks (M. K. Johnson et al., 2013). Furthermore, VWM storage capacity, VWM precision (the resolution of memory representation) and consolidation (the transfer of sensory information into VWM storage) is impaired in people with psychiatric disorders (Fuller et al., 2009; Gold et al., 2010; Zokaei, Burnett Heyes, Gorgoraptis, Budhdeo, & Husain, 2014). Therefore, understanding VWM mechanisms is very important for studies of human cognition.

Two broad theories have been proposed for the nature of mental commodity that supports VWM storage[1], a discrete slot-based theory and a continuous resource theory. The original model of the discrete slot-based theory, often called *classic slot model*, proposes that VWM has a limited number of available "slots", which store a limited set of discrete, fixed-precision representations (Cowan, 2001; Luck & Vogel, 1997; Vogel, Woodman, & Luck, 2001). When all slots are filled, no information about additional items can be stored, and the memory precision does not vary with the number of items. An updated version of the discrete slot-based theory advances a *slots + averaging model*, which proposes that if the number of to-be-represented items is below the maximum number of slots, then an item can be represented by multiple slots (Zhang & Luck, 2008). The discrete slot-based theory has received support from a number of empirical studies (Barton, Ester, & Awh, 2009; Donkin, Nosofsky, Gold, & Shiffrin, 2013; Rouder et al., 2008; Zhang & Luck, 2011). Alternatively, the other class of theories propose that the mental commodity supporting VWM storage is better described as a type of continuous resource. For example, the *flexible resource model* does not impose an upper item limit, but proposes VWM consists of a pool of resources that can be allocated flexibly to a small number of items to create high-precision representations or distributed among a large number of items to create low-precision representations (P. M. Bays, Catalao, & Husain, 2009; P. M. Bays & Husain, 2008; P. M. Bays, Wu, & Husain, 2011; Huang, 2010; Wilken & Ma, 2004). The fundamental difference between these two classes of theories is whether there exists an upper item limit[2]. Based on this difference, discrete slot-based theory predicts that precision would decrease with an increase in the number of stored items, but the maximum number of items is strictly limited by the number of slots. By contrast, continuous resource-based theory predicts that the monotonic declines

should be observable across much larger set sizes without any fixed item limit. Zhang and Luck (2008) used a standard mixture model and found that as the number of items stored in VWM increased from one to three, the VWM precision monotonically declined, but the precision was constant when the memory set size varied from three to six. Although their results supported the discrete slot-based theory, P. M. Bays et al. (2009) used a swap model and found no evidence to support a fixed upper limit on the number of items that can be held in VWM. Another challenge to slots + averaging model was the *variable-precision model*, which was a more recent model of continuous resource theory. This model proposes that the precision of VWM representations varies randomly from trial to trial (Fougnie, Suchow, & Alvarez, 2012; van den Berg, Shin, Chou, George, & Ma, 2012). The debate between the discrete slot-based models and continuous resource models has been intense and is currently still unresolved (Balaban & Luria, 2015; P. M. Bays, 2014; Paul M Bays, 2015; Franconeri, Alvarez, & Cavanagh, 2013; Luck & Vogel, 2013; Vogel & Machizawa, 2004). However, there is a general agreement that the mental commodity of VWM is an allocable resource of limited capacity.

The current debate between these two classes of VWM theories centers on the quantization of the mental commodity, which is not the focus of the present work. Instead, here we investigated how the mental commodity is allocated to store items, regardless of the discrete vs. continuous nature of the mental commodity itself (Suchow, Fougnie, Brady, & Alvarez, 2014). The mechanism of allocation addresses the general question of how people structure and process VWM representations, which is an important aspect of VWM that is not captured by the discrete slots vs. continuous resource debate (Brady, Konkle, & Alvarez, 2011; J. S. Johnson, Simmering, & Buss, 2014; Suchow et al., 2014). Previous studies suggested that there are two possibilities (Machizawa, Goh, & Driver, 2012; Murray, Nobre, Astle, & Stokes, 2012). Allocation may be based on the number of items via stimulus-driven factors, or it may be based on the task demands via voluntary control. We refer to the former as the involuntary allocation hypothesis, which predicts that VWM precision can only be determined by stimulus-driven factors at encoding and will not be affected by task demands. We refer to the latter as the voluntary allocation hypothesis, which predicts that VWM precision can be flexibly and voluntarily controlled according to task demands.

Previous studies have found support for both the involuntary and voluntary hypotheses (Gao, Yin, Xu, Shui, & Shen, 2011; He, Zhang, Li, & Guo, 2015; Machizawa et al., 2012; Murray et al., 2012; Ye, Zhang, Liu, Li, & Liu, 2014). For example, Murray et al. (2012) manipulated payoff schemes to emphasize either the quality or quantity of memory and found no voluntary resource allocation in VWM, supporting the involuntary allocation hypothesis. However, Machizawa et al. (2012) also manipulated the degree of memory precision by task demands and found that people can voluntarily enhance the precision of their VWM, but only for a few items, thus supporting the voluntary allocation hypothesis. To our knowledge, no satisfactory

explanations have been offered to reconcile these discrepant findings.

However, the involuntary and voluntary allocation may not be mutually exclusive. We note that the exposure durations used by the above studies supporting involuntary allocation were relatively short, about 25-50 ms/item (He et al., 2015; Murray et al., 2012; Ye et al., 2014). In contrast, the studies supporting voluntary allocation tended to use longer exposure durations, about 100-125 ms/item (Gao, Yin, et al., 2011; Machizawa et al., 2012). Previous work has demonstrated that the length of exposure duration will impact the VWM consolidation (P. M. Bays, Gorgoraptis, Wee, Marshall, & Husain, 2011). In the context of both slot-based and resource-based theories, VWM consolidation and mental commodity allocation are basically equivalent. Here, we propose that consolidation (or mental commodity allocation) contains two different phases. In the early phase (involuntary consolidation phase), mental commodity could be allocated only by stimulus-driven factors to create the initial representation. When the exposure duration is sufficiently long, allocation can enter the late voluntary phase, where allocation could be flexibly and voluntarily controlled according to task demands. Because the consolidation process is itself capacity or bandwidth limited (Becker, Miller, & Liu, 2013; Jolicoeur & Dell'Acqua, 1998; Liu & Becker, 2013; Mance, Becker, & Liu, 2012; Miller, Becker, & Liu, 2014; Vogel, Woodman, & Luck, 2006), whether participants can enter the late voluntary phase depends on the length of consolidation time and the number of memory items. This two-phase allocation model could account for previous discrepant findings.

In the current study, we gave participants instructions and incentives (in points of reward) to strategically control the balance between the number and precision of memory. We tested our model by manipulating exposure duration and set size. We predicted that when participants needed to remember items at a high set-size with a short exposure duration, the mental commodity allocation would still be in the early involuntary consolidation phase, making it impossible to vary VWM precision according to task requirements (Experiment 1). However, when there was enough exposure duration to enter the late voluntary phase, VWM precision variation would be observed either with a smaller set-size (Experiment 2) or with a longer exposure duration (Experiment 3). As we will discuss, these results and the new two-phase allocation model can further reconcile previous conflicting results (Gao, Yin, et al., 2011; He et al., 2015; Machizawa et al., 2012; Murray et al., 2012; Ye et al., 2014).

Experiment 1

In the first experiment, we aimed to test the early, involuntary, phase of mental commodity allocation. Thus we restricted stimulus presentation time such that participants could not enter the late, voluntary, phase. To do this, we needed to select a set-size and exposure duration such that the latter is just short enough to complete the involuntary consolidation of all the items. We chose a set-size of four items and an exposure duration of 200 ms, based on the following considerations: Woodman and

Vogel (2008) estimated that about 100 ms is needed to consolidate one orientation into memory, and our recent work (Becker et al., 2013; Liu & Becker, 2013; Miller et al., 2014) proposed that consolidation for orientation information is a serial process. Therefore, the consolidation time for four orientations would be about 400 ms. Moreover, previous studies found that, without a post mask[3], the visible persistence can still store stimulus information for at least 100 ms to 200 ms after stimulus offset due to retinal persistence (Averbach & Coriell, 1961; Brockmole, Wang, & Irwin, 2002; Coltheart, 1980; Di Lollo & Dixon, 1988). Thus, we adopted a more conservative estimate of the available time for VWM consolidation. Presenting four items for 200 ms is our best estimate of just enough time to complete the VWM involuntary consolidation phase. According to the two-phase allocation model, we expect to find no voluntary VWM precision variation in this experiment.

Methods

Participants

Forty-seven undergraduate students from Minnan Normal University (42 females, 46 right-handed, 19-23 years old) volunteered to participate in this experiment for course credit. They reported no history of neurological problems, reported having normal color vision and normal or corrected-to-normal visual acuity. Written informed consent was provided by each participant prior to the experiment. The study was conducted in accordance with the Declaration of Helsinki and was approved by the ethics committee of Liaoning Normal University.

Visual stimuli

Visual stimuli were generated using MGL (http://gru.stanford.edu/doku.php/mgl/overview), a set of custom OpenGL libraries running in MATLAB (The MathWorks, Natick, MA). The stimuli were sinusoidal gratings (contrast, 0.7; spatial frequency, 3 cycles/deg) in a circular aperture (size, 0.9°) presented on a gray background. The orientation of each stimulus was randomly selected from 90 possible angles evenly spaced from 0° to 180°, with the orientations separated by at least 12°. The edge of the aperture was smoothed such that no sharp change in luminance was present between the gratings and the background. The gratings could be presented in four possible locations, located at the corners of an imaginary square (eccentricity, 3°). A fixation dot (0.2°) was presented in the center of the screen throughout the experiment. The stimuli were presented on a 19" LCD monitor (1280×768 pixel), and participants viewed the display at a distance of 60 cm in a dark room.

Task and design

Participants were asked to perform an orientation recall task in two precision conditions with the trial structures depicted in Fig 1. Each trial started with the presentation of a fixation dot in the center of the screen. Four oriented gratings were

then presented for 200 ms. After a 1000 ms retention period, a location cue (a 1° square outline) appeared in one of the stimuli's location, along with an adjustable probe grating (presented at fixation). Participants adjusted the probe's orientation to match that of the cued grating. Three keys were used to rotate the probe grating (initial orientation was always vertical): two adjustment keys that rotated the probe grating by ±4° per key press. Participant could also move the cursor with the mouse and press the third adjustment key to rotate the probe grating to the cursor position. These parallel ways of adjustment allowed participants to adjust the orientation either finely (by the first two adjustment keys) or coarsely (by the mouse). Participants were told to make adjustments until they were satisfied, at which point they pressed the space bar to finalize their response. Participants were then provided with feedback that contained three values. The first value was "offset", which was the difference between their reported orientation and the actual orientation of the cued grating. The second value was "Score", which showed the number of points participants earned on that trial. The third value was "Total Score", which was the number of points participants had accumulated in the experiment. The next trial started 900-1100 ms after the feedback. In Experiment 1, there are two precision conditions: high-precision and low-precision. The participants were asked to memorize the orientations with different levels of precision. We manipulated the rule of earning points to encourage them using the corresponding memory precision. In the high-precision condition, participants earned 6 points if their offset was smaller than 10° and earned nothing otherwise. In the low-precision condition, participants earned 4 points if their offset was smaller than 30° and earned nothing for offset between 30° and 50°. To encourage participants to store in memory at least some information about every item in the low-precision condition, we penalized them 2 points for offset larger than 50°. In addition, participants received a base score of 100 points at the beginning of the experiment and they were fully informed of the reward rule. At the end of the experiment, the points were converted to a participation grade as part of their course credit.

INSERT FIGURE 1 ABOUT HERE

The two precision conditions were blocked and the order of blocks was counterbalanced across participants. There were 280 trials for each precision block. Each block was split into 7 mini-blocks of 40 trials each, with a break of at least 30s between mini-blocks and 2 min between blocks. The entire experiment lasted approximately 60 min. Before each block, there were at least 20 practice trials to ensure the participants understood the instructions.

Data analysis

Because it might take some time for participants to form the appropriate strategy given the feedback in each precision condition, we did not analyze the first 80 trials in

each block such that results were based on the subsequent 200 trials (including the first 80 trials into the analysis did not change the results).

For each trial, we calculated the offset (error) in the recalled orientation by subtracting the participants' orientation setting from the target orientation. We adopted the standard mixture model (Zhang & Luck, 2008) to fit the data using the MemToolbox (Suchow, Brady, Fougnie, & Alvarez, 2013). The standard mixture model assumes that performance on the orientation recall task is determined by a mixture of two types of trials. On a proportion of trials, participants did not consolidate the items into VWM, so they simply guessed, with the reported orientation conforming to a uniform random distribution. On the remaining trials, participants consolidated the item into VWM, which contains a noisy representation of the target orientation, modeled by a von Mises distribution. This allowed us to estimate the number of items stored (K) as well as the precision of the memory representation (SD)[4]. We fit the model to individual participant data in each condition and used paired t-tests to compare the model parameters at the group level to assess statistical significance between conditions. In addition, we also used the swap model and variable-precision model to fit the data of all experiments. These models have been suggested to provide a better description of the data under certain conditions (P. M. Bays et al., 2009; Fougnie et al., 2012). We generally observed highly consistent results no matter which fitting model was used. We report these additional modeling results in the supplemental material 1.

Results and Discussion

Participants earned an average of 714 points in the low-precision condition and 638 points in the high-precision condition. There was no main effect of which condition was encountered first for all dependent measures. We thus combined all participants in the following analysis, regardless of the presentation order.

We averaged parameters of all models for individual fits (Fig. 2a). For both the precision (SD) and the number of items stored (K), there was no significant differences between the low-precision condition and high-precision condition, $t(46) = 0.442$, $p = .661$ for SD, , $t(46) = 0.200$, $p = .842$ for K. A Bayes factor analysis showed that the null hypothesis (i.e., no difference between the low- and high-precision conditions) was 5.757 times (for SD) and 6.196 times (for K) more likely than the alternative hypothesis (Rouder, Speckman, Sun, Morey, & Iverson, 2009).

These results implied that participants are unable to strategically increase the number of items stored in VWM by reducing the precision of the representations or vice versa.

INSERT FIGURE 2 ABOUT HERE

We observed that participants were unable to trade off number and precision in VWM when exposure duration was short and set-size was large. That is, the mental commodity allocation appeared to be based on stimulus-driven factors, regardless of the task demands. These results validated our choice of set size and exposure duration and supported our prediction that the mental commodity allocation would be in the early, involuntary phase at this set-size and exposure duration. These results were also in line with findings from previous studies using similar settings (He et al., 2015; Murray et al., 2012). Next, we tested whether voluntary control is possible in a later phase of allocation in Experiment 2 and 3.

Experiment 2

According to the two-phase allocation model, when exposure duration is short, reducing the size of memory set should allow the allocation to enter the late phase, where more efficient voluntary control can be exerted. In this experiment, in order to ensure sufficient processing time to complete the early involuntary phase, we reduced the set-size from four to two. Given the estimated consolidation rate of 100 ms per orientation, an exposure duration of 200 ms should be sufficient to complete the early involuntary phase. Hence we expected that memory precision should vary depending on task requirements.

Methods

Participants

A new sample of fifty undergraduate students from Minnan Normal University (42 females, 49 right-handed, 18-23 years old) volunteered to participate in this experiment for course credit. They reported no history of neurological problems, reported having normal color vision and normal or corrected-to-normal visual acuity. Written informed consent was provided by each participant prior to the experiment. The study was conducted in accordance with the Declaration of Helsinki and was approved by the ethics committee of Liaoning Normal University.

Task and design

The design and procedure of Experiment 2 were identical to those of Experiment 1, except that the total number of items in the memory array was reduced to two. On each trial, two gratings were presented in two randomly chosen locations out of the four possible locations.

Results and Discussion

Participants earned an average of 966 points in the low-precision condition and 862 points in the high-precision condition. There was no main effect of which condition is encountered first for all dependent measures.

For the precision parameter (SD), there was a significant difference between the low-precision condition and high-precision condition, $t(49) = 7.355$, $p < .001$. But for the number of stored item (K), there was no significant difference between the two conditions, $t(49) = 0.681$, $p = .499$ (Fig. 2b). A Bayes factor analysis showed that the null hypothesis was 5.218 times more likely to be true than the alternative hypothesis for K. These results, which were different with Experiment 1, implied that memory precision was higher in high-precision than in low-precision condition but the number of memorized items remained the same across conditions. These results thus implied that participants could enhance the precision in VWM according to tasks demands when the load on consolidation is low.

In addition, we conducted a mixed-factor ANOVA with type III sums of squares by taking precision condition (high- vs. low-precision) as within-subject factor and experiment (Experiment 1 vs. 2) as between-subject factor on the SD and K parameter. For SD, there was a significant main effect of precision, $F(1, 95) = 18.933$, $p < .001$, and a significant interaction between precision and experiment, $F(1, 95) = 12.916$, $p < .001$, the main effect of experiment is not significant, $F(1, 95) = 1.418$, $p = .237$. The ANOVA further supported the conclusion that task demand did not influence memory precision (SD) in Experiment 1 but affected memory precision (SD) in Experiment 2. Furthermore, analyses of simple effects showed that in the high-precision condition, the main effect of experiment was significant, $F(1, 95) = 6.20$, $p < .05$, while in the low-precision condition, the main effect of experiment was not significant, $F(1, 95) = 0.25$, $p = .619$ for SD.

Another mixed-factor ANOVA for the K parameter only found the main effect of experiment to be significant, $F(1, 95) = 35.916$, $p < .001$, with neither the main effect of precision, $F(1, 95) = 0.003$, $p = .954$, nor the interaction between precision and experiment, $F(1, 95) = 0.194$, $p = .661$, reaching significance.

These results implied that when the set-size was two, participants can strategically control the precision of the memorized orientation. We found that set-size is the key factor responsible for the disparate results between Experiments 1 and 2. That is, reducing the number of memory items allow participants to exert voluntary control on mental commodity allocation. This is consistent with predictions of the two-phase allocation model.

Experiment 3

As explained in the Introduction, another prediction of the two-phase mental commodity allocation model is that, when exposure duration is long enough, the allocation will be able to enter the voluntary phase, even at a larger set-size. Thus, in Experiment 3, we used the same procedure as Experiment 1 but extended the exposure duration of the memory items from 200 ms to 500 ms, and tested whether

the precision and number of items could be traded off in VWM.

Methods

Participants

A new sample of forty-nine undergraduate students from Minnan Normal University (41 females, 47 right-handed, 19-23 years old) volunteered to participate in this experiment for course credit. They reported no history of neurological problems, reported having normal color vision and normal or corrected-to-normal visual acuity. Written informed consent was provided by each participant prior to the experiment. The study was conducted in accordance with the Declaration of Helsinki and was approved by the ethics committee of Liaoning Normal University.

Task and design

The design and procedure were identical to those of Experiment 1, except that we increased the exposure duration of the memory array to 500 ms.

Results and Discussion

Participants earned an average of 770 points in the low-precision condition and 682 points in the high-precision condition. There was no main effect of which condition was encountered first for all dependent measures.

For the precision parameter (SD), there was a significant difference between the low-precision and high-precision condition, $t(48) = 6.177$, $p < .001$. For the number of stored items parameter (K), there was also a significant effect of precision condition, $t(48) = 5.478$, $p < .001$ (Fig.2c). The results suggested that in the high-precision condition, participants maintained higher resolution memory representations but fewer memory items than in the low-precision condition.

In addition, we conducted a mixed-factor ANOVA with type III sums of squares by taking precision condition (high- vs. low-precision) as within-subject factor and experiment (Experiment 1 vs. Experiment 3) as between-subject factor on the SD and K parameter, respectively. For SD, there was a significant main effect of precision, $F(1, 94) = 24.014$, $p < .001$, a significant interaction between precision and experiment, $F(1, 94) = 18.625$, $p < .001$, but the main effect of experiment was not significant, $F(1, 94) = 1.158$, $p = .285$. The ANOVA further supported the conclusion that task demand did not influence memory precision in Experiment 1 but affected memory precision in Experiment 3. Furthermore, analyses of simple effects showed that the main effect of experiment was significant in the high-precision condition, $F(1, 94) = 8.18$, $p < .01$, but was not significant in the low-precision condition, $F(1, 94) = 1.77$, $p = .187$.

For K, the ANOVA showed that the main effect of precision was significant, $F(1, 94) = 16.006$, $p < .001$; the interaction between precision and experiment was also significant, $F(1, 94) = 18.159$, $p < .001$; but the main effect of experiment was not significant, $F(1, 94) = 0.820$, $p = .367$. These results again supported the conclusion that task demand did not influence memory number (K) in Experiment 1 but affect memory number (K) in Experiment 3. Furthermore, simple effects analyses showed that the main effect of experiment was not significant in the high-precision condition, $F(1, 94) = 0.70$, $p = .406$, but it was significant in the low-precision condition, $F(1, 94) = 5.64$, $p < .05$.

Here we again observed variations for both number and precision in VWM. As predicted by the two-phase model, these results demonstrated that the exposure duration is the key factor for entering the voluntary phase. For four memory items, more time is needed to enter the late, voluntary, phase, such that the quality and quantity of memory representation can be controlled.

General Discussion

The goal of the present study is to examine whether the memory mental commodity allocation is a hybrid of both voluntary and involuntary processes. We used a point reward system to differentially bias participants to store either high- or low-precision memory representations. In Experiment 1, we did not find any variation for either number or precision in VWM across conditions, indicative of an involuntary phase of mental commodity allocation. In Experiment 2, we adopted the same procedures as Experiment 1, but reduced the total number of items in the memory array from four to two. Here, we found memory precision was modulated by our reward manipulation but the number in VWM remained constant across conditions. In Experiment 3, we adopted the same procedures as Experiment 1, but increased the exposure duration from 200 ms to 500 ms. Here, we found higher memory precision and fewer memorized items in the high-precision condition than the low-precision condition. The results from Experiments 2 and 3 confirm that there is indeed a flexible commodity allocation in VWM by voluntary control, when sufficient time allows participants to enter the voluntary phase of allocation.

Since we found that participants set SD and K strategically in response to the task demands of Experiment 2 and 3, it is natural to ask whether this strategic adjustment allowed them to obtain more rewards. Under the standard mixture model, we can derive expected rewards with a particular combination of (K, SD) values and our reward rule. In Supplemental Material 2, we present this derivation and show that the observed (K, SD) combination in both Experiments 2 and 3 led to a higher expected reward in their respective conditions (high- vs. low-precision) than the alternative (K, SD). However, an exception was observed in the low-precision condition in Experiment 2, where we found had participants used the (K, SD) combination observed under high-precision condition they will obtain a higher reward. However,

this can be explained by the limited benefits due to strategic adjustment, caused by the small under-capacity set size (see more details of discussion in Supplemental Material 2). Thus, the voluntary adjustment of mental commodity allocation in response to different payoff schemes does on average lead to a higher reward. This finding is thus consistent with the suggestion that humans can perform probabilistic computations to maximize reward under certain task scenarios (Ma & Jazayeri, 2014).

A two-phase model of mental commodity allocation in VWM

We propose that mental commodity allocation is a hybrid of involuntary and voluntary process, with the voluntary allocation occurring after the involuntary allocation. In the involuntary phase, participants have to first consolidate each item by allocating a small amount of mental commodities (one slot or a small amount of resource) to create some low-resolution representations. Only after the completion of this involuntary phase, can they re-allocate the mental commodities voluntarily according to the task demand. From a cognitive processing point of view, voluntary allocation requires top-down control, which presumably takes extra processing time. In studies of selective attention, for example, it is known that it takes more time to deploy top-down attention than bottom-up attention (Jonides, 1981; Liu, Stevens, & Carrasco, 2007; Muller & Rabbitt, 1989; Pinto, van der Leij, Sligte, Lamme, & Scholte, 2013). From an information theoretical point of view, the involuntary phase can maximize the storage of information with little cost of control, thus providing an efficient mechanism for consolidation. From an ecological point of view, this arrangement also makes sense. When we first encounter a visual scene, it seems beneficial to sample as much information as possible, to detect potentially important objects. An automatic, involuntary process would be suitable for such a sampling purpose. This view is in line with Liesefeld, Liesefeld, and Zimmer (2014)'s findings that participants first have to process all items to a certain degree before they determine whether any irrelevant items are present. Interestingly, a recent study proposed that when a new item is encountered in the environment, it can gain access to VWM automatically without the need for executive resources (Allen, Baddeley, & Hitch, 2014), thus also lending support to our current proposal of the involuntary phase.

After the completion of this involuntary phase, participants should be able to consolidate more visual information for readjusting mental commodity allocation according to task demands. Such reallocation requires participants to use either free mental commodities (if available at the end of the involuntary phase) or release some mental commodities for reallocation among items (when all of the mental commodities have been used at the end of the involuntary phase). In both cases, memory precision for items that are represented by more mental commodities will be improved. Furthermore, this kind of storage likely needs to acquire new information from either the physical stimuli or their visible persistence, as simply duplicating information by existing representations should not increase the informational content,

hence the precision, of the memory. Because visible persistence decays rapidly over time, voluntary allocation would need longer stimulus duration than involuntary allocation. We have thus manipulated stimulus duration in our experiments and interpreted our findings in terms of consolidation of VWM representation. However, traditional consolidation studies tended to use post masks while manipulating stimulus-mask interval (Fuller et al., 2009; Fuller, Luck, McMahon, & Gold, 2005; Vogel et al., 2006). This raises the question of whether our effects could be due to differential amount of attention during perceptual encoding stage, which presumably precedes memory consolidation. We did not use masks because that would likely interfere with the mental commodity reallocation process we intended to study (see Footnote 3). Furthermore, had participants been able to strategically allocate differential amount of attention to items during encoding, by, for example, attending to fewer items in the high-precision condition, similar to what a "zoom-lens" model of attention would predict (Eriksen & St James, 1986), they should be able to trade off the number and precision of memory in Experiment 1. The absence of such trade-off suggests that our results are due to the later consolidation stage, rather than encoding. More studies are needed to further examine the flexibility of both the encoding and consolidation stage.

We would like to point out that the two-phase model is compatible with both the slot-based and resource-based theories of VWM. In the first phase, each item is stored with less mental commodities (slots or resources) as a result of rapid and effective consolidation; this process may not consume all the mental commodities. This can explain the results of Experiment 1. After the basic consolidation, mental commodity allocation become more flexible, such that resources could be prioritized to fewer items, which improves memory precision, but with a concomitant cost to other items. Thus, it is easy to understand that participants could reallocate their mental commodities voluntarily in Experiments 2 and 3. Importantly, both theories accept that mental commodities can be focused on a smaller number of items to improve precision. Thus our two-phase model is generally compatible with both slot- and resource-based theories.

Accounting for other results in the literature with the two-phase process

The two-phase model can also account for previous results on this topic. First, we would like to reiterate that if the memory array is presented briefly, not all of items can be consolidated. Under such conditions, memory performance may reflect a limit in consolidation instead of storage capacity. Indeed, we recommended 100 ms per item as the exposure duration when investigating VWM capacity based on our studies on VWM consolidation (Miller et al., 2014). Thus, it is worth noting that previous studies that found no trade-off between memory precision and number tended to use shorter exposure times than our recommended time. According to the two-phase model, participants are still engaged in the involuntary phase of mental commodity allocation at brief exposure times, hence no trade-off is possible.

On the one hand, Murray et al. (2012) used 200 ms exposure duration with four items, and Zhang and Luck (2011) used 200 ms exposure duration with four or six items (Murray et al., 2012; Zhang & Luck, 2011). Neither study observed trade-off in memory precision vs. number under various incentive instructions. Furthermore, in an ERP experiment that used the contralateral delay activity (CDA) to index the amount of information maintained in VWM (Luria, Balaban, Awh, & Vogel, 2016; Vogel & Machizawa, 2004),we used 100 ms exposure duration (with two to four items) and manipulated memory precision by asking participants to detect either a salient change (low-precision) or a subtle change (high-precision) in color. We found that the precision manipulation did not influence memory capacity, i.e., no trade-off between precision and number in VWM (Ye et al., 2014). Recently, He et al. (2015) also used 200 ms exposure duration (with two and four items) and replicated our results in similar experiments (He et al., 2015).

On the other hand, in Machizawa et al. (2012)'s study, where participants remembered two items at 200 ms exposure duration, it is possible that they have finished the involuntary phase and entered the voluntary phase where they could allocate more mental commodities to one item to raise the representation precision (Machizawa et al., 2012). Similarly, in Gao, Yin, et al. (2011)'s study, where participants remembered four items at 500 ms exposure duration, participant likely had enough time to consolidate all items into VWM, so they could have entered the voluntary phase (Gao, Yin, et al., 2011). Under this explanation, previous studies supporting the involuntary mental commodity allocation were likely caused by a lack of consolidation time, even though participant are able to allocate the mental commodities by voluntary control after the involuntary phase.

Although our results are generally in line with these previous studies, our study goes beyond these studies in that it offers a new model, i.e., the two-phase mental commodity allocation model, to reconcile discrepant findings from these studies. Our new model is based on new data obtained under better experimental control than previous studies. Our experiments were conducted with the same procedure using identical stimuli, allowing us to make direct comparisons across experiments. In addition, most of these prior studies adopted the change detection task and thus can only indirectly infer how memory precision changed based on a single accuracy measure of performance (He et al., 2015; Machizawa et al., 2012; Murray et al., 2012; Ye et al., 2014). In our study, we used an orientation recall task and performed quantitative model fitting to separately assess the probability that a memory was stored and the precision of the memory. We can thus directly observe the change in memory precision, going beyond the coarse measures obtained with the change detection task. Thus, our study offers further opportunity to systematically examine individual differences and the detailed mechanisms of mental commodity allocation.

Is the first phase mandatory?

An open question is whether participants could bypass the first phase and go directly to the second in some special conditions. Based on our results, it seems that the involuntary phase could not be avoided. However, it might be possible to shorten the time cost of first phase in some cases. For instance, if a pre-cue indicates one location before the memory items appear, participants could use attention to only encode the item at the cued location. They would only need to allocate mental commodity involuntarily to one item, which would take less time to complete. Since ERPs can provide a measure of stimulus-related processing with a high temporal resolution, future study could consider to use ERP component such as CDA, LPC (late positive component), which was believed to be related to the maintenance of working memory and reflect the top-down control activity of the PFC over the posterior regions (Gao, Xu, et al., 2011; Li, Li, & Luo, 2006), as the index to test this possibility.

Predictions of the two-phase model

Although the two-phase model can accommodate results in the current literature, one may wonder whether it can make novel predictions. We think the two-phase model can lead to a counterintuitive prediction, which is that when participants are asked to remember many items with high resolution, they would create more representations at short stimulus exposure duration than at long exposure duration. This is because participants would involuntarily allocate mental commodities to each item in the first involuntary phase, but reallocate the mental commodities to less complex items to create the high resolution representations in the second voluntary phase. This prediction is counter to the standard effect that memory rate increases as exposure duration prolongs (P. M. Bays, Gorgoraptis, et al., 2011). This prediction seems to have been supported by a recent ERP study. Gao, Ding, Yang, Liang, and Shui (2013) used the CDA component as a neural marker and asked participants to remember two and four complex shapes in different exposure duration conditions (100 ms vs. 500 ms). They observed that CDA was higher for four complex shapes than two complex shapes at 100 ms exposure duration, yet this difference vanishes at 500 ms exposure duration. They suggested that participants could remember three to four items at short exposure durations, but only one to two items during long exposure durations. These results are thus in broad agreement with the two-phase model. However, more direct evidence, as well as more thorough investigation of the time course of allocation is needed to further test this prediction in future studies.

Summary and Conclusion

In summary, our results support the notion that mental commodity allocation during VWM is a two-phase process. Participants initially allocate mental commodities via an involuntary consolidation process in a stimulus-driven mode, after which they could allocate mental commodities via voluntary control according to the task requirements.

Note

1. Here we use the neutral term *mental commodity*, following Suchow et al. (2014)'s to indicate the slots of slot-based theory or the resource of resource-based theory.
2. In addition to the previous models, there is another hybrid model of discrete slot-based theory and continuous resource theory called *bounded resource model*, which proposes a flexible continuous resources pool as well as a maximum number of how many items can be stored (Alvarez & Cavanagh, 2004; Awh, Barton, & Vogel, 2007; Suchow et al., 2014).
3. In general, the use of masks to control stimulus exposure time would have been a more rigorous approach in experimental design. But we know that masks can disrupt the consolidation process for memory items. One recent study found that in a recall task even the object-substitution masking can cause degradation in the precision of VWM representation (Harrison, Rajsic, & Wilson, 2015). We did not use masks because if the early phase of commodity allocation is involuntary, masks themselves can be consolidated into VWM, which was irrelevant information and would increase noise in our data.
4. The standard mixture model has two parameters, guess rate (G) and mnemonic precision (SD). The K value is calculated by multiplying the set size with the probability of memory encoding (i.e., 1- G).

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Figure 1.

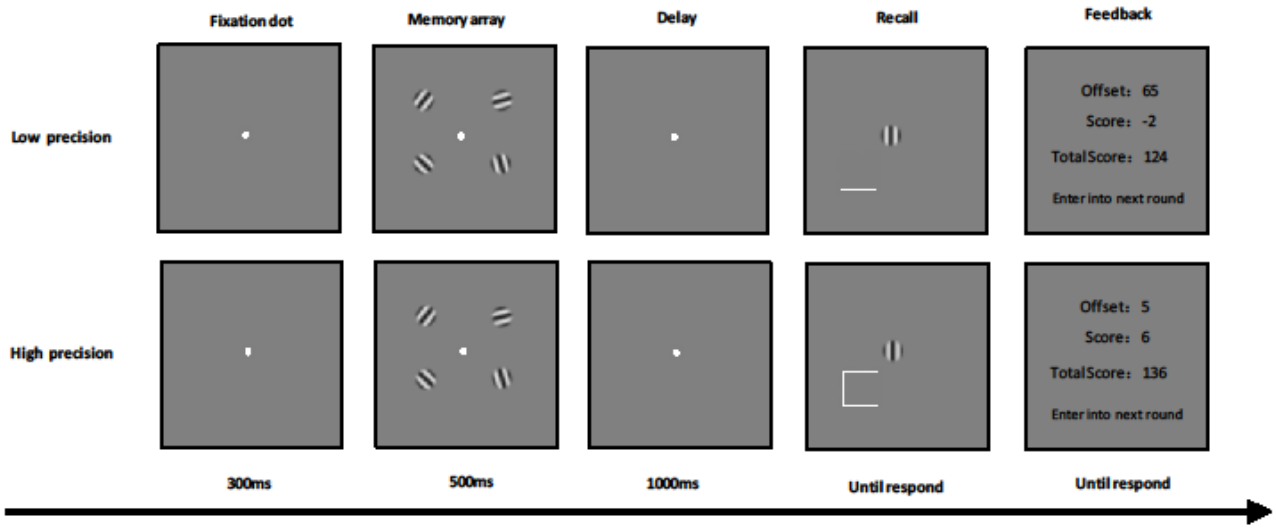

Fig.1 *Trial structure of Experiment 1. A low-precision condition (top row) and a high-precision condition (bottom row) were illustrated.*

Figure 2.

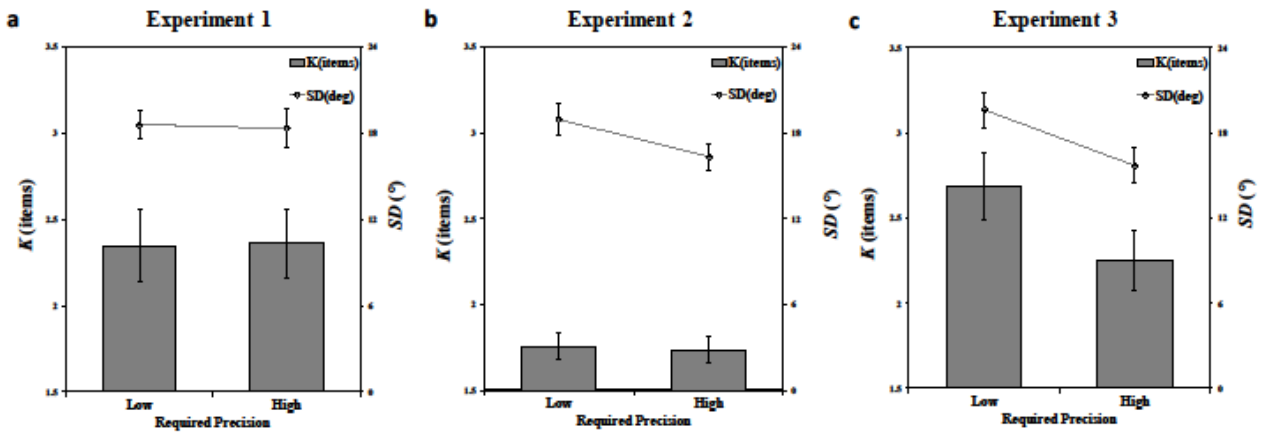

Fig.2 *The results of Experiment 1(a), 2(b) and 3(c), which each experiment in a column. The standard deviation (SD) and the mean number of items stored in memory (K) are plotted separately for the low-precision and high-precision conditions. Error bars are standard error of the mean.*