Dissociating models of visual working memory by reaction-time distribution analysis

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Abstract
There have been heated debates on whether visual working memory (VWM) represents information in discrete-slots or a reservoir of flexible-resources. However, one key aspect of the models has gone unnoticed, the speed of processing when stored information in memory is assessed for accuracy. The present study evaluated contrasting predictions from the two models regarding the change detection decision times spent on the assessment of stored information by estimating the ex-Gaussian parameters from change detection RT distributions across different set sizes (2, 4, 6, or 8). The estimation showed that the Gaussian components μ and σ became larger as the set size increased from 2 to 4, but stayed constant as it reached 6 and 8, with an exponential component τ increasing at above-capacity set sizes. Moreover, we found that an individual’s capacity limit correlates with the memory set size where the Gaussian μ reaches a plateau. These results indicate that the decision time for assessing in-memory items is constant regardless of memory set sizes whereas the time for the remaining not-in-memory items increases as the set size exceeds VWM storage capacity. The findings suggest that the discrete-slot model explains the observed RT distributions better than the flexible-resource model.

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1. Introduction

Visual working memory (VWM) is a cognitive construct, serving as an online workplace to temporally store a set of visual information that is no longer visible, and has been shown to play an important role for various perceptual and cognitive functions (Gazzaley & Nobre, 2012; Hollingworth & Luck, 2009; Süß, Oberauer, Wittmann, Wilhelm, & Schulze, 2002). Despite the important role, VWM storage capacity is highly limited with regard to the amount of information it can retain at a time (Cowan, 2001; Luck & Vogel, 1997). Many studies have demonstrated that VWM performance gradually declines as the number of to-be-remembered objects increases (Alvarez & Cavanagh, 2004; Luck & Vogel, 1997; Todd & Marois, 2004).

There have been intense debates on VWM models, with two contrasting hypotheses standing against each other (Bays & Husain, 2008; Zhang & Luck, 2008). First, the “slot” model proposes that VWM represents information according to a number of discrete fixed-resolution slots, determining VWM storage capacity (Awh, Barton, & Vogel, 2007; Luck & Vogel, 1997; Vogel & Machizawa, 2004; Zhang & Luck, 2008). Second, the “resource” model proposes that VWM rather represents information according to a limited pool of resources, flexibly allocated to each item as memory set size increases (Bays, Catalao, & Husain, 2009; Bays & Husain, 2008; Wilken & Ma, 2004).

The models critically differ in the expected variability in participants’ recall if the memory set size is over the VWM storage capacity limit (Bays & Husain, 2008; Zhang & Luck, 2008). The slot models expect that only the memory items selected for the slots are represented with high precision whereas the memory items not in the slots are represented with zero precision, and thus, recall errors made according to the items not in the slots must be random guesses. Contrastingly, the resource models expect that every item is represented in memory with fewer and fewer resources available for each item as the memory set size increases. Thus, recall errors must be made with some systematicity, for instance, a gradual increase of variability in recall responses as set size increases.

Nevertheless, evidence for each model so far appears inconclusive. Some supported the discrete-slot model’s account by showing constant precision of in-memory items over the VWM capacity limit (Zhang & Luck, 2008), while others demonstrated that the flexible-resource model outperforms the slot models when explaining VWM recall performances (Bays et al., 2009; van den Berg, Shin, Chou, George, & Ma, 2012).

Rather than analyzing errors, the present study focused on the decision processes for change detection where several items are briefly remembered and tested with a probe display with or without a change (Luck & Vogel, 1997). We assumed that change detection requires a
decisional process operating according to accumulated evidence and noise from in-memory items (Nosofsky & Palmeri, 1997; Usher & McClelland, 2001), which affect subsequent change detection reaction times (RTs). We also postulated that the change detection decision time is primarily determined according to the time spent on retrieving and recognizing the items in memory, or according to the time spent on guessing if the items are not available for accurate change detection (Donkin, Nosofsky, Gold, & Shiffrin, 2013; Nosofsky & Donkin, 2016).

Fig. 1 conceptualizes how the given items are represented in VWM (i.e., in-memory items) from the standpoint of the slot and resource models respectively, and their expected decision times spent on assessing the mnemonic evidence. The discrete-slot model assumes that approximately four slots with high precision are available for representing memory items in VWM, and the remaining items are completely discarded from memory, with virtually zero resolution if the total number of items exceeds the memory capacity limit. Excluding the items from the slots leads to completely random guesses to determine change presence or absence when recall is necessary (Zhang & Luck, 2008). In contrast, the resource models, which lack such slots, provide no expectation for in-memory items (Bays & Husain, 2008).

When memory set sizes are less than the presumptive storage capacity, both models would predict gradual increase of change detection decision time along with increasing memory set sizes for in-memory items. For instance, the major slot model proposes a slots-plus-averaging hypothesis, where resolution of the available slots is averaged to represent given memory items. This averaging process provides more accurate and faster decisions for change presence or absence as the set size decreases below the number of available slots (Zhang & Luck, 2008). The limited-resource model also predicts an analogous pattern of more accurate and faster change detection decisions at the corresponding set sizes, through which more resources become available for in-memory items (Bays & Husain, 2008).

The critical difference in the in-memory decision time between the models is found when set sizes exceed the capacity limit where retaining all of the given memory items becomes sufficiently challenging. Despite the challenge, the slot models guarantee immediate retrieval and recognition of the in-memory items for which high-resolution slots are available. Thus, the subsequent decision times are expected to be constant and reliable regardless of the increasing set sizes (i.e., plateau). In contrast, the resource models, which lack such slots, provide no guarantee of immediate retrieval and recognition. Rather, the models expect that the retrieval and recognition of the in-memory items is incrementally delayed with added variability as memory set size increases because the resources for each item becomes less and less available for the increased set sizes. The resource models thus expect the presence of guesses for in-memory items even with the earliest set sizes whereas the slot models expect few guesses unless the memory set size exceeds the presumptive storage capacity.

Unlike the decision for in-memory items, similar patterns of incremental decision times along the set sizes for both models can be expected in change detection for not-in-memory items at over-capacity set sizes. The slot models expect no precision at all for not-in-memory items, and thus expect random guesses when change presence or absence is determined. The probability of guessing is expected to increase as the set size becomes larger because the number of not-in-memory items increases along the set sizes, subsequently adding incremental delays and variability to the change detection decision time. The same principle applies to the limited resource model, where the precision of memory items decreases along the increasing set sizes in a gradual fashion rather than an all-or-nothing fashion. Regardless of whether the set sizes are under or over the storage capacity, the resource models expect probabilistic guesses to increase incrementally as the precision of memory items drops gradually with increasing set sizes. Therefore, for not-in-memory items, the key difference between the predicted decision time for the two models lies in the fact that the slot models expect the guesses to begin only if memory set size exceeds a known capacity limit (i.e., number of slots), whereas the resource models expect the guesses to be present from the earliest set size, at which the probability of the guesses increases further and further along the increasing set sizes. These predict a pattern of gradually-increasing decision times that is virtually analogous between the two models, especially if the memory set sizes exceed the capacity limit postulated by the slot models.

When using a popular conventional central tendency measure such as mean RTs where the decision times for both in-memory and not-in-memory items are incorporated and averaged, it may however be difficult to practically determine which models better explain the observed RTs at the over-capacity set sizes because they both expect the probability of guessing to increase gradually along the set sizes over the slots models’ capacity limit. When this pattern of over-capacity decision times is combined with the pattern of in-memory decision times, the slot models’ plateau, predicted at the set sizes, becomes vulnerable to the incremental delays added by the increased uncertainty in guessing for not-in-memory items. This vulnerability can lead eventually to a pattern of incremental delays for mean RTs that is analogous to the pattern expected for the corresponding set sizes from the limited-resource model. The conventional mean RT analysis therefore does not appear desirable for dissociating the two models unless there is a way to partition the change detection trials and their RTs depending on whether the...
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