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Recognition Decisions From Visual Working Memory Are Mediated by Continuous Latent Strengths

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Abstract

Making recognition decisions often requires us to reference the contents of working memory, the information available for ongoing cognitive processing. As such, understanding how recognition decisions are made when based on the contents of working memory is of critical importance. In this work we examine whether recognition decisions based on the contents of visual working memory follow a continuous decision process of graded information about the correct choice or a discrete decision process reflecting only knowing and guessing. We find a clear pattern in favor of a continuous latent strength model of visual working memory–based decision making, supporting the notion that visual recognition decision processes are impacted by the degree of matching between the contents of working memory and the choices given. Relation to relevant findings and the implications for human information processing more generally are discussed.

Keywords: Decision making; Working memory; Visual memory; Recognition; Short-term memory

1. Introduction

Do people utilize continuous or discrete processing during cognition? The quality of information to which we have access is a fundamental question for any cognitive process. This question is especially relevant in the domains of decision making and working memory, the latter being the immediately accessible information available for ongoing cognitive processing. Understanding the nature of decision making and how it interacts with working memory is crucial as working memory is needed in most domains of complex cognition (Barrouillet & Lecas, 1999; Daneman & Carpenter, 1980; Engle, Tuholski,

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Laughlin, & Conway, 1999; Kane et al., 2004; Kyllonen & Christal, 1990; Ormrod & Cochran, 1988; Süß, Oberauer, Wittmann, Wilhelm, & Schulze, 2002), and decision-making phenomena may be influenced by working memory processes (Hatfield-Eldred, Skeel, & Reilly, 2015; Hinson, Jameson, & Whitney, 2003; Shamosh et al., 2008). We explore whether recognition judgments involving the contents of visual working memory have access to continuous latent stimulus strengths or, rather, rely on discrete knowing and guessing states. It may be that we have access to a continuous measure of how well a stimulus matches the contents of memory, or we may only have access to discrete information about whether a stimulus matches the contents of working memory while the detailed information used to arrive at this conclusion remains inaccessible.

It is useful to start by clarifying what is meant by continuous and discrete processes. Most continuous latent strength approaches to information processing follow the basic principles of signal detection theory (Green & Swets, 1966). In signal detection, stimuli give rise to a continuously varying latent (internal) strength signal. This strength can vary from trial to trial even for repeated stimulus presentations. Across many trials, the distribution of latent signal strength for a particular stimulus depends on the strength of the stimulus itself, with stronger stimuli leading to stronger latent signals. In perceptual identification tasks, the stimulus is reported as observed if this latent strength exceeds some criteria level. Signal detection theories, and other approaches which include gradually graded evidence, are considered continuous approaches because the critical latent signal strength varies along a continuum.

Latent strength theories can be contrasted with discrete approaches to information processing in which detection of the presence or absence of stimulus is an all-or-nothing process with no quality or strength information maintained (Luce, 1963; Rouder et al., 2008). When the presence or absence of a stimulus is detected, a representation of the stimulus is created and judgments about the stimulus should be very accurate. If detection does not occur, no representation is created and all judgments regarding the stimulus must be guesses because no representation of the stimulus is available to the observer. These models are considered discrete in that a stimulus is either represented or it is not, there is no continuum of partial knowledge or partial signal strength.

Although the examples above concern detecting the presence or absence of a stimulus, the distinction between continuous and discrete signals is analog in other areas of cognition. Debates about whether a continuous or discrete resource determines the capacity of working memory has been a popular topic of research in recent years. These two approaches are often contrasted within the delayed production task paradigm. In this task participants must reproduce a set of studied colors, orientations, or shapes at test. Although both continuous and discrete models generally predict the same mean response error, the two approaches predict differing distributions of response errors.

Continuous approaches argue that there is only one memory resource, but that it is continuously divisible among any number of items (van den Berg, Awh, & Ma, 2014; Fougine, Suchow, & Alvarez, 2012; Ma, Husain, & Bays, 2014). As the number of items maintained increases, the amount of the resource devoted to each item shrinks, leading to decreases in representational precision. Within the delayed production task a continuous

resource model leads to the prediction that increases in the number of items maintained results in an increase in the standard deviation of errors centered on the studied angle. Discrete model approaches characterize the number of items that can be maintained as a limited and fixed number (Donkin, Nosofsky, Gold, & Shiffrin, 2013; Nosofsky & Donkin, 2016; Rouder et al., 2008; Zhang & Luck, 2008), generally around four items (Cowan, 2001; Luck & Vogel, 1997). As the number of items in the memory set increases above the capacity limit, the probability of storing an item drops because capacity is full and cannot accommodate the entire set. Under this model, each item is either maintained with relatively high precision or not at all. Within the delayed production task a discrete resource model leads to the prediction that increases in the number of items to maintain result in an increased probability that pure guessing will occur. Pure guessing is observed mathematically as a uniform distribution of random responses across the entire representation space. In general, continuous resource models tend to outperform discrete resource models if the continuous model includes parameters for variation in the amount of the resource deployed to any given item or on any given trial (van den Berg, Shin, Chou, George, & Ma, 2012; van den Berg et al., 2014). However, a number of researchers favoring discrete approaches have begun to question the validity of the underlying assumptions governing continuous variation in resource amount across trials and stimuli (for an example, see Nosofsky & Donkin, 2016).

Although most research examining differences between continuous and discrete models of working memory have focused on characterizing capacity resources, this approach has also been applied to several other aspects of working memory performance. For example, in the retrocue paradigm a single item within a memory set is cued during the retention interval of a working memory task. The cued item has a much higher likelihood of being tested and shows much better memory performance at test than do non-cued items (Murray, Nobre, Clark, Cravo, & Stokes, 2013; Souza & Oberauer, 2016; Souza, Rerko, & Oberauer, 2016; Williams, Hong, Kang, Carlisle, & Woodman, 2013). Continuous process models of the retrocue effect are consistent with the cued item receiving some degree of protection to its representational precision relative to non-cued items. Discrete process models of the retrocue effect are consistent with an increasing in the probability that the cued item will be in memory at the time of test. Results from this paradigm strongly favor a discrete process (Murray et al., 2013; Souza et al., 2016; Williams et al., 2013). Although some do find increases in precision at low set sizes (Williams et al., 2013), this can be accommodated by the discrete slots plus averaging model where subcapacity set sizes result in duplicate representations of the target item being maintained in separate memory slots (Zhang & Luck, 2008).

Other areas of focus for the modeling of continuous and discrete processing within working memory have included time-based forgetting (Souza & Oberauer, 2015; Zhang & Luck, 2009) and encoding into working memory (Bays, Gorgoraptis, Wee, Marshall, & Husain, 2011). In the realm of time-based forgetting, the effects of time are consistent with discrete loss of entire items and discordant with the continuous gradual loss of precision over time (Souza & Oberauer, 2015; Zhang & Luck, 2009). In contrast, encoding of

items has been characterized as a continuous process in which representational precision of memory items is gradually increased over time (Bays et al., 2011).

Here, we focus on understanding a different aspect of the working memory system. We examine whether the decision-making process relies on continuous signal strength or discrete knowing and guessing states during visual working memory recognition. The nature of the resource used in making a response decision has been neglected when compared to the amount of effort directed toward memory maintenance processing. We hold constant the contents of working memory, encoding demands, and maintenance demands within each of our experiments. As such, we do not and cannot make conclusions about the resource governing visual working memory storage capacity, encoding processes, or forgetting processes. Instead, we manipulate the difficulty of the decision process that occurs when making a recognition decision based on the contents of working memory. It may be that we have access to a continuous measure of how well a stimulus matches the contents of memory, or we may only have access to discrete information about which stimulus best matches the contents of working memory while the detailed information used to arrive at this conclusion remains inaccessible. In the following pages we answer this question.

Understanding how decision making and working memory interact is of importance given the involvement of working memory in non-optimal decision making (Finn, Gunn, & Gerst, 2015; Hatfield-Eldred et al., 2015; Pecchinenda, Dretsche, & Chapman, 2006). When making recognition decisions about the contents of working memory, it may be that people have access to rich continuously graded information reflecting how well a present stimulus matches the contents of memory. If this is the case, and if it holds for non-recognition decisions, we may be able to make use of this graded information to improve decision making more generally. Alternatively, people may only have access to basic discrete information about whether or not a stimulus matches the contents of working memory and no detailed information about the match quality or strength. While we do not investigate ways to improve general decision making in this work, understanding the basic processes involved in making working memory-based decisions is a necessary first step in this direction.

To assess whether recognition decisions about the content of working memory are mediated by latent strength or discrete states, we manipulate the difficulty of the decision-making step, while holding all other factors constant, and look for patterns in confidence rating responses which reflect either continuous or discrete decision-making processes. Confidence ratings have proven useful in differentiating continuous and discrete processes within long-term memory (Bröder, Kellen, Schütz, & Rohrmeier, 2013; Kellen, Singmann, Vogt, & Klauer, 2015; Morey, Pratte, & Rouder, 2008; Province & Rouder, 2012; Van Zandt, 2000), demonstrating their validity as an experimental tool. Our approach to assessing continuous versus discrete-state processing is similar to the approach used by Province and Rouder (2012) in long-term memory and Swagman, Province, and Rouder (2015) in perceptual word identification, although we differ from these studies here in that we manipulate the decision process and not the stimulus strength. We present memory items in a traditional visual working memory change

detection manner (Cowan, 2001; Luck & Vogel, 1997; Ricker & Cowan, 2010; Rouder et al., 2008), but at test we follow Province and Rouder and Swagman et al. and present two rather than one probe. The participant must simultaneously indicate which one of the two probes was part of the memory set and indicate his or her confidence by using a slider (see Fig. 1). Difficulty of the decision-making step is controlled by varying the similarity of target and lure probes during this two-choice test. By manipulating the overall decision difficulty and collecting confidence ratings we can assess whether the information available in making this decision varies continuously, following a latent strength representation, or if people enter discrete states of knowing or guessing based on the contents of working memory, and respond accordingly. The logic of this assessment is as follows:

1.1. Predictions for this research

In our paradigm, as in most other commonly used approaches to assessing working memory, latent strength and discrete-state models make exactly the same predictions concerning mean accuracy and mean confidence rating. Looking at the data in aggregate is not diagnostic of which process is at work. However, latent strength and discrete state models do make differential predictions about the distribution of individual confidence ratings across task difficulty levels. One of the key features of our paradigm is that the distribution of confidence under guessing, should it exist, may be isolated. To ensure that there are trials where the participant has no diagnostic information, we sometimes present two unstudied lure probes at test. In this *impossible condition*, the lures are equally distant from the true studied value. The impossible condition alone is not diagnostic, but will be critical nonetheless. Fig. 2a and b show the model distribution of confidence for latent strength and discrete-state models, respectively. The prediction for this impossible

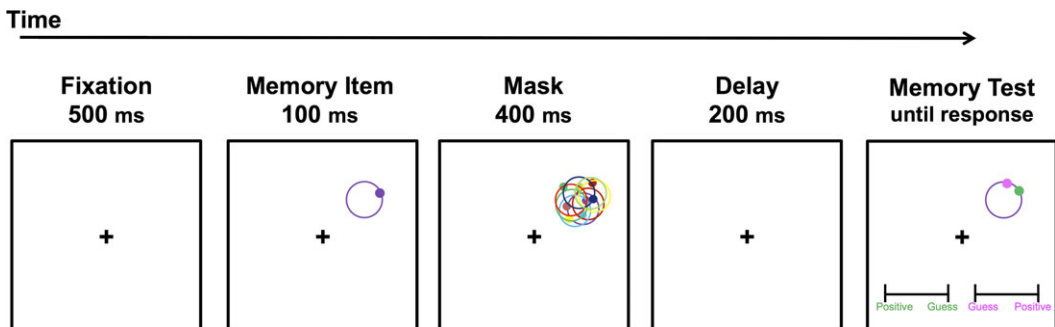


Fig. 1. An example of a single trial in Experiment 1. Participants were to indicate which of the two dots presented at test matched the memory item by moving the slider toward the appropriate side. The left side of the slider was always in green, matching the color of one dot. The right side of the slider was always in pink, matching the color of the other dot. Higher confidence in the response was indicated by moving the slider further away from the center position.

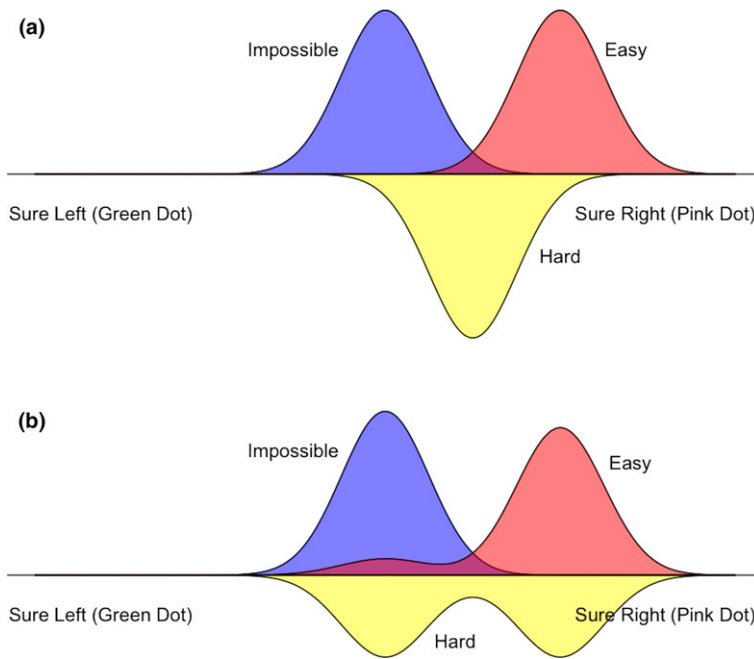


Fig. 2. Graphical depictions of the predicted confidence rating response frequency under each of our models, when the correct answer is on the right side of the response bar (i.e., the pink dot). Responses closer to the extreme ends of the response bar represent higher confidence. Each curve in this figure represents responses under a different condition; blue = impossible forced-guessing trials, yellow = hard trials, red = easy trials. The yellow curve is plotted down for clarity and overlap reduction, not to represent a negative response frequency. The latent strength model (a) predicts a shift in confidence as the condition becomes easier. The critical element of this model is that confidence ratings from the hard condition follow a unimodal distribution with values intermediate to the impossible and easy conditions. The discrete-states model (b) predicts a change in the mixture of responses from guessing and knowing states as the condition becomes easier. The critical element of this model is that confidence ratings from the hard condition follow a bimodal pattern reflecting a mixture of the impossible and easy conditions.

condition is shown as the centered blue distribution, and it is the same for the two models.

There are two other stimulus conditions, which we term the *easy condition* and *hard condition*. In the easy condition, the correct probe is presented along with a lure that is not at all similar to the memory item, resulting in highly accurate performance. Both models may capture this type of pattern as shown by the red distribution in Fig. 2.

The critical condition is the hard condition. Here, the incorrect lure probe has a high similarity to the correct probe. Latent strength models (LS model) predict that there should be high signal strength for both probe items, although on average higher strength for the correct probe than the highly similar lure. The model predicts a distribution of confidence responses with approximately the same shape as other conditions,

but a mean magnitude between those of the impossible and easy conditions. This distribution is shown in yellow, and it is projected downward rather than upward to reduce clutter and improve the clarity of the figure. Discrete-state models make a different prediction for the hard condition. Accordingly, responses are conditional only on the state of the observer, either a guess or know state, and the response reflects membership in this state. In the hard condition, discrete-state models predict that there should be a larger proportion of responses from the guess state than in the easy condition. There is no prediction of a shift in the magnitude of individual responses themselves, but rather a change in the proportion of responses in the guess and know states (see Fig. 2b). To summarize, differentiating between models can be done by observing whether the latent strength of the memory shifts from low confidence to high confidence with decreasing difficulty, or if responses are composed of a mixture of higher-confidence and lower-confidence responses, with changes in the proportionality of this mixture following changes in difficulty.

We use the logic presented in Fig. 2 and articulated above to assess whether latent strength or the know-or-guess discrete-state model better accounts for recognition decisions. In Experiment 1, a single item is presented in the study display. In Experiment 2, three items are presented in the study display more in line with what experimenters conventionally use to load working memory. To foreshadow, model-based analysis reveals that in both experiments the latent strength model provide a better account of recognition decision making, indicating access to a continuous resource in decisions based on the contents of working memory.

2. Experiment 1

In Experiment 1, we use a two-choice judgment task (Kellen et al., 2015; Province & Rouder, 2012; Swagman et al., 2015) but modify the procedure for use with common visual working memory task demands and stimuli. Previous work by Province and Rouder (2012) and Swagman et al. (2015) manipulated long-term memory stimulus strength and perceptual stimulus strength, respectively. In contrast, we manipulate the difficulty of the decision-making step while holding the memory stimulus constant across all conditions. This procedure will allow us to make direct attribution of our findings to the decision-making process used in evaluating the contents of visual working memory. Importantly, our conclusions will not depend on the nature of the capacity resource underlying visual working memory because encoding and maintenance demands are constant across all conditions.

The procedure in this experiment is similar to a standard visual working memory production task with two exceptions. This experiment only requires that participants remember a single item and requires a two-alternative forced-choice confidence response rather than a production or change detection response. Our memory items are the orientation of a stimulus, and responses are made by indicating which one of two probed angles was presented in the memory item.

2.1. Method

2.1.1. Participants

Twenty-nine college students (17 women) attending the University of Missouri participated in the experiment. Ages were between 18 and 23 years.

2.1.2. Materials

Memory items were hollow rings, 2.5 cm in diameter, with a single dot, 4 mm in diameter, located at some point along the ring. The task was to remember the location of this dot on the edge of the ring. The post-perceptual mask was composed of eight circles identical to the circles used to present the memory items, presented at the location of the memory item, but slightly displaced, as well as eight dots identical to the dots used in memory item presentation, presented at a random location within the area occupied by the eight masking circles. See Fig. 1 for a graphical depiction of these stimuli.

2.1.3. Design

Participants were instructed to indicate which one of the two dots was the memory item presented and, simultaneously, to indicate their confidence in their response by clicking on a response bar. Only one factor varied across trials, the displacement of the lure item relative to location of presentation for the memory item. Valid trials (easy and hard conditions) presented both the correct memory item and a lure item. Impossible trials presented two lure items to observe pure guessing responses. Valid trials composed 80% of the total trials, whereas impossible trials were presented on the remaining 20% of trials. On valid probe trials the lure was located 40° or -40° from the location of the correct dot on hard trials and 80° or -80° from the location of the correct dot on easy trials. Lure displacement was determined randomly on each trial. On impossible trials, the two lures were presented 20° and -20° from the memorized location. A subset of the participants was presented with a slightly different set of displacements: easy trials at 30° or -30° , hard trials at 15° or -15° , and impossible trials at 7.5° and -7.5° from true orientation. This was done between participants when exploring the difficulty of the task, and as both sets of displacement produced similar results, we ignore this difference going forward. There were 8 practice trials and five blocks of 60 experimental trials.

2.1.4. Procedure

An example of an experimental trial is presented in Fig. 1. The background color was black throughout the experiment. Each trial was initiated by pressing the space bar. Upon initiation a white fixation cross appeared on the screen for 500 ms. Next a single memory item was presented for 100 ms at one of eight possible locations. These locations were each 4.5 cm from fixation, directly above, below, to the right, and left of fixation, as well as the locations that would result from rotating this set 45° around fixation. Next, the item was masked for 400 ms. Memory item and mask descriptions can be found in the materials section above. A brief 200 ms delay followed the mask, after which the

response screen was presented. This screen consisted of the memory probes and a response bar.

The correct probe item was a representation of the memory item with the addition of a second lure probe on the circle. The probe dots were always colored one pink and one green, determined randomly. The response bar was a white horizontal bar 23 cm long, presented in the center of the bottom portion of the screen, below all possible presentation locations. There was a small 1 cm gap located at the middle of the bar indicating that participants could not respond agnostically with respect to which dot they thought was the originally presented dot. At the four end points of the bar, the left and right extremes and the edges of the gap in the middle, there were vertical lines 1 cm in length with their centers at the middle of the horizontal line. At these points the words *positive* and *guess* were written at the outer extremes and inner gap boundaries, respectively. The words on the left were green while the words on the right were pink.

The response screen lasted until the participant made a response. Participants were instructed to move a rectangular cursor along the response bar toward the side with words written in the color of the correct dot location and to click on the desired location. Further toward the outer edges of the response bar represented higher confidence in the response. In this way the accuracy and confidence rating were collected in a single response. After a response was entered an intertrial screen was presented with the phrase “press space to continue” presented in center of the screen. Practice trials were identical to the experimental trials. During the practice trials an experimenter monitored performance and offered any instruction necessary to be sure that the participants understood all task instructions.

2.1.5. Analysis

We instantiated the latent strength and discrete-state accounts as formal models. The first model, which we will refer to as the LS model, captures the latent strength prediction that moving from low-confidence responses to a strong-confidence response occurs due to a gradual increase in the discrimination signal as the separation between the probe and lure increases (see Fig. 2a). The second model, which we will refer to as the discrete-states model (DS model), captures the discrete-state prediction that the available information is only a function of being in one of two states, guessing and knowing (see Fig. 2b). The response is a mixture of responses from these two states with the proportion of guessing least in the easy condition, moderate in the hard condition, and at ceiling (1.0) in the impossible condition. Full specifications of the formal models are detailed in the Appendix for each model. A more approachable summary of each model is provided in the text below.

All data processing and modeling are done on the participant level. Inference is then drawn based on examination of model selection statistics across participants. We start by binning each confidence rating into one of eight response bins. The models on these bins for each individual are as follows.

2.1.5.1. Latent strength: The latent strength axis is divided up into eight intervals through seven criteria with each interval corresponding to a response bin. If the latent strength on a given trial falls in a certain interval, then the observed response falls in the corresponding bin. The distribution of strength for each condition follows a normal distribution with common variance set to 1.0 (this setting scales the latent axis and is made with no loss of generality). The mean for the impossible condition is set to 0.0 (this setting locates the latent strength axis and is made with loss of generality). The mean for the remaining two conditions are free parameters.

2.1.5.2. Discrete state: The discrete-state model is similar to the latent strength model in that there is a latent strength axis divided into intervals by criteria. The difference is that the distribution is a mixture of two normals, one for guessing and one for knowing. The mean and variance of the guessing distribution is set to 0 and 1, respectively, and this setting locates and scales the latent axis without any loss of generality. The mean of the knowing-state distribution is a free parameter (the variance is set to 1.0), and the probability of entering the know state for the easy and hard conditions is also free parameters. Hence, this model has one additional free parameter as compared to the latent strength model.

Both models were estimated using maximum likelihood estimation procedures within the R statistical computing language, specifically the *optim()* and *nlm()* functions.

We also perform *t* tests and ANOVA procedures to assess differences in the basic descriptive statistics across conditions. In these cases we use Bayes factor as our inferential statistic. The Bayes factor gives the probability of the data under one model divided by the probability of the data under all other models considered (Edwards, Lindman, & Savage, 1963; Rouder, Speckman, Sun, Morey, & Iverson, 2009; Wagenmakers, 2007). In this work all Bayes factors presented will compare the model containing the effect in question to the null model without such an effect, giving us a statistic indicating how much the data favor an effect being present. Whereas Bayes factors greater than 1 in this work favor an effect, Bayes factors less than 1 give positive evidence in favor of the null. We follow the development of Rouder et al. (2009) when performing *t* tests and the development of Rouder, Morey, Speckman, and Province (2012) when performing ANOVA.

2.2. Results

Mean accuracy across all conditions can be seen in Fig. 3a. Better performance is clear with larger lure displacement. Note that the impossible condition leads to chance performance because we arbitrarily labeled one answer correct in the absence of any actual correct response. A one-tailed *t* test of proportion correct exploring whether the easy lure condition led to better performance than the hard lure condition supports this observation, $t(28) = 7.36$, Bayes factor = 450,000. The presence of this effect demonstrates that mean accuracy increases with our manipulation of decision difficulty, in line with the predictions of both the LS and DS models. This validates our manipulation as both models predict this of results with respect to mean accuracy across conditions.

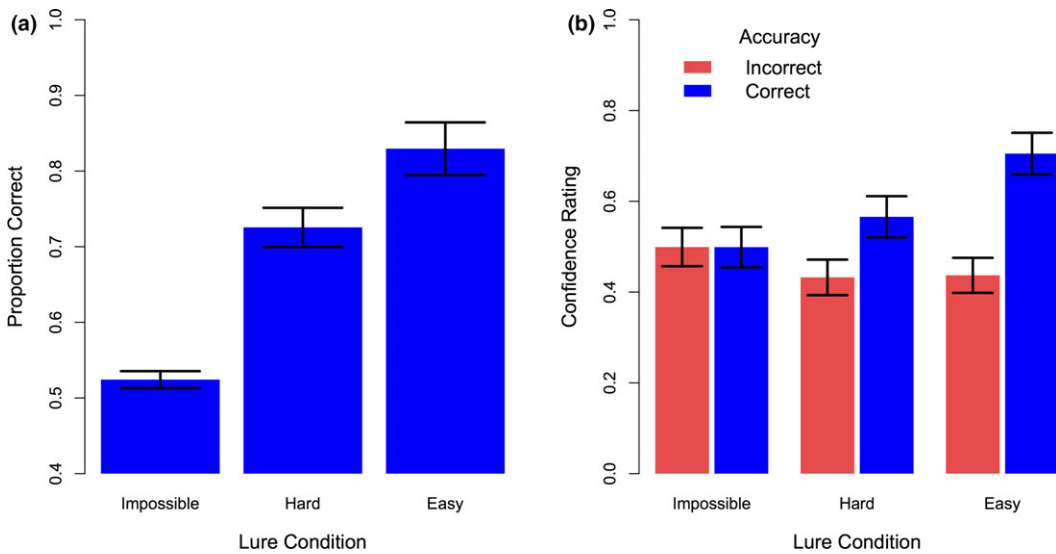


Fig. 3. Experiment 1 mean (a) accuracy as a function of condition, randomly determined for impossible trials, and (b) confidence rating as a function of condition and response accuracy. Confidence ratings are presented in absolute value, with 0 being the probe agnostic starting position and 1 representing the far extreme on the confidence scale. Error bars represent descriptive within-condition standard error of the mean.

As a second validity check before we applied our models of memory, we verified that confidence ratings reflect the memory-based decision process on a given trial. Although both the LS and DS models make identical predictions regarding the pattern of mean confidence ratings, our models assume that confidence ratings are driven by memory-based decision strength. This would be observed as increasing confidence for correct responses as the task becomes easier and either no change or a decrease in confidence for incorrect responses as the task becomes easier. Statistically, this would be represented as main effects of Accuracy and Condition as well as an interaction between the two. Alternatively, it is possible that participants decide which of the two probes are correct and then judge their confidence based on the magnitude of the physical distance between the two probe items. In this way, confidence would not be a function of the recognition decision process, but rather only of the perceptual characteristics of each trial. To check for this pattern of responding, we examine mean confidence ratings as a function of Accuracy and Condition (see Fig. 3b). If participants make confidence ratings based on the perceptual characteristics of the stimulus condition, we should see no effect of accuracy on confidence ratings and a main effect of condition on confidence ratings. Under this hypothesis, easy trials should demonstrate higher confidence than either hard or impossible trials, whereas hard and impossible trials should show equivalent confidence ratings. Note that both models make identical predictions regarding mean confidence rating and mean accuracy across conditions. Analysis on this level is meant as a validity check, not as a test of our competing hypotheses.

Confidence ratings appear to vary in a complex pattern based on accuracy and condition. A repeated-measures ANOVA of confidence rating with condition and accuracy as factors produces a main effect of Accuracy, $F(1, 28) = 48.96$, Bayes factor = 1.1×10^7 , a main effect of Condition, $F(2, 56) = 6.09$, Bayes factor = 1.87, and an interaction between these two factors, $F(2, 56) = 29.96$, Bayes factor = 4.6×10^5 . It is clear that displacement distance between the dots did not determine the confidence response patterns. The interaction between accuracy and condition points to the importance of a memory-based decision process as a driving factor behind confidence ratings.

The main focus of our analysis is model based with the goal of determining whether confidence ratings increased in a continuous manner, following the latent strength hypothesis, or in a discrete manner, following the discrete-states hypothesis. Because the models differ in overall number of parameters, but at an intuitive level seem fairly similar, we made inference via Akaike information criterion (AIC), which offers a modest penalty for models with greater numbers of parameters. AIC is a badness-of-fit statistic and lesser values are associated with better model performance. The difference between LS and DS model AIC values is plotted by participant in Fig. 4. As can be seen, overall and average AIC was better (lower in value) for the LS model than the DS model, indicating support for a LS model of signal strength. This ordering was true for the vast majority of participants; 23 of 29 individuals favored the LS model over the DS model.

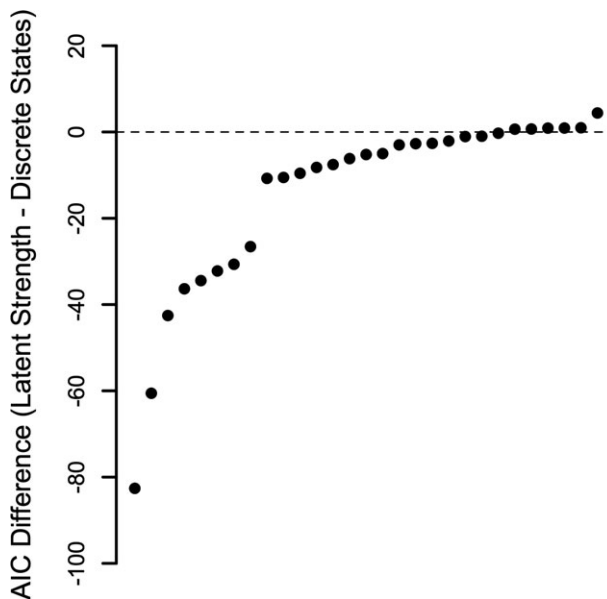


Fig. 4. The difference between the Akaike information criterion values for the latent strength and discrete states models for each participant in Experiment 1. A negative value indicates that the latent strength model was a better fit for that participant, whereas a positive value indicates a better fit by the discrete states model.

2.3. Discussion

Our results indicate that recognition decisions in a simple one-item visual working memory task rely on a latent strength process. Our model-based analysis indicates that as the decision became easier, the increase in confidence displayed by participants followed a gradual shift in the underlying information available to make the decision, rather than an increase in the mixture of know responses relative to guess responses. One key difference between the present task and standard working memory tasks is that this task required evaluation of only a single stimulus on any given trial while most investigations of working memory require the maintenance of multiple items simultaneously. With the present results we cannot be sure that our findings are generalizable beyond single-item situations. We were most concerned that constant focal attention on a single memory stimulus may be necessary to access the detailed information used in the latent strength decision process, motivating Experiment 2.

3. Experiment 2

In this experiment we extend the work in Experiment 1 by presenting multiple visual items at presentation rather than the single item we used previously. There are a number of findings that demonstrate that more than one item cannot be attended by focal attention at the same time (Garavan, 1998; McElree, 2001; Oberauer & Bialkova, 2009). Instead, multiple items are commonly thought to be maintained in working memory through rapid attentional shifts between items (Barrouillet & Camos, 2012; Oberauer & Lewandowsky, 2011; Vergauwe & Cowan, 2014). This limitation in system architecture should force attention to switch between memory items to encode and maintain them for use at test. If constant focal attention is needed to access the information necessary for a continuous recognition decision process, requiring the maintenance of multiple items should disrupt it. Instead, we should observe reliance on more coarse guess/know information in working memory and a discrete recognition decision process in Experiment 2.

3.1. Method

3.1.1. Participants: Thirty-one college students (19 women) attending the University of Missouri participated in the experiment. Ages were between 18 and 20 years.

3.1.2. Materials

All materials were the same as in Experiment 1.

3.1.3. Design

The only difference in design from Experiment 1 was in the number of experimental trials. The displacements used were the larger set used in Experiment 1, 40° or -40° on

easy trials, 20° or −20° on hard trials, and both 10° and −10° on impossible trials. In Experiment 2 there were eight blocks of 40 experimental trials.

3.1.4. Procedure

The procedure was largely the same as Experiment 1, but with the following changes. This experiment always required participants to remember three circle-dot stimuli, whereas Experiment 1 only required one to be remembered. Memory item presentation was simultaneous for all items and lasted a total of 800 ms. Mask presentation lasted 400 ms.

3.1.5. Analysis

All analyses are the same as in Experiment 1.

3.2. Results

Mean accuracy across all conditions can be seen in Fig. 5a. Better performance is clear with larger lure displacement. A one-tailed *t* test of proportion correct exploring whether the easy lure condition lead to better performance than the hard lure condition supports this observation, $t(20) = 12.92$, Bayes factor = 1.2×10^{11} .

Mean confidence ratings are presented in Fig. 5b as a function of condition and response accuracy. Note that both models make identical predictions regarding mean

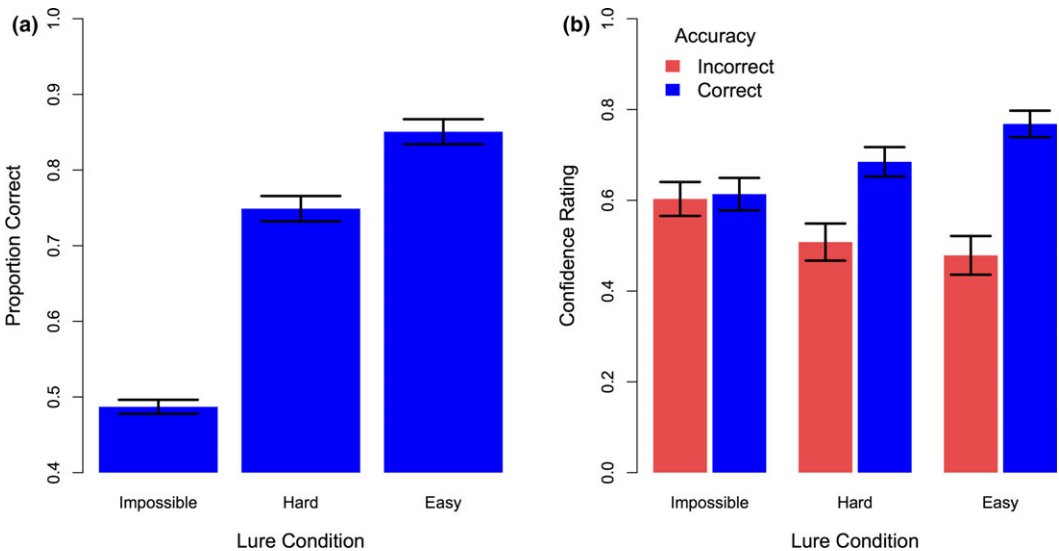


Fig. 5. Experiment 2 mean (a) accuracy as a function of condition, randomly determined for impossible trials, and (b) confidence rating as a function of condition and response accuracy. Confidence ratings are presented in absolute value, with 0 being the probe agnostic starting position and 1 representing the far extreme on the confidence scale. Error bars represent descriptive within-condition standard error of the mean.

confidence rating and mean accuracy across conditions. Analysis on this level is meant as a validity check, not as a test of our competing hypotheses. Confidence ratings vary based on an interaction between accuracy and condition, again demonstrating that a perceptual process is not driving responses just as in Experiment 1. A repeated-measures ANOVA of confidence rating with Accuracy and Condition as factors produces a main effect of Accuracy, $F(1, 30) = 65.56$, Bayes factor = 2.0×10^{15} , no main effect of Condition alone, $F(2, 60) = 3.03$, Bayes factor = 0.05, and an interaction between these two factors, $F(2, 60) = 44.04$, Bayes Factor = 3.0×10^{11} . It is important to note that the lack of a statistical main effect of condition in the presence of the strong interaction does not mean there is no effect of condition observed in the data; rather, the effect is different across accuracy levels but washes out when collapsed (see Fig. 5b).

The main focus of our analysis is model based with the goal of determining whether confidence ratings increased in a continuous manner, following the latent strength hypothesis, or in a discrete manner, following the discrete-states hypothesis. The difference between LS and DS model AIC is plotted by participant in Fig. 6. As can be seen, overall and average AIC was better (lower in value) for the LS model than the DS model, indicating support for a LS model of signal strength. As in Experiment 1, this ordering was true for the vast majority of participants; 27 of 31 individuals favored the LS model over the DS model.

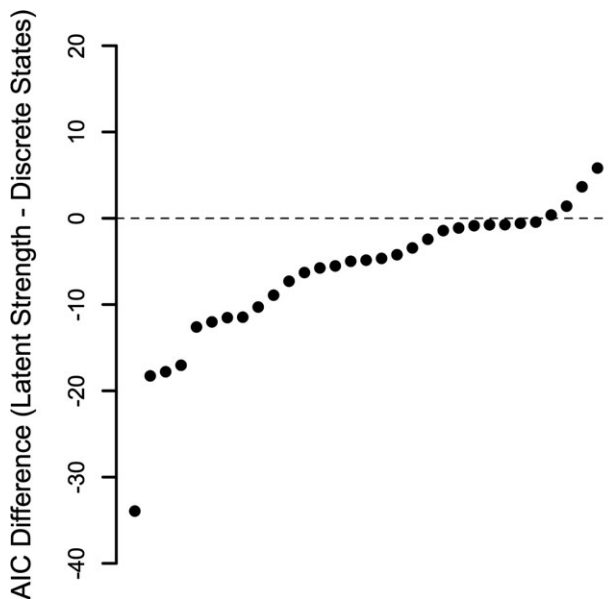


Fig. 6. The difference between the AIC values for the latent strength and discrete states models for each participant in Experiment 2. A negative value indicates that the latent strength model was a better fit for that participant, whereas a positive value indicates a better fit by the discrete states model.

3.3. Discussion

The addition of multiple items to the memory task in this experiment did not result in a discrete recognition decision-making process. This indicates that constant focal attention is not necessary to extract a continuous signal for use in making a recognition decision. Instead, a continuous latent strength process mediates recognition decisions with both single- and multiple-item visual working memory loads.

4. General discussion

The results of this study indicate that making recognition decisions about the contents of visual working memory relies upon a continuous latent strength process. This conclusion stems from the following finding: When recognition decision task demands are eased, we observed a gradual shift in the distribution of confidence ratings rather than a change in the confidence rating mixture proportions. This pattern is concordant with LS model and discordant with DS model. In other words, the pattern indicates that participants were not entering a state of either knowing the correct answer or guessing and responding accordingly, but rather were able to use the information about the similarity between the memory representation and the probe stimuli in making their response.

Our observation of a continuous recognition decision-making process could be a function of the stimuli used in this work. When processing angle information, one can compare the internal representation of a remembered angle to the representation of the perceived angle. The natural output of this comparison is in the same units, the difference in degrees of angle. The same is not true of categorical stimuli such as words. Although a continuous output could come from comparison of two words, such as frog and bowl, it would not be in terms of the natural units of the stimuli themselves. Instead, a continuous measure of conceptual or semantic relatedness or some other multifaceted internal similarity measure would have to be computed in non-word units. Continuous processing may only be the default when the natural output units of the comparison match the dimensionality of the stimuli themselves. In other words, there is still some doubt as to whether recognition decision making will follow a latent strength process when the working memory stimuli are categorical.

In this work we only manipulate recognition decision difficulty using continuous stimuli, not categorical stimuli such as words. This is due to the difficulty of identifying a manipulation of lure discriminability for use with categorical stimuli that is analog to the lure manipulation in this work. Maintaining the manipulation strength needed to dissociate continuous and discrete processing requires a particularly potent manipulation of discriminability. From previous pilot studies using words as memory items, for example, we have found only subtle decreases in accuracy when presenting lures semantically related to target items in two-choice recognition memory tasks. Investigation in this direction should be a priority going forward.

From a global view of human information processing, we can compare our results to those of studies which manipulate stimulus strength or memory set size, and some

tentative conclusions about the nature of information processing begin to emerge. Our findings contrast markedly with previous work conducted using a similar procedure in the domains of long-term recognition memory (Kellen et al., 2015; Province & Rouder, 2012) and visual word perception (Swagman et al., 2015). Province and Rouder (2012), Kellen et al. (2015), and Swagman et al. (2015) found that changes in stimulus strength, as manipulated by number of stimulus presentations or length of encoding time, resulted in discrete changes in the proportion of remembered items. Studies of working memory capacity using color stimuli, which can be labeled as a categorical color name rather than a continuous color value, have also produced results favoring discrete information processing (Donkin et al., 2013; Rouder et al., 2008; Zhang & Luck, 2008). On the other hand, many studies examining visual working memory capacity have indicated a continuous resource account (Bays & Husain, 2008; van den Berg et al., 2014; Ma et al., 2014). It seems that processing relies on discrete-state information when the stimuli are perceived as categorical (tasks using word stimuli, change detection with a small color set) and through underlying latent strength when stimuli are perceived to vary continuously (visual angle judgment, production of continuously varying color). Although it is by no means necessary that categorical information be processed discretely and continuous information be processed with latent strengths, this principle would be consistent with our description of how recognition decision making is carried out in this work and consistent with findings across several domains of cognition.

Considering the nature of cognitive processing as a function of the dimensionality of the stimuli rather than as an attribute of the mental task being performed would mark a significant shift in how we think about processing structure within the human mind. For example, the classic multi-component model of working memory (Baddeley, 1986) characterizes processing as following the verbal stream or visual stream, with processing dependent on which system is initiated and not based on the stimulus itself. In contrast, we propose that the qualities of the stimulus determine more than which system it will enter. This conceptualization follows the trend away from considering the brain as a set of specialized systems (Baddeley & Logie, 1999; Logie, 2009; Paivio, 1991) and toward a more general processing structure composed of many processing mechanisms (Francineri, Alvarez, & Cavanagh, 2013; Postle, 2006; Zimmer, 2008). Specific mechanisms recruited for successful task performance are flexible and determined by the processing the stimuli can support, not simply those associated with a pre-packaged system.

At first glance it seems plausible that the use of a continuous response slider to collect responses in our paradigm may have led to our finding in favor of the latent strength model. However, there are at least two problems with this critique. First, although participants may feel inclined to distribute their responses across the entire length of the slider, in order for this to lead to a bias in favor of the LS model, the artificial distribution of responses would need to be locked to the probe stimulus condition. There is no reason we can see to assume this behavior would be induced simply by providing a continuous response slider. Distribution of responses across the full range is easily handled by our discrete process model, so there is no inherent bias in having a continuous response space. Furthermore, both previous studies conducted using this response slider

methodology found strong results in favor of a discrete response process: Province and Rouder (2012) in the field of long-term memory and Swagman et al. (2015) in the field of word perception. Of the three studies using our response slider, only this work found support for the LS model. This provides a strong argument and strong evidence that the use of a response slider in and of itself does not lead to continuous response patterns.

Questions remain about the specific boundary conditions under which continuous information can be used in recognition decision making. We do not yet know whether the nature of the stimulus determines whether or not continuous information is available in recognition decision making. It is also an open question whether the decision-making process examined in this work is exclusive to visual working memory or is a more general mechanism working in service of many types of cognition. For example, if an analog response process decision was required, but relied on long-term memory, we may find different results. These questions are difficult and will require significant innovation to this experimental paradigm to answer.

The evidence presented here represents an important piece of the information processing puzzle. Information is not converted into a discrete response state during the decision-making process when recognition decisions are based on the contents of visual working memory. We show that confidence increases in a gradual manner as choices about the contents of memory become easier, following a continuous latent strength process and in conflict with the predictions of discrete-state models. Future work will test the bounds at which continuous information is available during decision processes involving working memory and clarify when continuous information is unavailable leading to discrete-state processing.

References

- Baddeley, A. D. (1986). *Working memory*. New York: Oxford University Press.
- Baddeley, A. D., & Logie, R. H. (1999). Working memory: The multiple component model. In A. Miyake & P. Shah (Eds.), *Models of working memory: Mechanisms of active maintenance and executive control* (pp. 28–61). Cambridge, England: Cambridge University Press.
- Barrouillet, P., & Camos, V. (2012). As time goes by: Temporal constraints in working memory. *Current Directions in Psychological Science*, 21, 413–419. doi:10.1177/0963721412459513
- Barrouillet, P., & Lecas, J. F. (1999). Mental models in conditional reasoning and working memory. *Thinking & Reasoning*, 5, 289–302. doi:10.1080/135467899393940
- Bays, P. M., Gorgoraptis, N., Wee, N., Marshall, L., & Husain, M. (2011). Temporal dynamics of encoding, storage, and reallocation of visual working memory. *Journal of Vision*, 11, 6. doi:10.1167/11.10.6
- Bays, P. M., & Husain, M. (2008). Dynamic shifts of limited working memory resources in human vision. *Science*, 321, 851–854. doi:10.1126/science.1158023
- van den Berg, R., Awh, E., & Ma, W. J. (2014). Factorial comparison of working memory models. *Psychological Review*, 121, 124–149. doi:10.1037/a0035234
- van den Berg, R., Shin, H., Chou, W. C., George, R., & Ma, W. J. (2012). Variability in encoding precision accounts for visual short-term memory limitations. *Proceedings of the National Academy of Sciences*, 109, 8780–8785. doi:10.1073/pnas.1117465109
- Bröder, A., Kellen, D., Schütz, J., & Rohrmeier, C. (2013). Validating a two-high-threshold measurement model for confidence rating data in recognition. *Memory*, 21, 916–944. doi:10.1080/09658211.2013.767348

- Cowan, N. (2001). The magical number 4 in short-term memory: A reconsideration of mental storage capacity. *Behavioral and Brain Sciences*, 24, 87–185. doi:10.1017/S0140525X01003922
- Daneman, M., & Carpenter, P. A. (1980). Individual differences in working memory and reading. *Journal of Verbal Learning and Verbal Behavior*, 19, 450–466. doi:10.1016/S0022-5371(80)90312-6
- Donkin, C., Nosofsky, R. M., Gold, J. M., & Shiffrin, R. M. (2013). Discrete-slots models of visual working-memory response times. *Psychological Review*, 120, 873–902. doi:10.1037/a0034247
- Edwards, W., Lindman, H., & Savage, L. J. (1963). Bayesian statistical inference for psychological research. *Psychological Review*, 70, 193–242. doi:10.1037/h0044139
- Engle, R. W., Tuholski, S. W., Laughlin, J. E., & Conway, A. R. (1999). Working memory, short-term memory, and general fluid intelligence: A latent-variable approach. *Journal of Experimental Psychology: General*, 128, 309–331. doi:10.1037/0096-3445.128.3.309
- Finn, P. R., Gunn, R. L., & Gerst, K. R. (2015). The effects of a working memory load on delay discounting in those with externalizing psychopathology. *Clinical Psychological Science*, 3, 202–214. doi:10.1177/2167702614542279
- Fougnie, D., Suchow, J. W., & Alvarez, G. A. (2012). Variability in the quality of visual working memory. *Nature Communications*, 3, 1229. doi:10.1038/ncomms2237
- Franconeri, S. L., Alvarez, G. A., & Cavanagh, P. (2013). Flexible cognitive resources: Competitive content maps for attention and memory. *Trends in Cognitive Sciences*, 17, 134–141. doi:10.1016/j.tics.2013.01.010
- Garavan, H. (1998). Serial attention within working memory. *Memory & Cognition*, 26, 263–276. doi:10.3758/BF03201138
- Green, D. M., & Swets, J. A. (1966). *Signal detection theory and psychophysics*. New York: Wiley.
- Hatfield-Eldred, M. R., Skeel, R. L., & Reilly, M. P. (2015). Is it random or impulsive responding? The effect of working memory load on decision-making. *Journal of Cognitive Psychology*, 27, 27–36. doi:10.1080/20445911.2014.982127
- Hinson, J. M., Jameson, T. L., & Whitney, P. (2003). Impulsive decision making and working memory. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 29, 298–306. doi:10.1037/0278-7393.29.2.298
- Kane, M. J., Hambrick, D. Z., Tuholski, S. W., Wilhelm, O., Payne, T. W., & Engle, R. W. (2004). The generality of working memory capacity: A latent-variable approach to verbal and visuospatial memory span and reasoning. *Journal of Experimental Psychology: General*, 133, 189–217. doi:10.1037/0096-3445.133.2.189
- Kellen, D., Singmann, H., Vogt, J., & Klauer, K. C. (2015). Further evidence for discrete-state mediation in recognition memory. *Experimental Psychology*, 62, 40–53. doi:10.1027/1618-3169/a000272
- Kyllonen, P. C., & Christal, R. E. (1990). Reasoning ability is (little more than) working-memory capacity?!. *Intelligence*, 14, 389–433. doi:10.1016/S0160-2896(05)80012-1
- Logie, R. H. (2009). Working memory. In T. Bayne, A. Cleeremans, & P. Wilken (Eds.), *The Oxford companion to consciousness* (pp. 667–670). Oxford, UK: Oxford University Press.
- Luce, R. D. (1963). A threshold theory for simple detection experiments. *Psychological Review*, 70, 61–79. doi:10.1037/h0039723
- Luck, S. J., & Vogel, E. K. (1997). The capacity of visual working memory for features and conjunctions. *Nature*, 390, 279–281. doi:10.1111/1467-9280.00339
- Ma, W. J., Husain, M., & Bays, P. M. (2014). Changing concepts of working memory. *Nature Neuroscience*, 17, 347–356. doi:10.1038/nn.3655
- McElree, B. (2001). Working memory and focal attention. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 27, 817–835. doi:10.1037/0278-7393.27.3.817
- Morey, R. D., Pratte, M. S., & Rouder, J. N. (2008). Problematic effects of aggregation in z ROC analysis and a hierarchical modeling solution. *Journal of Mathematical Psychology*, 52, 376–388. doi:10.1016/j.jmp.2008.02.001
- Murray, A. M., Nobre, A. C., Clark, I. A., Cravo, A. M., & Stokes, M. G. (2013). Attention restores discrete items to visual short-term memory. *Psychological Science*, 24, 550–556. doi:10.1177/0956797612457782

- Nosofsky, R. M., & Donkin, C. (2016). Qualitative contrast between knowledge-limited mixed-state and variable-resources models of visual change detection. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 42, 1507–1525. doi:10.1037/xlm0000268
- Oberauer, K., & Bialkova, S. (2009). Accessing information in working memory: Can the focus of attention grasp two elements at the same time? *Journal of Experimental Psychology: General*, 138, 64–87. doi:10.1037/a0014738
- Oberauer, K., & Lewandowsky, S. (2011). Modeling working memory: A computational implementation of the Time-Based Resource-Sharing theory. *Psychonomic Bulletin & Review*, 18, 10–45. doi:10.3758/s13423-010-0020-6
- Ormrod, J. E., & Cochran, K. F. (1988). Relationship of verbal ability and working memory to spelling achievement and learning to spell. *Literacy Research and Instruction*, 28, 33–43. doi:10.1080/19388078809557956
- Paivio, A. (1991). Dual coding theory: Retrospect and current status. *Canadian Journal of Psychology*, 45, 255–287. doi:10.1037/h0084295
- Pecchinenda, A., Dretsche, M., & Chapman, P. (2006). Working memory involvement in emotion-based processes underlying choosing advantageously. *Experimental Psychology*, 53, 191–197. doi:10.1027/1618-3169.53.3.191
- Postle, B. R. (2006). Working memory as an emergent property of the mind and brain. *Neuroscience*, 139, 23–38. doi:10.1016/j.neuroscience.2005.06.005
- Province, J. M., & Rouder, J. N. (2012). Evidence for discrete-state processing in recognition memory. *Proceedings of the National Academy of Sciences*, 109, 14357–14362. doi:10.1073/pnas.1103880109
- Ricker, T. J., & Cowan, N. (2010). Loss of visual working memory within seconds: The combined use of refreshable and non-refreshable features. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 36, 1355–1368. doi:10.1037/a0020356
- Rouder, J. N., Morey, R. D., Cowan, N., Zwillig, C. E., Morey, C. C., & Pratte, M. S. (2008). An assessment of fixed-capacity models of visual working memory. *Proceedings of the National Academy of Sciences of the United States of America*, 105, 5975–5979. doi:10.1073/pnas.0711295105
- Rouder, J. N., Morey, R. D., Speckman, P. L., & Province, J. M. (2012). Default Bayes factors for ANOVA designs. *Journal of Mathematical Psychology*, 56, 356–374. doi:10.1016/j.jmp.2012.08.001
- Rouder, J. N., Speckman, P. L., Sun, D., Morey, R. D., & Iverson, G. (2009). Bayesian t tests for accepting and rejecting the null hypothesis. *Psychonomic Bulletin & Review*, 16, 225–237. doi:10.3758/PBR.16.2.225
- Shamosh, N. A., DeYoung, C. G., Green, A. E., Reis, D. L., Johnson, M. R., Conway, A. R., & Gray, J. R. (2008). Individual differences in delay discounting relation to intelligence, working memory, and anterior prefrontal cortex. *Psychological Science*, 19, 904–911. doi:10.1111/j.1467-9280.2008.02175.x
- Souza, A. S., & Oberauer, K. (2015). Time-based forgetting in visual working memory reflects temporal distinctiveness, not decay. *Psychonomic Bulletin & Review*, 22, 156–162. doi:10.3758/s13423-014-0652-z
- Souza, A. S., & Oberauer, K. (2016). In search of the focus of attention in working memory: 13 years of the retro-cue effect. *Attention, Perception, & Psychophysics*, 78, 1839–1860. doi:10.3758/s13414-016-1108-5
- Souza, A. S., Rerko, L., & Oberauer, K. (2016). Getting more from visual working memory: Retro-cues enhance retrieval and protect from visual interference. *Journal of Experimental Psychology: Human Perception and Performance*, 42, 890–910.
- Süß, H. M., Oberauer, K., Wittmann, W. W., Wilhelm, O., & Schulze, R. (2002). Working-memory capacity explains reasoning ability—and a little bit more. *Intelligence*, 30, 261–288. doi:10.1016/S0160-2896(01)00100-3
- Swagman, A. R., Province, J. M., & Rouder, J. N. (2015). Performance on perceptual word identification is mediated by discrete states. *Psychonomic Bulletin & Review*, 22, 265–73. doi:10.3758/s13423-014-0670-x
- Van Zandt, T. (2000). ROC curves and confidence judgments in recognition memory. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 26, 582–600. doi:10.1037/0278-7393.26.3.582
- Vergauwe, E., & Cowan, N. (2014). A common short-term memory retrieval rate may describe many cognitive procedures. *Frontiers in Human Neuroscience*, 8, 126. doi:10.3389/fnhum.2014.00126

- Wagenmakers, E. J. (2007). A practical solution to the pervasive problems of p values. *Psychonomic Bulletin & Review*, 14, 779–804. doi:10.3758/BF03194105
- Williams, M., Hong, S. W., Kang, M. S., Carlisle, N. B., & Woodman, G. F. (2013). The benefit of forgetting. *Psychonomic bulletin & review*, 20, 348–355. doi:10.3758/s13423-012-0354-3.
- Zhang, W., & Luck, S. J. (2008). Discrete fixed-resolution representations in visual working memory. *Nature*, 453, 23–35. doi:10.1038/nature06860
- Zhang, W., & Luck, S. J. (2009). Sudden death and gradual decay in visual working memory. *Psychological Science*, 20, 423–428. doi:10.1111/j.1467-9280.2009.02322.x
- Zimmer, H. D. (2008). Visual and spatial working memory: From boxes to networks. *Neuroscience & Biobehavioral Reviews*, 32, 1373–1395. doi:10.1016/j.neubiorev.2008.05.016

Appendix: Formal model specification

We specify the models at the level of the participant and fit them separately for each individual. Let Y_{ij} denote the j th replicate in the i th condition, $i = 1, \dots, I$, $j = 1, \dots, J_i$. Although the responses are continuous slider positions, we bin them into K bins for analysis. Hence, Y_{ij} takes on values from 1 to K . For analysis here, $K = 8$.

Exposition of both models is aided by considering a normally distributed latent strength,

$$w_{ij} \sim \text{Normal}(\theta_{ij}, 1).$$

This specification is unidentifiable without constraints on θ_{ij} . We impose two different classes of constraints, discussed subsequently, and these classes will define the latent strength and discrete-state models. The k th response is produced if w_{ij} is between two criteria, c_k and c_{k+1} (with $c_1 = -\infty$ and $c_{K+1} = \infty$). Hence,

$$\Pr(Y_{ij} = k) = \Phi(c_{k+1} - \theta_{ij}) - \Phi(c_k - \theta_{ij}),$$

where Φ is the cumulative distribution function of the standard normal distribution.

1. Continuous latent strength (LS) model

The above model is incomplete because constraint is needed for θ_{ij} the mean of the latent strength on a trial. The LS model is implemented by making this trial mean depend only on condition, $\theta_{ij} = \mu_i$. To locate the space of all parameters, we set μ_1 , the mean for guessing condition, to zero. The remaining two condition means, μ_2 and μ_3 , serve as free parameters.

2. Discrete-states (DS) model

The DS model is implemented by making, θ_{ij} , the trial mean, dependent only on state. If the trial is mediate by the guess state, then $\theta_{ij} = 0$ (this specification serves to locate the space for the remaining parameters). If the trial is mediated by a detect state, then

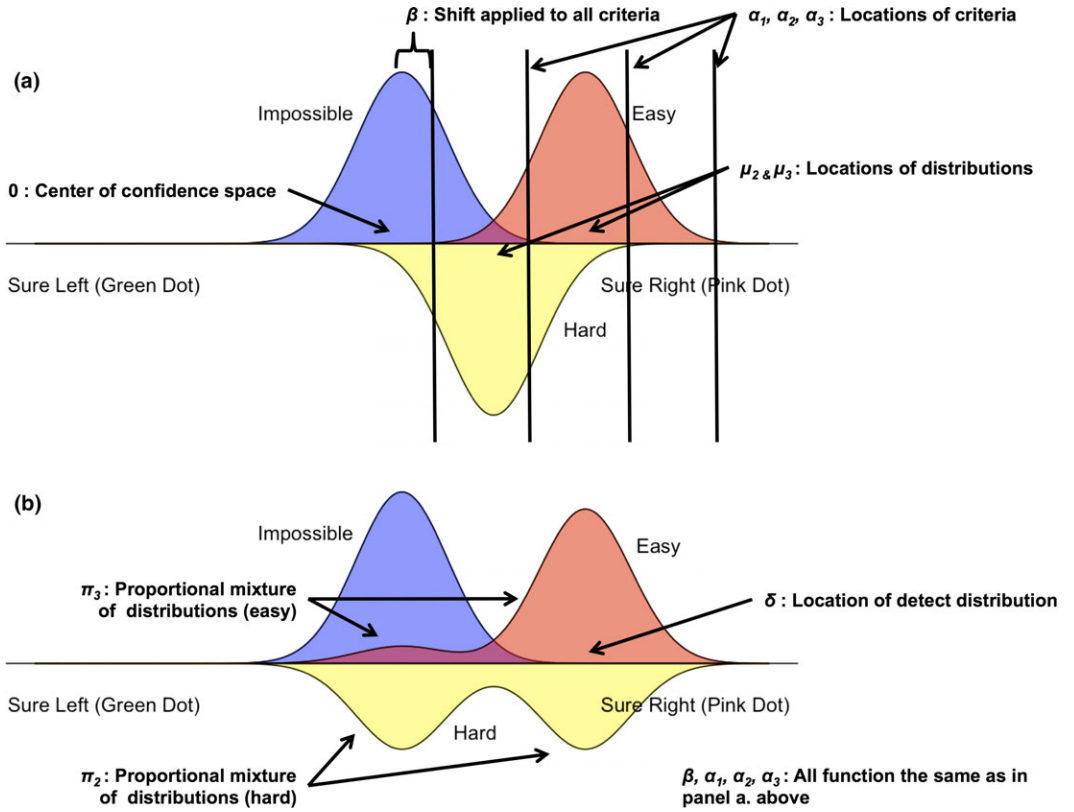


Fig. A1. All free parameters mapped onto graphical representations of (a) the continuous latent strength model and (b) the discrete-states model, when the correct response is “Sure Right.” Note that parameters β , α_1 , α_2 , and α_3 are used in both models but omitted from the depiction in (b) to reduce clutter. For further details on the meaning of the distributional representation, see Fig. 2.

$\theta_{ij} = \delta$, where δ is a free parameter. The probability that the response on a trial is mediated by the detect state is denoted π_j , where $\pi_1 = 0$ because there can be no detection by definition in the impossible condition, in which no correct stimulus is presented. Parameters π_2 and π_3 serve as free parameters.

3. Additional constraint on criteria

The presence of $K - 1$ freely estimated criteria seems overly flexible. We felt that the resolution of the data, especially when analyzed at the level of the individual, afforded perhaps the ability to estimate overall response bias and tendency toward extreme or mid-dling bins. We implemented the following parameter reductions for the case at hand with $K = 8$:

$$c_2 = \beta - \alpha_3$$

$$c_3 = \beta - \alpha_2$$

$$c_4 = \beta - \alpha_1$$

$$c_5 = \beta$$

$$c_6 = \beta + \alpha_1$$

$$c_7 = \beta + \alpha_2$$

$$c_8 = \beta + \alpha_3$$

In this parameterization, β serves as a response bias (with positive values favoring right-side responses) and $\alpha_1, \dots, \alpha_3$ serve as response bin widths. To account for the common case where middle categories (near “Guess”) and extreme categories (near “Sure”) are often endorsed, values of α_1 would be moderate, and increments to α_2 and α_3 would be small. Indeed, parameters estimate in this pattern.

With these reductions, the LS model had six free parameters ($\mu_2, \mu_3, \beta, \alpha_1, \alpha_2, \alpha_3$) and the DS model had seven free parameters ($\delta, \pi_2, \pi_3, \beta, \alpha_1, \alpha_2, \alpha_3$). See Appendix Fig. A1 for a graphical depiction of model parameters.