Cognitive influences on visual working memory

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Contents

Abstract

To produce a smooth perception of the world, our visual system relies on a memory system, termed "visual working memory," to retain and manipulate the necessary information vital for perception. Despite the rich visual world, the visual working memory system is surprisingly limited to approximately three to four items worth of information in storage capacity. In this dissertation, I take two approaches to exploring what factors influence this storage limit, the first from a bottom-up stimulus-driven perspective, and the second from a top-down cognitive perspective. In Chapter 1, I summarize key debates around the architecture of visual working memory that reflect this storage capacity limit, and the predictions these models make about how factors influence this storage limit. In Chapter 2, I examine the influence of stimulus complexity and familiarity on the visual working memory performance. In Chapter 3, I examine the influence of statistical learning on visual working memory performance. In Chapter 4, I examine the influence of chunking on a electrophysiological measure of memory capacity.

Chapter 1: Thesis Introduction

The visual system encounters an enormous amount of complex information that is processed to produce a smooth phenomenal experience of the world. The visual processes that achieve this remarkable feat require a memory store that encodes, retains and manipulates the visual information. For example, an active memory store integrates the information between saccades (Irwin & Andrews, 1996), orients where attention should be deployed (Awh & Jonides, 2001), and retains information about objects during visual tracking and search (Carlisle, Arita, Pardo, & Woodman, 2011). The system responsible for actively storing the visual information for perception has been termed "visual working memory" (VWM). Despite its necessity in everyday perception, the VWM system is surprisingly limited in the amount of information it can encode, approximately three to four objects (Luck & Vogel, 1997). This thesis explores the processes that contribute to this capacity limit with research that examines how memory performance can be boosted to overcome this limit. This chapter provides an overview of past visual working memory research.

1.1 The conception of working memory

Classical research separated memory into two distinct but interacting systems, short-term memory (STM) and long-term memory (LTM). The STM store has a highly limited capacity that holds current information in awareness, whereas LTM is thought to be unlimited in capacity, but the information stored is effortfully retrieved (Atkinson & Shiffrin, 1968). Atkinson & Shiffrin (1968) were one of the first to consider the STM system as "working"; "a system in which decisions are made, problems are solved and information flow is directed". That is, working memory functions as a mental work space for higher-level cognition (Nee & D'Esposito, 2018). However, this early conception of STM as "working" relied on the incorrect assumption that encoding of information into LTM, and therefore learning, required repeated maintenance in STM, which has since been shown to be untrue (Baddeley & Hitch, 1974). This was updated by Baddeley and Hitch's (1974) highly influential multi-component working memory model. Their first iteration contained three subsytems: the central executive, the phonological loop and the visuospatial sketchpad (Figure 1). The phonological loop and the visuospatial sketchpad, collectively known as the "slave systems", maintain verbal and visual information respectively. The visuospatial sketchpad is analagous to what researchers now refer to as the VWM system.

Baddeley and Hitch's (1974) model provided key foundations that defined working memory (Nee & D'Esposito, 2018). Firstly, the processes involved in the temporary

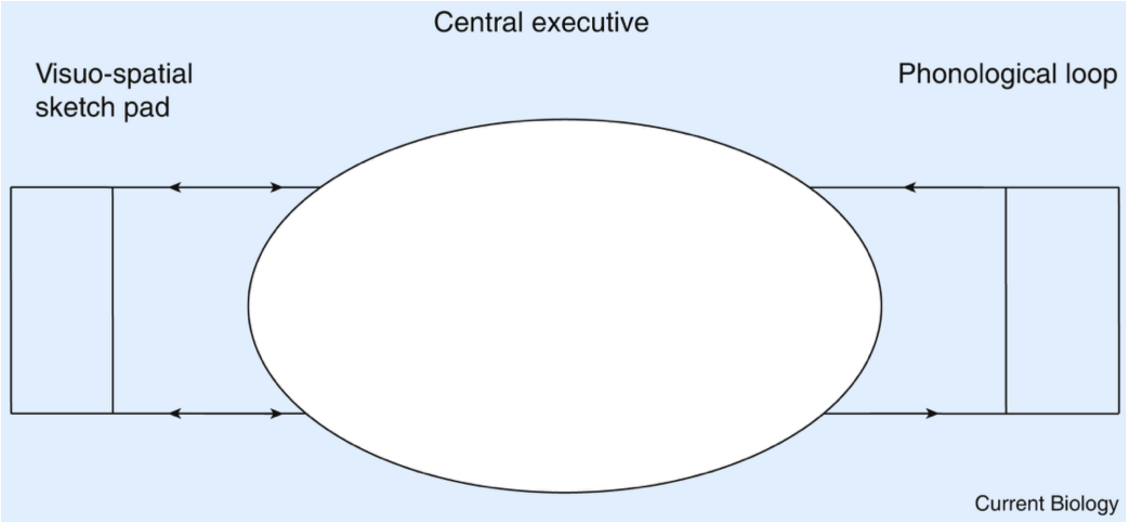

Figure 1: An early model of working memory proposed by Baddeley. Figure taken from Baddeley & Hitch (1974).

maintenance of information are distinguishable from those involved in permanent retention of information into long-term memory. Secondly, the processes that modulate and manipulate the retained information are dissociable from processes that only retain the information, such as those involved in iconic memory. Thirdly, the memory processes are modal such that visual materials are represented differently to verbal materials.

Individual differences in WM tasks has since been shown to predict cognitive ability and intelligence (Daneman & Carpenter, 1980; Unsworth, Fukuda, Awh, & Vogel, 2014). In fact, estimates of individual's VWM capacity, specifically the number of items held in VWM, correlate robustly with measures of fluid intelligence (Cowan et al., 2005; Fukuda, Vogel, Mayr, & Awh, 2010). Thus, an understanding of the factors that lead to capacity limits in VWM seems necessary to comprehend how perception and cognition occurs.

1.2 Measuring visual working memory capacity

The term "*visual working memory*" is often used synonymously with "*visual short-term memory*", which has led to much Luck & Vogel (2013) provides three defining aspects of VWM: the information represented is visual in nature, VWM information is actively maintained and that the information is accessed for cognitive use. In their seminal study, Luck & Vogel (1997) devised the change-detection paradigm for the measurement of VWM capacity. In this paradigm (see Figure 2), an initial array (*sample array*) of objects is presented to the observer for a brief duration, usually no longer than a second, before disappearing. After a short delay, a second array (*test array*) may appear identically to the sample array (*no-change* trials) or with one object replaced by another object (*change* trials). The observer has to respond with whether they think a change occurred or not on that trial.

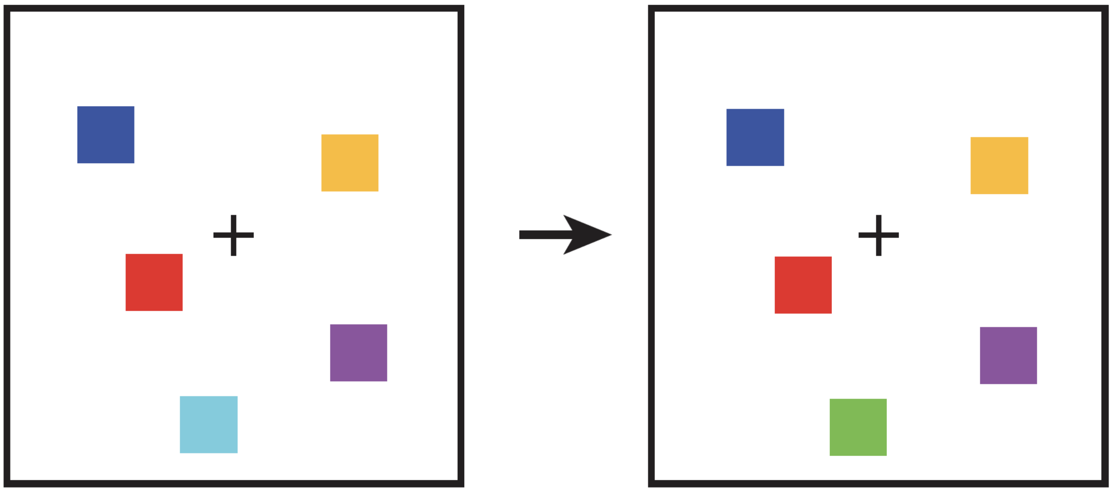

Figure 2: An example of what is displayed on a change-detection trial.

The proportion of trials that a participant correctly detects a change or no change occurred can be used to estimate the number of items held in visual working memory. Assuming the observer has stored a certain number of objects (K) from the sample array, a correct response on a change trial (a 'hit') will occur whenever the changed item is one of those K objects. If an array contains N objects, on average this will occur on K out of N change trials. Additional hits will occur on a porportion (G) of the remaining (N-K) out of N change trials (when the changed object is not among those encoded) if the observer correctly guesses that a change has occurred. For an unbiased observer, this will occur on half of the remaining trials (G = *0.5*), but G can be estimated using the observer's false alarm rate, the overall number of trials which a change is reported when no change occurred. This produces the model proposed by Pashler (1988):

$$H = \frac{K}{N} + \frac{(N - K)}{N} * G \tag{1}$$

where H is the probability of a hit on a change trial. Rearranged to make K the subject:

$$K = \frac{N * (H - G)}{1 - G} \tag{2}$$

However, this equation assumes VWM has no bearing on a no-change trial (Cowan et al., 2005). On no-change trials, the guesswork is limited to items not stored in VWM (N-K). Cowan estimates that the subject will that a change has not occurred with a probability of *1 - G*, where *G* is the probability of guessing a change had occurred. This was updated by Cowan (2001) to include the correct rejection rate (*CR*):

$$CR = \frac{K}{N} + \frac{(N-K)}{N} * (1-G) \tag{3}$$

Adding this to Equation 1:

$$H + CR = \frac{2K}{N} + \frac{(N-K)}{N} = \frac{(K+N)}{N} \tag{4}$$

Rearranging to make *K* the subject:

$$K = N * (H + CR - 1) \tag{5}$$

1.3 The capacity of visual working memory

Despite its necessity, the capacity of visual working memory is surprisingly limited to approximately 3-4 items' worth of information. Luck & Vogel (1997) presented sample arrays containing from 1 to 12 coloured squares for 100ms, before showing the test array approximately a second later. They found performance was almost perfect for arrays of 1 to 3 colour blocks and declined from 4 to 12 colour blocks. This pattern remained when observers were given two digits to rehearse aloud to suppress any influence of verbal working memory (see Figure 3a), when the sample duration was displayed for a longer duration, and when observers were required to only make a decision about a single cued item in the array (see Figure 3b). Estimating VWM capacity from the change-detection accuracy (see Equation 2) indicated observers stored approximately four items in VWM.

Despite agreement of this capacity limit for simple visual objects, there has been contention over the architecture of VWM producing this limit. In addition to simple colours, Luck & Vogel (1997) increased the number of relevant features in the visual stimuli presented in the same change-detection task and found an identical pattern of memory performance when presenting colours. For example, with conjunctions of colour and orientation, VWM performance was no different when instructed to detect changes in only colour, only orientation or in either feature (see Figure 3c). This pattern was also replicated with stimuli that were conjunctions of four features: colour, orientation, size and the presence of a gap (see Figure 3d) and conjunctions of the same feature type, such as two colours (see Figure 3e). Since increasing the number of relevant features in the visual stimuli did not influence memory performance, Luck & Vogel (1997) proposed that the architecture of VWM is 3 to 4 'slots' where each slot stores a representation of the visual object with its features integrated, rather than the individual features of the object.

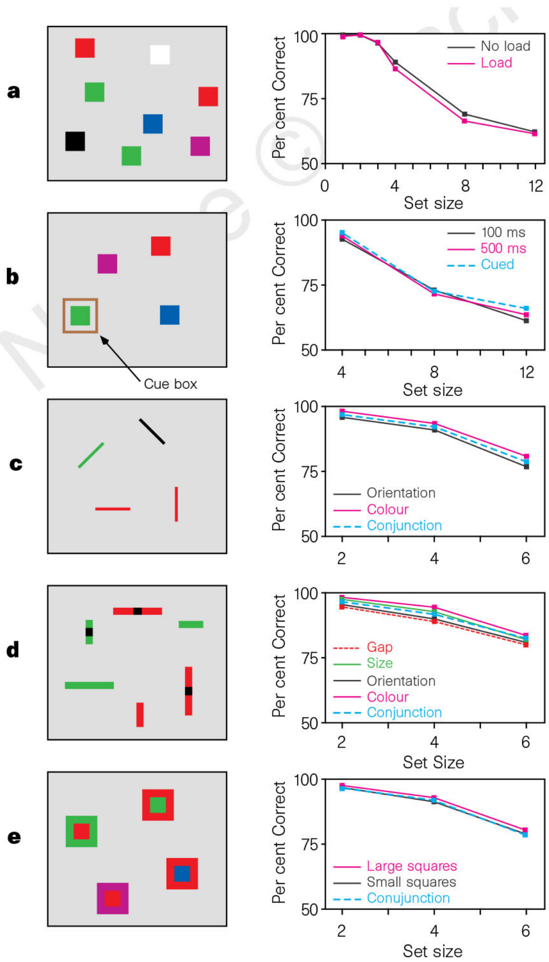

Figure 3: Stimulus arrays and memory performance from multiple experiments in Luck & Vogel (1997).

The ‘slots’ model was directly opposed by the findings of Alvarez & Cavanagh (2004). In their study, participants completed the same change-detection task as in Luck & Vogel (1997) but with different stimulus sets. The stimuli sets included colour squares as Luck & Vogel (1997) had done, but also Snodgrass line drawings, shaded cubes, random polygons, Chinese characters and English letters (see Figure 4). VWM capacities were significantly different for the stimulus sets contradicting what would be predicted by the ‘slots’ model.

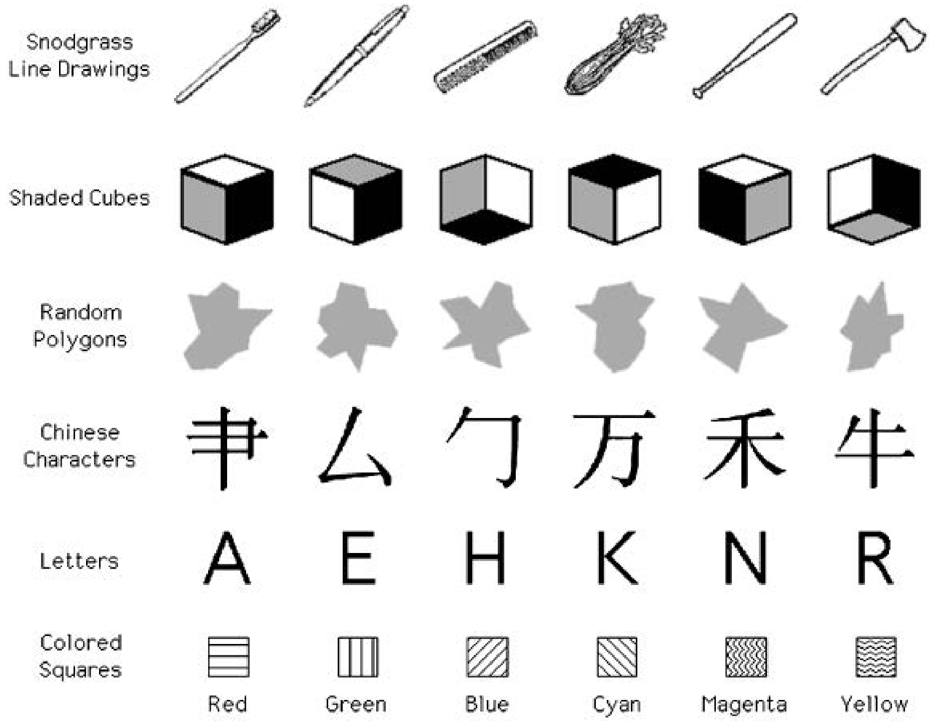

Figure 4: The stimuli sets used in Alvarez and Cavanagh (2004)

Critically, Alvarez & Cavanagh (2004) indexed the *complexity* of each stimulus set by conducting a visual search task with the same stimulus sets. In the visual search task, observers were presented a target object before asking to locate whether that target was present in an array of objects from the same stimulus set. The arrays contained either 4, 8, or 12 objects and included the target object on half the trials. The *visual search rate*, their measure of stimulus complexity, was the estimated amount of additional reaction time taken to respond that the target was present with each additional item in the array. Estimating capacity as the number of objects for each stimulus set that would correspond to 75% accuracy on the change-detection task, visual search rate was very strongly correlated (r = .992) to the inverse of capacity (see **??**).

Luck & Vogel (1997) and Alvarez & Cavanagh (2004) provide contrasting findings. While Luck & Vogel (1997) show VWM capacity is consistently approximately 4 objects

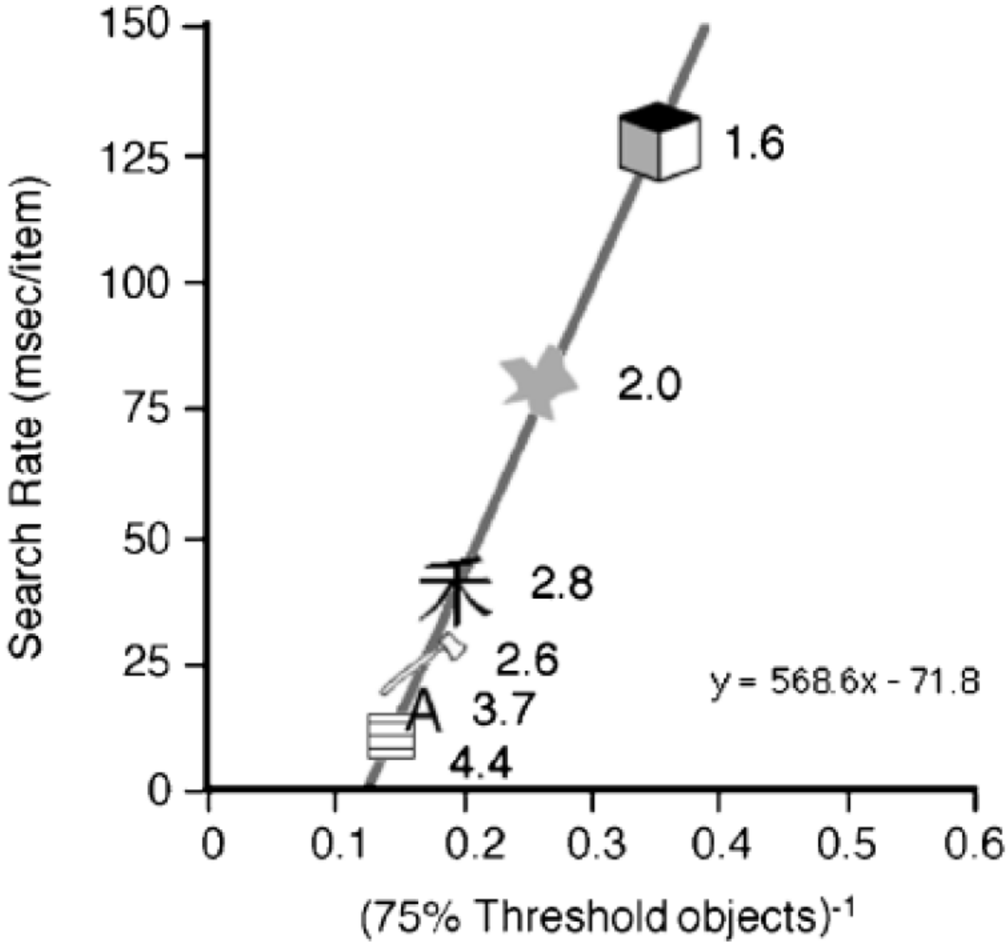

Figure 5: The visual search rate is highly correlated to the number of objects that corresop-nds to 75% accuracy on the change-detection task. The values beside each stimulus item is the calculated capacity for each stimulus set. Taken from Alvarez and Cavanagh (2004)

when varying the number of features being combined, whereas (**???**)(**???**) find VWM capacity is different for stimuli of varying complexity. Alvarez & Cavanagh (2004) suggested VWM capacity is limited by total amount of visual information rather than the number of objects as Luck & Vogel (1997) suggested in their 'slots' model. They posited the 'resource' model, which suggests that more complex visual items (those with more features) require more resources to be encoded and stored. Thus, as the visual stimuli get more complex, less items are maintained in VWM.

Awh, Barton, & Vogel (2007) disputes whether the varying VWM capacities found by Alvarez & Cavanagh (2004) was due to stimulus complexity. They suggest that the variation in VWM performance is due to an increase in comparison errors made when the object stored in memory is visually similar to the object that changed in the test array. To examine this, Awh et al. (2007) gave participants a change-detection task with memory arrays containing 4 or 8 items selected from a stimulus set of 6 shaded cubes and 6 Chinese characters. This meant that either a *within-category* change would occur, where a shaded cube changed to another shaded cube or a Chinese character changed to another Chinese character, or a *cross-category* change would occur, where a shaded cube would change to a Chinese chracter or a Chinese character would change to a shaded cube. A *within-category* change is more likely to produce more errors as the to-be compared items come from the same stimulus set, whereas the to-be compared items in a *cross-category* change come from the other stimulus set and are therefore, relatively dissimilar. If stimulus complexity influences the number of items stored in VWM, then there should be no benefit of a *cross-category* change compared to a *within-category* change. But if stimulus complexity influences the comparison decision, there should be an improvement in performance for *cross-category* changes relative to *within-category* changes. They found that memory performance for *within-category* changes was significantly worse, although significantly worse for a Chinese character compared to a shaded cube. Additionally, change-detection performance for *cross-category* was equivalent for change-detection performance with colours, which has relatively low *sample-test similarity*.

From this, Awh et al. (2007) concluded that the number of items represented in visual working memory is fixed, regardless of the complexity of those items. However, their findings did not contradict the basic conclusion of Alvarez & Cavanagh (2004) that stimulus complexity does influence change-detection performance. A key insight from the Awh et al. (2007) paper is that rather than the stored number of items, it may be the resolution with which objects are stored in visual working memory may be the key limiting factor in change-detection performance. That is, more complex objects are stored with a limited resolution such that it is more difficult to detect *within-category* changes, leading to poorer overall change-detection performance at the same set size.

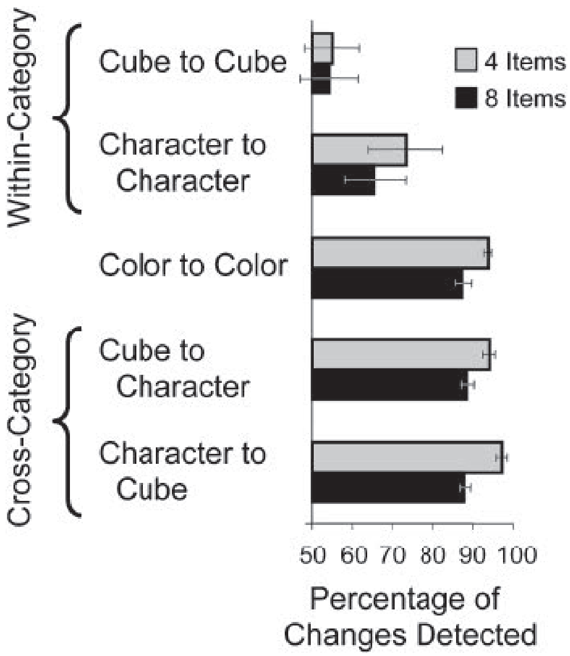

Figure 6: Results of Experiment 2 from Awh et al. (2007), showing that change-detection accuracy was significantly better for cross-category changes compared to within-category changes.

1.4 The precision of representations in visual working memory

1.5 Current models of visual working memory

However, the effect of training participants to be familiar with stimuli on visual working memory performance is unclear. To train recognition to polygons, Chen, Eng and Jiang (2006) presented four polygons out of a training set of eight, before presenting two polygons, one the same and one from the unpresented set. Despite being able to recognise the trained polygon, this familiarity did not improve visual working memory performance for the trained polygons over novel polygons. However, Blalock (2015) found a positive effect of familiarity training on visual working memory performance. Blalock (2015) presented a target polygon before asking the participant to select the target out of an array of four polygons. This recognition training produced better change-detection performance for trained polygons over the novel polygons. Another notable discrepancy between these studies is the sample size. While Chen et al. (2006) used twelve participants in each of their experiments, Blalock (2015) used over seventy and 102 in each of theirs. This difference in the statistical power of experiments may explain the contrasting results of familiarity training.

Chapter 2: The effect of complexity and familiarity on visual working memory

Experiment 1 of this chaper was included in Ngiam, Khaw, Holcombe and Goodbourn (2018), published in *Journal of Experimental Psychology: Learning, Memory and Cognition*.

2.1 Abstract

2.2 Introduction

A common method employed by visual working memory (VWM) researchers is manipulating the stimuli used in the change-detection task and examine the resulting effect on memory performance. A major point of contention central to the current debate over the architecture of VWM is the influence of stimulus complexity on VWM processes. Contrasting findings regarding the influence of stimulus complexity brought about two conflicting models of VWM architecture that have shaped much of the research, the *slots* model and the *resources* model. Defining complexity is difficult and varying metrics of complexity have likely contributed to different results. The experiments reported here introduce an objective estimate of stimulus complexity known as perimetric complexity. These experiments reveal that an overlooked influence on the VWM system and the complexity of a stimulus itself is the observers' familiarity with the stimulus. This chapter examines the influence of stimulus complexity and familiarity on two parameters of VWM, the encoding rate and capacity.

2.2.1 Varying models of VWM architecture

Proponents of the *slots* model suggest the information capacity limit of VWM is defined strictly by the number of *objects* to be stored, regardless of the complexity of the stored items. In their seminal paper, Luck & Vogel (1997) increased the stimulus complexity by adding relevant features where change could potentially occur in the to-be-remembered stimuli. They found change-detection performance was unchanged despite the increase in the number of relevant features. In their most striking result, when the stimuli were conjunctions of features from four dimensions (colour, orientation, size and the presence or absence of a gap), change-detection accuracy was equivalent when changes occurred in one dimension compared to when changes could occur in all dimensions and necessitates attention to all features of the stimulus. This result suggests the VWM system stores items with their features integrated, filling up a limited number of 'slots'.

On the other hand, proponents of the *resources* model suggest storing more complex objects expends additional limited resources, lowering overall VWM capacity. Alvarez & Cavanagh (2004) manipulated complexity by employing various stimlus sets, ranging from the more complex random polygons and Chinese characters to the simpler colour squares, in a change-detection task. Alvarez & Cavanagh (2004) reported varying capacities for the different stimulus sets, a finding at odds with the *slots* model. Critically, they indexed each stimuli's complexity by conducting a visual search task with those stimuli. In the visual search task, observers had to locate a target object amongst an array of 4, 8 or 12 objects from the same stimulus class. They quantified complexity as the visual search rate, the additional time it took to find the target with each additional item in the search display. That is, the more complex objects produced increasingly slower visual search rates with larger search arrays. Alvarez & Cavanagh (2004) found that the visual search rate was almost perfectly correlated with working memory capacity (r = -0.992). This finding that stimulus complexity not only influences but almost perfectly accounts for VWM performance motivated Alvarez & Cavanagh (2004) to propose the *resources* model, which suggests that the VWM system allocates a finite pool of resources to storing stimuli. As more complex items require more resources, less items can be stored in VWM.

Although the object-based *slots* model (Luck & Vogel, 1997) and the feature-based "resources" model (Alvarez & Cavanagh, 2004) have been influential in VWM research, the manner in which object complexity influences VWM processes, the main difference that these models are predicated on, is still contended. Firstly, the results that these models are based upon have not been perfectly replicated. In their direct replication, Hardman & Cowan (2015) were unable to reproduce Luck and Vogel's (1997) most striking result where change detection accuracy for objects possessing features from four different dimensions was equal, regardless of which feature or the number of features the participants were required to remember. However, Hardman & Cowan (2015) suggested that despite finding an effect of feature load on VWM performance, there was significant evidence to support that VWM capacity was constrained by an object load. This rules out the pure *slots* account where the number of items is the sole factor limiting VWM performance, but that the number of items is a significant contributor to the capacity limit of VWM.

Attempts at perfectly reproducing the findings of Alvarez & Cavanagh (2004) have been similarly unsuccessful. Eng, Chen, & Jiang (2005) were able to replicate the Alvarez & Cavanagh (2004) finding that visual search rate negatively correlated with VWM capacity with various memory display presentations (500, 1000 ms and 3000 ms). However, they did not replicate the near perfect negative correlation found by Alvarez & Cavanagh (2004), finding a weaker magnitude correlation (r = -.51) with 3000 ms memory display presentations. This suggests that complexity explains approximately 30% of the variation in VWM capacity, rather than all the variation as posited by the *resources* model. Additionally, Eng et al. (2005) found the visual search rates were better predictors of VWM capacities at shorter presentation durations compared to longer durations. If storage capacity was purely determined by the complexity of the stimulus, it should not be influenced by extended duration presentation. Thus, Eng et al. (2005) suggests that increased stimulus complexity limits perceptual encoding when items are being consolidated into VWM rather than overall VWM capacity.

Awh et al. (2007) suggest the differences in VWM capacity found by Alvarez & Cavanagh (2004) were not due to stimulus complexity *per se* or perceptual encoding as suggested by Eng et al. (2005) but rather because of confusion at the comparison stage in change-detection. Awh et al. (2007) manipulated whether the changed object in the test array came from the same stimulus set (*within-category*) or from a different stimulus set (*cross-category*). Change-detection accuracy for *within-category* changes, such as a shaded cube changing to another shaded cube, decreased with increasing stimulus complexity, replicating the finding of Alvarez & Cavanagh (2004). However when changes were *cross-category*, such as a shaded cube changing to a Chinese character, change-detection accuracy was equivalent to change-detection accuracy with simple colours. Jackson, Linden, Roberts, Kriegeskorte, & Haenschel (2015) confirmed this finding by directly manipulating the visual similarity of the test object. They used contained sets of simple polygons and complex polygons and asked participants for subjective similarity ratings of polygon pairs within each set. They found change-detection accuracy decreased for complex polygons for test objects subjectively rated as similar, but no difference between simple and complex polygons when the test items were rated dissimilar. Therefore, as objects that were more complex were more visually similar (high *sample-test similarity*), within-category changes produced more errors made when detecting changes in the test array, lowering estimates of VWM capacity. The same visual mechanisms comparing highly similar stimuli that lead to lower estimates of VWM capacity are likely to contribute to slower visual search rates as well, providing an explanation for the significant correlations between the two measures found by (**???**) and Eng et al. (2005).

It is still unclear whether effects of stimulus complexity on VWM are entirely attributable to sample-test similarity. The conclusions of Jackson et al. (2015) rely on matched subjective ratings of simple polygon pairs and complex polygon pairs. It is not evident however whether a change of a simple polygon to another "similar" simple polygon is equivalently confusable to a change from a complex polygon to another "similar" complex polygon, despite being matched on subjective similarity ratings. Furthermore, Jackson et al. (2015) report capacity estimates for both simple and complex polygons using dissimilar test items (approximately 1.5 items) that are far lower than equivalent estimates reported by Awh et al. (2007) (3.5 items for Chinese characters, 3.6 items for colours, 4.2 items for shaded cubes). These findings do not completely rule out Alvarez and Cavanagh's basic claim that VWM performance is influenced by stimulus complexity. For example, a more complex object may be represented at a lower resolution, with fewer intact features. A degraded representation of a complex object, such as a Chinese character, might be easily distinguishable from a coloured square, but not from another character with similar features. Prolonging encoding time may allow VWM representations of complex objects to have equivalent resolution and produce comparable estimates of VWM capacity for simple objects.

2.2.2 Encoding rate

Like the capacity of VWM, the encoding rate of information into VWM is limited. The encoding rate was first quantified by Vogel, Woodman, & Luck (2006), who presented four colours for a fixed duration (100 ms) to observers in a change-detection task before interrupting encoding with a backward mask. Vogel et al. (2006) varied the *stimulus onset asynchrony* (SOA), the duration before the onset of the backward mask available to encode durable representations into VWM. They found change-detection performance improved with longer encoding durations up to 200 ms, before plateauing. Each colour block took approximately 50 ms to encode prior to reaching an asymptote of approximately 2.5 object.

Although the encoding rate reflects early VWM processing to create durable memory representations, it is often ignored by researchers despite the possibility that influences on early VWM processing might systematically limit VWM capacity estimates. Typically the time between memory and mask is kept constant throughout an experiment, but limiting encoding to brief durations may lead to underestimating VWM capacity. In our study, we adpoted the Vogel et al. (2006) paradigm with various stimulus sets to examine whether the encoding rate is influenced by stimulus complexity. This allows us to determine whether a stimulus set with items containing more features (more complex) takes longer to encode into VWM. Increasing object complexity may slow the rate of encoding into VWM, such that complex objects will require more time to saturate VWM capacity. This would confound conclusions made from comparisons of VWM capacity for objects of different complexity with the same memory array durations, such as those found by Alvarez & Cavanagh (2004).

2.3 Defining complexity

Inconsistent definitions, measures and manipulations of complexity may have lead to the vastly differing models of VWM architecture. For example, Luck & Vogel (1997) manipulated stimulus complexity by increasing the number of relevant features in the stimuli, whereas Alvarez & Cavanagh (2004) varied stimulus sets and indexed complexity by measuring visual search slopes. In the present chapter, we defined stimulus complexity using *perimetric complexity*, the square of the combined inside and outside perimeters of a letter, divide by its area (Attneave & Arnoult, 1956). There are many merits to using perimetric complexity to define stimulus complexity over previous manipulations and measures. Perimetric complexity has a nearly perfect negative linear relationship with letter identification efficiency, such that as letters increase in perimetric complexity, they are identified increasing inefficiently (Pelli, Burns, Farell, & Moore-Page, 2006). Pelli et al. (2006) suggests this relationship occurs because complex letters require more features to be bound together, and perimetric complexity directly corresponds to the number of features. Perimetric complexity also provides an objective measure of complexity derived from the stimulus, that corresponds well to subjective figural goodness (Attneave, 1957) and apparent information load (Y. V. Jiang, Shim, & Makovski, 2008; Makovski & Jiang, 2008). An increase in perimetric complexity reflects an increase in stimulus complexity without the addition of extra feature dimensions. In the present study, we selected letters of the English alphabet and varied the perimetric complexity by presenting the letters in four different fonts (Experiment 1), as well as presented characters from four alphabets that were unfamiliar to our participants (Experiment 2).

2.4 Familiarity

An additional factor that has been shown to influence consolidation and storage in VWM is familiarity. For example, chess experts showed an improved memory performance for chess game positions compared to novices, but equivalent memory performance when the chess pieces were random on the board (Chase & Simon, 1973). More recently, higher VWM capacities have been found for famous faces over unfamiliar faces (Jackson & Raymond, 2008), as well as for Pokémon (characters from a popular childhood cartoon) from an original generation over a recent generation only for those reporting familiarity with the characters (Xie & Zhang, 2016). Similarly, those familiar showed a higher encoding rate for Pokémon (Xie & Zhang, 2017). Although, these studies do not control stimulus complexity and it is unknown whether these effects of familiarity are independent of stimulus complexity. We examined this in Experiment 3, controlling for stimulus complexity by using the Brussels Artificial Character Set (BACS) (Vidal, Content, &

Chetail, 2017). The BACS is designed to have the same number of junctions, strokes and terminations as English letters but is unfamiliar to the observer. Another critical aspect of the BACS characters is that they match the similarity between characters found with English letters [Vidal et al. (2017). Additionally, we matched the perimetric complexity of the BACS to the English letters.

It is unclear how different qualities of the stimulus in terms of complexity, familiarity and similarity interact and contribute to VWM performance. The experiments presented in this chapter attempt to explicate the interaction by focusing primarily on familiarity.

2.5 Modelling VWM performance

Encoding and capacity limits in VWM might best be described in terms of *objects*, as in the "slots" model or in terms of *features*, as in the "resources" model. If feature intergration limits the encoding rate into VWM, more complex letters will be encoded at a slower rate. If this is not the case, encoding rate will not vary with stimulus complexity. Similarly, if the number of features limits VWM capacity, fewer items will be stored from more complex alphabets. Otherwise, VWM capacity maybe be determined by the number of items, and will not vary with stimulus complexity. These models are shown in Figure 1.

Chapter 3: The effect of statistical learning on visual working memory

3.1 Abstract

In the previous chapter, the effect of familiarity on VWM was examined…

3.2 Introduction

Given the strict capacity limit of VWM and its robust correlations to measures of cognitive ability such as fluid intelligence and scholastic achievement (A. R. A. Conway, Cowan, Bunting, Therriault, & Minkoff, 2002; Cowan, Chen, & Rouder, 2004; Fukuda et al., 2010; Unsworth et al., 2014), there is sustained interest in manipulations that potentially enhance VWM capacity. An influential paper by Brady, Konkle, & Alvarez (2009) demonstrated including regularities in the color pairs shown in displays improved VWM recall performance relative to displays without any regularities. That is, when specific pairs of colours were more likely to appear in the display, observers were able to use this to their advantage and improve recall accuracy. This chapter explores This set of experiments investigated the mechanism of learning that produces the enhanced memory performance, and how that maps on to the architecture of VWM.

3.2.1 Chunking

Improvement in memory performance has classically been explained using *chunking*. Miller (1956) proposed learning allowed greater amounts of information to be stored more efficiently in "chunks", with the absolute number of chunks stored into memory remaining constant (Miller, 1956). For example, experts recall chess positions from real matches significantly better than novices, but not better when these positions are random distributed chess pieces (**???**). As recall performance was equivalent on random positions, this suggests chess masters do not have a larger VWM capacity but instead use their expertise to efficiently "chunk" game positions, which novices cannot do.

Brady et al. (2009) show chunking models provide an accurate approximation of how observers may take advantange of the statistical regularities.

Chapter 4: Chunking on electrophysiological measures of visual working memory

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Chapter 5: Thesis Discussion

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