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Contrasting predictions of low- and high-threshold models for the detection of changing visual features

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Abstract. Change blindness is the failure of observers to notice otherwise obvious changes to a visual scene when those changes are masked in some way (eg by blotches or a blanking of the screen). Typically, change blindness is taken as evidence that our representation of the visual world is capacity limited. The locus of this capacity limit is thought to be visual short-term memory (vSTM). The capacity of vSTM is usually estimated with a high-threshold model which assumes that each element in the stimulus array is either fully encoded or not encoded at all, and, furthermore, that false alarms can arise only by guessing, not by noise. Low-threshold models, by contrast, suggest that false alarms can arise by noise at the level of detection/discrimination and/or decision. In this study, we use a well-controlled stimulus display in which a single element changes over a blanking of the screen and contrast predictions from a popular high-threshold model of vSTM with the predictions of a low-threshold model (specifically, the sample-size model) of visual search and vSTM. The data were better predicted by the low-threshold model.

Keywords: change blindness, visual search, vSTM, sample size

1 Introduction

Change blindness is the failure to detect changes in a scene when those changes are masked in some way. Masks used include a series of blotches ('mudsplats') presented simultaneously with the change (O'Regan et al 1999), or a blanking of the screen that occurs with the change (ie the 'flicker' paradigm—see Rensink et al 1997 and figure 1). The failure to see the change is thought to be due to the absence of a motion transient that normally accompanies a change to a scene (ie when that change is not masked) (Kanai and Verstraten 2004; Rensink et al 1997).

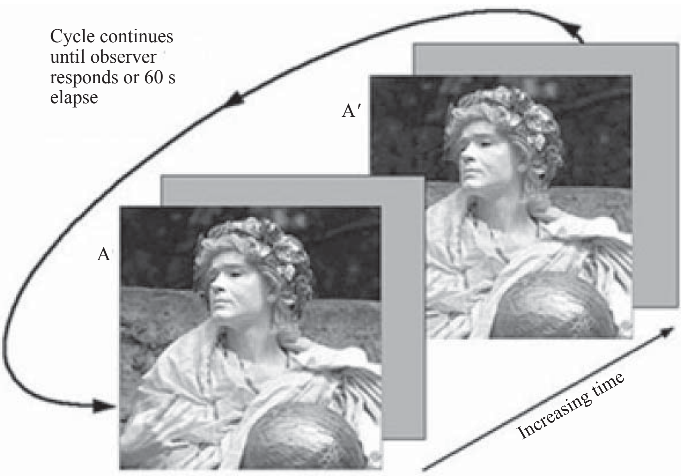

Figure 1. A depiction of the flicker paradigm, in which a picture (A) and a modified version of it (A′) are presented with a blank in-between until the observer responds. In this case, the change is to the height of the wall in the background. Reproduced from Rensink (2000).

However, if humans had an unlimited capacity to take in and retain information from a visual scene (as might be naively thought from an observer's point of view), there would be no failure, even in the absence of a motion transient (Rensink 2000). Obviously then, there is a problem of limited capacity when it comes to selecting and/or retaining information from a visual scene. We can eliminate selection as an information-processing bottleneck by using only a few objects/stimuli at a time. With this in mind, a change-detection paradigm in which only a few distinct objects are presented at any one time can be and has been utilised in the study of vSTM.

Luck and Vogel (1997) used a change-detection paradigm to examine the capacity of vSTM for simple features (colour, orientation, size). Their task required observers to monitor an array of a small number of elements across a blank interval, during which one of the elements could change on one or two features. It was found that performance decreased monotonically with the number of elements when this number was greater than 4 (see figure 2a). Furthermore, the performance vs number of elements function was the same when observers were required to monitor for one of two changes compared to when they were required to monitor for just one change (see figure 2b and figure 2c). Therefore, it appeared that it was the number of objects rather than the number of features that determined performance, and so the authors suggested vSTM codes information as complete objects rather than separate features.

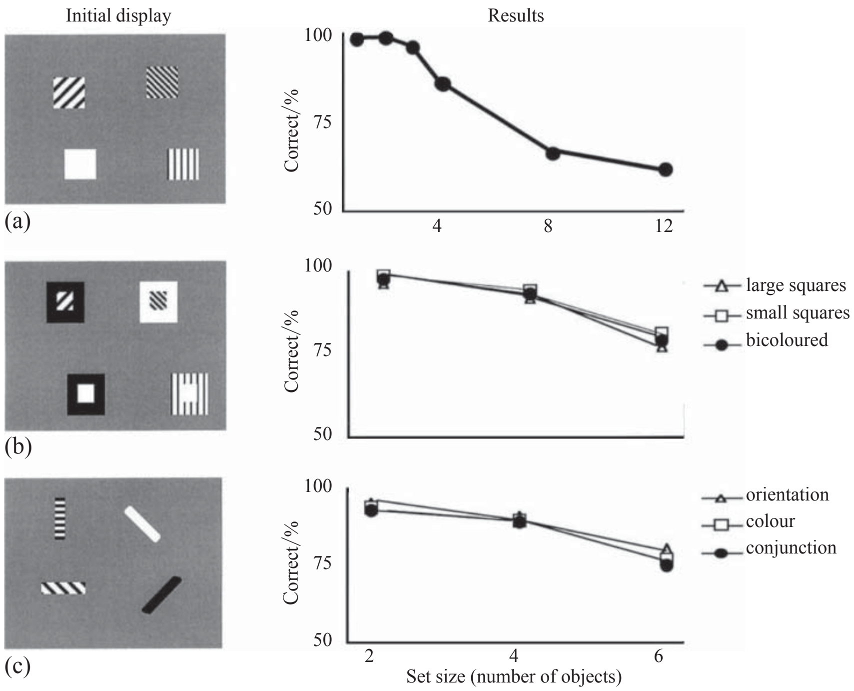

Figure 2. The critical conditions and data from the Luck and Vogel (1997) experiment. Reproduced from Wheeler and Treisman (2001).

1.1 *Modelling vSTM capacity—the Pashler–Cowan formula*

Luck and Vogel (1997) also estimated vSTM capacity from the data of their experiments using the Pashler–Cowan formula (see Pashler 1988 and Cowan 2001), given in equations 1–4. P represents the probability of encoding an individual item in vSTM, H represents the hit rate, k represents capacity (number of items that can be compared), n represents set size, and g is the probability of guessing that a change occurred (ie the false alarm rate). This equation is based on a number of assumptions, as follows:

- No partial information (eg parts of objects) is encoded; each item is either completely encoded or not at all.
- All errors are the result of a maintenance, rather than a comparison process.
- The measured hit rate (H) is a combination of the likelihood that a changed element was encoded in vSTM (P) and the false alarm rate (g).

$$P = \frac{k}{n}\,, \tag{1}$$

$$H = P + (1 - P)g\,, \tag{2}$$

$$H = \frac{k}{n} + \frac{n-k}{n}g\,, \tag{3}$$

$$k = \frac{N(H-g)}{1-g}\,. \tag{4}$$

Using equation (4), it was found that observers were retaining information consistently for around 4 objects (ie k was consistently around 4). Based on these results, Luck and Vogel (1997) (see also Cowan 2005; Pashler 1988; and Vogel et al 2001) describe a model of vSTM in which capacity is limited to 3 or 4 objects, because the vSTM system contains 3 or 4 independent 'slots' each capable of representing a single object at a fixed resolution. Other studies, however, have found that the precision (resolution) with which items are stored in vSTM is critically dependent on how many items are stored (Alvarez and Cavanagh 2004; Awh et al 2007; Bays et al 2009; Wilken and Ma 2004). Precision can be measured by, for example, getting participants to respond on a colour wheel regarding the identity of to-be-measured colours and looking at the error distribution by comparing response values with target values for different set sizes (Bays et al 2009). The question of whether the resolution of items in vSTM can vary relates to the noisiness of those representations, or, in other words, the degree of uncertainty with which they are stored. The importance of noise and uncertainty in the representation of items in vSTM relates to the division between high and low thresholds of vSTM, which is explained in the next section.

1.2 *Low- and high-threshold theories of change detection*

The Pashler–Cowan equation [equation (4)] represents a high-threshold formulation of the change-detection problem because it assumes that the selection/discrimination process involved in the task sometimes fails to detect a target, but will never mistake a distractor for a target. The false alarm rate in the context of such a theory represents a rate of guessing that a target is present when one is not. In contrast, a low-threshold theory would assume that sometimes an observer will mistake a distractor for a target, owing to noise alone. This means that, for a low-threshold formulation, at the level of detection/discrimination and/or the level of decision, the level of noise can be high enough that the noise and signal distributions are indistinguishable for a given criterion. Because the 'threshold' of decision can be reached by noise alone, the threshold is low as compared to one in a high-threshold formulation, where noise alone cannot be confused with the signal.

The 'fixed slots' model of vSTM discussed above represents an instance of a high-threshold model of vSTM. Low-threshold models, in contrast to high-threshold models, deal with noise (uncertainty) as a central factor in their formulation. Low-threshold models of vSTM and visual attention/visual search are commonly related to signal-detection theory (SDT) (see Green and Swets 1974 for details of SDT). SDT describes decision making under conditions of uncertainty. The most common performance measure used by SDT is d', computed from standardised measures of the hit rate (responding 'yes' when a signal was present) and false alarm rate (responding 'yes' when a signal was not present).

1.3 *The sample-size model*

One SDT model that can be applied to visual-search situations is the sample-size model, which suggests performance in a search or memory task is limited by the total amount of information the observer can process from the scene (Palmer 1990; Shaw 1980). Information is used here in the information-theoretic sense, to mean the reduction of uncertainty (Shannon 1948). In other words, more information means less uncertainty in the perceptual decision. In this model, perception is constructed from a finite number of internal samples of sensory representations (Palmer 1990). The samples are distributed evenly over the number of sensory representations that are relevant to the task at hand. Therefore, when presented with more relevant information, the quality of the encoding of the information will decrease as the amount of information (number of samples per unit time) that can be extracted remains constant. More formally, Shaw (1980) states:

> "With this model, each internal random variable X_{k_i} is a sample mean based on N_k observations of that location, where the total number of observations over all locations remains constant. Thus, the variance of each X_{k_i} depends directly upon N_k."

This statement indicates that each location can be sampled one or multiple (N_k) times and that the total number of observations across all locations is constant, meaning that the number of times an individual location is sampled (N_k) will decrease when the total locations sampled increases. In the case where all locations are equally sampled then, N_k will be inversely proportional to the total number of locations sampled, N. Furthermore, the variance of each internal random variable (X_{k_i}) depends directly upon N_k and so we can say that the variance of X_{k_i} ($\sigma^2_{x_{k_i}}$) is inversely proportional to N_k because from central limit theorem (Rice 1965), we know that as more samples of a population (in this case, the stimulus) is taken, the mean approaches a central limit and the variance of the sampling distribution decreases. In the case where all locations are sampled equally, then we can say that given that N_k is inversely proportional to N and that $\sigma^2_{x_{k_i}}$ is inversely proportional to N_k, then $\sigma^2_{x_{k_i}}$ is proportional to N (the variance of the internal random variable is proportional to the number of locations sampled in the scene).

1.4 *Deriving a relationship between N and d'*

By this account, in a vSTM task involving a number of elements presented on a computer screen the amount of information collected from each element will vary inversely with set size, and therefore so will the precision (cf resolution) of the internal representation of each element. Statistically, precision is the reciprocal of variance, and so equation (5) relates the variance of the internal representation (which is assumed to be normally distributed) to the number of elements sampled. This variance is proportional to the number of elements. In signal-detection theory under the assumption of equal, normally distributed variances for the noise (ie false alarm) and signal+noise (ie hit) distributions, sensitivity (d') is equal to the hit rate (H) minus the false alarm rate (F) divided by their common standard deviation [see equation (6)] (Macmillan and Creelman 2005).

$$\sigma^2 \propto N \,. \tag{5}$$

The standard deviation referred to in equation (6) is the standard deviation of the internal representations of signal and signal+noise, and is common because both the H and F distributions have the same variance under the equal-variance assumption. Given that both the sample-size model and signal-detection theory use a measure of the variance of a normally distributed internal representation of an external signal, we use this measure to relate d' to the sample-size model. Specifically, combining equation (5) and equation (6) gives equation (7), which shows that the sample-size theory predicts d' to be inversely proportional to the square root of the set size (Palmer 1990). By contrast, the high-threshold model outlined in equations (1) to (4) implies that d' will be inversely proportional to set size (and not its square root) [see equation (8) for development of this relationship].

$$d' = z(H) - z(F) = \frac{H - F}{\sigma}\,, \tag{6}$$

$$d' \propto N^{1/2}\,, \tag{7}$$

$$k = \frac{N(h - g)}{1 - g} = \frac{N(d' * \sigma)}{1 - g}\,. \tag{8}$$

The relationship between d' and N predicted by the sample-size model is summed up by Palmer (1990), as follows (pages 346–347):

> "Assume that each stimulus attribute is characterized by an independent Gaussian random variable. Then the mean of the samples of that variable will have a variability that is inversely proportional to the number of samples. With equal allocation of samples, an increase in the set size decreases the number of samples proportionally. Therefore, the variability of the sample mean is proportional to set size. Combining this with a signal-detection model in which d' is inversely proportional to variability predicts that d' is inversely proportional to $n^{1/2}$, where n is set size."

1.5 *The current experiment*

The current experiment uses elements that are presented in a ring around a central fixation cross, and these elements do not change their position during the trial. Therefore, the eccentricity of stimuli is controlled relative to fixation. The sinusoids of each Gabor move left or right randomly, and their colour, speed of motion, orientation, and size are all manipulated. On half of the trials, a single target element changed across a blanking of the screen and the observer was required to indicate (yes/no) whether a change occurred. Set size was manipulated by having a different number of Gabors present on the screen, however the Gabors could only occupy six fixed positions around fixation. Set-size effects were measured for changes to the stimulus dimensions, colour, orientation, speed, and size. The relationship between performance (d') and the set size N was then graphed and compared against relationships predicted by both high- and low-threshold models. The presentation conditions were very similar to those used in Burmester and Wallis (2011a, 2011b). However, in Burmester and Wallis (2011b), observers responded in a 2AFC manner indicating whether the change was in the left or right half of the screen. Also, the experiments in Burmester and Wallis (2011a) used a cue to manipulate relevant (cued) set size while the experiments in Burmester and Wallis (2011b) did not manipulate the displayed set size or the relevant (cued) set size.

2 Method

2.1 *Introduction*

In a typical visual-search experiment the target is different from all of the distractors on some featural dimension such as colour, size, orientation, or spatial frequency. In the current study, however, targets were elements that underwent a change along some featural dimension across a blank interval (ie before the blank interval they were unchanged, and after it they were changed).

2.2 *Participants*

Four participants took part in the experiment. All were female undergraduate students recruited through an employment website at the University of Queensland. They were each paid \$10 for their participation. Their mean age was 20.75 years (range 18–26 years). Before doing the experiment, participants had to take a basic colour-vision and acuity test, which was run using the Bausch and Lomb Vision Tester. The colour-vision test used four pseudoisochromatic plates that were corrected for instrument illumination. The acuity test used a series of non-letter stimuli arranged in rows where each square was progressively smaller than the last. These tests were administered with a scoring card and participants were required to fulfil recommended criteria in order to continue.

2.3 *Equipment and stimuli*

The experiment was run on an SGI Onyx 300 machine using custom software. A Silicon Graphics (Sony Trinitron) CRT monitor with a display size of 43 cm × 29 cm and resolution of 1280×1024 (fully anti-aliased) was used, with participants sitting with their eyes 100 cm from the surface of the display. The display therefore subtended 24.26 × 16.50 deg of visual angle. The centre of each of the four Gabors was 5.0 deg from the centre of the fixation cross, and 5.0 deg from the centre of either of the two adjacent Gabors. The programme controlling stimulus presentation explicitly coded size, orientation, colour on the red–green axis, speed of motion (temporal frequency), direction of motion, and spatial frequency.

In real-world visual stimuli, many featural dimensions covary (eg colour and luminance). To ensure that covariation along featural dimensions could be controlled, the current study employed the following measures:

- Peak colour values for the Gabors were made isoluminant (lightness of 22 lux).
- The movement of Gabors was constrained so they could only move in the two directions orthogonal to their orientation.
- The Gabors were always defined with a Gaussian window of 1.8 deg or more and at least two bars were visible.
- The density of the Gabors (ie the spatial frequency) was controlled and kept constant.

Because the colours used were isoluminant, all colour values were preset (ie no online modification). To do this, the red and green values of the RGB computer colour space were varied so that a series of points were created that were progressively less red and more green, but all of the same lightness value (as read by a Minolta CL-100 colorimeter operating in CIE 1976 $L^*a^*b^*$ colour space, where L is lightness). The use of this procedure means that space between consecutive colour points is not uniform on a metric scale—the placement of consecutive colour points was instead made on the basis of colour appearance, so that each subsequent point appeared (to the experimenter) to be as distinct from the previous as other pairs on the scale and all points were made isoluminant. Each colour point was measured in $L^*a^*b^*$ colour space and these coordinates were converted as shown in equation (9) to give values in the L^*C^*h colour space (C and h represent chromaticity and hue) so that each colour point could be described by a single value—h.

$$h = \tan^{-1}(b/a) . \tag{9}$$

2.4 *Procedure and design*

The progression of a trial in this experiment can be schematised as:

$$\text{Fixation}_{(1500\text{ ms})} \rightarrow \text{A}_{(1500\text{ ms})} \rightarrow \text{B}_{(120\text{ ms})} \rightarrow \text{A}'_{(1500\text{ ms})} \rightarrow \text{B} \rightarrow \text{A} \rightarrow \text{B} \rightarrow \text{A}' \rightarrow \text{response},$$

where A is the pre-change presentation, A′ is the post-change presentation, and B is a blank screen. On trials in which no change occurred, the elements in A′ are the same as the elements in A. Figure 3 shows an example trial. The response prompt “Did you see a change?” was presented on the screen in the response phase at the end of the A→B→A′→B→A→B→A′ presentation sequence. It was presented until the observer responded "yes" or "no" with one of two designated keys on the keyboard. Participants could only respond once the response prompt had been presented on the screen, and so could not respond in the body of the trial.

Independent variables in this experiment were: the presence of change (present or absent), the type of change (colour, speed, size, orientation), the set-size (1, 2, 4, or 6), and the magnitude of change (2–5 steps, where 1 step is equivalent to moving from one of the stimulus values to the neighbouring greater value—the values used are given in the next section). Therefore, there were 64 unique trials in which a change occurred and 64 trials in which no change occurred. The experiment was run in two blocks, each containing 128 trials (64 change and 64 no change) run in a random order. At the end of each block, the participant could take a break. A message on the screen prompted them to press the enter key to continue to the next block.

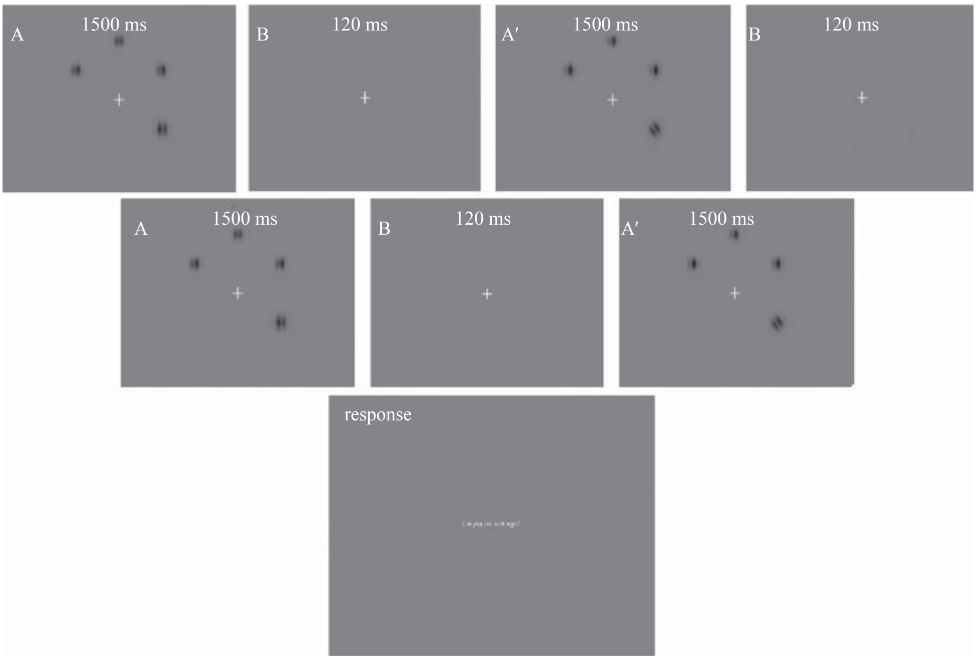

Figure 3. An example trial with an orientation change and a set size of 4. The changing element is below and to the right of the fixation cross.

2.5 *Stimulus configuration*

In each trial, elements adopted a value for colour, orientation, size, and speed selected randomly from the points listed below. The starting point of changing features was constrained so that they could only change from one of the points listed to another (within a dimension). The manipulation of change magnitude represents a change from one of the featural values listed below (in presentation A) to another value on the same dimension (in presentation A′). As mentioned previously, colour values are not uniformly spaced, but were set to be progressively more red and less green while being isoluminant and with each step appearing (to the experimenter) to be approximately equally perceptually distinct.

- Colour (hue): 0.98, 1.01, 1.04, 1.08, 1.11, 1.21, 1.24, 1.27, 1.30, 1.32
- Orientation/deg: 0, 15, 30, 45, 60, 75, 90, 105, 120, 135, 150
- Size/deg: 1.8, 2.07, 2.38, 2.74, 3.15, 3.62, 4.16, 4.78, 5.50
- Speed/deg s^{-1}: 0.3, 0.47, 0.72, 1.12, 1.73, 2.68, 4.16, 6.45, 10.00

The luminance of elements was constant throughout. This was done so that variations in colour were independent of variations in luminance, in keeping with the psychophysical principle of varying one stimulus dimension independently of others (see Palmer 1994). The values for speed and size lie on a logarithmic scale, and follow Weber's law, such that the difference between two neighbouring values is proportional to the magnitude of the lower value. This was done because it was found in pilot testing that the discriminability of successive increments in change magnitude remained the same only if the size of these increments followed Weber's law (for speed and size changes). Spatial frequency was fixed at 1.5 and Gabors could drift left or right relative to their orientation and this direction was randomised.

3 Results

Figure 4 shows average hit rate for the different observers (and all observers) as a function of set size; figure 5 shows the average hit rate at different change magnitudes (2–5—see section 2.5 for exact values) for different change types, while figure 6 shows the average hit rate at different set sizes (ie set-size effects) for different change types.

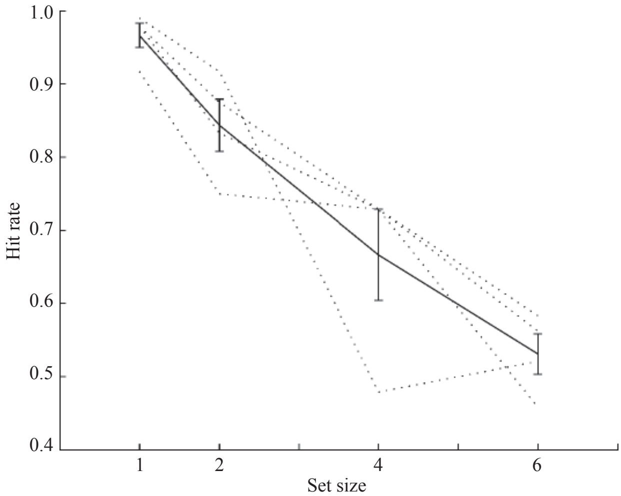

Figure 4. Average hit rate (filled line) at different set sizes. Also shown is hit rate for each observer (dashed lines).

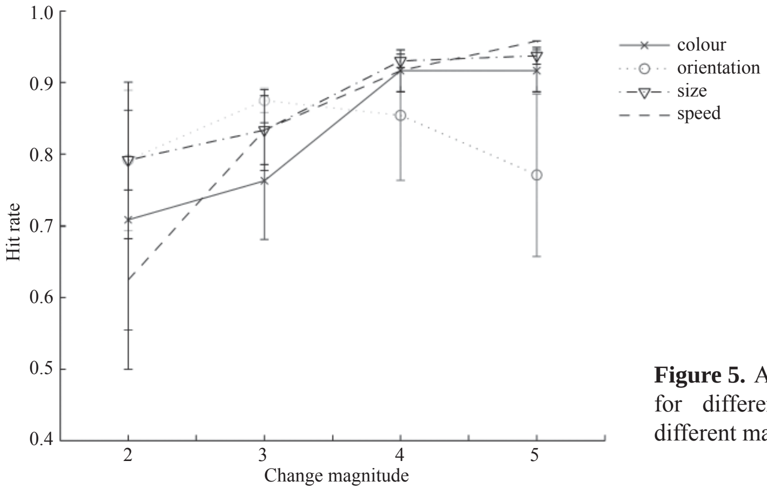

Figure 5. Average hit rate shown for different change types at different magnitudes of change.

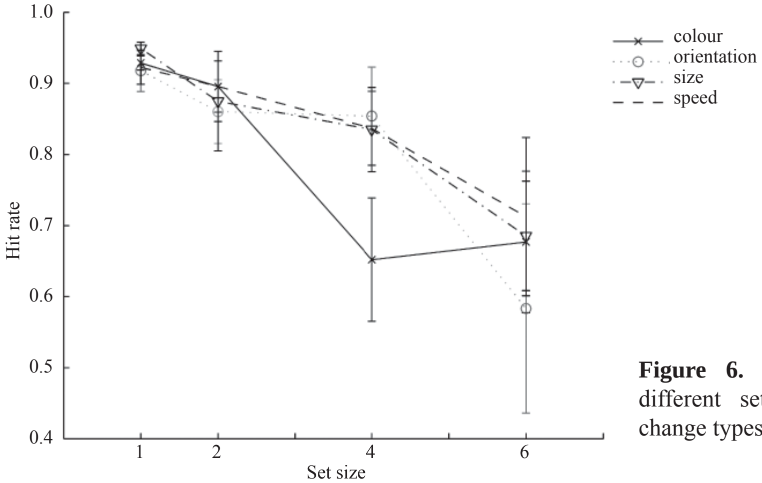

Figure 6. Average hit rate at different set sizes for different change types.

It is clear from these results that performance is relatively similar for all change types across set size, the exception being colour changes at a set size of 4, which have a significantly lower hit rate than the others. Orientation and colour have the largest set-size effects (largest rate of performance decrement with increase in set size), and speed and size have lower set-size effects that are similar to one another. d' values were calculated for each of the average hit rates and false alarm rates in each condition. These were then compared with d' values predicted by both a sample-size model and a high-threshold model. Table 1 and figure 7 show that regression coefficients were higher for the sample-size model than the high-threshold model for all change types. However, every r^2 value was significant to $p < 0.05$.

Table 1. The way the sample-size model and the high-threshold model predict the data from experiment 1.

Feature dimension	r^2 for $N^{-1/2}$	r^2 for N^{-1}
Colour	0.95	0.73
Orientation	0.74	0.54
Size	0.90	0.65
Speed	0.77	0.49

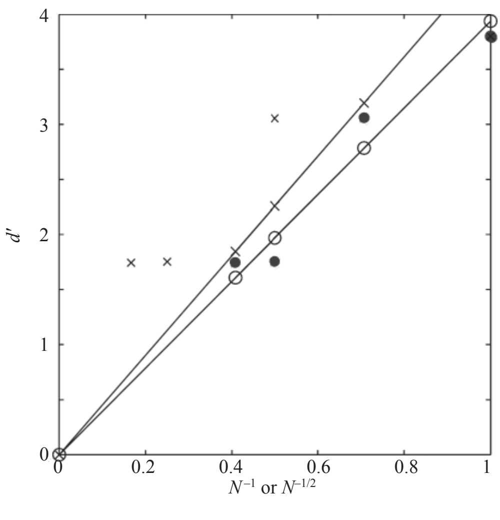

Figure 7. A demonstration how well the sample-size model and the high-threshold model predict the data from experiment 1. Filled dots are d' vs $N^{-1/2}$ and the corresponding regression fit is the line through the open dots. Crosses are d' vs N^{-1} and the corresponding regression fit is the line through them.

4 Discussion

The experiment utilised a simple Gabor-change-detection paradigm in which the number of Gabors present was varied in order to determine whether data were better fitted by a high- or low-threshold model of vSTM . The sample-size model (Shaw 1980) was found to fit the data better than a popular high-threshold model (Cowan 2001; Pashler 1988).

Although the results of the current experiment appear to support the sample-size model over a high-threshold one, there are several considerations which may weaken this interpretation. These will be addressed before moving on. First, the experiment utilised only four participants, which may lessen the generality of the results found. However, it was thought that four would be enough, given that the relationship between the models and data was looked at for each observer individually (and for each it was found that the sample-size model yielded a much better fit than the high-threshold model). Also, in this experiment, the display set-size was manipulated directly (ie by having more or less elements physically present) rather than cuing the relevant set size on each trial, as has been done elsewhere (Burmester and Wallis 2011a; Palmer 2000). Manipulating the display set-size directly is likely to introduce sensory effects not present in a cuing/relevant set-size paradigm. However, this display set-size manipulation is the one used by most studies looking at change detection and using it allows more comparability with them. Another consideration is that the results, while in favour of a low-threshold model in comparison to a high-threshold one, cannot rule out a model which is a hybrid of the two (ie the slots + averaging model of Zhang and Luck 2009). This is because this model suggests that the vSTM system acts according to the sample-size model for set sizes 4 and below but has a discrete item limit at set sizes of 4 and above. Although the experiment reported here went above a set size of 4, there was only one step above 4 (ie 6) and a fuller test of this model would require the use of more set sizes above 4.

In finding that the data were better fitted by the sample-size model, the experiments here indirectly support the findings of Wilken and Ma (2004) who found that sensitivity to change (measured by d') was better explained by a signal-detection model of change detection and visual memory than the high-threshold model put forward by Luck and Vogel (1997) and other authors (see, for example, Cowan 2005; Pashler 1988). The sample-size model is a specific instance of a more general signal-detection approach, because it rests on the same assumptions as signal-detection theory [(i) perceptual attributes can be represented by normally distributed random variables; (ii) an observer's threshold for a "yes" response can be reached by noise alone; (iii) noise will increase with the number of items required to be represented to make the discrimination]. The sample-size model is more specific than such models because it adds the further constraint that there is a finite number of samples taken of the external stimulus display in a given time period. However, a limitation of the sample-size model is that it does not state at which stage(s) (ie perception vs decision) noise is a limiting factor. However, this limitation is not relevant to the purpose of the current study, which was to test an instance of a low-threshold theory against the dominant high-threshold one.

The support for the low-threshold theory has implications for the functional architecture of the visual attention–memory system. Specifically, it suggests that, in this task, memory is better modeled in terms of information, rather than in terms of features or objects. This idea is more compatible with the conception of vSTM capacity being limited by a shared cognitive resource distributed across the to-be-remembered information, rather than it being limited to a fixed number of coherent objects, protoobjects or features. Given that the sample-size model conceptualises the vSTM capacity limit as being quantified by the amount of information that can be extracted from a scene at one time, rather than, say, the number of objects (each of which may vary in the amount of information it contributes to the scene), it supports a more information-theoretic approach of visual attention/vSTM. Such an approach suggests that the visual system will exploit redundancies across space and time to make coding in vSTM more efficient (eg see Brady et al 2009). In other words, repeated presentations of the same stimulus types will make the capacity for those stimuli appear higher if measured in terms of the features or objects remembered. However, the capacity has remained the same in terms of the information extracted from the scene. Therefore, the capacity of vSTM may not be best understood in terms of features or objects represented (and in the context of a high-threshold theory), but, instead, in the context of a low-threshold theory, in terms of information extracted from the scene, where information is defined as a reduction in uncertainty.

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