



Visual memory for random block patterns defined by luminance and color contrast

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Abstract

We studied the ability of human subjects to memorize the visual information in computer-generated random block patterns defined either by luminance contrast, by color contrast, or by both. Memory performance declines rapidly with increasing inter-stimulus interval, showing a half-life of approximately 3 s. We further show that memory performance declines with eccentricity approximately as a Gaussian function of position. Memory decay functions did not depend on whether the patterns were defined by luminance or color contrast. Changing both luminance and color components of block patterns in conjunction did not improve performance suggesting a single memory mechanism is used to store luminance and color derived pattern information. Our results further suggest that color identity (hue, saturation) and pattern information extracted from color- or luminance-contrast are stored independently of each other. © 2000 Elsevier Science Ltd. All rights reserved.

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1. Introduction

Elementary stimulus parameters such as the spatial frequency or velocity of simple sinewave grating stimuli can be held in visual memory without loss of precision over periods of up to at least 30 s (Regan, 1985; Magnussen, Greenlee, Asplund & Dyrnes, 1990; Magnussen & Greenlee, 1992). Within-trial variation of grating orientation does not affect the ability to remember the spatial frequency of a single grating (Regan 1985; Magnussen et al., 1990). This finding suggests that visual memory operates on a level of processing where orientation and spatial frequency are processed independently, rather than at a level where these two dimensions are still linked, such as in primary visual cortex (Regan, 1985; Magnussen, Greenlee, Asplund & Dyrnes, 1991).

Although the ability to remember spatial frequency appears to be perfect, memory for contrast decays over time (Greenlee, Magnussen & Thomas, 1992; Lee & Harris, 1996; Magnussen, Greenlee & Thomas, 1996). Magnussen et al. (1996) suggest that this difference in memory performance for extensive (spatial frequency, velocity, orientation) and intensive (contrast) information is caused by the way they are represented in the central nervous system. According to this account, extensive information is encoded in terms of the distribution of the activity among labeled detectors, whereas intensive information is represented by the overall magnitude of the activity of these detectors. These results are consistent with the concept of a perceptual memory system that consists of independent, parallel special-purpose memory stores, each devoted to a particular attribute of the visual stimulus (Magnussen et al., 1996). Alternative interpretations, based on sequential criterion setting, have been put forth (Lages & Treisman, 1996).

Contrary to such simple periodic patterns, natural images contain a broad spectrum of spatial frequencies. Information about complex patterns, containing multi-

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ple spatial frequencies, cannot be precisely retained over time. Using textures made up of nine, non-harmonic spatial frequency components, Harvey (1986) found an exponential decline in memory performance with inter-stimulus intervals of up to 10 s. To understand how visual memory works, performance of subjects should be investigated for patterns consisting of multiple spatial frequencies and orientations. Random block patterns, i.e. matrices randomly filled with black and white blocks, lend themselves well to the study of visual memory. Since their configurations are randomly determined, they defy any simple schemes of semantic categorization. The amount of information can be manipulated by varying the number of blocks in the patterns. At the same time, the magnitude of the difference between reference and test patterns can be varied by varying the number of blocks that change. Fig. 1 presents an example of such a pattern. Random block and dot patterns have been used in the past to test the limits of short- and long-term recognition memory (Phillips, 1974; Avons & Phillips, 1987; Kikuchi, 1987; Inui, 1988; Irwin, 1991; Pelli & Farell, 1992). Pelli and Farell (1992) estimated that subjects can store pattern information from about eight blocks in visual short term memory. Indeed, even the configuration of relatively small random block patterns (3×3 or 4×4 blocks) cannot be precisely retained over time. Performance declines with increasing pattern size and does so approximately exponentially over time (Phillips, 1974; Inui, 1988). The decay over time of more complex pattern information is generally thought to be caused by interference (Baddeley, 1992), or interactions between dedicated memory stores (Magnussen et al., 1996). Previous studies have varied memory load by

varying the overall size and complexity of block patterns. This approach confounds, however, sensory and mnemonic factors. By varying the number of blocks that change in block patterns of equal complexity (e.g. 10×10 matrices) we can explore memory capacity under constant sensory processing demands.

In addition to luminance based pattern information, natural images contain color information that can be used for object recognition and pattern segmentation. Color is an interesting stimulus for challenging visual short term memory, as it contains both extensive (hue) and intensive aspects (saturation). Visual memory for color appears to be particularly efficient, exhibiting some memory decay, albeit at a slower rate than contrast information. After normalization, the decline in color matching accuracy reported by Nilsson and Nelson (1981) is about half the size of the decline in contrast discrimination accuracy as reported by Magnussen et al. (1996). Although the data for this comparison come from two different studies, they suggest that color information can be retained over time with greater precision than luminance information. The results of Sachtler and Zaidi (1992), who compared memory for color and luminance information over short (1 s) intervals, confirm this idea. Color and form, as well as other perceptual attributes such as motion and depth, are thought to be processed by largely independent pathways in the visual system (Livingstone & Hubel, 1988; Zeki, 1993). To our knowledge, no study so far has explored the effect of color on the retention of pattern information. By comparing memory performance for patterns defined by luminance contrast to patterns defined by color contrast, we can explore the extent to which color affects memory performance.

In a series of experiments, we examine the effects of the number of blocks that change in the patterns, the stimulus color and contrast, and the inter-stimulus interval (ISI) on memory performance. In addition, by comparing performance for changes in the luminance or color components of patterns defined by both these attributes we explore the extent to which color and luminance derived pattern information is stored independently. We applied signal detection theory to quantify the changes in performance and response bias in a same-different forced choice task. Our inspiration comes from earlier studies that applied signal detection theory to short term memory (Murdock, 1965) and visual search (Eckstein, Thomas, Palmer & Shimozaki, 1997). In analogy to receptive field mapping, we compute 'memory performance maps' based on spatial two-dimensional likelihood functions of performance that show how the limited capacity of visual memory is spatially distributed over the patterns the subjects had to remember.

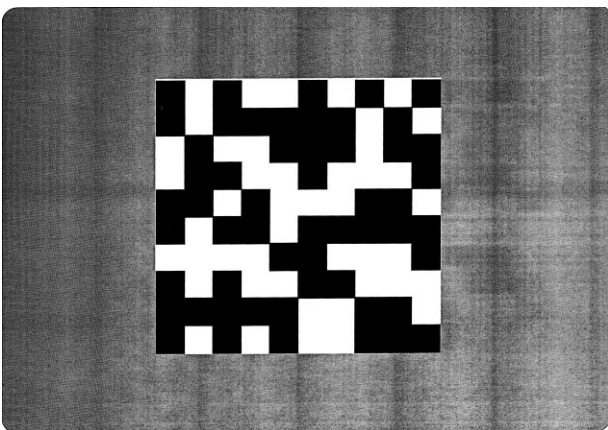


Fig. 1. An example of a 10×10 random block pattern. In most of our experiments, the patterns were defined by either luminance- (dark gray, light gray) or color- contrast (red–green, yellow–blue). In our final experiment, patterns were defined by both color- and luminance-contrast.

2. Method

2.1. Stimuli

The stimuli were presented on an EIZO Flexscan 661 color display with a 21" Trinitron tube that was under control of a computer equipped with a video graphics board (VSG2/2, Cambridge Systems, UK). The computer was also used for controlling the experiment and collecting subjects' responses. For the latter purpose a response box (CB1, Cambridge Systems, UK) was connected to the computer. Color and luminance calibration was performed with a Spectra 704 spectral radiometer. Subjects viewed the screen binocularly at a viewing distance of 1.0 m, at which the display subtended $19.3 \times 14^\circ$. The experimental room was dark except for the light emitted by the monitor.

Each random block pattern (see Fig. 1) consisted of a 10×10 array of small blocks. Within each pattern, half the number of blocks was set to a positive contrast and the other half to a negative contrast. On trials where reference and test patterns differed, a predefined number of blocks were selected randomly and inverted from light to dark or vice versa. Care was taken to assure that half of the blocks that changed were inverted from light to dark and half from dark to light, so as to avoid any differences in the average luminance or color of the patterns. Pilot work on three subjects indicated that performance depended on block size for sizes below 0.25° . For blocks smaller than 0.25° performance decreased linearly with the log of block size. Above a block size of 0.25° , performance remained constant for all three observers. These measurements were conducted for patterns defined by luminance contrast, which was adjusted to be ten times the detection threshold level. In the experiments presented here we used $0.5 \times 0.5^\circ$ blocks, well within the range of constant performance. Hence, a test or reference pattern measured $5 \times 5^\circ$.

The colors used in the patterns were chosen from the color space as described by MacLeod and Boynton (1979) and varied such that they either differentially stimulated the long (L) and middle (M) wavelength sensitive cones only (LM-condition) resulting in patterns that appeared approximately red–green in color, the short (S) wavelength sensitive cones only (S-condition) resulting in patterns that appeared approximately yellow–blue in color, or all three cone classes simultaneously (LUM-condition) resulting in gray level patterns. In all conditions and all our experiments, the background on which these patterns were presented was a neutral gray (CIE 1931 values x : 0.33, y : 0.33) with a luminance of 25 cd/m². Transformations between cone stimulation units and monitor units were done on the basis of Vos–Walraven cone primaries (Vos & Walraven, 1971).

In most of the experiments presented here (except for those in which the effect of contrast was investigated), the contrast at which the patterns were presented was set at ten times the individual subject's threshold for the axis from which the colors were chosen. This precaution was taken in an attempt to prevent sensitivity differences from influencing the results. Detection thresholds for each of the three axes in color space were determined for 2×2 block patterns using a two alternative forced choice technique (2AFC) and the Best PEST parameter estimation technique (Lieberman & Pentland, 1982). Subjects were required to fixate a small fixation mark in the middle of the screen. Computer-generated sounds indicated two 200-ms intervals in which the pattern could appear. Subjects indicated whether the pattern was presented in the first or second interval. In the detection experiment, within trials the color axis was constant, across trials three color axes were randomly interleaved. The threshold values used in the memory experiments were each based on six staircases per color axis.

2.2. Experimental procedure

A schematic illustration of the temporal sequence of a typical trial is given in Fig. 2. On a trial, the subject was first shown a random block pattern (referred to as the reference pattern), and then after some retention interval was shown a second block pattern (referred to as the test pattern). This test pattern could either be the same as or be different from the reference pattern. Trials containing two identical stimuli occurred in 50% of all trials. In the other trials, the stimuli differed. After presentation of the reference pattern, the subject had to judge whether the two patterns were identical or whether they were different. Subjects were instructed to 'respond as accurately and quickly as possible'.

Color axis and inter-stimulus interval (ISI) were held constant within a given measurement block (except for the experiments used to obtain the data of Fig. 6 where axis and ISI were randomly interleaved within blocks). ISI varied across blocks between 1000 and 10 000 ms (500 and 16 000 for data of Fig. 6). The reference and test patterns were both shown for 200 ms. During the ISI, a 240 ms dynamic visual mask was presented that filled the display. This mask was a random block pattern with blocks of the same size, contrast and color as the test and reference patterns. In between the offset of the reference pattern and the appearance of the mask the screen was blank for a short period of time. The length of this period was randomly varied from 200 to 400 ms. During the presentation, the blocks within the mask changed randomly from positive to negative contrast (or vice versa) three times and as such appeared as coarse dynamic noise. The screen was blank (except for the fixation mark) from the offset of the mask until the

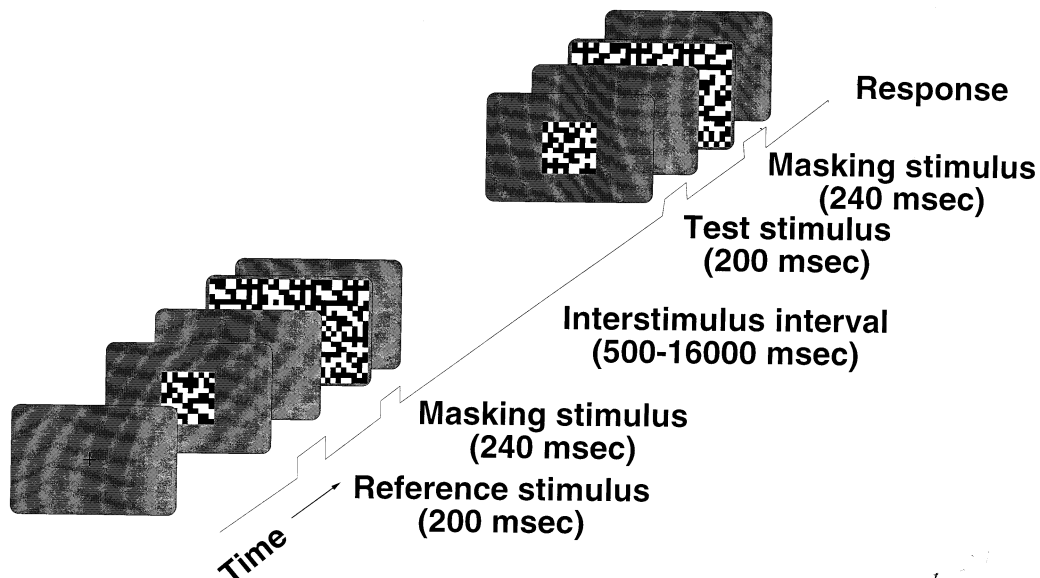


Fig. 2. Schematic illustration of the stimulus presentation during a single trial, depicting the presentation of reference, test and masking stimuli. For more details see text.

appearance of the test pattern. Although the period between stimulus offset and mask onset could vary in length the total ISI was kept constant by varying the duration of the post mask period. The mask was added to control the amount of time given for visual processing and to eliminate the effect of any retinal afterimages.

The presentation of the test pattern was followed by a second mask with the same spatial and temporal characteristics as the first mask. After its disappearance the screen turned blank and a white fixation point cued the subject to respond. The subject did so by pressing the left or right switch on the response box indicating that he thought the reference and test patterns had either been the same or different. Subjects received feedback on their performance via a computer-generated sound that indicated incorrect responses. The inter-trial interval was 1 s. The different stimulus conditions were presented in random order.

2.3. Observers

Four observers participated. Three observers, the two authors (FWC and MWG) and a paid subject (EM), were corrected to normal myopes and the other observer (MK) was emmetropic. At the time of experimentation, three of the observers were between the ages of 20 and 30 years and one between the age of 30 and 40 years. All subjects had normal trichromatic color vision.

2.4. Data analysis

During the experiments the hit and false alarm rates,

and reaction times were recorded (the latter are not reported here). The parameter for performance we use in this paper is d' . In general, data in the graphs are based upon two to three independent runs of approximately 50 trials each per condition per subject. ANOVA for repeated measures was performed on the dependent variables.

3. Results

3.1. Suprathreshold contrast level

The first experiment addresses the question how memory performance depends on the contrast level for the different color axes. The random block patterns were presented at fixed multiples of each subject's individual detection threshold for the particular color axis. Any differences in sensitivity that might affect memory performance could thus be minimized. In this experiment, the ISI was kept constant at 1 s. During a run, the different contrast levels were interleaved in random fashion.

The results of this experiment are shown in Fig. 3. The index of performance, d' , is plotted as a function of the suprathreshold contrast level (ranging from threshold contrast to 24 times threshold level). The different symbols give the results for the luminance and the two color axes. The results for each of the three observers are shown in separate panels. Performance at threshold contrast level is at or near chance levels (d' approximately zero). For both color and luminance defined patterns, d' increases as stimulus contrast is

increased, reaching the same asymptotic performance levels at about eight times threshold contrast.

An analysis of variance was performed to test the main effects of observer, color axis and contrast level, as well as the interactions between these effects. As can readily be seen in Fig. 3, the effect of the observer is highly significant ($F(2, 8) = 18.83$; $P < 0.01$). This difference is mostly due to the relatively good performance of subject EM, whereas observers FWC and MK perform in a similar way. The effect of suprathreshold contrast is, of course, highly significant ($F(5, 20) = 26.8$; $P < 0.0001$). Overall the effect of color axis is not significant ($F(2, 4) = 1.98$; $P < 0.2$, n.s.), but its interaction term with suprathreshold contrast level is significant ($F(10, 40) = 2.99$; $P < 0.007$). A significant effect of color axis on discrimination performance ($F(2, 8) = 5.1$; $P < 0.04$) is evident for values below the asymptotic d' level. This trend in the data suggests that

discrimination performance saturates at different levels of suprathreshold contrast, saturation being reached at lower levels of suprathreshold contrast for luminance than for color contrast.

As a subsidiary condition, we tested the effect of adding a small dark luminance grid superimposed upon the block patterns to highlight the edges. The color-contrast defined edges in our block patterns may have been less distinct compared to the luminance-contrast defined ones, so performance for the color patterns might have been attenuated for this reason. However, we found comparable performance for our regular color-contrast defined patterns and for the colored patterns with the additional grid. Hence, we conclude that the similarity of visual performance for color- and luminance-defined pattern information is a genuine finding.

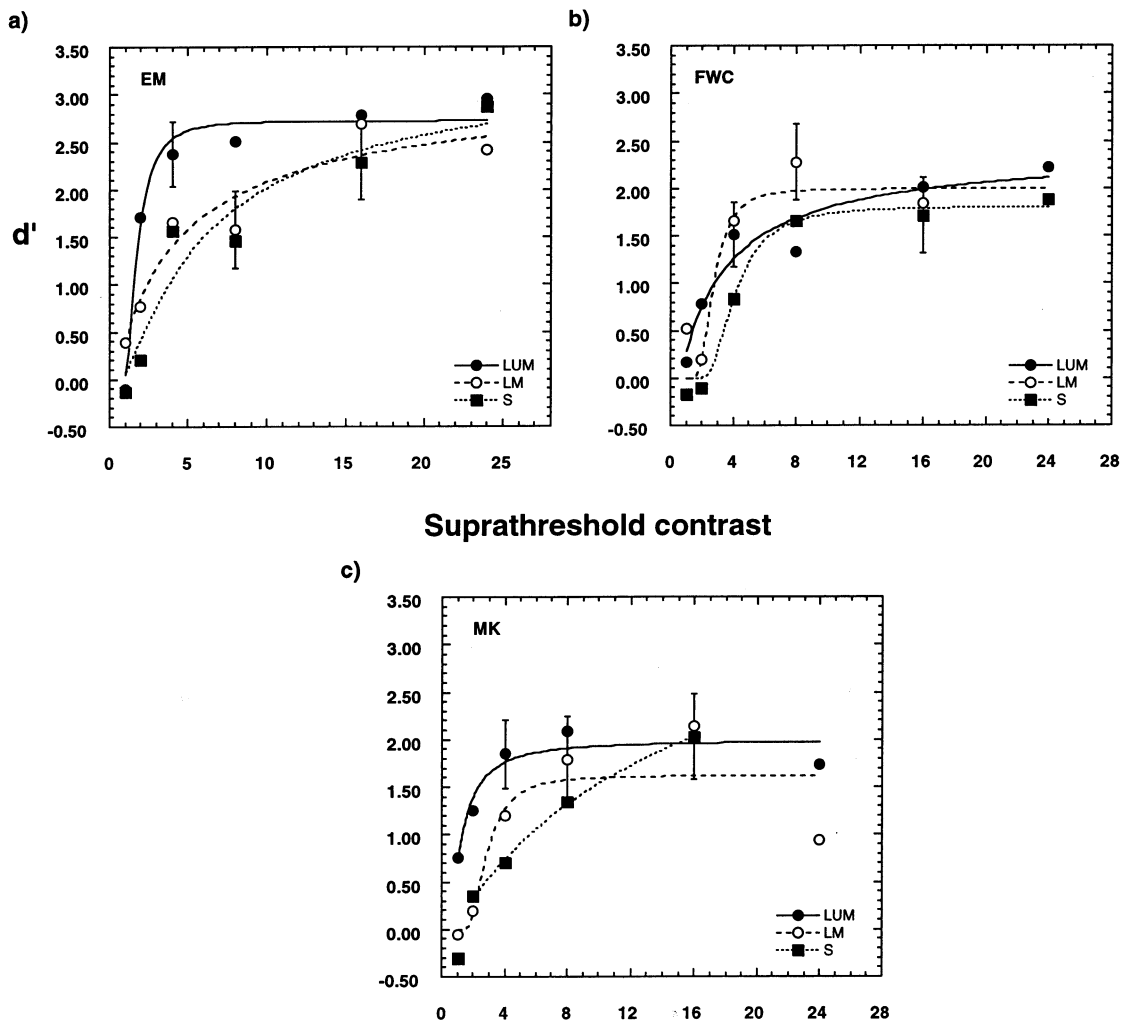


Fig. 3. Effect of suprathreshold contrast on discrimination performance. The symbols show the mean of three runs and the error bars show ± 1 S.E. of these means. The results for each of the three observers are shown in separate panels. The index of performance, d' , is plotted as a function of the suprathreshold contrast level (factor ranging from contrast at detection threshold level to 24 times threshold level). ISI was 1 s and the number of blocks that changed on different trials was eight. Symbols present the results for the different color axis conditions.

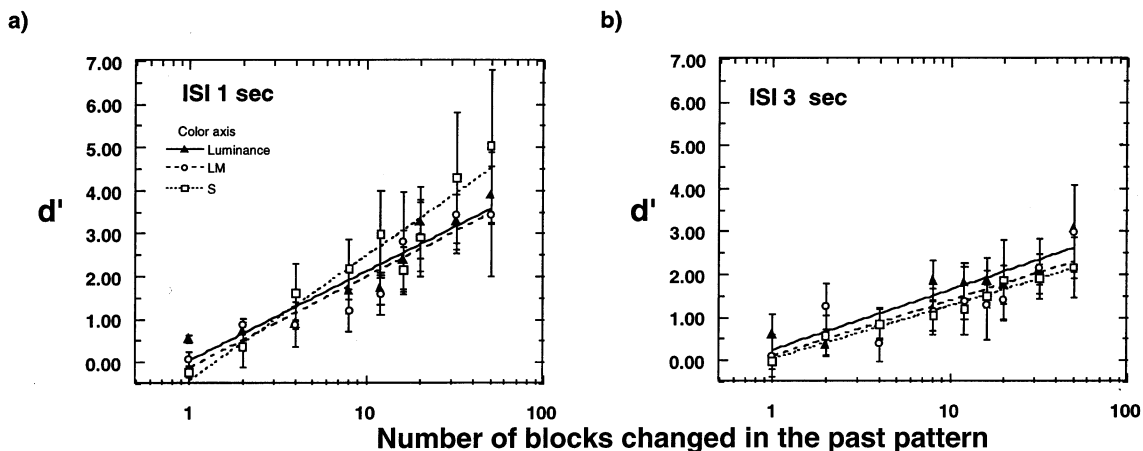


Fig. 4. Discrimination performance as a function of the number of blocks that differed between the reference and test patterns. The results are shown for ISIs of 1 and 3 s and are averaged over two subjects. Different symbols present the findings for the different color axes. The lines are linear functions fitted to the data (note the logarithmic x -axis).

3.2. Color axis and number of blocks changed in the test patterns

The next experiment addresses the question how discrimination performance depends on the number of blocks that change within the random block pattern and on the color of the pattern. Fig. 4 shows the results for two ISI conditions (1 and 3 s) based on data averaged over two subjects: d' is shown as a function of the number of blocks that changed between the reference and test pattern. The different symbols give the results for the luminance (LUM), red–green (LM) and yellow–blue (S) conditions. The patterns were shown at a contrast ten times detection level. As expected, d' increases as the number of blocks that changed in the pattern increases to up to 50 blocks (the number of changes that maximized the structural change in the pattern). The asymptotic value of d' declines with increasing retention interval. The effect of the number of blocks that changed in the pattern was independent of the color axis (LUM, LM or S).

Signal detection theory (SDT; Green & Swets, 1966) has been applied to a number of areas in sensory physiology and psychophysics to describe results in detection and discrimination tasks. We attempt to apply a few simple principles from SDT and probability summation to account for some of the findings reported above. In essence, our SDT model tests the extent to which we can predict how performance increases with an increasing number of blocks changed in the pattern based on an estimate of how well we can detect a change in a single block. The main assumptions in our model are independent processing of the blocks and probability summation. As we will see later, memory performance declines for blocks located away from the center. This decline is included in the model as a

2D-Gaussian weighting function. Hence, the contributions of blocks near fixation are higher than those on the perimeter of the pattern. Such a weighting profile could either be the result of an attentional mechanism, which would act at the encoding stage, or a memory mechanism, which would act at the storage and retrieval stages.

Fig. 5 presents mean data from two subjects and different stimulus conditions and the model fit to the data. Table 1 gives the values for the best fitting parameter values used in the model and the explained variance for each ISI condition. The fact that this model describes the data so well suggests that once we know the likelihood of detecting a change in a single block, we can predict performance for any number of blocks. The model is described more extensively in the Appendix.

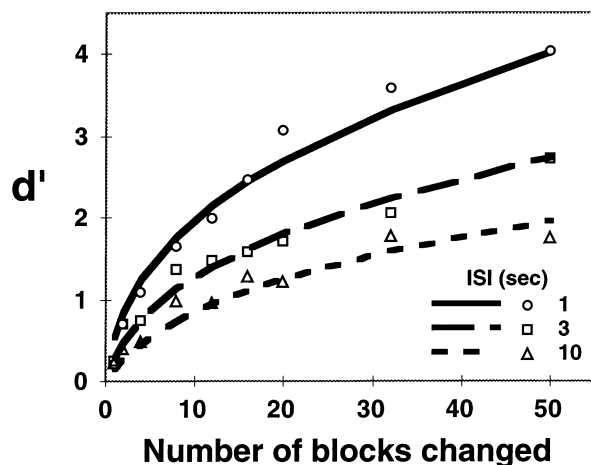


Fig. 5. Index of performance (d') is shown as a function of the number of blocks that changed in the pattern. The symbols show the mean values (averaged over two subjects) for the three ISI conditions. The curves present the model fits with parameters given in Table 1.

Table 1

Values of parameters used to fit the model based on signal detection theory (see Appendix) to the data shown in Fig. 5^a

ISI	d'_{block}	λ_{block}	R^2
1	5.14	1.92	0.98
3	2.39	2.47	0.97
10	1.77	2.98	0.96

^a For all conditions, the standard deviation of the Gaussian weighting function that is part of the model was kept constant at a value of 1.0 derived on the basis of the 'memory performance maps' (see Table 2). d'_{block} is the (hypothetical) performance value for detecting a change in a single block in the pattern. λ_{block} is the (hypothetical) criterion set by the subject for discriminating between noise and an actual change. R^2 is the explained variance of the model. Model parameters were fit using a least squares estimation.

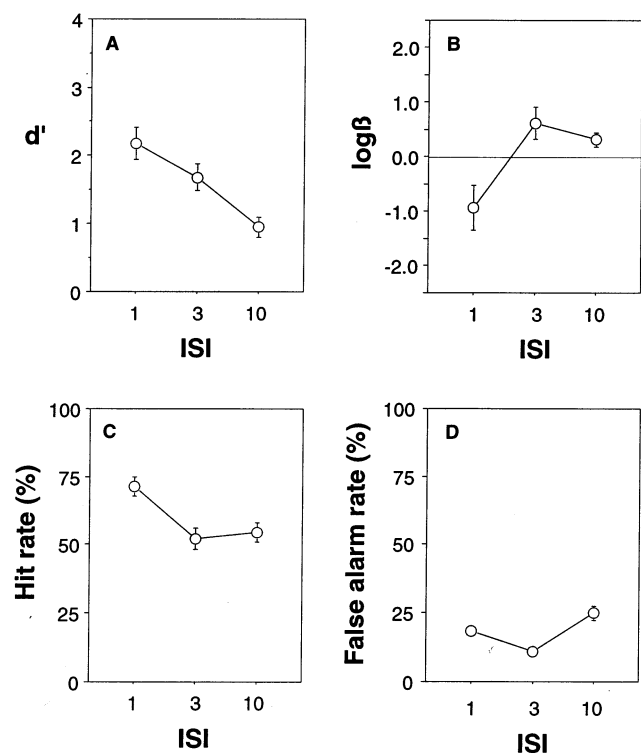


Fig. 6. Panels a–d show (A) d' ; (B) $\log \beta$; (C) the hit rate and (D) the false alarm rate, respectively as a function of the inter-stimulus-interval (ISIs). Averages for observers EM and FWC for the luminance condition. Data are taken from the experiment shown in Fig. 5 and are averaged over the different number of blocks changed.

3.3. Response bias

The results shown above indicate that the observers' ability to detect a change in the random block patterns is co-determined by the ISI. Until now we have assumed that this factor affects only the detectability of the change in the patterns. However, it cannot be ruled out that changing the ISI could also affect the strategies used by the subjects to optimize their performance. Such changes in strategy could result in a shift in the

response criterion used by the subject to decide whether reference and test patterns are identical or different. Signal detection theory allows us to estimate changes in response bias, where $\log \beta = \log(f_s(\lambda)/f_n(\lambda))$, or the log of the likelihood ratio at the response criterion λ . An optimal criterion would be the point where noise and signal distribution cross, i.e. $f_s(\lambda) = f_n(\lambda)$, and thus $\log \beta = 0$. Negative values of $\log \beta$ would indicate $f_s < f_n$, whereas positive values indicate $f_s(\lambda) > f_n(\lambda)$. Fig. 6 presents the results averaged over observers EM and FWC for each ISI condition for the luminance data only. Panels a–d show d' , $\log \beta$, and the hit and false alarm rates, respectively. With increasing ISI, d' declines and $\log \beta$ initially increases. The hit rate and false alarm rate shown in panels c and d were used to derive these values. As can be seen, subjects have a relatively low false alarm rate which increases slightly for the longest ISI condition.

3.4. ISI

The next experiment was designed to more extensively test whether there is a difference in the memory decay for patterns defined by luminance or color differences. Although the results presented in Fig. 4 already suggested there was none, the trials for the different ISI's and color axes were run in blocks. We therefore conducted a further experiment, with a larger span of ISI's (from 0.5 to 16 s), and with ISI and color axis varied within blocks. We used patterns that were a factor of 10 above detection threshold. On different-trials, a fixed number, eight, of the 100 blocks changed. Fig. 7 shows the results for two observers. For both observers tested, d' declines exponentially with increasing ISI. Based on these functions, d' should approach zero, and performance should thus approach guessing levels, at an ISI of approximately 35 s. Neither the position nor the slope of the curves differed significantly across the luminance and color contrast conditions, confirming the finding shown in Fig. 4 that the pattern information in visual short-term memory decays at a similar rate for luminance- and color contrast-defined patterns.

3.5. Memory for patterns defined by both color and luminance

The similarity in memory performance we have found thus far for luminance and color-contrast defined patterns strongly suggests that a single memory mechanism stores the pattern information. Our experiments and results leave open the possibility that luminance- and color-defined pattern information are stored independently in mechanisms with similar operating characteristics. To address this issue, we performed an experiment in which we compared memory perfor-

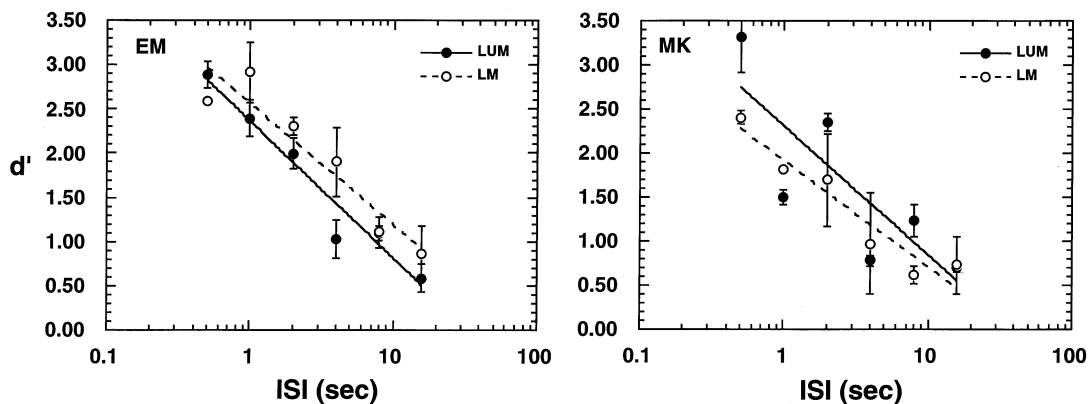


Fig. 7. Effect of ISI on discrimination performance for two observers: d' is shown as a function of the inter-stimulus interval, which ranged from 0.5 to 16 s. Note that ISI is plotted on a logarithmic axis. The different symbols show the results for the luminance (LUM) and the red–green-color (LM) contrast conditions. The curves show the best fitting logarithmic functions. In this experiment, contrast was $10 \times$ the observer's threshold and eight blocks changed in the different conditions.

mance for changes in luminance, color or both in conjunction. Contrary to the reference patterns used thus far the ones used in this experiment were defined by both luminance and color (so each block had both a color and a luminance component). We compared memory performance in three conditions. In the first condition, ten blocks in the test pattern changed only in the L–M color component, whereas in the second only the luminance component of ten blocks changed. In the third and final condition, ten blocks changed in both their color and luminance components. Therefore, the three conditions in this experiment differ only in the way the reference and test patterns differed from each other, i.e. in luminance, in color, or in both luminance and color. Assuming we are dealing with memory mechanisms with at least partly independent sources of noise the prediction is straightforward. If color and luminance defined pattern information are stored independently we expect that performance would be better when both color and luminance change in synchrony than when only one of the two components change. If, on the other hand, color- and luminance-derived pattern information is stored in a single memory buffer we expect that when both color and luminance change performance will be similar to that found in the other two conditions.

Fig. 8 shows the results for this experiment. The results are clear. For both subjects, a change in both the luminance and color component simultaneously is not better remembered than a change in a single component. (Note that although for subject MWG performance for a color change was slightly worse than for the conjunctive change, the latter did not result in a better performance than in the luminance-change condition.) A repetition of this experiment at higher levels of contrast for both the luminance and color component gave the same result. The finding provides strong evidence for the idea that a single memory mechanism

stores the pattern information derived from color and luminance contrast.

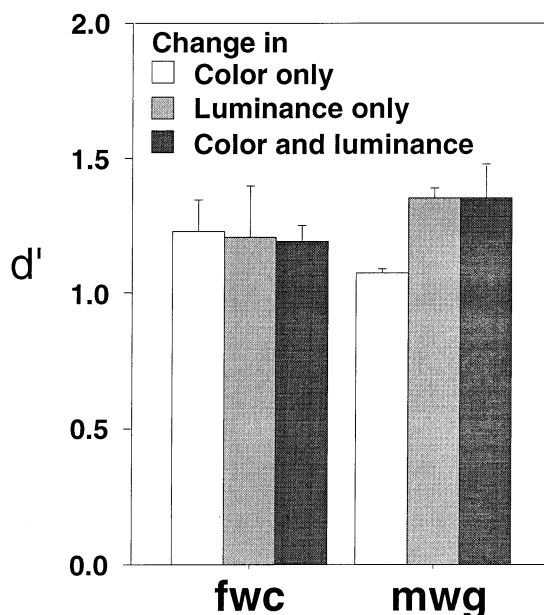


Fig. 8. Memory performance for changes in the luminance component, the color component or both components in conjunction of patterns defined by both luminance and color contrast. Results for two observers. The different symbols give the mean values for the different color axis conditions. In this experiment, we used an ISI of 1 s, a luminance contrast of 10%, a L–M color contrast of 3% (both contrasts were well above our observers' thresholds). In the different conditions ten of the 100 blocks in the pattern changed in contrast polarity. On color and luminance change only conditions, the ten blocks changed either in their luminance or in their color component, respectively. On conjunctive changes these ten blocks changed both in their color and luminance components (so the color and luminance changes were always perfectly correlated). Conditions were presented in random order, so subjects were unaware of what type of change to expect.

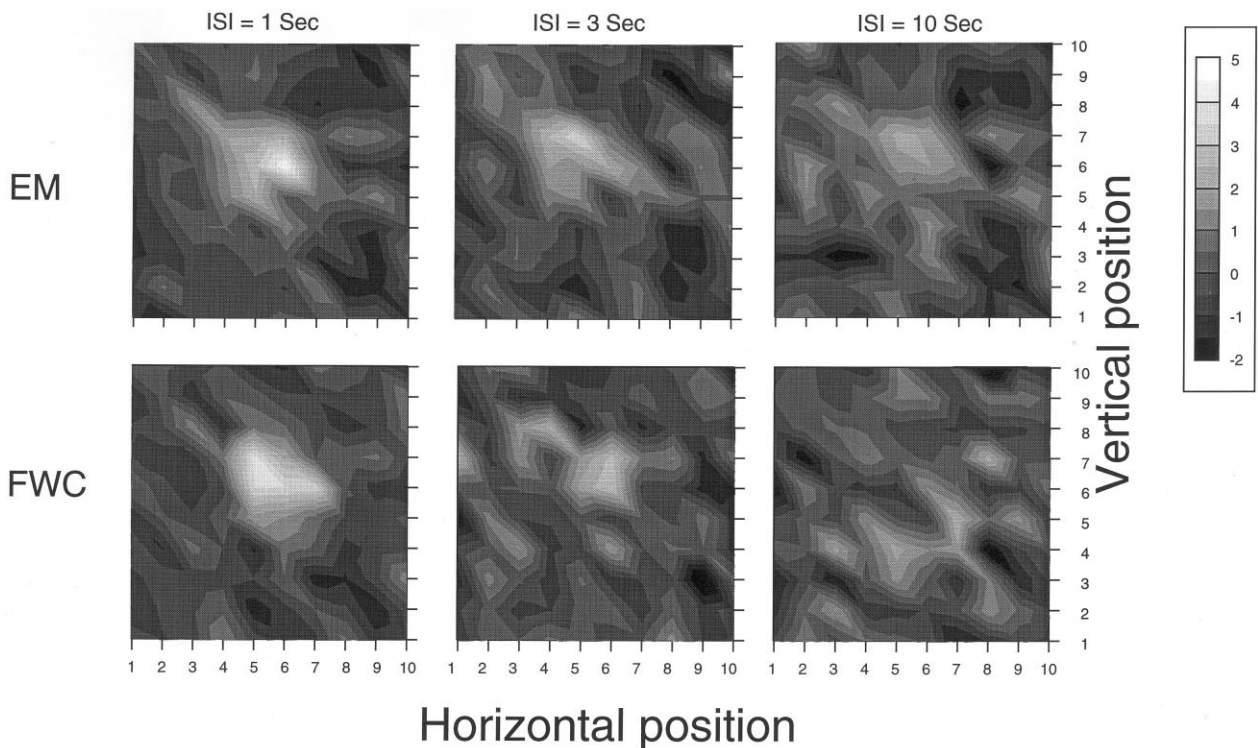


Fig. 9. Two-dimensional likelihood maps of memory performance. The x and y axes represent the horizontal and vertical position of the block that changed in the pattern, the upper left hand corner of the pattern corresponding to the upper left corner in the pattern. The gray-scale z -axis shows the standard score of the log probability ratio of getting the trial right over getting the trial wrong (the log probability ratio was standardized by subtracting the mean and dividing by the standard deviation). The z -axis ranges from $+5$ to -2 . Brighter regions indicate areas in which performance was better than average (which has a value of 0.0), whereas the darkest regions show areas in which performance was below average. The results are shown for the 1, 3 and 10 s ISI conditions and for observers EM and FWC.

3.6. Memory performance maps

The results of the experiments presented thus far indicate that memory capacity for random block patterns is limited. It might be asked how this limited memory capacity is allocated over the pattern. Are all positions in the pattern remembered equally well? To determine the importance of the position of the blocks that changed within the pattern, we reanalyzed the (luminance) data, some of which were presented in Fig. 4. We sorted the different trials into two groups, depending on whether the trial was performed correctly or incorrectly. For each block of the 10×10 matrix we calculated the ratio of the likelihood that the trial was performed correctly or incorrectly, for those trials in which that particular block changed. This was conducted for conditions in which not more than 20 blocks changed in the pattern. This was done on the results from the three ISI conditions (1, 3, and 10 s) separately. Fig. 9 shows the results of this analysis for subject EM and FWC. For the 1 s ISI condition, there is a pronounced distribution of the z -scores with a clear peak in the central region of the pattern. This peak gradually dissipates as the retention period is increased to 3 s and again to 10 s. When the retention interval is short,

subjects best remember the central part of the pattern, evident in the high z -score whenever the centrally located blocks changed. To see whether this strategy might change over time, we fitted a 2D circular symmetric Gaussian weighting function to the data. Using a least squares technique we estimated the standard deviation and amplitude of this Gaussian spatial sensitivity profile for the three ISI conditions. The position for all three ISI conditions was determined by first fitting the model to the data averaged over all conditions. The best fitting parameters are shown in Table 2.

Table 2

Amplitude and standard deviation (in blocks) used to fit a 2D circular symmetric Gaussian weighting function to the log likelihood data for the three ISI conditions^a

ISI	S.D. (blocks)	Amplitude	R^2
1	1.0	4.3	0.63
3	1.0	2.9	0.34
10	2.1	1.3	0.17
10 (S.D. = 1)	1.0	1.6	0.11

^a Data are shown in the 'memory performance maps' in Fig. 9. The last column shows the model fit when the standard deviation in the ISI = 10 condition was forced to 1 (as in the 1 and 3-s ISI conditions). R^2 is the explained variance of the model.

For the short ISI of 1 s this simple model quite accurately describes the distribution of memory performance as a function of spatial position. Unfortunately, the model's fit to the data for the ISI is 3 and 10 s conditions is rather poor so it is difficult to determine conclusively whether this distribution changes over time or not. One reason for this poorer fit is that we had fewer trials for the longer ISI conditions, so that the distribution could be less well estimated.

4. Discussion

We have examined human subjects' ability to retain visual information contained in random block patterns defined by luminance or color. We find that both absolute memory performance and the decline in performance over time are the same for color- and luminance-defined pattern information once their contrast is sufficiently above threshold (about ten times threshold). At low suprathreshold contrast levels performance for luminance-defined patterns slightly exceeds that for color-defined patterns. This effect is more related to sensory than to memory effects; luminance patterns can be discriminated somewhat better at low suprathreshold contrast levels. Another reason for performance differences for luminance and color contrast may be that we scaled pattern contrast with respect to each subject's *foveal* sensitivity for luminance and color. The patterns extended into parafoveal vision. A differential decline with eccentricity of sensitivity for color versus luminance could then suffice to explain this small difference at low supra-threshold contrasts.

Our findings show that visual memory performance for color-defined patterns is not better than that for luminance-defined patterns. As mentioned before, this result at first glance appears to be at odds with the finding that memory for color is superior to that for luminance. A likely reason for us obtaining different results from those of Sachtler and Zaidi (1992) is that their task was different. In their study, subjects had to retain color identity (hue and saturation). In our experiments, color vision was necessary to segment the pattern but the task itself did not necessarily require the storage of color identity (although the contrast sign of the blocks or phase information had to be remembered). Nevertheless, we had expected that subjects would use their superior memory for color to optimize task performance had they been able to do so, which was clearly not the case.

From these findings, we can deduce that color identity and pattern information extracted from color- or luminance-contrast are stored independently of each other. This conclusion is in line with the results of a study by Stefurak and Boynton (1986), who, using a different method, concluded that visual memory for

form and color are independent. This interpretation is also in concordance with the finding that information on spatial frequency and contrast of periodic patterns is stored independently (Magnussen et al., 1996). Within the context of the model of the perceptual memory system proposed by Magnussen et al. (1996), color therefore appears to be placed in memory stores that are parallel to and independent of those that hold the spatial frequency information.

Our final experiment strongly suggests that luminance- and color-defined pattern information are stored by a single memory mechanism. This suggests that visual memory operates on a level of processing where color- and luminance-derived pattern information is processed together rather than at a level where these two dimensions are still processed separately such as in primary visual cortex (e.g. Livingstone & Hubel 1988). This result is also in line with the finding that in patients with focal lesions in temporal or prefrontal cortex memory for color- and luminance-based pattern information was affected to the same extent (Greenlee, Koessler, Cornelissen & Mergner, 1997).

Is independent storage in visual short term memory of color identity and pattern information advantageous? We believe so. Independent storage may result in hue invariance of form that enables recognition of form independent of a specific color. Analogous to color constancy, which allows us to recognize colors despite changes in illuminant, hue invariance allows us to recognize objects even if a shadow is cast over them or when the illuminant changes (e.g. when walking underneath trees in a forest). In fact, the independence of color and form may help us to quickly search a scene for a particular form or color, often referred to as parallel search (e.g. Treisman & Gelade, 1980). Further, color information may serve to highlight objects to be encoded, stored and recalled, thereby improving overall memory and recognition performance for complex images. This idea is supported by a recent study of Gegenfurtner, Wichmann and Sharpe (1998). In their experiment, subjects had to remember images of natural scenes. Retention performance for colored images was found to be about 5–10% better than for black and white images.

Working memory experiments with eye position recordings suggest that subjects prefer to store only very little task-related information and retain this for only a very brief period of time (Ballard et al., 1995; Hayhoe et al., 1998). In a block pattern copying task, subjects, instead of storing larger amounts of task-related information, tended to make eye-movements to obtain the information at the moment they needed it. In the task used by Hayhoe et al. (1998), e.g. color and location information were acquired and stored during separate fixations. As a result, the type of information stored in memory is directly related to the immediate

requirements of the task at hand. Our results indicate similar trends. Subjects only used (and probably retained) the information necessary to perform the task, i.e. the pattern information. In Gegenfurtner et al.'s (1998) natural image experiment, subjects made use of the color to improve memory performance, although it is not clear in what way they used it. Given our current results, it is unlikely that the color information improved subjects' retention of pattern information although the color information may have revealed additional structural information hidden to a luminance mechanism. More likely, they optimized their memory performance by using retained color identity information. Color identity can be better retained than luminance contrast as shown by Sachtler and Zaidi (1992). In that study, it was also shown that perceptual categorization might improve memory performance for both luminance and color contrast. Due to the binary nature of our patterns, subjects might have used perceptual categorization to solve the task, in which case we would predict that increasing the number of contrast levels in the pattern might influence the results. In any case, the differences in results between the various studies raises the question as to what aspects in an image or of a task probe the use and retention of color (identity) information. For example, subjects would likely use different task solving and memory strategies if, in our final experiment, they would have been required to discriminate between color and luminance changes instead of pattern changes.

The 'memory performance maps' shown in Fig. 9 indicate that memory performance declines with eccentricity approximately as a Gaussian function of location. Since we scaled pattern contrast for foveal sensitivity, the decline with eccentricity could be due to the lower resolution and sensitivity of parafoveal vision. The drop in sensitivity with eccentricity can be equated for post-hoc by scaling performance according to the cortical area that analyzes part of the pattern (*m*-scaling) (Rovamo, Virsu & Nasanen, 1978; Rovamo & Virsu, 1979). However, we found that this only negligibly changed the shape of the memory profile. Also, performance for different block sizes did not significantly change above 0.25° (results of pilot work not presented) confirming that block size was not a limiting factor in our experiments. The performance profiles therefore appear genuine which would suggest that high-precision visual short-term memory is a foveal specialization. However, a factor other than memory that might have contributed to the shape of the performance profile is visual attention. Visual attention has been shown to have a limited capacity (e.g. Vergheze & Pelli, 1992) and can be approximated by a Gaussian profile (Steinman, Steinman & Lehmkuhle, 1995). Hence, rather than reflecting a pure memory limitation, the Gaussian decline in memory perfor-

mance probably is the result of a limitation in visual attention, or a combination of mnemonic and attentional limitations. The present results do not allow us to distinguish between these explanations.

In the signal detection model we developed (see Appendix) to explain the change in performance as a function of the number of blocks that changed in the pattern, we assume that the comparison of the reference and test patterns takes place on the basis of independently processed blocks. The assumption that performance for a particular block is completely independent from that of its neighbors is parsimonious but probably incorrect. Subjects will probably remember e.g. four similar blocks in line better than four different ones. Indeed, certain configurations are more easily retained than others (Inui, 1988). One could also imagine that comparison takes place on the basis of the spatial frequencies and orientations present in the pattern. Still, we believe our model shows that probability summation of single detection events is an important and powerful factor when explaining memory performance for pattern information.

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Appendix A

A.1. Signal detection model of short term visual memory performance

In this appendix, we describe a model based on signal detection theory (SDT) in an attempt to account for some of our results. In the model, we assume that there is a noisy representation of each block in the image stored in memory and that the internal response for a block (be it either dark or light) can be approximated by a Gaussian distribution. We also assume that changes from light to dark and vice versa are symmetrical. We further assume that the internal responses for both a block changed and a no change event have a Gaussian distribution. In addition, we assume equal variances for these distributions and the distance between the means of these distributions $X_{\text{no change}}$ and X_{change} to be d'_{block} . Hence we formulate the following:

$$X_{\text{no change}} \sim N(0, 1) \text{ and } X_{\text{change}} \sim N(d'_{\text{block}}, 1) \quad (1)$$

The model assumes that the internal representation of a block becomes noisier over time so that d'_{block} decreases and that in addition the observer may change his decision criterion λ_{block} with increasing ISI. Using d'_{block} and λ_{block} we can estimate the chance of correctly detecting a change in a single block, the hit rate for a single block, which we call $P(\text{YES/Change})_{\text{block}}$, and the false alarm rate for a block, i.e. the likelihood that the observer decides a block has changed when in fact it did not, which we call $P(\text{YES/No Change})_{\text{block}}$. These have their complementary likelihood values in:

$$P(\text{NO/Change})_{\text{block}} = 1 - P(\text{YES/Change})_{\text{block}} \quad (2)$$

and

$$P(\text{NO/No change})_{\text{block}} = 1 - P(\text{YES/No change})_{\text{block}} \quad (3)$$

On the basis of the performance for single blocks we can derive an estimate of performance for the entire block pattern. We assume that the observer's performance depends on how well he remembers each one of the total number of blocks n in the pattern. It further depends on the number of blocks that changed c in the pattern. Two steps are required to solve the task: (1) to detect a change in at least one block that changed on different trials; (2) to correctly identify all blocks that remain unchanged as such. The likelihood that the observer scores a hit we call $P(\text{Hit}_{\text{patt}})$. $P(\text{Hit}_{\text{patt}})$ can be derived with knowledge of its complementary value $P(\text{Miss}_{\text{patt}})$ such that:

$$P(\text{Hit}_{\text{patt}}) = 1 - P(\text{Miss}_{\text{patt}}) \quad (4)$$

A change in a block pattern goes undetected whenever the observer misses all changes in the changed blocks and correctly assigns a not changed to all of the unchanged blocks (note that the observer could get the trial correct by assigning changed to an unchanged block). Hence,

$$P(\text{Hit}_{\text{patt}}) = 1 - (P(\text{NO/Change})_{\text{block}})^c \times P(\text{NO/No change})_{\text{block}}^{(n-c)} \quad (5)$$

in which n is the total number of blocks in the pattern and c the number of blocks that changed.

An observer makes a false alarm whenever he or she erroneously judges that the pattern changed when in fact it did not. $P(\text{False alarm}_{\text{patt}})$ can be derived from its complementary value $P(\text{Correct rejection}_{\text{patt}})$ according to:

$$P(\text{False alarm}_{\text{patt}}) = 1 - P(\text{Correct rejection}_{\text{patt}}) \quad (6)$$

The observer correctly reports that there was no change whenever he or she correctly assigns a not changed to all of the unchanged blocks (and does not incorrectly assign a change to any one of them). Hence,

$$P(\text{False alarm}_{\text{patt}}) = 1 - P(\text{NO/No change})_{\text{block}}^n \quad (7)$$

From the two values $P(\text{Hit}_{\text{patt}})$ and $P(\text{False alarm}_{\text{patt}})$ we can calculate d'_{patt} for memory performance according to:

$$d'_{\text{patt}} = z(\text{False alarm}_{\text{patt}}) - z(\text{Hit}_{\text{patt}}) \quad (8)$$

where z stands for the standard scores of the normally distributed response levels. So far the model assumes that memory performance is the same for each block in the pattern. From Section 3.6, we know that this is not the case. Performance declines approximately as a Gaussian function of both horizontal and vertical position. Hence, the contributions of blocks near fixation are higher than those on the perimeter of the pattern. We can adapt the SDT model to include this finding by making performance a function of position within the pattern. Hence, for each block at position (x, y) in the pattern:

$$P(\text{YES/Change})_{\text{block}_{x,y}} = P(\text{YES/Change})_{\text{block}} \exp \frac{-(x-x_0)^2(y-y_0)^2}{\sigma_x^2 \sigma_y^2} \quad (9)$$

and

$$P(\text{YES/No change})_{\text{block}_{x,y}} = P(\text{YES/No change})_{\text{block}} \exp \frac{-(x-x_0)^2(y-y_0)^2}{\sigma_x^2 \sigma_y^2} \quad (10)$$

We assume that the two dimensional Gaussian weighting function is centered in the middle of the block pattern (i.e. x_0, y_0) with an amplitude of 1.0 and a standard deviation of one block. The next step is to calculate the $P(\text{Miss}_{\text{patt}})$ and $P(\text{False alarm}_{\text{patt}})$ values for changes occurring at each position (x, y) and averaging these values. To predict the mean performance we assume that each block has an equal likelihood of changing on different trials. The formula and calculation becomes easier by using the log likelihood values, rather than the actual likelihood. That way, multiplications become summations. This can be expressed as follows:

$$\begin{aligned} \log P(\text{Miss}_{\text{patt}}) &= \left(c^* \sum_{x=1}^j \sum_{y=1}^k \log P(\text{NO/Change})_{\text{block}_{x,y}} \right. \\ &\quad \left. + (n-c)^* \sum_{x=1}^j \sum_{y=1}^k \log P(\text{NO/No Change})_{\text{block}_{x,y}} \right) / n \end{aligned} \quad (11)$$

in which n is again the number of blocks in the pattern and c the number of blocks that changed. $P(\text{Hit}_{\text{patt}})$ is calculated now through:

$$P(\text{Hit}_{\text{patt}}) = 1 - 10^{\log P(\text{Miss}_{\text{patt}})} \quad (12)$$

The false alarm rate is calculated in a similar way through the correct rejection rate according to:

$\log P(\text{Correct rejection}_{\text{patt}})$

$$= \sum_{x=1}^j \sum_{y=1}^k \log P(\text{NO/No Change})_{\text{block}_{x,y}} \quad (13)$$

and

$$P(\text{False alarm}_{\text{patt}}) = 1 - 10^{\log P(\text{Correction rejection}_{\text{patt}})} \quad (14)$$

d'_{patt} can now be calculated using Eq. (8). Using a least squares estimation, we fitted this three parameter model (d'_{block} , λ_{block} and σ of the Gaussian weighting function) to the data of the experiment in which we varied the number of blocks that changed in a pattern (shown in Fig. 5). The best fitting parameter values are listed in Table 1. Although the model contains three parameters, the standard deviation of the Gaussian weighting functions was kept constant at a value of 1.0 (derived on the basis of the ‘memory performance maps’, see Table 2), so that only two parameters were allowed to vary.

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