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"Pop-out" of targets modulated in luminance or colour: the effect of intrinsic and extrinsic uncertainty

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Abstract

Targets defined by attributes such as colour or brightness are said to "pop-out" from a cluttered scene, with little or no dependency on the size of the set to be searched, while search for other attributes can depend strongly on set-size. We measured contrast thresholds for increments and decrements in luminance or colour and show that they increase strongly with set-size (as previously observed for orientation). However, in some conditions, where the potential distractors were not salient visual targets, there was no dependency of set-size at all ("pop-out"). All the data can be modelled by assuming two main sources of uncertainty: the intrinsic uncertainty due to the number of detectors monitored during a specific task and the extrinsic uncertainty introduced by increasing the number of items displayed. The strength of the effect is well explained by a simple signal detection theory "signed-max" model suited for two-tailed tasks [Journal of Vision 2 (8), 559]. The results suggest that "pop-out" is not peculiar to luminance or colour, but may occur in conditions when the intrinsic uncertainty is so high as to saturate the effects of further uncertainty sources.

Keywords: Vision; Attention; Uncertainty; Contrast sensitivity; Colour

1. Introduction

The mechanism for visual search of a target among distractors has been under dispute for decades. A series of studies based on the influential Feature Integration Theory (Nakayama & Silverman, 1986; Treisman & Gelade, 1980; Wolfe, 2000) provided evidence for serial processes when searching for targets defined by a unique conjunction of elementary features. According to this theory, targets defined by single features would be searched in parallel as the saliency map allowing successful search coincides with the feature map describing the stimulus. However, more recent studies have clearly shown marked set-size effects on threshold search for single features such as orientation or motion (Baldassi & Burr, 2000; Burr, Verghese, Morrone, & Baldassi, 2003; Morgan, Ward, & Castet, 1998; Verghese & Nakayama, 1994). The evidence regarding targets defined by colour or brightness are less obvious. While some studies assume "pop-out" of these features from a cluttered scene, with little or no dependency on the size of the set to be searched (Bonnel, Stein, & Bertucci, 1992; Theeuwes & Lucassen, 1993), other studies do find significant set-size effects under certain conditions (e.g., Monnier & Nagy, 2001; Nagy & Thomas, 2003; Palmer, Ames, & Lindsey, 1993).

Recently, the idea that set-size dependency implies serial processing has been drawn into question. One reason is that the set-size dependency often depends on attentional load (Joseph, Chun, & Nakayama, 1997). But more interestingly, many of the effects of set-size on response time and accuracy have been shown to be explicable by simple models of parallel processing, based on various sources of uncertainty (Eckstein, 1998; McElree & Carrasco, 1999; Palmer, 1994; Palmer et al., 1993; Shaw, 1980). In this study we investigated visual search for stimuli differing either in luminance or in colour. When the stimuli are perceived as visually salient objects, thresholds for low to mid set-sizes depended

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heavily on the set-size, in exactly the same way that it does for other attributes. However, when the colour or luminance increments were displayed on a homogeneous or noisy background, or when the set-size was high, the task was indeed "pop-out", with no measurable set-size effects. We show that the dependence on set-size can be well explained by the intrinsic and extrinsic uncertainty of the stimuli, and modelled quantitatively by a simple "signed-max" model based on signal-detection theory (Baldassi & Verghese, 2002).

2. Methods

The stimuli were generated by framestore (Cambridge VSG 2/3) and displayed on the face of a Barco Calibrator monitor at a refresh rate of 120 Hz. The subjects viewed the monitor in a dimly light room from a distance of 114 cm.

The stimuli were Gaussian blobs (space constant 0.5°), displayed symmetrically around a notional circle of 5° radius for 100 ms. For luminance discriminations, the target was either brighter or darker than the background or distractors (see below), with the subject being required to identify the direction of luminance (without having to report its position). For chromatic (equi-luminant red–green) discriminations, the target was either redder or greener than the distractors, and the subject was required to identify the direction of colour change.

For both the luminance and colour discriminations, there were three conditions: in two conditions the distractors were clearly visible as yellow Gaussian blobs (same size as the targets) standing out against a pinkish background of different chromaticity and luminance. In practice this was achieved by adding to the background a faint blue, 25% of the maximum blue strength, sparing the target and distractors, following a Gaussian profile of 0.5° space constant (see Fig. 1(a) and (b)). The centre of the distractors had no blue illumination, and was 24 cd/m^2 ($x = 0.493$, $y = 0.448$). The background was 27 cd/m^2 ($x = 0.354$, $y = 0.299$). The easiest way to envisage this condition is a blue celluloid overlay, with blurred holes over the distractors. In the other condition, the blue content was removed from the background, and the target and stimuli were identified only by blue spokes pointing to them (Fig. 1(c)). When present, the spokes were came on and went off together with the targets and distractors (100 ms).

Stimuli were immediately followed by 150 ms of post-mask covering the whole display, to minimize processing based on stimulus persistence after its offset. The mask was appropriately luminance or chromatic noise in which squares of 4×4 pixels (0.05°) varied randomly over a 50% contrast range.

For the partial cueing conditions, a subset of stimuli (always including the target) was cued by a set of blue spokes ($0.025 \times 3.5°$) originating at fixation and pointing to the centre of the stimuli. In all the above conditions, set-size was varied from 1 to 16 elements, one of which was always the target.

In one experiment we tested larger set-sizes ($1 \leqslant n \leqslant 128$) with a variant of the visible blobs condition, with sharp-edged disks of 0.3° of radius (without Gaussian blurring). Here the stimuli were scattered pseudo-randomly in a radial region of eccentricity ranging from 1° to 9°, not just around a circumference. The target occupied a random position.

We report data for two observers, one of them naïve to the goals of the study. For the major conditions (all except those with external noise), we also measured two additional naïve observers, not reported in the graphs, but confirming the results shown here. In blocked sessions, subjects were required to indicate whether the target was brighter or darker, or redder or greener than a standard, matched in colour and luminance to the distractors according to a 2 Alternative Forced Choice

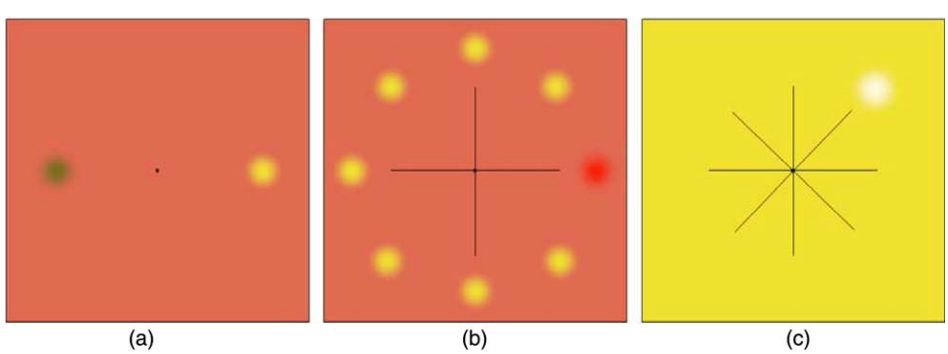

Fig. 1. Illustrations of the three conditions used in this study. (a) Visible blobs: example for luminance discrimination of set-size 2, where one is distractor and the other a dark target. (b) Cued blobs: example of an effective set-size of 4, where four stimuli were cued by the spokes, one of which is the target. (c) Cued locations: example for an effective set-size of 8, with the target brighter than the background. In all the examples shown here the contrast is higher than in the real experimental conditions, where it hovered around threshold. For all these conditions we measured both luminance and colour discrimination thresholds.

(2AFC) procedure. For a set-size of 1, subjects had a clear representation of the standard, acquired through practice sessions with acoustic feedback. For each condition, the magnitude of luminance or chromatic increments was set by the adaptive QUEST algorithm (Watson & Pelli, 1983). Cumulative Gaussians were then fit to the psychometric functions to determine threshold (defined as 75% correct response). For each subject, subjective equi-luminance was determined by the standard technique of flicker fusion photometry.

3. Results

3.1. *Effect of set-size under different conditions of stimulus and cue*

We measured contrast sensitivity for luminance and colour increments under three conditions of visual search. For the first experiment, a variable number of yellow Gaussian blobs were arranged symmetrically around a 5° radius perimeter. In the luminance study, one of these—the *target*—was either brighter or darker than the *distractors* (all of equal luminance). Observers were required to identify the sign of the brightness difference (without necessarily knowing which was the target). Thresholds for luminance discrimination are reported as a function of set-size in Fig. 2 (filled circles). Thresholds show a strong dependency on set-size that is well approximated by a square root relationship.

We next varied the effective set-size by *partial cueing* (Grindley & Townsend, 1968; Palmer, 1994): eight stimuli were presented on all trials, and a subset comprising the target were cued by symmetric spokes, simultaneous with the Gaussian stimuli (see Fig. 1(b)).

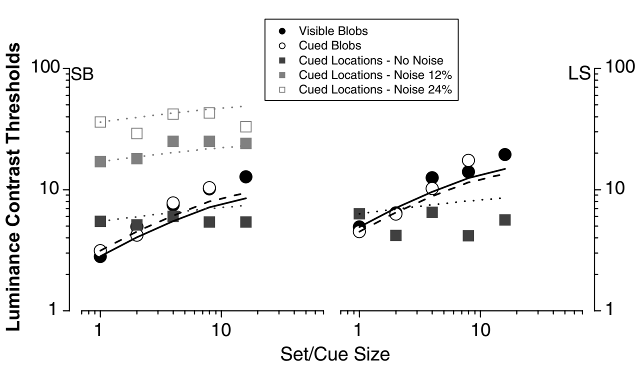

Fig. 2. Thresholds for discrimination of luminance increments and decrements of the target as a function of the effective set-size. Filled circles refer to the condition where the set-size was varied by physically varying the number of patches; empty circles to where the set-size was varied by partial cueing; squares to where the background was the same colour as the distractors, with no noise (filled black), 12% (filled grey) and 24% noise (open grey). The straight, dashed and dotted lines are the results of the simulation of the Max-Model (see Model section ahead) for the three conditions, respectively.

The open circles of Fig. 2 show the results for this condition. The data virtually superimpose those of the previous experiment, showing that cueing the distractors was as effective in improving thresholds as physically reducing the number of stimuli. Clearly the processes that allow vision to exclude the distractors from the analysis are not merely automatic, but under topdown attentional control.

In the third variant, the "cued locations" condition, we removed the colour contrast between background and distractors, so they became empty spatial locations signalled by a spoke, rather than salient yellow blobs (Fig. 1(c)). The possible positions of the target were again indicated by the spokes, and all other conditions remained unchanged (except the lack of the colour contrast with the background: compare Fig. 1(b) and (c)). The task for the subject was the same as before, to identify the sign of the brightness increment, without knowing which of the possible (cued) positions contained the target. Although this manipulation left the luminance and chromaticity of both the target and the distractors unchanged, as well as the uncertainty of spatial location dependent on cue-size, the results (square symbols) were quite different in this condition. Here there was virtually no dependency on set-size, with slopes very close to zero. Removing contrast with the background had little effect for cue-size 1, as may be expected, given that the background did not impinge on the stimuli themselves, and differed primarily in chromaticity, not luminance. For the other cue-sizes thresholds were considerably lower than the other conditions. The other sets of square symbols of Fig. 2 for observer SB show further measurements made in the presence of visual noise at 12% and 24% contrast. Under these conditions, the noise reduced overall sensitivity, but did not change the slope of the function.

Fig. 3 shows a similar set of results for chromatic discrimination. Here the target was always the same luminance as the distractors (equi-luminance judged by

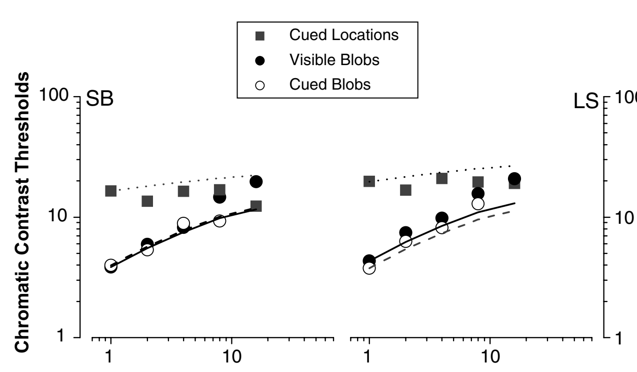

Fig. 3. Thresholds for discrimination of colour increments and decrements of the target as a function of the effective set-size. Symbols and lines reproduce the same conditions and models of Fig. 2.

flicker-fusion photometry), but either redder or greener. The general pattern of results was similar to that obtained with luminance: there is a strong square-root dependency on set-size when the stimuli were contrasted with the pinkish background, but again no set-size dependency whatsoever when the stimuli blended into the background. There was a difference in the absolute thresholds of the various conditions (these curves cross at set-sizes near 8 rather than 1–2 for luminance), but the trend is otherwise identical.

3.2. Large set-size

The results from the first part of this study show that as long as target and distractors are defined as salient stimuli, thresholds are strongly dependent on set-size. However, when a distractor is an empty location signalled by a spoke, thresholds do not follow the number of possible locations. In the experiments reported here we measured the dependency on set-size of a larger range (up to 128), using smaller but salient elements scattered over the whole field. The symbols in Fig. 4 show the thresholds for the two observers of this experiment. Thresholds initially increase strongly with set-size, as previously observed, but at larger set-sizes the dependency becomes progressively less, flattening off completely at very large set-sizes.

4. Modelling of results

In an early study, we showed that the dependency of orientation discrimination on set-size is consistent, to a first approximation, with a simple process that simply sums the orientation signals of low-level detectors, together with their associated visual noise (Baldassi & Burr, 2000). However, on more stringent testing, it was shown that the summation model does not explain all aspects of the data, such as the slope of the psychometric functions and the interaction between threshold criteria and set-size. The uncertainty-based "signed-max" model proposed by Baldassi and Verghese (2002) captures many of these aspects better.

We tested both these models against the data of this study. The predictions of the uncertainty and summation models are shown in the figures as continuous and dashed lines respectively. In all cases the presumed noisiness of each detector was determined by the threshold of a single element with no distractors. There were no other free parameters in either model. The predictions of linear summation are simply that thresholds increase with the square-root of set-size, as each additional element contributes both signal and noise (the signal grows proportionally, while the noise grows with the square root: Baldassi & Burr, 2000). For the signed-max model we performed the Monte Carlo

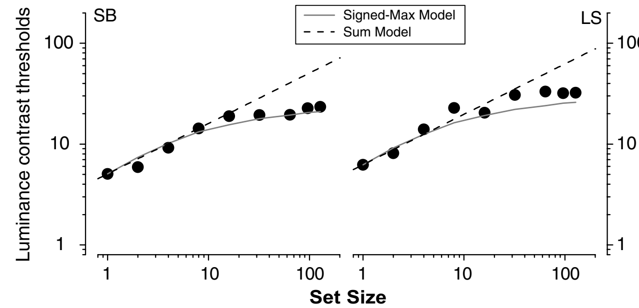

Fig. 4. Thresholds for discrimination of luminance increment directions of a sharp-edge circular target as a function of displayed set-size, for subjects SB and LS. The circles represent the data from the two observers. The dotted line plots the prediction of a Sum model (which predicts indefinite square root relationship: (Baldassi & Burr, 2000)), while the smooth grey lines are the curves generated from the Monte Carlo simulation of the signed-max model applied to our task. Both models were parameter-free, except for the assumed noise distribution, given by the threshold for set-size 1 for each observer.

simulation described in the caption to Fig. 5 (for more details see: Baldassi & Verghese, 2002). Basically, the deterioration of performance with increased number of distractors results from the greater probability that at least one distractor has a larger deviation from mean than the target as more distractors are added (Fig. 5(c)).

For the basic experiments of Figs. 2 and 3, both models predicted well the data for the two conditions where the distractors were salient objects. The predictions are very similar making it difficult to choose between the two. However, they do begin to diverge at set-size 16, and it was for this reason that the data of Fig. 4 were collected with large set-size, where the divergence of the two models is more obvious. Here it is quite apparent that the signed-max model captures the trend of the data much better than the summation model, predicting the progressive flattening of the curve. It is not simple to modify the summation model to take account of the crowding effects, as these predict the opposite result. If the blobs fall so close as to stimulate a single detector, the expected summation will tend to linear rather than square root summation (as noise is not being introduced by recruitment of detectors).

The results for cued locations were less easy to model. Without modification, both the summation and signed-max models predict a strong dependence on set-size, curves parallel to those that fit the other two conditions of Figs. 2 and 3. Furthermore, as the effects did not depend on the level of added noise, it is not possible to model them by assuming ceiling or floor effects, such as central noise sources.

One possible candidate for the lack of set-size effect is "intrinsic uncertainty", which was shown to be very high for contrast detection (Pelli, 1985). If (for reasons we will discuss later) there were high intrinsic uncertainty in the conditions of cued locations, then the extra uncertainty introduced by the experiment should have

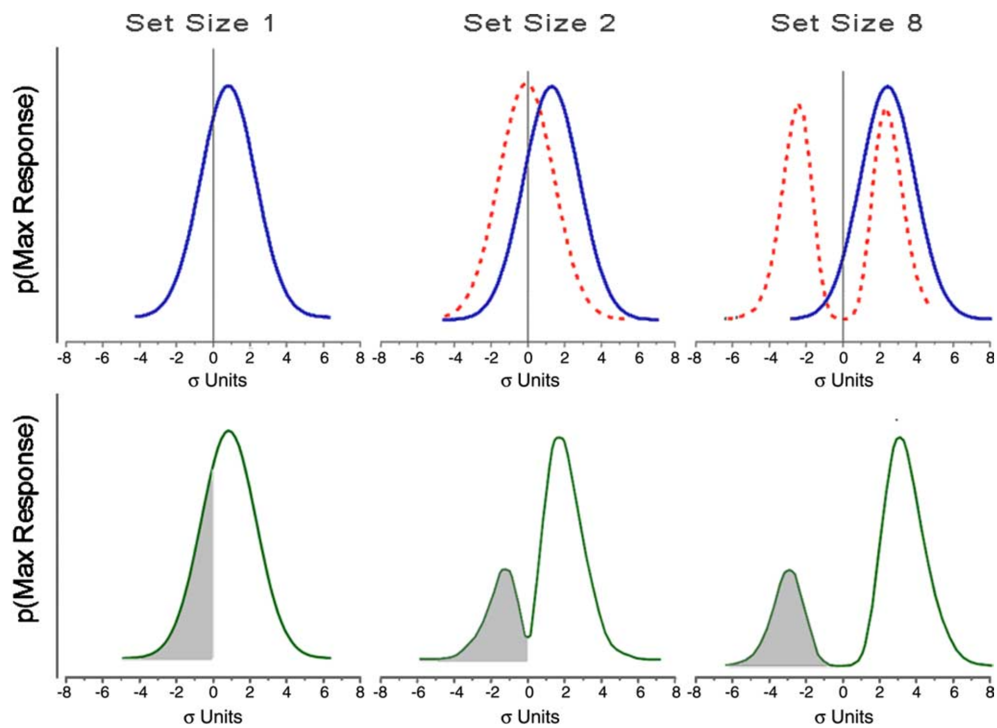

Fig. 5. Probability distributions of maxima at threshold for set-sizes of 1, 2 and 8, calculated by Monte Carlo simulations. For each iteration, a sample was drawn from a Gaussian distribution of mean 0 for the $n-1$ distractors and of variable mean for the target. Standard deviation was set to 1 threshold unit. For each iteration, the maximum was chosen from the target and the $n-1$ distractors: if this maximum was positive it was scored correct, otherwise as error. The percent correct was calculated over 50,000 iterations at any target strength. Target strength was then varied to home in on 75% correct. The panels report the distribution of the maxima for 50,000 iterations at threshold for three representative set-sizes. The left panels plot distributions of maxima for the Set Size 1 condition, the middle panels for set-size 2 and the right panels for the Set Size 8 condition. The upper panels show the distribution of maxima for the target (straight line) and the distractors (dashed line) separately. The lower panels show the joint distributions of maxima for the whole set of stimuli, giving 75% positive (correct) responses. The grey shaded areas represent the errors.

little effect. The saturating effect of uncertainty is evident from the dotted curve of Fig. 4. The initial effects of uncertainty are strong, about the same as summation, but the curve soon flattens out considerably. The effects of increasing uncertainty from 50 to 100 are very negligible indeed.

5. Discussion

The results of this study suggest that under some experimental conditions, but not others, luminance and colour discrimination may be independent of set-size, and hence "pop-out" from the background. Dependency of performance on set-size for stimuli modulated in colour and luminance has been shown in previous studies, but under different conditions (e.g., Monnier & Nagy, 2001; Nagy & Thomas, 2003; Palmer et al., 1993). In the present study, when the stimuli contrast with the background so as to be seen as salient objects, thresholds for identifying luminance or colour decrements in a target increase strongly with set-size, as has been observed for other attributes such as orientation (Baldassi & Burr, 2000) or speed discrimination (Verghese & Stone, 1996). The increment in thresholds occurs both when the set-size is set by physically removing distractors, and when it is set by attentional control through partial cueing. However, when the stimuli were not salient objects, but regions within a homogeneous or noisy visual field, there was no dependency on set-size at all. This difference cannot be accounted for by a straight-forward account pointing to differences in the difficulty or attentional load in the two conditions (Joseph et al., 1997), as we measured contrast thresholds in all cases, defined as 75% correct performance.

Adding external noise decreased sensitivity by up to a log-unit, but did not affect the lack of dependency on set-size when the stimuli were not salient objects. This excludes floor and ceiling effects (that may result from central noise sources). It also shows that results are not due to non-linearities in the contrast discrimination function, presumed responsible for the "dipper function" in contrast discrimination (Legge & Foley, 1980) and shown to be affected differently by attentional processes (Foley & Schwarz, 1998; Lee, Itti, Koch, & Braun, 1999; Solomon, Lavie, & Morgan, 1997); the noise shifted the contrast discrimination task to different parts of the contrast transducer function, without affecting the slope of the set-size dependency.

In this experiment the background was created by modulating the blue gun of the monitor, which was unused for the other conditions. The addition of blue outside the region of the target or distractor should have little direct effect on the early mechanisms responsible for detecting luminance or colour increments, as it never impinged directly on the patches being discriminated. It is interesting to note at this point, that although luminance and colour are almost certainly analysed by separate early mechanisms, interactions do occur between them, such as facilitation of luminance sensitivity by colour and vice-versa (Mullen & Losada, 1994). However, facilitation between luminance and colour behaves differently from facilitation within the same channel (luminance–luminance or colour–colour), most notably in that it is phase dependent. This points to a possible role of *uncertainty* reduction, where a red–green grating can reduce the uncertainty of a luminance grating, provided they are in the same phase. Similar processes may be occurring in this study.

In an early study, we showed that the dependency of orientation discrimination on set-size is consistent, to a first approximation, with a simple process that simply sums the orientation signals of low-level detectors, together with their associated visual noise (Baldassi & Burr, 2000). However, on further investigation, it became clear that the summation model did not account for more subtle aspects of performance, such as the slope of the psychometric functions and the interaction between threshold criteria and set-size, that were better explained by the uncertainty-based "signed-max" model (Baldassi & Verghese, 2002). In this study the signed-max model also proved more successful than the summation model, most evident for the data with large set-size, where performance does not decrease uniformly with set-size, but levels off after about eight items. This saturation was not likely to result from "crowding" in the large set-size condition, as this should in principle cause thresholds to worsen even more for the large set-sizes, when the elements are adjacent and may therefore stimulate the same early mechanisms, predicting linear summation. The saturation was well predicted by the signed-max model, but not by the summation model.

Some readers may find it surprising that uncertainty predicts such strong effects. In general uncertainty predicts much smaller effects, log–log slopes of around 0.2 (Palmer, 1994; Palmer et al., 1993). The reason for the stronger predicted effects in this experiment is the unusual nature of the task, in reporting the *sign* of the contrast of the target. It is the fact that necessity of identifying the sign of the target that leads to the signed-max model. In practice two (rather than one) detectors need to be monitored for each stimulus (bright/dark, red/green etc), and this leads to much steeper effects of added uncertainty (see Fig. 7 of Baldassi & Verghese, 2002).

It is important to note that the uncertainty model explains the effects of distractors on threshold as a simple probabilistic consequence of noisy detectors. There is no need to evoke notions of serial processing: parallel processing predicts strong set-size effects. Counter-intuitively, it does not predict the lack of set-size effects observed when regions of space were cued, rather than salient objects. As mentioned earlier, one possible parsimonious explanation is that there is high intrinsic uncertainty under these conditions, as suggested by Pelli (1985). Possibly, when the exact site of the target is specified by the salient blob, its position is made explicit and fewer detectors need be sampled. However, when a spoke points to a more generic region of space, perhaps many detectors need to be sampled to find the most active. This would mean that these conditions had effectively much more uncertainty than the others. The effect of this on the signed-max model would be to shift the curves leftwards, so the curves would be much flatter than otherwise. In other words, as the psychometric function steepens with uncertainty (Baldassi & Verghese, 2002; Palmer, Verghese, & Pavel, 2000; Pelli, Legge, & Schleske, 1985; Tanner, 1961; Verghese & McKee, 2002), under our detection task intrinsic uncertainty would have dominated over extrinsic uncertainty introduced by the number of cues of our experiment. The high number of detectors used for the task would have pushed the psychometric functions to their maximum slope, making the measure insensitive to the further change introduced by the number of spokes. What this does not explain is the absolute levels of thresholds. For the colour condition the presence of the background always reduced thresholds, as one may expect from a reduction in uncertainty. However, for the luminance condition, the absolute levels were different, with thresholds in the cued blobs and cued locations equating for one or two items, so thresholds for cued blobs were generally higher than the cued locations. It is not clear why this should be so, and why there should be a difference for luminance and colour. Possibly the blue background also had a small masking effect in the luminance but not the colour condition. However, this does not change the general argument, amply supported by the fact that the general pattern of results is the same for the luminance and colour conditions.

The suggestion that the flat cued location curves result from high intrinsic uncertainty is testable by measuring the slope of the psychometric function under each condition. However, as this was not the initial goal of the study, the data were not collected in a way to yield an accurate estimate of psychometric function slope, so we cannot verify the suggestion with the current data. However, in a similar study of motion pop-out (Burr et al., 2003) we did measure the steepness of the psychometric functions, and found that they did follow the predictions of uncertainty.

Another prediction that follows directly from the model illustrated in Fig. 5 is that observers should make more high-confidence errors when there are many distractors than when there are few. Choosing the absolute maximum of all stimuli (test and distractors) leads to a bimodal distribution where the most probable signal strengths are far from the mean, both when they are correct and when they are errors. This implies that errors should be 'seen' with high confidence. With only the test present, the distribution is unimodal, with the peak near zero. The most probable errors are very close to zero, and should not be perceived with great confidence. Preliminary results from our laboratory bear out this prediction (Baldassi, Burr, & Megna, in press).

To conclude, this study shows that luminance and colour are not in themselves "pop-out" attributes for visual search, but can show a strong dependency on set-size, similar to that observed for other attributes (Baldassi & Burr, 2000; Morgan et al., 1998). Pop-out is not a property of the attributes themselves, but may occur in conditions of high intrinsic uncertainty, where additional uncertainty of distractors has little effect. The slope of the set-size function is not an absolute metric to classify different visual search tasks (Palmer, 1994; Palmer et al., 1993); intrinsic and extrinsic uncertainty can change within and between tasks, affecting the shapes of the set-size functions.

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