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Attentional Effects in Visual Search: Relating Search Accuracy and Search Time

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In this article, I will describe a program of research that distinguishes among the leading theories of divided attention. Divided attention has often been studied using set-size effects in visual search. A typical search task is illustrated in Figure 1. In both panels the task is to search for the target disk which has a higher luminance than the distractor disks. The subject is to respond "yes" when the higher luminance disk is present and "no" when it is absent. The target is present in both of the panels of Figure 1. The panels differ in the number of disks present: the panel on the left has a set size of 2, and the panel on the right has a larger set size. Increasing set size usually decreases performance. These set-size effects have been measured both in accuracy paradigms that use brief displays to prevent multiple eye fixations and in response time paradigms that allow extended inspection of the display with multiple eye fixations. Such set-size effects are of interest because different theories of attention predict set-size effects of different magnitudes.

Two Contrasting Hypotheses

I will focus on two classes of hypotheses, unlimited-capacity perception versus limited-capacity perception. Both predict set-size effects, but for different reasons. According to the *unlimited-capacity perception hypothesis*, the internal representations that arise from each of the individual stimuli are independent of the number of stimuli presented. Despite this independence in perception, there will still be set-size effects on behaviour due to other phenomena such as decision and memory. In particular, if the individual representations are noisy, then there will be a set-size effect in search due to the need to integrate the multiple noisy inputs. In contrast, the *limited-capacity perception hypothesis* presumes that the internal representations of the individual stimuli are interdependent because they require some kind of attentional processing. For example, there may be a processing resource that must be distributed across the stimuli. This resource might be in the form of a sampling process or perhaps even eye movements. Thus, the more

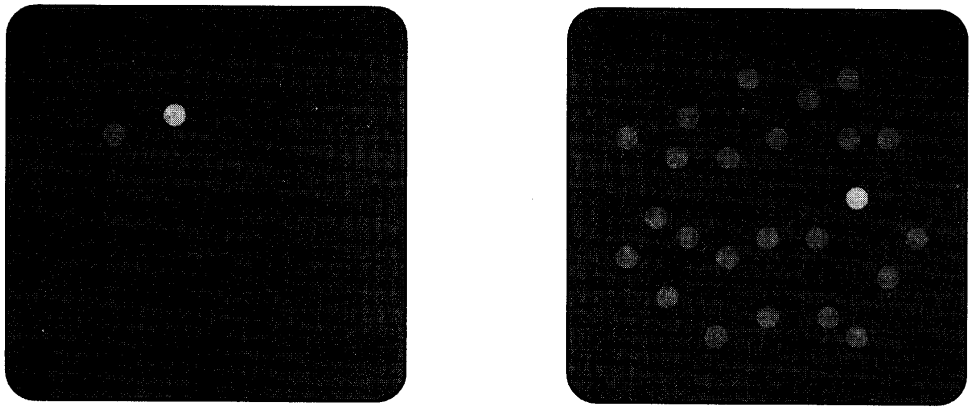

Figure 1: An illustration of the set-size manipulation for a contrast increment search task. Set Size 2 is shown in the left panel, and a large set size is shown in the right panel.

stimuli, the less processing each individual stimulus receives per unit time, and hence performance decreases with set size.

Each of these hypotheses has a history. Models incorporating independent processing of separate stimulus features go back at least to Helmholtz's (1896; see Wyszecki & Stiles, 1982, for a review in English) theory of colour discrimination. More relevant to visual search, Tanner (1961) was the first to point out that tasks such as visual search introduce the necessity of integrating multiple sources of information. From Tanner's findings, one can infer that set-size effects are not inconsistent with unlimited-capacity perception. His work was largely in auditory frequency detection. Since then, one of the best known examples of an unlimited-capacity model is Shiffrin and Gardner's (1972) "independent channels model" which was applied largely to letter perception. There has also been a considerable body of work in psychophysics. Particularly productive is the analysis of uncertainty effects on near-threshold visual patterns using the independent spatial-frequency-channels model. This is summarized by Graham (1989); for an introduction, see Davis, Kramer, and Graham (1983). In addition, Shaw (1980, 1984) extended this model to several search accuracy tasks.

The development of models of limited-capacity perception also goes back over 40 years. Perhaps the earliest quantitative model was the single-channel theory proposed by Welford (1952). According to the single-channel theory, only one source of information can receive processing at a time – hence, it is also known as an all-or-none model – and it focuses on attention switching rather than attention sharing. Broadbent (1958) generalized the concept by allowing multiple, simultaneous processes with the restriction that the processing of the total system is limited. The limit was defined as the processing of a constant amount of information per unit time. This allowed one to consider the strategies of attention switching or attention sharing. Since then there have been several efforts to generalize the idea of capacity (e.g., Kahneman, 1973; Navon & Gopher, 1979). For more empirical studies, the limited-capacity perception hypothesis has provided an interpretation of response time experiments in both cueing and visual search (e.g., Posner, Snyder, & Davidson, 1980; Hoffman, 1978). Also relevant is Townsend's theoretical analysis of these response time models (Townsend, 1974; Townsend & Ashby, 1978, 1983; Townsend & Nozawa, 1995). In particular, Townsend relates capacity to other issues such as parallel versus serial processing.

In addition to work which focuses on either unlimited- or limited-capacity perception, there is a large body of work that embraces both. In visual search, these theories are often called *two-stage theories* (Hoffman, 1979). Such theories presume that some kinds of visual search can be accomplished by unlimited-capacity perceptual processing of the individual stimuli and other kinds of search require limited-capacity perceptual processing (Hoffman, 1979; Treisman & Gelade, 1980; Wolfe, Cave, & Franzel, 1989). For example, identifying a letter may require capacity even though detecting a luminance increment does not.

Two preliminary comments are in order about this distinction between unlimited- and limited-capacity perception. First of all, I am using the term *limited capacity* in the sense of non-independence rather than with a particular view of capacity. When Broadbent described his limited-capacity model, he had a very specific view of capacity in terms of information theory. Here I am going to follow later researchers and use limited capacity as a general term for any reduction in capacity relative to capacity being independent of the number of stimuli (i.e., unlimited capacity, Townsend, 1974). To refer to more specific theories such as Broadbent's, I will use more specific labels, such as the *fixed-information-capacity hypothesis*. This hypothesis predicts a specific reduction in capacity with each additional stimulus.

The second comment has to do with the question: to what does capacity refer? There are at least three usages of the term. In the beginning, Broadbent defined capacity with respect to the entire behaviour. The organism was treated as a single, unitary communication channel. I will refer to this molar use of the term as *system capacity*. As the theories became more detailed, there was interest in specifying limits on performance due to distinct component processes. Some of the more refined theories involving network models of separate processes focus on the capacity of individual component processes (e.g. Townsend, 1974). In this work, the term *capacity* could be applied to different "levels" of the system. One could refer to the capacity of components or to any particular subsystem of components. Here, I will refer to *component capacity* as the capacity of the most elemental components of a theory. It is quite possible that the components have unlimited capacity but that they are arranged in such a way that a subsystem of the same components has limited capacity. For example, serial scanning with unlimited-capacity components results in a limited-capacity system. The performance of each component is independent of set size, but the processing time of the subsystem does depend on set size. Finally, there is a third usage of capacity which is the focus of this article. In terms of level, it is somewhere between the component and the system. The idea is to identify a subsystem of components such as perception, memory, or decision (e.g., Broadbent, 1971; Shaw, 1980). Then one can specify the capacity of the perceptual subsystem. To determine this, one must distinguish performance limits due to perception from other limits due to decision-making, memory, and early sensory processing such as limits on peripheral vision. For unlimited-capacity perceptual processing, the perception of individual stimuli must be independent of the number of stimuli (the set size). I will refer to this usage as *perceptual capacity*. In this article, my focus will be on this last usage.

Critical Experiments

I now turn to the central concern of this chapter: what kinds of experiments will distinguish unlimited-capacity perception from limited-capacity perception? These hypotheses have been investigated in several domains (for a review, see Sperling & Dosher, 1986). The two that I review in detail are search accuracy (Palmer, Ames, & Lindsey, 1993; Palmer, 1994) and search time. I will not review here, but do recommend, the related work on how duration affects search accuracy (Bergen & Julesz, 1983a; 1983b; Verghese & Nakayama, 1994). The temporal phenomena of these duration effects may be related to temporal phenomena of search time. Other relevant domains not reviewed here include comparisons between sequential and simultaneous displays (Shiffrin & Gardner, 1972; Hung, Wilder, Curry, & Julesz, 1995) and dual tasks performed simultaneously (Duncan, 1980; Kantowitz, 1974; Pashler, 1989).

To begin, consider the measurement of search time as a function of set size. A typical search task is illustrated in Figure 2. In this example, an initial fixation display indicates to a subject where to direct his or her gaze. Then, a stimulus display is presented. In the figure, the display is a set of disks which may or may not vary in luminance. Half the time the display contains the target, a high luminance disk (Target Present); and the other half of the time the target is absent (Target Absent). The subject indicates the presence or absence of the target using

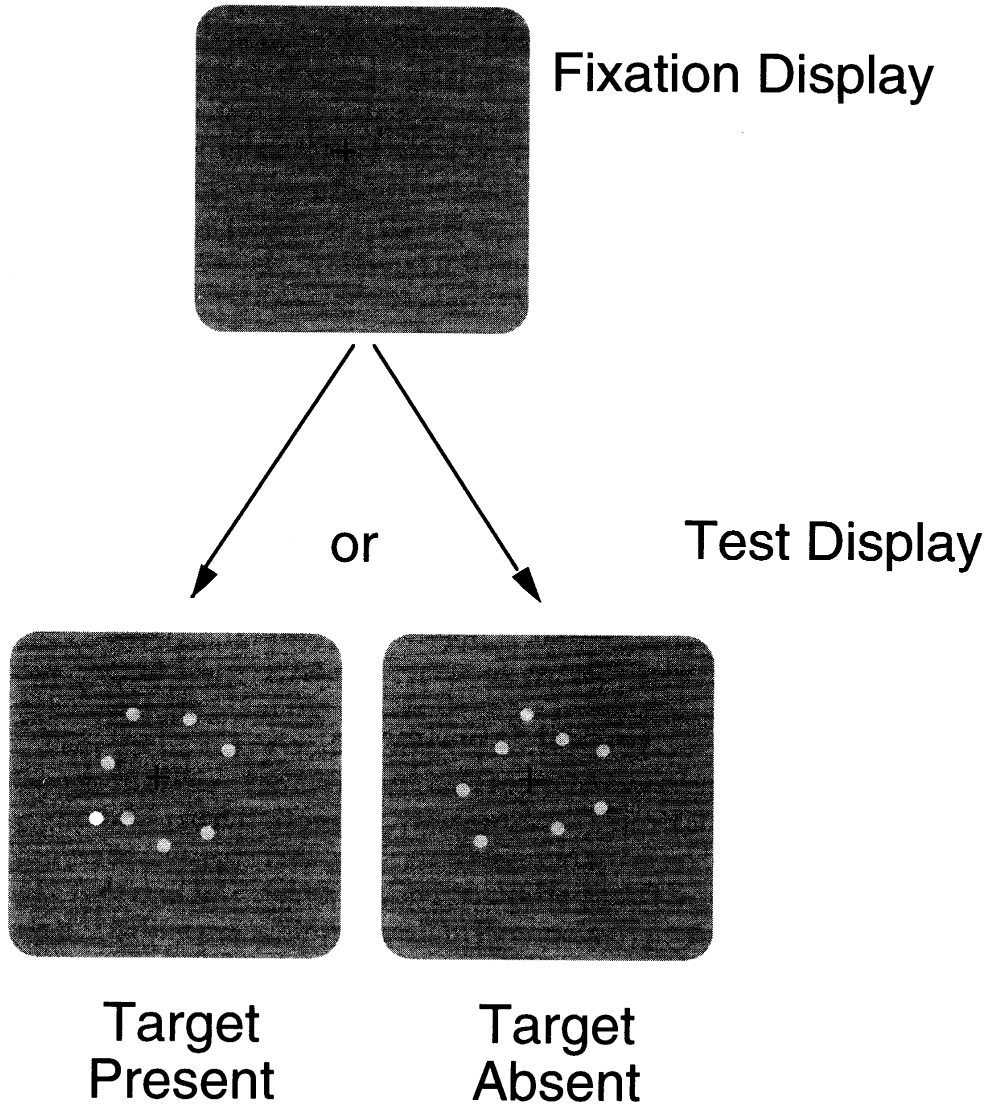

Figure 2: An illustration of the procedure for a Yes-No search task.

one of two key presses. One special feature was that subjects were instructed to maintain an error percentage of 10%. To make this possible, conditions were blocked and extensive error feedback and training were used. As shown at the bottom of the forthcoming graphs, subjects were nearly always successful at staying within 1% or 2% of the intended 10% error percentage.

The results of the experiment depend strongly on the contrast difference between targets and distractors (the contrast increment). In the left panel of Figure 3, the target had a contrast of 52% and the distractors had a contrast of 20%, resulting in a large contrast increment of

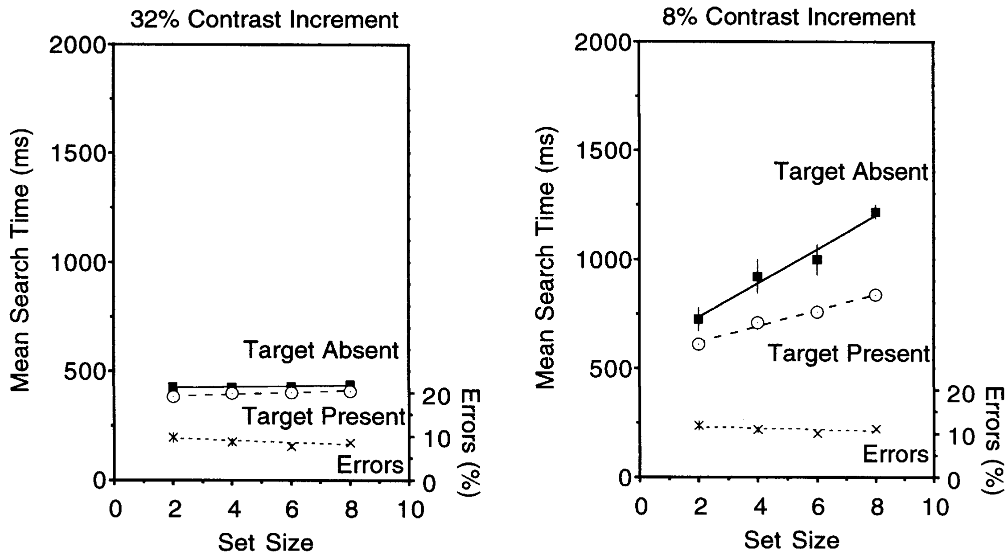

Figure 3: In the left panel, search time as a function of set size for a large contrast increment; in the right panel, search time as a function of set size for a small contrast increment. Error bars here and in all figures represent standard errors.

32%. The mean search time for four subjects is plotted as a function of set size. There was very little effect of set size on search time. Thus, search behaviour was essentially independent of set size for this large contrast increment.

In the right panel of Figure 3, the target had a contrast of 28% and the distractors had a contrast of 20%, resulting in a small contrast increment of 8%. Mean search times for the same four subjects increased from around 750 ms to 1300 ms. Thus, behaviour was definitely not independent of set size for this small contrast increment.

Does such a set-size effect rule out the unlimited-capacity perception hypothesis? Some interpret this result in terms of serial processing. Some go much further and conclude that such large set-size effects are inconsistent with unlimited-capacity perception of the individual stimuli. This conclusion is premature if not wrong. I show here that such set-size effects in themselves are not a critical test of the unlimited-capacity perception hypothesis.

Search Accuracy, Search Time, and Their Relation

I can now introduce the three specific topics addressed within the body of this article. First, I will review briefly whether or not set-size effects for search accuracy are consistent with unlimited- or limited-capacity perception. Second, I would like undertake exactly the same analysis for search time. However, this analysis is too broad a step, and instead I will discuss two narrower subtopics. The second topic becomes: how can one compare set-size effects for accuracy and time? Specifically, how can one conduct a search-time experiment that is modeled after the search-accuracy experiments that have previously distinguished the two hypotheses. This leads to a third topic on the relation between the search-time data and the search-accuracy data: is there a common process mediating the set-size effects for accuracy and time? My analysis does not resolve contradictions between hypotheses about the unlimited-capacity and limited-capacity perception. However, this approach helps to clarify what will be necessary to resolve them.

Search Accuracy

Search accuracy experiments from my lab have distinguished between prominent special cases of the unlimited- and limited-capacity perception hypotheses (reviewed in Palmer, 1995). In particular, they illustrate how even the simplest unlimited-capacity perception model is consistent with set-size effects.

Methods

Overview for Search Accuracy and Time The principal innovation is to exploit the effect of the stimulus difference between the target and the distractors (cf. Bergen & Julesz, 1983a; Duncan & Humphreys, 1989; Pashler, 1987; Verghese & Nakayama, 1994). In particular, we measure the interaction between set size and the stimulus difference (i.e., the contrast increment). It is this interaction that is crucial to distinguishing the alternative hypotheses.

A measure of the effects of the stimulus difference and set size is developed in four steps. First, a psychometric function describes performance as a function of the stimulus difference; second, this function is summarized by a difference threshold; third, the threshold is measured for each set size to obtain a threshold-versus-set-size function; fourth, the effect of set size on threshold is summarized by the slope of a linear regression on a log-log graph.

Search Accuracy Methods Stimuli were briefly displayed for 100 ms to minimize eye movements. The accuracy of search was measured as a function of the contrast increment and the set size. Then, for each set size, I estimated the contrast increment that yields 75% correct discrimination – the *contrast increment threshold* (for a review of these psychophysical methods see Gescheider, 1985). Examples of the displays are shown in Figure 4. The four panels represent Set Sizes of 2, 4, 6, and 8 and in all cases a target is shown. In these displays, a number of sensory phenomena were controlled that might affect performance if

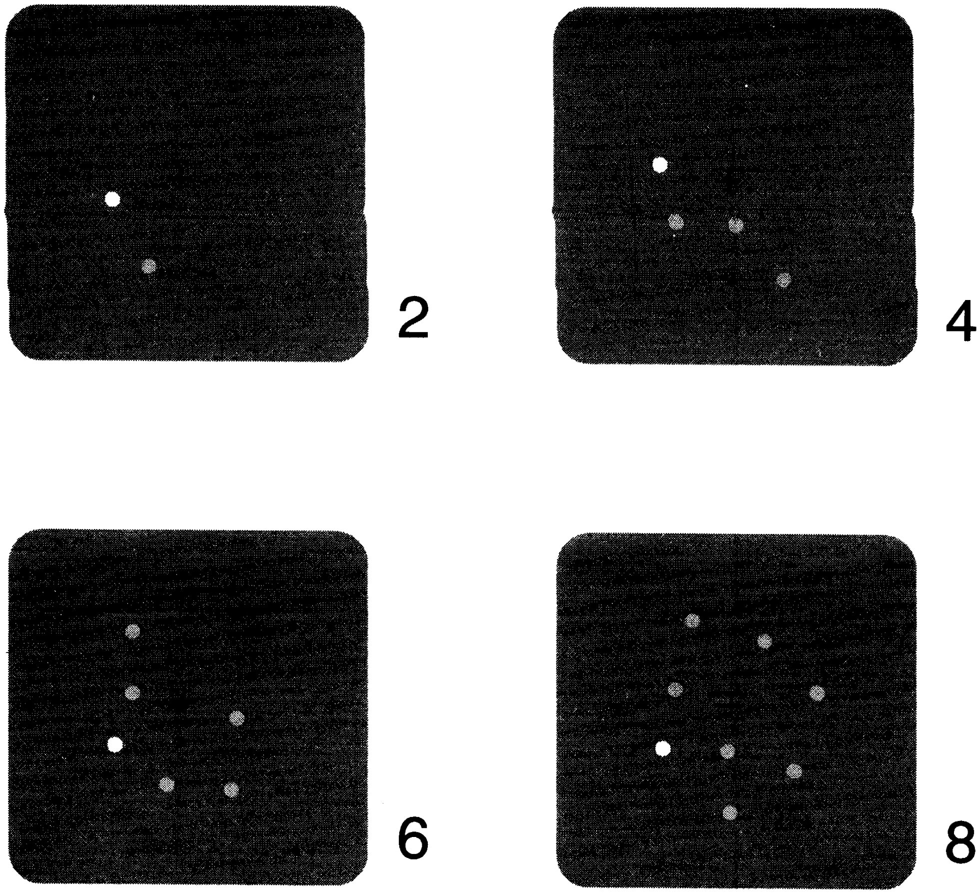

Figure 4: An illustration of the displays for Set Sizes 2, 4, 6, and 8. A target stimulus is shown in each display.

they were allowed to covary with set-size: The stimuli fell in a limited range of eccentricities and had a limited distribution of interstimulus spacing. A complete description of these experiments can be found in Palmer (1994).

Results

Psychometric Functions and Thresholds A sample of the results of this experiment is shown in Figure 5. This is a psychometric function that shows the probability correct as a function of the contrast increment for one subject. The curve parameter is set size; circles and squares indicate the Target Absent and Target Present conditions, respectively. The contrast increment produces a large effect on performance. As the contrast increment increases, performance rises from near chance to over 90 percent correct. In addition, there was an effect of set size that is fairly large for the smaller increments and smaller with large

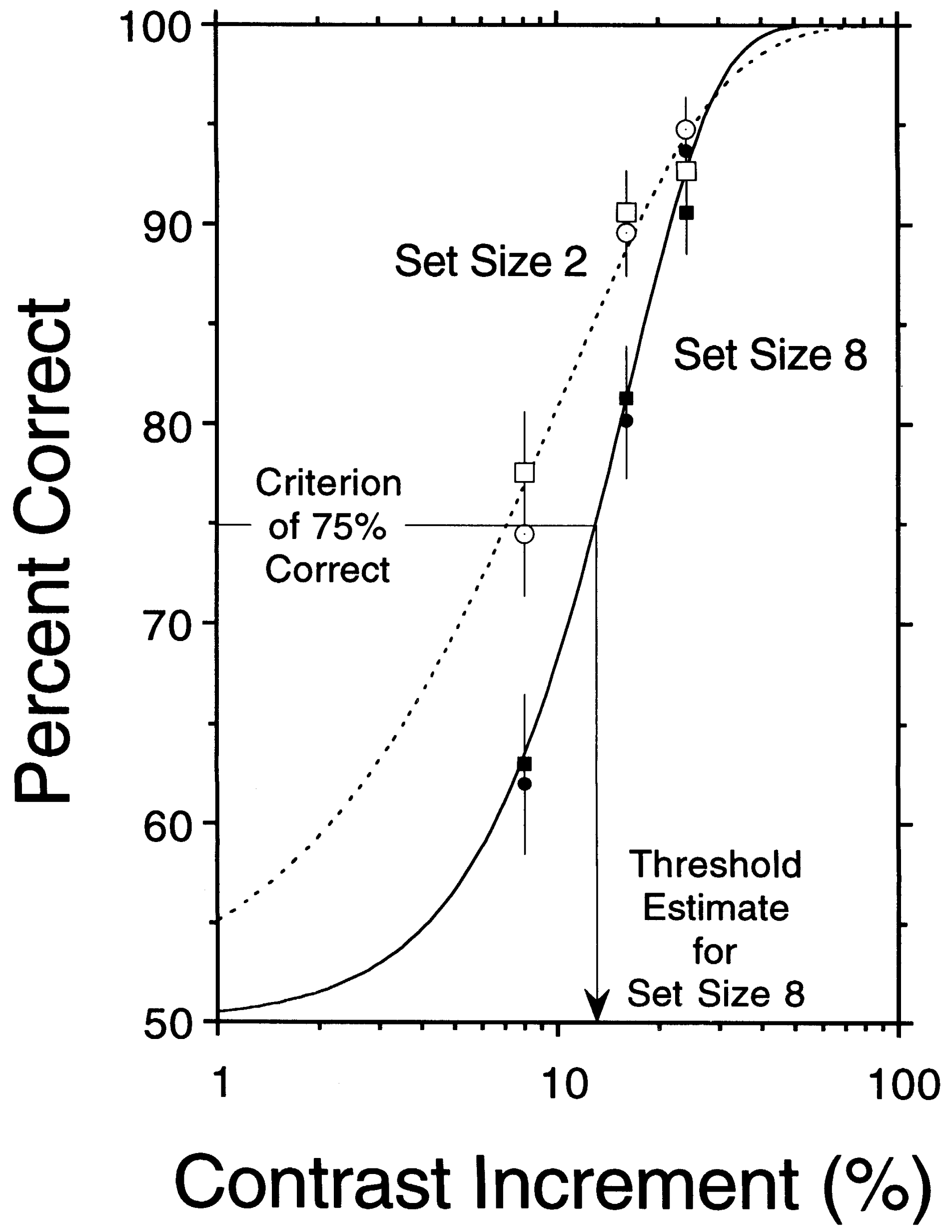

Figure 5: Psychometric Functions: percent correct for a single subject as a function of the contrast increment. Threshold estimation is illustrated using the best fitting Weibull function and a criterion of 75% correct. The circles represent Target Absent conditions (correct rejections) and the squares represent Target Present conditions (hits).

increments. The results for each set size were fit with a Weibull function with parameters for threshold and slope (Watson, 1979). In Figure 5, the estimation of the threshold parameter is graphically illustrated for Set Size 8. A contrast increment of around 13% yields 75% correct discrimination.

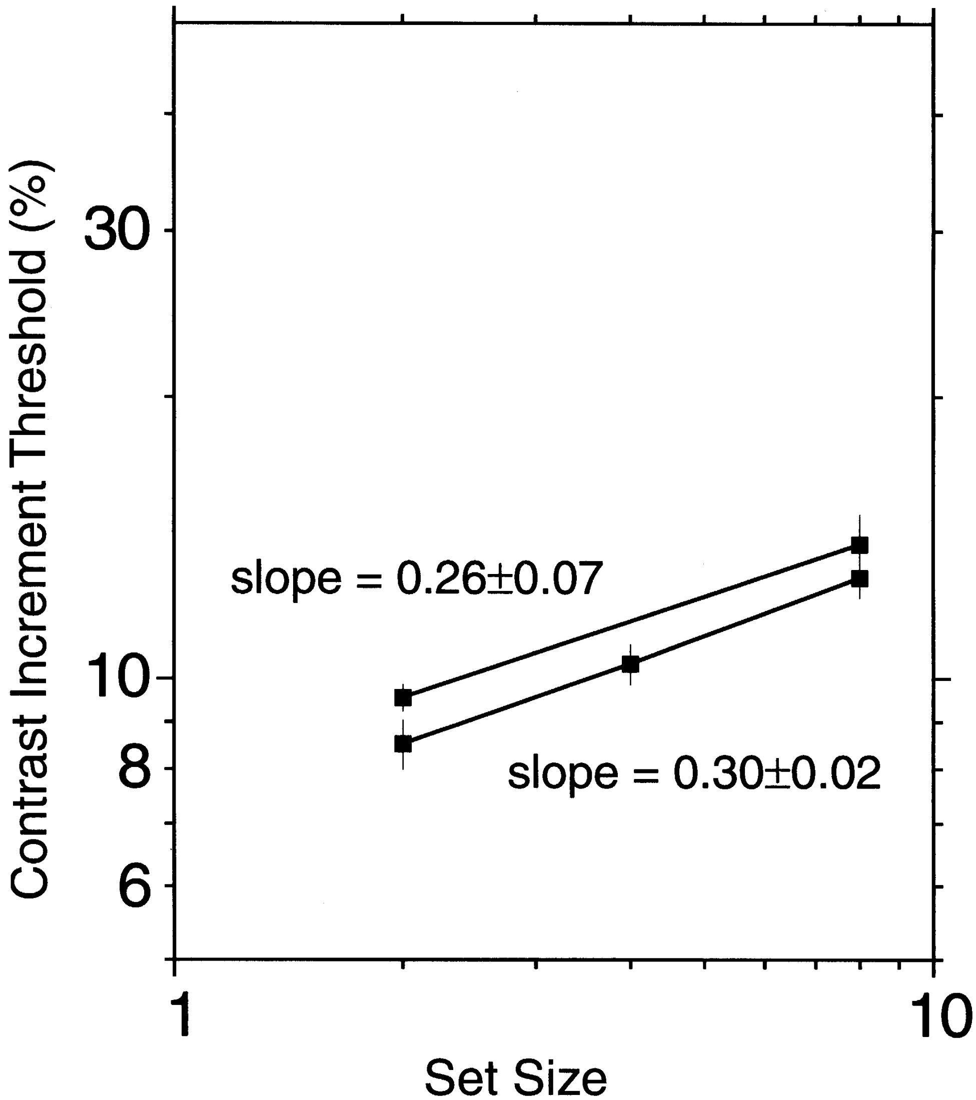

Figure 6: Mean threshold for four subjects as a function of set size; 75% correct criterion was used. Two separate experiments are shown and summarized using the slope on log-log coordinates.

Threshold-versus-Set-Size Functions The results can be further summarized by plotting the contrast increment thresholds as a function of set size, as in Figure 6. This figure has both axes scaled logarithmically. The results from two experiments are shown: one with Set Sizes 2 and 8 and another with Set Sizes 2, 4, and 8 (Palmer, 1994; Experiments 2 and 1 (less Set Size 1)). The data are the mean thresholds for four subjects.

Log-Log Slope These results are further summarized in terms of the slope on these log-log axes. For the two experiments, the slopes were 0.26 and 0.30. This measure was used to make the slope independent of the units of the stimulus (percent increment contrast). In addition, the log-log slope is independent of the response units because the thresholds are for a constant level of accuracy. It also measures the set-size effect for a fixed level of discriminability. Thus, the use of the log-log slope provides a built-in control for the degree of discriminability across stimuli and tasks (cf. Duncan & Humphreys, 1989). The slope of threshold versus set size on log-log coordinates will be used as the summary measure of the magnitude of the set-size effect, and will be referred to as simply the *log-log slope*.

Predictions Based on Unlimited-Capacity Perception Perhaps the simplest version of the unlimited-capacity perception hypothesis is the "independent channels model" (summarized in Graham, 1989). This model includes the defining characteristic of unlimited-capacity perception, that the relevant internal representations are independent of set size. In addition, this model adopts five additional assumptions. First, for judgments of a single stimulus dimension such as a contrast increment, the model uses the usual assumptions of signal detection theory: the relevant internal representation is one-dimensional, and is linearly related to the relevant stimulus difference between the targets and the distractors (Green & Swets, 1966). Second, the relevant internal representation is noisy. This is in contrast to a deterministic "high-threshold" model in which false alarms can only arise from guessing (Green & Swets, 1966). Third, these noisy representations are statistically independent. In other words, the trial-to-trial variability on one representation is independent of the other representations. Fourth, independent decisions (Shaw, 1982) are made concerning each individual stimuli. For a yes-no task, independent decisions result in the stimulus with the maximum value of the relevant internal representation determining the response. This "max rule" is nearly optimal for this situation. Fifth, to make numerical predictions, I assume a constant-variance normal distribution for the noise. However, the results can be derived for any distribution (Palmer et al., 1993).

The consequences of these assumptions are presented graphically in Figure 7. The top panel of Figure 7 is the typical situation in signal detection theory in which there is a single stimulus and it is either a distractor or a target. Shown in the figure is the probability density of two random variables, one that corresponds to the distribution of the internal representations of a single distractor and the other that corresponds to the distribution of the internal representations of a single target.

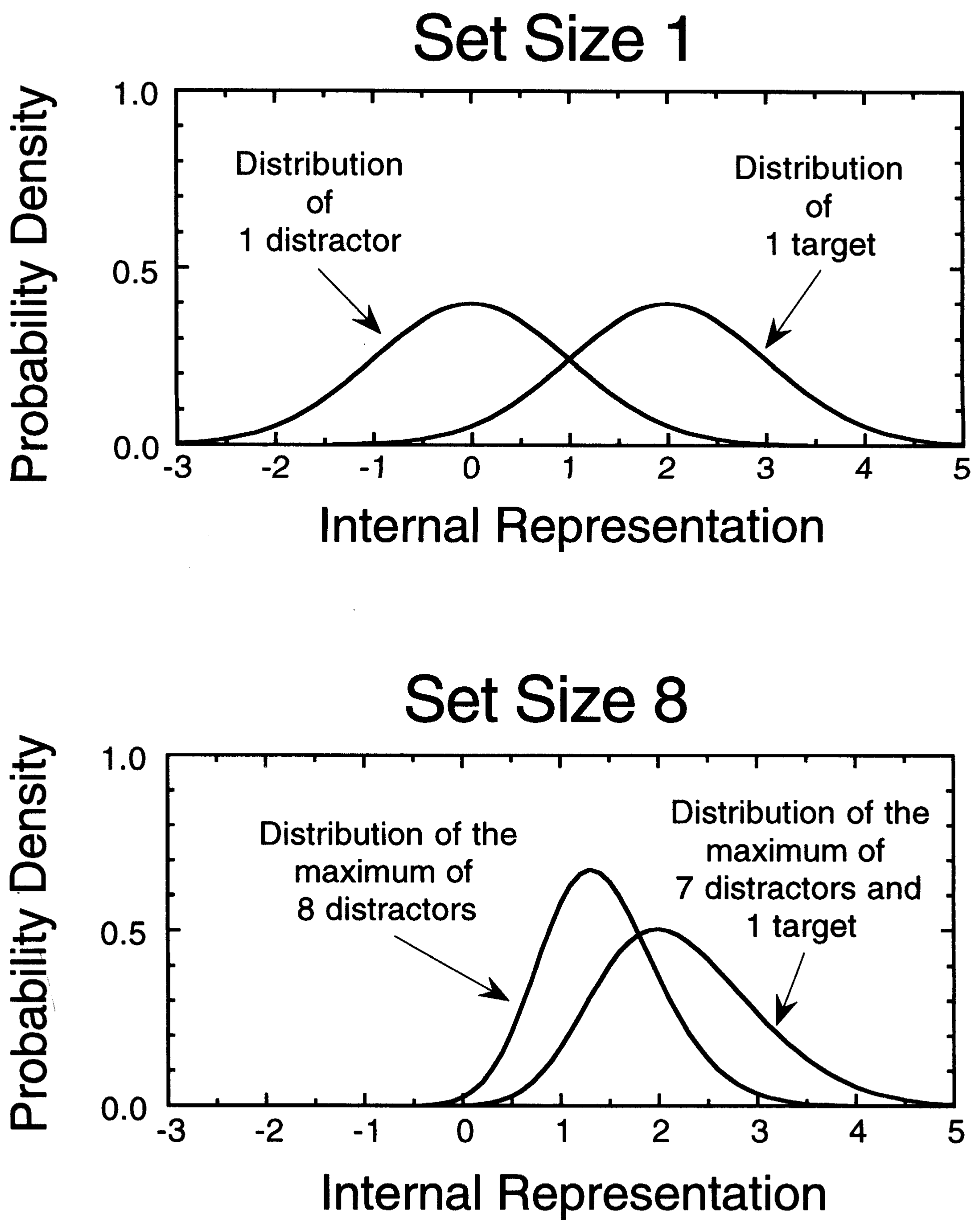

Figure 7: An illustration of the independent channels version of the unlimited-capacity perception hypothesis. Probability distributions for the relevant internal representations are shown for Set Sizes 1 and 8.

Here the probability distributions are assumed to be constant-variance normal. To make a judgment, the subject picks a criterion value somewhere along the internal representation axis and responds "yes" if the representation on a particular trial is higher than the criterion value.

Now consider what happens when set size increases (Graham, 1989; Pelli, 1985; Tanner, 1961). Each distractor adds noise and makes the decision more difficult. The relevant stimuli have eight distractors or have seven distractors and one target. The corresponding distributions for this case are shown in the bottom panel. The leftmost is the distribution of the maximum of eight samples from the distribution for a single distractor. This maximum distribution is shifted to higher values relative to the distribution for a single distractor (top panel). The second distribution in the bottom panel is the distribution of the maximum of one sample from the target distribution and seven samples from the distractor distribution. It, too, is shifted to the right but mostly in just its lower tail. The upper tail is little changed because it is largely determined by the one sample from the target distribution. On a given trial, the subject compares a sample from one of these two maximum distributions to a criterion value. For any criterion value, performance in the Set Size 8 condition is worse than the Set Size 1 condition.

Palmer et al. (1993) quantified this analysis of the threshold-versus-set-size function. Specifically, we assumed target distributions identical to the distractor distributions with a shift proportional to the stimulus difference, representations that are statistically independent, a decision based on the max rule, and the threshold defined at a criterion accuracy with equal bias. The predicted threshold was proportional to

$$F^{-1}(k^{1/n}) - F^{-1}[(1-k)/(k^{((n-1)/n)})], \quad (1)$$

where n is set size, k is the accuracy criterion (usually .75) and, F is the assumed cumulative distribution of both target and distractor representations. A special case of this equation was given for k = .75 in Palmer et al. (1993, Equation A14).

Assuming the normal as the relevant distribution, one can predict the relative threshold as a function of set size. On the log-log graph in Figure 8, the predicted negatively accelerated function is shown by the dashed line. For Set Sizes 2 to 8, it is well approximated by the linear function shown by the solid line. The linear function has a log-log slope of 0.22. (This is equivalent to an exponent of a power law on linear coordinates.)

Equation 1 also captures the effect of the accuracy criterion. For most common distributions, the increasing set size will steepen the predicted psychometric function. Thus, the predicted set-size effect on a threshold will be smaller if the threshold is defined by a higher accuracy criterion. For these set sizes and the normal distribution, the predicted log-log slope decreases from 0.42 to 0.14 as the accuracy criterion increases from .6 to .9.

Assuming an analytic cumulative distribution with an analytic form allows for an analytic prediction. For example, the logistic

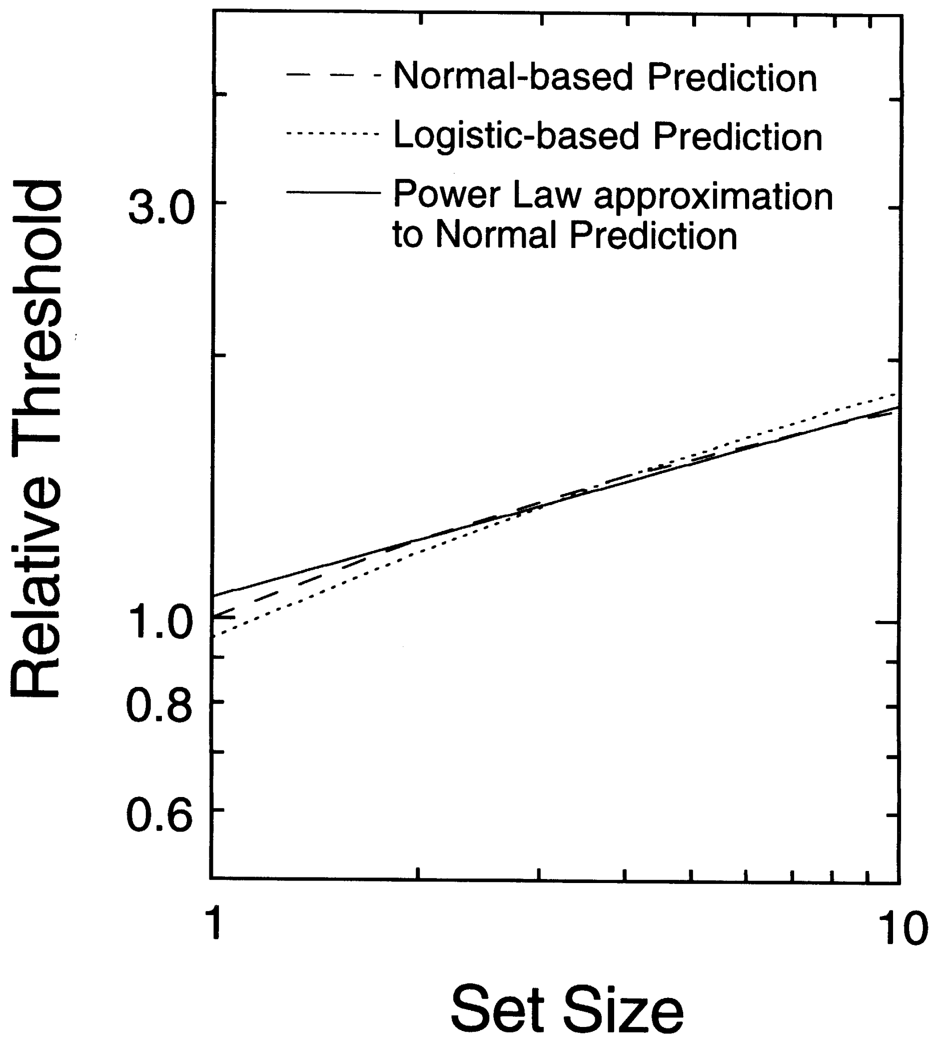

Figure 8: Relative thresholds are predicted as a function of set size for alternative versions of the unlimited-capacity perception hypothesis. Exact predictions are shown for normal (dashed curve) and logistic (dotted curve) distributions. In addition, the normal prediction is approximated from Set Size 2 to 8 by a linear function on log-log coordinates (solid line).

distribution, which is very similar to the normal, has an analytic cumulative distribution function,

$$1/(1+e^{-x}). \quad (2)$$

With this distribution, the threshold is proportional to:

$$\mathrm{Log}(k^{1/n}) - \mathrm{Log}[(1-k)/k^{(n-1)/n)}] - \mathrm{Log}(1-k^{1/n}) + \mathrm{Log}[1-(1-k)/k^{(n-1)/n)}]. \quad (3)$$

For Set Sizes 2 to 8, this function is also nearly linear on a log-log graph, and is shown by the dotted curve in Figure 8. It has a linear approximation on log-log coordinates with a log-log slope of approximately 0.28 for Set Sizes 2 to 8 (this approximation is not shown).

The Prediction of the Limited-Capacity Hypothesis In contrast, consider a similar model with the same decision process and with the addition of limited-capacity perceptual processes along the lines described by Broadbent (1958) using information theory. In this model, perception can be considered a sampling process (see the sample size model, Lindsay, Taylor, & Forbes, 1968; Shaw, 1980; Taylor, Lindsay, & Forbes, 1967). When only one stimulus is relevant, then all of the samples can be concentrated on the single relevant stimulus. This results in the maximum possible precision for judgments of that one stimulus. When n stimuli are relevant, then the samples are distributed across the relevant stimuli. If they are equally allocated, the number of samples per stimuli will be reduced by a factor of $1/n$. This can be shown to result in the precision of the representation dropping by a factor of $1/\sqrt{n}$. Such a model can be formalized by making similar assumptions as made above for the independent channels model. This *fixed-information-capacity model* predicts a log-log slope of 0.72 (for details see Palmer et al., 1993).

These predictions can be compared to the observed set-size effects which had log-log slopes that ranged from 0.26 to 0.30. The 0.22 log-log slope predicted by the independent channels model falls near this range, while the 0.72 log-log slope predicted by the fixed-information-capacity model clearly falls outside of this range. Thus, the independent channels model is sufficient to describe the observed results, and the fixed-information-capacity model can be rejected.

Generality The above analysis has been repeated using a second procedure and several other stimuli. Of particular interest is the use of a procedure that eliminates any non-attentional account of these effects. This can be done using the cueing procedure shown in Figure 9. The stimulus sequence ends in the same way as the previous visual search experiments, a display of eight stimuli. What differs is the cue. In the case shown in the top right panel, the cue display contains a central fixation point and dark crosses at the location of all eight stimuli. This display indicates that all eight stimuli may be the target, and this condition is referred to as having a *relevant set size* of 8. In contrast, the display in the top left panel is a central fixation cross surrounded by two dark crosses that indicate the two locations where the target will appear, if it appears anywhere. In addition, the white crosses indicate locations where distractor disks will appear and that one can safely

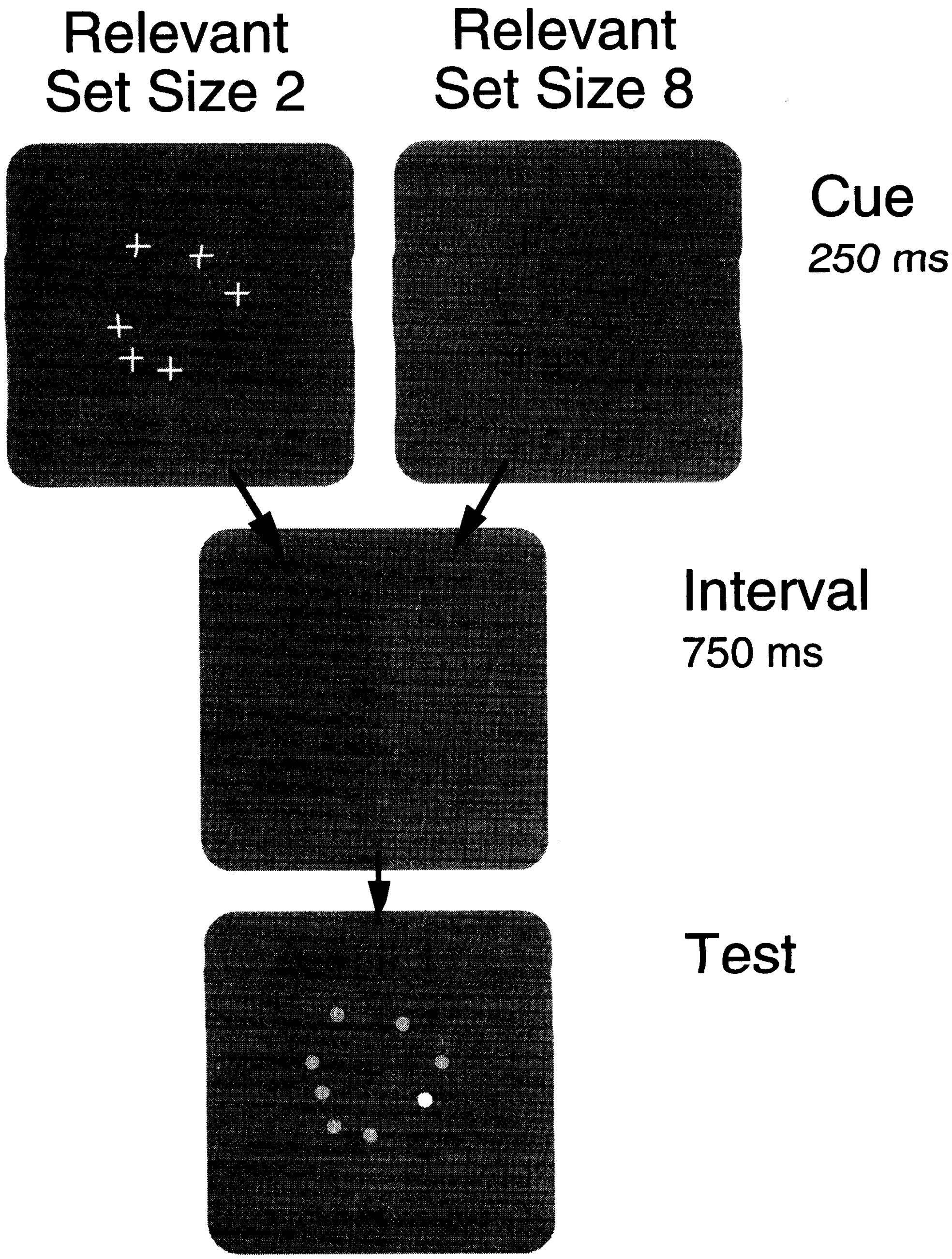

Figure 9: An illustration of the cueing procedure. The final test display is constant, and cues specify relevant set sizes of 2 and 8.

ignore. This condition reduces the relevant set size to 2. Because of the use of identical test stimuli, any effect of the cues must be due to some sort of selective attention phenomenon.

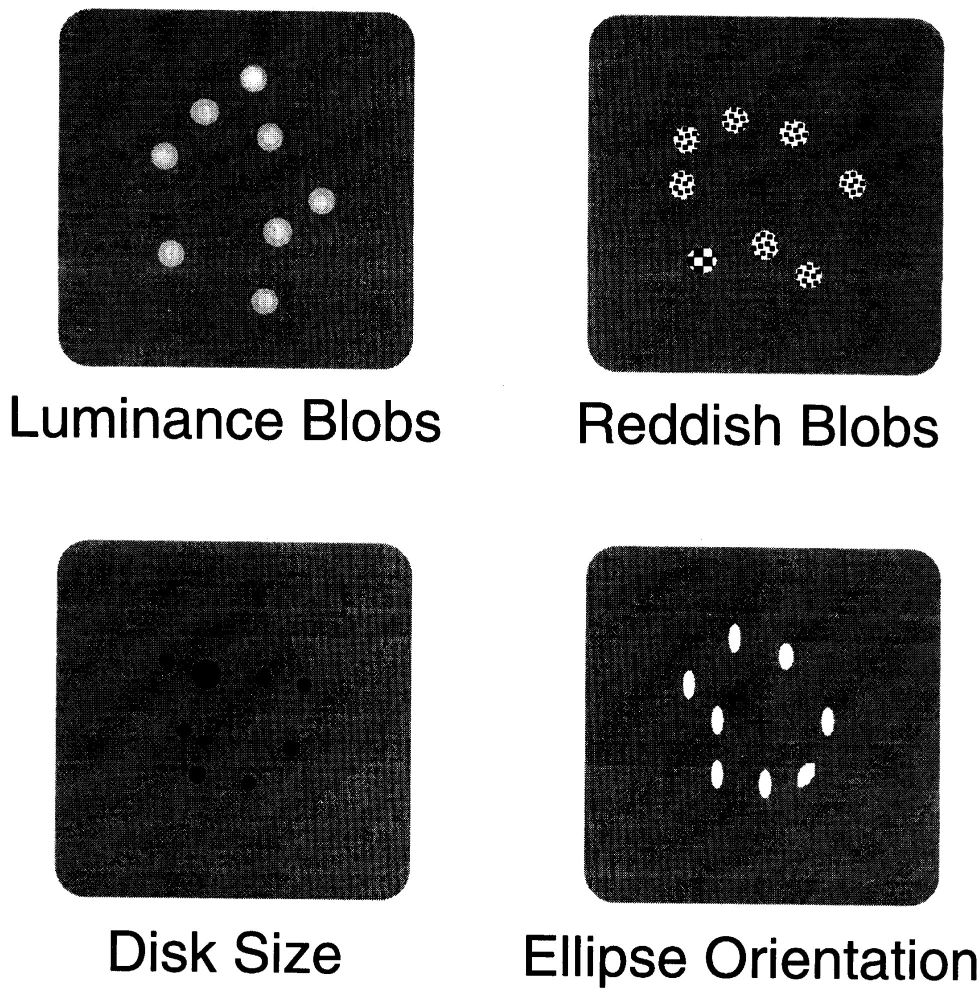

Figure 10: An illustration of the displays used in four additional search tasks. For the reddish blob condition, the coarser texture is intended to represent increasing saturation. The stimuli themselves contained no such texture.

The display-set-size and cueing procedures were combined with four new stimulus judgments which are depicted in Figure 10 (see Palmer, 1994 for details) and summarized as follows: (a) another contrast increment task using luminance "blob" stimuli which were varied in space and in time according to a normal probability distribution profile (eliminating any sharp edges or abrupt onsets); (b) a colour task using reddish blobs in which the target was a more saturated blob then the distractors; (c) a size task in which the target was larger in size than the distractors; (d) an orientation task with small ellipses in which the target differed in orientation from the distractors.

Results of the new cueing procedure and new stimulus judgments are shown in Figure 11 along with the original set-size procedure and

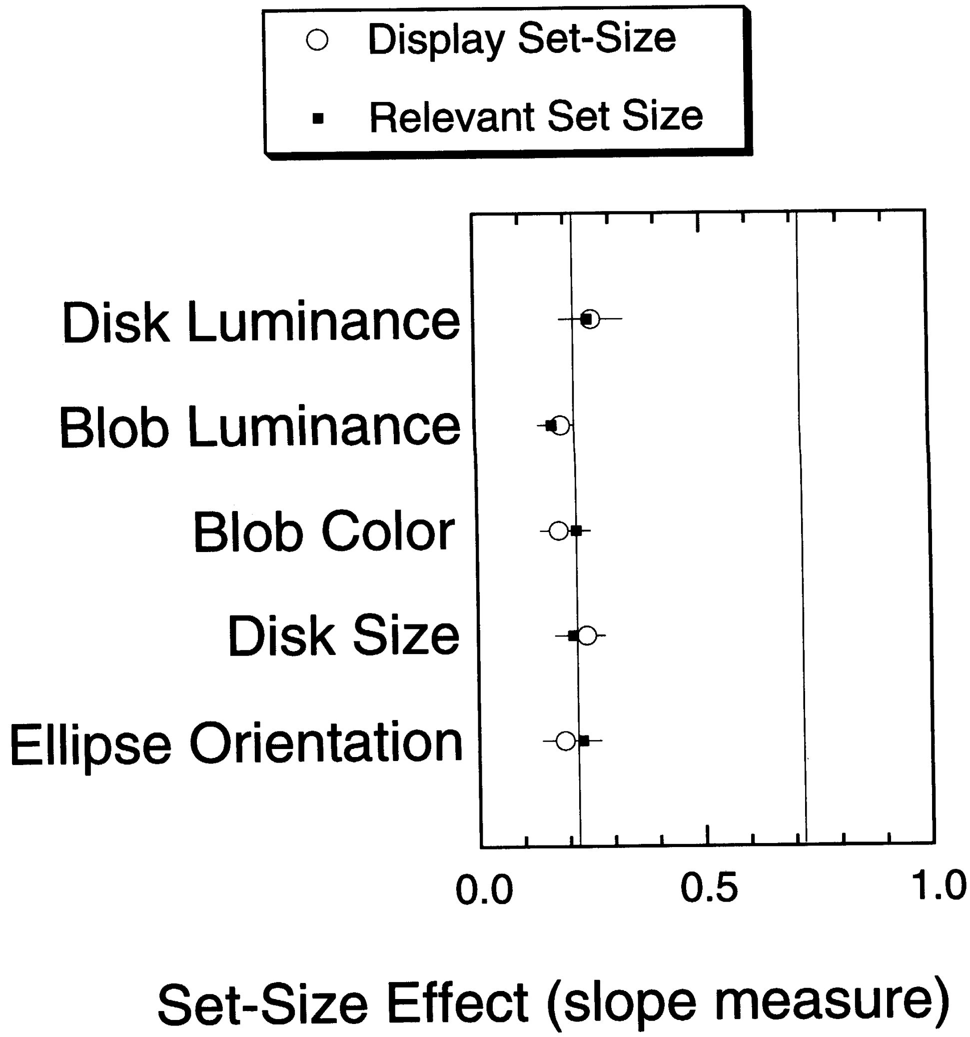

Figure 11: The set-size effect measured by the mean log-log slope for five tasks, using both the display-set-size and cueing procedures. The vertical line on the left indicates the prediction of the independent channels model (unlimited capacity), and the line on the right indicates the prediction of the fixed-information-capacity model (limited capacity).

contrast increment task. This figure plots the mean value of the log-log slope for each task conducted both as a display-set-size experiment and as a cueing (relevant-set-size) experiment. For both measures and for all five tasks, performance ranged from 0.20 to 0.25. This range is consistent with the 0.22 log-log slope predicted by the independent channels model that is shown by the vertical line on the left of the graph. For comparison, the 0.72 log-log slope predicted by the fixed-information-capacity model is shown by the vertical line at the right of the graph. Thus, the results of all of these search accuracy experiments are consistent across a variety of stimulus judgments and with both cueing and traditional visual search paradigms. Similar results have been reported for motion by Verghese and Stone (1995, Experiment 2) and for letters by Bennett and Jaye (1995).

Key to obtaining this consistency is the use of a fixed level of discriminability and a summary measure independent of the stimulus units. If discriminability were not controlled (as is common current practice) then this consistency would be absent. Consider, as an example, the wide range of response-time-versus-set-size slopes reported by Treisman and Gormican (1988). The analysis presented here reveals a consistency that has previously been hidden.

In summary, for observed results, the unlimited-capacity perception hypothesis is sufficient; the proposed version of the limited-capacity perception hypothesis can be rejected.

Search Time

Prototype Experiment

Methods The search time experiments were identical to the search accuracy experiments that manipulated display set size, except for three differences. (a) The stimuli were displayed until the subject responded. (b) Subjects were required to respond as quickly as possible while maintaining 10% errors. This was made possible by blocking the set size and contrast increment conditions and giving feedback about errors. (c) Search time rather than accuracy was measured as a function of the contrast increment and set size.

Results The results are shown in Figure 12. The mean search time is graphed as a function of the contrast increment, with both axes scaled logarithmically. The curve parameters are set size and the presence or absence of the target. In addition, the curves at the bottom of the graph show the error percentage for Set Sizes 2 and 8. The mean errors were within 2% of the 10% goal for all set size and contrast increment conditions.

There were large effects of both manipulations on search time. As the contrast increment was increased, the search time dropped dramatically until it approached 400 ms. There were also large set-size effects for the smaller contrast increments. For the Target Absent conditions, the mean search time increased from less than 800 for Set Size 2, to around 1,500 ms for Set Size 8. The set-size effects were reduced for larger contrast increments, and approached very small values for very large increments.

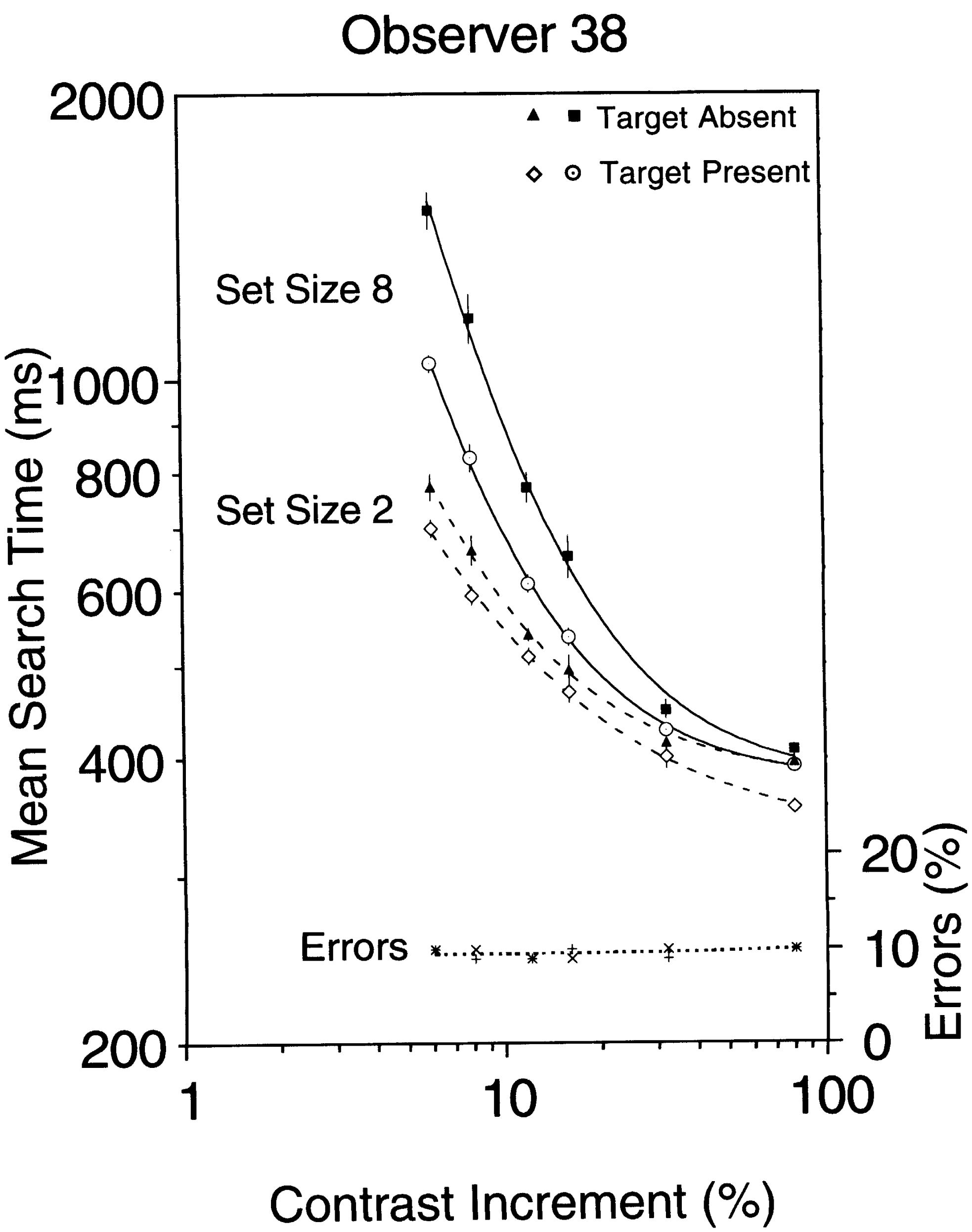

Figure 12: Mean search time for a single subject is shown as a function of the contrast increment. The curve parameters are Set Size 2 versus Set Size 8, and Target Absent versus Target Present.

The smooth curves are the best fitting *modified power functions* (Mansfield, 1973). They represent search time, y, as a function of contrast increment, x, for each condition, by

$$y = c\,(x/d)^b + t_0, \tag{4}$$

where b is the power law exponent, d is the contrast increment threshold, and t_0 is the asymptotic search time. The threshold is defined as the contrast increment that yields a c ms increase over the asymptotic search time. This is a change of parameters from the modified power function defined by Mansfield (1973):

$$y = a\,x^b + t_0. \tag{5}$$

In particular, the d parameter is equal to $(c/a)^{(1/b)}$. For a further discussion of stimulus intensity effects including alternatives to the power function, see the analysis of such effects on choice reaction time by Schweikert, Dahn, and McGuigan (1988).

The three parameters, b, d, and t_0, can be interpreted using the illustrations of Figure 13. In this figure, each of the panels shows how one of the parameters affects the shape of the search-time-versus-contrast-increment function. The top panel shows what happens as the exponent b is varied. The exponent determines the shape of the curve on these log-log axes. In the middle panel, the threshold parameter d is varied. On log-log axes, the threshold parameter determines the horizontal position of the curve. In the bottom panel, the asymptotic search time t_0 is varied. On log-log axes, the asymptotic time determines the vertical position.

This modified power-law model fits the data very well for all set sizes and conditions that have been examined. An illustration of these fits is shown in Figure 14. This figure shows the Target Absent condition for Set Sizes 2 and 8 for four subjects. Each subject has reasonable fits, and in particular the subject in the upper-left panel showed an excellent fit in which most of the error bars were the size of the points or smaller.

Similar results were found using the cueing procedure as described previously for search accuracy. The results of both the cueing experiment that manipulated relevant set size and the display-set-size experiment are given in Figure 15. The open symbols and dotted curves are the results and fits, respectively, for the cueing conditions, and the solid symbols and solid lines are for the display-set-size conditions. For the sake of simplicity, only the Target Absent condition is shown. Results for the cueing conditions were similar to the corresponding display-set-size conditions. There were large set-size effects at small contrast increments, which diminished with larger contrast increments. Particularly striking is the fact that the relevant-set-size manipulation has large effects despite the use of identical stimulus displays for Relevant Set Sizes 2 and 8. For small contrast increments, the cue manipulation increased search time by a full second, even though the stimulus displays were unchanged.

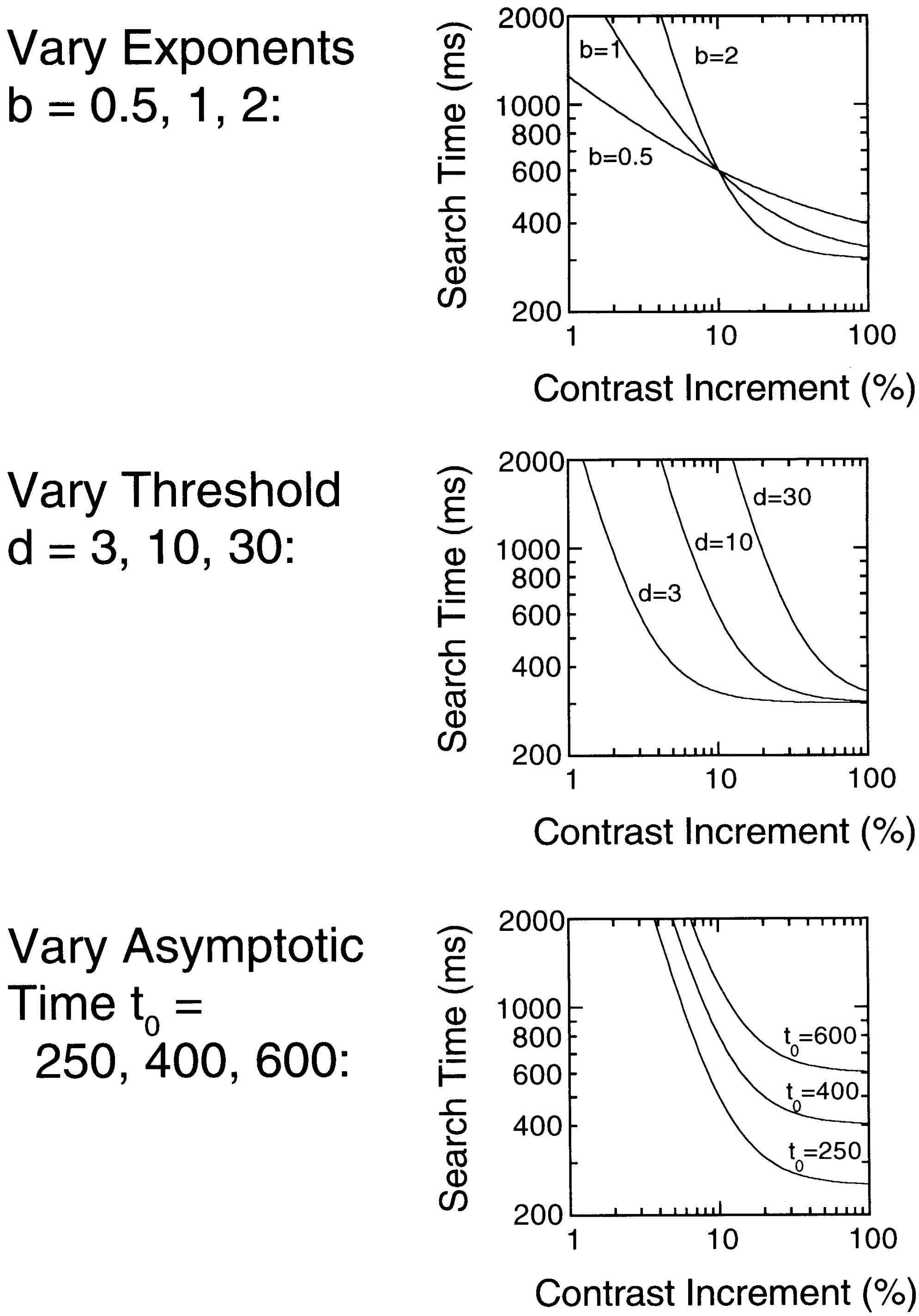

Figure 13: Each panel illustrates the effect of one parameter of the modified power-law model. In the top panel, the slope of the curve is specified by the exponent. In the middle panel, the horizontal position of the curve is specified by the threshold parameter. In the bottom panel, the vertical position of the curve is specified by the asymptotic search time parameter.

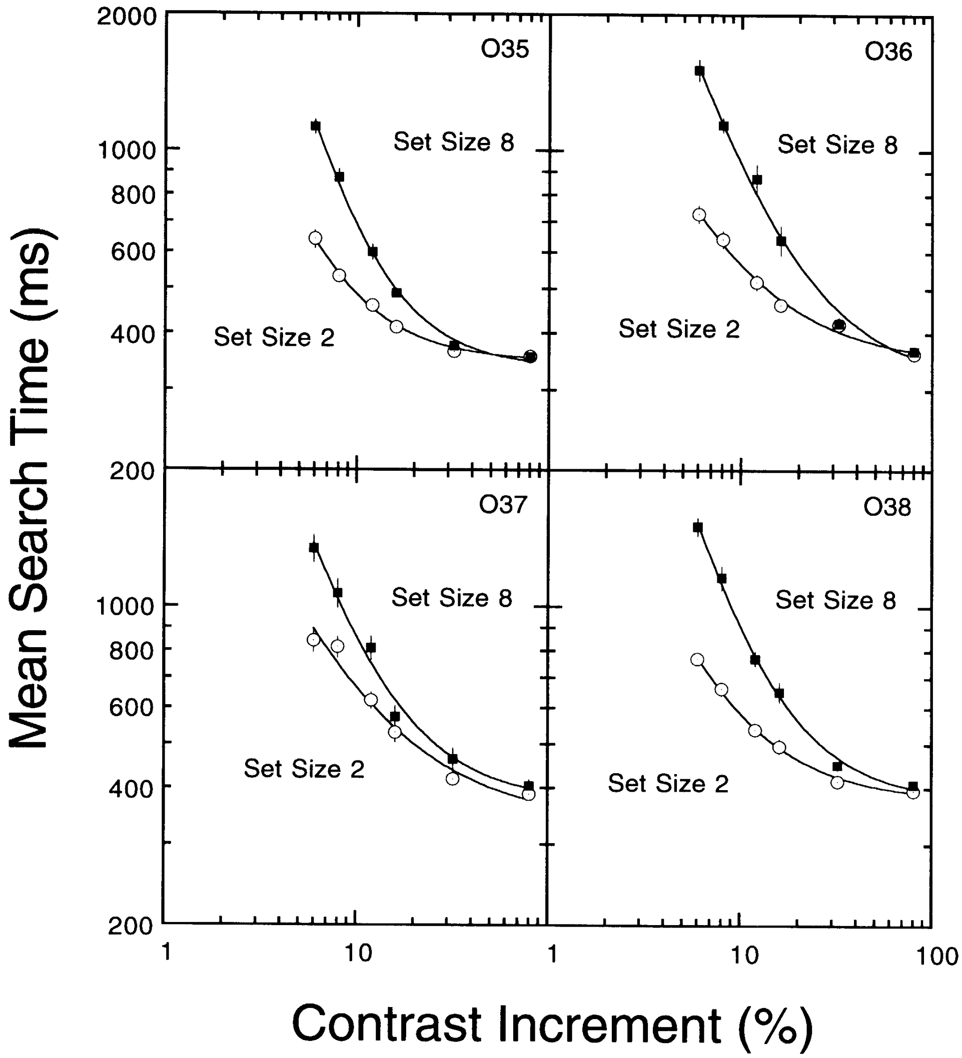

Figure 14: The mean search time for four subjects is shown as a function of the contrast increment for Set Sizes 2 and 8. Functions are shown for Target Absent only.

Estimating Thresholds for Search Time

The next step of this analysis was to estimate a threshold value for search time that is analogous to the threshold value estimated for search accuracy. Similar estimates have been made before for certain colour search tasks by Nagy and Sanchez (1990). Here, the search time data were fit with the modified power-law model, and were used to estimate the contrast increment that yields a search time of a particular criterion value above the asymptotic search time. I assumed a criterion value of +100 ms. This value is essentially arbitrary, although 100 ms is well under the time needed for a second eye movement. The impact of this choice will be considered in detail in the last part of this article.

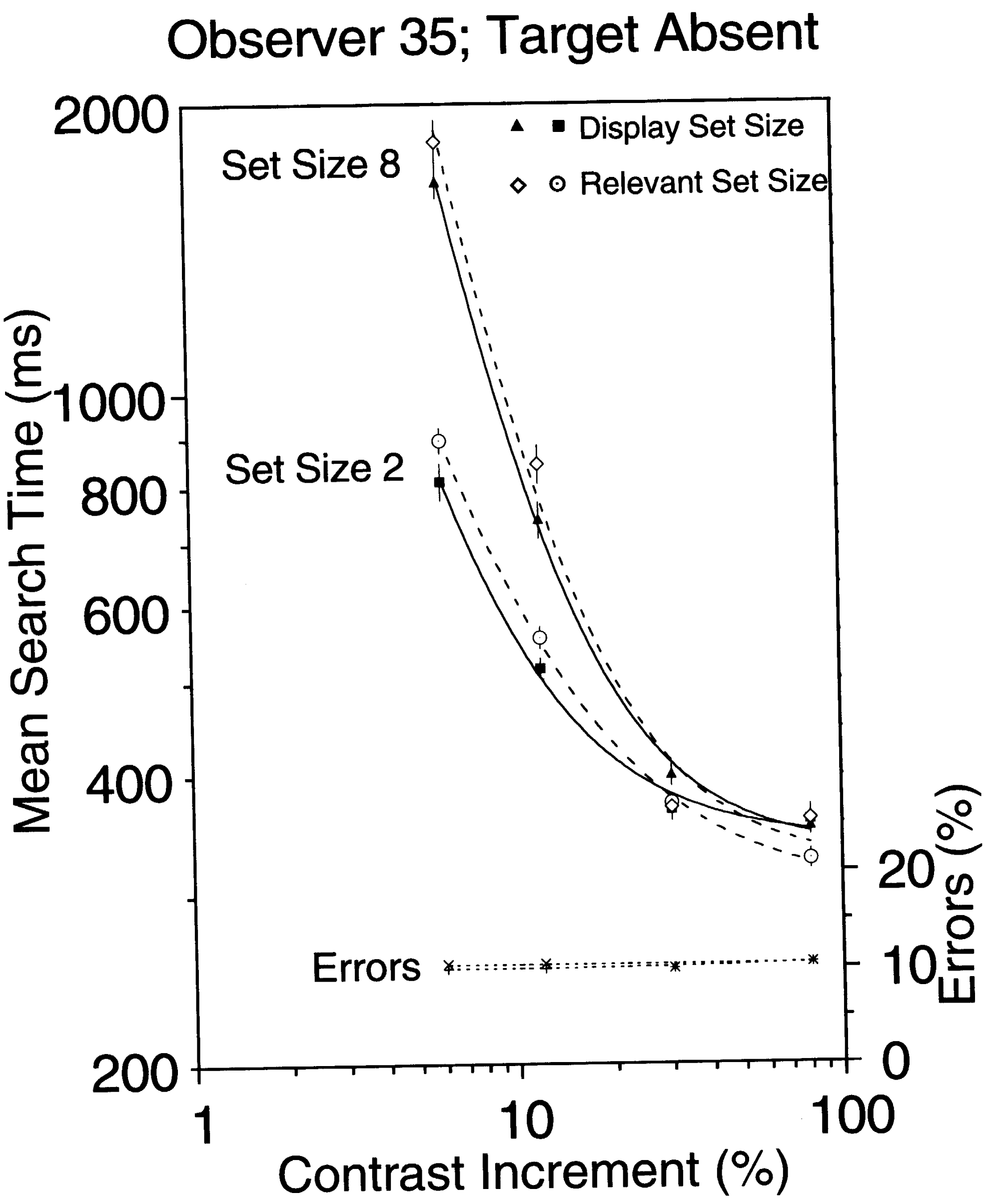

Figure 15: The mean search time is shown as a function of the contrast increment for variations of both display-set-size and relevant-set-size. The two manipulations produce similar results. For simplicity, data are shown for Target Absent only.

The analysis also focused on the Target Absent condition, which has the largest effects and the simplest theory.

An illustration of the threshold analysis is given in Figure 16, which is a plot of the Target Absent data from Figure 12. In particular, the asymptotic search time for the Set Size 2 condition is shown by the bottom horizontal line and a +100 ms additional criterion time is marked by the upper horizontal line. The intersection of the upper line and the

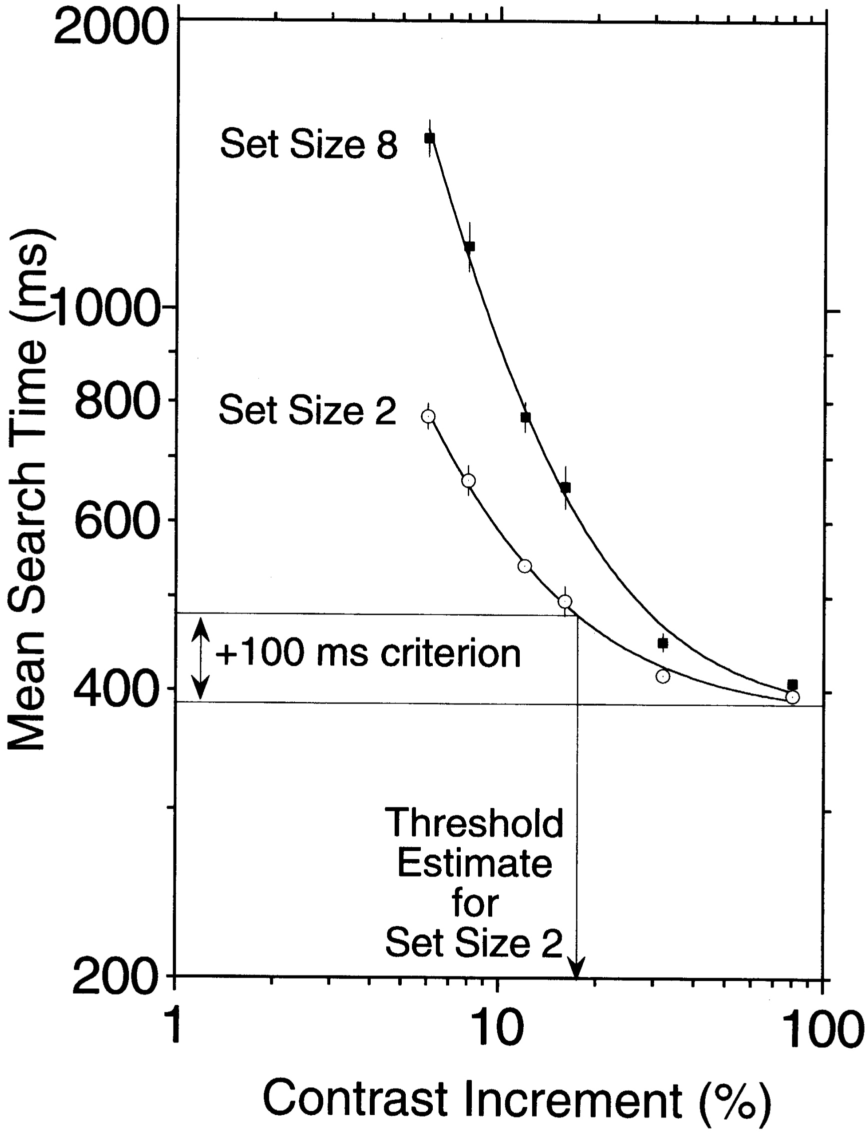

Figure 16: An illustration of the estimation of a time threshold. The curve is the best-fit modified power law, and a +100 ms criterion is used to define the threshold contrast increment.

curve fit for Set Size 2 is the contrast increment threshold estimate for Set Size 2, approximately a 17% contrast increment.

In Figure 17, the results of the search time experiment are plotted in the same format used for the search accuracy experiments. The axes are the same as before: log contrast increment threshold versus log set size. The accuracy data shown before in Figure 6 appear again at the bottom of this graph. The results of two search time experiments appear near the top of the graph. All of the points represent the means of four subjects. There was a consistent set-size effect and the log-log slope was around 0.3 for the 100 ms time criterion. Thus, threshold performance can now be defined by either a time criterion or by an accuracy criterion.

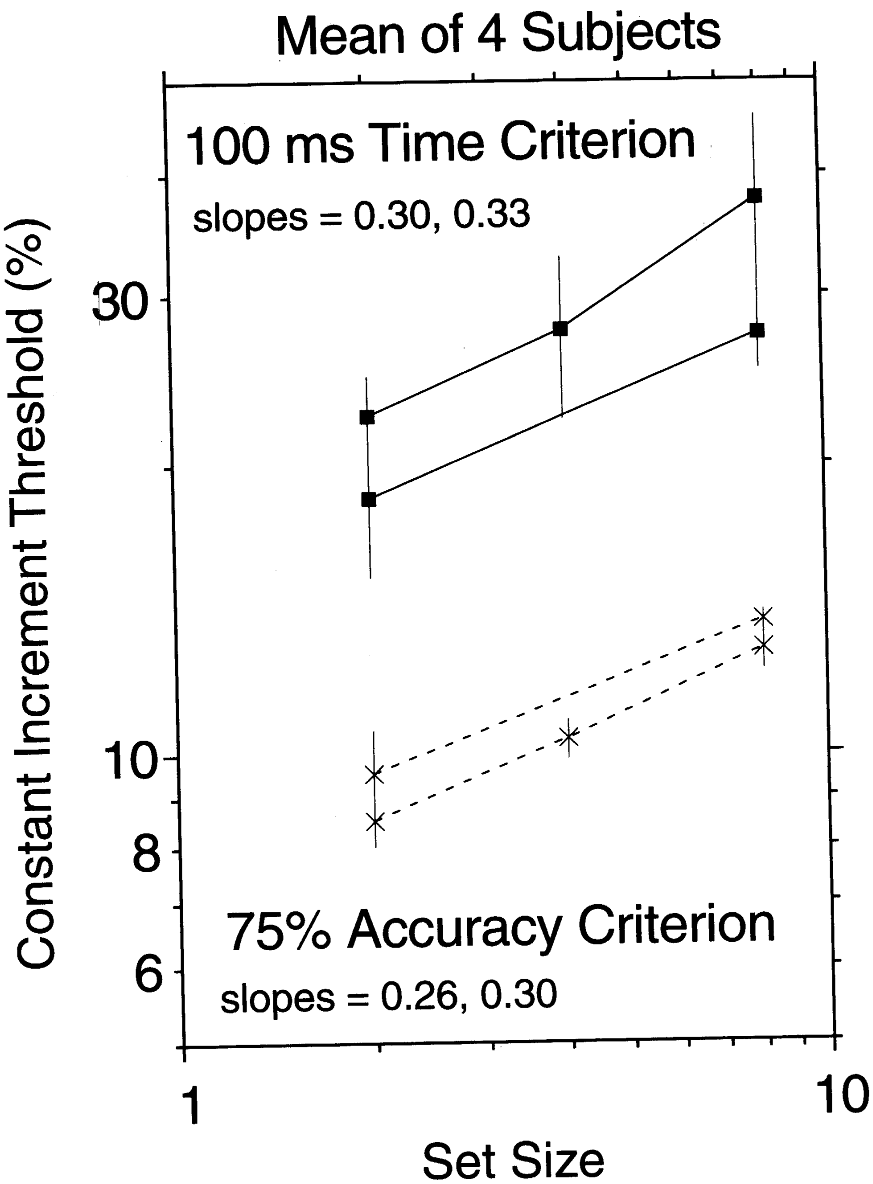

Figure 17: Mean threshold for four subjects as a function of set size. At the bottom are previously shown results for search accuracy; at the top are the new results for two search time experiments.

Criterion Effects

The analysis thus far is successful in allowing one to summarize the results of the accuracy and time experiments in a common fashion. This approach, however, leads to a final problem: there is no justification for comparing the 75% accuracy criterion to the particular 100 ms time criterion. These criteria would not matter if the functions describing probability correct as a function of contrast increment and search time as a function of contrast increment had constant shapes for all set sizes.

Unfortunately, these functions do not have consistent shapes. As the set size increases, the functions steepen on these log-log graphs for both accuracy and time. For accuracy, the independent channels model predicts this change in the psychometric function (e.g., the effect of k in Equation 1, see also Pelli, 1985). But for search time, I do not yet have an unlimited-capacity perception model that is detailed enough to make a prediction. While the analysis thus far showed the two experimental paradigms to be similar, it remains unclear what time criterion can be justified as being comparable to the 75% accuracy criterion. This problem is addressed in the next section, which considers general theories that relate search accuracy and search time.

Before proceeding, I will make a brief aside about the possible nature of an unlimited-capacity perception model for search time (see Pavel, 1990; Pavel, Econopouly, & Landy, 1992). There are at least two general approaches. Geisler and Chow (1995) focus on the fact that in many search time experiments, the stimuli are presented until the subjects respond, and thus the subjects have the opportunity to make eye movements. Indeed, for some kinds of stimuli, the limitations of peripheral vision require that an eye movement be made to each individual stimulus to allow an accurate judgment. Geisler and Chow use the limits due to peripheral vision to estimate how many eye movements are required for a given level of accuracy. As the stimuli become more confusable to peripheral vision, there must be more and more eye movements. Moreover, for confusable stimuli, an increase in set size increases the noise, and thus requires additional eye movements. Thus, this model has the correct qualitative properties to predict the results shown here. It highlights the potential importance of limitations of peripheral vision as a mediating factor for set-size effects.

The second approach is to extend to search time the analysis of the integration of noisy information. This was the heart of the unlimited-capacity perception hypothesis discussed above. The key is to consider models that describe the response time as a function of the confusability of the targets and distractors. Begin by recalling the analysis of search accuracy. For confusable stimuli, increasing the set size increases the noise affecting the decision. In most stochastic models of response time, an increase in noise will result in a slower accumulation of information. Thus, increasing the set size must increase the search time. Such models have not yet been detailed for visual search, but a starting point can be found in Palmer and McLean (1995). See also the related models of similar response time phenomena (the memory search model of Ratcliff, 1978; alternative stochastic processes are developed by Link, 1975; or Rudd, 1996). For a general review, see Luce (1986).

The strategy that I pursue here is to set aside the question of developing a specific model for search time, and instead to turn to more general models of the relation between search accuracy and search time. These models will provide a context in which one can compare accuracy and time experiments.

Relating Search Accuracy and Search Time

Here I will introduce a more general theoretical question: Is there a common bottleneck that determines the set-size effects for both search accuracy and search time? I begin by describing what I mean by a common bottleneck, and then describe a method to test the predictions of such a hypothesis. In addition, this analysis reveals the effects of criterion that bedevilled the previous comparison between search accuracy and search time.

The Common Bottleneck Hypothesis

I focus my analysis again on the interaction between the stimulus difference and set-size manipulations. In particular, assume that both dependent variables depend on a *common bottleneck* that accounts for the interaction between the stimulus difference and set size. By a common bottleneck, I mean that a common, single-valued representation mediates the set-size effect for both dependent measures. To my knowledge, this idea was first formalized by Bamber's (1979) "state-trace analysis." His analysis is an example of a decomposable representation (Krantz, Luce, Suppes, & Tversky, 1971). Such decomposable representations have been used in similar applications including light adaptation (Stiles & Crawford, 1932) and identifying visual features (Palmer, 1986).

For a formal definition, denote the set size by n and the stimulus difference by d. In addition, let S denote a single-valued function of n and d, and let F and G denote monotonic real-valued functions. The common single-variable representation corresponds to the value of the function S within the following system of two equations:

$$\text{Probability correct} = F\,[S(n, d)], \text{ and} \tag{6}$$

$$\text{Mean response time} = G\,[S(n, d)].$$

The function S corresponds to the internal representation that combines the effects of the stimulus difference and set size for both dependent variables. One can think of S as describing the signal-to-noise ratio that results from the two manipulations. This single representation is then related to the two different response measures by two different monotonic functions. Thus, this is also an example of a decomposable representation.

While this theory is very general, it does predict a particular property on equivalence relations. To define that property, denote the equivalence relation by ~ and the different set size and stimulus difference conditions by subscripting n and d. In addition, the response to the condition with set size n_i and stimulus difference d_i is denoted by the ordered pair (n_i, d_i). With this notation, the predicted equivalence property is:

$$(n_1, d_1) \sim (n_2, d_2) \text{ for search accuracy, if and only if} \quad (7)$$

$$(n_1, d_1) \sim (n_2, d_2) \text{ for search time.}$$

This equivalence property is very similar to the threshold measures mentioned earlier. For example, the stimulus difference thresholds for 75% correct at two different set sizes defines an example of estimating one of the equivalence conditions for accuracy. The new aspect is that the same pairing of stimulus difference and set size conditions will be equivalent for search time. It does not, however, predict for what response time they will be equivalent. The two conditions that match for 75% correct in search accuracy must match for some search time, but one does not know if they will match for a search time of 500 ms, or 600 ms, or what have you. The prediction only specifies that there does exist a search time that will always match.

The nature of this equivalence property is shown by the graphs in Figure 18. The top panel of Figure 18 is a small reproduction of the threshold-versus-set-size functions already shown. In that graph, the set-size effect is the difference in threshold for the two set sizes. The same information is plotted in a single point in the scatterplot in the bottom panel (this analysis builds on that of Bamber, 1979). The axes are the increment contrast threshold for Set Size 8 plotted against the increment contrast threshold for Set Size 2. The results for one equivalence relation is summarized by a single point in this graph. The x value on the scatterplot is taken from one of the points of the upper panel and the y value is taken from the other point in the upper panel. With this new scatterplot, the magnitude of the set-size effect is the vertical shift above the diagonal line that marks identical thresholds for the two set sizes. The point shown is for an accuracy criterion of 75% correct.

The next step is to plot the thresholds for a variety of criteria. This offers the additional benefit of showing off the effect of the accuracy criterion. These results are shown in Figure 19. This scatterplot has the same point for the 75% criterion along with results for 60%, 90%, and 95%. There are set-size effects for all criteria, but the effect is reduced for higher criteria. This effect was also shown in Figure 5 in the psychometric functions.

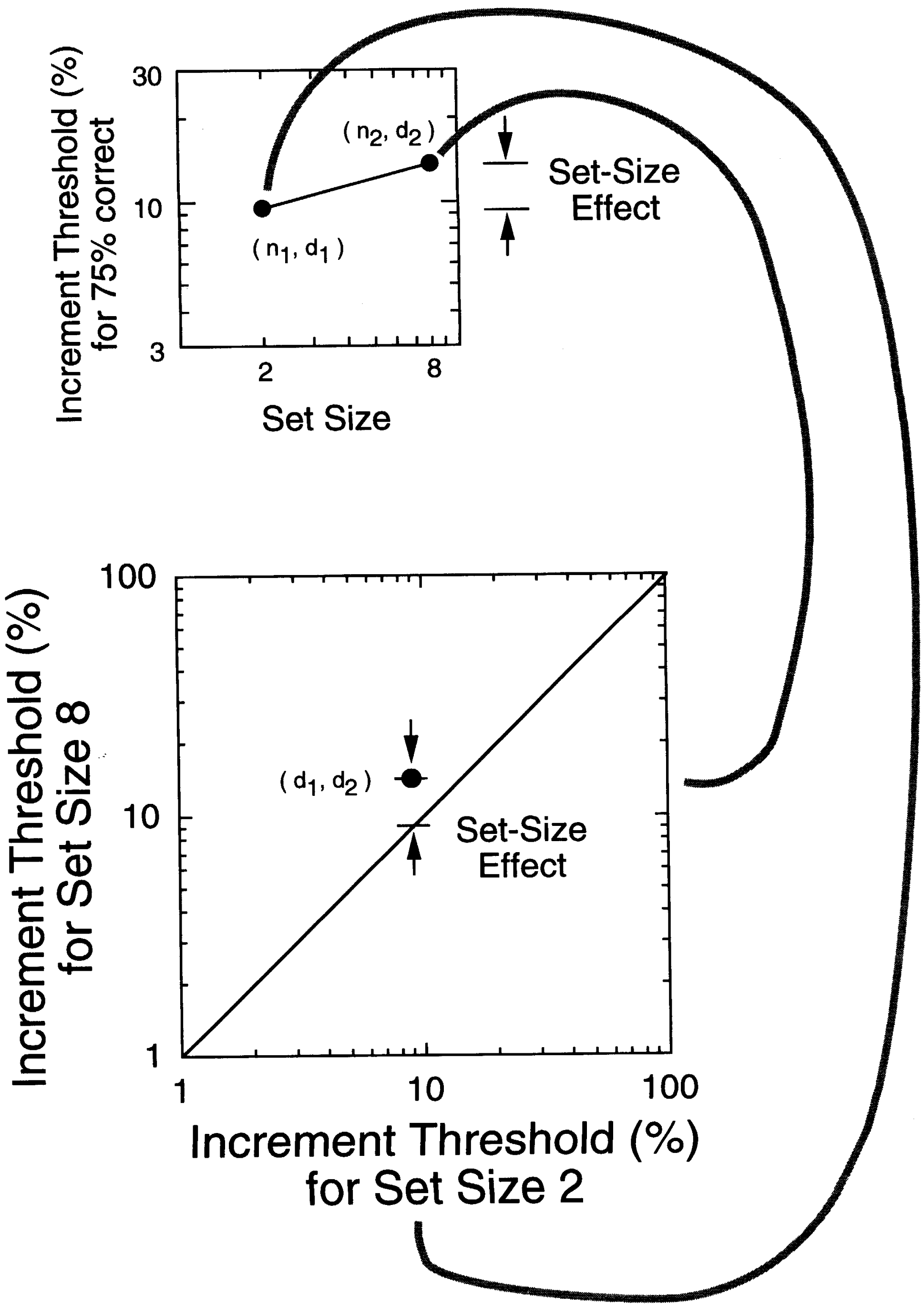

Figure 18: An illustration of how a scatterplot of the set-size effects is constructed from a threshold-versus-set-size function.

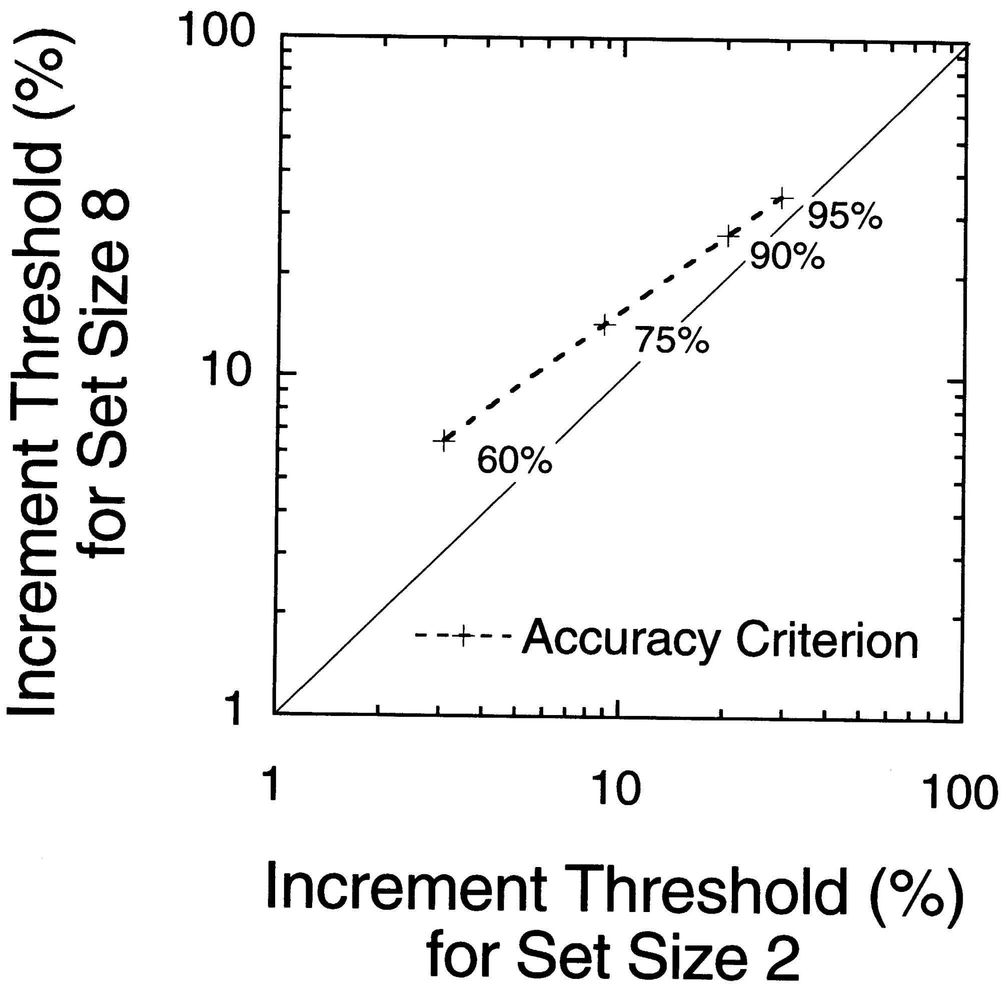

Figure 19: A scatterplot of the threshold for Set Size 8 versus the threshold for Set Size Estimated thresholds are shown for four different accuracy criteria.

With this machinery, one can state again the prediction of the common bottleneck hypothesis. It requires that the search time thresholds fall along the same contour as that defined by the search accuracy thresholds. There is no prediction about where the particular 100 ms criterion will fall, but it must fall somewhere along the contour made by the accuracy criteria.

Testing the Common Bottleneck Hypothesis The results are shown in Figure 20. The solid curve and open diamonds indicate the results for the search time, and the dashed curve and pluses indicate the results of search accuracy. They coincide quite closely. Thus, the common bottleneck hypothesis is sufficient to account for both search accuracy and search time.

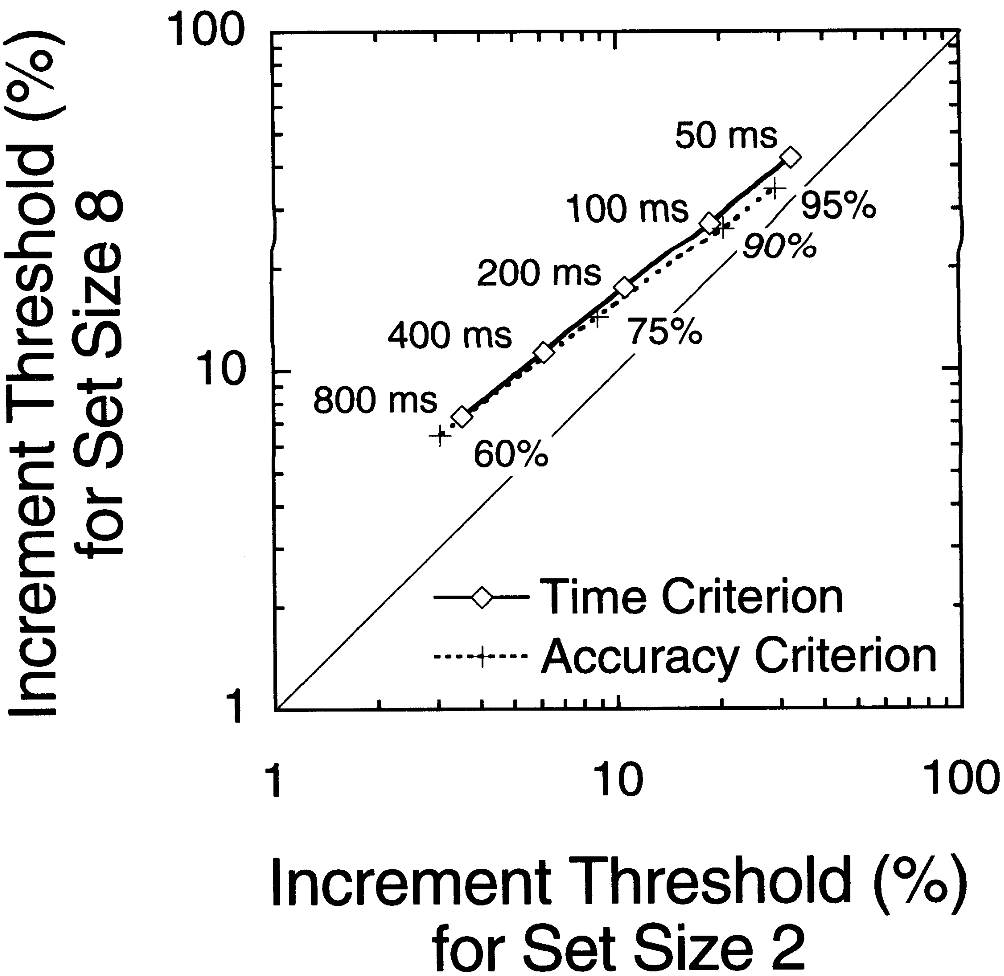

Figure 20: A scatterplot of the threshold for Set Size 8 versus the threshold for Set Size 2. Estimated thresholds are shown for both search accuracy and search time.

To complete this analysis, I consider a measure of the reliability of these estimated equivalences. This is particularly important in the current situation because the graphs presented thus far can be misleading in one respect. The points on the contours shown in Figures 19 and 20 do not represent independent data points. Rather, they are a series of estimates for different performance criteria based on the same data. Thus, their consistency need not indicate consistent data. Consequently, one needs another way to represent the variability of these data. This was accomplished by estimating these contours independently for each subject. The individual subject contours were described by straight lines in these log-log scatterplots and summarized in terms of the two parameters of a line, a slope and a particular y-intercept. The first parameter is the usual slope as defined on a log-log scatterplot. It represents the effect of the criterion. No effect of the criterion would result in a slope of 1, and the observed slope was around 0.8, which reflects the smaller set-size effects for more accurate or more rapid response criteria. The second parameter is the y-value (vertical position) of these lines above the identity line at a particular x-value (horizontal position). This y-intercept is specified by the set-size effect at a 10% increment contrast. This set-size effect was expressed in terms of the equivalent log-log slope on the threshold-versus-set-size functions that were used previously. Specifically, let T_8 be the estimated threshold for Set Size 8 at the criterion that yielded a contrast increment threshold of 10 for Set Size 2. Then, the set-size effect is defined by the log-log slope,

$$(\text{Log } T_8 - \text{Log } 10) \,/\, (\text{Log } 8 - \text{Log } 2). \quad (8)$$

With this definition, the log-log slopes were around 0.35.

Using these two summary measures for each individual subject, the means and standard errors are plotted in Figure 21. The figure shows the criterion effect plotted against the set-size effect. One point represents the search accuracy experiment and the other point represents the search time experiment. The two points fall close enough that their error bars overlap. Thus, the differences between accuracy and time measure are not reliably different.

Summary I defined a model that specifies a common bottleneck for the interaction between the stimulus difference and set size, and then showed that this common bottleneck was sufficient to describe these effects for search accuracy and search time.

Discussion

Relations among Theories

Consider the relations among the various hypotheses using the implication diagram of Figure 22. Such an implication diagram shows the relations among more specific versus more general hypotheses. Any specific hypothesis that implies a more general hypothesis is shown by an arrow that points to the more general hypothesis. The resulting diagram can be thought of as the family tree of related hypotheses.

In Figure 22, one can begin at the middle left side with the contrasting unlimited- and limited-capacity perception hypotheses. This is the contrast at the heart of this article. In the analysis of the search accuracy experiments, I derived specific predictions for special cases of each of these hypotheses. For the unlimited-capacity perception hypothesis, the special case was the independent channels model; for the limited-capacity perception hypothesis, the special case was the fixed-

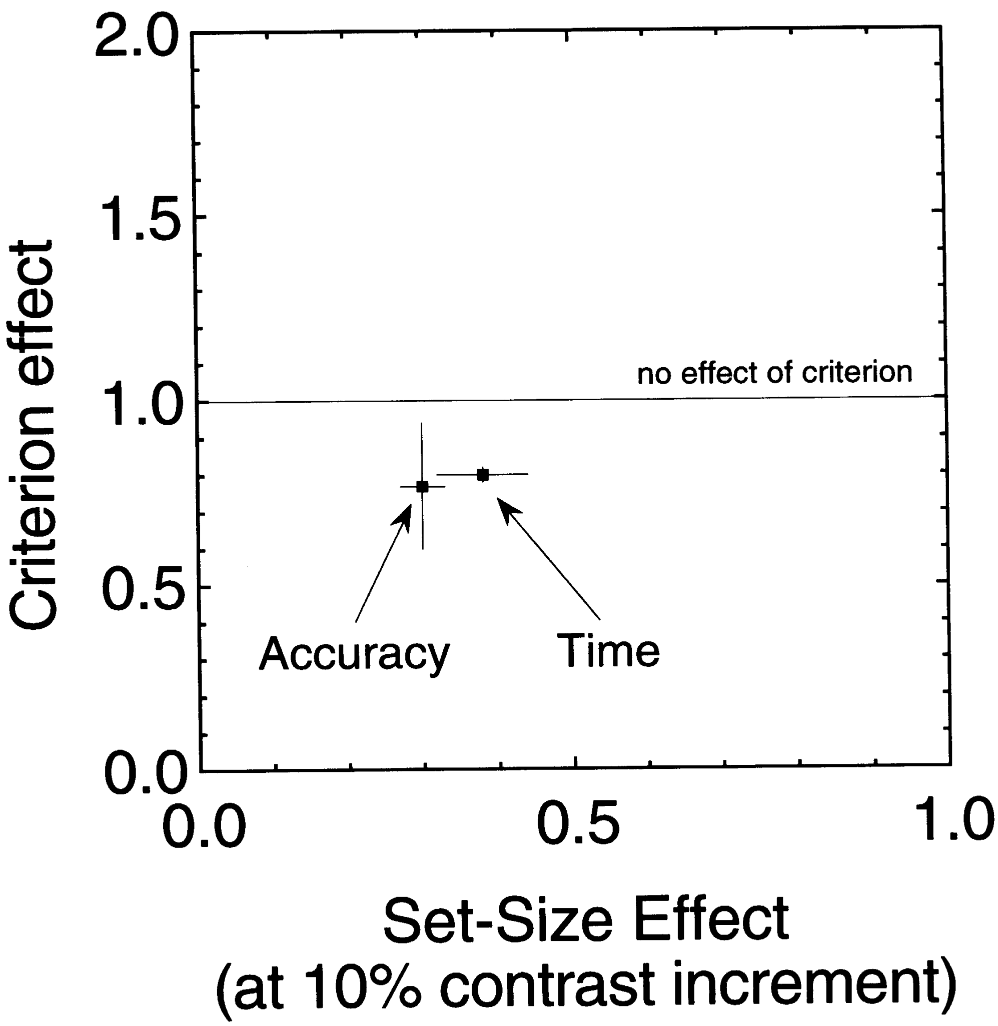

Figure 21: A scatterplot of the summary statistics estimated for both the search accuracy and search time paradigms.

information-capacity model. The independent channels model was sufficient to account for all the search accuracy results, and the fixed-information-capacity model was rejected.

In the last part of the article, I addressed the more general issue of whether or not set-size effects in search accuracy and in search time were accounted for by a common single-valued representation. I referred to this as the common bottleneck hypothesis. One possibility is that regardless of whether there is unlimited or limited-capacity perception, there is a common representation on which the two dependent measures are based. In the implication diagram, this is illustrated by the common bottleneck hypothesis implied by either the unlimited- or limited-capacity perception. In contrast to the common bottleneck hypothesis is a hypothesis that allows multiple bottlenecks. One example

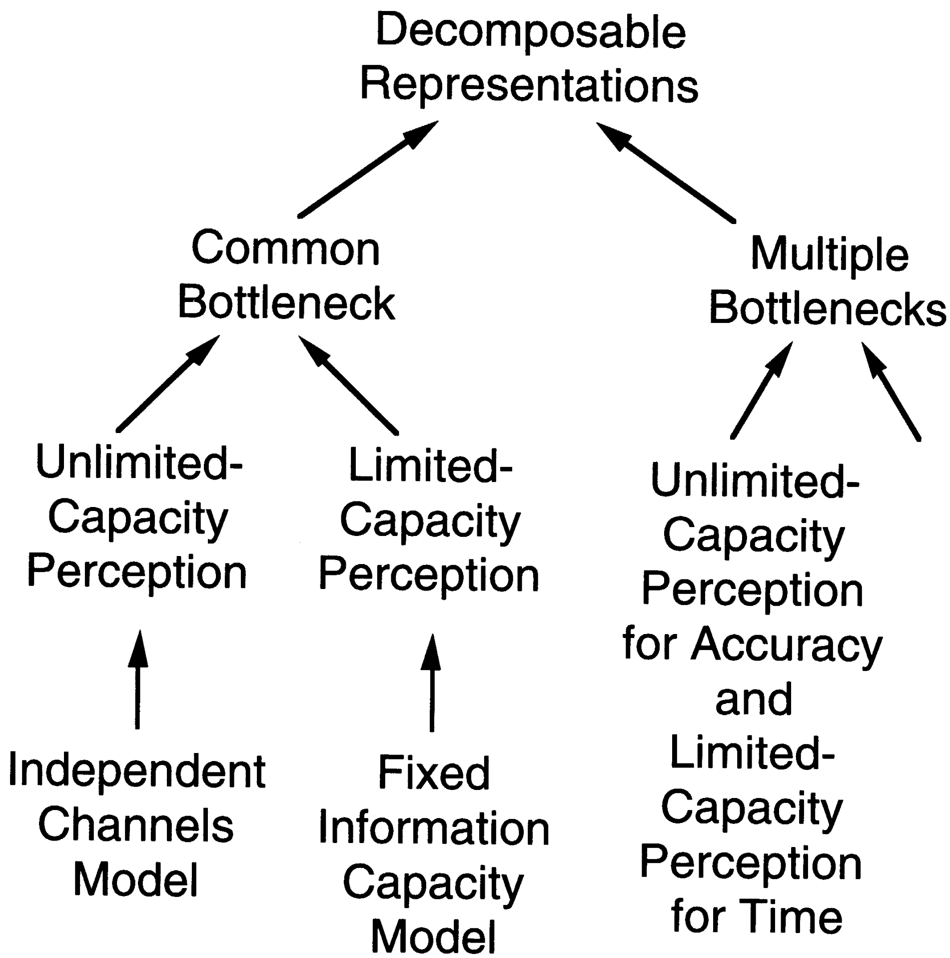

Figure 22: An implication diagram illustrating the relations among the hypotheses discussed in this article. The arrows indicate the special case hypotheses that imply more general hypotheses.

is to have unlimited-capacity perception for accuracy and a limited-capacity perception for time. This could result from a serial scanning that introduces a capacity effect on response time but has accuracy independent of the number of component processes. More stimuli take longer but do not affect the precision of the representation of any individual stimulus.

A prediction was derived for the common bottleneck hypothesis and the test of that prediction showed that this hypothesis was sufficient to account for the interaction between stimulus difference and set-size manipulations. Something that I did not do was to reject a specific version of the multiple bottleneck hypothesis. Indeed, an initial step for the future is to work out predictions for some of the special cases of the multiple bottleneck hypothesis. It is unknown at present whether or not the interesting special cases make a distinctive prediction from the common bottleneck hypothesis. Resolving that issue and coming up with more detailed predictions for the unlimited-capacity perception model for search time will answer the questions raised at the beginning of this article.

Applications to More Complex Search Tasks

The analysis presented here can be applied to a variety of search tasks. Figure 23 shows a schematic illustration of some of the more complex search tasks in the visual search literature. The top panel illustrates an orientation and contrast conjunction task in which a subject has to find a target of a particular orientation and contrast (Treisman & Gelade, 1980). The middle panel shows an illustration of a task in which one has to find a target that consists of a rotated T-like character among rotated L-like characters (Beck & Ambler, 1973; Egeth & Dagenbach, 1991). The bottom panel shows a spatial relations task in which one has to judge the orientation of a pair of opposite polarity points (O'Connell & Treisman, 1990). Key to this last example is that the task involves a relation among distinct objects rather than an attribute of a single grouped object. Grouping is minimized by the use of widely spaced dots of opposite contrast (Zucker & Davis, 1988). The existing literature on each of these tasks has shown relatively large set-size effects, and they have been interpreted as demonstrating some kind of limited-capacity perception.

I have begun to analyze each of these tasks using the methods of the search accuracy experiments described here. An initial analysis of the conjunction tasks suggests that once one controls for discriminability using threshold measures, the differences between conjunction tasks and feature tasks are much reduced (Aiken & Palmer, 1992). The remaining differences may well be accounted for by the differences in the decision models necessary for integrating information across multiple attributes as well as across multiple objects. Thus, I question whether large set-size effects are inherent in the conjunction task.

For the rotated T's and L's experiment, controlling discriminability only modestly reduces the set-size effects. On the other hand, the comparison between the cueing paradigm and the display-set-size paradigm indicates that under conventional conditions there are probably large sensory interactions among the stimuli. The experiments were repeated with very large separations among the stimuli to eliminate differences between the cueing paradigm and the display-set-size paradigm. Under these conditions, the set-size effects were reduced to be within the range of those predicted by an unlimited-capacity perception

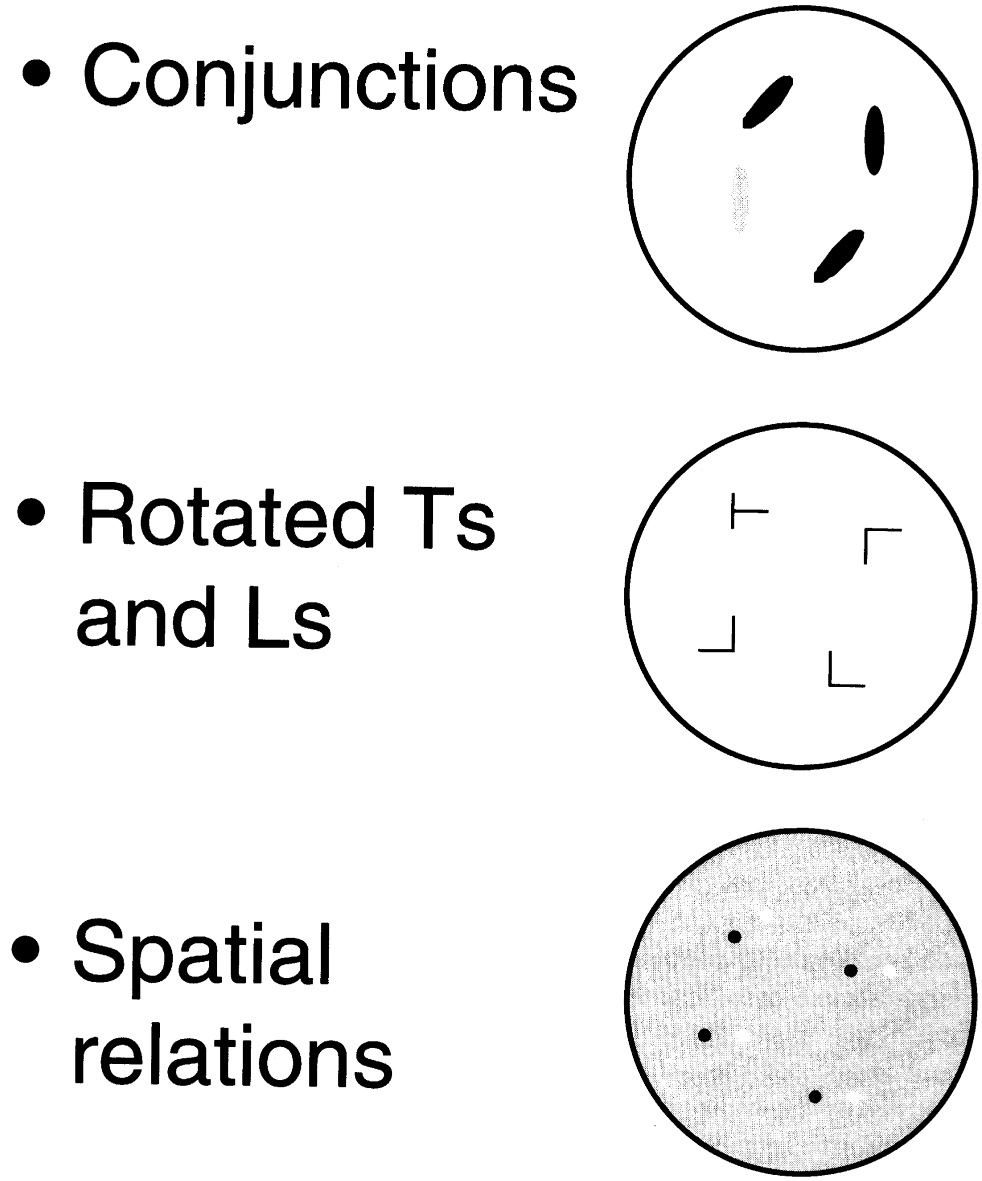

Figure 23: Illustrations of three search tasks that have been claimed to result in inherently large set-size effects.

model (Palmer, 1994). Thus, I suspect that the previously reported large set-size effects for the rotated T's and L's stimuli may not be fundamentally due to attentional phenomena, but rather may have more to do with configural or textural phenomena. In addition, a recent study by Bennett and Jaye (1995) has measured set-size effects for a variety of letter search tasks, and has shown many of them to be consistent with unlimited-capacity perception.

Only for the spatial-relations task do I find consistently larger set-size effects than with simple stimuli. For a typical experiment, the log-log slopes are around 0.5, which is about twice that found for simple tasks (Palmer, 1994). This is still not as large as predicted by the information-theory special case of the limited-capacity model described earlier. Curiously, however, this is exactly what one would predict from an information-theory, limited-capacity hypothesis that considers the whole behaviour as a communication channel rather than considering merely the perceptual stage as a communication channel (system capacity rather than perceptual capacity). Thus, this task does satisfy the definition of limited capacity as originally proposed by Broadbent (1958).

Conclusion

There are several novel aspects to this work: (a) the isolation of attentional phenomena with the cueing paradigm; (b) the control of discriminability using threshold measures; (c) the comparison of set-size effects for both accuracy and time; and (d) the test of the common bottleneck hypothesis for accuracy and time. The focus, nevertheless, must remain on the contrast between unlimited-capacity perception and limited-capacity perception. The analysis of the search accuracy experiments has provided one critical test distinguishing these hypotheses. This analysis will soon be generalized to search time. Together, these two analyses revise the foundation for theories of visual search.

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