Imperfect, Unlimited-Capacity, Parallel Search Yields Large Set-Size Effects

John Palmer and Jennifer McLean

University of Washington

Abstract

Many analyses of visual search assume error-free component processes. These analyses range from Sternberg's earliest serial models to Townsend's sophisticated theorems of serial-parallel equivalence. Consider a simple "yes-no" visual search task with a set-size manipulation. For the correct positive responses, an error-free, unlimited-capacity, parallel search model predicts no effect of set size on response time. In contrast, the prediction is quite different if the component processes are imperfect (even 1%-5% errors). Such imperfect processing is commonly assumed in stochastic models (such as a random walk model) but rarely have been applied to search. We have examined a stochastic model that assumes unlimited-capacity, parallel component processes which are imperfect. For this model, there are significant set-size effects for both positive and negative responses. In particular, the less discriminable the stimulus, the larger the set-size effect. In conclusion, a more realistic assumption about the error in component processing forces one to reconsider how to distinguish among serial and parallel models.

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Send correspondence to:

John Palmer
University of Washington
Psychology, Box 351525
Seattle, WA 98195-1525
E-mail: jpalmer@u.washington.edu

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Our goal is to reexamine two of the common distinctions made among theories of visual search: unlimited vs. limited capacity and parallel vs. serial processing. We extend previous work by allowing component processes to be imperfect. By imperfect, we mean that the processes specific to each stimulus introduce error. Thus, error will increase with increases in set size.

Slide 1

In the past, many have assumed that the processing specific to each stimulus is perfect and that error only arises from other processes such as error in the motor response. Such perfect processing has been assumed by most if not all of the previous analyses of parallel and serial processing (e.g. Townsend, 1974). In visual search, such an assumption is implausible because errors typically depend on set size.

Slide 2

Here is an outline of this talk. First, we will review a search experiment that measured response time as a function of set size and discriminability. As described below, it is this interaction that is the key to distinguishing among the models. Second, we will describe a stochastic model that has imperfect component processing. Third, we will compare models that have alternative assumptions about capacity and parallelism.

Slide 3

A Search Experiment

Here are on the methods used for our prototype experiment. (Palmer, in press). It was a yes/no visual search task in which subjects searched for a target disk that had a higher contrast than the distractor disks. The displays were present until subjects responded. The one unusual feature of the experiment was that subjects were instructed to maintain 10% errors. This was made possible by blocking all of the conditions, providing error feedback, and requiring a few sessions of training. We manipulated the set size as shown by the examples of Set Size 2 and 8 in Slide 3; we also manipulated the discriminability of the targets versus the distractors by varying the contrast difference between them (measured by the percent contrast increment of the target relative to the distractor).

Slide 4

The next slide (Slide 4) shows a typical result for a low level of discriminability. In this case, the targets and distractors differed by a small amount: an 8% contrast increment (distractor contrast = 20%, target contrast = 28%). Mean search time for four subjects is plotted as a function of the set size. The search time increases for both the target absent and target present conditions with the set-size effect for the target absent condition approximately twice as large as for target present. Also shown at the bottom of the slide are the errors in each set-size condition. As one can see, the subjects were successful in maintaining 10% errors.

Slide 5

In this slide, search time is shown as a function of set size as before, but now for each level of discriminability. For simplicity, only target absent conditions are shown on this and following slides. When the targets and distractors are harder to discriminate, the set-size effects are large as shown by the 5% contrast increment condition at the top of the graph; when they are easy to discriminate, the set-size effects drop to zero as shown by the 40% and 80% conditions at the bottom of the graph. Intermediate discriminability yields intermediate set-size effects. This is typical of the interaction between discriminability and set size (Duncan & Humphreys, 1989; Nagy & Sanchez, 1990; Pashler, 1987).

Slide 6

The same data can be plotted another way. In Slide 6, search time is plotted as a function of the contrast increment (cf. Mansfield, 1973). Generalized power functions are fit to the data for each set size with a parameter for the <u>asymptotic response time</u> which is the fastest possible response with highly discriminable stimuli (about 400 ms in the slide).

Slide 7

This analysis is repeated on the next slide that shows the results of another experiment that examined more values of the contrast increment manipulation. The generalized power function fits well for the search task as it has in the past for simple and choice response time tasks. (e.g. Mansfield, 1973; Schweickert, Dahn & McGuigan, 1988) Now to further quantify the set-size effects, we used methods from psychophysics to determine a threshold for each set size. Specifically, we determined the contrast increment that produces a criterion response time (Nagy & Sanchez, 1990). To do this, we picked a criterion of +100 ms above the asymptotic response time as estimated from the generalized power function. An 18% contrast increment results in the +100 ms criterion for Set Size 2 and a 30% contrast increment results in the criterion level for Set Size 8.

Slide 8

Next, these thresholds are plotted as a function of set size to provide a final measure of the magnitude of the set-size effect (for a similar analysis of search accuracy, see Palmer, Ames & Lindsey, 1993; Palmer, 1994; Palmer, 1995). Shown in Slide 8 is the contrast increment threshold as a function of set size for two criterion levels of response time performance. At the top are the thresholds for the +100 ms criterion. The data can be fit by a power function with a 0.3 slope on log-log coordinates. We refer to this summary statistic as the <u>log-log slope</u>. One complication is that if one chooses other criteria, such as +400 ms, then the log-log slope is different as shown at the bottom of the slide. In general, the log-log slopes increase for longer criterion times (Palmer, in press).

Slide 9

All of these results are summarized in the following slide (Slide 9) that repeats three of the graphs that we have just shown. The top panel shows search time as a function of set size for different levels of discriminability. For this plot, the magnitude of the set-size effects vary widely depending on discriminability. The middle panel shows search time as a function of discriminability for different set sizes. These functions are fit by a generalized power function that has an exponent between -1 and -2 depending on set size. The bottom panel shows the contrast increment threshold as a function of set size. For this plot, the log-log slopes range from 0.3 to 0.5 as the criterion ranges from 100 to 400 ms. We will leave up this data summary for the rest of the talk.

Slide 10

The Unlimited-Capacity, Parallel Model

The second part of the talk introduces the stochastic model. What we want is an unlimited-capacity, parallel model with imperfect processing in each component. There are a number of options for the stochastic process that will be the kernel of this model. We could use discrete or continuous random walks (Link, 1975; Ratcliff, 1978). We could use various counting or timing models (Green & Luce, 1974; Rudd, in press). Here, we make use of Roger Ratcliff's diffusion model which is described in his 1978 Psychological Review article. We chose this model for two reasons. First, he has already worked out the application of the model to a search task. Second, the mathematics for this model are more complete than many of the alternatives in that expressions for the predicted response time distributions are analytic (but not closed form) and practical to compute. Nonetheless, we are not wedded to the diffusion model and intend to investigate alternatives. We invite all of you to tell us your favorite choice.

Slide 11

The General Model

To begin, consider the diffusion process as a model for a yes-no response time task with a single stimulus. The diffusion process is a continuous random walk with continuous time and a continuous value of the relative evidence toward one of outcomes. It is applied to the yes-no situation by having the random walk correspond to the accumulation of evidence supporting one or the other of the two responses. One boundary is associated with each response. A sample path of the random walk is shown in the top panel of Slide 11 which plots the relative evidence as a function of time. At time 0, the stimulus is presented and evidence for a "yes" or a "no" response begins to accumulate in infinitesimal steps up and down. The random walk of the accumulated information for a single trial is illustrated by the jagged contour. If enough evidence supporting a "yes" response accumulates, the random walk will reach the top boundary. This boundary represents the criterion amount of evidence to trigger a "yes" response. Alternatively, if enough evidence accumulates that supports a "no" response, then the random walk will reach the bottom boundary and trigger a "no" response.

The parameters for the diffusion process are listed at the bottom of the slide. The two bias parameters that specify the boundaries are traditionally represented by the position of the yes response boundary, $\underline{a}$, and the starting position, $\underline{z}$. These parameters control both the bias for "yes" versus "no" responses and the bias for speed versus accuracy in the response. With no loss of generality, the no-response boundary is fixed at zero (Feller, 1964). There are two drift parameters, one when a target is present, $\underline{u}$, (which is illustrated in the slide) and another when a distractor is present, v. Each of these represents the mean drift rate of the random walk for a given stimulus condition. Finally, there is a parameter for the variance of the drift, s^2. For our application, this parameter can be set to one without any loss of generality. Ratcliff (1978) went on to generalize this basic diffusion process by considering a mixture of diffusion processes with drift parameters drawn from a normal distribution. In this talk, we will restrict attention to the basic diffusion process rather than the more general treatment of Ratcliff.

Slide 12

Two predictions from the model are shown in Slide 12. The top equation gives the probability of a correct rejection in a form closely related to the cumulative distribution function of the logistic (Link, 1992). The bottom panel gives the cumulative distribution function in terms of an infinite sum. While lengthy, the essence of the equation is a weighted sum of simple exponential functions. Ratcliff (1978) derives similar functions for the probability of a hit and for the cumulative distribution functions for hits, misses, and false alarms.

Slide 13

This diffusion process has a very simple relation to the standard case of signal detection theory. To illustrate that, Slide 13 shows the relative evidence as the function of time with the two boundaries removed. The slide shows the distribution of evidence values at a time t for target present and target absent conditions. The result is two normal distributions that are separated by an amount that can be described by the d' statistic of signal detection theory. The d' statistic is the difference in the mean position of the two distributions divided by their standard deviation. This value can be derived from the parameters of the diffusion model by the equation shown at the bottom of the slide. It is the difference in the two drift parameters u-v over the standard deviation of the drift s times a function of time t. Thus, u-v is proportional to d' and can be considered the sensitivity parameter of this model.

Slide 14

So far the diffusion model was applied to a yes-no response time task for a single stimulus. Now, it must be generalized for a search task with n stimuli. This is done by assuming n independent and parallel diffusion processes. Following Ratcliff (1978), these n diffusion processes are assumed to have identical parameters. Each diffusion process represents a decision about an individual stimulus that is being made in parallel. In this model, a "no" response is indicated when all n processes reach the "no" boundary. The time this takes will be the maximum duration of all n processes reaching the "no" boundary. A "yes" response is indicated at the first time a process reaches the "yes" boundary. This time will be the minimum duration of the processes that reach the "yes" boundary.

Slide 15

The Restricted Model

The model presented so far requires 5 parameters for each condition (a, z, u, v and the asymptotic response time). It does not take into account the additional structure imposed by the search experiment described above that had 3 set sizes and 4 levels of discriminability. This structure can be used to sharply reduce the number of parameters and hence simplify the model (see Slide 15).

First, we assume that the sensitivity parameter u-v is independent of set size which is the defining assumption of an unlimited-capacity model.

Second, we assume that the sensitivity parameter, u-v, is proportional to the contrast increment x: u-v = k x. The constant of proportionality, k, sets the sensitivity of the model by relating the contrast increment to the sensitivity parameter u-v. This restriction is motivated by accuracy experiments in which d' is shown to be proportional to the contrast increment (e.g. pedestal experiments in Leshowitz, Taub & Raab, 1968).

Third, we adjust the two bias parameters a and z to maintain the accuracy that was specified in our experiments. Our subjects were instructed to maintain 10% errors: 10% false alarms on Target Absent trials and 10% misses on Target Present trials. Thus, we adjusted the two bias parameters to do the same thing in the model.

Fourth, we assume symmetric drift parameters, u=-v. This amounts to assuming equivalent rates of evidence accumulation from targets and distractors.

Fifth, we assume a common asymptotic response time parameter for all conditions.

To summarize, these restrictions reduce the number of parameters required to fit the 12-condition sample experiment from 60 (12 * 5) to 2, the parameter k and the asymptotic response time.

Slide 16

The Predictions

Next, we present detailed predictions for the unlimited-capacity, parallel diffusion process model. To foreshadow the remainder of this talk, we are not going to investigate alternatives to the detailed assumptions of the restricted model. We think our restrictions are reasonable. Instead, we will focus on using the model to contrast the predictions of the unlimited-capacity, parallel diffusion process model to those of serial models and limited-capacity models.

To make the comparisons, we fixed the values of the two parameters: an asymptotic response time of 400 ms and a sensitivity of u-v = 4. (This is equivalent, for example, to specifying the use of a contrast increment of 1% and k = 4.) Slide 16 shows the predicted search time as a function of set size for target absent and target present: Response time increases substantially with set size for both conditions. This prediction is the most important point of this talk. Once error is introduced, the unlimited-capacity, parallel model predicts substantial set-size effects. This prediction is in contrast to the prediction of unlimited-capacity, parallel search models with perfect component processing. Those models predict some set-size effects for target absent conditions but no set-size effects for target present conditions.

Consider the following explanation of the source of these effects within the diffusion model. Increasing set size while maintaining a constant response time results in more errors. In particular, the additional distractors each create an additional chance to make a false alarm. To maintain constant errors as instructed, the subjects shift their biases to slow down for larger set sizes. In particular, they raise their criterion for making a "yes" response to prevent the false alarms. This increases the response time for hits. In addition, the additional distractors will slow down the "no" responses because the maximum duration of $\underline{n}$ processes will increase with $\underline{n}$. Thus, even though the individual processes are independent of set size, the response time for $\underline{n}$ processes increases.

Slide 17

Here are other predictions of the model. Slide 17 shows the predictions for discriminability manipulations by adjusting the sensitivity parameter (or, equivalently, manipulating the contrast increment). For conditions of low discriminability (small $\underline{u-v}$ values), one obtains arbitrarily large set-size effects.

Slide 18

Slide 18 shows performance as a function of discriminability by manipulating the contrast increment between the target and the distractors (or, equivalently, the sensitivity parameter). The model predicts a large effect of discriminability that can be described by the generalized power function with an exponent of -2.

Slide 19

The interaction of the set size and discriminability effects is shown in Slide 19. It shows the predicted contrast increment threshold as a function of set size. The model predicts a function that can be approximated over this range of set sizes by a power function with a log-log slope of 0.26, independent of criterion. This slope is close to that observed for a +100 ms criterion above the asymptotic response time, but not for larger criteria such as +400 ms (compare to Slide 8). Thus, the unlimited-capacity, parallel model predicts the right magnitude for the responses within 100 ms of the asymptotic response time but does not predict the longer responses.

Slide 20

Summary

The unlimited-capacity, parallel model makes several predictions that match the observed results (compare Slides 9 and 20). It predicts a range of set-size effects for search time as a function of discriminability; it predicts generalized power functions for search time as a function of discriminability; and, it predicts reasonable log-log slopes for the contrast increment threshold as a function of set size.

Slide 21

Comparisons between Alternative Models

The Limited-Capacity, Parallel Model

In this, the third part of the talk, we consider alternative models. First consider a parallel diffusion model as before, but now with limited instead of unlimited capacity. It will have a drift rate that depends on set size. In particular, we assume a version of the sample size model (Lindsay, Taylor & Forbes, 1968; Shaw, 1980). The idea is that one has a fixed number of samples that can be distributed among relevant stimuli. If one has more stimuli, then one must dedicate fewer samples to each stimulus. As a result, the drift rate will be inversely related to set size.

Slide 22 and 23

The predictions of this model are shown in the next two slides. Slide 22 shows search time as a function of set size. One can obtain arbitrarily large or small set-size effects depending on the level of discriminability. The new feature is that the predicted functions are positively accelerated. This prediction is also shown in the top panel of Slide 23 along with two other predictions. The middle panel shows that search time as a function of discriminability is predicted to be a generalized power function. The bottom panel shows the predicted contrast increment thresholds as a function of set size. For these set-sizes, the curve can be approximated by a power function with a log-log slope of 1.26. This value is much higher than ever seen in the data (compare Slides 9 and 23) and poses a problem for this model.

Slide 24

The Serial Model

Next consider a serial model. We assume that there are a sequence of independent diffusion processes with identical parameters. We also assume that this sequence is self-terminated when one of the diffusion processes reaches the "yes" boundary (but not the "no" boundary).

Slide 25

The predictions are shown in Slide 25 in the same format as the predictions from the other models (Slide 20 and 23) and the data (Slide 9). The top panel shows predictions for search time as a function of set size. As with the other models, one obtains set-size effects with a variety of magnitudes and they look linear. However, this serial model actually predicts functions that are positively accelerated. The deviation is slight for the illustrated conditions. The middle panel shows search time as a function of the contrast increment. Again, the model predicts a generalized power function with an exponent of -2. The bottom panel shows the predicted thresholds as a function of set size. For these set-sizes, the curve can be approximated by a power function with a log-log slope of 0.54. This value is on the high side but it is similar to observed thresholds with a +400 ms criterion (see Slide 9).

Summary

In sum, the limited-capacity, parallel model predicted set-size effects that are too large when quantified by the log-log slope. In contrast, the serial model does about as well as the unlimited-capacity parallel model. Both of these models fit many aspects of the data. Both models also have problems. A key to their problems is that the generalized power function for response time as a function of discriminability is predicted to have the same shape regardless of set size. This is in conflict with the data that show steeper functions for larger set sizes. If the model predicted a function that varied with set size, then it would also predict an increase in the log-log slopes for different threshold criteria. (A model with this general characteristic has been described by Maloney and Wandell, 1984).

Slide 26

Conclusion

This work introduces an analysis of search models that allows component processes to be imperfect. To date, the strongest conclusion is that an unlimited-capacity, parallel model makes plausible predictions once it has component processes that are imperfect. We next aim to develop more general stochastic models to pursue the distinctions among alternative search models.

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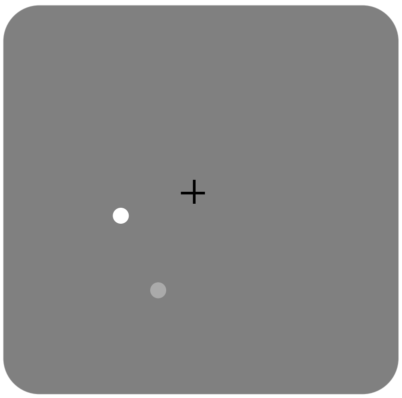
Goals

- Address two distinctions among theories of visual search:
  - Unlimited- vs. limited-capacity processing, and
  - Parallel vs. serial processing.
- Extend previous work by allowing component processing to be imperfect.

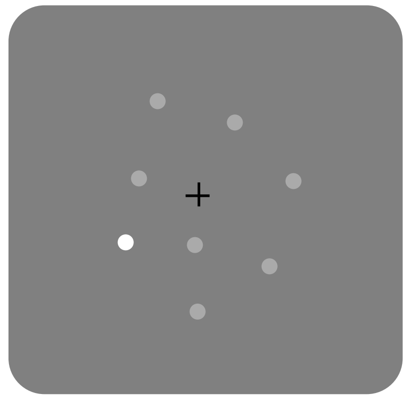
Outline

- Review a search experiment with RT as a function of set size and discriminability.
- Describe a stochastic model with imperfect component processing.
- Contrast models with alternative assumptions about capacity and parallelism.

Methods



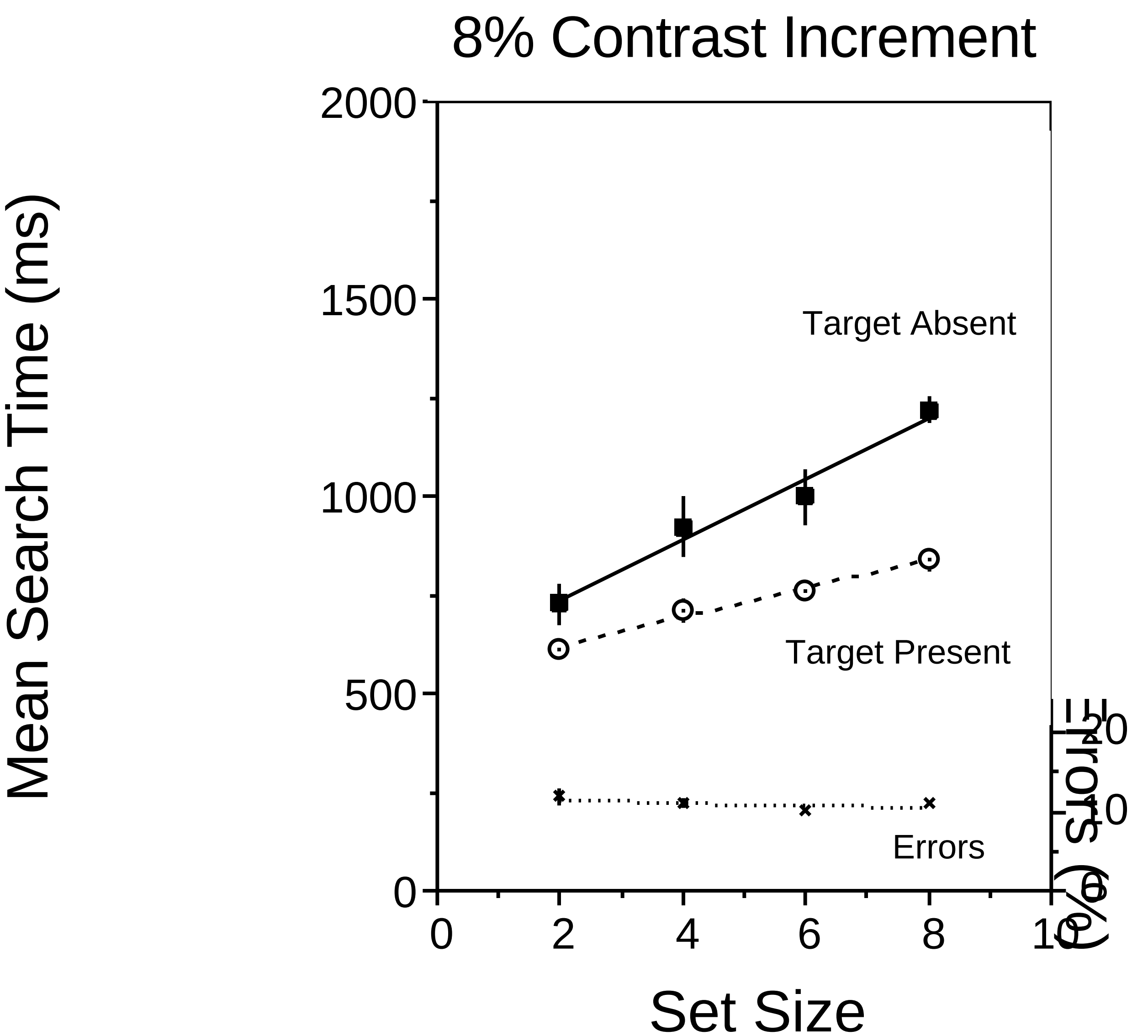
Set Size 2



Set Size 8

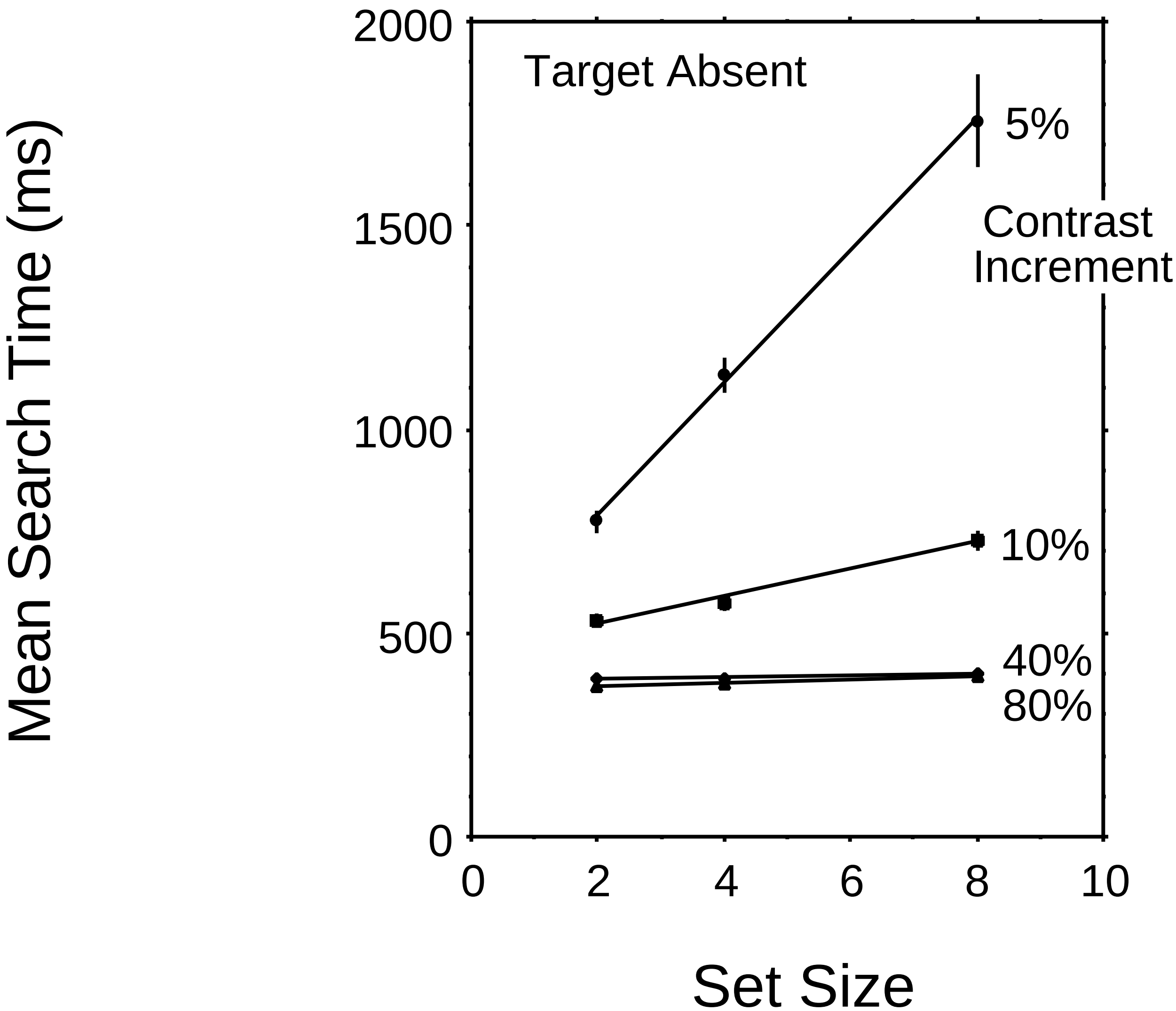
- Yes-No search task for luminance increments
- Display until response
- Maintained errors at 10%
- Varied set size and discriminability

RT vs. Set Size



s32/36 4o 4/8s

RT vs. Set Size



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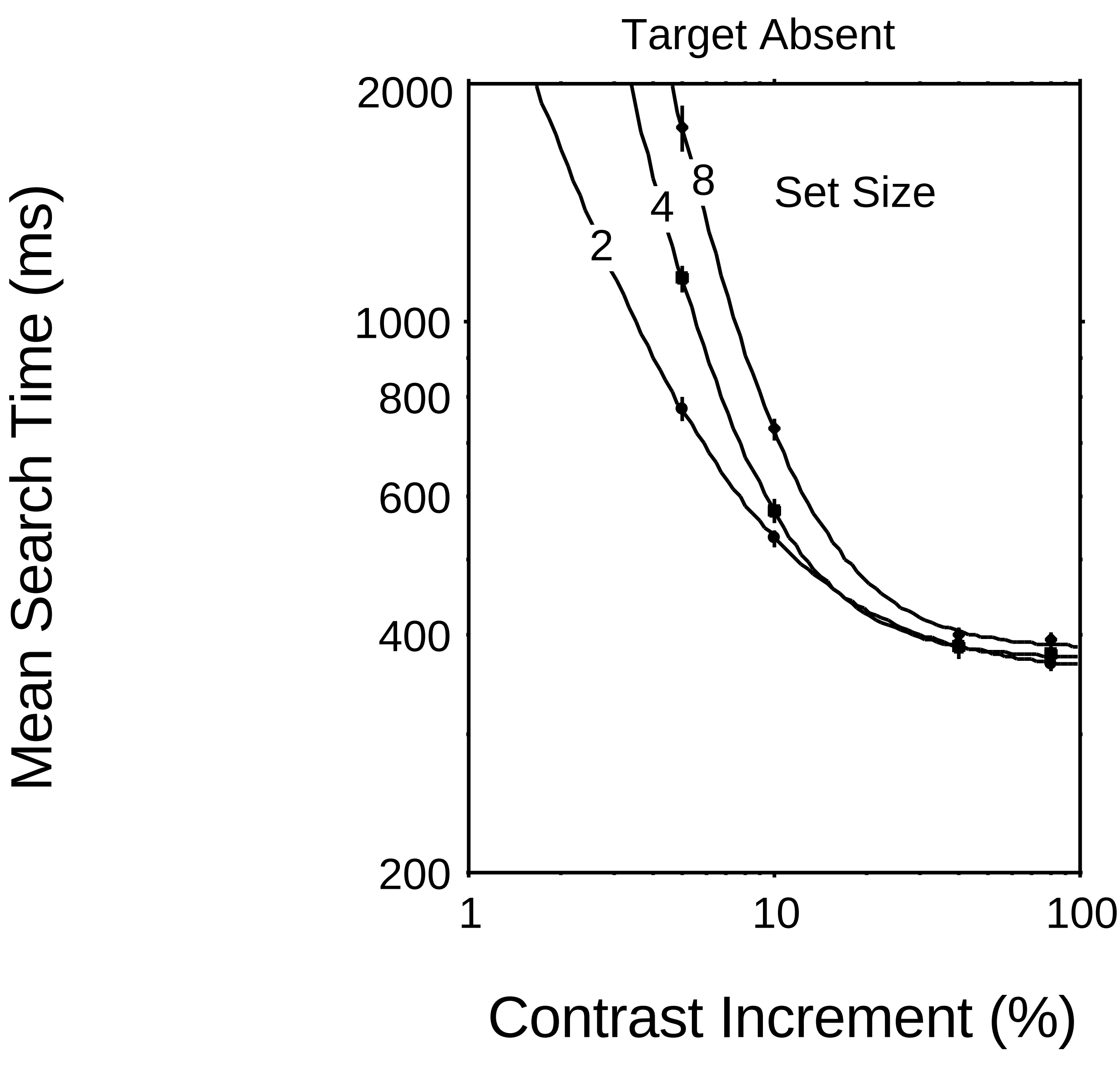
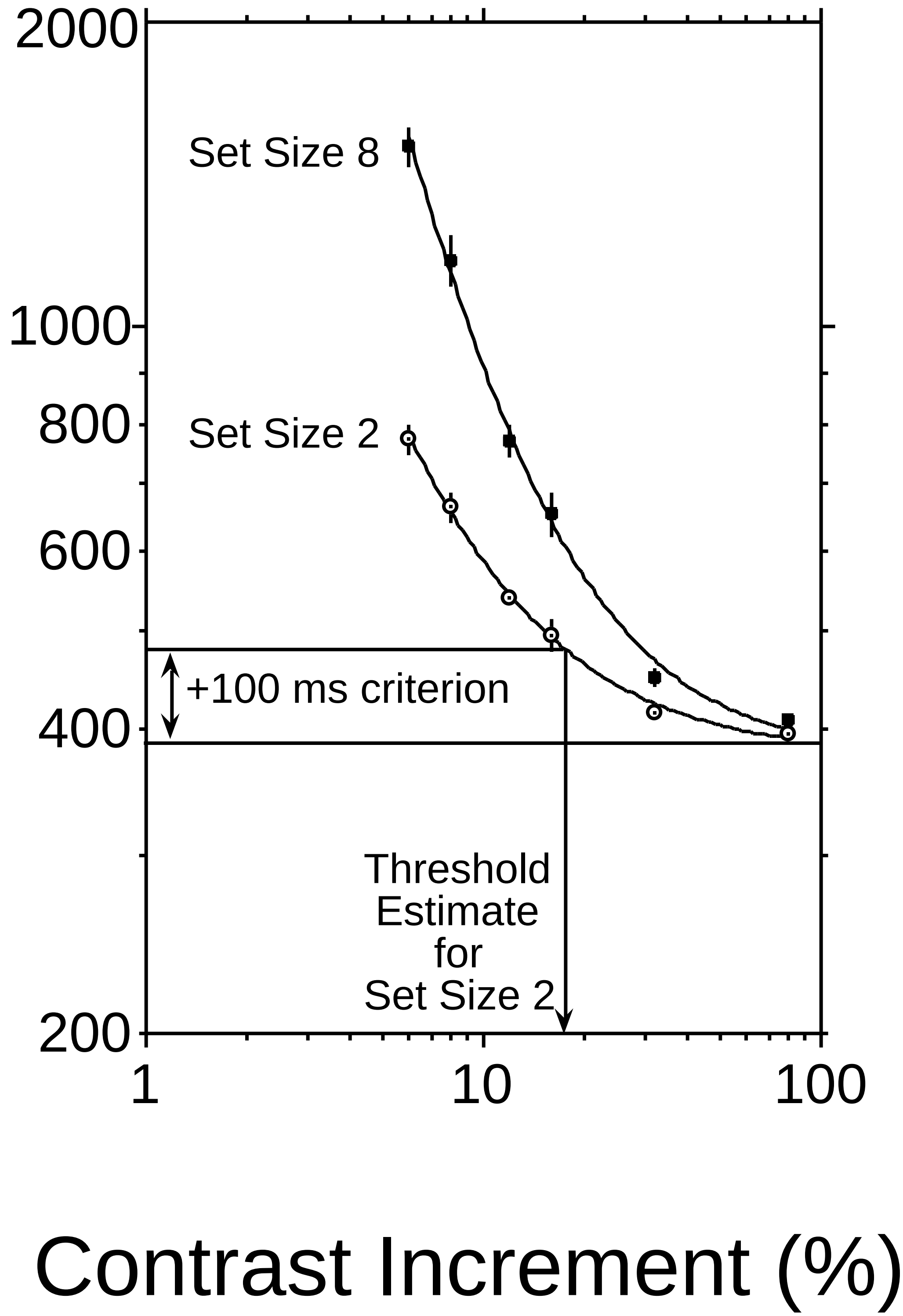
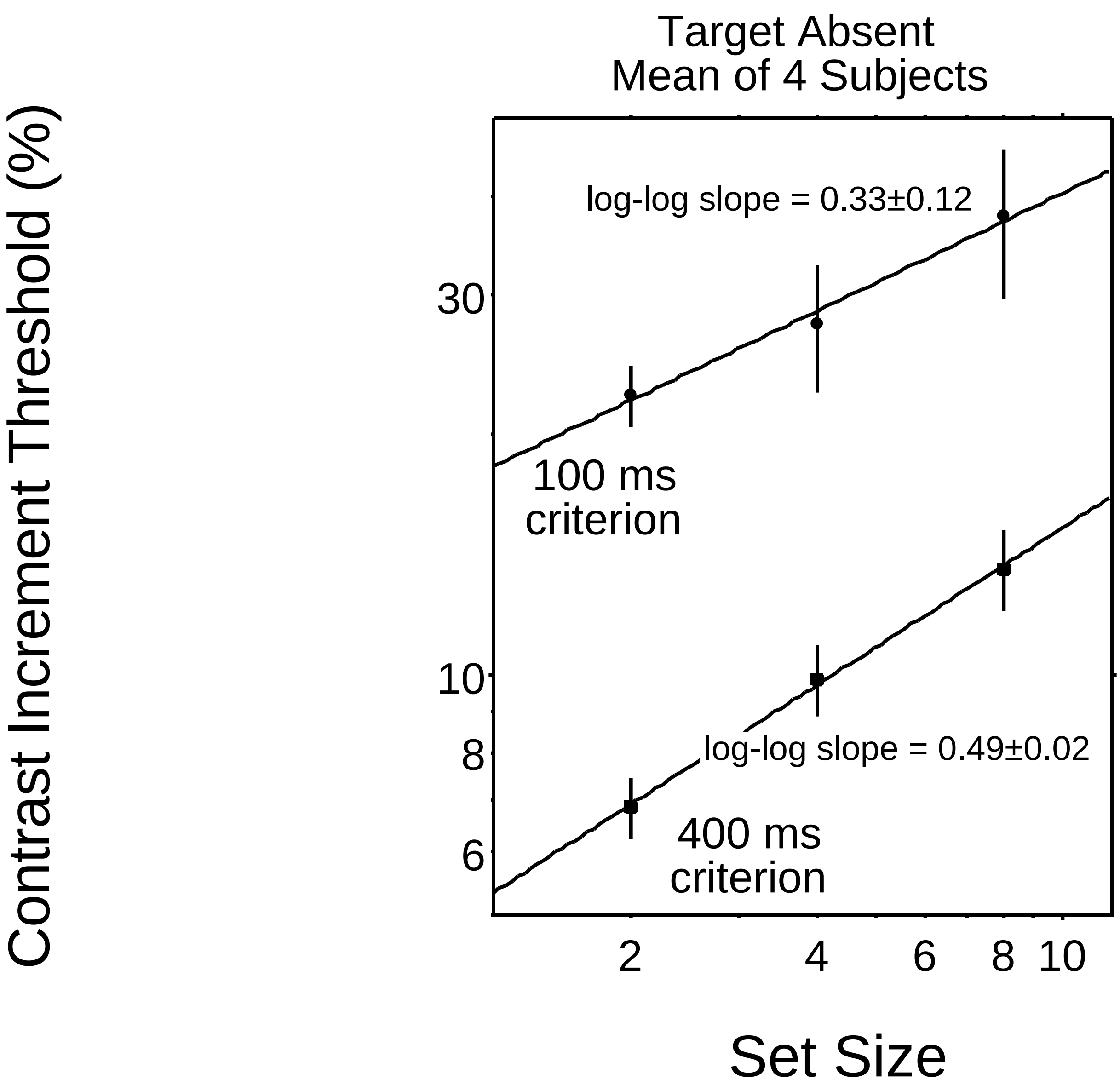
RT vs. Stimulus Difference

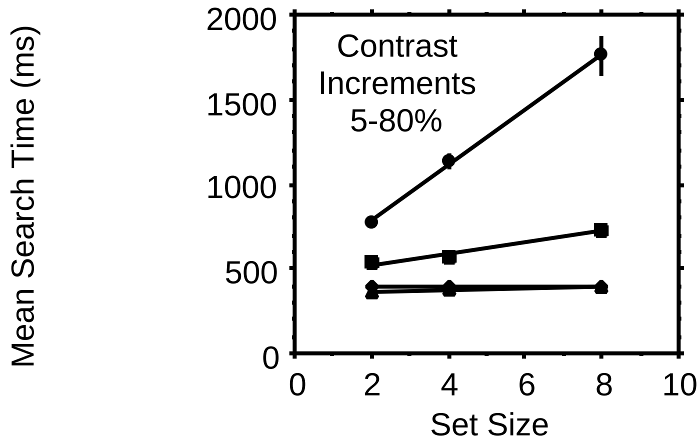



2000
1000
800
600
400
200
1
10
100
Set Size 8
Set Size 2
+100 ms criterion
Threshold
Estimate
for
Set Size 2
Contrast Increment (%)

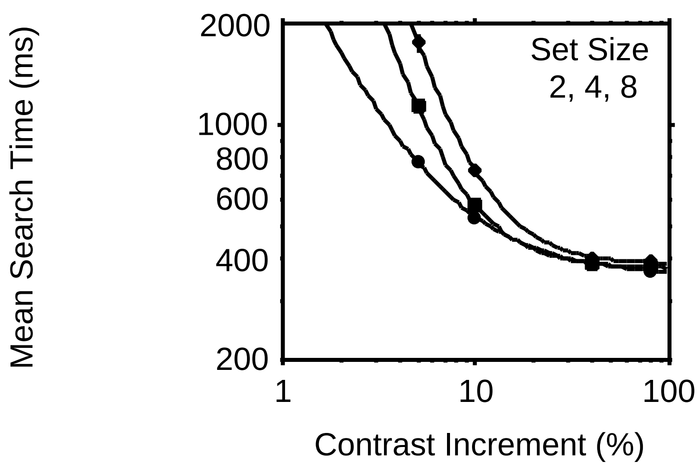
Threshold vs. Set Size



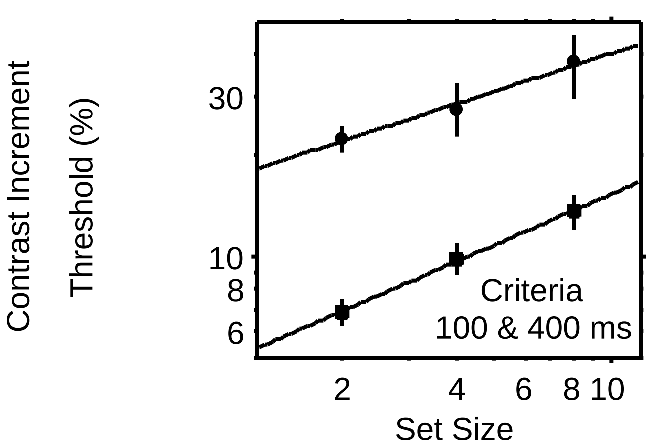
Data



- Slopes vary from
  0 to 200+.



- Exponents vary from
  -1 to -2.



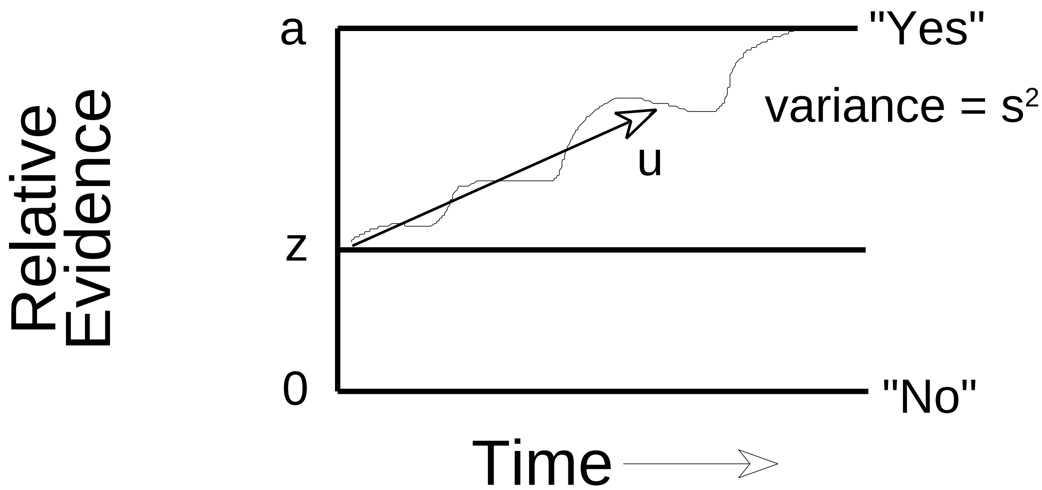
- Log-log slopes vary from
  0.2 to 0.6.

Introduction to the Models

- Need an unlimited-capacity, parallel model with imperfect processing in each component.
- Options: discrete or continuous random walks, counting or timing models, etc.
- Initial choice: Roger Ratcliff's Diffusion Model.

The Diffusion Process

- A continuous random walk



- Parameters
  - a Boundary for "Yes" response
  - z Starting position
  - u Drift for target stimulus
  - v Drift for distractor stimulus
  - s^2 Variance of drift

Sample Equations

- Probability Correct Rejection:

$$P = [\mathrm{Exp}(-aA)-\mathrm{Exp}(-zA)] \;/\; [\mathrm{Exp}(-aA)-1],$$

where $A = 2v / s^2$.

- CDF of a Correct Rejection:

$$F(t) = 1 - \sum_{k=1}^{\infty} \frac{B\,C(k)}{D(k)} \,\mathrm{Exp}(-D(k)\,t)$$

where $B = (\pi s^2) / (a^2 P)\ \mathrm{Exp}(-zv/s^2)$,

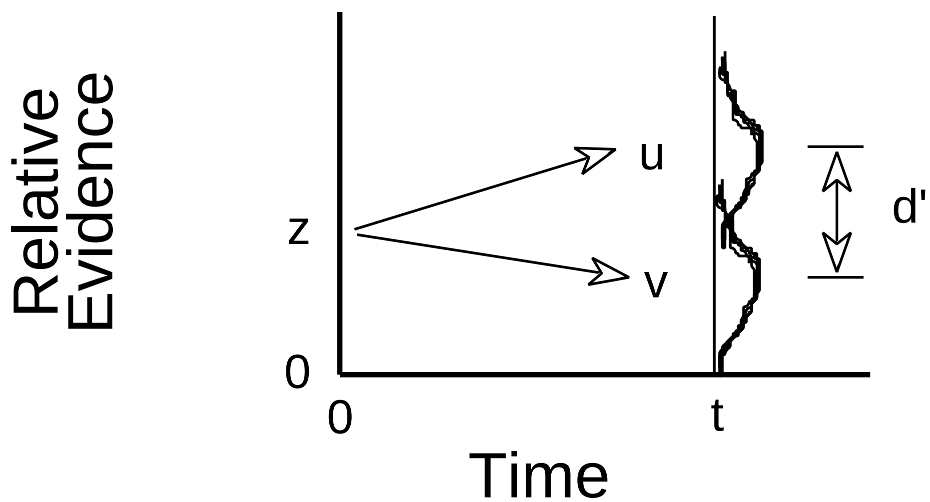
$C(k) = k\,\mathrm{Sin}(k\pi z/a)$, and

$D(k) = [\,(v/s)^2 + k^2 (\pi s/a)^2\,] / 2.$

(Ratcliff, 1978)

Relation to Signal Detection Theory

- Evidence distributions at time t



- Sensitivity Parameter

$$d' = \frac{u - v}{s\sqrt{1/t}}$$

(Ratcliff, 1978)

Generalization to Search

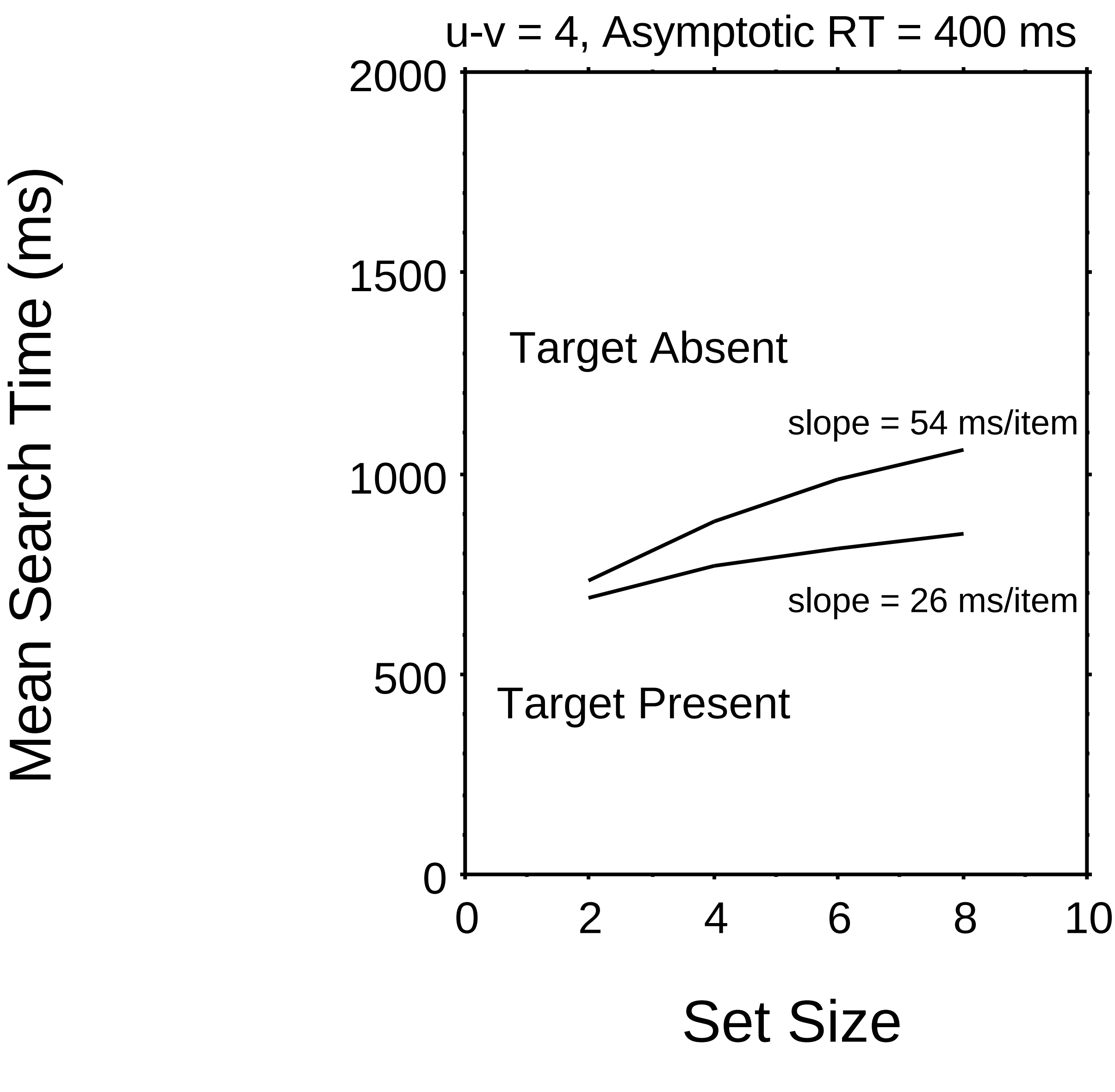
- Assume n independent, parallel diffusion processes with identical parameters
(n = set size).
- Respond "No" when all n reach the "No" boundary.
- Respond "Yes" when the first reaches the "Yes" boundary.
- Add a constant for the asymptotic response time.

(Ratcliff, 1978)

Our Restrictions

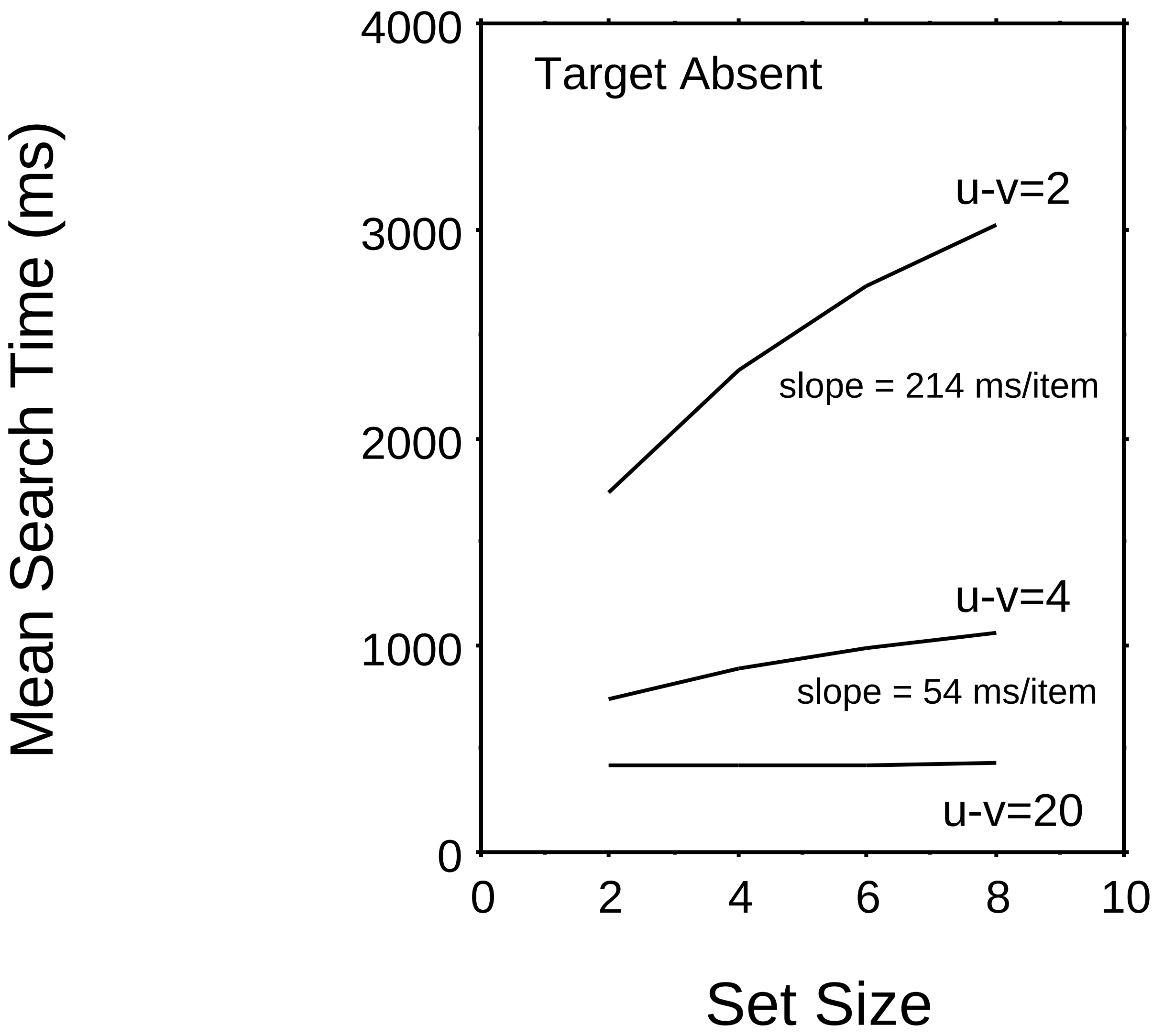
- Restrict parameters:
  - Assume the sensitivity parameter, u-v, is independent of set size.
  - Assume that sensitivity is proportional to the contrast increment x: u-v = k x.
  - Adjust bias parameters (a, z) to maintain a fixed accuracy criterion.
  - Assume symmetric drift parameters, u = -v.
  - Assume a common asymptotic time.
- Two free parameters: sensitivity and the asymptotic time.

Predicted RT vs. Set Size
Target Absent and Present



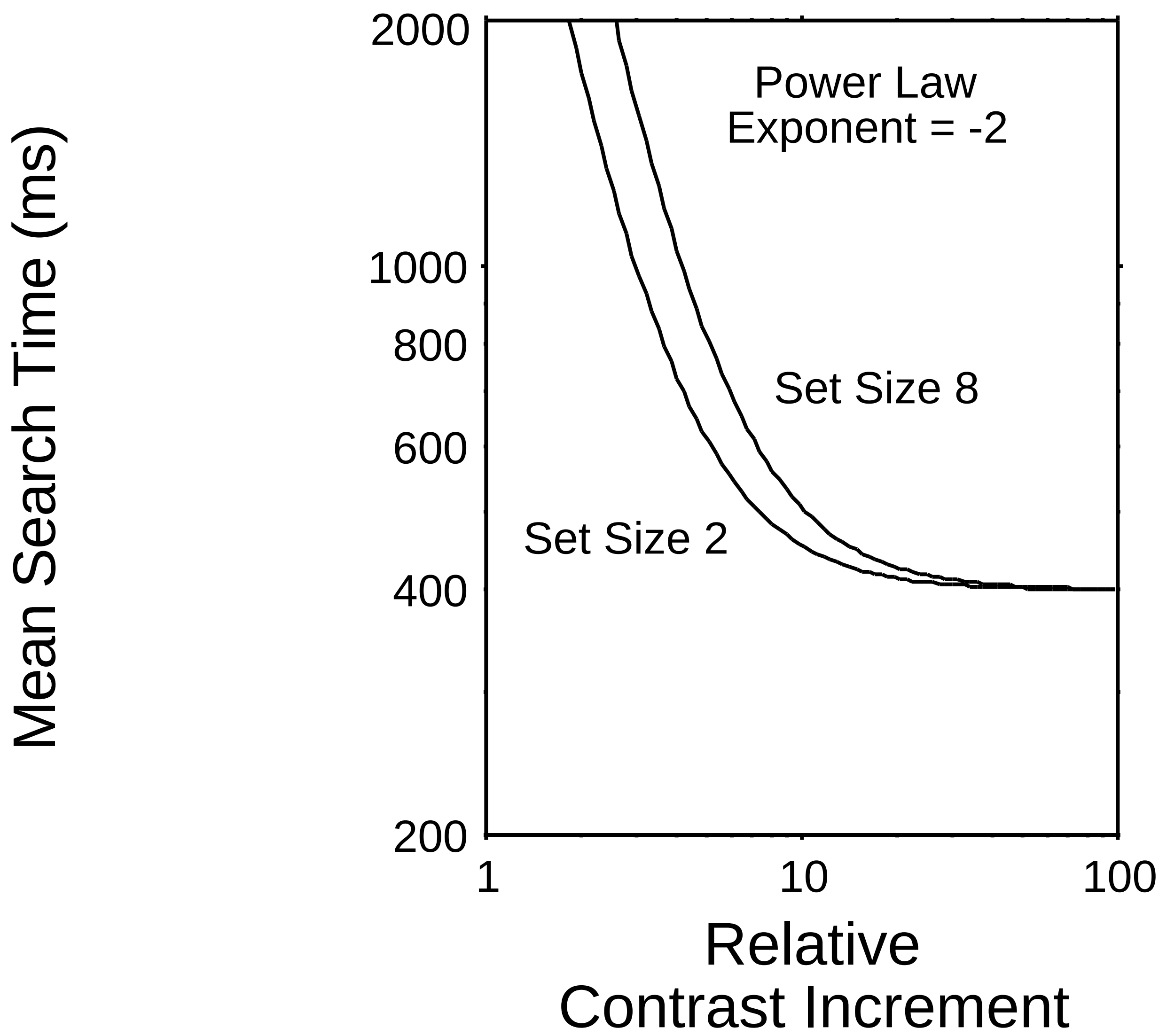
Parallel Diffussion Model

Predicted RT vs. Set Size
Discriminability Effects



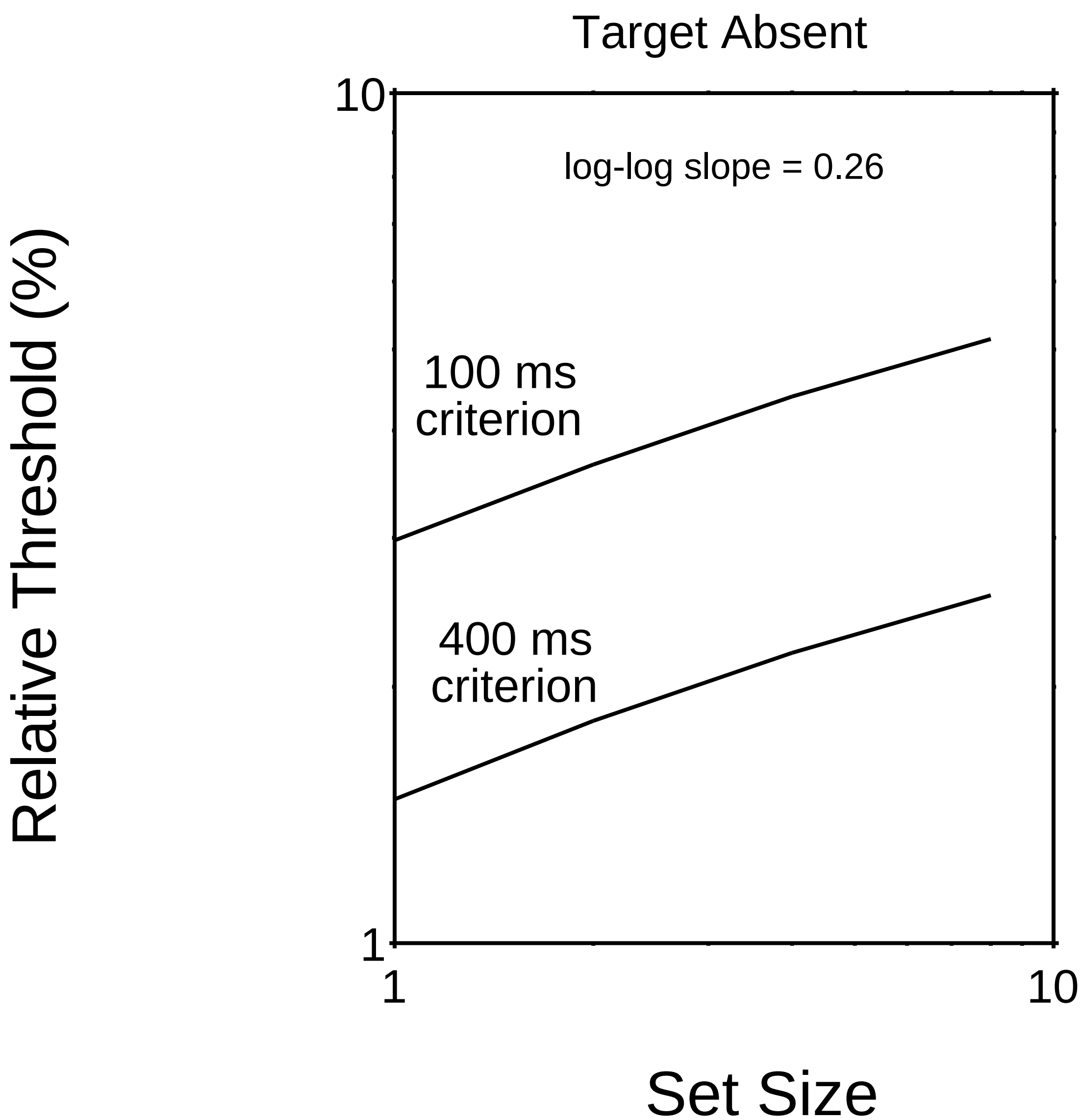
Parallel Diffussion Model

Predicted
RT vs. Discriminability



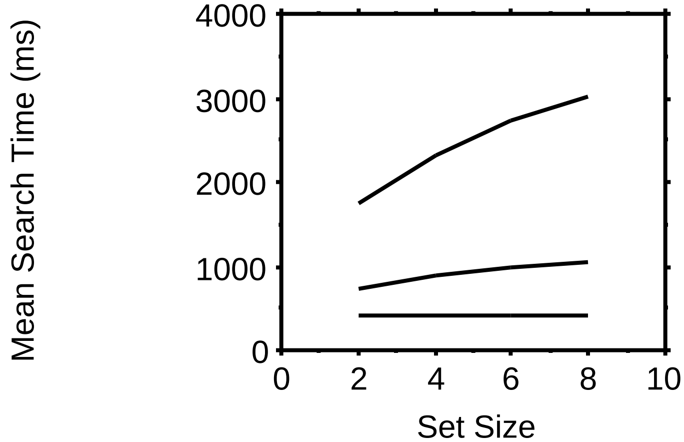
Parallel Diffusion Model

Predicted
Threshold vs. Set Size

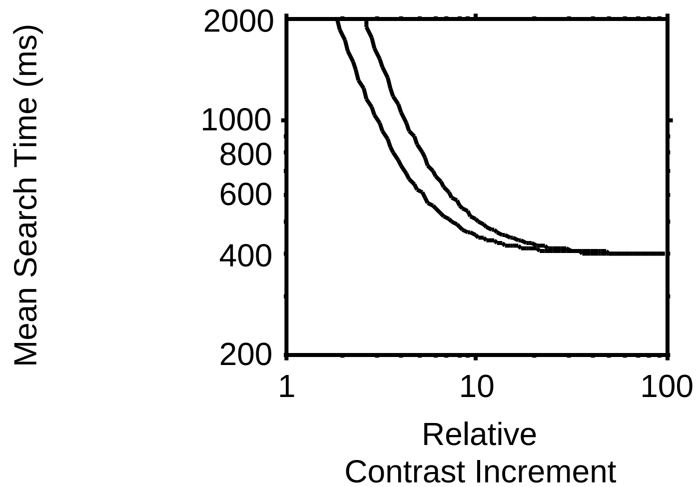


Parallel Diffusion Model

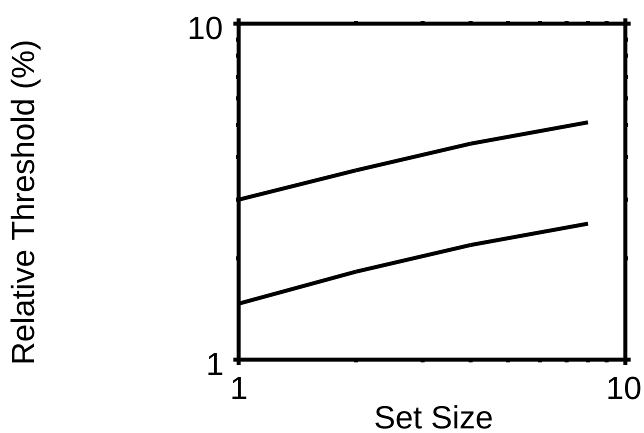
Unlimited-Capacity Parallel Model



- Slopes vary from 0 to 200+.



- Exponent = -2.

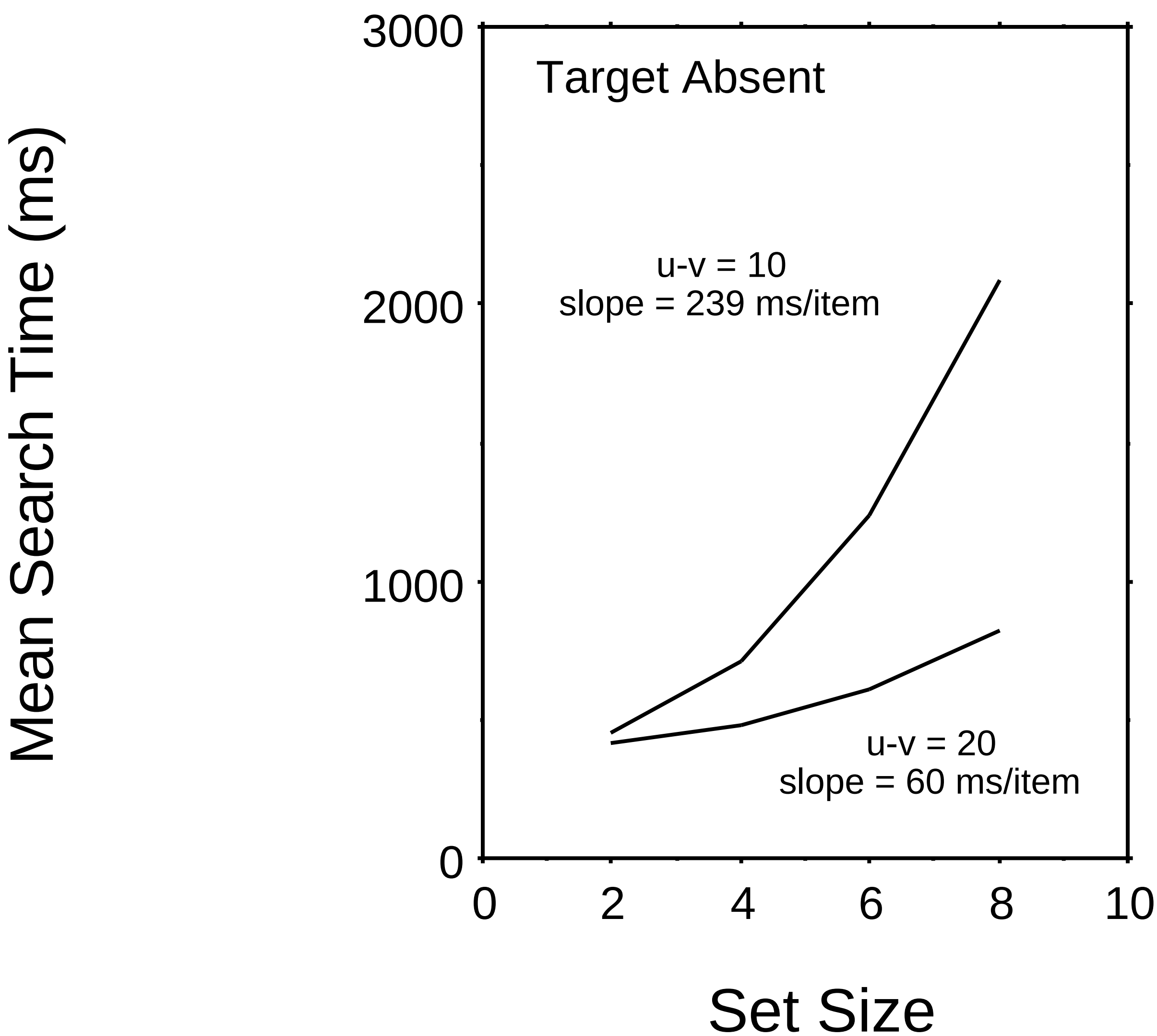


- Log-log slope ~ 0.26.

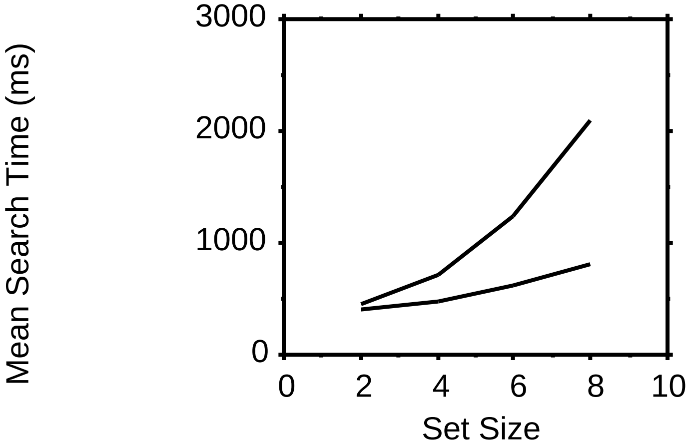
Limited-Capacity, Parallel Diffusion Model

- Drift rate depends on set size.
- Assume a sample-size model. In it, the drift rate is inversely related to set size.

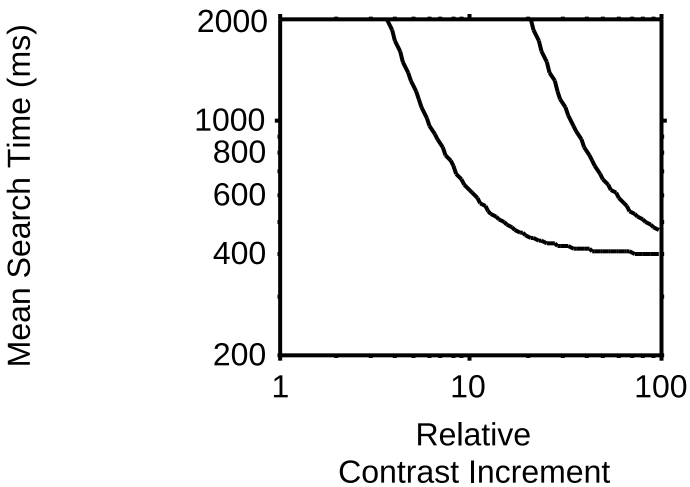
LC Predictions: RT vs. Set Size



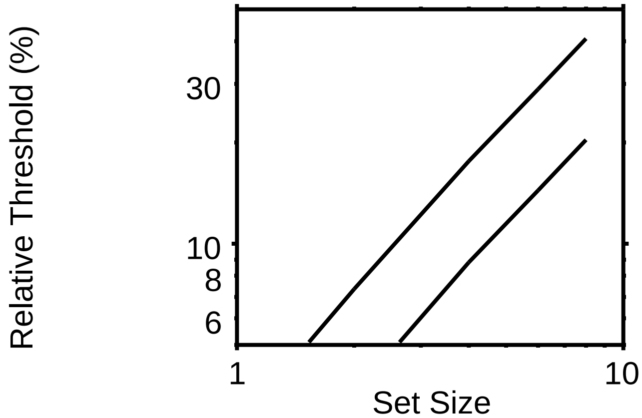
Limited-Capacity Parallel Model



- Slopes vary from
  0 to 200+.



- Exponent = -2.

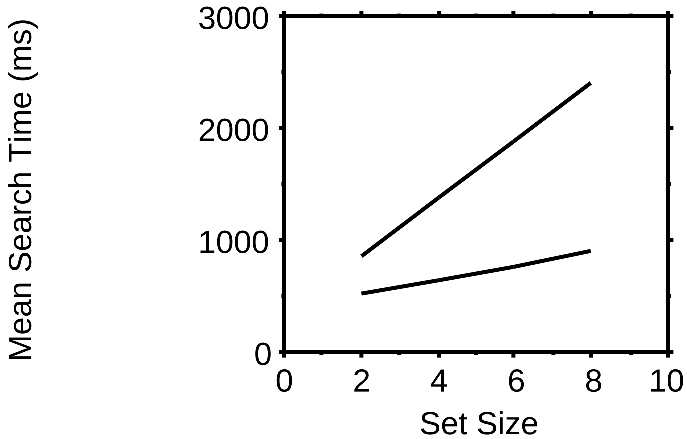


- Log-log slope ~ 1.26.

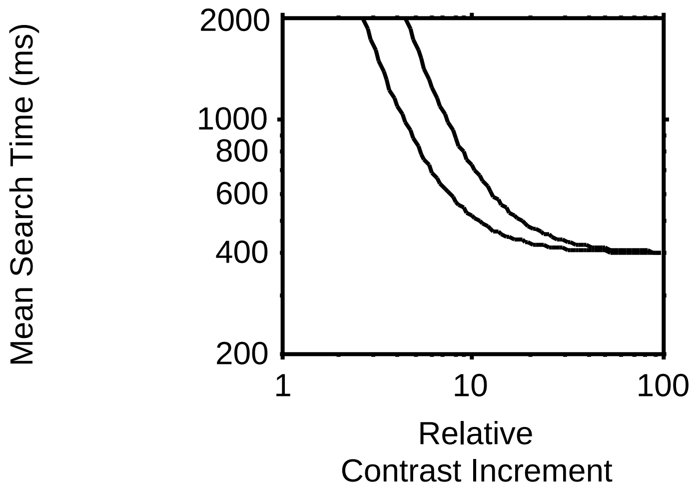
Serial Diffusion Model

- Assume a sequence of independent diffusion processes with identical parameters.
- Assume a self-terminating search.

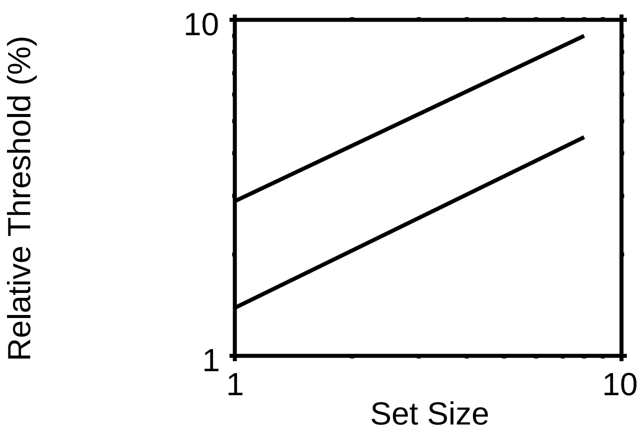
Serial Model



- Slopes vary from
  0 to 200+.



- Exponent = -2.



- Log-log slope ~ 0.54.

Discussion

- Contrasted models with unlimited vs. limited capacity and parallel vs. serial processing.
- Concluded that the unlimited-capacity, parallel model is plausible for visual search.
- Seek alternative and more general models to make these contrasts.