Research Article

WHAT CAN 1 MILLION TRIALS TELL US ABOUT VISUAL SEARCH?

Jeremy M. Wolfe

Center for Ophthalmic Research, Brigham and Women's Hospital, and Department of Ophthalmology, Harvard Medical School

Abstract—*In a typical visual search experiment, observers look through a set of items for a designated target that may or may not be present. Reaction time (RT) is measured as a function of the number of items in the display (set size), and inferences about the underlying search processes are based on the slopes of the resulting RT × Set Size functions. Most search experiments involve 5 to 15 subjects performing a few hundred trials each. In this retrospective study, I examine results from 2,500 experimental sessions of a few hundred trials each (approximately 1 million total trials). These data represent a wide variety of search tasks. The resulting picture of human search behavior requires changes in our theories of visual search.*

The visual search paradigm has been a pillar of research in visual attention for more than 20 years. In a typical visual search experiment, observers are presented with a display containing a number of items. On each trial, the observers must determine if a specific *target* item is or is not present among the *distractor* items. The number of items (*set size*) varies from trial to trial. Experimenters measure the reaction time (RT), the amount of time that is required to make a "target-present" or "target-absent" response. They also note the accuracy of that response. Changes in accuracy and RT as a function of set size constitute the preferred measures of search performance (for a review, see Wolfe, in press).

The search paradigm is valuable because performance on these tasks varies in a systematic way with the nature of the search stimuli. For some tasks, performance does not depend on set size. For example, in a search for a red spot among green spots, the number of green spots is irrelevant. Accuracy will be high and RT fast for all set sizes. The slope of the RT × Set Size function will be near zero. The independence of RT and set size is consistent with parallel processing of all items. For other tasks, RT is a roughly linear function of set size. For example, in a search for an *S* among mirror-reversed *S*s, RTs will increase at a rate of approximately 20 to 30 ms/item for target-present trials and 40 to 60 ms/item for target-absent trials. The linear increase in RT and the 2:1 ratio between target-absent and target-present slopes is characteristic of a serial, self-terminating search, though it is also consistent with various limited-capacity (Townsend, 1971, 1990) and unlimited-capacity (Palmer & McLean, 1995) parallel search processes.

In part because of results of this sort, searches have been divided into parallel searches, in which all items can be processed in a single step, and serial searches, in which attention is deployed from item to item until the target is found. Treisman and Gelade (1980) proposed that searches for basic features like color, motion, and orientation are parallel, whereas other searches, like those for *S*s among mirror-reversed *S*s, are serial. Further, they argued that *conjunction* searches fall into the serial category. These are searches in which the target is defined by two or more basic features. For example, the target might be a small blue item among big blue and small yellow items. Subsequent research has shown that many conjunction searches are more efficient than would be predicted by a strictly serial search (e.g., Cohen, 1993; Cohen & Ivry, 1991; Dehaene, 1989; Egeth, Virzi, & Garbart, 1984; McLeod, Driver, & Crisp, 1988; McLeod, Driver, Dienes, & Crisp, 1991; Nakayama & Silverman, 1986; Sagi, 1988; Theeuwes & Kooi, 1994; Treisman & Sato, 1990; von der Heydt & Dursteler, 1993; Wolfe, 1992; Zohary & Hochstein, 1989). A variety of models have attempted to explain this range of results by proposing a continuum of search tasks from highly efficient to inefficient (Duncan & Humphreys, 1989; Nakayama, 1990; Treisman, 1993; Wolfe, 1994; Wolfe, Cave, & Franzel, 1989; Wolfe & Gancarz, 1996). For example, I have argued that all searches require the deployment of attention to the target and that different tasks vary only in the degree to which they can use parallel processes to guide the deployment of attention.

Arguments about the mechanisms of visual search are generally based on search experiments involving 5 to 15 subjects. The purpose of this article is to present an analysis of data from 2,500 sessions drawn from 10 years of research in my laboratory. Each session involved a single subject doing a single search task. The data yield 2,500 target-present and 2,500 target-absent slopes—the product of approximately 1 million search trials. These data can be used to present a statistical picture of search performance that has been hitherto unavailable. The results are inconsistent with a number of the assumptions that appear regularly in the search literature. However, they can provide new benchmarks for the analysis of search experiments.

WHAT IS IN THE DATA SET?

The slopes come from experiments with the following general characteristics. The observer was told to look for a specific target item during a block of 300 to 500 trials. A target was present on 50% of the trials. The display was visible until the subject responded. The subject was asked to respond as quickly and as accurately as possible. Error rates (which are not presented) were almost always less than 10%, and the majority were less than 5%. Three or more set sizes were randomly intermixed during a block of trials. The range of set sizes varied widely across experiments. In a standard experiment, 10 subjects were tested, yielding 10 target-present and 10 target-absent slopes. Some studies had fewer subjects, others more, but 10 is the modal value. Subjects were generally young (ages 18–30). All had normal or corrected-to-normal acuity and could pass the Ishihara color test. Testing was binocular. An average subject would have had limited practice in visual search tasks (several hundred trials).

Selection of experiments for inclusion in this sample was driven, frankly, by convenience. If the slopes were readily accessible on archive disks, the experiment was included. This process is unlikely to have made this sample systematically different from the full set of standard search experiments conducted in this lab. Search tasks that fell outside the domain of "standard search tasks" were excluded. Nonstandard tasks include searches for multiple types of targets (e.g., search for the red vertical or the green horizontal item), searches for multiple instances of one type (e.g., Are there one or two red vertical items?), and searches for properties of more than one item (e.g., Is there a pair of lines that

Address correspondence to Jeremy M. Wolfe, Center for Ophthalmic Research, Brigham and Women's Hospital, 221 Longwood Ave., Boston, MA 02115; e-mail: wolfe@search.bwh.harvard.edu.

form an acute angle?). The set of tasks included in this analysis is necessarily skewed by the interests of my laboratory over the past decade. Thus, experiments on conjunction search and orientation search are overrepresented, and motion searches, to offer just one example, are underrepresented. Given this inevitable bias, some questions cannot be meaningfully addressed (e.g., What percentage of all search tasks will have slopes less than 10 ms/item?). The possibility of expanding this data set with results from other labs is discussed at the end of this article.

The 2,500 pairs of slopes can be divided into six categories:

- *Feature searches:* 490 pairs (19.6%). These are searches in which the target is defined by a unique single feature. Most of these are orientation or color searches.
- *Hard feature searches:* 80 pairs (3.2%). These are orientation searches in which the target is defined by a unique orientation but in which, for theoretical reasons, search is expected to be uncharacteristically difficult. Specifically, my colleagues and I have found that orientation feature searches are inefficient if the target cannot be specified as categorically different from the distractors. Efficient search requires that the target be the only item that is steep or shallow or tilted to the left or to the right. This issue is discussed in Wolfe, Friedman-Hill, Stewart, and O'Connell (1992), the source of most of these data.
- *Conjunction searches:* 1,218 pairs (48.7%). In all of these conjunction searches, the targets are defined by conjunctions of two different featural dimensions, such as color and orientation or curvature and size. There are various other searches that have been described in the literature as conjunction searches. For instance, it is possible to consider a purple target to be defined by a conjunction of red and blue. Such searches are not considered to be conjunction searches in this analysis.
- *Within-dimension conjunction searches:* 182 pairs (7.3%). In my lab, we have conducted many experiments in which targets are defined by a conjunction between two instances of the same type of feature. An example would be a Color × Color conjunction search in which subjects search for a target that is red and blue among distractors that are either red and yellow or blue and yellow. This sample includes Color × Color, Size × Size, and Orientation × Orientation conjunction searches.
- *Spatial-configuration searches:* 205 pairs (8.2%). These are searches in which the target is defined not by any simple feature properties, but rather by the spatial arrangement of line segments. Spatial relationships do not appear to be processed in parallel across multiple items (Logan, 1995). These tasks represent something of a gold standard for "serial" search (Braun & Sagi, 1990; Egeth & Dagenbach, 1991; Kwak, Dagenbach, & Egeth, 1991; Moore, Egeth, Berglan, & Luck, 1996) because models that hold that subjects are attending to one item at a time would predict serial, self-terminating search in these cases. The two tasks represented in this group are a search for a *T* among *L*s (with *T*s and *L*s rotated by 0°, 90°, 180°, or 270°) and a search for an *S* among mirror-reversed *S*s (or vice versa). In some versions, these stimuli are upright. In others, they are rotated by 90°.
- *Other searches:* 325 pairs (13%). The remaining 325 pairs of slopes are drawn from a variety of tasks that do not fit well into the categories just given. These include a number of tasks in which subjects search for a target defined by its unique shape. These are not feature searches because it does not appear that overall shape is a basic feature in search (Wolfe & Bennett, 1997), nor are these "gold-standard" serial searches. Also included in this category are a variety of hybrid conjunction tasks, for example, Color × Color × Orientation search.

The bulk of the analysis reported here compares the feature, conjunction, and spatial-configuration categories because those have been the topics of the most general theoretical interest. Data from most of the individual experiments included in this sample have been reported in previous publications. The purpose of this report is not to review those individual results but to analyze the combined data set.

The 2,500 pairs of slopes do not come from 2,500 different subjects, as subjects were generally tested in several conditions. A reasonable estimate is that these data represent about 650 subjects. Thus, the slopes are not fully statistically independent. However, this limitation does not appear to have important consequences for the present analysis.[1]

RESULTS

Properties of the Sample as a Whole

Figure 1 shows a histogram of all slopes less than 150 ms/item counted in bins that are 5 ms/item wide. Not included are the 8 target-present slopes and 54 target-absent slopes greater than 150 ms/item. Table 1 gives the basic statistics for the two distributions.

The most important point is that the distributions are unimodal. When the data in the region from 0 to 25 ms/item are examined at a finer grain with bins 1 ms/item wide, there is still no evidence of a bimodal distribution. This result suggests that any effort to divide tasks into serial and parallel search on the basis of search slope alone will be futile. Many people in many places have tried to lay this dichotomy to rest, yet the literature remains replete with efforts to characterize search tasks as either parallel or serial on the basis of slope magnitude. A favorite strategy has been to invoke a mythical threshold of about 10 ms/item that divides parallel from serial search. I refrain from offering specific citations of this error in the literature lest someone look at my previous publications and suggest that one without sin should cast the first citation. In any event, the present analysis makes it quite clear that a successful model of human search behavior should not produce a bimodal or multimodal distribution.

1. Because subjects were tested in multiple experiments, the data presented here violate strict assumptions about the statistical independence of measures. Subject identity was not preserved in this data set, but it is possible to estimate the worst-case effects of this lack of independence. The sample of 2,500 slope pairs represents an estimated 650 subjects. Suppose there is no within-subjects variability (an intraclass correlation of 1.0—the worst case). In that case, a conservative approach would be to use the number of subjects minus 1 as the degree of freedom rather than the number of observations minus 1. For most of the t statistics, such a change in the degrees of freedom will be essentially irrelevant because the degrees of freedom will still be large and p values change little when $df > 50$. Decreasing degrees of freedom by a factor of 4 would double the 95% confidence interval (e.g., Fig. 7). In fact, the situation is better than this. It is possible to estimate an intraclass correlation from experiments in which subjects were tested twice on the same task. R is approximately .5, suggesting that the problem is less severe than the worst case.

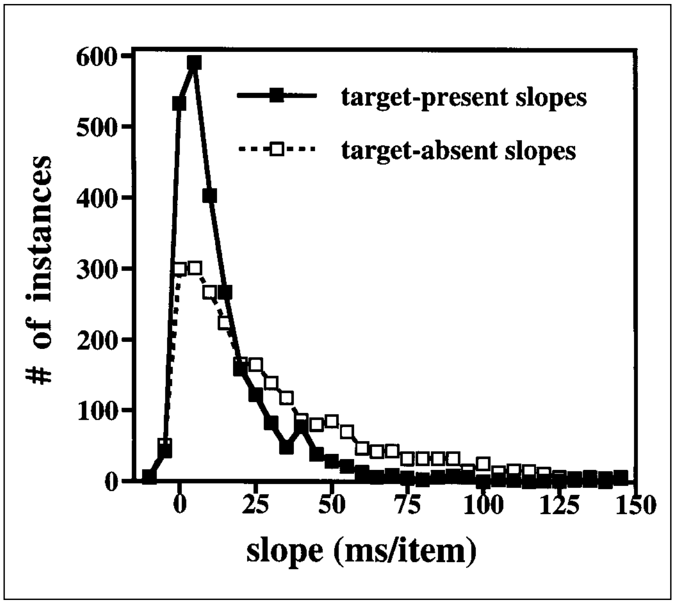

Fig. 1. Distribution of search slopes for the entire data set.

Two notes about this conclusion: First, it does not mean that there are no meaningful differences between search tasks. As I illustrate later, different search tasks produce different patterns of results. Rather, this conclusion simply means that readers should be suspicious of claims such as "The slopes averaged less than 10 ms/item; therefore, this is a parallel search." Second, the exact distribution shown here is dependent on the mix of search tasks, though it is worth noting that the distribution is not bimodal even if restricted to only feature and spatial-configurations tasks.

The Relationship of Target-Present to Target-Absent Slopes

Target-present and -absent slopes are strongly positively correlated. The regression line relating target-absent slope to target-present slope has a slope of 1.8 and an r^2 value of .785. This regression line might be unduly influenced by the few very large slopes included in the sample. Though there are other reasons for very steep search slopes (Wolfe & Bennett, 1997), mandatory eye movements should be suspected when target-present slopes are greater than 100 ms/item or target-absent slopes are greater than 200 ms/item. Figure 2 shows the results of restricting the analysis of the relationship of target-present and target-absent slopes to those cases in which target-present slopes are less than 60 ms/item. This analysis retains 2,426 (97%) pairs of slopes.

The regression slope of 2.0 does not mean that the slope ratios are 2:1, as would be predicted in a serial, self-terminating search. Note that the regression line does not pass through the origin. In fact, the mean slope ratio differs significantly from 2.0. The distribution of slope ratios is shown in Figure 3 and Table 2. Log ratios are plotted because the distribution of untransformed ratios is strongly positively skewed. A log transform makes the distribution roughly normal.

The mean slope ratio is greater than 2.0 using either raw ratios or their logs, log(slope ratio): $t > 7.0$, $df > 2200$, $p < .0001$. N is less than 2,500 because of the removal of cases in which the slope ratio is negative. There are 1,292 ratios greater than 2.0 and 1,155 less than 2.0 in this data set.

Table 1. *Distribution statistics for the entire sample*

Statistic	Target-present slopes (ms/item)	Target-absent slopes (ms/item)
Mean	14.6	33.0
Standard deviation	20.9	42.6
Minimum	–12.8	–19.4
Maximum	207.2	476.4
10th percentile	0.5	1.0
50th percentile (median)	8.4	20.1
90th percentile	37.0	82.0

Slope ratios become large as the denominator, the target-present slope, approaches zero. However, mean slope ratios remain significantly greater than 2.0 over a wide range of target-present slopes. This can be seen in Figure 4, where slope ratio is plotted as a function of target-present slope. To compensate for the positive skew of the raw ratio data, the figure also shows mean log(ratio) and median ratio as a function of target-present slope. Although these manipulations reduce the magnitude of the effect of small target-present slopes, it remains

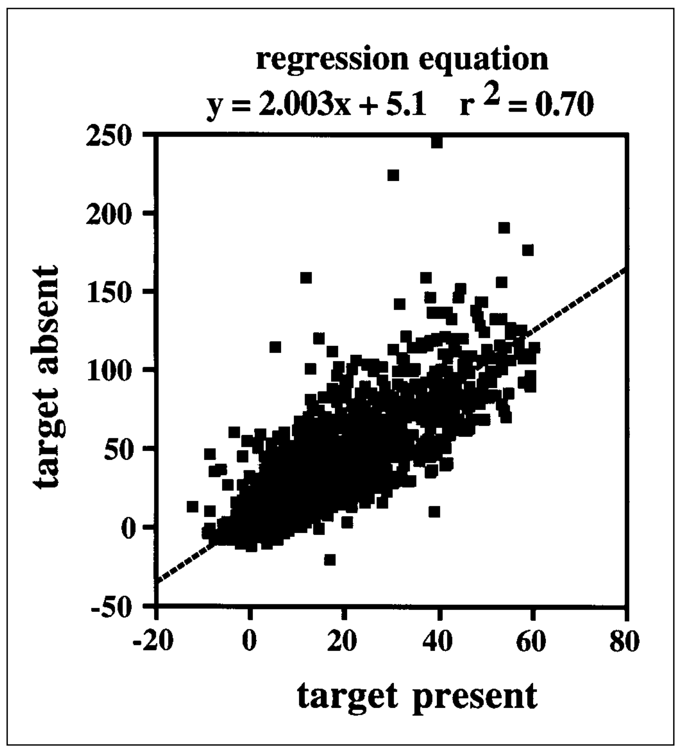

Fig. 2. Target-absent slopes as a function of target-present slopes for the 97% of data points for which the target-present slope is less than 60 ms/item.

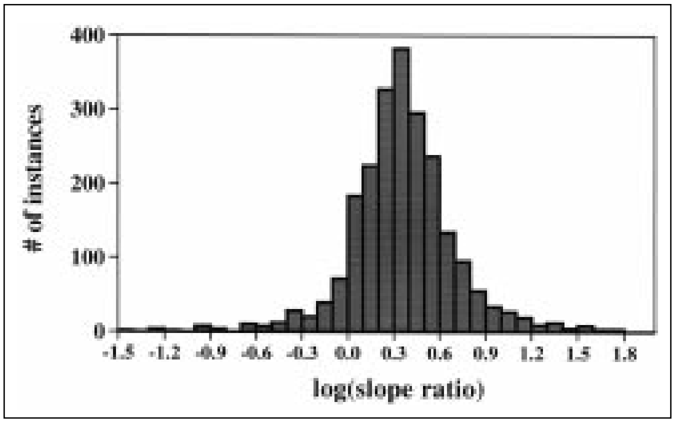

Fig. 3. Distribution of log(slope ratios) for all the data.

the case that slope ratios are elevated above 2.0 for the more efficient searches. Statistical tests on the log(ratio) data and raw ratio data produce similar results.

Instead of analyzing ratio data, one can test the following hypothesis:

$$\text{target-absent slope} - (2 * \text{target-present slope}) = 0 .$$

For the four most efficient slope categories (slopes < 20 ms/item), t tests reject this hypothesis ($p < .001$).

The analysis of slope ratios suggests that a successful model of search behavior will produce ratios that are on average a bit greater than 2.0 and that the regression line relating target-absent to target-present slope will have a slope of about 2.0 and a positive y-intercept.

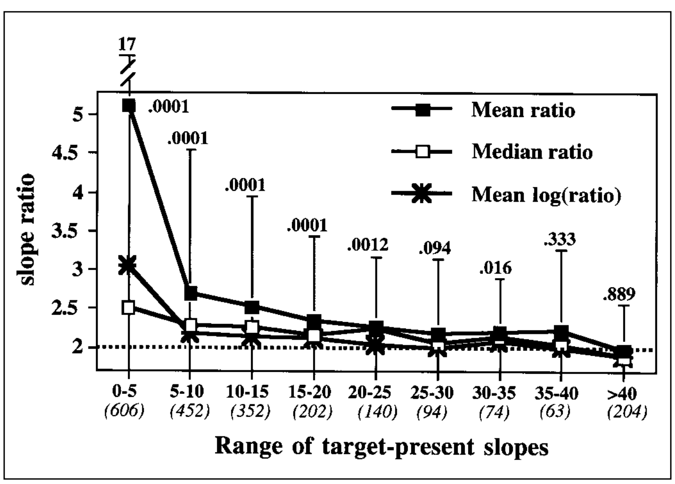

Fig. 4. Slope ratio as a function of target-presents slope. Values at the tops of the bars are significance values for two-tailed t tests for the hypothesis that log(ratio) = log(2.0). These are not corrected for multiple comparisons. Degrees of freedom are based on the number of slopes in each category, shown in parentheses on the x-axis. Error bars (± 1 *sd*) are shown for mean ratios.

Table 2. *Distribution statistics for the log(slope ratios)*

Statistic	Log value	$10^{\text{log value}}$
Mean	0.355	2.26
Standard deviation	0.344	2.21
Minimum	–1.57	0.027
Maximum	1.79	61.66
10th percentile	0	1.0
50th percentile (median)	0.350	2.24
90th percentile	0.748	5.60

Differences Between Types of Search Task

Thus far, the analysis has treated search tasks as a homogeneous set, but they are not. To begin, it is a relief to see that “feature,” “conjunction,” and “spatial configuration” are not arbitrary distinctions in visual search. Figure 5 shows the mean slope for target-present and target-absent trials for each of these three tasks. With the large numbers of data points involved, standard errors are very small (invisible on this graph), and all differences are highly significant ($p < .0001$ by t test, with $df > 100$ for all tests).

These data show that if you know the search task, then you can predict the slope (if P, then Q). However, neither the data nor the rules of logic permit the reverse inference: If you know the slope, then you can infer the type of task (if Q, then P). The failure of the reverse inference is made apparent when the distributions of target-present slopes are plotted for feature, conjunction, and spatial-configuration searches. The distributions are shown in 5-ms bins in Figure 6. Although it is true that a slope of 15 ms/item is unlikely to come from a feature search, and a slope of 5 ms/item is unlikely to come from a spatial-configuration search, the distributions overlap considerably.

The lack of a clear division between serial and parallel tasks has been accepted by most recent models of visual search. Indeed, they have often taken the opposite position, positing that one mechanism underlies all these different types of search. For example, the guided

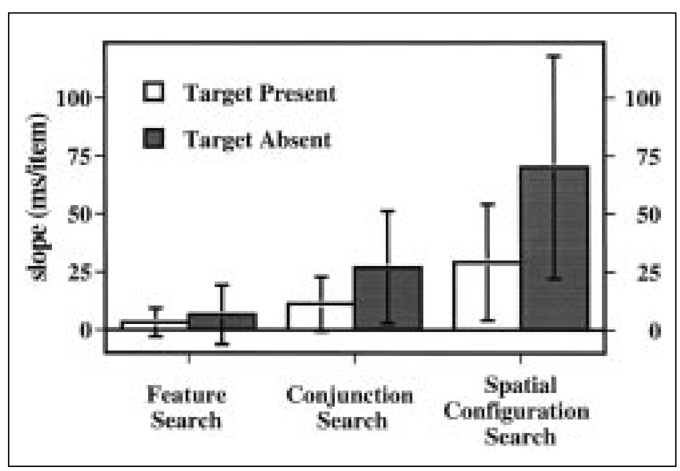

Fig. 5. Mean target-present and target-absent slopes as a function of search task. Error bars show ± 1 *sd*.

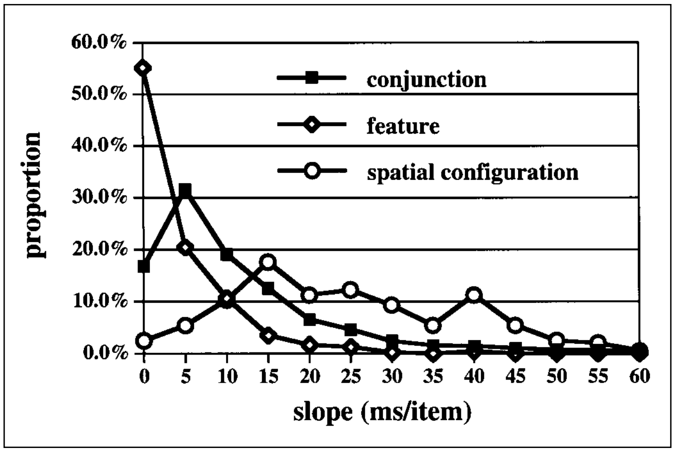

Fig. 6. Distribution of target-present slopes (ms/item) for different classes of search tasks.

search model holds that feature, conjunction, and spatial-configuration search differ from each other only in the amount of guidance that preattentive feature processes can provide. More guidance yields shallower slopes (Wolfe, 1994; Wolfe et al., 1989; Wolfe & Gancarz, 1996). Other theories lead to similar conclusions by rather different routes (e.g., similarity theory, Duncan & Humphreys, 1989; or signal detection approaches, Chun & Wolfe, 1996; Eckstein, Thomas, Palmer, & Shimozaki, 1996; Hübner, 1993; Palmer, 1994; Swensson & Judy, 1981; Verghese & Nakayama, 1994).

If tasks differ only in the strength of the target signal, and if target-present slopes reflect that strength, then all searches with the same target-present slope should be the same. For instance, searches with the same target-present slope should have the same target-absent slope and, thus, the same slope ratio. This hypothesis can be rejected by examining the slope ratio data in Figure 7. Because ratio measures become very unstable as the denominator gets close to zero, cases in which the target slope is less than 1.0 are eliminated in this analysis.

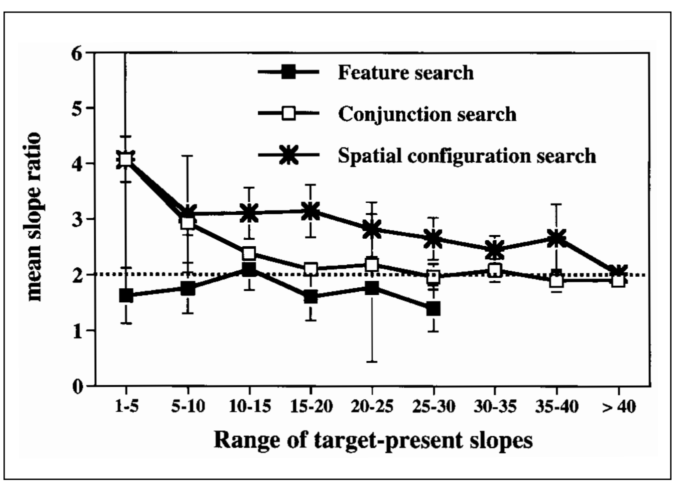

Fig. 7. Slope ratio as a function of target-present slope for different search tasks. Error bars show ± 1 *sd*. The dotted line shows the 2:1 slope ratio predicted by simple serial, self-terminating search models.

This restriction reduces the range of slope ratios from (–617, 198) to (–3, 40). The mean slope ratio for feature searches in this range is 1.7, significantly less than the mean slope ratio of 2.9 for conjunction searches or 2.8 for spatial-configuration searches, unpaired $t > 3.0$, $df > 100$, $p < .0001$. Conjunction and spatial-configuration searches do not differ significantly overall. However, if analysis is restricted to the roughly asymptotic range of the data (target-present slopes between 15 and 60 ms/item), then the mean ratio for conjunction searches, 2.1, is significantly less than the mean ratio for spatial-configuration searches, 2.6, unpaired $t = 6.5$, $df > 100$, $p < .0001$. Because the ratio distribution is positively skewed, the estimates of the ratios are all somewhat lower if medians or log(ratios) are used. However, the pattern of results is not changed.

These results mean that even when target-present slopes are equated, the behavior of subjects on target-absent trials depends on the task. Subjects will terminate unsuccessful feature searches more readily than unsuccessful conjunction searches and unsuccessful conjunction searches more readily than unsuccessful spatial-configuration searches. This is not a speed-accuracy trade-off because error rates tend to be lowest for feature searches and highest for spatial-configuration searches. A speed-accuracy trade-off would require the opposite pattern.

These task differences represent a challenge and an opportunity for models of search behavior. Models with a signal detection flavor have generally assumed that the target is a signal of some size and the distractors are drawn from a noise distribution, generally assumed to be normal. The ratio results suggest that the distractors in different tasks make different noise distributions. These different distributions could induce subjects to adopt different criteria for quitting unsuccessful searches. The challenge for models is to capture these differences.

The ratio differences are an opportunity because they offer a new hope of categorizing search tasks on the basis of RT × Set Size functions, the very act I derided earlier in this article. Although it would not be wise to declare a task to be a feature search simply because the average slope is below 10 ms/item, shallow slopes combined with suitably low slope ratios would be diagnostic. Diagnostics of this form, combining slopes and ratios, have been proposed before, but these data show that we have been using the wrong benchmarks. For instance, if feature searches were really unlimited-capacity parallel searches, then slopes should be near zero and similar for both target-present and target-absent trials. Real feature searches differ systematically from these predictions. If experimenters had a new candidate for a basic feature, they would do better to test the similarity of their data against data from established features rather than against a theoretical ideal that appears to be invalid. The benchmarks from this data set could be used as the priors in a Bayesian strategy for categorizing search tasks. A similar argument can be made about less efficient searches. If such searches were serial and self-terminating, then slope ratios should average 2.0. However, the ratios in the data are systematically greater than 2.0, suggesting that a simple serial, self-terminating account is inadequate.

AND THERE IS MORE ...

Many more nuggets can be mined out of these data. For example, this short article did not discuss the categories of hard feature searches and within-dimension conjunction searches. More important, although this may be the largest published data set on visual search, it still includes only the data from one lab. It is possible, if unlikely, that this limitation skews the results for tasks included in the set. It is unquestionable that there are many basic types of search task that are not in the data set at present. Accordingly, the data set is posted on our web site (www.dahlen.com/kari/wolfe.html), and visitors to that site will find a description of a procedure for adding their published visual search results to the database, which will be maintained by my lab. Other researchers are welcome to use the data set to address their own questions. We would like to be kept informed and request that the support of the Air Force Office of Scientific Research be noted in any publications.

PUNCHLINES

The take-home messages from the analyses reported here are as follows:

1. The overall distribution of search slopes is unimodal and provides no support for a simple, data-driven division of searches into "serial" and "parallel" (or anything else).
2. Different types of search task (as defined by the nature of the stimuli) produce slopes that differ in their means and distributions.
3. Those distributions overlap sufficiently so that no simple slope threshold can be used to divide one class (e.g., feature, or pop-out, search) from another (e.g., conjunction).
4. The average ratio of target-absent to target-present slopes is greater than 2:1.
5. Slope ratios vary systematically with search efficiency and with search task.
6. It follows from Item 5 that search tasks of similar efficiency (as measured by target-present slopes) are not identical.
7. The different patterns of slopes and slope ratios for different tasks could be used to create diagnostic tests that could categorize search tasks (e.g., one could argue, "*X* is a basic feature in visual search because it produces shallow slopes and ratios significantly less than 2.0.").
8. Your favorite theory of visual search is wrong. So is mine. No current model of visual search generates the pattern of results in this data set. This is not to say that no current model could do so. Models must be adjusted to fit this new picture of reality.

Finally, suppose one were to take the most depressing view of these data and conclude that it is simply impossible to categorize search tasks on the basis of slope data. Would this somehow render the visual search paradigm useless? The answer, unequivocally, is "no." Search is an important visual behavior. Some search tasks are efficient and some are not. That fact demands explanation if we want to understand how to find needles in haystacks or friends on the beach. When brought into the lab, these differences in the ease of search show up as differences in the slopes of RT × Set Size functions. A substantial difference in the slopes of two search tasks can tell us about the rules for the allocation of visual attention even if those slopes cannot tell us that these tasks lie on opposite sides of some mythical divide between serial and parallel search.

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