REPORT DOCUMENTATION PAGE

Form Approved OMB No. 0704-0188

1. REPORT DATE *(DD-MM-YYYY)*
31-03-2006

2. REPORT TYPE
Final Report

3. DATES COVERED *(From - To)*
15/02/03-31/12/05

4. TITLE AND SUBTITLE
The Deployment of Visual Attention

5a. CONTRACT NUMBER

5b. GRANT NUMBER
F49620-03-1-0145

5c. PROGRAM ELEMENT NUMBER

6. AUTHOR(S)
Jeremy M Wolfe

5d. PROJECT NUMBER

5e. TASK NUMBER

5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)

Brigham and Women's Hospital
75 Francis St, Boston, MA 021115

Visual Attention Laboratory
of Brigham and Women's Hospital
64 Sidney St., Suite 170
Cambridge, MA 02139

8. PERFORMING ORGANIZATION REPORT NUMBER

9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES)
AFOSR/NL Mail Room 3112
875 North Randolph Street
Arlington, VA 22203-1768

Dr Larkin

10. SPONSOR/MONITOR'S ACRONYM(S)

11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION / AVAILABILITY STATEMENT

Approved for public release; distribution is unlimited. – A

AFRL-SR-AR-TR-06-0102

13. SUPPLEMENTARY NOTES

14. ABSTRACT

The world presents more information to the visual system than the visual system can analyze. One response to this problem is selective attention, the ability to direct processing resources to some stimuli at the expense of others. This research project seeks to understand how attention is deployed in visual search tasks in which observers look for target items in visual scenes containing distracting items. The work described under Aim 1 concerns the development of the Guided Search model and includes a discussion of a new, 2-pathway architecture describing the route(s) from input to visual awareness. The evidence summarized under Aim 2 leads to the conclusion that there is only a very small capacity memory for the progress of a visual search (e.g. which distractors have been rejected?). Finally, Aim 3 reviews support for multiple modes of attentional deployment operating under very different "speed limits"

15. SUBJECT TERMS

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT	b. ABSTRACT	c. THIS PAGE			19b. TELEPHONE NUMBER *(include area code)*

20060601065

Aim 1: Transcending the serial/parallel dichotomy in visual search

The basic phenomena of visual search

(Note: Some of this prose is borrowed from prior annual reports.)
The long-term goal of this project is to produce a model of human visual search behavior. We aim to explain a larger body of findings than most models. It is worth briefly reviewing the set of findings that we want to capture in Guided Search 4.0 (GS4). GS4 is a model of simple search tasks done in the laboratory with the hope that the same principles will scale-up to the natural and artificial search tasks that are performed continuously by people outside of the laboratory. In the figure below, we briefly describe eight aspects of the data that GS4 would like to account for. In each illustration, the left-hand member of the pair is the easier search task.

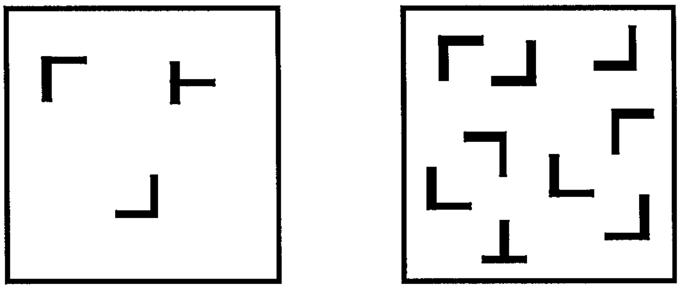
Visual search is one response of the nervous system tot he fact that the world presents us with far more information that we can process at any one time. In visual search tasks, an observer seeks to find a target object in a world filled with other, distracting objects. That task may be a laboratory-based search for one item among others on a computer screen. It might be a natural search task like the search for ripe berries on a bush. Importantly, it can be a search task created by our technology, like the search for threats in carry-on luggage or for cancer in an x-ray. The goal of our research program is to understand how visual attention is deployed in tasks of this sort. What information guides deployment? How fast is deployment? Are there multiple controllers?

This report covers work during the last three years. The original proposal described three specific aims. We will describe work in each area. The aims, as originally stated were:

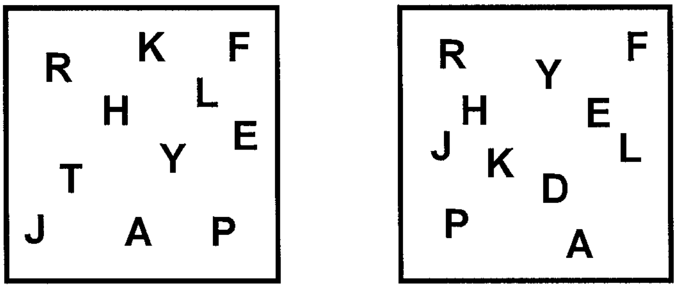
Aim 1: Transcending the serial/parallel dichotomy in visual search: Guided Search, our model of human visual search behavior, has proposed that "preattentive" visual processes guide the deployment of attention from item to item in a serial, item-by-item fashion. Others have argued for deployment of attention to multiple items in parallel. These views have been seen as opposed to one another. The work in this aim is intended to reconcile them in a single framework.

Aim 2: Understanding the role of memory in visual search: Standard serial models of attention have assumed that items in the display are sampled *without* replacement. In the previous grant period, we have shown that the data reject this assertion of perfect memory for rejected distractors. We have proposed that items are sample *with* replacement in typical search tasks. Data from other labs suggest the possibility that some partial memory (perhaps coulometer) discourages deployment to recently attended items. In the next grant period, we will investigate the theoretical and practical consequences of visual search with limited memory for previous deployments of attention.

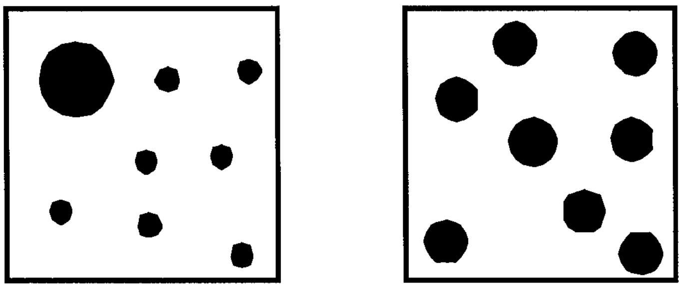
Aim 3: The relationship of different modes of attentional control. There are multiple processes that can control attention. Some of these appear to be very fast. Others are closely coupled with eye movements. The work in Aim 3 is intended to determine how these share control of visual attentional resources.



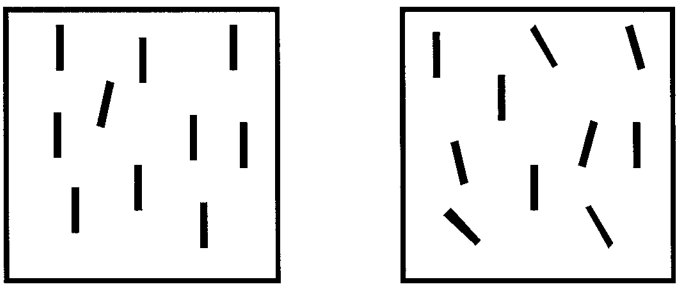
A. Set size: All else being equal, it will be harder and will take longer to find a target (a "T" in this example) among a greater number of distractors than lesser. (J. Palmer, 1995)



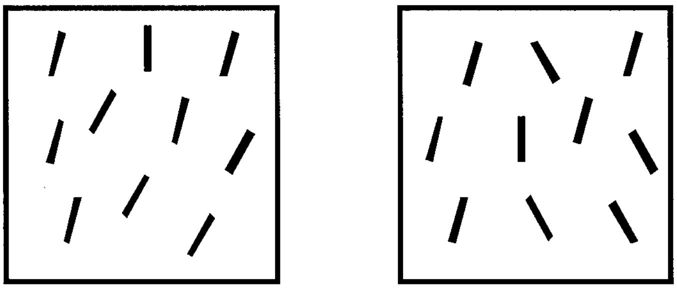
B. Presence/Absence: Under most circumstances, it will take longer on average to determine that targets (again "T") are absent than to determine that they are present. (Chun & Wolfe, 1996).



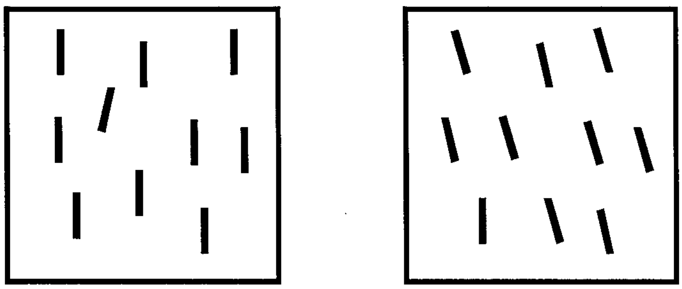
C. Features and target-distractor similarity: There are a limited set of basic attributes that support very efficient search (Jeremy M Wolfe & Horowitz, 2004). The larger the difference between target (here, a large disk) and distractors, the more efficient the search (Duncan &



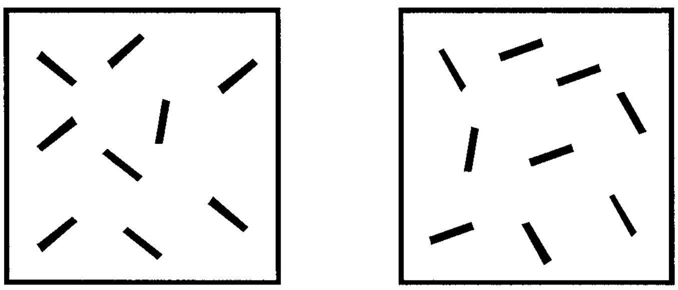
D. Distractor heterogeneity: The more heterogeneous the distractors, the harder the search (Duncan & Humphreys, 1989). Note that this is true in this example, even though the heterogeneous distractors are less similar to the target (line tilted to the right) than the homogeneous. (R. Rosenholtz, 2001)



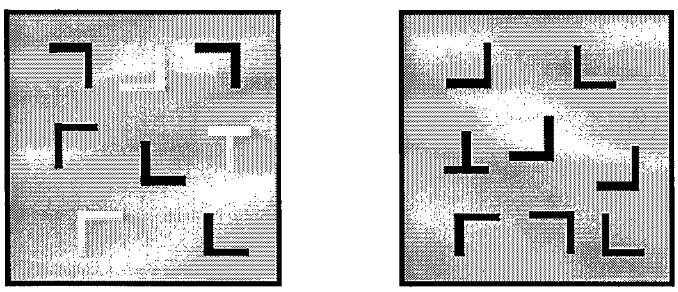
E. Flanking / Linear separability: For the same target - distractor distances, search is harder when distractors flank the target. In this case, 0 deg among +15 and -30 is harder than 0 vs +15 & +30. See linear separability in the 2D color plane (Bauer. Jolicœur. & Cowan.



F. Search asymmetry: Search for A among B is often different than search for B among A. Here 0 among -15 deg is harder than -15 among 0 (R Rosenholtz, 2001; Treisman & Souther, 1985; J M Wolfe, 2001)



G. Categorical processing: All else being equal, targets are easier to find if they are categorically unique. On the left, the "steep" target is easier to find than the "steepest" target on the right. The geometric relationships are constant. (J M Wolfe, Friedman-Hill, Stewart, & O'Connell, 1992)



H. Guidance: Of course, GS must explain guidance. It is easier to find a white "T" on the left than to find the "T" on the right. Color/polarity guides attention (Egeth, Virzi, & Garbart, 1984; J.M. Wolfe, Cave, & Franzel,

Figure One: Eight properties that should be accounted for by a good model of visual search.

Each of these effects is reflected in mean reaction time (RT) data. If one measures the time that it takes to find a target or to declare that the target is absent, that RT will

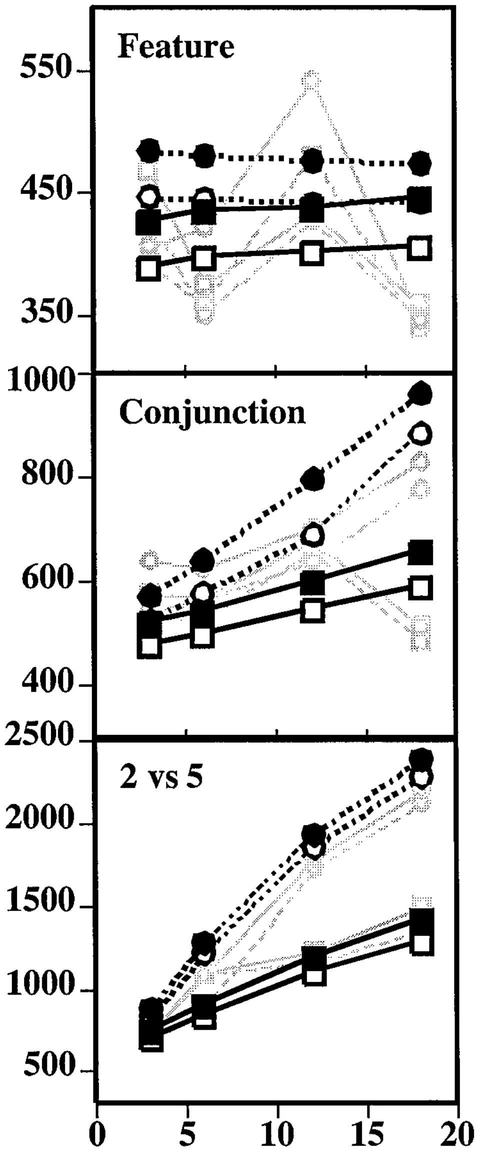


Figure Two: Average RTs for 10 Os tested for 1000 trials per set size in three tasks: Feature (red among green), conjunction (red vertical among red horizontal and green vertical) and a search for a 2 among 5 (the mirror-reversed item). In black, squares are Hits, circles are correct absent responses; closed symbols are means, open are medians. In gray are the errors; squares are false alarms (very rare), circles are misses.

typically increase as a function of "set size", the number of items in the display. The slope of the RT x set size function is measure of the efficiency of the search, expressed in items processed per unit time.

Typical data for some classic search tasks are shown in Figure Two. "Feature" searches are searches where the target is defined by a single basic feature. In this case, a red target among green distractors. Such searches are typically very efficient with RT x set size slopes near zero. A full discussion of list of candidate "basic features" can be found in Wolfe and Horowitz's (2004) Nature Reviews Neuroscience article.

Conjunction searches are tasks where the target is defined by a combination of two (or more) features. In Fig 2b, the target is RED VERTICAL among distractors that are RED-horizontal and green-VERTICAL. The core idea of Guided Search is that basic feature information can be used to guide attention to likely target items (Cave & Wolfe, 1990; J M Wolfe, 1994, 2006; J.M. Wolfe et al., 1989). Slopes are about 8-12 msec/item for target present trials and a bit more than twice that for target absent.

Most real-world searches are probably made reasonably efficient by this sort of guidance. Thus, search for a coffee mug in the kitchen is not a random search over the entire space or even over all objects. Attention will be restricted to objects having the relevant size, color, and, perhaps, other surface properties like luster and curvature.

Fig 2c shows results for an inefficient search for a 2 among 5s. Targets and distractors are composed of the same three horizontal and two vertical lines. Only the spatial arrangement changes. (The target is a mirror-image of the distractors.). Here no guidance is possible and slopes are about 30 msec/item for target-present trials and a bit more than twice that for target-absent. These results are typical for stimuli large enough to avoid acuity limits. If the eyes need to fixate each item, slopes are much steeper. Here we are measuring the impact of covert attention limits.

The Nature of the limits

Slopes of inefficient search tasks (Fig 2c) yield 20-40 items per second as an estimate of the throughput of the search mechanism. However, estimates from almost any other measure of the time required to identify objects are on the order of 100-200 msec per objects. These estimates would be incompatible if we assumed that a single object was being identified at any one time. Instead, we model object identification as an asynchronous diffusion process. The core idea is shown in cartoon form in Figure Three.

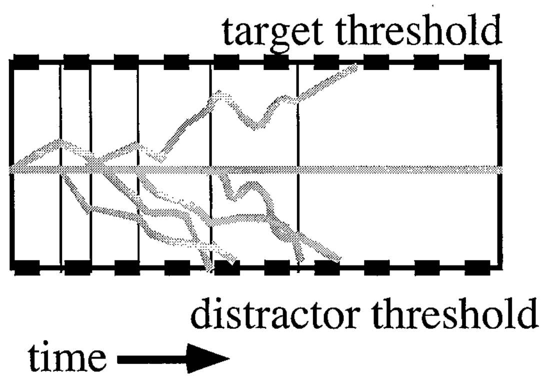


Figure Three: In GS4, the time course of selection and object recognition is modeled as an asynchronous diffusion process. Information about an item begins to accumulate only after that item has been selected into the diffuser.

When an item is selected for identification, information begins to accumulate. The object will be identified as a target if information reaches a target threshold. It will be rejected as a distractor if it reaches the distractor threshold. The diffusion process need not be finished for one item before another item can start its diffusion.

An asynchronous diffuser has many potentially free parameters as illustrated in Figure Four.

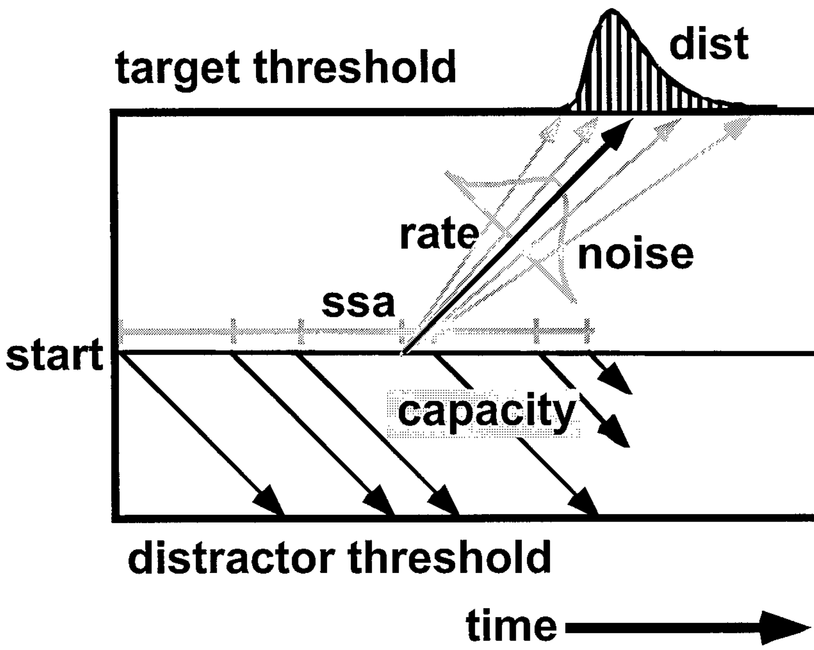


Figure Four: The parameters of an asynchronous diffusion model

These parameters include the rate and variability of the diffusion, the positions of the thresholds, the interval between selections, (stimulus selection asynchrony or SSA on the figure) and the number of items allowed to diffuse at the same time. Another factor to consider is the fate of rejected distractors. Can they be selected again (selection with replacement) or not (selection without replacement). This question of memory in visual search is discussed later in this report. While there are many parameters in this model, the goal is to uncover a set that, once fixed, allows the model to predict human behavior in a wide range of conditions. That is, one would like to establish that searches of various levels of efficiency are consistent with a diffuser with a single rate parameter, a single capacity, and so forth. One might imagine that stimulus conditions would alter the positions of target and distractor thresholds (similar to criterion shifts in signal detection) but it would be unappealing to have a model in which all parameters were free to change with each change in experimental conditions. More details are given in Wolfe (2006)

RT distributions

Figure Four also makes a graphical prediction about the distributions of reaction times. Specifically, diffusion models produce positively skewed RT distributions (Van Zandt & Ratcliff, 2005) as do search experiments (E. M. Palmer, Wolfe, & Horowitz, 2004). We have a large data set of 4000 trials per subject per condition in a range of different search tasks (the data shown in Figure 2, in fact). Using this data set, we have made a number of important discoveries about the distribution of RTs in visual search tasks. We developed a normalization method that allows us to combine RT distributions across observers and to compare RT distributions across conditions. This x-norm procedure is, in essence, a non-parametric z-transform of the data. Each data point in Figure 2 represents a distribution of RTs. Once normalized, the most striking aspect of these distributions is how similar they are. Changes in task, target presence or absence, and set size make little or no difference to the shape of the normalized distribution.

There are some statistically reliable differences (e.g. between the inefficient searches at larger set sizes and the other search tasks). However, those differences are strongly correlated with errors and the suspicion is that they may reflect versions of speed-accuracy trade-offs.

Could this be a boring by-product of the normalization procedure? After all, finding that X/X = Y/Y would not be much of a discovery. One answer comes from simulating standard models of search. Standard models (e.g. serial self-terminating search, limited capacity parallel search) produce RT distributions that differ in shape when x-normed. In particular, most models of search predict that x-normed distributions should vary in shape as set size varies. The actual data do not support this. Developing models that are not subject to this failing is an ongoing challenge.

The Guided Search model in a larger context

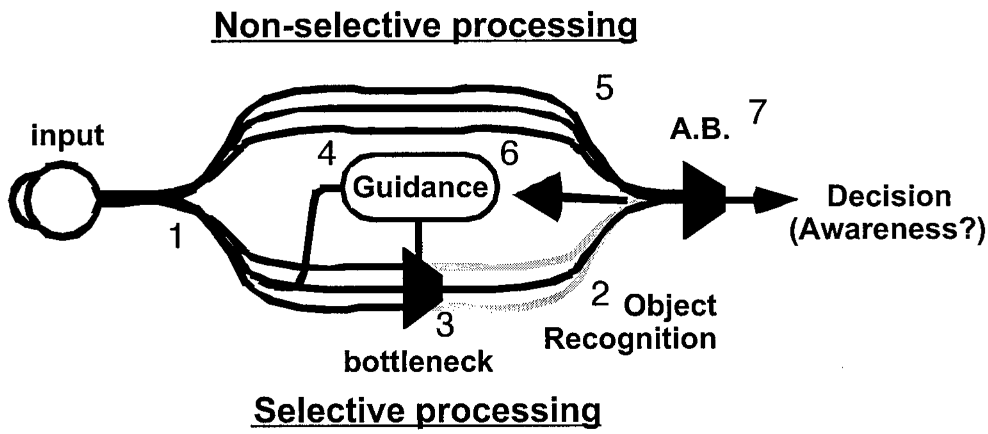


Figure Five: The large-scale structure of GS4

Figure Five shows the large-scale architecture of pathways from input to awareness as we currently understand them. "Classic" Guided Search is embodied in the lower "selective" pathway. In that pathway, parallel processes in early vision (1) provide input to object recognition processes (2) via a mandatory selective bottleneck (3). The bottleneck submits one preattentive object file (J M Wolfe & Bennett, 1997) at a time for object recognition at a rate of about one every 50 msec. As described above, object recognition is modeled as an asynchronous "diffusion" process (R Ratcliff, 1978; R. Ratcliff, Gomez, & McKoon, 2004). To recapitulate, information sufficient to identify a target takes more than one hundred msec to accumulate. Thus, if items are selected in series in GS4 ever 50 msec or so, multiple objects will be in the process of identification at the same time. This makes the current version of Guided Search a hybrid serial/parallel model (Moore & Wolfe, 2001; J M Wolfe, 2003).

"Guidance" in Guided Search comes when information from early visual processes guides access to the selective bottleneck (3). In GS4, we have moved guidance to a position as a control device, sitting to one side of the pathway from input to object recognition (4). It has been clear for a long time that guiding attributes have properties that are different from those of early vision (1) or later processes (2). We think of it as a specific, coarse and categorical abstraction of the information extracted in parallel in early vision. The full details of this argument are found in our Nature Reviews Neuroscience paper (Jeremy M Wolfe & Horowitz, 2004).

The Problem of Visual Awareness

A variety of phenomena, studied in our lab and elsewhere suggest that observers attend to only one (or perhaps a very few objects at one time). As an example, look at Fig 6a. Then, without looking back at 6a, give the color (black or white) of the hidden dot in 6b.

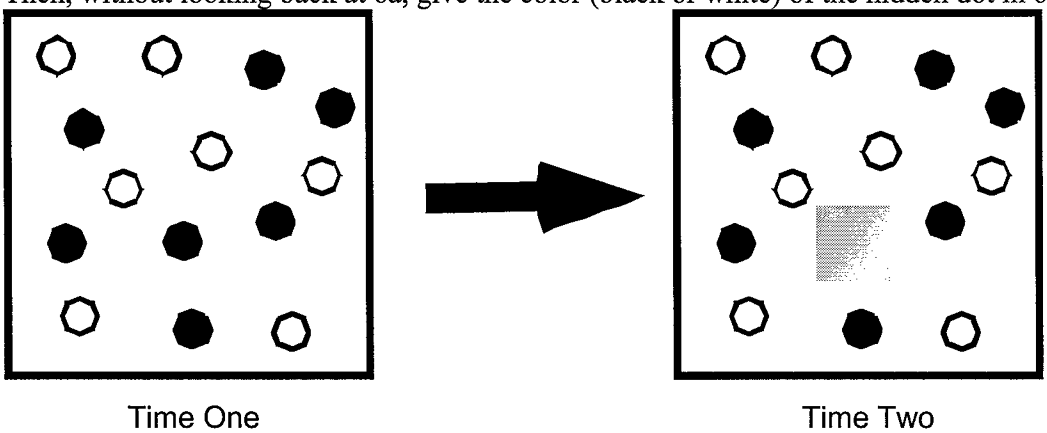


Figure Six: Cartoon version of the method of Wolfe, Reinecke, and Brawn (2006)

You might get the right answer. The chance rate, after all, is 50%. When observers in a laboratory session viewed a collection of dots, they were very close to chance performance when asked to name the color of a dot that had just been hidden (J M Wolfe, Reinecke, & Brawn, 2006). In a range of tasks, observers performance was consistent with an ability to monitor the current status of 2-3 items. This behavior is related to the phenomenon of change blindness (Rensink, 2000; Simons & Levin, 1997) and the very small capacity of Visual Short Term Memory (Luck & Vogel, 1997). A number of researchers have suggested that we are only aware of the current object of attention (O'Regan, 1992) and that the apparently rich percept of the visual world is a "grand illusion" (for a critical discussion see Noe, Pessoa, & Thompson, 2000).

The problem is that, when you look at Figure 6a, it is perfectly clear that you are looking at a bunch of black and white dots even if you seem unable to specify if a specific dot was black or white. Moreover, observers can report on the statistical properties of the whole array (Ariely, 2001; Chong & Treisman, 2003) and they can make limited semantic assertions about the presence of an animal or the category of a scene (e.g. "beach") while attention is diverted or in a time so short that only one or two objects would have been selected (eg. Oliva & Torralba, 2001; VanRullen, Reddy, & Koch, 2004).

To account for these empirical and phenomenological findings, we propose a second, "non-selective" route to visual awareness. As shown in Figure Five, it bypasses the selective bottleneck. It is important to recognize that the non-selective pathway is limited in its abilities (or we would not need a selective pathway). It is capable of processes like analysis of texture statistics (Ariely, 2001) (Chong & Treisman, 2003) and even some crude semantic analysis of scenes ("beach" or "city street", not "corner of 4th and Main) (Oliva & Torralba, 2001). However, it is not capable of the feature binding required for object recognition.

In principle, this two-pathway architecture could be mapped on to the popular What vs Where model (Ungerleider & Mishkin, 1982) that proposes a ventral pathway involved in object recognition and a dorsal pathway involved in localization and spatial attention. Note that a lesion of our hypothetical selective pathway would produce object recognition deficits reminiscent of the agnosia seen with temporal lobe lesions (Ruddock, 1991). A lesion of the non-selective pathway might leave a patient with symptoms like that of a Balints patient (Driver, 1998; Friedman-Hill, Robertson, & Treisman, 1995), an ability to identify individual objects combined with an inability to place that object into a coherent visual world.

Returning to Figure Five, it is probable that some relatively late information can influence guidance (6). Examples include some of this non-selective scene information (Torralba, 2003). This is implied in models like Ahissar and Hochstein's "Reverse Hierarchy Model" (Ahissar & Hochstein, 2004; Hochstein & Ahissar, 2002). It seems likely that these guidance by this sort of information becomes available relatively slowly during the course of a search. That is, guiding attention to "red" will be possible before it is possible to guide attention to the likely location of people in a scene.

As shown in Figure Five, GS4 envisions at least two bottlenecks in processing since the selective bottleneck in visual search (3) seems to be separable from the bottleneck (7) that produces effects like the attentional blink (Shapiro, 1994). For example, while some scene processing may be possible via a non-selective pathway, perception of that scene seems to be fully blocked by the attentional blink (Marois, Yi, & Chun, 2004)

Aim 2: Understanding the role of memory in visual search:

The Standard Model

A number of factors combine to determine where attention will next be deployed during a search. Work in the previous section studied how the featural properties of objects might drive search. In addition, it has long been assumed that past attentional deployments determine future deployments, in that attention is assumed to avoid objects which have already been searched. In other words, visual attention is thought to use sampling without replacement from the search array.

This assumption is explicit in a wide range of search models which employ a serial component (Schneider & Shiffrin, 1977) (Treisman & Gelade, 1980) (Koch & Ullman, 1985) (Itti & Koch, 2001) (Grossberg, Mingolla, & Ross, 1994) (Cohen & Ruppin, 1999) including earlier versions of Guided Search (J M Wolfe, 1994; J.M. Wolfe et al., 1989). Despite their differences, all of these models state that attended items are never resampled. Moreover, the assumption is implicit in many other papers. For instance, the routine claim that a serial model should produce a 2:1 ratio of target absent to present slopes is based on this assumption. Therefore, we will call the sampling without replacement option the Standard Model.

One weakness of the Standard Model is that it requires the assumption of perfect, high capacity memory. Another problem is that the absent:present slope ratio turns out to be reliably different from the predicted 2:1 (J M Wolfe, 1998). Here we outline our work to test the model more directly. Note that the question of memory in visual search can be divided empirically into two domains, concerning covert and overt deployments of attention respectively. The answer may prove to be the same for both eye movements and attentional deployments, but it may not.

Evidence against the Standard Model

We have developed two paradigms for addressing the question of memory for covert deployments of attention. The *randomized search* paradigm (Horowitz & Wolfe, 1998, 2003) employs a logic akin to lesion studies: If we prevent observers from keeping track of rejected distractors, is search performance impaired? In the *dynamic* condition, each trial consists of a series of frames. The stimuli in each frame are identical, except that their locations are shuffled randomly from frame to frame. The target is present in every frame. This manipulation enforces memoryless search, because remembering where a distractor was at time t_1 does not tell you where that same distractor ends up at t_n. The *static* control condition resembles a typical search trial in which a single static frame is presented. Here, observers could use memory if they had it. In both cases we vary set size and measure reaction time (RT). The RT × set slope from the static condition measures how efficiently observers can locate the target under normal circumstances. The slope from the dynamic condition reflects how efficiently they can find the target without keeping track of the locations of rejected distractors. If observers have perfect memory, they will be substantially impaired in the dynamic condition, where that memory is useless. In this case, the dynamic slope will be twice the static slope, because memoryless search is half as efficient as search with memory (for the mathematical derivation of this statement, see Horowitz & Wolfe, 2001). On the other hand, if observers do not use memory even in the static condition, then disabling this memory will have no effect, and the two conditions will have the same slope. Across a number of experiments with varying stimulus conditions, we found little evidence for steeper slopes in the dynamic condition, and clear evidence against a doubling of the slope from static to dynamic. These findings have been replicated in other laboratories (Gibson, Li, Skow, Brown, & Cooke, 2000; Kristjansson, 2000; von Muhlenen, Muller, & Muller, 2003). In short, all evidence from these experiments points to the conclusion that search in the static condition is just as memoryless as search in the dynamic condition.

In the second paradigm (Horowitz & Wolfe, 2001), we sought a signature of memory within a single stimulus condition. Here we relied on the mathematics of sampling distributions. Perfect memory corresponds to sampling without replacement from the search array, while no memory corresponds to sampling with replacement. Varying set size with search for a single target is ambiguous, because both sampling modes will produce a linear increase in RT. However, when there are multiple targets in a single display, the two modes make qualitatively different predictions. The time to find successive targets is constant under sampling without replacement. As each target is found, the pool of available targets left to find shrinks, but the pool of distractors which have not been attended yet shrinks proportionately. Under sampling with replacement, however, the pool of distractors is constant, while the number of available targets shrinks, leading to an accelerating function. Of course, it is methodologically difficult to measure RTs to successive targets, since the times between target detection might be smaller than the minimum time required to lift a finger and put it down again. However, we devised a method which allowed us to measure the lag between locating successive targets in a multiple-target display.

In this paradigm (Horowitz & Wolfe, 2001), the number of targets in a display (of fixed display set size) is varied within a block of trials, and observers are asked to determine whether or not there are at least *n* targets in the display, where the value of *n* is varied between blocks. We assume that the RT on "yes" trials measures the time to find the *n*th target in such a display. By averaging data from trials with the same number of targets in the display across different blocks of trials, we can plot the RT to find the *n*th target of some fixed number of targets across a range of *n*. In our experiments, we varied *n* from 2 to 5 and analyzed data when there were 5 targets. We found highly accelerated functions, consistent with sampling with replacement (memoryless search). However, Takeda (2004) has argued that this pattern is due to an increased memory load with increasing values of *n*. We have shown that this increase in search rate with memory load is at least partially due to Takeda's choice of stimuli (Horowitz, Wolfe, & Birnkrant, 2003), but the debate has not yet been resolved (see also McCarley, Kramer, Boot, & Peterson, 2004)

The question of sampling with or without replacement would seem easier to resolve in the domain of overt attention, or eye movements, where one can actually measure directly where the eyes are directed and determine if any refixation occurs. However, there is surprisingly little agreement in this literature. Peterson and his colleagues reported perfect memory for eye movements (Peterson, Kramer, Wang, Irwin, & McCarley, 2001), while Gilchrist & Harvey (2000) measured the rate of refixation to be around 50%, and suggested that they may have underestimated the true value (Iain D. Gilchrist & Harvey, 2006).

How much memory does visual search have?

Rather than continuing to argue about whether visual search has no memory or perfect memory, we have moved on to ask: how much memory does visual search have? The question acknowledges that the assumption of perfect, infinite memory for all distractors is unrealistic. However, abandoning this assumption does not require us to assume pure amnesia, or "visual search in the eternal present", as we once put it (Horowitz & Wolfe, 1997). Instead, it is likely that the deployment of attention is guided to some extent by the history of the search. The empirical question becomes how much of that history can be used.

This is not an entirely new framing of the question. Horowitz & Wolfe (2001) fit a set of limited-capacity memory models to their data, estimating that observers could avoid revisiting the last three to five rejected distractors (see also Horowitz, Wolfe, & Alvarez, submitted). Takeda's (2004) data produced much larger estimates of 20-25 rejected distractors. In the oculomotor domain, McCarley and colleagues (McCarley, Wang, Kramer, Irwin, & Peterson, 2003), using an innovative saccadic choice procedure, estimated that there was a memory for the previous three eye movements (see also R. M. Klein & MacInnes, 1999)

If we want to know how much memory visual search has, we need to know what the metric is. How do we quantify memory? The work described above has employed what we will call a "stack model". This model assumes that the last few deployments of attention are recorded, so that if the observer is currently attending to the nth item in the sequence, the n + 1th deployment of attention can avoid the n – 1th, n – 2th... n - cth items, where c represents the hypothesized capacity. Once deployment $n + 1$ is completed, however, the nth item is placed on the stack, and the n - cth item drops out. After the first c items have been attended, the model enters a steady state in which the number of potential targets for attention is the number of total objects minus the capacity. If we adopt the stack model, then the metric c is capacity. How many previous items are remembered?

A variant of the stack model might be called the "decay model". Working from the premise that inhibition of return (IOR) serves as the mechanism for implementing memory in visual search (R. Klein, 1988; Posner & Cohen, 1984), several researchers have claimed that if attention is directed to several locations via a sequence of cues, an inhibitory trace can be observed at those locations. This inhibition decays over time such that the most recently cued location shows the strongest inhibition, and the first cued location the weakest (Dodd, Castel, & Pratt, 2003; Pratt & Abrams, 1995; Wright &

Richard, 1996). The important parameter for decay models is obviously the decay rate. However, results are usually translated into a capacity estimate by assuming a rate of deployment and computing how many inhibitory traces are still above threshold when the model reaches the steady state (e.g. McCarley et al., 2003; Wright & Richard, 1996), We have reintroduced a third option, the "variable memory model" (Arani, Karwan, & Drury, 1984). While models of visual search have implicitly assumed perfect memory for some time (Schneider & Shiffrin, 1977; Treisman & Gelade, 1980), the term "memory" was not employed in this context in the cognitive psychology literature until our 1998 paper (Horowitz & Wolfe, 1998). The assumed mechanism for preventing attention from returning to rejected distractors was IOR (R. Klein, 1988; Posner & Cohen, 1984), which is not generally conceived of as a memory system, and models which asserted that rejected distractors were "marked off" (Grossberg et al., 1994; J.M. Wolfe et al., 1989) were vague about exactly how this marking off might have been implemented. Our claim that "visual search has no memory" was based on the fact that sampling with replacement is referred to in the probability literature as "memoryless" (Johnson & Kotz, 1977).

The variable memory model was developed by Arani, Karwan, & Drury (1984)to describe memory for eye movements. This model has a number of advantages over stack and decay models. First, it predicts latency distributions, rather than just means. Second, data can be characterized along two or three psychologically interesting dimensions. Finally, since it was originally developed to model eye movements, it can allow us to compare data from eye movement studies and RT studies primarily aimed at covert attention.

The model has three free parameters: θ, ϕ, and p'. θ represents encoding probability, ϕ recall probability, and p' the probability of correctly identifying a target Assume that each epoch of the model represents a single deployment of attention. The heart of the model is the memory term, describing the probability ($P_{i,k}$) that on the ith epoch, the system will remember that a particular item was attended during the kth epoch: $P_{i,k} = \theta\phi^{i-k}$. Thus, the system is more likely to forget that a particular item was attended as the trial goes on. If both ϕ and θ are set to 1.0, then the system has perfect memory. If either parameters is 0.0, the system is amnesic. The interesting cases are in between the two extremes.

The model produced cumulative distribution functions describing the probability of detecting a target over time. Since the model is recursive, there is an exponential increase in the complexity of the equations as the number of deployments of attention increases. When the model was initially published, the authors resorted to simulations rather than attempting to fit their data (Arani et al., 1984). However, thanks to improvements in computing technology since that time, we are now able to apply the analytic version of the model to data.

We have begun applying the model to the dataset described in the previous section, under **RT distributions**. The model predicts the shape of the cumulative distribution functions reasonably well, as shown in Figure Seven:

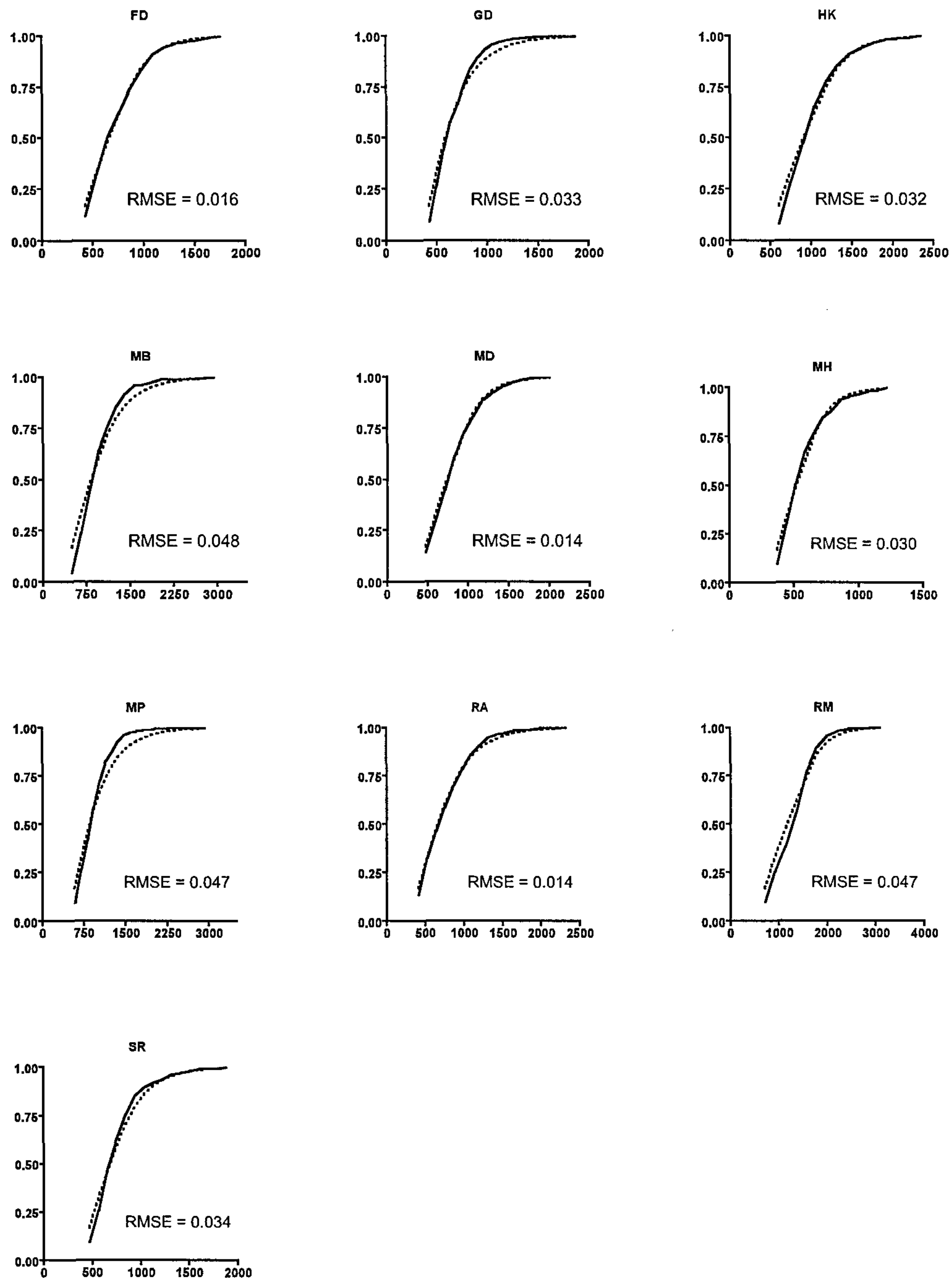


Figure 7. Cumulative distribution functions of RT for each of the ten observers. RT is on the x-axis and cumulative proportion of trials on the y-axis. Solid lines represent data. Dotted lines represent the best-fitting model. Root mean square error (RMSE) between data and model is listed on each panel.

Fitting the model to the data in this way allows us to characterize the behavior of each sbuject in a memory space defined by encoding probability (θ) and recall probability (ϕ), as shown in Figure Eight.

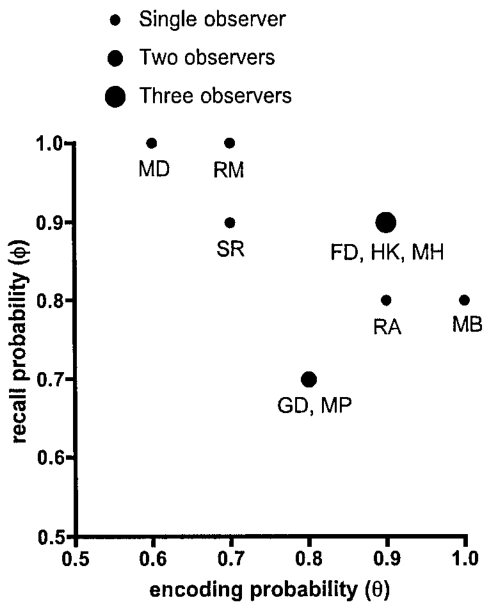


Figure 8. Closest-fitting model parameters for each of the ten observers. θ (encoding probability) values are plotted on the x-axis, ϕ (recall probability) on the y-axis. Size of the symbol indicates how many observers are represented at that point. Observers' initials are indicated below each point.

Looking at the individual results in Figure Eight, it is clear that there are substantial differences among observers. The three observers in the upper left portion of the graph have relatively poor encoding, but are quite good at recalling what they do manage to encode. Observers GD and MP are better at encoding locations, but more likely to forget them. There is also a cluster of three "eidetic" observers who are quite efficient at both encoding and recall. These analyses are meant to illustrate the potential for this class of model to illuminate results from visual search experiments. Further explorations with this dataset are necessary. For instance, it would be important to show that the model parameters derived across different conditions (such as set size) showed some within-observer correlations, and it would be interesting to see if the parameters varied systematically with set size.

The variable memory model provides a useful way to characterize the behavior of observers in terms that are easy to relate to the memory literature. Certain applications suggest themselves naturally. For instance, manipulating the display with "landmarks" (Boot, Peterson, McCarley, & Kramer, 2003) might be expected to affect the encoding parameter θ, while varying memory load should affect recall probability ϕ. While the memory parameters did not predict global performance measures such as slope or RT in these data, we suspect that they might predict performance differences between conditions which rely on memory, such as in our randomized search experiments

(Horowitz & Wolfe, 2003). One obvious application is to return the model to its native environment, the study of eye movements. In this context, several aspects of the model can be extracted directly from the data. Epochs are fixations, and epoch duration is fixation time. While the model was originally designed to accommodate eye movement data, as far as we can tell it has not been applied in the 20 years since its original publication, possibly because computing power was inadequate to implement the model when it was first published. This is less of an issue today, and will be even less so in the future.

Aim 3: The relationship of different modes of attentional control.

How quickly can we shift the focus of visual attention? The answer two this question depends on the nature of the shift. Figure Nine illustrates the distinction between free or anarchic deployments of attention and volitional or commanded deployments.

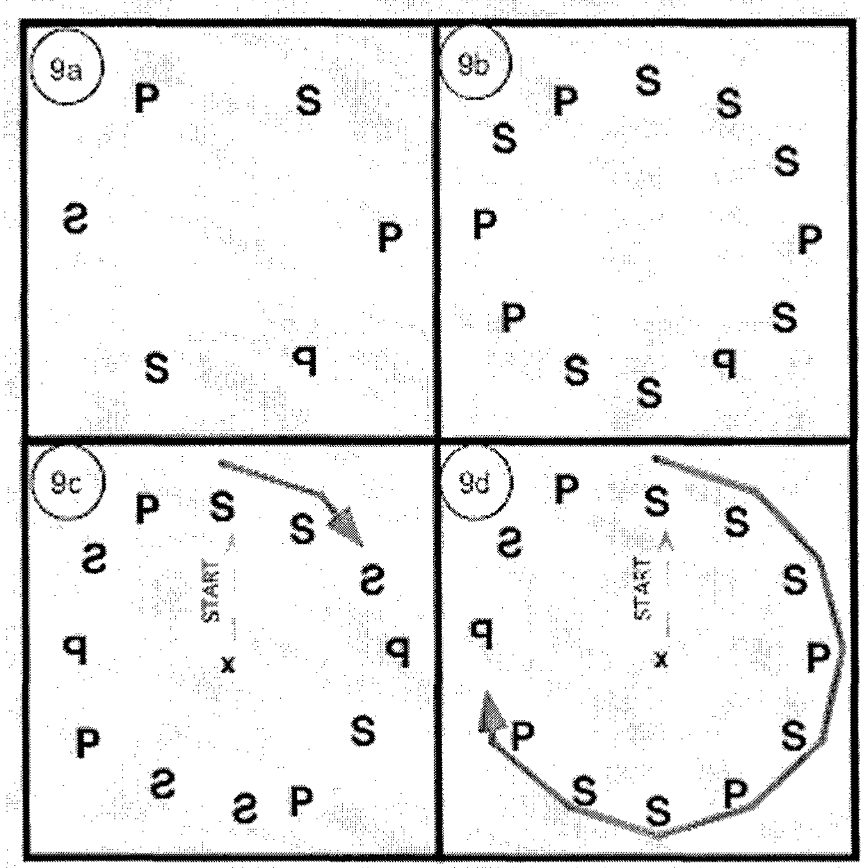


Figure Nine: In the top half of the figure, the observers task is to find and identify the mirror-reversed item (free or anarchic attentional deployment). In the bottom half, the task is to identify the first mirror-reversed letter in starting from 12 o'clock on the circle and moving clockwise (volitional or commanded deployment). Anarchic deployment is much faster than commanded.

The task, in all cases, is to identify a mirror-reversed letter as an "S" or "P". In 9a & 9b, there is just one target. Observers can deploy attention in any manner that they wish. RT in 9b will be 300 msec (or less) longer than in 9a, because there are 12 items in 9b and only 6 in 9a. Depending on one's model of search (e.g. with or without replacement), this yields an estimate of the rate of deployment between 25 and 50 msec/item. In 9c and 9d, Os are instructed to begin at 12o'clock on the circle and name the first mirror-reversed item that they encounter in a clockwise series of attentional deployments. In this case, the RT for 9d will be about 1750-2100 msec longer than in 9c because the target item is in position 3 in 9c and position 10 in 9d. When attention must be deployed in a fixed manner, the rate of deployment seems to be slowed to one deployment every 250-300 msec – a rate very similar to the rate of saccadic eye movements (J. Wolfe, Alvarez, & Horowitz, 2000). More recent experiments have confirmed that this is true even when subjects cannot make eye movements during the task.

In more recent work, (Horowitz, Holcombe, Wolfe, Arsenio, & DiMase, 2004) we compared the *attentional saccades* of Figure 9c&d to the speed of *attentional pursuit*. In the pursuit task, observers used attention to track pointer as it moved around a circle. We determined the fastest speed at which observers could do this by flashing a letter at the location where attention should have been if the observer was successfully tracking. Observers could answer correctly only if they had managed to pursue the moving pointer. We found that attentional pursuit was faster than attentional saccades.

Can these different modes of deployment coexist within the same task? That is, can observers make a volitional movement 3 or 4 times a second and, at the same time, make more rapid anarchic deployments? We ran several experiments to answer this question but, unfortunately, the answers were inconclusive. This is a question awaiting a new method.

REFERENCES CITED:

Ahissar, M., & Hochstein, S. (2004). The reverse hierarchy theory of visual perceptual learning. *Trends Cogn Sci, 8*(10), 457-464.

Arani, T., Karwan, M. H., & Drury, C. G. (1984). A variable-memory model of visual search. *Human Factors, 26*(6), 631-639.

Ariely, D. (2001). Seeing Sets: Representation by statistical properties. *Psychological Science, 12*(2), 157-162.

Bauer, B., Jolicœur, P., & Cowan, W. B. (1996). Visual search for colour targets that are or are not linearly-separable from distractors. *Vision Research, 36*(10), 1439-1466.

Boot, W., Peterson, M. S., McCarley, J. S., & Kramer, A. (2003). The spatial dynamics of memory representations formed during visual search, *Object Perception & Memory* (Vol. 11, pp. 3).

Cave, K. R., & Wolfe, J. M. (1990). Modeling the role of parallel processing in visual search. *Cognitive Psychology, 22*, 225-271.

Chong, S. C., & Treisman, A. (2003). Representation of statistical properties. *Vision Res, 43*(4), 393-404.

Chun, M. M., & Wolfe, J. M. (1996). Just say no: How are visual searches terminated when there is no target present? *Cognitive Psychology, 30*, 39-78.

Cohen, E., & Ruppin, E. (1999). From parallel to serial processing: A computational study of visual search. *Perception and Psychophysics, 61*(7), 1449-1461.

Dodd, M. D., Castel, A. D., & Pratt, J. (2003). Inhibition of return with rapid serial shifts of attention: Implications for memory and visual search. *Perception & Psychophysics, 65*(7), 1126-1135.

Driver, J. (1998). The neuropsychology of spatial attention. In H. Pashler (Ed.), *Attention* (pp. 297-340). Hove, East Sussex, UK: Psychology Press Ltd.

Duncan, J., & Humphreys, G. W. (1989). Visual search and stimulus similarity. *Psychological Review, 96*, 433-458.

Egeth, H. E., Virzi, R. A., & Garbart, H. (1984). Searching for conjunctively defined targets. *J. Exp. Psychol: Human Perception and Performance, 10*, 32-39.

Friedman-Hill, S. R., Robertson, L. C., & Treisman, A. (1995). Parietal contributions to visual feature binding: Evidence from a patient with bilateral lesions. *Science, 269*(11 August 1995), 853-855.

Gibson, B. S., Li, L., Skow, E., Brown, K., & Cooke, L. (2000). Searching for one versus two identical targets: When visual search has a memory. *Psychological Science, 11*(4), 324-327.

Gilchrist, I. D., & Harvey, M. (2000). Refixation frequency and memory mechanisms in visual search. *Current Biology, 10*, 1209-1212.

Gilchrist, I. D., & Harvey, M. (2006). Evidence for a systematic component within scanpaths in visual search. *Visual Cognition, 14*(5-7).

Grossberg, S., Mingolla, E., & Ross, W. D. (1994). A neural theory of attentive visual search: Interactions of boundary, surface, spatial
and object representations. *Psychological Review, 101*(3), 470-489.

Hochstein, S., & Ahissar, M. (2002). View from the top: Hierarchies and reverse hierarchies in the visual system. *Neuron, 36*, 791-804.

Horowitz, T. S., Holcombe, A. O., Wolfe, J. M., Arsenio, H., & DiMase, J. S. (2004). Attentional pursuit is faster than attentional saccade. *J of Vision, 7*(6), 585-603.

Horowitz, T. S., & Wolfe, J. M. (1997). Visual search in the eternal present. *Abstracts of the Psychonomic Society, 2*(Nov 1997), 3.

Horowitz, T. S., & Wolfe, J. M. (1998). Visual search has no memory. *Nature, 394*(Aug 6), 575-577.

Horowitz, T. S., & Wolfe, J. M. (2001). Search for multiple targets: Remember the targets, forget the search. *Perception and Psychophysics, 63*(2), 272-285.

Horowitz, T. S., & Wolfe, J. M. (2003). Memory for rejected distractors in visual search? *Visual Cognition, 10*(3), 257-298.

Horowitz, T. S., Wolfe, J. M., & Alvarez, G. A. (submitted). Looking for memory in visual search using attentional reaction time methods. *Cognitive Psychology*.
Horowitz, T. S., Wolfe, J. M., & Birnkrant, R. S. (2003). Search for multiple targets: Search rate depends on what is being remembered., *Abstracts of the Psychonomic Society* (Vol. 8).
Itti, L., & Koch, C. (2001). Computational modelling of visual attention. *Nature Reviews of Neuroscience, 2*(3), 194-203.
Johnson, N. L., & Kotz, S. (1977). *Urn Models and Their Applications*. New York: John Wiley & Sons.
Klein, R. (1988). Inhibitory tagging system facilitates visual search. *Nature, 334*, 430-431.
Klein, R. M., & MacInnes, W. J. (1999). Inhibition of return is a foraging facilitator in visual search. *Psychological Science, 10*(July), 346-352.
Koch, C., & Ullman, S. (1985). Shifts in selective visual attention: Towards the underlying neural circuitry. *Human Neurobiology, 4*, 219-227.
Kristjansson, A. (2000). In search of rememberance: Evidence for memory in visual search. *Psychological Science, 11*(4), 328-332.
Luck, S. J., & Vogel, E. K. (1997). The capacity of visual working memory for features and conjunctions. *Nature, 390*(20 Nov), 279-281.
Marois, R., Yi, D.-J., & Chun, M. M. (2004). The neural fate of consciously perceived and missed events in the attentional blink. *Neuron, 41*, 465-472.
McCarley, J. S., Kramer, A., Boot, W., & Peterson, M. S. (2004). Oculomotor behavior and attentional strategies during visual search for multiple targets: Further evidence against the evidence for memory-free visual search. *Visual Cognition, this volume*.
McCarley, J. S., Wang, R. F., Kramer, A. F., Irwin, D. E., & Peterson, M. S. (2003). How much memory does oculomotor search have? *Psychol Sci, 14*(5), 422-426.
Moore, C. M., & Wolfe, J. M. (2001). Getting beyond the serial/parallel debate in visual search: A hybrid approach. In K. Shapiro (Ed.), *The Limits of Attention: Temporal Constraints on Human Information Processing* (pp. 178-198). Oxford: Oxford U. Press.
Noe, A., Pessoa, L., & Thompson, E. (2000). Beyond the grand illusion: What change blindness really teaches us about vision. *Visual Cognition, 7*(1), 93-106.
O'Regan, K. (1992). Solving the 'real' mysteries of visual perception. The world as an outside memory. *Canadian J. of Psychology, 46*, 461-488.
Oliva, A., & Torralba, A. (2001). Modeling the shape of the scene: A holistic representation of the spatial envelope. *International Journal of Computer Vision, 42*(3), 145-175.
Palmer, E. M., Wolfe, J. M., & Horowitz, T. S. (2004, April 29 - May 4, 2004). *Response time distributions constrain models of visual search*. Paper presented at the Visual Sciences Society, Sarasota, FL.
Palmer, J. (1995). Attention in visual search: Distinguishing four causes of a set size effect. *Current Directions in Psychological Science, 4*(4), 118-123.
Peterson, M. S., Kramer, A. F., Wang, R. F., Irwin, D. E., & McCarley, J. S. (2001). Visual search has memory. *Psychol Sci, 12*(4), 287-292.

Posner, M. I., & Cohen, Y. (1984). Components of attention. In H. Bouma & D. G. Bouwhuis (Eds.), *Attention and Performance X* (pp. 55-66). Hillside, NJ: Erlbaum.

Pratt, J., & Abrams, R. A. (1995). Inhibition of return to successively cued spatial locations. *J. Experimental Psychology: Human Perception and Performance, 21*(6), 1343-1353.

Ratcliff, R. (1978). A theory of memory retrieval. *Psych. Preview, 85*(2), 59-108.

Ratcliff, R., Gomez, P., & McKoon, G. (2004). A diffusion model account of the lexical decision task. *Psychol Rev, 111*(1), 159-182.

Rensink, R. A. (2000). Visual sensing without seeing. *Nature, ms 7.20.00.*

Rosenholtz, R. (2001). Search asymmetries? What search asymmetries? *Perception and Psychophysics, 63*(3), 476-489.

Rosenholtz, R. (2001). Visual search for orientation among heterogeneous distractors: experimental results and implications for signal-detection theory models of search. *J Exp Psychol Hum Percept Perform, 27*(4), 985-999.

Ruddock, K. H. (1991). Spatial vision after cortical lesions. In D. Regan (Ed.), *Spatial Vision* (Vol. 10, pp. 261-289). Boca Raton: CRC Press.

Schneider, W., & Shiffrin, R. M. (1977). Controlled and automatic human information processing: I. Detection, search, and attention. *Psychol. Rev., 84*, 1-66.

Shapiro, K. L. (1994). The attentional blink: The brain's eyeblink. *Current Directions in Psychological Science, 3*(3), 86-89.

Simons, D. J., & Levin, D. T. (1997). Change blindness. *Trends in Cognitive Sciences, 1*(7), 261-267.

Takeda, Y. (2004). Search for multiple targets: Evidence for memory-based control of attention. *Psychonomic Bulletin & Review, 11*(1), 71-76.

Torralba, A. (2003). Modeling global scene factors in attention. *Journal of Optical Society of America A, 20(7)*(Special Issue on Bayesian and Statistical Approaches to Vision).

Treisman, A., & Gelade, G. (1980). A feature-integration theory of attention. *Cognitive Psychology, 12*, 97-136.

Treisman, A., & Souther, J. (1985). Search asymmetry: A diagnostic for preattentive processing of seperable features. *J. Exp. Psychol. - General, 114*, 285-310.

Ungerleider, L. G., & Mishkin, M. (1982). Two cortical visual systems. In D. J. Ingle, M. A. Goodale & R. J. W. Mansfield (Eds.), *Analysis of Visual Behavior* (pp. 549-586). Cambridge, MA: MIT Press.

Van Zandt, T., & Ratcliff, R. (2005). Statistical mimicking of reaction time data: Single-process models, parameter variability, and mixtures. *Psych Bulletin & Review, 2(1), 20-54.*, 2(1), 20-54.

VanRullen, R., Reddy, L., & Koch, C. (2004). Visual search and dual tasks reveal two distinct attentional resources. *J Cogn Neurosci, 16*(1), 4-14.

von Muhlenen, A., Muller, H. J., & Muller, D. (2003). Sit-and-wait strategies in dynamic visual search. *Psychol Sci, 14*(4), 309-314.

Wolfe, J., Alvarez, G., & Horowitz, T. (2000). Attention is fast but volition is slow. *Nature, 406*, 691.

Wolfe, J. M. (1994). Guided Search 2.0: A revised model of visual search. *Psychonomic Bulletin and Review, 1*(2), 202-238.

Wolfe, J. M. (1998). What do 1,000,000 trials tell us about visual search? *Psychological Science, 9*(1), 33-39.
Wolfe, J. M. (2001). Asymmetries in visual search: An Introduction. *Perception and Psychophysics, 63*(3), 381-389.
Wolfe, J. M. (2003). Moving towards solutions to some enduring controversies in visual search. *Trends Cogn Sci, 7*(2), 70-76.
Wolfe, J. M. (2006). Guided Search 4.0: Current Progress with a model of visual search. In W. Gray (Ed.), *Integrated Models of Cognitive Systems*. New York: Oxford.
Wolfe, J. M., & Bennett, S. C. (1997). Preattentive Object Files: Shapeless bundles of basic features. *Vision Research, 37*(1), 25-43.
Wolfe, J. M., Cave, K. R., & Franzel, S. L. (1989). Guided Search: An alternative to the Feature Integration model for visual search. *J. Exp. Psychol. - Human Perception and Perf., 15*, 419-433.
Wolfe, J. M., Friedman-Hill, S. R., Stewart, M. I., & O'Connell, K. M. (1992). The role of categorization in visual search for orientation. *J. Exp. Psychol: Human Perception and Performance, 18*(1), 34-49.
Wolfe, J. M., & Horowitz, T. S. (2004). What attributes guide the deployment of visual attention and how do they do it? *Nature Reviews Neuroscience, 5*(6), 495-501.
Wolfe, J. M., Reinecke, A., & Brawn, P. (2006). Why don't we see changes? The role of attentional bottlenecks and limited visual memory. *Visual Cognition, in press.*
Wright, R., & Richard, C. (1996). Inhibition-of-return at multiple locations in visual space. *Can. J. Exp. Psychol., 50*(3), 324-327.

PUBLICATONS:
Published papers (* indicates substantial AFOSR support for the work)

*Wolfe JM. 2003. Visual Search: Are some enduring controversies moving toward solution? *Trends Cogn Sci* 7: 70-6

* Wolfe JM, Butcher SJ, Lee C, Hyle M. 2003. Changing your mind: On the contributions of top-down and bottom-up guidance in visual search for feature singletons. *J Exp Psychol: Human Perception and Performance* 29: 483-502

* Horowitz, T. S., & Wolfe, J. M. (2003). Memory for rejected distractors in visual search? *Visual Cognition, 10*(3), 257-298.

Wolfe, J. M., & DiMase, J. S. (2003). Do intersections serve as basic features in visual search? *Perception,* 32(6), 645-656

Horowitz, T., Cade, B., Wolfe, J., & Czeisler, C. (2003). Searching night and day: The influence of circadian phase and sleep deprivation on visual attention. *Psychological Science,* 14(6), 549-557

* Wolfe, J. M., & Horowitz, T. S. (2004). What attributes guide the deployment of visual attention and how do they do it? *Nature Reviews Neuroscience, 5*(6), 495-501.

* Wolfe, J. M., Horowitz, T. S., Kenner, N., Hyle, M., & Vasan, N. (2004). How fast can you change your mind? The speed of top-down guidance in visual search. *Vision Research, 44*(12), 1411-1426.

* Horowitz, T. S., Holcombe, A. O., Wolfe, J. M., Arsenio, H., & DiMase, J. S. (2004). Attentional pursuit is faster than attentional saccade. *J of Vision, 7*(6), 585-603.

Oliva A, Wolfe JM, Arsenio HC. 2004. Panoramic search: The interaction of memory and vision in search through a familiar scene. *J. Exp. Psychol: Human Perception and Performance* 30: 1132-46

Thornton, I. M. & Horowitz, T. S. (2004) The Multi-item localization (MILO) task: Measuring the spatio-temporal context of vision for action. *Perception & Psychophysics,* **66**(1), 38-50.

Santhi, N., Duffy, J. F., Horowitz T. S., & Czeisler, C. A. (2005). Scheduling of sleep/darkness affects the circadian phase of night shift workers. *Neuroscience Letters,* **384**(3), 316-320.

Wolfe, J. M., Birnkrant, R. S., Horowitz, T. S., & Kunar, M. A. (2005). Visual search for transparency and opacity: Attentional guidance by cue combination? *J of Vision, 5*(3), 257-274.

Wolfe, J. M. (2005). On topology's place in the psychophysical structure of human vision. *Visual Cognition, 12*(4), 675-682.

Wolfe, J. M., Horowitz, T. S., & Kenner, N. M. (2005). Rare items often missed in visual searches. *Nature, 435*, 439-440.

* Alvarez, G. A., H. C. Arsenio, et al. (2005). "Do multielement visual tracking and visual search draw continuously on the same visual attention resources?" J Exp Psychol Hum Percept Perform **31**(4): 643-667.

Submitted Papers

* Wolfe, J. M., Reinecke, A., & Brawn, P. (in press). Why don't we see changes? The role of attentional bottlenecks and limited visual memory. *Visual Cognition,.*

Wolfe JM, Michod KO, Horowitz TS. 2004. Visual Search: Linear reaction time by set size functions are not really linear. *Percept Psychophys* ms submitted

Kunar MA, Michod KO, Wolfe JM. 2005. When do we use the context in contextual cueing: Evidence from multiple target locations. *Percept Psychophys submitted*

Horowitz, T. S., Horvitz, J., Choi, W. Y., Côté, L. J. & Mangels, J. (in press). Visual search deficits in Parkinson's disease are attenuated by bottom-up target salience and top down information. *Neuropsychologia.*

Horowitz, T. S., Birnkrant, R. S., Fencsik, D. E., Tran, L., & Wolfe, J. M. (in press). How do we track invisible objects? *Psychonomic Bulletin & Review.*

*Horowitz, T. S. (in press). Revisiting the variable memory model of visual search. *Visual Cognition.*

Horowitz, T. S., Klieger, S. B., Fencsik, D. E., Yang, K. K., Alvarez, G. A., & Wolfe, J. M. Tracking unique objects. submitted to *Perception & Psychophysics, accepted pending revision*

Fencsik, D. E., Klieger, S. B., & Horowitz, T. S. The role of location and motion information in the tracking and recovery of moving objects. submitted to *Perception & Psychophysics, accepted pending revision.*

Kunar, M. A., Flusberg, S. J., & Wolfe, J. M. (in press). Contextual cueing by global features. *Percept Psychophys, ms* (submitted 6/1/05, accepted with revisions, 12/05)

Kunar, M. A., Flusberg, S., & Wolfe, J. M. (2005). Repeated search revisited: Neither visual nor memory search becomes efficient with repetition. *Percept Psychophys, ms.* Submitted 12/05

* Horowitz, T. S., Fine, E. M., Fencsik, D. E., Yurgenson, S., & Wolfe, J. M. (2005). Fixational eye movements are not an index of covert attention. *Psychological Science, submitted 1/06*

Wolfe, J. M., Place, S. S., & Horowitz, T. S. (2005). Multiple Object Juggling: Changing what is tracked during extended multiple object tracking. *Psych Bulletin & Review, submitted 1/06*

* Wolfe, J. M., Horowitz, T. S., Fencsik, D. E., & Flusberg, S. J. (2006). Visual search has no foresight: An event-related measurement of signal strength during a visual search trial. *Nature Neuroscience, submitted.*

Li, X., Cave, K., & Wolfe, J. M. (2006). Can subjective contour guide attentional deployment? *Perception & Psychophysics, ms submitted March 1, 2006.*

Proceedings of Meetings (with published text)

*Wolfe, J. M. (2005). How might the rules that govern visual search constrain the design of visual displays? *2005 Society for Information Display, International Symposium Digest of Technical Papers, 2*, 1395-1397.

Book Chapters

Wolfe, J. M. (2003). The level of attention: Mediating between the stimulus and perception. In L. Harris (Ed.), *Levels of Perception: a Festschrift for Ian Howard* (pp. 169-192). New York: Springer Verlag.

* Wolfe, J. M. (2005). Guidance of Visual Search by Preattentive Information. In L. Itti & G. Rees & J. Tsotsos (Eds.), *Neurobiology of attention* (pp. 101-104). San Diego, CA: Academic Press / Elsevier.

* Horowitz, T. S., & Wolfe, J. M. (2005). Visual Search: The role of memory for rejected distractors. In L. Itti & G. Rees & J. Tsotsos (Eds.), *Neurobiology of attention* (pp. 264-268). San Diego, CA: Academic Press / Elsevier. *(NOTE: Sadly, Wolfes name was left off the final, published version – a lesson to us all to read our proofs with care!)*

* Wolfe, J. M. (2006). Guided Search 4.0: Current Progress with a model of visual search. In W. Gray (Ed.), *Integrated Models of Cognitive Systems*. New York: Oxford.

INTERACTIONS AND TRANSITIONS

Invited Conference Talks based significantly on AFOSR work

2003 talk Modeling visual search: Guided search and its friends. Invited Keynote, Munich Symposium on Visual Search, Holzhausen am Ammersee, Bavaria, Germany (June, 2003).

2003 talk Speed limits on the top-down guidance of attention. Invited talk, International workshop on Visual Attention. San Miniato, Italy (June, 2003).

2004 talk Reconfiguring your visual system: How and how fast do you change your mind? Invited talk: Visual Cortex: A variety of viewpoints. Satellite meeting of the Australian Neuroscience Society, (Melbourne, Jan 27, 2004)

2004 talk A two-pathway architecture for visual attention (w/ Todd Horowitz): Invited Talk: Australian Neuroscience Society, (Melbourne, Jan 29, 2004)

2004 talk The role of selective attention in human vision: A two pathways account. Invited Talk: Eighth International Conference on Cognitive and Neural Systems, Boston University on May 19-22, 2004.

2004 talk What Are We Searching For? Seeking Guidance in the Study of Visual Attention. Invited Plenary Talk: Annual meeting of the American Psychological Association, Honolulu, July 28 – Aug 1, 2004

2005 talk Guided Search: Invited talk at Modeling Integrated Cognitive Systems (MICS) Saratoga Springs, NY, March 3-5, 2005

2005 talk How Might the Rules that Govern Visual Search Constrain the Design of Visual Displays? Invited talk - Society for Information Display May 22-27, 2005 Boston, Massachusetts USA

Additionally, about 24 colloquium-style invited talks at universities and other research settings.

Conference talks with published abstracts

170. Jeremy M Wolfe, Anne Treisman, &Todd S Horowitz: What shall we do with the preattentive processing stage: Use it or lose it? *Paper presented at the Vision Sciences Society (VSS), Sarasota, FL., May, 2003*

171. Todd S Horowitz, Randall S Birnkrant, & Jeremy M Wolfe: Rapid visual search during slow attentional shifts. *Paper presented at the Vision Sciences Society (VSS), Sarasota, FL. , May, 2003*

172. Jennifer S DiMase, George A Alvarez, Todd S Horowitz, & Jeremy M Wolfe: Constraints on task switching in multielement tracking and visual search. *Paper presented at the Vision Sciences Society (VSS), Sarasota, FL. , May, 2003*

173. Naomi Kenner & Jeremy M Wolfe: An exact picture of your target guides visual search better than any other representation. *Paper presented at the Vision Sciences Society (VSS), Sarasota, FL. , May, 2003*

174. Randall S Birnkrant, Jeremy M Wolfe, & Hermie Mendoza: Is opacity a basic feature? It's not transparent. *Paper presented at the Vision Sciences Society (VSS), Sarasota, FL. , May, 2003*

175. Wolfe, J M Modeling Visual Search: Guided Search and Its Friends. *Paper presented at the Munich Symposium on Visual Search. Holzhoausen, Germany, June 2003*

176. Wolfe, JM Speed limits on the top-down guidance of visual search. *Paper presented at the International Workshop on Visual Attention, San Miniato, Italy, June 2003*

177. Horowitz, T. S., DiMase, J. S., & Wolfe, J. M. (2003) Visual search asymmetry for Brownian and ballistic motion trajectories. Perception, **32** (supplement). *Paper presented at the European Conference on Visual Perception (Paris)*

178. DiMase, J. S., Oliva, A., Horowitz, T. S. & Wolfe, J. M. (2003). The role of attended objects in picture recognition memory. *Paper presented at the Object Perception, Attention & Memory Meeting, (OPAM)* **9** (Vancouver, BC).

179. Horowitz, T. S., Wolfe, J. M., & Birnkrant, R. S. (2003). Search for multiple targets: Search rate depends on what is being remembered. *Abstracts of the Psychonomic Society*, **8**. *Paper presented at the meeting of the Psychonomic Society (Vancouver, BC)*

180. Wolfe, J. M., & Horowitz, T. S. (2004) A two-pathway architecture for visual attention. *Paper presented at the Australian Neuroscience Society, Melbourne, VIC, Australia. (Jan 29, 2004)*

181., Birnkrant, R. S., Wolfe, J. M., Kunar, M., & Sng, M. (2004, April 29 - May 4, 2004). *Is shininess a basic feature in visual search?* Paper presented at the Visual Sciences Society, Sarasota, FL.

182. Fencsik, D. E., Horowitz, T. S., Klieger, S. B., & Wolfe, J. M. (2004, April 29 - May 4, 2004). *Target reacquisition strategies in multiple object tracking*. Paper presented at the Visual Sciences Society, Sarasota, FL.

183. Horowitz, T. S., Birnkrant, R. S., Wolfe, J. M., Tran, L., & Fencsik, D. E. (2004, April 29 - May 4, 2004). *Tracking invisible objects.* Paper presented at the Visual Sciences Society, Sarasota, FL.

184. Kenner, N., & Wolfe, J. M. (2004, April 29 - May 4, 2004). *How exact is exact? In visual search a re-sized, re-oriented, or mirrored cue is just as effective as an exact cue.* Paper presented at the Visual Sciences Society, Sarasota, FL.

185. Klieger, S. B., Horowitz, T. S., & Wolfe, J. M. (2004, April 29 - May 4, 2004). *Is Multiple Object Tracking Colorblind?* Paper presented at the Visual Sciences Society, Sarasota, FL.

186. Michod, K. O., Wolfe, J. M., & Horowitz, T. S. (2004, April 29 - May 4, 2004). *Does guidance take time to develop during a visual search trial?* Paper presented at the Visual Sciences Society, Sarasota, FL.

187. Palmer, E. M., Wolfe, J. M., & Horowitz, T. S. (2004, April 29 - May 4, 2004). *Response time distributions constrain models of visual search.* Paper presented at the Visual Sciences Society, Sarasota, FL.

188. Wolfe, J. M. (2004, April 29 - May 4, 2004). *A new, two pathway model describes the role of selective attention in human vision.* Paper presented at the Visual Sciences Society, Sarasota, FL.

189. Horowitz, T. S., Klieger, S. B., Wolfe, J. M., George A. Alvarez, & Fencsik, D. E. (2004). Do you know what you're tracking? *Perception, ECVP abstracts*(Paper presented at the 2004 ECVP meeting, Budapest).

190. Wolfe JM, Palmer EM, Horowitz TS, Michod KO. 2004. Visual search throws us a curve. *Abstracts of the Psychonomic Society, 9, Paper presented at the meeting of the Psychonomic Society (Minneapolis, MN)*

191. Horowitz TS, Klieger SB, Wolfe JM, Fencsik DE, Alvarez GA. 2004. How many unique objects can you track? *Abstracts of the Psychonomic Society, Paper presented at the meeting of the Psychonomic Society (Minneapolis, MN)*

192. DiMase, J., Chun, M., Scholl, B., Wolfe, J., & Horowitz, T. (2005). Learning scenes while tracking disks: The effect of MOT load on picture recognition. *Paper presented at the Visual Sciences Society, Sarasota, FL., (May 6 - 11, 2005).*

193. Fencsik, D., Horowitz, T., Place, S., Klieger, S., & Wolfe, J. (2005). Target Tracking During Interruption in the Multiple-Object Tracking Task. *Paper presented at the Visual Sciences Society, Sarasota, FL., (May 6 - 11, 2005).*

194. Flusberg, S., Kunar, M., & Wolfe, J. (2005). In visual search, can the average

features of a scene guide attention to a target? *Paper presented at the Visual Sciences Society, Sarasota, FL., (May 6 - 11, 2005).*

195. Kunar, M., Michod, K., & Wolfe, J. (2005). When We Use the Context in Contextual Cueing: Evidence From Multiple Target Locations. *Paper presented at the Visual Sciences Society, Sarasota, FL., (May 6 - 11, 2005).*

196. Michod, K., Horowitz, T., & Wolfe, J. (2005). Picture Memory Demands Attention. *Paper presented at the Visual Sciences Society, Sarasota, FL., (May 6 - 11, 2005).*

197. Place, S., & Wolfe, J. (2005). Multiple Visual Object Juggling. *Paper presented at the Visual Sciences Society, Sarasota, FL., (May 6 - 11, 2005).*

198. Wolfe, J., Kenner, N., & Horowitz, T. (2005). Visual search: The perils of rare targets. *Paper presented at the Visual Sciences Society, Sarasota, FL., (May 6 - 11, 2005).*

199. Fencsik, D. E., Urrea, J., Place, S. S., Wolfe, J. M., & Horowitz, T. S. (2005). Differences in speed aid visual search and multiple-object tracking. *Paper presented at the Object Perception, Attention & Memory Meeting, (OPAM), Toronto.*

200. Wolfe, J. M., Flusberg, S. J., Fencsik, D. E., & Horowitz, T. S. (2005). Visual search has no foresight: An event-related signal-detection approach to speeded visual search tasks. *Paper presented at the Psychonomics Society Meeting*(Toronto, Canada (Nov, 2005)).

Horowitz, T. S. & Place, S. S. (2005). How do distractors affect performance on the multiple object tracking task? *Abstracts of the Psychonomic Society*, **10**.

Horowitz, T. S. & Place, S. S. (2005). Rapid recovery of targets in multiple object tracking. *Journal of Vision*, **5**(8), 29.

Santhi, N., Horowitz, T. S., Hilton, M. F., & Shea, S. A. (2005). Efficiency of temporal selective attention is modulated by circadian phase and duration of wakefulness. *Sleep*, **28** (supplement).

Santhi, N., Horowitz, T. S., & Czeisler, C. A. (2005). Night shift work impairs decision-making in visual search. *Sleep*, **28** (supplement)

Fencsik, D. E., Horowitz, T. S., Klieger, S. B., and Wolfe, J. M. (2004). Target reacquisition strategies in multiple object tracking. *Journal of Vision*, **4**(8), 370.

Thornton, I. M. & Horowitz, T. S. (2003). Moving with the MILO task. *Abstracts of the Psychonomic Society*, **8**.

Choi, W. Y., Horowitz, T. S., Horvitz, J., & Mangels, J. (2003). Impaired visual search guidance in Parkinson's disease. *Cognitive Neuroscience Society*, **10**.

Thornton, I. M. & Horowitz, T. S. (2003). Searching for multiple moving targets. European Society for Cognitive Psychology.

Invited Colloquia – Jeremy M Wolfe

Rockefeller U, NY (1/03)	
Concordia U, Montreal (2/03)	Harvard Psych (3/03)
MGH-Navy Yard, Boston (3/03)	MIT-BCS (4/03)
Boston U Beck Memorial Symposium (9/03)	
Macquarie U, Sydney, Australia (1/04)	
Dartmouth (3/04)	Stanford (8/04)
TSA/Atlantic City (10/04)	Duke (3/05)
Columbia (3/05)	U. Illinois (3/05)
Analogic Corporation (6/05)	Northeastern U (9/05)
U Houston (11/05)	

PATENTS & INVENTIONS – NONE

HONORS – Jeremy M Wolfe

Fellow of the American Psychological Association (Div 6)	1995
Fellow of the American Psychological Association (Div 3)	1997
Elected to Society of Experimental Psychologists	2001
Fellow of the American Psychological Association (Div 1)	2002
Fellow of the American Psychological Society	2002
Fellow of American Assoc. for the Advancement of Science	2002