Benefits of Distributional Analyses in Visual Search: Bounded Exponential Distributions Falsify Dichotomous Architectures of Search

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Abstract

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Bruno Richard

Visual search is one of the most common paradigms used to study attention, for it allows the effective mimicking of tasks we perform naturally in our environment while maintain a larger amount of control over possible confounding variables. Although the paradigm in of itself has been quite beneficial to the field of attention research, the analyses that accompany it, focused predominantly on mean response times, and their positive slopes through increasing set sizes, have been demonstrated to be severely limited when describing the underlying architecture of search (parallel versus serial). In addition, the omnipresent skew of response times distributions nullify the possible interpretations typically associated with central tendency measures such as means.

We investigated how distributional analyses, which assess the entire response time distribution could accurately describe changes in response times through typical manipulations of visual search paradigms (set size, target presence and difficulty). We used the Weibull distribution, a left-bounded distribution to fit the response time data. Results demonstrated that search in of itself is not a dual architecture that changes under search difficulty, but a single mechanism that simply increases the duration of search when the difficulty conditions increased. The Weibull is therefore strongly recommended when analyzing response time data collected in visual search paradigms.

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Visual search is one of the most common paradigms in assessing visual attention. The paradigm allows for the mimicking and replication of tasks that we perform regularly in our natural world. Additionally, it allows for an increased control over the manipulation of variables such as display duration, properties of the stimulus, and the possible responses from participants (Cousineau & Shiffrin, 2004; Wolfe, Palmer, & Horowitz, 2010). The use of visual search paradigms in perception research have lead us to an overwhelming amount of data about search, including how one might perform a search task by integrating the information subjects are presented with, the ability to recognize the target and select the appropriate response, and how visual search might be terminated (Logan, 2004; Wolfe, Cave & Franzel, 1989; Wolfe, 1994; Wolfe, 1998; Wolfe et al., 2010). Most of these effects have been based on changes observed in measures of central tendency - such as means and medians - when conditions in the visual search paradigm are changed to become more difficult (Logan, 2004; Townsend & Ashby, 1983;Wolfe, 1998; Wolfe et al., 2010). Usually search is made more difficult by increasing the number of stimuli present (Treisman & Gelade, 1980), or by decreasing the difference between the target and the other stimuli present (Baldassi & Burr, 2000; Treisman & Sato, 1990). Research that has dwelled in the analysis of response times have demonstrated that means and medians might not be an appropriate method to represent results this being largely due to the omnipresent skew seen in most response time distributions (Bricolo, Gianesini, Fanini, Bundesen, & Chelazzi, 2002; Hockley, 1984;

Ratcliff & Murdock, 1967; Sung, 2008; Townsend & Ashby, 1983; Townsend & Wenger, 2004; Wolfe et al., 2010).

Previous experiments have demonstrated that increases in averaged response times collected from various cognitive paradigms were actually due to changes in the skew of distributions, and not their mean (Ratcliff & Murdock, 1976; Hockley, 1984). Therefore, there is a need to assess response times accurately by incorporating the skew of their distributions in visual search analysis (Heathcote, Popiel, & Mewhort, 1991; Townsend & Wenger, 2004; Wolfe et al., 2010). As such, measures describing the shape of response time distributions, and how they can affect the mean response times usually observed should be investigated (Rouder & Speckman, 2004; Rouder, Lu, Speckman, Sun, & Jiang, 2005; Townsend & Wenger, 2004; Wolfe et al., 2010). Distributional analysis could answer how search difficulty or conditions affect response times better than the typical mean or median (Compton & Logan, 1991; Ratcliff & Murdock, 1976). Consequently, the aim of the current research is to assess the advantages of parameter fitting over traditional mean analyses, and to investigate how the parameters vary with changes of search difficulty.

Visual Search

In its most basic form, the visual search paradigm requires an individual to scan through an array of stimuli, in which one element (henceforth termed the *target*) may differ from all other elements (henceforth termed *distractors*) within the array (Wolfe, 1998). A typical experiment will separate half of the trials as target present, and the other half as target absent (i.e. all elements are distractors). After each trial, the observer must indicate which condition was presented (i.e. target present versus target absent). This permits a measure of accuracy from the observer (percent correct), and a measure of the time taken to make that judgement. Response times are typically assessed as a function of set size (i.e., the number of distractor present) and separated by target presence (Treisman & Gelade, 1980). A slope that depicts the increase of response times as a function of the number of distractors can be calculated; giving an estimation of the amount time spent investigating a single item within the search array (Treisman & Gelade, 1980; Wolfe et al., 1989).

The ability to measure the amount of time exploring a single item is greatly beneficial to visual search, since different types of stimuli will lead to different latencies of response from participants (Palmer, 1993; Wolfe, 1998; Wolfe et al., 2010). Stimuli, which differentiate the target from distractors on a single feature, (e.g., colour, contrast, luminance, shape) will typically elicit very rapid responses, and be independent of the number of distractors presented with the target (Treisman & Gelade, 1980; Treisman & Sato, 1990; Wolfe Wolfe, 1998). The rapidity of response is attributed to a search being performed in parallel (i.e., encompassing the entire search array at once), and the target "popping-out" from the distractors, making its identification simple and rapid (Klein & Farrell, 1989; Treisman & Gelade, 1980, Treisman & Sato, 1990; Wolfe et al., 1989).

Stimuli that differentiate the target from the distractors on a conjunction of two or more features will require more time as a function of set size (Treisman & Gelade, 1980; Wolfe et al., 1989). The task cannot be performed in parallel, for the "pop-out" effect of a single feature has been greatly diminished, and each stimulus must be explored individually to assess whether it is the target or a distractor. This process is arguably performed in a serial manner since each object is explored individually, moving from one to the next until all stimuli are explored. Individually exploring each stimulus permits the integration of multiple features into a cohesive whole (Treisman & Gelade, 1980). This individual exploration of stimuli results in a larger amount of time spent on each item (usually 10 ms/item: Tresiman & Gelade, 1980; Wolfe, 1991; Wolfe et al., 2010), resulting in longer reaction times that increase as a function of the number of distractors (Treisman & Gelade, 1980; Wolfe et al., 2010). The golden rule of 10ms/item to describe a conjunction search is only an average of the findings from multiple conjunctions of features, as it has been demonstrated that these various combinations can lead to relatively large changes to the slope of response times (Cavanaugh, Arguin & Treisman, 1990; Duncan & Humphreys, 1989; Palmer, 1995; Treisman & Sato, 1990; Sung, 2008; Ward & McClelland, 1989). Target presence will also affect response times in a conjunction search. When exploring each item, search can be terminated early if the target is found prior to the entire display being searched, while if a target is absent, the entire array must be explore prior to termination of search, making "target absent" responses longer than "target present" responses (Wolfe et al., 2010). A ratio between the slope values for both types of responses can be calculated, and for conjunction search it will typically lie around 2:1 for target absent to target present search slopes (Treisman & Gelade, 1980).

Feature searches (i.e., single features) and conjunction searches (i.e., two or more features) are the most common types of search paradigms, and are the basis of most visual search models (Logan, 2004; McElree & Carrasco, Treisman & Gelade, 1980; Townsend & Ashby, 1983; Treisman & Sato, 1990; Wolfe et al., 1989; Wolfe, 1994; Wolfe, 2007; Wolfe et al., 2010). Other search paradigms can also have differential effects on response times. Spatial configuration tasks, where the physical properties of the stimulus do not change but their configuration does (e.g., 2 VS 5), can typically illicit large set size effects (i.e. larger than a conjunction search). It yields the largest amount of time spent on each item (around 30 ms/item), and therefore the longest response times in comparison with other types of search (Wolf et al., 2010). Spatial-configuration search is an ideal paradigm when assessing large set size effects search, and have recently been taken into consideration when modelling visual search (Wolfe et al., 2007).

Models of Visual Search

From the three search conditions mentioned above, feature searches and conjunction searches have been the most extensively modelled (Bundensen, 1990; Townsend & Ashby, 1983; Townsend & Wenger, 2004; Treisman & Gelade, 1980; Treisman & Sato, 1990; Wolfe et al., 1989). Models of visual search have tried to depict how the temporal process of search may be reflected in slopes obtained from response times. Two families of architecture (i.e., serial and parallel) seem to dominate the literature (Townsend & Wenger, 2004). Some models of search incorporate both architectures, while others tend to focus on a single one. However, none have yet proposed a definitive explanation to how response times change according to various visual search paradigms. As such, the question of architecture in visual search remains popular today (Townsend & Wenger, 2004). Following is a brief review of some of the popular models of visual search, and how they include one or both families of architecture.

Serial models.

Serial models of visual search all have the same underlying assumptions; they all assume an independent processing of each stimulus element (Townsend, 1990; Townsend & Colonius, 1997; Townsend & Wenger, 2004). Capacity in serial search is limited to a single object at a time, and search cannot go on to the next element until the current object has been processed (Townsend & Wenger, 2004). In addition to independence, processing speed during the search is assumed to be constant for each individual item, and therefore attention is moved at the same speed from one trial to the next.

Popular models of visual search that include a serial architecture, such as Feature Integration Theory (Triesman & Gelade, 1980; Treisman & Sato, 1990) and Guided Search (Wolfe et al., 1989; Wolfe, 1994; Wolfe, 2007) propose a dual architecture of search, beginning with a pre-attentive unlimited capacity parallel stage, and if need be, and additional serial search stage. In the Feature Integration Theory (Treisman & Gelade, 1980), the unlimited capacity parallel stage can process single feature stimuli without the deployment of attention, making response times rapid and unaffected by set size. Conjunction search paradigms, where two or more features describe the stimuli cannot be processed in parallel, and therefore require a serial search to identify the target (Treisman & Gelade, 1980). The serial search is putatively required to bind the multiple features into a uniform representation of the stimuli permitting their classification as a target or a distractor.

Similarly to the Feature Integration Theory, the Guided Search Theory proposes the same dual architecture, but adds that the parallel process of identifying a single feature can aid in guiding the serial search process towards only the relevant features

(Wolfe et al., 1989). The parallel process can only assess individual features, as it is assumed to do in the Feature Integration Theory, and therefore when initially presented with the search array, individuals can focus search on objects that contained the desired feature by creating a saliency map, which is reflective of how salient the desired feature is amongst the distractors. In a single feature search, this filtering of the search array would guide attention to the target directly, while in conjunction search, it could facilitate the search, minimizing the cost of having to search each item individually (Wolfe et al., 1989). Guidance, in the Guided Search models, which can also be thought of as attention serves to more than simply bind specific features, as proposed by the Feature Integration Theory, but in addition, can adjust the strength of the signal received from the array of stimuli presented to the participant. As such, the information gained from the parallel stage is not lost once a serial search is used to complete the task (Wolfe et al., 1989).

Both models acknowledge the asymmetries found in conjunction searches. As previously mentioned, the steepness of the search slope in conjunction search, or the increase of response times as a function of set size, can vary as a function of the features that compose the stimuli for some features, such as color have been demonstrated to be simpler to identify than others, such as orientation (Baldassi & Burr, 2000; Cavanaugh et al. 1990; Duncan & Humpreys, 1989; Treisman & Sato, 1990). The Guided Search Theory (Wolfe et al., 1989) stipulated that guidance is not identical across all types of features, and that the range of slopes found in conjunction search paradigms would mostly be based on the ability of the pre-attention parallel mechanism to guide attention effectively (Wolfe et al., 1989; Wolfe, 2007). A similar revision of the Feature Integration Theory has been brought on by the growing evidence of parallel processing in conjunction searches (Duncan & Humphreys, 1989; Palmer, 1995; Townsend, 1990). Treisman and Sato (1990) found that conjunction search with highly discriminable features such as colour and contrast (Wolfe, 2007) can be performed in parallel, while others, such as shape, or colour and orientation cannot. The findings indicate that the target / distractor similarity can greatly affect performance (Duncan & Humphreys, 1989; Sung, 2008; Treisman, 1991; Treisman & Sato, 1990; Wolfe, 2000).

In addition to the processing of a single or multiple features, serial models of visual search also describe the rules that depict the termination of a search. In single feature trials, target presence seems to affect response time very little. A target is quickly identified, or diagnosed as absent, and a response made (Treisman & Gelade, 1980; Wolfe et al., 1989; Wolfe, 1992). Conjunction searches, on the other hand, where a serial search is required to find the target will terminate differently on target present and target absent trials (Treisman & Gelade, 1980; Wolfe, 1992). This is because target present searches are evidently terminated once the target is found and correctly identified (termed *Self-Terminating*; Shriffin & Schneider, 1977; Treisman & Gelade, 1980; Wolfe et al, 1989). However, target absent searches can only be terminated once the entire search array has been investigated, either serially or in parallel and all objects have been classified as distractors (termed *exhaustive*). Treisman & Gelade (1980) proposed to look at the variability of target present and absent response times in order to assess whether or not search was self-terminating. Since exhaustive termination suggests that responses of "target absence" will only occur at the end of the complete exploration of the search array, and that the rate (or speed) of search is constant, then the variance terms between trials of identical set sizes should be similar (if not identical). Conversely, "target present" responses can occur at any moment during the search leading to greater variance. They found that such was the case; variability of target absent responses was much smaller than target present trials. Similar effects have also been found in search conditions that create large set size effects (Bricolo, Gianesini, Fanini, Bundesen & Chelazzi, 2002), but have not been replicated in other visual search paradigms (Wolfe et al., 2010).

Termination in the Guided Search Theory (Wolfe, 1994) varies slightly from the Feature Integration Theory (Treisman & Gelade, 1980). Since it focuses largely on guidance from the parallel stage to the serial stage, termination in the Guided Search Theory (Wolfe, 1994) functions by setting a termination threshold as a part of saliency map created by the parallel stage. If the output from the map is strong, meaning that the target is highly discriminable from the distractors, then the threshold will be low maximizing rapid responses for "target present", while lower thresholds (target absent) would reinforce an exhaustive search, verifying that all stimuli are distractors prior to the "target absent" response (Wolfe, 1997; Wolfe, 2007).

Parallel models.

Unlike serial models, parallel models assume that the entire array can be processed simultaneously, without serial shifts of attention, regardless of stimulus composition or set size (Townsend, 1990; Townsend & Wenger, 2004). Parallel models (Palmer, 1995; Ratcliff, 1976), just as in serial models, are subject to issues of capacity, and can be limited, where groups of stimuli can be processes simultaneously. However, adding more groups will slow down processing or unlimited, in which the number of distractors, will not affect response latencies (McElree & Carrasco, 1999; Palmer, 1995;

Townsend, 1990; Townsend & Wenger, 2004; Wang, Kristjansson & Nakayama, 2005; Ward & McClelland, 1989). Importantly, the unlimited capacity in visual searches refers to the speed of the search, and how it is unaffected by increases in the demands of the task. Yet it does not assume that the mechanism in and of itself is of infinite capacity, infinitely demanding tasks will overwhelm the mechanism. Limited capacity models, which are capable of processing chunks of stimuli simultaneously are affected by set size, can produce positive slopes found in conjunction search paradigms (Townsend & Ashby, 1983; Townsend & Wenger, 2004).

Popular classes of parallel processing models of visual search are race and random walk models (Cousineau et al., 2002; Ratcliff, 1978; Townsend & Ashby, 1983). Both models predict that there is an accumulation of information over time until a certain threshold (i.e. criterion) is reached and a response (either a target present or target absent) is made (McElree & Carrasco, 1999; Ratcliff, 1978; Townsend & Ashby, 1983). Although both models describe visual search as information accumulation over time, they differ in how this information is accumulated. Race models assume that the accumulation process is independent for all stimuli (Townsend & Ashby, 1983). Therefore, multiple counters, which gather information, are activated when an array is presented, and the first counter to accumulate enough information (as in a race) will elicit a response. The counts can be interpreted at many different levels, but Townsend and Ashby (1983) favoured the possibility of counts resembling action potentials that travel down some neural pathway. When asked to identify a line of a specific orientation, horizontal for example, there would be a feature detector that would respond most strongly to such a horizontal stimuli. The recognition of the horizontal line would therefore become a matter of counting the action potentials, and according to the strength of the action potentials, generating a response. The rate of accumulation is dependent on the capacity of the counters, but they are typically believed to accumulate information over chunks of stimuli, which vary in size according to the feature composition of the stimuli (Bundesen, 1990; Townsend & Ashby, 1983).

Unlike counting models, random walk models assume there is only a single counter that accumulates information from the entire array over time, eventually leading to a response, which must be dichotomous (i.e. target present versus target absent). Since the response is dichotomous, and therefore a response is contingent on the other not been true, the accumulation of evidence towards a specific response is evidence against the other (Ratcliff, 1978; Townsend & Ashby, 1983). The diffusion model (from the random-walk family) proposes that criterions are set as to identifying either target absent or present. Search will begin at a specific position and will at a certain point during search exceed a specific boundary, eliciting a response (Ratcliff, 1978).

Bundesen (1990) suggested that termination in parallel models would function as a race of alternatives in target present searches, where speed would be affected by the amount of interference or distraction, brought forth by the distractors. As such, feature searches, where distractors interfere little with the target will end rapidly, the opposite is true when the distractors interfere greatly with the distractor (i.e., conjunction search). The self-terminating rules for target present searches that were proposed in serial models also apply to the parallel models of search (Townsend & Colonius, 1997). Once enough information is accumulated to identify a target, search is terminated. Target absent searches, one the other hand, would follow a “time-out” procedure, since the absence of a target could elicit a self-termination (Bundesen, 1990).

Model mimicking.

Both parallel and serial models can elicit similar response times even though the underlying architectures are fundamentally different, leading to difficulties in distinguishing between serial and parallel architectures. The propensity for different models to generate similar results is called model mimicking (Cousineau & Shiffrin, 2004; Townsend & Wenger, 2004*)*. When modelled, parallel architectures can elicit steep search slopes when the rate of accumulation is varied between trials, or when set size is increased (Townsend & Ashby, 1983; Townsend & Colonius, 1997; Townsend & Wenger, 2004). In addition, specific types of conjunction search that are believed to enforce a serial search architecture (Treisman & Gelade, 1980) can produce shallow search slopes, indicating that search is as efficient, or as rapid as single feature conditions (Treisman & Sato, 1990; Wolfe, 1983). This can be due to the efficiency of the saliency map at distinguishing the target from the distractors, or simply to the high stimulus discriminability (Bundensen, 1990; Wolfe et al., 1983). Combinations of colour and motion, or colour and orientation, have been found to elicit efficient search slopes even if the target is a combination of two features (Cavanaugh et al., 1990; Treisman & Sato, 1990; Wang, Kristjansson, & Nakayama, 2005; Wolfe et al., 1989). Feature search conditions can also elicit more serial-like search slopes when the difference between the target and distractor is reduced, for example, from a red / green search to a red / orange colour feature search (Wolfe, 1998), or with varying orientation criteria for the target and distractors (Cavanaugh et al., 1990; Wolfe, 1998). Careful modification of single features can easily produce the 2:1 slope ratio typically used to assess a serial architecture, making its validity in the process questionable.

Model mimicking typically occurs when scanning rates vary with the set size (Logan, 2004; Ratcliff & Murdock, 1976), or if target rejection is not an independent process (Townsend & Colonius, 1997). In parallel models, independence refers to the processing of *n* items within a specific time interval, while serial models describe independence as the processing time of each succeeding item as independent from one another (Townsend & Wenger, 2004). Violations of independence in either parallel or serial models lead both to produce similar results for the regulations of how many items can be assessed simultaneously will no longer be constant, and prevent a clear-cut understanding of the type of architecture at play within visuals search when simple mean analyses are used.

Analyses of Reaction Time Search Data

Search slopes.

Models of search have predominantly focused on response times and how they translate to search efficiency, or the overall slope of response times (flat slopes are considered efficient while steep slopes are not). Such differences can be measured by calculating the ratios between positive (target present) and negative (target absent) response times slopes across all levels of set sizes (see Figure 1). Search slopes, and their ratios have been used in assessing results of visual search paradigms, though they have long been considered as insufficient evidence when describing effects of visual search paradigms (Bricolo et al., 2002; Cousineau & Shiffrin, 2004; Hockley, 1984; Ratcliff & Murdock, 1976; Wolfe et al., 2010). Although a slope of response time means can fit the data well (R^2 are typically above .90: Wolfe, 1991), it cannot differentiate between different models of visual search architecture (Townsend, 1990; Townsend & Wenger, 2004; Wolfe, 1991; Wolfe et al., 2010). The association between response times to set size has been demonstrated to occur in both parallel and serial models of search, making the distinction unclear (Duncan & Humphreys, 1989; Townsend & Ashby, 1983; Townsend & Wenger, 2004; Wolfe, 1998; Wolfe et al., 2010). Search slopes, therefore, do not distinguish between architecture but at best simply demonstrate that search can be of limited capacity when they increase as function of set size (Townsend, 1991). Search slopes are not necessarily detrimental to describing visual search in details, and allow a rapid overview of the effects of the search paradigm on response latencies, but are not stringent enough to thoroughly argue an architecture of search over another, or properly assess the changes of the response time distribution, for they only represent the arithmetic mean (Bricolo et al., 2002; Heathcote, Popiel & Mewhort, 1991; Townsend & Ashby, 1983; Townsend, 1990; Townsend & Wenger, 2004; Wolfe et al. 2010).

In addition to the visual interpretation of search slopes, ANOVAs or Regressions are typically used in the analysis of response times to measure the effects of target presence and set sizes. Null hypothesis significance tests (NHST) such as ANOVAs are convenient methodologies to either support of reject the null hypothesis, but have a few assumptions that cannot be violated in order to interpret their results (Klein, 2004). More importantly, NHST assume that the underlying distribution(s), which is being tested, is normally distributed. However, response time distributions are notoriously skewed, violating an assumption of NHST and rendering the interpretation of central tendency measures as means and medians to be unclear as opposed to when the underlying

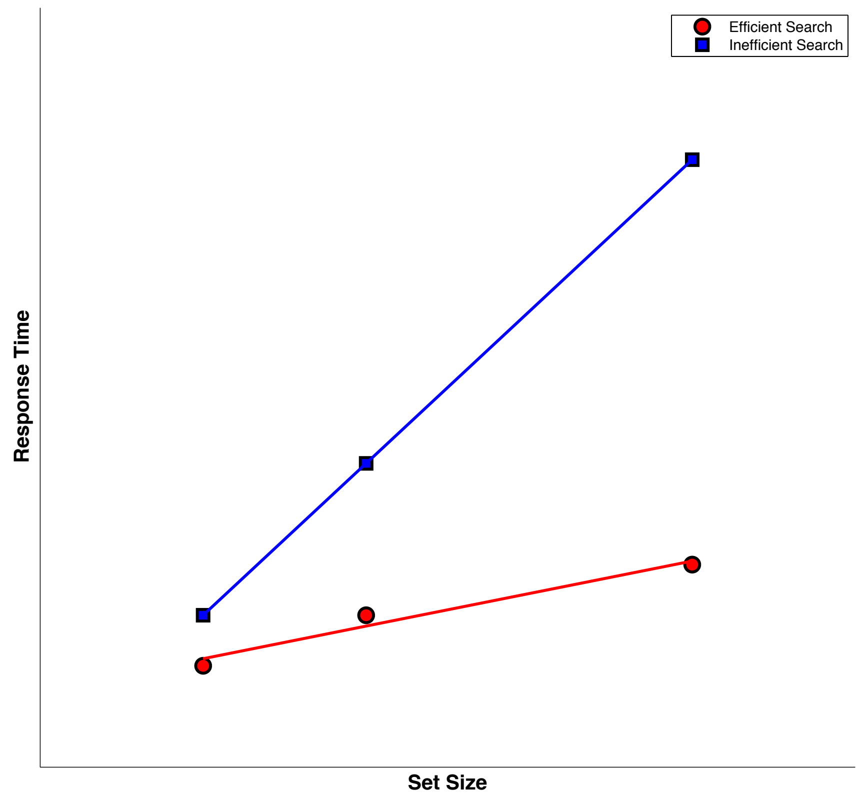

Figure 1. Typical representation of search slopes when analysing response time data from a visual search paradigm. The red line is considered efficient for it is shallower than the blue line, indicating that set size has less of an effect on the search latencies represented in red than it does on the search latencies represented in blue. The markers on the figure represent the data points while the lines show the fit of a slope onto the three points.

distribution is normal (Heathcote et al., 1991; Wolfe, 1991; Wolfe et al., 2010).

Skew.

Describing the shape of distributions can be particularly beneficial when analysing response time distributions since it can describe the skew (deviation from the normal distribution), a property of response time distributions unexplained by response times means or their slopes (Heathcote et al., 1991). The skew can stem from the extreme scores, which occur in a few trials, and the minimum possible response time bounding the lower tail of the distribution. Skewness has either been viewed as an effect of the paradigm and should therefore be analysed, or noise within a paradigm that typically yields normal distributions, in which case it should be removed (Heathcote et al., 1991; Wolfe et al., 2010). Removing the skew of distributions can be accomplished in various ways, such as recursive outlier analyses, simple trimming of the dataset or transformation of the distributions such as Vincentizing, or normalization techniques (z- transform: Heathcote et al., 1991; Hockley, 1984; Ratcliff & Murdock, 1976; Wolfe et al., 2010). Evidently, changing a distribution to better fit the assumptions of NHST assumes that the skew of such a distribution is produced by noise within the task, and not an actual effect. Yet, distributional analyses use in the past on other paradigms than visual search, have demonstrated that mean changes typically observed a task is not brought on by the mean of the response time distribution but a change in its skew, reinforcing the importance of considering the skew when analysing response time data, and finding alternatives to the significance testing of search slopes based off of central tendency statistics (Ratcliff & Murdock, 1976; Hockley, 1984).

Distributional Analyses of Reaction Time Data

Ex-Gaussian.

The importance of investigating how skew may change in response time distributions as a function of experimental condition and insufficient evidence for architecture brought forth by search slopes have stimulated the use of distributional analyses in cognitive paradigms that use response times as a dependent variable. Ratcliff and Murdock, (1976) used a memory search paradigm, which investigated the ability to differentiate a novel word from an old one after a serial presentation of words. Unlike previous experiments, the authors chose to parameterize their dataset with a mixture distribution (Ex-Gaussian) in an effort to get a complete understanding of the effects of recognition memory paradigms on response time distributions. The Ex-Gaussian distribution is a convolution (the integral of the product of the two functions) of a normal and exponential distribution (see Figure 2) with a location (the mean or μ) parameter, a variance parameter (the standard deviation, or σ) and a shape parameter (the exponential drop off, τ; Ratcliff & Murdock, 1976; Lacouture & Cousineau, 2008). The Ex-Gaussian probability density function is described as:

$$f(x_i \mid \mu, \sigma, \tau) = \frac{1}{\tau} \exp\left(\frac{\mu}{\tau} + \frac{\sigma^2}{2\tau^2} - \frac{x}{\tau} \right) \phi\left(\frac{x - \mu - \sigma^2/\tau}{\sigma} \right)$$

Where ϕ is the cumulative density function of the standard Gaussian distribution.

Typical mean analysis of response times demonstrated that the correct identifications (i.e. hits) were faster than correct rejections, and that increasing the output position, or the delay until it would be shown again, of the old word in the testing phase increased response times. In addition, the mean response times for both the hits and correct rejection increased as the number of words to be memorized increased, demonstrating an effect of list length (Ratcliff & Murdock, 1976). In contrast, the distributional analysis revealed that changes in the mean values of responses between hits and correct rejections for output position were not mediated by changes in the mean of the distribution, but in its exponential parameter (τ). Changes in the list length, on the other hand, produced changes in both the mean parameter (μ) and the exponential parameter (τ). Therefore, increases in response times did not necessarily reflect an increase in actual time, but the normalization (loss of skew) of the response time distributions (Ratcliff & Murdock, 1976). Ratcliff and Murdock (1976) demonstrated that response time distributions in a memory paradigm could change differently based on the manipulations of the paradigm. Therefore, different cognitive tasks could elicit very different changes in the mean component of the distribution and its skew. In an effort to assess how the parameters of the Ex-Gaussian may change under different cognitive demands, Hockley (1984) replicated the analysis methodology proposed by Ratcliff & Murdock (1976) and used different cognitive paradigms; a visual search, and judgement of recency and a force-choice recognition paradigm.

The visual search paradigm used by Hockley (1984) was composed of a series of non-words presented to observers (either two or six letters long) that either contained a target letter (e.g. Z or Q) or did not (Neisser, 1963). Both conditions could be targets depending on the trial. Previous results based on the mean response time of participants demonstrated that such searches were serial for both target conditions (the target word either contained a target letter or did not), self-terminating in target present search and exhaustive in target absent searches. Secondly, Hockley (1984) used a memory search

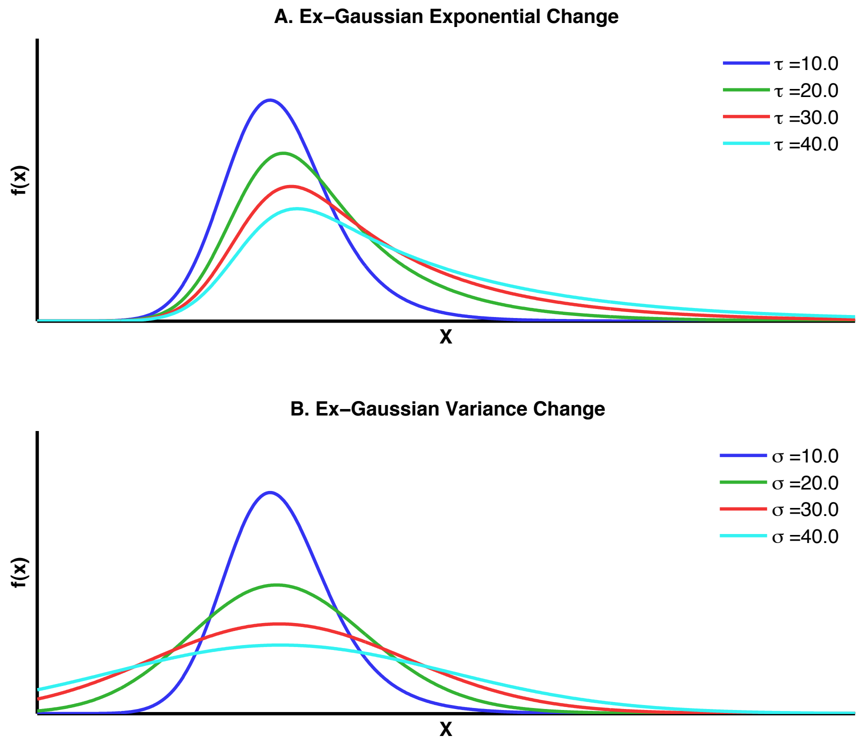

Figure 2. A. The Ex-Gaussian distribution as its exponential parameter (τ) changes but all other parameters are kept constant ($\mu = 50$; $\sigma = 10$). B. The Ex-Gaussian distribution as its variance parameter changes but all other parameters are kept constant ($\mu = 50$, $\tau = 10$). The location parameter, μ was not changed here for it only shifts the distribution without affecting its shape.

designed by Sternberg (1966), which presented an array of one to six single digits to observers for 1.2 seconds and, after a two second delay, were probed with a digit. Participants had to respond whether or not the probe had been part of the array. The results demonstrated positive slopes of response times as a function of set size, while target present and absent slopes were relatively similar (Sternberg, 1966). In addition, the same observers performed both types of search task permitting a within subject analysis of the changes in the response time distribution. When applying a convolution distribution (Ex-Gaussian) analysis to both visual search paradigms, Hockley (1984) demonstrated that in the response times of Neisser's (1963) paradigm were mostly modulated by μ, although τ did increase slightly in target present searches, consistent with a serial processing search architecture, for they supported the assumptions that the process was not very variable (i.e. small changes in σ) or skewed (small to no changes in τ; Hockley, 1984).

Increases in response times of the memory paradigms were brought on by τ and not μ, suggesting a loss of skewness actually created the positive slopes, and not increases in response latencies. Both response time slopes for target present and absent conditions greatly resembled the increase in the values of the Ex-Gaussian parameters across set size. Consequently, for results of the memory search to be consistent with a serial model, its comparison process would have to be variable (Hockley, 1984), suggesting that another process may be at play.

The Ex-Gaussian has been used more recently to assess changes in response time datasets for various paradigms such as Stroop Tasks and Problem-Size effects. Heathcote and colleagues (1991) proposed using the Ex-Gaussian distribution to characterise a response time distribution from a Stroop task. When analysing a Stroop task, researchers typically look for either a facilitation effect or an interference effect (Heathcote et al., 1991). This is accomplished by having three different stimulus conditions: A neutral condition, where the words presented to participants are a series of Xs of a certain colour they must name, and word stimuli where the word and the color may match (facilitation) or be incongruent (interference).

In the mean analysis, Heathcote and colleagues (1991) found interference in the incongruent condition, but no facilitation effect in the congruent condition (i.e. same as baseline). Therefore, participant response was significantly longer when the word and the colour did not match, but did not benefit (as compared to baseline) when they did. When performing their distributional analysis, they found that μ (i.e. the mean of the Ex-Gaussian) was greater than baseline in the incongruent condition, but was also shorter in the congruent condition. They also found that τ (i.e. the exponential component of the Ex-Gaussian) showed interference in both the congruent and incongruent conditions, indication that the shape of the distribution in both conditions were increased as compared to base line. The increase in τ, which may not normally be seen when simply calculating the mean of the response times by Stroop condition demonstrated that although the mean response time in congruent conditions may remain relatively short (lying between the baseline and incongruent condition) the shape of the distribution did increase, indicating a larger proportion of scores lying above the mean as compared to the base line condition. Therefore facilitation effects, typically demonstrated by the lack of a mean change between baseline and congruent conditions were not as well defined as previously believed for the distribution did change between both tasks (Dunbar & MacLeod, 1984; Heathcote et al., 1991).

Other cognitive paradigms have also benefited from distributional analyses to clarify theories behind the problem-size effect, which describes how larger mathematical problems take longer to complete than simpler ones (Penner-Wilger, Leth-Steensen & LeFevre, 2002). The response time difference between simple and complex problems has mostly been attributed to the process undertaken by the individual to solve the mathematical dilemma. Longer responses are typically attributed to the individual decomposing the equation they were asked to solve versus simply extracting it from memory, which would be much faster, although such an assumption seems to still be debated within the problem-size effect literature (Penner-Wilger et al., 2002). This occurs mainly because slopes of response times in problem size effects can only demonstrate that the decomposition slope is higher than the memory slope, but can not identify the subtle changes occurring within the distribution.

Penner-Wilger and colleagues (2002) explored how these differences could come about using an Ex-Gaussian distributional fitting of their response time data. They theorized that if participants were decomposing the formulas to answer the questions, there should be an increase in the longer response times, or in the tail of the distribution, which would affect its skew, while if they used memory there should be changes in the mean. Participants that could complete the problem from memory had no change in τ from a simple mathematical problem to a more complex one, but did have a small increase in μ from simple to complex equations. Participants who had to decompose had large increases in both the μ and τ parameters suggesting that as the problem became harder, the amount of longer response times increased as well (i.e. larger probability of falling above μ). Parameters can change differently depending on the cognitive demand making it possible to test the assumptions of underlying processes via their changes (Penner-Wilger et al., 2002).

Non-parameterized distribution analyses.

Assessing how the parameters of the Ex-Gaussian may change across conditions has been quite beneficial on describing the actual changes in the response time distributions and how they could possibly reflect certain processes over others. These parameters could therefore be very informative on testing the architecture beliefs of visual search. Although individual distributions may properly characterize the response time data, some can argue that this is a problematic approach. The appropriate distribution to use to fit response time data is still unclear for many different types of distributions can fit response time data equally as well (Bricolo et al., 2002; Cousineau, Goodman & Shiffrin, 2002; Cousineau & Shiffrin, 2004; Logan, 2002; Palmer, Horowitz, Torralba, & Wolfe, 2011; Ratcliff & Murdock, 1976; Rouder, Lu, Speckman, Sun & Jiang, 2005; Wolfe et al., 2010). In addition, parameterizing a distribution of response times could lead to a desire to infer that they represent cognitive processes, and although the changes in parameters could aid in ultimately identifying such processes, they should not be interpreted as direct reflection of cognitive process (Wolfe et al. 2010). Consequently, others, investigating visual search directly, have opted to approach distributional analyses without defining parameters, such as location, mean or standard deviations, for their distributions (Bricolo et al., 2002; Sung, 2008).

Models of visual search predict that as search difficulty increases, serial search mechanisms must be used to identify the target (Baldassi & Burr, 2000; Treisman, 1991; Treisman & Gelade, 1980; Treisman & Sato, 1990; Wolfe et al., 1989; Wolfe, 2007). Yet, as mentioned, the distinction within the literature on when a serial search is required is unclear. In an effort to demonstrate that set size effects are due to a serial search mechanism, Bricolo and colleagues (2002) manipulated difficulty in search by increasing stimulus-distractor similarity (Treisman, 1991), leading to inefficient search. They used an orientated T paradigm with orientations 0° (upright), +90°, 180°, -90°). All orientations, except for the upright condition, could define the target throughout the entire experiment. Slope analyses revealed that the effect of set size in their task was quite large. Target absent slopes average over 250 ms per items while target present slopes averaged at about 126 ms per items. From the large set size effects found, a serial architecture was believed to be underlying the response times from participants. Following the large set size effects, Bricolo and colleagues (2002) measured the cumulative distribution of their data in an effort to assess the termination rules followed by the participants. As expected from the Feature Integration Theory (Treisman & Gelade, 1980), they found that in target present conditions, the minima did not vary across set size, indicating a self-terminating search. However, it did change in the target absent condition, suggesting an exhaustive termination of search. Although the cumulative distribution described the termination rule of participants when completing the search task, it could not reveal on the actual architecture of participants. Therefore, Bricolo and colleagues (2002) developed two models, a parallel and a serial model, and fitted both to their data. They found that both models could fit the data relatively well, but that a serial approach using the convolution of multiple exponential distributions (about 1 per item in the display) better represented the investigation of individual items (cycles) of a serial search.

Since both the parallel model and serial model could explain the data well, Bricolo and colleagues (2002) developed a second experiment, where they manipulated the serial position of the same target that was previously used, they found that the same serial model could still explains the results while a new, limited capacity parallel model, was required to explain the results of the serial position experiment. Since only one serial model of search was required to explain both experiments, while two parallel models were required, Bricolo and colleagues (2002) suggested that a serial self-terminating model of search was best suited to explain their results. Although a serial search model accounted for the results found by Bricolo and colleagues, such results seemed to only stem from large set size effects when search is inefficient and slopes are quite steep (> 250 ms/item). In addition, they did not compare how their participants performed in simpler tasks, which would normally elicit shallower search slopes.

Although Bricolo and colleagues (2002) demonstrated that serial search could occur in difficult search conditions that elicit large set size effects, both experiments that supported their theory could of also stem from different parallel mechanisms that would respond differently under various demands, preventing a clear distinction of architecture in search (Logan, 2004). As such, an investigation of search paradigms that would directly elicit the second stage (serial) of processing in search placed in context with simpler search paradigms could clarify whether inefficient search necessarily reflects a serial mechanism (Sung, 2008). In addition to using stimuli that should elicit serial mechanisms of search, Sung (2008) used a modified distributional analysis of response time data termed interaction contrast. Interaction contrasts use pairs of processes that are related to each other in one of two ways: either they must follow each other or neither does (i.e. they are simultaneous). The visual experiments consisted of factors (stimulus type) and two difficulty levels (easy and hard), and could be presented in four possible combinations, where both factors are presented at either both their easy level, one easy and one difficult (interchangeable between the two) and when both are difficult. They then measured the interaction contrast across the entire cumulative distribution of response times for all conditions. If both processes were sequential, the interaction contrast would be positive at the beginning, but then change its sign to negative afterwards, and the total area under the distribution if interaction contrasts would be equal to 0 or a negative value. If they were simultaneous, the mean interaction contrast would remain positive across time, indicating parallel processing (Sung, 2008).

In two of the three experiments, Sung (2008) found that parallel processing was responsible, even though some search slopes reached 20 ms/item. Experiment 1 used a conjunction task of shape a colour while experiment 2 manipulated stimulus similarity with orientated T’s and adding circles, which greatly differed from the T’s, to make search easier (Bundesen, 1990). The third experiment replicated the visual search paradigm developed by Bricolo et al. (2002) to generate large set size effects, and showed that serial processing was required for participants to complete the task. Sung (2008) concluded that although parallel processes seemed to be mostly responsible for visual search, some serial processing could can occur, but only when the set size effects were quite large (search slopes of about 100 ms/item), following the proposition that attention requires at least 80 ms per scan, and then shift from one object to another (Hoffman, 1972). In addition, the changes in search slopes found within the dataset suggested that although parallel processing seems responsible for search, this process is limited in capacity. Search in parallel could therefore be completed when it is possible to search through a certain number of targets simultaneously (i.e., limited capacity), with that number changing depending of the difficulty of search, while serial search would only occur when only one object can be examined at a time (Fisher, 1982; 1984; Sung, 2008).

Current Project

Previous studies have demonstrated via search slopes and distributional fitting that search architecture is not as clearly defined as once believed (McElree & Carrasco, 1999; Sung, 2008; Logan, 2004; Logan, 2002; Hockley, 1984; Townsend & Ashby, 1983; Townsend & Wenger, 2004). Although analyses of response time distributions have been used in the past, most experiments that precisely focused on visual search paradigms approach the analysis without a specified distribution, making the possible interpretations more qualitative than quantitative (Bricolo et al, 2002; Sung, 2008). Specified distributions that have been used previously consisted mostly of the Ex-Gaussian, a distribution that seems to fit data well, but is not necessarily representative of the cognitive processes modelled in visual search (Cousineau et al., 2002; Logan, 1992, 1995; Rouder et al., 2005). Consequently, the current research will assess how the parameters of the Weibull distribution change across conditions of visual search, and assess how these changes can clarify the architecture issue behind the various visual search paradigms. Such an approach to visual analyses, to our knowledge, has not been conducted prior to the work completed by Palmer and colleagues (2011), who focused predominantly on assessing which distribution functions may best fit response time data. In addition to testing common stimulus sets of visual search (i.e. feature, conjunction, spatial configuration), and in an effort to replicate the results of Bricolo and colleagues (2002) and Sung (2008), we designed an orientation feature search that would elicit large set size effects and as expected, a seemingly serial mechanism.

As demonstrated in Bricolo and colleagues (2002), orientation feature searches can also elicit large differences in results, contrary to what would initially be predicted in searches for individual features. Previous studies have demonstrated that performance in orientation feature search is largely dependent on the ability to easily classify the target as categorically different from the distractors (Wolfe, Friedman-Hill, Stewart & O'Connell, 1992; Wolfe, 1998). If the angular difference is small (< 90°) and participants cannot classify the object with ease (such as vertical or horizontal) search slopes will be steep, indicating a serial architecture is responsible for the search (Wolfe et al., 1992). In addition, tilt, orientation from vertical, in concordance with the target, in the same direction (i.e. leftwards or rightwards) seem to aid in identifying the presence of a target, while impeding its detectability, the opposite is also true when distractors tilt in the opposite direction to the target (Baldassi & Burr, 2000). Other search asymmetries in orientation feature search can also be elicited when the tilt between the target and the distractors is changed. When a target is tilted while distractors are kept vertical, search will typically elicit flat parallel slopes, just as is normally found in single feature searches, while title the distractors and making the target vertical will elicit serial search slopes (Cavanaugh, Arguin, & Treisman, 1990). Orientation feature search can therefore elicit either very rapid responses, such as feature searches, or large set size effects, such as the ones found in spatial-configuration tasks depending on the orientation difference, and therefore, similarity between the target and distractors. Orientation feature searches therefore provide a large array of modifications that can facilitate search or complicate it. In the current project, we opted to reduce the distractor-target similarity to increase the difficulty of the task. In addition, we tilted distractors in two directions and kept the target vertical to prevent rapid identification, and ensure slopes would be steep.

The ex-Gaussian has previously been shown to fit response time data well, its parameters are also simple and easy to understand, since they greatly resemble the parameters of the Normal distribution (Ratcliff & Murdock, 1976; Hockley, 1984; Heathcote et al., 1991; Lacouture & Cousineau, 2008; Palmer et al., 2011; Penner-Wilger et al., 2002). Yet, distributions of time for any cognitive component must certainly be restricted to positive values and be greater than zero (Cousineau, Goodman & Shiffrin, 2002; Logan, 2002; Logan, 2005; Rouder et al., 2005). A lower bounded distribution, such as the Weibull, would therefore reflect the response time data more accurately than a distribution that is not bounded (Cousineau et al., 2002; Logan, 1992). The Weibull has also been found to fit response time data quite well (Cousineau et al., 2002; Cousineau, 2009a; Logan, 2002; Logan, 2005; Rouder et al., 2005) although it may not always fit as well as the Ex-Gaussian distribution, as suggested by the results of Palmer and colleagues (2011) were the Weibull had slightly higher chi-square statistics than the other distributions.

Depending on the desired analysis, the Weibull can be characterized by either two or three parameters (Cousineau, 2009a; Cousineau, 2009b; Logan, 1995; Thoman, Bain, &

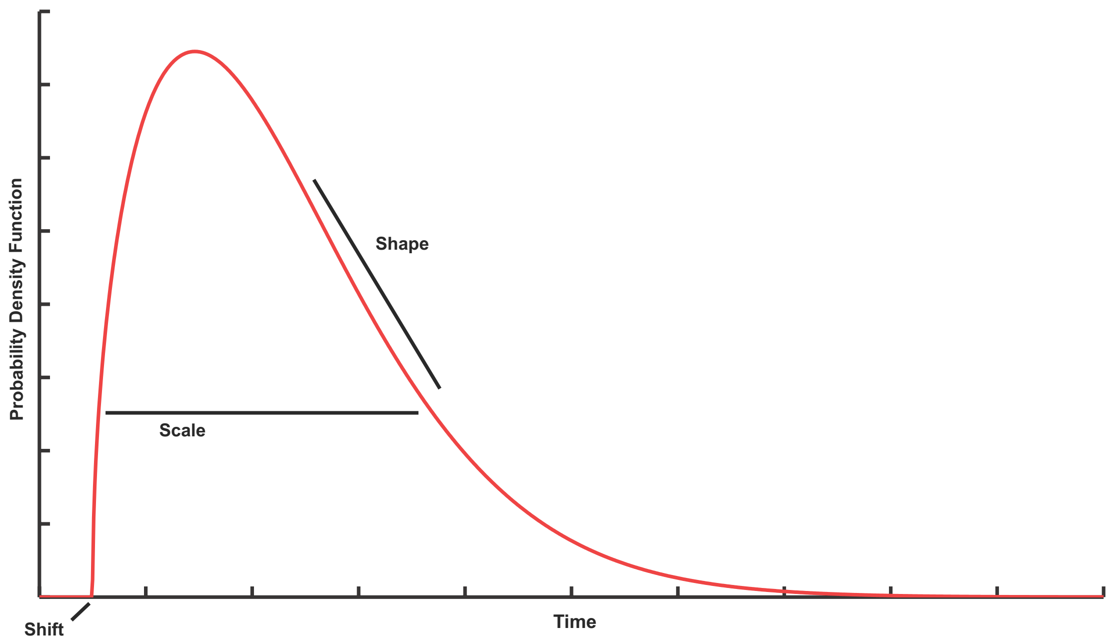

Figure 3. Each parameter of the Weibull distribution will change a specific aspect of the distribution. The shift modulates where the Weibull will cross zero, the scale changes the spread and the shape will change how exponential or normal like the distribution is.

Antle, 1969). The two-parameter Weibull distribution, which comprises a scale (λ) and shape (γ) parameter is non-shifted, and therefore is bounded at zero on the x-axis (see Figure 3). λ describes the spread of the Weibull distribution, and is in the same units as the dependent variable (here milliseconds). γ describes the overall shape of the distribution. Changes in γ can greatly change the appearance of the Weibull; at low values ($0 < \gamma < 1$), the Weibull resembles an exponential distribution, while at larger values ($\gamma \sim= 3$) it is normal like (see Figure 4). γ is also considered the slope for it is equal to the slope of a regression line in a probability (QQ) plot of the Weibull distribution.

$$f(x|\lambda,\gamma) = \begin{cases} \frac{\gamma}{\lambda}\left(\frac{x}{\lambda}\right)^{\gamma-1} e^{-\left(x/\lambda\right)^{\gamma}} & x \geq 0, \\ 0 & x \leq 0, \end{cases}$$

The two-parameter Weibull is a survival function, since it reflects the probability of survival, or not failing at time *x* (Townsend & Ashby, 1983). Such functions are very useful in survival analyses and reliability studies (Carroll, 2003), but for response time data, a shifted version of the Weibull distribution better reflects the actual data. The additional parameter of the shifted Weibull distribution is the shift (θ) that describes the spatial location of the minimum value of the Weibull (see Figure 3; Cousineau, 2009a; Cousineau, 2009b; Heathcote, Brown, & Cousineau, 2004; Rouder, Lu, Speckman, Sun, & Jiang, 2005). The probability density function therefore becomes as follows when the shift is included:

$$f(x|\theta,\lambda,\gamma) = \frac{\gamma(x-\theta)^{\gamma-1}}{\lambda^{\gamma}} e^{-\left(\frac{x-\theta}{\lambda^{\gamma}}\right)^{\gamma}}, \text{ for } x > \theta$$

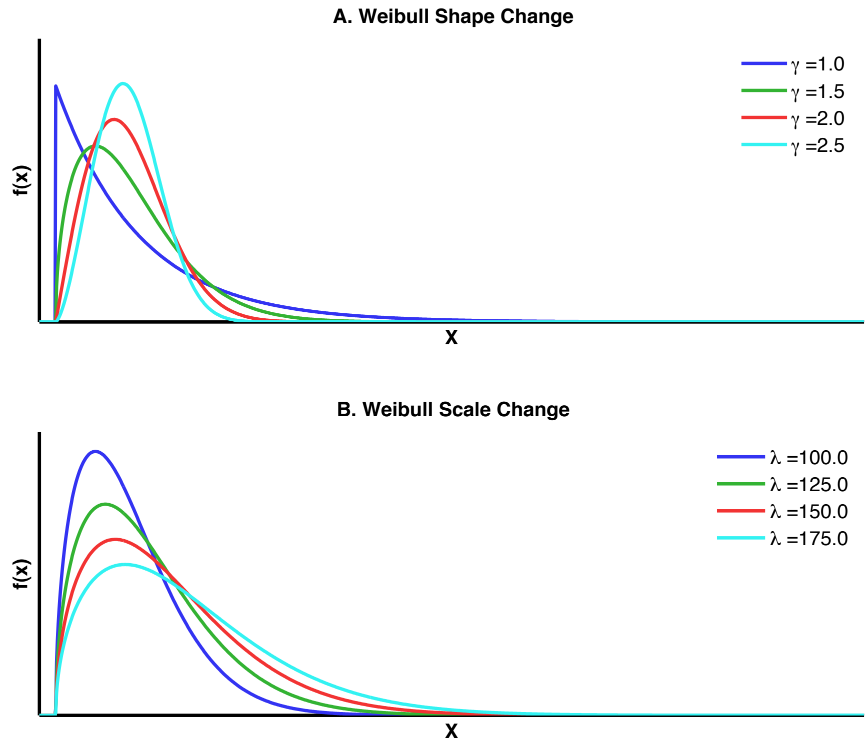

Figure 4. Changes in the scale of the Weibull distribution with other parameters kept constant, θ = 20, γ = 1.5, λ = 100, 250, 400, 550. Changes in the shape of the Weibull distribution with other parameters kept constant; θ = 20, γ = 1, 1.5, 2.0, 2.5, 3.0, λ = 250. One can see that changing the shape parameter of the Weibull leads to the distribution taking a variety of forms from purely exponential to a normal like distribution (when the shape is about 3).

We believe that the Weibull distribution is best suited in the analysis of response time distributions for as recommended by Townsend and Wenger (2004), when investigating search architecture, an analysis that focuses on the theoretical components of the architecture, and not simply on common statistical analyses, such as ANOVAs, would be better suited to answer the research question. The Weibull has been shown to fit data well, and strongly recommended when assessing the likelihood of race models in visual search (Cousineau et al., 2002) and random-walk models of numerical distance effects (Rouder et al., 2005). In addition, its parameters are interpretable descriptively (i.e., without further calculations), and can reflect properties of search, such as the minimum capacity of search directly measured by θ, that are not demonstrated with search slopes, or the overall variability of response times via the scale (λ) parameter (Logan, 1992; Cousineau et al., 2002; Cousineau 2009a).

Consequently, increases or decreases of the Weibull parameters according to search difficulty, set size and target presence may be indicative of separable process in visual search such that specific parameters may change in certain conditions such as increases in set size, but not in others, such as the target presence, as previously found when assessing the changes of the Ex-Gaussian distribution (Heathcote, 1991; Hockley, 1984; Penner-Wilger, 2002; Ratcliff & Murdock, 1976). According to Feature Integration Theory (1980) the capacity of the parallel (unlimited) and the following serial (single item) architectures should reflect changes in the shift parameter (θ), which should increase when requirement changes from one search condition, in which the parallel architecture is sufficient to a more complex search (i.e. conjunction). In addition, the shape (γ) of the Weibull distribution should also increase as search difficulty increases. If search is performed serially with a reduced capacity, then there should be increases in the proportion of longer response times, which would be reflected in the Weibull shape parameter. Consequently, the Weibull distribution and its parameters could aid in verifying if architectures in visual search change from one search type to the next, as suggested by the Feature Integration Theory (Treisman & Gelade, 1980; Treisman & Sato, 1990) and the Guided Search Theory (Wolfe, et al., 1989; Wolfe, 1991; Wolfe, 2007), or if they remain constant as suggested by Random-Walk class models (Bundense, 1990; Cousineau et al., 2002; Ratcliff, 1978). Consequently, the predominant goal of this study in to endeavour in the preliminary explorations of the usefulness of the Weibull distribution in disassociating the different architectures of search and do so without violating assumptions of null hypothesis testing, or in the ill-described manner of search slopes.

Method

In order to assess if the parameters (θ, λ, γ) of the Weibull distribution could reflect changes in response time distributions of response times across set size, target presence and search difficulty, we used to datasets, the first created by the Jeremy Wolfe lab, and available online (http://www.wolfelab.com**),** and the second created within our lab called the Orientation Feature Search.

Wolfe Datasets

The online datasets provided by Jeremy Wolfe contain three types of visual search, feature conjunction and spatial configuration (Figure 5). The sum number of trials of this dataset, including errors, is of about 80 000, making it an ideal candidate for distributional fitting. These datasets, and the following description of their methodology can be found on Jeremy Wolfe's website (http://www.wolfelab.com).

Participants.

Participants (N = 9 for feature, N = 10 for conjunction, N = 9 for spatial configuration) sat 57.4 cm away from the screen. Each participant performed about 4000 trials across all search types.

Stimuli.

The stimuli for all search types were created in Mathworks MATLAB (version 7.1, Natick, MA) and the psychophysics toolbox extensions (Brainard, 1997; Kleiner, Brainard, Pelli, 2007; Pelli, 1997), and presented on a Macintosh computer in a 22.5° region of the computer monitor. In the feature search, the target was a red vertical rectangle while distractors were green vertical rectangles. Both target and distractors

Figure 5. This figure is a representation of the three visual search conditions that comprise the Wolfe dataset (http://www.wolfelab.com). The target of each condition is in the bottom left corner of each condition.

subtended 3.5 by 1 degrees of visual angle. As for the conjunction search the target was a red vertical rectangle amongst red horizontal rectangles and green vertical rectangles. Stimuli in the conjunction search were kept as the same size as in the feature search. Finally, the spatial configuration search contained white 2 (targets) and white 5's (distractors) that subtended 1.5 by 2.7 degrees of visual angle (see Figure 5).

Procedure.

Procedures for all three visual search paradigms were identical. Participants were asked to input, via keyboard press, whether or not a target was present in the search array. Targets were present in 50% of the trials and presentation was randomized across trials. Participants underwent 12 blocks of 30 practice trials and 300 experimental trials and 1 block of 30 practice trials and 400 experimental trials totalling 4000 experimental trials and 390 practice trials per search condition. Trials contained 3, 6, 12 or 18 distractors.

Orientation Feature Search

Participants.

Participants consisted of ten (5 females) Concordia University undergraduate Psychology students. All students were between the ages of 22-45 (*M* = 28, *SD* = 10.12) and had normal or corrected to normal vision (*cut off* = 25/20), which was assessed with the Early Treatment Diabetic Retinopathy Study chart (Bailey & Lovie, 1976). All students received compensation via the participant pool credit system of Concordia University.

Materials and apparatus.

Participants rested their head on a chin-rest 60 cm from a linearized video monitor (Viewsonic 19" CRT Graphic series G90fb, 1024 x 768 pixel resolution, 100Hz refresh rate) controlled by a Dell Precision T3400, with a core2 quad processor. A custom code was used to generate Gabor patches with Mathworks MATLAB (version 7.1; Natick, MA) and psychophysics toolbox (version 3; Brainard, 1997; Kleiner, Brainard, Pelli, 2007; Pelli, 1997). These Gabors were used as the target and distracters stimuli in this experiment. Orientation of the Gabor defined the target and the distracters. The target was oriented at 90° while the distractors oriented at both plus or minus 30°, 20° or 10° from 90° (Figure 6). Gabor patches were 0.5° of visual angle when viewed at 60 cm from the screen (16 pixels). The Gabor patches consisted of a sinusoidal grating windowed by a two-dimensional Gaussian function. The sinusoidal grating in our Gabor patches had a period of 0.25 degrees (8 pixels), which corresponds to a spatial frequency of 4 cycles per degree. The positive zero-crossing of the sinusoid was always at the center of each patch, (so the "dark bar" of the sinusoid was to the left of the center for vertical patches and on top for horizontal patches). The Gaussian function had a full-width-at-half-height of 0.25 deg (8 pixels). The contrast of our Gabor patch was computed by taking the difference between the luminance at the peak of the Gaussian and the mean luminance of the pattern, and then dividing that difference by the mean luminance. Gabor's patches were presented on a 6 by 6 grid pattern, subtending 20 degrees at a 60cm viewing distance. Position of the target and the distracters was randomized over trials and counterbalanced within each condition.

Procedure.

Instructions for the experiment were displayed on the screen, and read by the experimenter. Participants were instructed to find the vertical Gabor within the array of

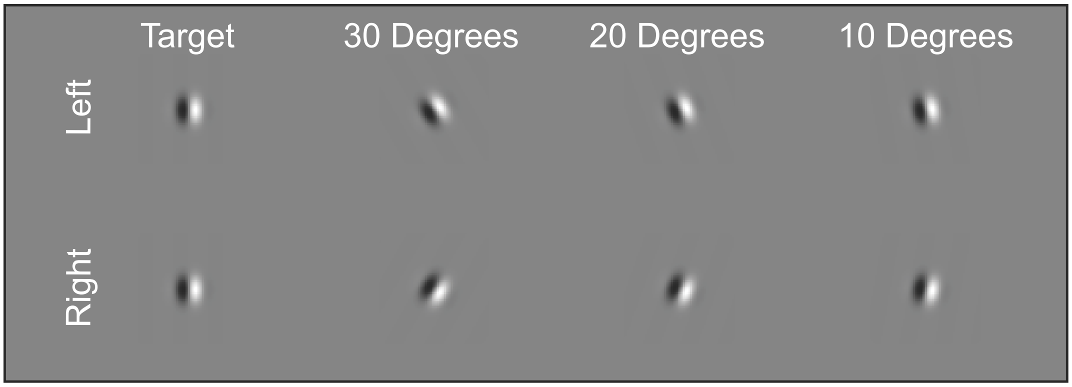

Figure 6. Gabor stimuli used within the orientation feature search. The left panels contain the target. The number in the top left of each panel is the set size.

distractors, to try and be as accurate as possible (via feedback on accuracy at the end of the trial) while trying to complete the task quickly. Once the participants received the instructions, they began the visual search task by pressing the spacebar on the keyboard. Participants were at all times in control of when they started a trial, since they could only begin when the spacebar was pressed on the keyboard. Participants began the experiment with 44 practice trials at the beginning of the experiment and then went on to complete 10blocks of 102 trials totalling 1020 trials per participants for each distractor angle condition (3060 trials in total). Target present and absent trials were intermixed within blocks, therefore participants completed 51 target absent trials, and 51 target present trials per block. Set size was also manipulated within each block. Set size randomly varied from 4 to 8 to 16 distractors. Participants had to indicate by pressing on the keyboard if the target (vertical Gabor) was present or absent within the array of Gabor patches. Participants were provided feedback on their accuracy at the end of each trial.

Data analysis.

Data analysis was conducted in the same way for both the Wolfe data set and the orientation feature search. Prior to the data analysis, a data screening procedure identified all incorrect trials and removed them from the distributional analysis. The proportion of incorrect trials that can be attributed to misses or false alarms can be found in figure 8 and 10 in the results section.

The Kolmogorov-Smirnov statistic (KS; Anderson, 1961; Best, 1994; Darling, 1957; Massey Jr., 1951; Wilcox, 1997) was used to assess if distributions of response times across set sizes were different from each other prior to distributional fitting.

$$KS_{nn'} = \sqrt{\frac{nn'}{n+n'}} \sup_x \left| F_n(x) - F_{n'}(x) \right|$$

The KS test quantifies the distance (maximum vertical deviation) between the two empirical cumulative distributions, $F_n(x)$ and $F_{n'}(x)$, and calculates significance by comparing $K_{n,n'}$ (the statistic of the difference) to its alpha level, KS_α (in this experiment $\alpha = 0.05$; for a table of critical values for different sample sizes see Massey Jr, 1951). The KS assesses whether differences are statistically significant from two datasets by comparing the maximum difference ($\sup_x$) of two cumulative distributions, weighted by their sample size, against a critical value (resulting in $K_{nn'}$; Best, 1994; Darling, 1957; Massey Jr, 1951; Wilcox, 1997).

Distributional fitting.

Secondly, we fitted our response time data with a three-parameter Weibull distribution using maximum likelihood estimation procedures (MLE). The distributions were fitted to the individual participant response time data by minimizing the negative log likelihood using the Optimization Toolbox for MATLAB 7.0.4, in particular, the *fminsearchbnd* function within it, based on the Nelder-Mead simplex search algorithm, which permits the fitting of bounded parameters, such as in the Weibull distribution (as described in Palmer et al., 2011; Lagarias, Reeds, Wright & Wright, 1998). There are assumptions that must be met when fitting distributions using MLE procedures. The first, and one of the most important is that data are sampled from independently and identically distributed (IID) random variables from the underlying distribution that is being estimated (Logan, 1992; Cousineau et al., 2002; Palmer et al., 2011). Although there is no clear method of assessing whether or not our data were IID, we ensured that participants had sufficient training and rested often as to not falsify IID assumptions. In addition, the parameters of the Weibull were allowed to vary independently, and have continuous densities, meeting requirements of the MLE procedure (Azzalini, 1996). Both datasets also collected multiple observations per participants, which has been shown to increase the reliability of the MLE procedure, and as demonstrated by Cousineau (2009a), greatly minimizes the variability of the fits.

In addition to fitting the three individual parameters of the Weibull distribution to the response time data, we repeated the procedure to calculate confidence intervals around the fits. Using a bootstrap sampling methodology, we fitted the parameters to the data 500 times, and subsampled 10% of the dataset with replacement. The lowest 2.5% and highest 2.5% of the distribution of parameters values were used as the limits for our 95% confidence interval of the fit (see Figure 7 for an example of an individual fit). Finally, in order to assess the overall quality of the fits, we performed χ^2 statistics on our entire set of fits from each individual participant. For the χ^2 statistics of all individual fits, see Tables 3, 4, 5, and 6. Once the χ^2 statistics were calculated, we averaged the parameters for the individual participant fits to simplify the comparison between search slope analyses and our current approach.

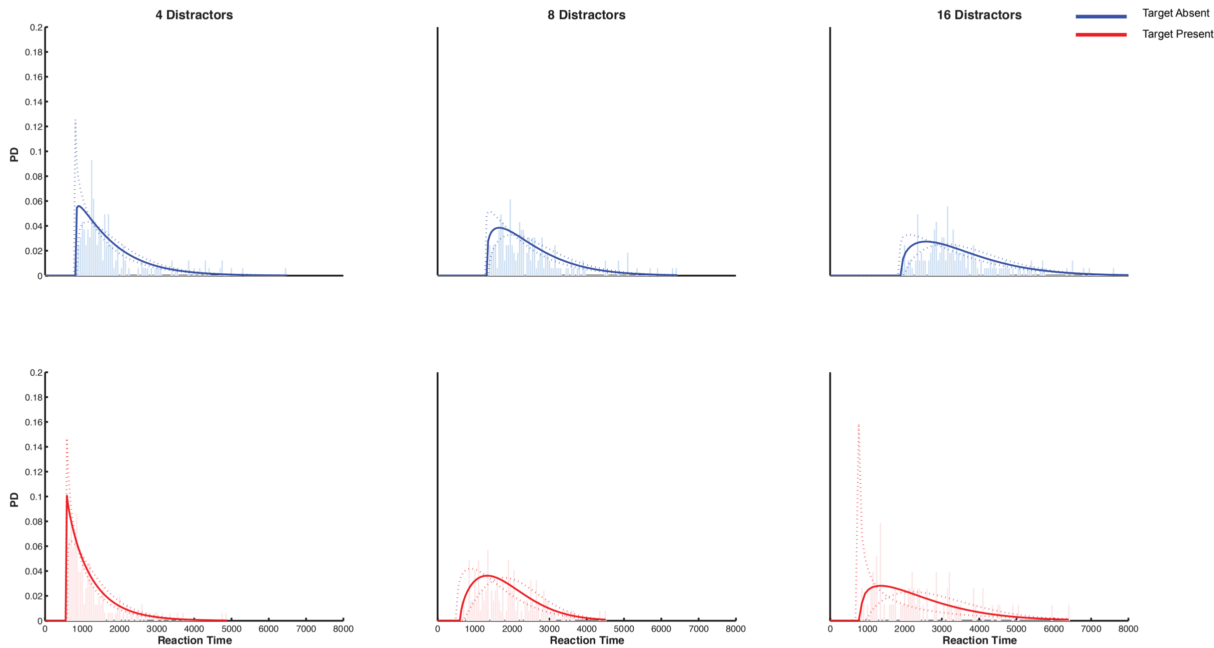

Figure 7. Example of an individual fits for a single participant in the 10 degree search condition. The solid lines represent the actual fit of the distribution while the dotted lines are the 95% confidence interval of the distributional fitting.

Results of Response Time Data

In an effort to properly compare the distributional fitting results to the current norm in the visual search literature, we calculated the slopes and assessed statistical significance across both datasets. As a consequence, we could compare how the slopes of response time, created from mean data compared to the distributional analyses.

Wolfe Dataset

Error analysis.

The miss rate in the Wolfe dataset was quite low throughout all search conditions (type and set sizes), but did peek in the spatial configuration search at the largest set size (18 distractors). False alarm rates on the other hand were consistent across search condition and seemed to decrease slightly as the set size increased (see Figure 8).

Slope analysis.

Slopes for all three visual search conditions follow the stereotypical findings of feature, conjunction and spatial configuration searches (see Figure 9). Feature search yielded search slope very close to 0 (Present: 0.55, Absent: =-0.51), conjunction search had a slope ratio of 2.7:1 (Present: 9.24, Absent: 25.70) and finally the spatial configuration search also had a slope ratio of 2.2:1 (Present: 42.71, Absent: 95.29).

Feature search.

A main effect of target presence of the feature search task, $F(1, 8) = 15.18$, $p = .005$, $\eta_p^2 = .65$, was found to be statistically significant, indicating that reaction times for target present searches ($M = 409.83$, $SD = 71.91$) were significantly faster than target absent searches ($M = 431.07$, $SD = 68.87$) irrespective of set size. No interaction of set size by target presence, $F(3, 24) = 1.61$, $p = .212$, $\eta_p^2 = .17$ nor a main effect of set size, *F*

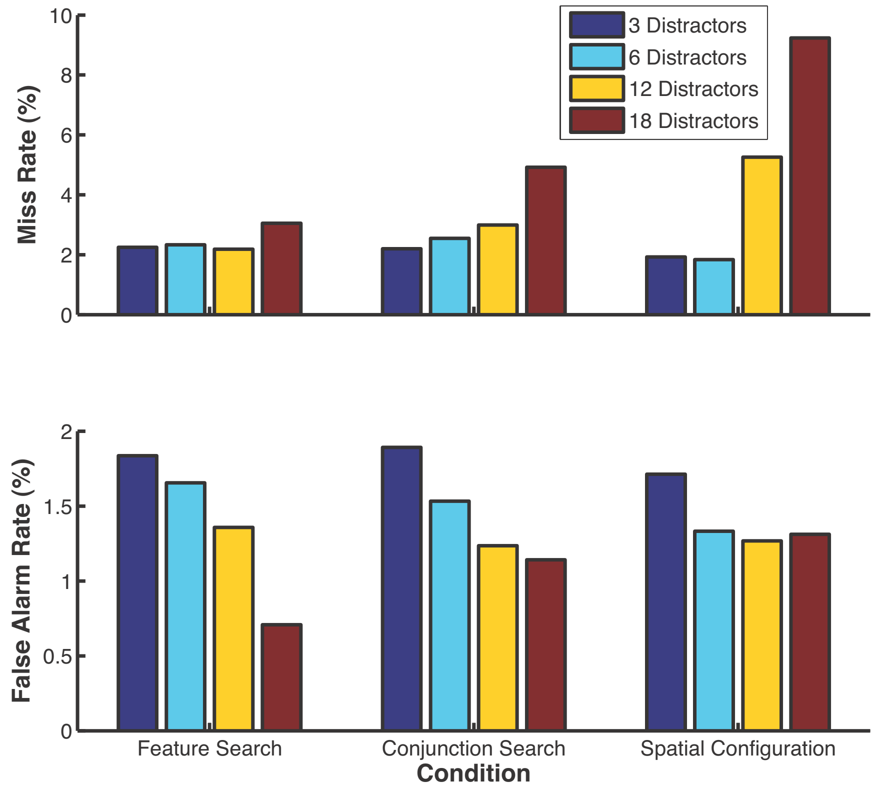

Figure 8. The error analysis of the Wolfe dataset for all three-search conditions. The error values are comparable to previous results of feature, conjunction and spatial configuration searches.

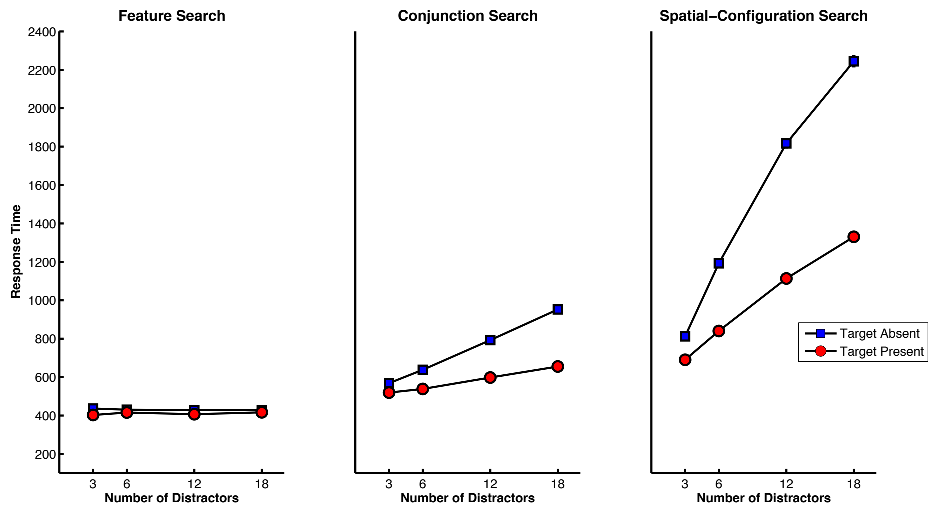

Figure 9. Response time slopes for the three search types from the Wolfe dataset. The error bars, although quite small (due to the large number of trials) represent the 95% confidence interval of the mean response time.

(3, 24) = 0.52, p = .67, η_p^2 = .06, were found. Therefore, the mean response time across set sizes were not significantly different from each other at 3 distractors (M = 418.64 ms, SD = 69.54), 6 distractors (M = 423.43 ms, SD = 77.29), 12 distractors (M = 417.13 ms, SD = 65.55) or 18 distractors (M = 421.58 ms, SD = 69.44).

Conjunction search.

The repeated measures ANOVA found a significant interaction effect of set size by target presence for the conjunction search, $F(3, 27) = 9.54$, $p < .0001$, η_p^2 = .52. Mean response time for target present searches were shorter at all set sizes (3: M = 519.11 ms, SD = 76.97; 6: M = 538.02 ms, SD = 81.90; 12: M = 599.46 ms, SD = 99.01; 18: M = 658.94 ms, SD = 117.10) than for the target absent searches (3: M = 568.76 ms, SD = 98.22; 6: M = 636.23 ms, SD = 120.51; 12: M = 791.16 ms, SD = 195.84; 18: M = 954.81 ms, SD = 339.44). In addition, a main effect of target presence, $F(1, 9) = 25.71$, p = .001, η_p^2 = .74 and a main effect of set size, $F(3, 27) = 22.23$, $p < 0.0001$, η_p^2 = .71, were found to be statistically significant.

Spatial-configuration search.

The repeated measures ANOVA found a statistically significant interaction effect between set size and target presence, $F(3, 24) = 53.97$, $p < .0001$, η_p^2 = .87. Response times for target present searches were shorter across all set sizes (3: M = 688.64 ms, SD = 123.09; 6: M = 838.75 ms, SD = 153.21; 12: M = 1119.23 ms, SD = 212.31; 18: M = 1331.72 ms, SD = 259.29) then target absent searches (3: M = 813.92 ms, SD = 174.54; 6: M = 1193.22 ms, SD = 288.03; 12: M = 1825.96 ms, SD = 443.97; 18: M = 2246.72 ms, SD = 539.67). In addition, a main effect of set size, $F(3, 24) = 107.08$, $p < .0001$, η_p^2 = .93, and a main effect of target presence were found, $F(1, 8) = 72.09$, $p <.0001$, η_p^2 = .90.

Orientation Feature Search

Error analysis.

The miss rate (Figure 10) in the orientation search task was quite high for all three orientation conditions (10, 20 and 30-degrees), but seemed to decline slightly as the orientation difference between the target and distractors increased. Evidently, miss rate was greatest when the set size was large, and was much lower at smaller set sizes (4). False alarm rates (mistakenly identifying a distractor as a target) were high when the difference between the target and distractors was small (10 degrees) but decreased to "normal" levels (Wolfe, 2010) as the orientation difference increased. False alarm rates did not decrease, as the set size increased as found in the Wolfe dataset, but seemed to increase instead.

Slope analyses.

The set size effects, according to slope values, were quite large (see Figure 11). At an orientation difference of 30-degrees, the slope ratio between target present and target absent searches was 2.7:1 (Present: 44.18, Absent: 121.30), at a difference of 20-degrees, the slope ratio was 2:1 (Present: 78.76, Absent: 161.86) and at a difference of 10-degrees, the ratio was 2.3:1 (Present: 59.60, Absent: 135.46).

The ANOVA found an interaction effect of set size by target presence, $F(2, 10) = 32.88$, $p = 0.0001$, $\eta_p^2 = 0.79$. The slope for target absent response times was much steeper when the set size increased from 4 (present: $M = 1036.83$ ms, $SD = 195.93$; absent: $M = 1519.14$ ms, $SD = 357.61$) to a set size of 8 (present: $M = 1385.76$, $SD = 291.15$; absent: $M = 2247.50$, $SD = 627.24$) to a set size of 16 distractors (present: $M =$

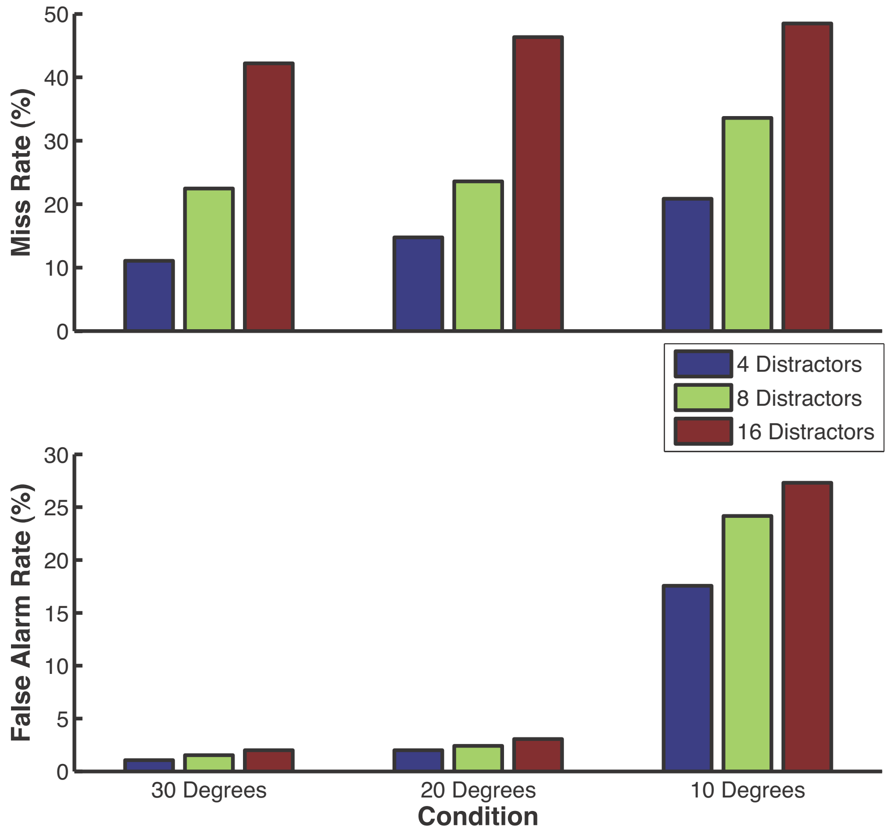

Figure 10. Error analysis for the orientation feature search. The false alarm rates for the 30 degree and 20 degree conditions are quite low, but the 10 degree condition is abnormally high, indicating that participants had a very low threshold at answering "target present" when it was absent (mostly due to the small difference in angles).

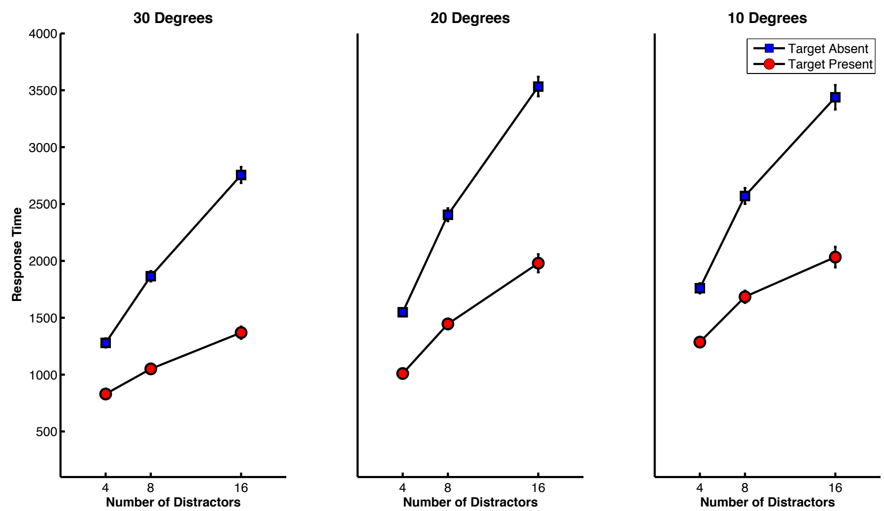

Figure 11. Search slopes for the orientation feature search conditions. Error bars represent the 95% confidence interval of the mean response time.

1795.81 ms, *SD* = 444.33; absent: *M* = 3188.64 ms, *SD* = 1058.90; see Figure 11). No interaction between distractor orientations, set sizes and target presence were found in this ANOVA. In addition to the interaction effect of set size by target presence, we found a main effect for the angle of the distractors, $F(2, 18) = 7.32$, $p = 0.005$, $\eta_p^2 = 0.45$. Response times were shortest when the angular difference between target and distractors differed by 30-degrees (*M* = 1520.85 ms, *SD* = 481.07), and increased at a difference of 20-degrees (*M* = 1974.84 ms, *SD* = 880.43) and at a difference of 10-degrees (*M* = 2091.15 ms, *SD* = 952.03). A main effect of set size was also found, $F(1.09, 9.68) = 60.36$, $p = 0.0001$, $\eta_p^2 = 0.87$, with a Greenhouse-Geisser correct for the degrees of freedom. Response times increased when the set size increased from 4 distractors (*M* = 1277.99 ms, *SD* = 386.66) to 8 distractors (*M* = 1816.63 ms, *SD* = 640.45) and 16 distractors (*M* = 2492.23 ms, *SD* = 1050.00). Finally, a main effect of target presence was also found, $F(2, 18) = 52.62$, $p = 0.0001$, $\eta_p^2 = 0.85$. Target present response times (*M* = 1406.14 ms, *SD* = 432.99) were quicker than target absent response times (*M* = 2318.43 ms, *SD* = 956.68) across all distractor orientations and set sizes.

Results of the Distributional Fitting

Wolfe Dataset

Feature search

KS.

The average KS statistic demonstrated that the target present and target absent response time distributions were significantly different from each other at a set size of 3 ($KS = 0.23$, $p = 0.002$) but not at set sizes of 6 ($KS = 0.19$, $p = 0.11$), 12 ($KS = 0.17$, $p = 0.06$) or 18 ($KS = 0.15$, $p = 0.05$). Figure 12 demonstrate the probability function of the response time distributions for the feature search task.

Scale.

The scale of the Weibull distribution remained relatively flat throughout all set sizes, with fits for both target present response times and target absent response times overlapping largely. Scale parameter values for the target absent response time distribution varied from 174.47ms (CI: 148.12 - 199.56) at 3 distractors**,** to 177.98 ms (CI: 151.67 - 196.83) at 6 distractors, 164.16 ms (CI: 143.34-185.36) when 12 distractors were present and 176.11 ms (CI: 148.08-194.70) at 18 distractors. Target present parameter values for scale varied from 158.63 ms (CI: 133.12 - 175.62) at 3 distractors, to 165.02 ms (CI: 140.77 - 182.75) at 6 distractors, 171.79 ms (CI: 144.25 -190.13) at 12 distractors and finally, 171.14ms (CI: 143.08 - 193.14) at 18 (Figure 15).

Shift.

The shift parameter fitting in the feature search revealed that the shift (minima) of the Weibull distribution remained relatively flat just as the scale parameter. Shift values

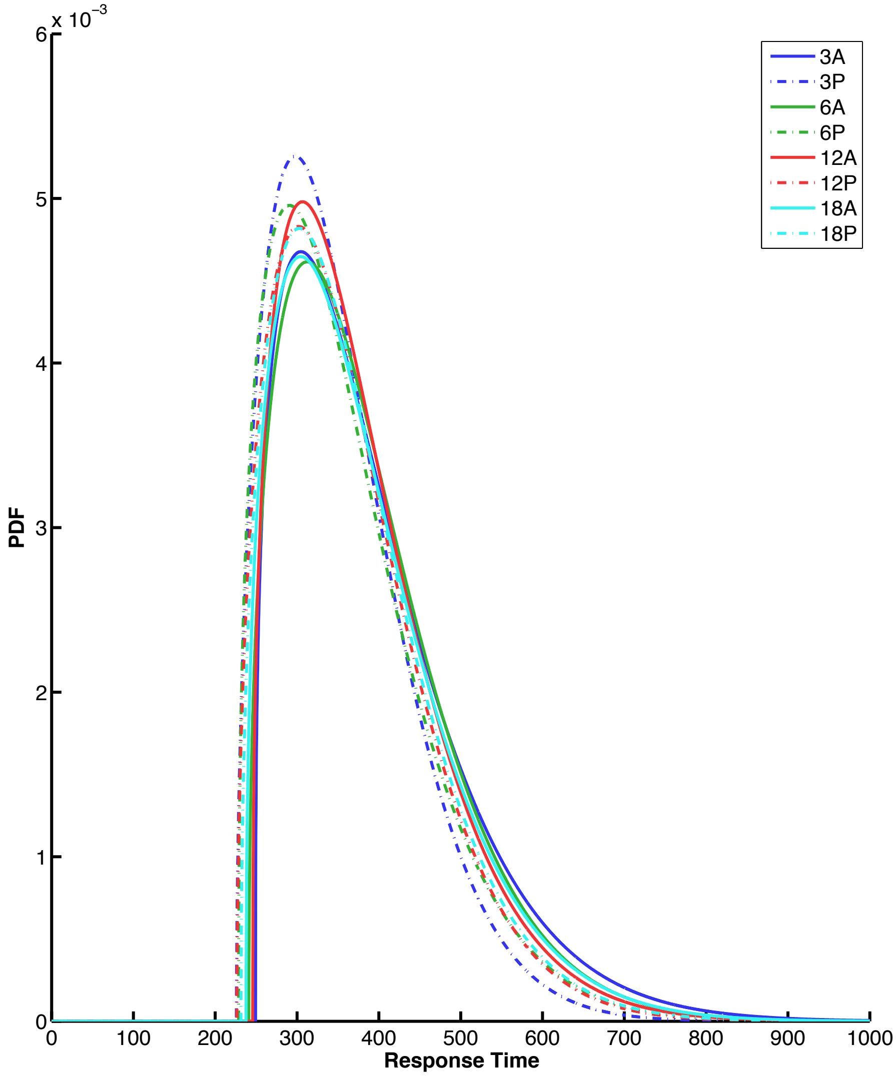

Figure 12. Probability density function from the parameters obtained in the feature search condition. The figure demonstrates how similar all the distributions for each set size and target presence are to each other.

for target absent response time distributions, 276.99 ms (CI: 266.31 - 293.84) at 3 distractors, 267.93 ms(CI: 259.77 - 285.65) at 6 distractors, 273.25 ms (CI: 263.04 - 286.43) at 12 distractors and 264.23 ms (CI: 256.93 - 281.13) at 18 distractors, and the present response time distributions at 3 distractors, 251.02 ms (CI: 242.33 - 269.93), 6 distractors, 254.08 ms (CI: 246.31 - 272.32) at 12 distractors, 251.76 ms (CI: 242.72 - 272.95) and 18 distractors 257.24 ms (CI: 245.25 - 278.17) did not vary across distractor set sizes and although target absent shift values remain greater than target present values, confidence intervals overlapped with each other at all set sizes (Figure 15).

Shape.

Similar to the scale and shift parameters of the feature search, the shape parameter did not vary between set sizes, nor did target presence affect the shape of the Weibull distribution. The values for the shape parameter throughout set sizes for the target absent response time distribution varied from 1.48 (CI: 1.21 – 1.80) at 3 distractors, to 1.61 (CI: 1.32 – 1.90) at 6 distractors, 1.56 (CI: 1.29 – 1.85) at 12 distractors and 1.57 (CI: 1.28 – 1.84) at 18 distractors. Target present shape values ranged from 1.71 (CI: 1.31 - 2.03) at 3 distractors, 1.57 (CI: 1.29 - 1.86) at 6 distractors 1.68 (CI: 1.36 - 2.10) at 12 distractors and 1.64 (CI: 1.30 - 2.00) at 18 distractors. The response time distribution remained relatively exponential throughout the various conditions with shape values never reaching more than 2.10 (Figure 15).

Conjunction search.

KS.

According to the KS statistic, target present and target absent response time distributions were not statistically different from each other at a set size of 3 distractors

($KS = 0.29$, $p = 0.05$), but were at a set size of 6 (KS = 0.35, $p = 0.001$), of 12 ($KS = 0.43$, $p = 0.001$) and 18 ($KS = 0.46$, $p = 0.001$). Figure 13 shows the probability density functions of the conjunction search response times.

Scale.

The scale parameter for the conjunction search demonstrated no large differences between target present, at 3 distractors, 189.67 ms (CI: 163.10 - 212.33) and 6 distractors, 218.41 ms (CI: 189.62 - 239.94) and target absent fits, at 3 distractors 243.57 ms (CI: 187.57 - 281.62) and at 6 distractors, 262.82 ms (CI: 224.26 - 291.33). However, results showed a larger increase of the target absent parameter fits at a set size of 12 distractors, 394.42 ms (CI: 347.23 - 433.96) and a set size of 18 distractors, 542.78 ms (CI: 488.65 - 590.51) compared to target present fits at 12 distractors 266.33 ms (CI: 236.23 - 291.53) and 18 distractors, 314.46 ms (CI: 283.23 - 343.47).

Shift.

Fitting for the shift parameter demonstrated that the minimum value of the Weibull distribution had a much larger increase according to set sizes than the target present distribution. Shift values for the target absent response time distribution increased from 345.48 ms (CI: 325.55 - 385.62) at 3 distractors to 390.21 ms (CI: 381.46 - 412.15) at 6 distractors, to 428.70 ms (CI: 413.68 - 456.28) at 12 and 466.37 ms (CI: 448.52 - 497.48) at 18 distractors. Target present shift values also seemed to increase slightly over set size condition, but the overlap of error bars would suggest that such is no the case, and that minimum value of the Weibull remained constant throughout target present conditions, 336.50 ms (CI: 328.34 - 350.13) at 3, 334.87 ms (CI: 327.71 - 353.45) at 6, 349.80 ms (CI:

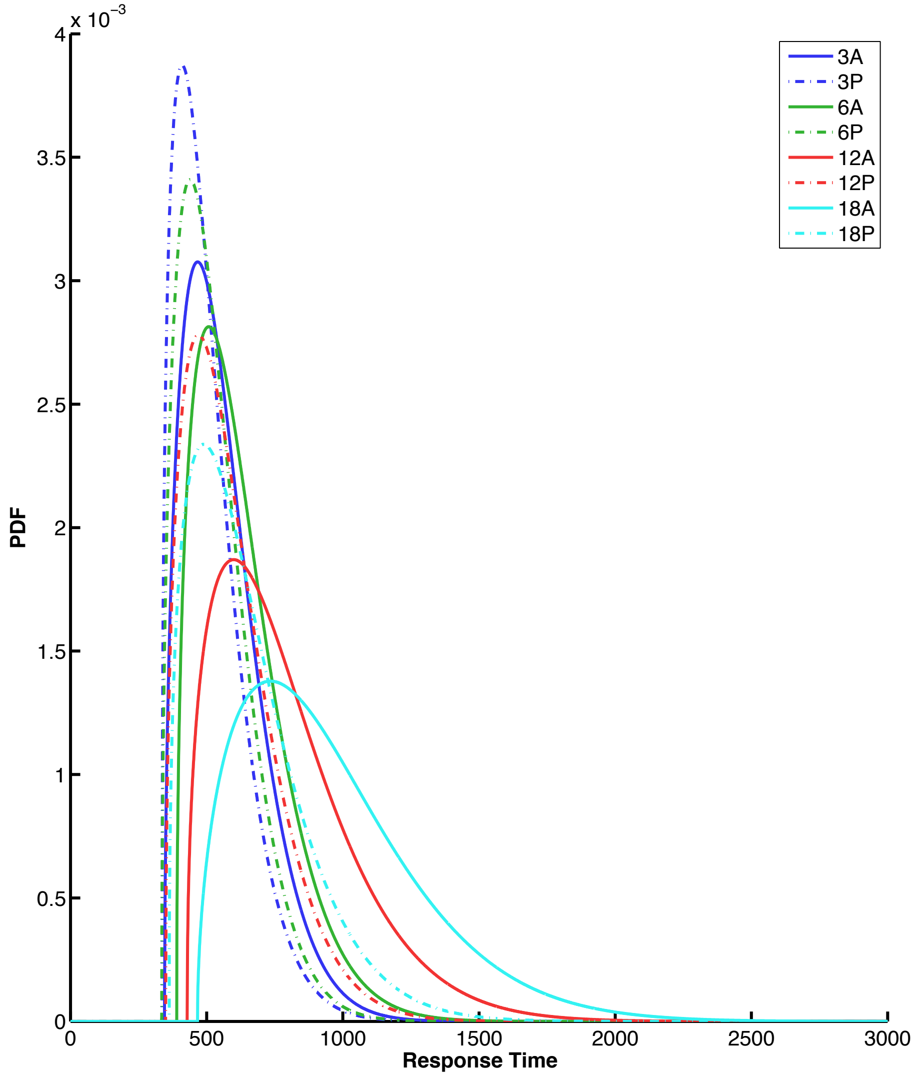

Figure 13. Probability density function from the parameters obtained in the conjunction search condition. The figure demonstrates how similar all the distributions for each set size and target presence are to each other, will small deviations in absent 12 and 18 distractors.

343.14 - 368.10) at 12, and 362.64 ms (CI: 354.44 - 378.93) at 18 distractors (see Figure 15).

Shape.

The shape of the response time distributions remained constant, similarly as found in the feature search response time distributions, for all set sizes in the conjunction search. In addition, the shapes for the target present distributions at all set sizes, 1.37 (CI: 1.19 - 1.57), 1.50 (CI: 1.28 - 1.70), 1.46 (CI: 1.26 - 1.65) and 1.39 (CI: 1.22 - 1.56) and absent distributions at all set sizes, 1.53 (CI: 1.27 - 1.82), 1.45 (CI: 1.24 - 1.66), 1.43 (CI: 1.24 - 1.60) and 1.52 (CI: 1.35 - 1.70) were quasi-identical with significant amounts of overlap between them (see Figure 15).

Spatial-configuration search.

KS.

Similarly to the conjunction search, the target present and absent distribution were statistically different from each other at set sizes of 6 ($KS = 0.45$, $p = 0.001$), 12 ($KS = 0.55$, $p = 0.001$) and at 18 ($KS = 0.56$, $p = 0.001$) but not at a set size of 3 distractors ($KS = 0.16$, $p = 0.30$). Figure 14 shows the probability density functions of the spatial-configuration search response times.

Scale.

The spread of the Weibull distribution increased greatly as the number of distractors increased. This increase was also much more prominent in the target absent response time distribution than for the target present response time distribution. Values for target absent increased from 419.90 ms (CI: 349.60 – 469.20) at 3 distractors to 703.00 ms (CI: 625.40 – 760.10) at 6 distractors, 1264.00 ms (CI: 1085.90 – 1386.40) at

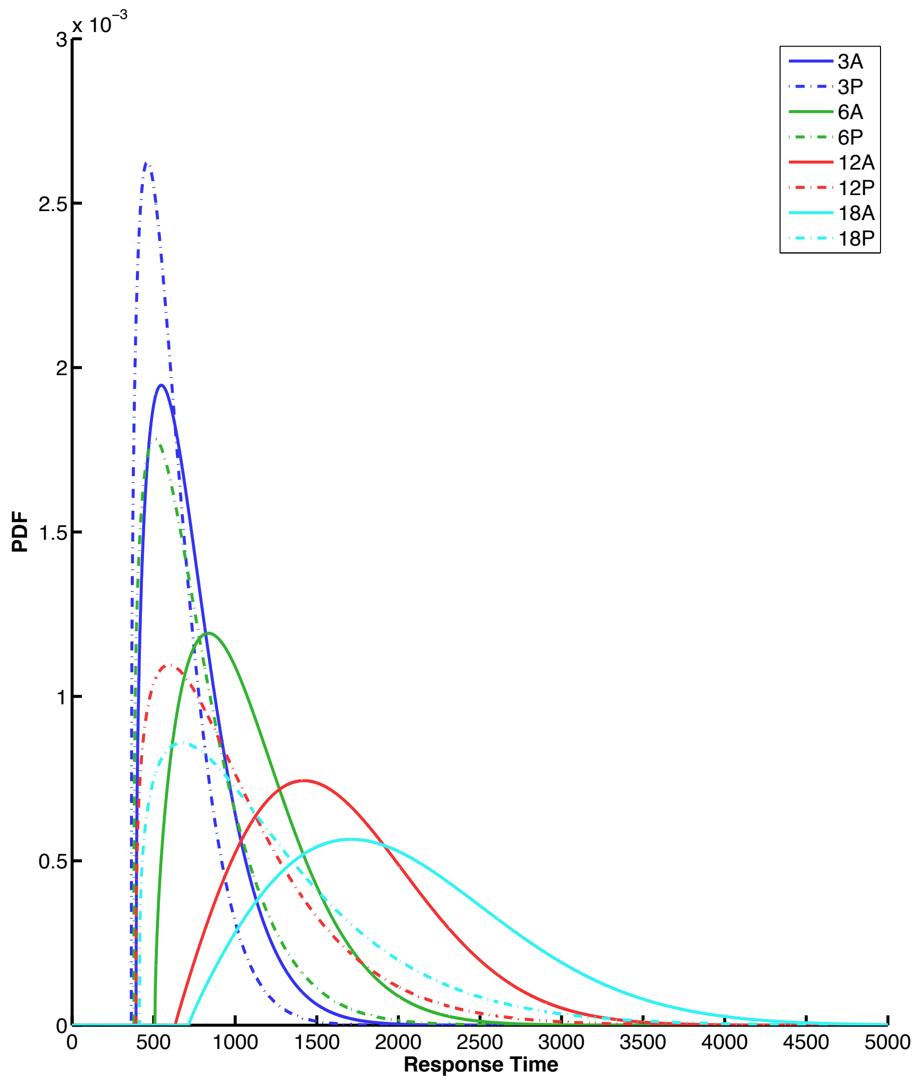

Figure 14. Probability density function from the parameters obtained in the conjunction search condition.

12 distractors and 1635.00 ms (CI: 1453.00 – 174.93) at 16. Target present values on the other hand increased from 310.84 ms (CI: 281.11 – 337.50) at 3 distractors to 459.46 ms (CI: 412.74 – 498.40) at 6, 749.09 ms (CI: 682.91 – 807.00) at 12 and 955.83 ms (CI: 875.01 – 1030.80) at 18 distractors (see Figure 15).

Shift.

The shift parameter for the target absent response time distributions increased greatly across set sizes, going from 436.48 (CI: 410.02 - 488.69) at 3 distractors, to 564.64 (CI: 534.58 - 626.54) at 6 distractors, 702.10 (CI: 607.04 - 852.23) at 12 distractors and 793.49 (CI: 713.41 - 949.31) at 18 distractors. Instead of increasing like the target absent shift, the shift for the target present response time distribution remained constant throughout all set sizes, from 403.43 (CI: 395.89 - 420.81) at 3 distractors to 421.41 (CI: 410.45 - 448.08) at 6, 436.42 (CI: 423.84 - 468.00) at 12 and 459.86 (CI: 443.13 - 490.58) at 18 distractors.

Shape.

Similarly to the shift of the response time distribution for the spatial configuration search, the shape of the distribution changed in the target absent condition but not in the target present condition. Shape parameter values varied from 1.56 (CI: 1.34 - 1.82) at 3 distractors to 1.73 (CI: 1.48 - 1.97) at 6 distractors, to 2.17 (CI: 1.82 - 2.52) at 12 distractors and 2.12 (CI: 1.83 - 2.38) at 18 distractors, while target present shape values remain stable from 3 distractors, 1.48 (CI: 1.26 - 1.69) to 6 distractors, 1.42 (CI: 1.26 - 1.57), to 12 distractors, 1.41 (CI: 1.28 - 1.54) and 18 distractors, 1.42 (CI: 1.28 - 1.56).

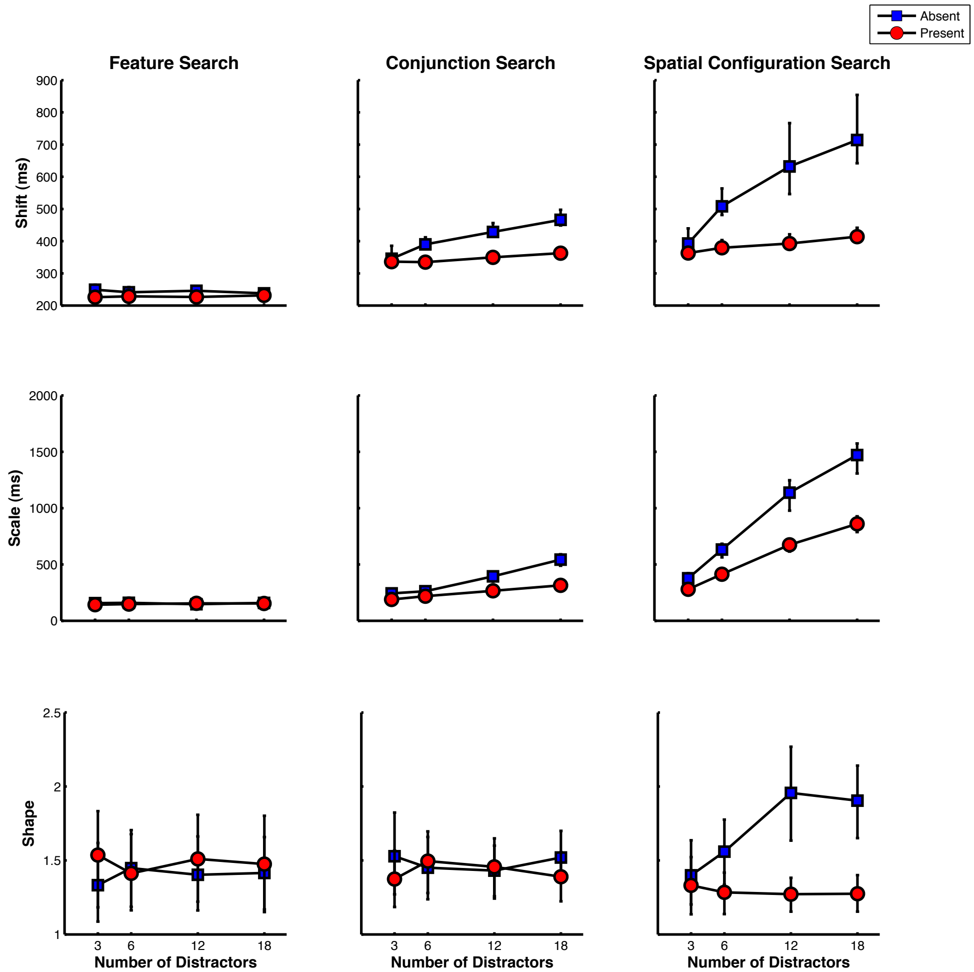

Figure 15. The parameter changes of the Weibull distribution in the three search conditions of the Wolfe dataset. Error bars represent the 95% confidence interval built via bootstrapping procedure around the fit of the Weibull to the response time distribution.

Orientation Feature Search

30-degrees.

KS.

The Kolmogorov-Smirnov statistic demonstrated that both the response time present and absent distributions were significantly different from each other at a set size of 4 (KS = 0.51, p = 0.001) at a set size of 8 (KS = 0.56, p = 0.001) and at a set size of 16 (KS = 0.62, p = 0.002). Figure 16 show the changes in the probability density function of the 30-degree search.

Scale.

The scale parameter fitting on the 30° orientation search demonstrated a linear increase in the spread of the distribution across set sizes (see Figure 19) The parameter values for the target absent distribution were consistently greater than the parameter values for the target present distribution, increasing from 708.90 ms (CI: 580.00 – 828.00) at a set size of 4, to 1243.00 ms (CI: 1058.00 - 1401.10) at 8 distractors and 2106.20 ms (CI: 1741.30 – 2415.40). In addition, the scale fits for the target present response time distribution increased slightly across set size condition, 374.42 ms (CI: 304.29 –458.40) at four distractors, 573.04 ms (CI: 460.02 – 680.10) at 8 distractors and 830.68 ms (CI: 641.67 – 1006.10).

Shift.

Unlike the scale values for the response time distributions, the shift values for the orientation search remained relatively flat across distractor set sizes. Although it seems that set size did not increase the minimum values of the response distributions, the shift for the target absent distribution, at 4 distractors, 604.18 ms (CI: 579.32 – 657.20), at 8

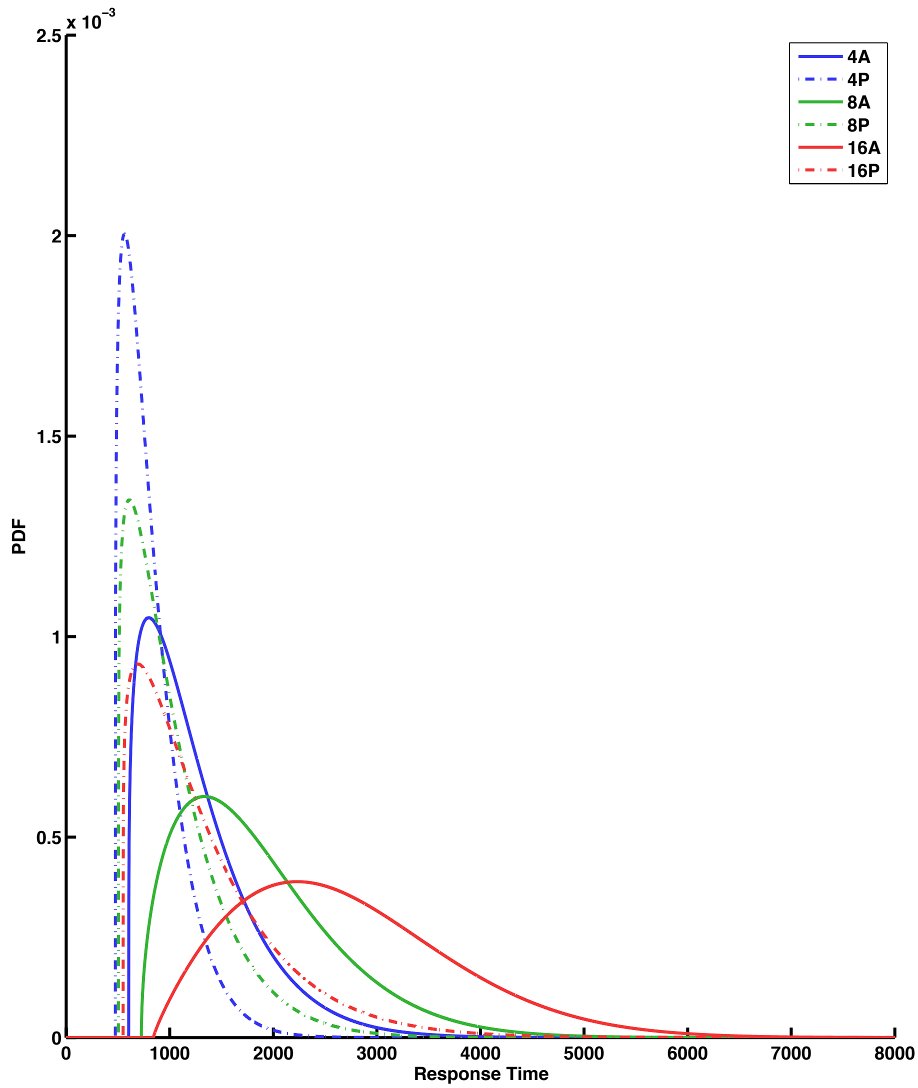

Figure 16. Changes in the response time distributions as a function of set size and target presence in the 30-degree condition of the orientation feature search.

distractors, 726.62 ms (CI: 667.96 – 827.40) and 16 distractors, 842.01 ms (CI: 639.50 – 1102.9), was consistently greater than for the target present distribution at 4 distractors, 475.58 ms (CI: 455.63 – 507.50), at 8 distractors, 505.58 ms (CI: 488.82 – 553.24) and at 16 distractors, 550.76 ms (CI: 526.15 – 603.59).

Shape.

The shape parameter fitting revealed two different patterns for the target absent and present response time. Although the confidence intervals were quite large, the shape of the target absent response time distribution seemed to increase from 4 distractors, 1.25 (CI: 1.02 – 1.51) to 8 distractors, 1.51 (CI: 1.26 – 1.79) and 16 distractors, 1.86 (CI: 1.48 – 2.27), while the target present distribution slowly decreased (more exponential-like) from 4 distractors, 1.21 (CI: 0.97 – 1.47) to 8 distractors, 1.16 (CI: 0.91 – 1.40) and 16 distractors, 1.15 (CI: 0.85 – 1.40). The target present and absent distribution had different shaped, as marked by the non-overlap of the confidence interval at 16 distractors and were completely overlapping at a set size of 4 (see Figure 17).

20-degrees.

KS.

The KS test showed that the target present and target absent response time distributions were significantly different from each other across all set sizes, (4: KS = 0.56, p = 0.0001; 8: KS = 0.55, p = 0.0002; 16: KS = 0.58, p = 0.0008) in the 20° visual search condition. Figure 17 show the changes in the probability density function of the 20-degree search.

Scale.

The scale parameter fitting in the 20° visual search revealed a similar pattern as in

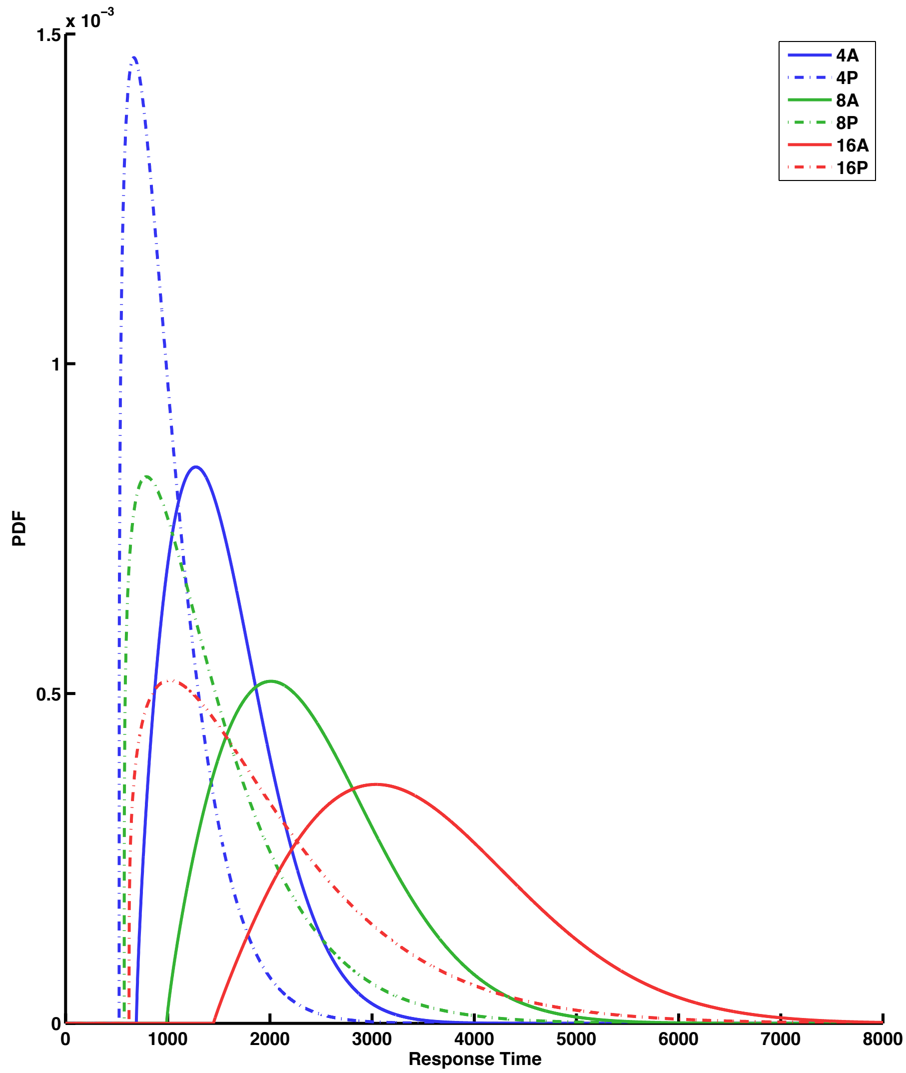

Figure 17. Changes in the probability density function in the 20-degree orientation feature search.

the 30° condition. Scale values were consistently greater in the target absent condition than in the target present condition, and started a little higher than in the 30° condition. Target absent values increased from 941.20 ms (CI: 782.60 – 1068.60) at four distractors to 1568.70 ms (CI: 1296.90 – 1788.00) at 8 distractors and 2318.20 ms (CI: 1870.90 – 2710.00) at sixteen distractors. Unlike in the 30° condition, scale values for the target present condition did increase without overlap in their confidence intervals across set size, from 4 distractors, 505.60 ms (CI: 424.00 – 589.10) to 8 distractors, 904.40 ms (CI: 745.20 – 1069.70) and 16 distractors 1425.90 ms (CI: 1086.40 – 1752.80). See figure 19 for individual parameter changes.

Shift.

The parameter fitting revealed that the response time distributions in the target absent conditions shifted greatly from zero as the number of distractors increased from 4; 693.60 ms (CI: 624.20 – 795.6), to 8; 989.2 ms (CI: 869.6 – 1210.30) and 16; 1447.60 ms (CI: 1159.30 – 1809.90) distractors. Yet, unlike the target absent shift values, the target present shift values did not change across conditions. At 4 distractors, 524.57 ms (CI: 510.59 – 558.25) 8 distractors, 574.91 ms (CI: 548.08 – 617.89) and 16 distractors 621.74 ms (CI: 543.48 – 737.09).

Shape.

The shape for both the target present and target absent distributions remained constant across all distractor set sizes in the 20° visual search, with a slight overlap of confidence intervals at the 4 and 16 distractors set sizes. Shape values for the target absent distribution ranged from 1.75 (CI: 1.42 – 2.13) at 4 distractors, 1.83 (CI: 1.50 – 2.21) at 8 distractors and 1.93 (CI: 1.52 – 2.45) at 16 distractors. Target present shape values ranged from 1.26 (CI: 1.04 – 1.49) at 4 distractors to 1.21 (CI: 0.96 – 1.47) at 8 distractors and 1.25 (CI: 0.91 – 1.62) at 16 distractors.

10-degrees.

KS.

According to the Kolmogorov-Smirnov statistic, the target absent distributions and the target present distributions were significantly different from each other at all set sizes (4: $KS = 0.44$, $p = 0.0001$; 8: $KS = 0.44$, $p = 0.002$; 16: $KS = 0.47$, $p = 0.0001$). Figure 18 show the changes in the probability density function of the 10-degree search.

Scale.

Similarly to both the 30° and 20° conditions, the scale parameter for the target absent and present response time distributions increased as a function of set size. The target absent scale parameters were greater than for the target present scale parameters throughout all of the set sizes, with a little overlap of confidence intervals at the 4 and 8 distractor set sizes. Scale values ranged from 1059.60 ms (CI: 875.40 – 1205.30) at 4 distractors, to 1681.80 ms (CI: 1341.00 – 1958.90) at 8 distractors and 2600.40 ms (CI: 2516.60 – 2956.00) at 16 distractors. Target present scale value ranged from 858.90 ms (CI: 678.90 – 1021.30) at 4 distractors, to 1224.30 ms (CI: 999.90 – 1443.30) at 8 distractors and 1584.10 ms (CI: 1187.90 – 1964.60) at 16 distractors.

Shift.

Shift values for the target present and absent response time distributions remained relatively stable across set size. A small increase can be seen from 4 to eight distractors for both the target present and absent shift values, but confidence intervals overlapped greatly, making this increase likely due to error. The shift values for the target absent distribution varied from 770.31 ms (CI: 712.08 – 905.00) at 4 distractors to 970.84 ms (CI: 823.64 – 1206.10) at 8 distractors and 970.74 ms (CI: 828.49 – 1292.40) at 16 distractors. Target present values ranged from 478.95 ms (CI: 413.42 – 584.96) at 4 distractors to 553.41 ms (CI: 466.48 – 653.08) at 8 distractors and 575.41 ms (CI: 463.87 – 721.02) at 16 distractors.

Shape.

Shape values for both the response time present and response time absent distribution overlapped greatly with each other and remained flat through all set sizes. Shape parameters for the target absent response time distributions ranged from 1.76 (CI: 1.34 – 2.20) at a set size of 4, to 1.80 (CI: 1.35 – 2.27) at a set size of 8, and 2.01 (CI: 1.53 - 2.47) at a set size of 16 while the shape parameters for the target present distributions ranged from 1.45 (CI: 1.15 – 1.80) at set size 4, to 1.49 (CI: 1.15 – 1.89) at set size 8, and 1.36 (CI: 0.85 – 1.76).

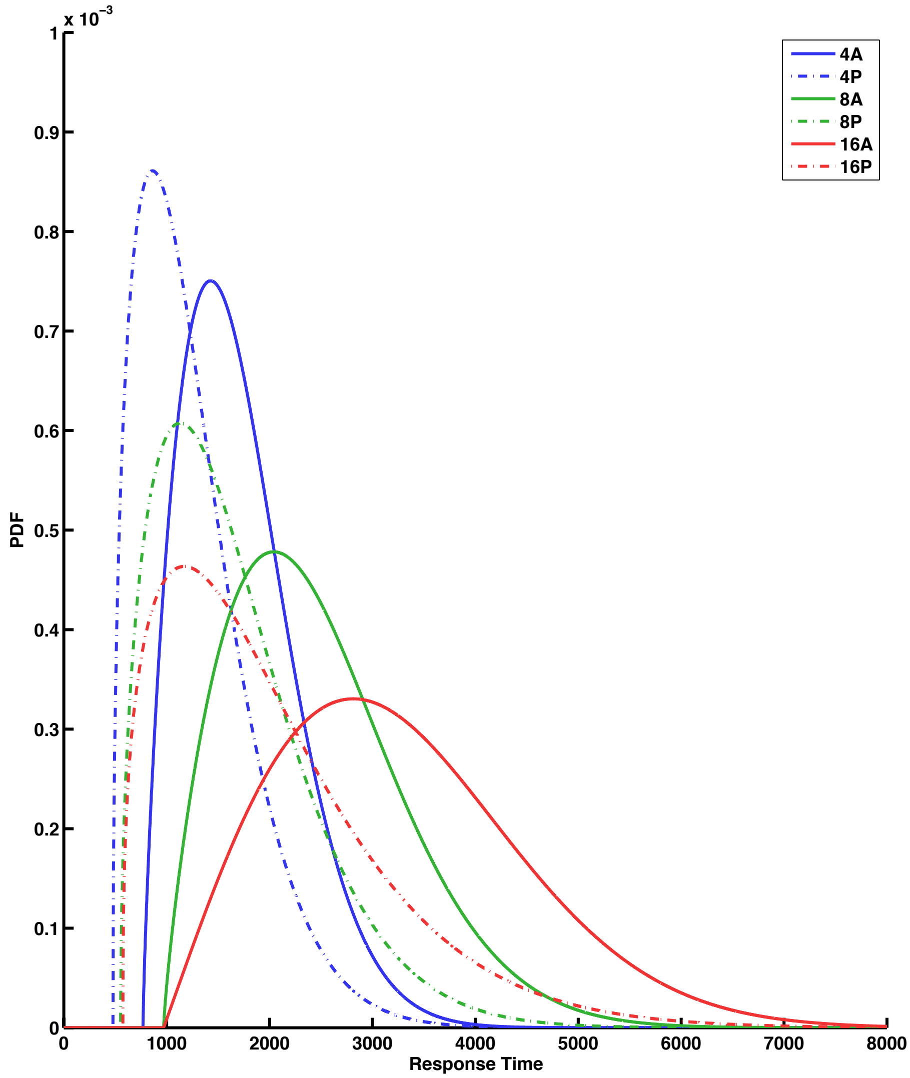

Figure 18. Changes in the probability density function in the 10-degree orientation feature search.

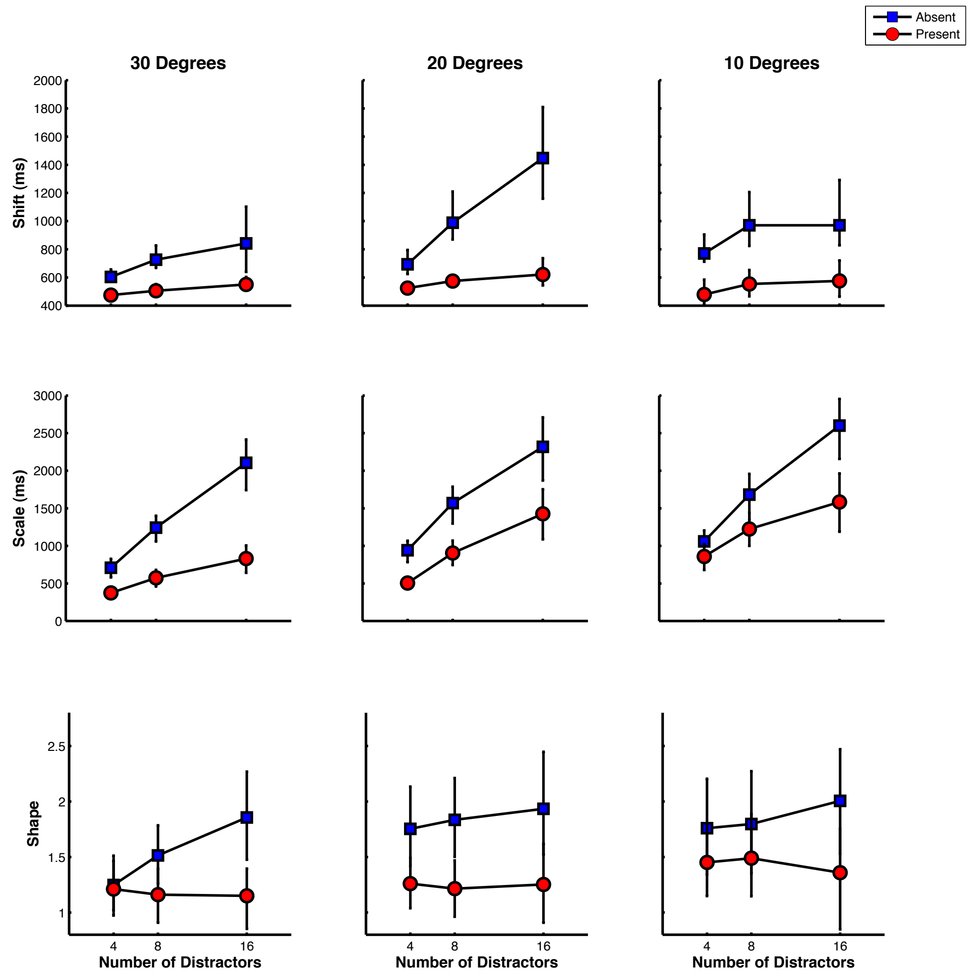

Figure 19. Parameter values of the Weibull distribution across all three orientation feature search conditions and set sizes. Error bars represent the bootstrapped 95 % confidence interval of the fit.

Discussion

Visual search is one of the most exhaustively studied attentional paradigms since the cognitive revolution in the 1950s (Logan, 2004). The effects of search condition on the response times collected in visual search paradigms have made possible the identification of mechanisms responsible for visual search. As such, when response times increase linearly as a function of set size, a serial mechanism is believed to be modulating search, however, when response times remain flat across set size, then a parallel mechanism is believed to be used in order to complete search (Treisman & Gelade, 1980). Although the distinction of parallel and serial search mechanisms has remained relatively popular within the literature, no true consensus has been reached on how they may interact, or which is mostly responsible for search (Carrasco, 2011; Logan, 2004; Townsend & Wenger, 2004; Wolfe, 1991). This has mostly been attributed to model mimicking, or the propensity for two fundamentally different mechanisms to generate the same patterns of results, preventing the clear identification of one versus the other (Townsend & Ashby, 1983; Townsend & Wenger, 2004). Model mimicking is the process in that parallel models can generate positive search slopes while serial models can generate flat slopes, leading to confusion on the architecture at hand. Positive search slopes from parallel models will mostly occur when the model is limited in capacity and large set sizes are presented (Townsend & Wenger, 2004), or if target rejection is not an independent process (Townsend & Colonius, 1997). In parallel models, independence refers to the processing of *n* items being processed within a specific time interval while serial models describe independence as the processing time of each succeeding item as independent from one another (Townsend & Wenger, 2004). Consequently, if target rejection (classifying an object as distractor) is not independent, serial architectures can migrate to following stimuli without having clearly rejected the target and do so at a later point, decreasing the overall search time and generating shallower slopes than expected. In addition, if the individual item processing time at larger set sizes is faster than at smaller ones, a serial search will once most generate shallow slopes. Therefore, the use of slope analysis that is traditionally used to analyze visual search data provides insufficient evidence to distinguish the type of architecture in visual search, and a more comprehensive approach to the analysis of response times is required (Cousineau, 2009b; Townsend & Wenger, 2004; Wolfe et al., 2010)

Distributional analyses seem to be better suited to the analysis of datasets from different search types, without limiting the methodology to the extent of signal detection measures. In the current research, we analysed two datasets, one provided by the Wolfe lab (comprising feature, conjunction, and spatial-configuration search), and the other containing an orientation feature search collected within our laboratory, and used the Weibull distribution to characterize response time distributions. Prior to the discussion of the Weibull parameter fitting to the response time data, which fitted the data quite well, a discussion on the typical analyses of response time data in visual search is presented as an appropriate comparison to our own results.

Slope Analyses of Reaction Time Data

Wolfe dataset.

In an effort to better compare the normative search slope analyses to the currently proposed distribution fitting approach, an interpretation of the current findings following the Feature Integration Theory and the Guided Search Theory is beneficiary. Yet, it is important to maintain model mimicking in mind, as it is very likely that the positive slopes of response time data could be due to a parallel model, and not a serial model, or vice versa.

The feature, conjunction and spatial configuration search tasks all demonstrated typical effects of search type and set size from similar experiments such as Treisman and Gelade (1980), and Wolfe and colleagues (1989). The feature search slopes were flat across set size, and did not differ between the target present and target absent conditions, in congruence with a parallel search architecture, as demonstrated by the Feature Integration Theory (Treisman & Gelade, 1980). Since feature searches contain stimuli that comprised a single feature, a “pop-out” effect of the target can occur, and permits a search of the entire array simultaneously, regardless of set size. Consequently, response times in the feature search condition did not vary from one set size to the next. These results are identical to single feature search performed by Treisman and Gelade (1980) and other single feature visual search paradigms (McElree & Carrasco, 1999; Townsend, 1990; Treisman & Sato, 1990; Wolfe, 1991; Wolfe et al., 2010).

Statistical significance tests demonstrated that interaction effects were found for both conjunction and spatial-configuration search paradigms. Response times increased more as a function of set sizes when the target was absent than when it was present, a typical finding for both paradigms (Bricolo et al., 2002; Treisman & Gelade, 1980; Wolfe et al., 2010). The conjunction and spatial configuration searches had slope ratios that surpassed the 2:1 ratio typically expected in serial search (Treisman & Gelade, 1980; Treisman & Sato, 1990; Wolfe et al., 1989; Wolfe, 1991). In addition, the set size effect of the spatial configuration search task was much greater than the conjunction search task, reflecting the increased difficulty for this type of search. Slopes for the conjunction search were similar to other conjunction search previously reported, albeit greater than typical slopes for conjunctions of orientation and colour (Cavanagh et al., 1990; Treisman & Gelade, 1980; Treisman & Sato, 1990; Wolfe et al., 1989). Target present response times were only slightly affected by set size, while target present responses demonstrated a larger effect. The slopes of the conjunction search would therefore reflect a serial architecture of search (equal to or greater than 10 ms per item: Treisman & Gelade, 1980), where attention needs to be serially shifted from one stimulus to the next in order to collect the required amount of information to identify it as a target or distractor (Treisman & Gelade, 1980; Tresiman & Sato, 1990). Yet, following evidence brought forth by Hoffman (1972), these search slopes are well below the temporal limit of attentional shifts, which typically lie between 100 ms and 250 ms. The response time slopes from the spatial configuration task followed the same, although more pronounced, relationship as the conjunction search slopes, demonstrating an increase in difficulty in the task, leading to larger response times.

Following the Feature Integration Theory (Treisman & Gelade, 1980), the slope results of the Wolfe dataset suggest that two mechanisms of search are responsible, a parallel architecture was sufficient to complete the feature search, reflected by the slopes of response times, while a serial architecture of search was responsible for both the conjunction and spatial-configuration conditions, as demonstrated by the linear increase in the slopes and their 2:1 ratio between target absent and present conditions. Guided Search (Wolfe et al., 1989; Wolfe, 1994; 2007) would also offer two architectures of search for all three conditions, and explains the difference in search slopes between the conjunction and spatial-configuration paradigms as an efficacy of guidance, meaning that the parallel stage could guide the observer towards the target with reasonable ease while it could not do so in the spatial-configuration search task. Since the parallel system is strongly feature based, and in conjunction search paradigms, the target shares a feature with half of the distractors and the other with the other half, filtering of features, or increasing the saliency of a feature over another could be easily performed by the parallel mechanism and therefore increase performance of the search. Spatially configured stimuli, which contain the exact same features, would not permit the filtering of a single feature for both target and all distractors share are form of the same features, therefore reducing the effectiveness of guidance offered by the parallel system.

Orientation feature search.

Our observers found the orientation feature search was found to be quite difficult, and demonstrated a larger number of misses (in which the target was present, but classified as absent) and false alarms (in which a target was absent, but classified as present), more so than found in the Wolfe dataset. The error analyses for miss rates and false alarms demonstrated that misses were high, especially in the 10-degree difference condition, and decreased as search became simpler, although they did remain consistently higher than in the spatial-configuration task. False alarm rates were also high in the 10-degree condition, and increased slightly as the set size increased. The difference in miss and false alarm patterns in the orientation feature search as compared to the spatial-configuration task (the most difficult) within the Wolfe dataset suggest either our experimental paradigm was more difficult, or that our participants were less conservative when responding, indicating that they may have biased speed over accuracy. Since the discrepancy in false alarm rates is only really found in the 10-degree condition, it most likely that it is search difficulty that is responsible for the difference, and not the overall criterion set by our participants. If our participants were more liberal in their responses than Wolfe's participants, we should have seen this reflected in the other conditions as well as in the 10-degree condition. Furthermore, previous study of orientation visual search demonstrated that error rates increased as orientation difference between the target and distractors decreased (Wolfe et al., 1992). Using tilted lines as stimuli for a visual search paradigm Wolfe and colleagues (2002) found that errors almost doubled when the orientation difference between the vertical target (90 degrees) and tilted distractors was reduced. Consequently, error rates increased from 5 percent when the distractors were tilted at plus or minus 40 degrees from vertical to 10 percent when the distractors were tilted plus or minus 20 degrees from the vertical target (Wolfe et al., 1992). It is consequently feasible to believe that increasing the complexity of the stimulus, as we did here using Gabor stimuli, and further reducing the orientation difference between targets and distractors would largely increase the difficulty of the task and therefore the error rates as well.

Overall, all three search difficulty levels demonstrated patterns of response times typical of a serial architecture, as previously found in other orientation feature search experiments, which had similar conditions to our own (Baldassi & Burr, 2000; Bricolo et al., 2002; Cavanagh et al., 1990). There was an overall effect of orientation difference in the search task. Larger differences in orientation between the target and the distractors made it simple to identify the target, leading to faster response times and less misses and false alarms, but search slopes that were still suggestive of a serial mechanism. As the angular difference between the target and distractors increased, response times slowed, search slopes became steeper and errors increased. Search slopes ratios were a little larger than the typical 2:1 ratio expected, indicating that attention travelled through the array serially (Cavanaugh et al., 1990). Although search was expected to become more difficult as orientation between the target and distractors was decreased, we found that this only occurred from the 30- to 20-degree condition, as slopes from the 10-degree condition were similar to those of the 20-degree condition. Consequently, although the decrease from 30- to 20-degrees in angular difference between target and distractors seemed to slow the speed of the serial search, decreasing the difference further did not seem to have any noticeable impact on speed. It is also possible that the large amount of error rates, and therefore the reduced dataset, in comparison to the other search tasks may have affected the slopes of the 10-degree search condition, masking the further increase in response times that would be expected. Never the less, previous work on visual search with orientation as a defining feature for the target and distractors has also demonstrated that using a tilted distractor and a vertical target elicits steep search slopes, and inferred that a serial architecture was therefore responsible for the search process (Bricolo et al., 2002; Cavanaugh et al., 1990).

Distributional Analyses

Wolfe dataset.

Although the Kolmogorov-Smirnov (KS) statistics indicated that the feature search response times were different, all three parameters (i.e., shape, shift, & scale) of the Weibull distribution fitting of the reaction time data from the feature search remained flat across set sizes. Observe in figure 15 that the actual fit values did show small differences from one condition to the next, and the large sample size inflated the significance of the KS test. Compared to the changes found in the other search conditions, it would seem that the large sample size was the only reason for the statistical difference found. Further, the distributions for all search conditions overlapped almost completely, demonstrating that although there were small changes from one set size to the next, and between target present and absent distributions, most of the distributions were identical to each other. These two findings reinforce the belief that a parallel process is involved in feature search, were the response time distributions are not affected by target presence or set size, indicative of unlimited capacity parallel search models (Townsend & Ashby, 1983; Townsend & Wenger, 2004). Consequently, the results of the search slope for a single feature is identical to the interpretation of the Weibull parameters: single features can be processed in parallel, and the capacity to do so is unlimited for the minima of the Weibull distribution did not change across the increases in set size (Bricolo et al., 2002; Ratcliff & Murdock, 1976).

The findings from the conjunction search showed a small increase in the shift parameter across set sizes (i.e. target absent only), and an increase in the scale parameter for both target present and absent conditions. Similarly, the spatial-configuration condition displayed the same pattern of results, albeit more extreme than the conjunction search, demonstrating the increased in response latency from the conjunction task. The shape parameter for the conjunction search did not change across either set size or target presence and remained similar to the shape parameter of the feature search. However, the spatial configuration search task did demonstrate an increase in the shape parameter, meaning there was a reduction in the skew of the distribution as the set size increased from twelve distractors to eighteen in the target absent condition. The increase in the shape parameter suggests that the distribution becomes more normal-like as the set size increases, although it is by no means a normal distribution, since the Weibull is only really normal-like when the shape is a little over three and a half, while the shape parameter it only reached two in the search condition. In addition, the shape seemed to plateau at a set size of twelve and did not increase further at eighteen distractors. Although this change does reflect a reduction in the skew of response time distributions (i.e. they are more symmetrical), it is by no means normally distributed. The Weibull is considered normal when its shape parameter reaches about 3.4, while the shape of response times in the spatial-configuration tasks remained well below such a cut-off.

Previous research conducted on the response time distributions has demonstrated that within visual search paradigms, changes in the mean response time were modulated by mean parameter of the Ex-Gaussian distribution (Hockley, 1984). Conversely, the variance and skew of the distribution remained constant across set sizes, with no significant difference between target present or absent conditions (Hockley, 1984). The results from the Ex-Gaussian distribution resemble greatly the results from the current Weibull distributional fitting for the conjunction search. The response time distributions for the feature search and conjunction searches resemble each other greatly, and only varied slightly in their minima and scale. The mean difference found by the search slopes for each set size was therefore not due to an increase in skew, but a small change in the location and overall spread of the response times.

The lack of a change in the shape of the distributions for the feature and conjunction search reflects how similarly distributed the response times were for both conditions in that the proportion of larger response time data as compared to the shorter scores remained the same. This is of main interest for that previous work on conjunctions of colour and orientation found that they typically elicited the largest slopes amongst other conjunction conditions (Treisman & Sato, 1990). Although these slope values, which are similar to our own, would of typically lead to infer a serial architecture of search for conjunction stimuli, the large amount of overlap between the feature search and conjunction search response times, in addition to the lack of change in the actual shape of the distributions would seem to suggest that they are only slightly shifted version of each other. Dual architecture models, which argue the involvement of two different mechanisms in search were based off effects measured from mean response times slopes, which as can be seen in figure 9, seem very distinctive from one another as set size increases and as a function of target presence. Yet, assessing the entire distributions has demonstrated that although the mean differences seemed far apart, the distributions overlapped greatly, suggesting more similarity between search conditions than previously demonstrated by only analysing the mean values. Subsequently, it would seem unlikely that two completely different mechanisms would elicit such similarities in response times.

Scarcity of changes in the shape parameter of the Weibull distribution seemed to support a single architecture of search for both feature and conjunction stimuli. Therefore, the increase in the shape parameter in the spatial configuration search could indicate another architecture is being used to complete the task. Although one may implicitly assume this architecture would be serial, it is difficult to actually support such a claim. Convolving multiple exponential distributions to mimic the cycles of a serial search, as done by Bricolo and colleagues (2002) can only increase the shape of the distribution (Cousineau et al., 2002). Therefore, convolving three exponential distributions produces an asymptotic distribution of type III, such as the Weibull distribution, which will have a shape value of three. However, it should be noted that the measured shape values within our current datasets (both Wolfe's and our own) and in Logan's (2002) memory search data never surpass two (Cousineau et al., 2002). Consequently, although a convolution of multiple exponential functions can replicate the individual cycles of serial search as demonstrated by Bricolo and colleagues (2002), these cycles do not seem to occur within our datasets. The shape parameter of a distribution will inflate a function of the number of convolutions involved in best fitting the data. Bricolo and colleagues (2002) found that the number of exponential functions required to fit her data followed the number of distractors minus one. Therefore, in a set size of eight, seven exponentials function would have been convolved with a Gaussian distribution in order to represent the data and demonstrate that each cycle of serial search is responsible for an individual amount of time in response time datasets. Yet, such convolutions would have largely increased the shape of the distribution, an effect that was not reflected within our own analyses, suggesting that such an interpretation of serial search may not be valid with the datasets used here. It is possible that a serial mechanism may still be used by the observers when completing the visual search task, yet if so, then the serial mechanism would have to be dependent in that each cycle of serial search would not be contingent on the termination of the previous, or that each would not necessarily reflect an individual exponential function (Townsend & Wenger, 2004).

In addition to the architecture of search used by participants, the Weibull distribution can also aid in identifying the termination rules followed by the participants during search. If search is self-terminating, there are some trials that would end quickly if participants ended search as soon as they identified the target, and this irrespective of set size. This should therefore be reflected in the minimum value of the Weibull distribution (Ratcliff & Murdock, 1976; Townsend & Ashby, 1983). We found that for all search types, the shift value for target present conditions did not vary as a function of set size. There was a small increase of target present shift from features searches to conjunction searches, but they remained the same from conjunction to spatial-configuration. As such, the shift values would seem to indicate that participants in the target present condition followed a self-terminating rule of search. Although the target absent shift values did increase as a function of set size, suggestions made by Townsend and Colonius (1997) would suggest that it is insufficient evidence towards an exhaustive termination rule. The shift value can indicate that the minimum capacity is changing when set size increases, but can not describe how the proportion of longer score, which would be indicative of an exhaustive termination rule may change as a function of target presence. Including the shape parameter, which does describe the proportion of rapid and slower scores within the distribution (by describing its skew) demonstrated that the proportions of rapid responses and slower responses did not change between target present and absent trials, even though the minima of the Weibull was slightly shifted as set size increased in target absent conditions (Townsend & Colonius, 1997). As such, it would indicate that an exhaustive search termination, in which longer response times should become more prominent, would be an unlikely option followed by our participants. Self-termination or target absent trials, guided by a certain factor, which is currently unknown, may have guided observers to end their search when a target was absent.

Orientation feature search.

Fitting of the Weibull distribution to response times collected in the orientation feature search demonstrated similarities to the Wolfe dataset distributional fitting, although the shift values did behave differently. In the 30-degree, 20-degree and 10-degree conditions, the shift of target present response time distributions remained flat, which just as previously mentioned would suggest that participants followed a self-terminating rule, where search ended as soon as they found the target. Target absent distributions had shift values that increased with set size, and once more, indicated that search termination was exhaustive when the target was absent. Interestingly, the shift values for the target absent distributions in the 10-degree condition increased from a set size of four to eight, but plateaued when the set size was increased further from eight to sixteen. The most likely explanation for the lack of increase in the 10-degree condition is due to the large miss and false alarm rates that participants made in this condition. The response speed is most likely due to participants guessing on whether or not the target was present, rather than them actually being as quick as identifying a target which differs by 30-degrees from the distractors, which would seem improbable.

The scale parameter of the Weibull, which reflects the spread, or the width of the distribution increased as a function of set size and search difficulty, demonstrating that reducing the difference in orientation between distractors and target increased the overall variability of response times. The scale parameter was the only parameter that seemed to change systematically as a function of set size and target presence. As such, it would seem that the mean differences from the slope analyses were mostly attributed to increases in the spread of the Weibull distribution, and to slight variations in the location of the Weibull (shift), and once more, not fully due to a change in the shape of the distribution.

The shape parameter remained constant over the increases in set size for both the 20 and 10-degree conditions. Similarly to the Wolfe dataset, the shape parameter of the orientation feature search did not vary as a function of set size, suggesting that the skewness of the response time distribution remained the same. In addition, the shape parameter never surpassed values of 2.5. Unlike the Wolfe dataset distributional fitting results for the shape parameter, values for target present and absent conditions were clearly distinct from one another. Target absent response time distributions seemed to be, in general, less skewed than target present distributions. Just as previously mentioned when discussing the Wolfe dataset, having such a small shape value is contradicts the predictions made from serial architectures (Bricolo et al., 2002; Cousineau et al., 2002; Logan, 2002; Treisman & Sato, 1990). Since the shape values for target present and target absent searches seemed relatively distinct from each other, but not affected by set size, it would seem that the distributions of response times across the three set sizes were simply shifted versions of each other, within the target presence conditions. Target absent distributions did seem to have a larger proportion of longer response latencies than the target present conditions, yet this would not speak of the underlying architecture per se, but the actual termination rule, for the mechanism that modulate search is unaware of target presence prior to completing the task. The distinction between the proportion of scores lying in the upper end of the distribution between target present and absent searches would suggest that participants followed an exhaustive termination rule in target absent conditions (Townsend & Colonius, 1997).

Previous distributional analyses of response time data found that, depending on the type of memory search (Ratcliff & Murdock, 1976; Hockley, 1984), or other cognitive paradigms (Heathcote, 1991; Penner-Wilger et al., 2002) changes in mean response times could be either fully attributed to the decreases in the skew of the distribution, or to its actual location (μ in the Ex-Gaussian, or θ with the Weibull). Mean response times used to generate search slopes reflect not a change in the location of the response time distribution but a tendency for the distribution to be more normally distributed in memory search experiments (Ratcliff & Murdock, 1976; Hockley, 1984). Visual search experiments, as demonstrated by Hockley (1984), can attribute changes in the mean response time to a change in the location parameter of the distribution. The asymmetry in the results of different tasks illustrates the ability for distributional fitting to distinguish the mechanisms that are used in different visual paradigms which would normally elicit similar mean response time slopes (Hockley, 1984). Assessing parameter changes in distributional fitting can therefore indicate how the response times are changes as a function of the independent variables used in a more useful and informative way than a slope analysis.

Over the four different search types investigated here, from the Wolfe dataset and our own, we consistently found that the shape parameter did not change in most conditions (or had overlapping confidence intervals). Target absent distributions had a shape parameter of about two in the most difficult conditions. The stability of the shape parameter of the Weibull distribution was even greater in target present conditions, where it remained flat across all set sizes, for all the search conditions presented here. If visual search mechanisms would shift from an unlimited capacity parallel mechanism at one condition to a drastically reduced in capacity serial search should be reflected in the proportions of longer response times within the response time distribution. In a parallel mechanism, longer response times should occur rarely, while in a serial search, it should be much more common to have much slower response times, something that should be reflected in the shape parameter of the Weibull distribution. Thus, we believe that the lack of change in the shape of a distribution, maintaining the skew, over varying set sizes is evidence for a continuum of search and not for a dichotomous architecture as previously suggested (Treisman & Gelade, 1980; Wolfe, 1998). The cyclical nature of serial search would have a much larger impact on the shape of the distribution, for as described by Bricolo and colleagues (2002) it can be best represented as an additive convolution process of exponential distributions. Yet these multiple convolutions (most likely one cycle per item in the array) would increase the shape of the Weibull distribution (Cousineau et al., 2002), making it more normal like as the set size increases, which was not observed in our data (Townsend & Ashby, 1983; Townsend, 1991; Townsend & Wenger, 2004). Since the shape parameter did not change as a function of task, target presence (Wolfe dataset) or set size, it is unlikely that a serial mechanism is involved in the response times collected here. Keeping model mimicking in mind, if search was somewhat serial within our datasets, then each cycle would have to be dependent, and contribute much less than what would be expected from the research conducted by Bricolo and colleagues (2002; Cousineau et al., 2002).

Conclusions

The independent cycles of serial search therefore does not seem to be supported by the Weibull distributional analysis. Henceforth, it may be more plausible to assume a parallel architecture of search when looking at the results of the Weibull parameters for the orientation feature search task, a result supporting previous findings of parallel search for orientated targets, even though response times were set size dependent (Baldassi & Burr, 2000).

Whether or not the capacity of the model is unlimited or limited can be inferred from the shift parameter of the Weibull distribution. Since the shift parameter is an estimation of the shortest possible time to perform the search, it can speak towards the minimum capacity of the architecture at hand (Townsend & Colonius, 1997). This would mostly be from the target absent shift values for target present trials typically don't reflect how long it would take to search an entire array (due to the high probability of finding a target at the beginning of a trial). Since we found increases across set sizes in the target absent shift values, and that the shape parameters does not support the involvement of a serial architecture, we believe that a limited-capacity model of visual search would be best suited at explaining the results found from our distributional analysis. Limited-capacity models describe a simultaneous accumulation of information over time until a specific threshold is reached, and a target present or an absent answer is given (either with a single, or multiple accumulators; Ratcliff & Rouder, 1998; Ratcliff, 1973; Townsend & Ashby, 1983). If enough evidence were accumulated for a target presence or lack there of early on, then participants following a self-terminating rule would end the search and answer, making the target present and absent distributions overlap greatly, as it was found here. In addition, limited-capacity parallel models account for set size effects through the limited amount of resources and how they affect the speed at which the accumulator collects information when set size increases (Ratcliff, 1973; Ratcliff & Rouder, 1998; Townsend & Ashby, 1983; Townsend & Wenger, 2004).

A limited-capacity parallel approach to visual search does seem to conflict with previous results which demonstrated a serial mechanism involved in visual search when the task is quite complex (Bricolo et al., 2002; Sung, 2008). The differences found between the current results and the previous findings of serial search in Bricolo and colleagues (2002) may most likely be due to the stimulus and therefore the overall difficulty of the task. The slope values reported by Bricolo and colleagues (2002) were quite variable and reached values as high as 604 ms per item, while the slopes values measures here never surpasses 160 milliseconds per item in the orientation search task or 95 milliseconds per item in the Wolfe dataset. When dealing with the extreme slope values presented by Bricolo and colleagues (2002), it is evident that an incredibly slow process, typically described as a serial mechanism, would be responsible for the visual search task, while tasks which demonstrate faster responses could easily be explained by a parallel mechanism (Sung, 2008).

Limitations and Future Research

Although the shape parameter of the Weibull distribution supported the use of a single architecture to complete both the visual search paradigms (our own orientation feature search and Wolfe's dataset), the shape parameter may be subject to model mimicking, and consequently indicative of either a serial or parallel architecture. For a serial search to generate the values for the shape parameter as we found here, it would have to be a dependent process in which investigation of a future target is not dependent of the termination of the previous investigation (Townsend & Ashby, 1983; Townsend & Wenger, 2004). As a consequence, the results would greatly resemble the expected results of a parallel architecture. However, in all theory and measurements, assumptions must be made when characterizing the patterns of results, and associating them with a specific architecture (Townsend, 1990). Using a distributional analysis, which better segregates data into individual components may aid in reducing the number of assumptions required to associate a pattern of results with architecture. In addition, there are techniques that can aid further to disassociate which of the two architectures, serial or parallel, may be involved in visual search (for review, see Townsend, 1990). Of main interest when using a distributional analysis is the possibility of cognitive reflectance within the parameters of the distribution, as suggested by Rouder et al., (2005). Although a direct association of cognitive properties to parameters at the moment would be an unwise approach to differentiating between architectures responsible for search, developing paradigms that would directly target a specific process, and assessing how parameters may change, could lead to a better understanding of how a distribution changes based on the cognitive demands or mechanisms involved (Rouder et al., 2005; Townsend, 1990).

The analysis applied here focused on a limited subset of the currently existing search paradigms. Colour feature searches, such as the one tested within the Wolfe dataset, are known to be more complex. Conjunction searches of various combinations can also elicit various search slopes, and therefore lead to different, or perhaps similar changes to the parameters of the Weibull distributions as the ones found here. Expanding the use of the Weibull distribution to other search paradigms, such as conjunction searches of various difficulty, could greatly aid in gaining a larger understanding of how the parameters of the Weibull distribution vary under such circumstances.

Distributional fitting requires a large number of trials for the fitting procedure to be reliable and indicative of any possible effect. Consequently, collecting the required amount of data can be tedious for the researchers and participants, leading to longer hours of participation and possibly fatigue. Such demands are most likely responsible for the limited number of datasets currently existing with enough trials to allow distributional fitting. Although long experiments may be more complicated to manage, we strongly believe that such an investment may be beneficial to future investigations visual search. As demonstrated earlier, simpler investigations of response times, predominantly search slopes, are not an accurate depiction of the effects being measured, and as such, the methodological convenience of small datasets do not out way the accuracy of distributional analyses.

The error rates in the orientation feature task were quite high when compared with the previous visual search literature (Wolfe et al., 2010). The 10-degree orientation task elicited nearly a 50% miss rate, indicating that participants missed the target in almost half to the trials in which it was present. Such high error rates could be due to the cortical organization of simple cells in the primary visual cortex. As demonstrated by Hubel and Wiesel (1959), simple cells in the visual cortex are selective to specific orientations, with receptive field size varying from 4 to 10 degrees of visual angle. Consequently, although we do have an intrinsic ability to detect vertical orientations (Baldassi & Burr, 2000), detecting small deviations for vertical, such as the 10-degree condition presented here would most likely generate the same strength of responses between cells sensitive to vertical and slightly tilted orientations, leading to a large miss rate on behalf of the participants. Evidently, future research with the orientation feature search paradigm should ensure that such high error rates are avoided, either by affording appropriates amount of training or by actively monitoring the error rates from the participants as they are completing the task.

In addition, the fitting procedure used here was a modification of a Maximum Likelihood Estimation procedure, using the Nelder-Mead simplex algorithm found in the optimization toolbox in MATLAB. Yet, it has been shown that when sample sizes for the fitting procedure are small, MLE can underestimate or overestimate the true population parameters of the Weibull distribution (Cousineau, 2009a). Other fitting procedures, such as those offered by Cousineau (2009a) can reduce this bias in estimating population parameters, such as a weighted-MLE procedure. The weights are used to nullify biases, and two of the weights used in the fitting procedure depend solely on sample size. Although the weighted-MLE is an advantageous alternative, properties, which are described for all sample sizes, are not for asymptotic cases, such as the Weibull distribution, making its implementation complex.

Estimating the parameters of the response time distributions can be an informative tool when trying to properly describe the underlying architecture of the search by assessing how the skew or the location of the distribution may change as a function of target presence and set size. Evidently, the usefulness of characterizing the shape of response time distributions is not limited to visual search paradigms. As previously demonstrated, they have been used in other cognitive paradigms in order to clarify or falsify effects typically supported by slopes of response time, or NHST analyses. Previous literature has predominantly focused on analyses using the Ex-Gaussian distribution, and therefore our use of the Weibull may be questioned. There are other asymptotic distributions that follow the exponential component of response times that could fit the data as well, and as such, choosing a single distribution to fit and describe the data may seem limited in scope. It is true that many other distributions can characterize the skew of response time distributions (for review, see Palmer et al., 2011), and the Weibull is only one of possibilities. Of primary importance when testing response times, as suggested by Townsend and Wenger (2004) is to approach the analysis in a statistically sound and theoretically sound approach. We chose the Weibull distribution, as its properties can properly describe limited capacity race models in visual search, the architecture of visual search we believe to be strongly involved in target identification (Cousineau et al., 2002). Other distributions may better characterize the theoretical implications of other domains of cognition, and should therefore be explored.

In addition to using distributional fitting within other fields of cognitive sciences, using the Weibull distribution in future modelling of visual search would also be of great interest. Distributional fitting can demonstrate that the parameters of the Weibull distribution vary according to search difficulty and could possibly reflect underlying cognitive processes that are of prime interest when modelling visual search. Further investigations into the possible applications of the Weibull are required prior to such objectives; of primary interest would be the shape parameter of the distribution. As previously mentioned by Cousineau and colleagues (2002) and Logan (1992) and observe here, it seems that the shape of the Weibull distribution when fitting response time data from visual search never really exceeds values of about two, even in very complex searches were skew is expected to be greatly reduced since the distribution should contain larger scores. Cousineau and colleagues (2002) thus considered the shape parameter as more of a constant than a free-parameter, making the modelling of visual search from the Weibull distribution a two-free and one-constrained parameter response model.

Distributional fitting of response time distributions is not a new concept in the analysis of response time data, and has been used multiple times before, and in many different types of cognitive paradigms (Ratcliff & Murdock, 1976; Heathcote et al., 1991; Hockley, 1984; Logan, 1992; Penner-Wilger et al., 2002; Rouder & Speckman, 2004; Townsend, 1990; Van Zandt, 2002). Endeavours in the use of distributional analyses have typically been brought on by the limited information gained from typical analyses of response times, such as slopes and their ratios between target present and target absent conditions. Here, we proposed the use of the Weibull distribution when fitting response time data, a distribution, which to our knowledge, has not been used in such analyses before. Although fitting a distribution to data can seem problematic, for it can enforce a belief of direct cognitive interpretations, the use of characterized distribution remains more informative when approached correctly. Future research in the parameters of the Weibull distribution, including models of visual search possibly based on the Weibull might lead to gaining a better understanding of how the parameters may reflect certain properties of cognition (Rouder et al., 2005).

The parameters of the Weibull distribution approached as a descriptive analysis of response time data in an effort to one, assess how these parameters changed under the varying conditions of search, and how the parameters could better inform us on the architecture of search as opposed to the mean response time analyses has been sufficient and informative, without attributing direct cognitive implications to the parameters. Distributional analyses can greatly aid in analysing results of search, and do so by encompassing the skew of response time distributions, permitting an in depth analysis of searched effects. As such, it is strongly recommended that others consider the use the Weibull distribution when analysing their results from visual search paradigms. Although over-interpreting parameters of response time distributions may be ill advise, a descriptive statistics approach can be quite informative in understanding the typical effects of visual search. The shift, scale and shape parameter are meaningful characteristics, and could be, ultimately, used as an ANOVA commonly would, with the added bonus of a more realistic and meaningful result than a mean response time.

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Tables

Table 1

Individual Kolmogorov-Smirnov Statistics of the Wolfe Dataset

	Feature Search				Conjunction Search				Spatial Configuration Search			
Ss	3	6	12	18	3	6	12	18	3	6	12	18
1	0.13	0.16	0.12	0.13	0.34	0.30	0.31	0.31	0.34	0.49	0.55	0.62
2	0.27	0.28	0.26	0.20	.05*	0.18	0.30	0.36	0.21	0.44	0.66	0.69
3	0.53	0.49	0.43	0.34	0.16	0.29	0.39	0.50	0.45	0.64	0.66	0.63
4	0.15	0.10	0.08	.07*	0.31	0.46	0.52	0.49	0.25	0.45	0.53	0.48
5	0.10	.03*	0.11	0.12	0.39	0.54	0.52	0.47	0.28	0.38	0.38	0.44
6	0.35	0.26	0.21	0.17	0.38	0.37	0.43	0.55	0.33	0.28	0.38	0.35
7	0.11	0.10	.08*	0.14	0.30	0.34	0.43	0.43	0.25	0.58	0.66	0.63
8	0.34	0.21	0.16	0.11	0.43	0.48	0.53	0.54	0.30	0.33	0.49	0.46
9	0.17	0.12	.06*	.06*	0.20	0.21	0.26	0.25	0.26	0.51	0.65	0.69
10	-	-	-	-	0.29	0.34	0.55	0.72	-	-	-	-

Note. All values not marked by an asterix were statistically significant at an α level = 0.05. The second row represents the set size for each search condition. Ss = Subjects.

Table 2

Individual Kolmogorov-Smirnov Statistics of the Orientation Feature Search

	30-Degree			20-Degree			10-Degree		
Ss	4	8	16	4	8	16	4	8	16
1	0.54	0.54	0.58	0.61	0.55	0.51	0.46	0.51	0.54
2	0.55	0.71	0.60	0.69	0.64	0.62	0.52	0.51	0.53
3	0.51	0.60	0.81	0.62	0.63	0.76	0.54	0.57	0.50
4	0.52	0.54	0.61	0.52	0.49	0.45	0.40	0.42	0.35
5	0.34	0.40	0.62	0.49	0.54	0.54	0.33	0.22	0.34
6	0.31	0.31	0.24	0.45	0.34	0.31	0.52	0.39	0.48
7	0.49	0.63	0.59	0.67	0.63	0.76	0.41	0.57	0.57
8	0.62	0.71	0.78	0.39	0.53	0.58	0.39	0.55	0.53
9	0.61	0.56	0.71	0.55	0.56	0.61	0.41	0.37	0.37
10	0.59	0.62	0.68	0.56	0.60	0.62	0.43	0.35	0.47

Note. All values were statistically significant at an α level = 0.05. The second row represents the set size for each search condition. Ss = Subjects.

Table 3

Individual X^2 Statistics for the Fits of the Wolfe Data Set (Target Absent)

	Feature Search				Conjunction Search				Spatial Configuration Search			
Ss	3	6	12	18	3	6	12	18	3	6	12	18
1	1.17	0.95	1.04	1.05	0.91	1.06	0.92	.75	0.71	0.34	0.17	0.12
2	0.94	1.03	1.42	1.01	1.13	1.33	0.76	0.62	0.71	0.42	0.30	0.20
3	2.75	3.05	3.04	2.49	0.75	0.45	0.24	0.12	0.32	0.20	0.12	0.10
4	0.86	0.92	0.94	0.84	2.43	1.76	1.59	1.19	0.35	0.25	0.18	0.15
5	1.86	1.37	1.36	1.49	0.97	0.80	0.95	0.50	0.46	0.36	0.23	0.13
6	2.22	2.26	2.10	2.16	1.07	0.71	0.27	0.17	0.80	0.45	0.24	0.18
7	1.18	1.36	1.43	1.38	1.08	0.78	0.60	0.49	0.53	0.26	0.14	0.12
8	1.08	1.03	1.04	1.8	0.87	0.67	0.50	0.28	0.67	0.24	0.10	0.07
9	1.18	1.30	1.23	1.14	1.13	0.85	0.58	0.60	0.59	0.32	0.18	0.12
10	-	-	-	-	1.25	0.95	0.36	0.17	-	-	-	-

Note. Ss = Subjects.

Table 4

Individual X^2 Statistics for the Fits of the Wolfe Data Set (Target Present)

	Feature Search				Conjunction Search				Spatial Configuration Search			
Ss	3	6	12	18	3	6	12	18	3	6	12	18
1	1.08	1.07	1.28	1.14	1.44	1.07	1.04	0.94	1.08	0.60	0.23	0.18
2	1.28	1.17	1.25	1.31	1.41	1.21	0.81	0.79	0.90	0.64	0.31	0.26
3	2.76	1.74	1.95	1.62	0.87	0.81	0.63	0.46	0.65	0.30	0.15	0.13
4	1.16	0.96	0.87	1.02	2.51	1.95	1.34	1.20	0.44	0.38	0.24	0.20
5	1.69	1.65	1.32	1.70	1.29	1.09	1.15	0.67	0.51	0.35	0.16	0.12
6	2.50	1.88	1.83	1.88	0.97	0.75	0.52	0.37	0.88	0.53	0.44	0.29
7	1.19	1.11	1.04	1.11	1.11	0.99	0.77	0.62	0.60	0.39	0.24	0.13
8	1.68	1.67	1.44	1.21	1.19	0.76	0.66	0.58	0.66	0.40	0.23	0.17
9	1.47	1.38	1.30	1.42	1.03	1.02	0.93	0.68	0.81	0.47	0.26	0.24
10	-	-	-	-	1.11	1.22	0.72	0.71	-	-	-	-

Note. Ss = Subjects.

Table 5

Individual X^2 Statistics for the Fits of the Orientation Feature Search (Target Absent)

	30-Degree			20-Degree			10-Degree		
Ss	4	8	16	4	8	16	4	8	16
1	0.01	0.03	0.03	0.01	0.04	0.06	0.05	0.06	0.08
2	0.01	0.03	0.02	0.01	0.05	0.03	0.02	0.08	0.10
3	0.01	0.02	0.04	0.02	0.03	0.05	0.04	0.06	0.14
4	0.03	0.04	0.04	0.05	0.05	0.04	0.07	0.08	0.08
5	0.02	0.03	0.02	0.03	0.05	0.03	0.05	0.08	0.10
6	0.01	0.02	0.02	0.02	0.03	0.03	0.04	0.06	0.05
7	0.06	0.12	0.07	0.08	0.02	0.14	0.10	0.27	0.22
8	0.02	0.03	0.02	0.04	0.04	0.02	0.08	0.08	0.06
9	0.01	0.02	0.03	0.03	0.02	0.05	0.08	0.04	0.09
10	0.04	0.03	0.02	0.05	0.03	0.04	0.08	0.07	0.09

Note. Ss = Subjects.

Table 6

Individual X^2 Statistics for the Fits of the Orientation Feature Search (Target Present)

	30-Degree			20-Degree			10-Degree		
Ss	4	8	16	4	8	16	4	8	16
1	0.02	0.02	0.04	0.03	0.05	0.09	0.04	0.10	0.17
2	0.06	0.05	0.02	0.04	0.08	0.10	0.04	0.20	0.14
3	0.02	0.02	0.08	0.04	0.04	0.13	0.06	0.11	0.25
4	0.02	0.03	0.03	0.03	0.05	0.06	0.09	0.13	0.14
5	0.05	0.02	0.03	0.05	0.05	0.08	0.08	0.09	0.12
6	0.01	0.02	0.03	0.02	0.04	0.07	0.04	0.07	0.09
7	0.03	0.07	0.09	0.04	0.10	0.15	0.09	0.22	0.31
8	0.02	.02	0.06	0.03	0.08	0.11	0.08	0.13	0.15
9	0.01	0.02	0.05	0.03	0.04	0.07	0.06	0.08	0.15
10	0.01	0.02	0.04	0.04	0.07	0.08	0.13	0.12	0.19

Note. Ss = Subjects.