A unified Bayesian observer analysis for set size and cueing effects on perceptual decisions and saccades

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Visual search and cueing tasks have been employed extensively in attentional research, with each having a standard effect (visual search: set size effects, cueing: cue validity). Generally these effects have been treated with different (but often similar) attentional theories. The present study aims to consolidate cueing and set size effects within an ideal observer approach. Four observers performed a yes/no contrast discrimination of a Gaussian signal in a task combining cueing with visual search. The signal appeared in half the trials, and effective set size (*M*, 2 to 8) was determined by one primary precue (having 50% validity in signal present trials) and *M*-1 secondary precues. There were two stimulus durations: 1 second (eye movements allowed), and the first-saccade latency (in the 1 second duration condition) minus 80 milliseconds. Simulations found that an ideal observer for the perceptual yes/no decisions and the first saccadic localization decisions predicted both set size and cueing effects with a single weighting mechanism, providing a unifying account. For the human observer results, a modified ideal observer (with performance matched to human performance) fit the yes/no perceptual decisions well. For the first saccadic decisions, there was evidence of use of the primary cue, but the modified ideal observer was not a good fit, indicating a suboptimal use of the cue. We discuss possible underlying assumptions about the task that might explain the apparent suboptimal nature of saccadic decisions and the overall utility of the ideal observer for cueing and visual search studies in visual attention and saccades.

Introduction

One general definition of visual attention might be the mental process that selects visual information across the visual field. Studies of visual attention have been heavily influenced by two paradigms: visual search and cueing (see Pashler, 1998, for a review). These two tasks, their results, and the main theoretical considerations are summarized in Table 1. In a visual search task, an observer typically detects or localizes a target amongst a field of items that might be mistaken as the target (distractors). The common manipulation is to change the number of distractors, or set size, which often leads to a set size effect, a decrease in performance (measured usually with accuracy or reaction time) with increasing set size (e.g., Baldassi & Verghese, 2002; Cave & Wolfe, 1990; Eckstein, 1998; Eckstein, Thomas, Palmer, & Shimozaki, 2000; Kinchla, 1974; Palmer, 1995; Palmer, Ames, & Lindsey, 1993; Palmer, Vergh-

ese, & Pavel, 2000; Shaw, 1980; Shaw, 1982; Shaw, 1984; Treisman & Gelade, 1980; Verghese, 2001; Wolfe, 1994; Wolfe, 2007; Wolfe, Cave, & Franzel, 1989; Wolfe & Gancarz, 1996). In a cueing task, observers typically detect a target that might appear in two or more locations. The defining characteristic of this task is a precue indicating one location to which the observers might direct their attention, typically by giving the most likely location of the target and/or inducing an automatic orienting of attention. The standard result is the cueing validity (or cueing) effect, in which a valid cue (the cue correctly indicating the target location) leads to better performance than an invalid cue (the cue incorrectly indicating a nontarget location), (e.g., Dosher & Lu, 2000; Eckstein, Shimozaki, & Abbey, 2002; Eriksen & St. James, 1986; Eriksen & Yeh, 1985; Folk, Remington, & Johnston, 1992; Gobell & Carrasco, 2005; Golla et al., 2004; Jonides, 1981; Jonides, 1983; Kinchla, Chen, & Evert, 1995; Lu & Dosher,

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	Visual search	Cueing
Task	Detect or localize a signal in a field of distractors.	Detect a signal with a predictive precue.
Main result	*Set size effect* – Performance decreases with increasing number of distractors.	*Cueing effect* – valid cues (precues that predict signal locations) lead to better performance.
Some standard limited capacity explanations	*Feature Integration Theory* - Treisman & Gelade, 1980. *Guided Search* – Cave & Wolfe, 1990; Wolfe, 1994; Wolfe, 2007; Wolfe, Cave, & Franzel, 1989; Wolfe & Gancarz, 1996.	*Enhancement* - Posner, 1980. *Zoom Lens* –Eriksen & St. James, 1986; Eriksen & Yeh, 1985. *Tuning (spatial resolution/acuity changes)* – Gobell, & Carrasco, 2005; Golla et al., 2004; Spitzer, Moran, & Desimone, 1988; Yeshurun & Carrasco, 1998, 1999.
Representative SDT/IO descriptions	*Set size effects* - Kinchla, 1974; Palmer, 1995; Palmer, Verghese, & Pavel, 2000; Shaw, 1980, 1982, 1984; Verghese, 2001. *Feature/conjunction searches* -Eckstein, 1998; Eckstein, Thomas, Palmer, & Shimozaki, 2000. *Search asymmetries* – Vincent, 2011a. *Distractor heterogeneity* - Ma et al., 2011; Vincent et al., 2009.	*SDT weighted integration*- Kinchla, 1977; Kinchla, Chen, & Evert, 1995. *Ideal observer*- Eckstein, Shimozaki, & Abbey, 2002; Shimozaki, Eckstein, & Abbey, 2003.

Table 1. A summary comparison of visual search and cueing tasks.

1998; Lu & Dosher, 2000a; Lu & Dosher, 2000b; Posner, 1980; Prinzmetal, Ha, & Khani, 2010; Shimozaki, Eckstein, & Abbey, 2003; Spitzer, Desimone, & Moran, 1988; Theeuwes, 1991; Yeshurun & Carrasco, 1998; Yeshurun & Carrasco, 1999). As in set size effects, this effect is often measured as a difference in reaction time or accuracy.

Both set size and cueing effects have been characterized as the result of visual attention mechanisms operating upon the visual scene. Specifically, a common depiction of visual attention in these cases is a mechanism operating as a spatially contiguous visual area (a *spotlight*) moving serially, either from location to location in a visual search task (e.g., Cave & Wolfe, 1990; Treisman & Gelade, 1980; Wolfe, 1994; Wolfe, 2007; Wolfe, Cave, & Franzel, 1989; Wolfe & Gancarz, 1996), or to the cued location in the cueing task (e.g., Eriksen & St. James, 1986; Eriksen & Yeh, 1985; Jonides, 1983; Posner, 1980). What is often implied in these descriptions is that attention improves vision within the spotlight, at a cost to the unattended areas (Dosher & Lu, 2000; Gobell & Carrasco, 2005; Golla, Ignashchenkova, Haarmeier, & Thier, 2004; Lu & Dosher, 1998; Lu & Dosher, 2000a; Lu & Dosher, 2000b; Spitzer, Desimone, & Moran, 1988; Yeshurun & Carrasco, 1998; Yeshurun & Carrasco, 1999). In other words, attention is a limited capacity resource allocated to different regions of visual space. This is a clearly valid inference in the case of overt visual attention and the orienting of the fovea and it seems intuitive to make the same suggestion for covert visual attention.

However, this singular view of covert visual attention has been disputed by Signal Detection Theory (SDT) and ideal observer (IO) approaches, both in the case of visual search (e.g., Baldassi & Verghese, 2002; Eckstein, 1998; Eckstein et al., 2000; Kinchla, 1974; Ma et al., 2011; Najemnik & Geisler, 2005; Palmer, 1995; Palmer, Ames, & Lindsey, 1993; Palmer, Verghese, & Pavel, 2000; Schoonveld, Shimozaki, & Eckstein, 2007; Shaw, 1980; Shaw, 1982; Shaw, 1984; Thornton & Gilden, 2007; Verghese, 2001; Vincent, 2011a; Vincent et al., 2009) and cueing (Eckstein, Shimozaki, & Abbey, 2002; Kinchla, 1977; Kinchla, Chen & Evert, 1995; Shimozaki, Eckstein, & Abbey, 2003; Vincent, 2011b; see also Dayan, Kakade, & Montague, 2000; Droll, Abbey, & Eckstein, 2009; Eckstein, Peterson, Pham, & Droll, 2009; Ehinger et al., 2009; Glimcher, 2003; Shimozaki, 2010; Shiu & Pashler, 1994; Shiu & Pashler, 1995; Smith, 1998; Smith, 2000; Torralba et al., 2006; Yu & Dayan, 2005a; Yu & Dayan, 2005b). These studies propose that both set size effects and cueing effects may be found without a spotlight of attention, but instead by models of attention that simply select information in parallel, without cost to the unattended areas. Also, there has been growing evidence that attention may select across multiple noncontiguous cued locations (Awh & Pashler, 2000; McMains & Somers, 2004; McMains & Somers, 2005; Müller, Malinowski, Gruber, & Hillyard, 2003). The parallel hypothesis of attention is notable, as it represents a fundamental difference from the common conceptualization of attention as a spotlight that improves the sensitivity of visual processing at the attended (cued) locations at the cost of the sensitivity at the unattended (uncued) location.

Signal Detection Theory (SDT) is a general statistical theory for decisions in tasks performed in the presence of stochastic noise (Green & Swets, 1974) and

it has a longstanding history of use and success within vision research. Bayesian ideal observer (IO) analysis, which may be considered a subset of SDT, predicts the best possible performance for a given task. It may be employed as an absolute standard of comparison or as a starting point for quantitative models. A number of studies have employed ideal observer analyses to assess various topics in vision, for example, detection and discrimination (Barlow, 1978; Burgess, Wagner, Jennings, & Barlow, 1981; Green & Swets, 1974), motion (Weiss & Adelson, 1998), object recognition (Liu, Knill, & Kersten, 1995; Tjan, Braje, Legge, & Kersten 1995), perceptual learning (Gold, Bennett, & Sekuler, 1999; Eckstein, Abbey, Pham, & Shimozaki, 2004), heading (Crowell & Banks, 1996), eye movements in visual search (Najemnik & Geisler, 2005), and reading (Legge, Klitz, & Tjan, 1997). In terms of visual attention, the studies mentioned in Table 1 have demonstrated that SDT/IO analyses do predict both set size and cueing effects, and also can predict human performance in many cases.

It should be noted that Table 1 only refers to cueing tasks in which the cue is predictive (more valid than invalid) of the cue location. SDT/IO analyses of cueing tasks only predict cue validity effects in this situation. Thus, a priori it is known that there are a number of significant cases in which the SDT/IO models cannot apply. These include Inhibition of Return (reversed cueing effects with longer cue stimulus onset asynchronies [SOAs], e.g., Klein, 2000; Posner & Cohen, 1984), the differences between automatic and voluntary attention (e.g., Jonides, 1981; Müller & Rabbitt, 1989; see review by Wright & Ward, 2008), and cue validity effects for anti-predictive (more invalid than valid) cues (e.g., Posner, Cohen, & Rafal, 1982; Warner, Juola, & Koshino, 1990). Notably, SDT/IO models do not predict cueing effects with nonpredictive and sudden onset cues that are thought to drive a reflexive or automatic attentional response, commonly known as attentional capture (e.g., Folk, Remington, & Johnston, 1992, Experiment 3; Jonides, 1981, Experiment 2; Theeuwes, 1991). Thus, the scope of this study will be restricted to the case of predictive cues.

It also should be noted that the modeling is necessarily specific for the tasks in the study and may not apply to other versions of cueing tasks (which would require different formulations of the ideal observer). In particular, the models describe tasks with a single decision for each trial across a single stimulus array, either yes/no signal presence or signal localization. One type of task not covered in this study includes a concurrent paradigm in which a separate identification or discrimination must be made for more than one location (e.g., Downing, 1988; Müller & Humphreys, 1991; Sperling & Melchner, 1978a, 1978b; and as discussed by Sperling & Dosher, 1986). Another type of

task not covered might be described as a contingent-judgment paradigm (e.g., Carrasco, Ling, & Read, 2004; Folk, Remington, & Johnston, 1992; Remington, Folk, & McLean, 2001) in which observers must find the relevant signal based upon a particular feature (for the cited studies: contrast, color, and color/motion, respectively) and then make a discrimination of the signal based on an unrelated feature (for the cited studies: orientation, X vs. =, and T vs. L, respectively).

The SDT/IO approach to both visual search and cueing can be summarized by a number of assumptions. First, it is assumed that the response from each location is subject to noise; for an ideal observer, the noise is external to the observer, and for a real/human observer, this noise can be both external and internal. Second, it is assumed that attention is seen only as a selective mechanism; in other words, attention works in parallel across the visual scene, without a cost to unattended areas. The SDT/IO models have been called *noisy-parallel* or *unlimited capacity* to reflect these aspects of the approach. Set size effects are predicted within this approach because each location must be considered in the eventual decision. As the set size increases, more locations must be considered, each subject to noise, and therefore more noise is added to the decision. For the cueing task, the ideal observer assumes that, thirdly, the response of each location has an optimal weighting equal to the prior probability of target occurrence at that location or the cue validity. This third assumption leads to a cueing effect in a cueing task with a parallel-noisy or unlimited capacity attentional mechanism.

In terms of limited capacity models, it is assumed that visual attention processes determine both set size effects in visual search studies and cueing effects in cueing studies, and one can argue that the same attentional mechanism is often implied. However, while it appears that such an explicit connection for set size and cueing effects could be done, studies typically do not assess set size and cueing effects jointly, and the discussion of limited capacity theories for set size (e.g., Cave & Wolfe, 1990; Treisman & Gelade, 1980; Wolfe, 1994; Wolfe, 2007; Wolfe, Cave, & Franzel, 1989; Wolfe & Gancarz, 1996) and cueing (e.g., Dosher & Lu, 2000; Eriksen & St. James, 1986; Eriksen & Yeh, 1985; Gobell & Carrasco, 2005; Golla et al., 2004; Jonides, 1983; Lu & Dosher, 1998; Lu & Dosher, 2000a; Lu & Dosher, 2000b; Posner, 1980; Spitzer, Desimone, & Moran, 1988; Yeshurun & Carrasco, 1998; Yeshurun & Carrasco, 1999) effects also tend to be separated. Perhaps the clearest example may be the two predominant early models of attention, *Feature Integration Theory (FIT)* for set size effects in visual search (Treisman & Gelade, 1980), and *enhancement* for cueing effects (Posner, 1980). In neither of these seminal studies do the authors discuss how set size

and cueing effects are related or could be explained together.

One early notable example of combining set size and cueing effects is the zoom lens hypothesis (Eriksen & St. James, 1986; Eriksen & Yeh, 1985). Across these two studies of yes/no letter detection, and amongst results suggesting the zoom lens hypothesis, there were cue validity effects (Eriksen & Yeh, 1985) and set size effects within one to three cued locations. The zoom lens assumes that attention improves acuity or sensitivity within the attended area and works in parallel across the attended area, with decreasing acuity with the increasing attended area size. This leads to predictions of cueing effects across cued and uncued areas and set size effects within the cued area. Another example is the biased competition model (Desimone, 1996; Desimone, 1998; Desimone & Duncan, 1995; Duncan, 1998), which describes items as competing for limited attentional resources antagonistically and biased by a number of bottom-up (stimulus-driven) and top-down factors, such as behavioral relevance. It has been employed specifically to describe both the neural behavior during target selection in visual search (e.g., in Desimone & Duncan, 1995; Chelazzi et al., 1993), and for the neural behavior of selective attention (i.e., cueing effects) within receptive fields (e.g., in Desimone, 1998; Luck et al., 1997; Moran & Desimone, 1985) in which the biased competition model assumes that "prior knowledge of the target's spatial location is just another type of attentional template that can be used to bias competition in favor of the target" (Desimone & Duncan, 1995, p. 200). Another more recent example is Prinzmetal, Ha, and Khani (2010). They state that a serial attention mechanism predicts larger cueing effects with increasing set size (in reaction times), as the difference in attending to the target and attending to any one uncued location (the cueing effect) will increase with more items to search.

Also, while not addressing set size and cueing effects, studies have assessed whether predictions from Feature Integration Theory and cueing enhancement could be combined (e.g., Briand & Klein, 1987; Carrasco, Giordano, & McElree, 2006; Prinzmetal, Presti, & Posner, 1986). For example, Briand and Klein (1987) found that, for exogenous cueing (cueing the location directly, as opposed to a symbol, such as an arrow), stronger cueing effects were found in conditions more likely to lead to illusory conjunctions (of the kind addressed in Treisman & Gelade, 1980, Experiment 4; i.e., mistaking P's and Q's as R's compared to P's and B's). This result suggests that the attentional mechanism oriented by cueing is the same attentional mechanism that binds features in FIT (and leads to less illusory conjunctions). Despite these examples, the issue remains that often the connections between set size and cueing effects have not been made explicit.

Also, the SDT/IO treatments of set size and cueing effects so far generally have been separated, with the one notable exception of Kinchla (1974; 1977; Kinchla, Chen, & Evert, 1995) discussed below. However, as shown later, combining set size and cueing effects within an ideal observer framework is straightforward. An ideal observer model can consolidate both set size and cueing effects as the result of selective weights, with the weights representing the prior probabilities of signal presence at a particular location. For a standard visual search task, the ideal observer assigns equal weightings distributed across the relevant locations, and no (zero) weighting to the irrelevant locations. For a standard cueing task, the weightings also reflect the validity of the cued location(s), and thus are unequal across the relevant locations (higher for cued and lower for uncued) when the cue is predictive. While trivial mathematically, theoretically this could be an important aspect for a model of attention, as it explicitly states that set size and cueing effects can be modeled equivalently.

Kinchla presents the same basic concept of selective weighting in his SDT *weighted integration* model for both set size (1974) and cueing (Kinchla, 1977; Kinchla, Chen, & Evert, 1995) effects. The difference between Kinchla's model and the ideal observer is that his model weights the responses to the stimuli at each location, whereas the ideal observer weights the likelihoods of target presence at each location. While Kinchla's weighted integration model and the weighted likelihood model make qualitatively similar predictions of set size and cueing effects, Shimozaki, Eckstein, & Abbey (2003) directly compared the predictions of these two models quantitatively with increasing signal contrast and found better fits to human performance for the ideal observer.

The present study measured performance for both perceptual and saccadic decisions in a task that combines predictions of set size and cueing effects. Observers performed a yes/no contrast discrimination task of a small Gaussian signal in Gaussian image noise with set sizes of 2, 3, 5, or 8 (see Figure 1). The signal appeared on half the trials and observers judged on the presence of the signal. There were two types of precues (500 milliseconds), primary (square), and secondary (circle). There was always a single *primary* cue location, which had 50% validity when the signal was present, and the rest of the cued locations (1, 2, 4, or 7 locations) had secondary cues, with the remaining 50% validity equally divided amongst the secondary cue locations. There were two stimulus durations, a *long* condition in which eye movements were allowed and eye position was monitored, and a *short* condition with durations equal to the mean latencies for the first saccades in the long condition, minus 80 milliseconds. The short stimulus durations were chosen so that the
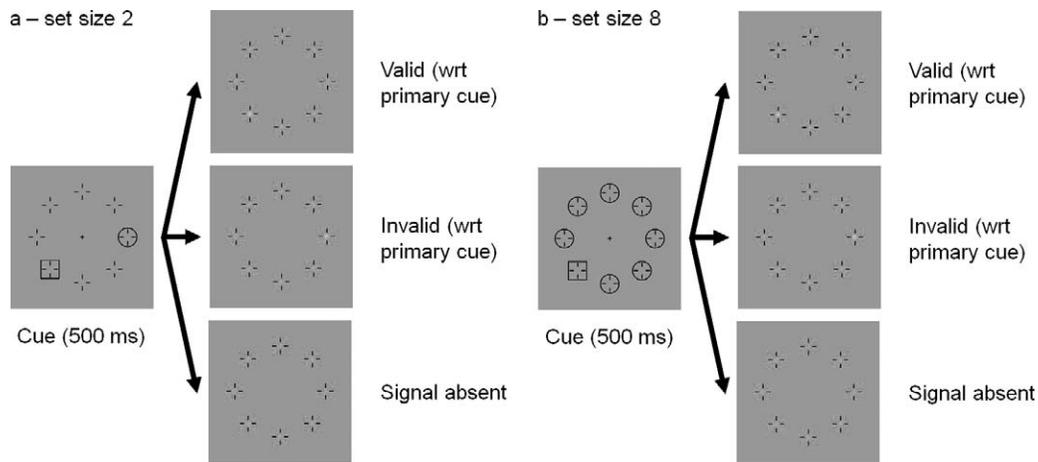
Figure 1. Stimulus configuration. A (left) – set size 2; B (right) – set size 8. Observers made a yes/no judgment on the presence of a small Gaussian signal contrast increment presented in Gaussian white image noise. A 500 ms cueing display preceded the stimulus display (left images of A and B) and always contained one primary cue (square) that was 50% valid. One to seven secondary cues (circles) appeared to give effective set sizes of 2, 3, 5, and 8, and the validity across all secondary cues was 50% (so that validity for each secondary cue was 50%/# secondary cues). There were three types of trials: valid (with respect to the primary cue) in which the signal appeared at the primary cue location (top right images of A and B); invalid (with respect to the primary cue) in which the signal appeared at one of the secondary primary cue locations (middle right images of A and B); and signal absent (bottom right images of A and B). The stimulus displays were either long (1 s) or short (first saccade latency – 80 ms).

amount of processing time matched approximately the processing time for the first saccade in the long trials, with the 80 millisecond subtraction chosen to account for the *dead time* involved in saccades caused by the delay in the initiation of a saccade by motor programming (e.g., Becker, 1991; Caspi, Beutter, & Eckstein, 2004).

The goal of the study was to compare the effect of cues and set size on human performance to the ideal observer predictions for: a) the perceptual yes/no decisions in the 1-second (long) condition with multiple saccades; b) the perceptual yes/no decisions for the short stimulus durations while the observers maintain central fixation; and c) the saccadic localization decisions of the first saccade in the 1-second (long) trials. Note that the first saccades (fixations) were classified as localization decisions, in which the potential signal location nearest the first fixation was taken as the saccadic localization decision. Also note that the saccadic localizations occurred for both the signal present and signal absent trials of the yes/no perceptual decision (long duration) task. Lastly, note that the modeling for the saccadic localizations in the signal present trials is equivalent to the modeling for a forced-choice procedure (*M*-alternative forced choice [AFC], *M* = number of locations) for these conditions.

The study had two primary aims. First, in tasks with elements of typical visual search and cueing studies, the study assessed ideal observer performance with respect to set size and cueing effects. Second, the study assessed how effective the human observers were in using the information provided by the cues, relative to an ideal observer, for perceptual (yes/no) and saccadic (localization) decisions.

Description of the ideal observer for this task

The task incorporated predictions for both set size and cueing effects, with the validity of each secondary cue decreasing as set size increased. Figure 2 depicts the ideal observer model for this task, both for the perceptual (yes/no) decisions and the saccadic (localization) decisions. The figure starts with a stimulus image for a given trial. The observer must detect the presence or localize a single signal stimulus (S_1) amongst other nonsignal stimuli (S_0), with the figure depicting the signal present in the lower left. At each location, the model generates a response (x_i) by cross-correlating the stimulus at that location for that trial (a_i) with the ideal template. The cross correlation is the standard assumption for ideal observers (Barlow, 1978; Burgess, Wagner, Jennings, & Barlow, 1981; Green & Swets, 1974; see also Eckstein, Shimozaki, & Abbey, 2002) and is also known as the Linear Amplifier Model (e.g., Murray & Gold, 2004). The stimulus at each location is either the signal or nonsignal with added Gaussian image noise, and the ideal template in white Gaussian noise is the difference between the signal and the nonsignal stimuli ($S_1 - S_0$).
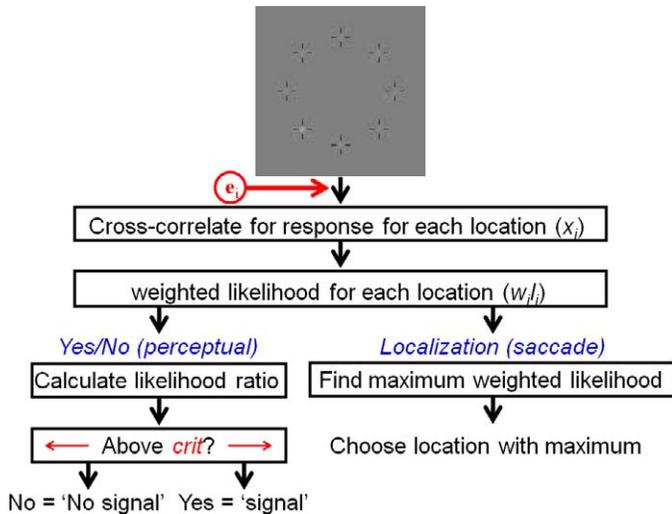
Figure 2. Ideal observer calculation for the cued visual search task, both for the yes/no task (perceptual decisions), and the localization task (first saccadic decisions). The observer must detect or localize a signal pattern (S_1) in a field of no signal patterns (S_0) out of M (=8) possible locations. A sample stimulus image is shown on the top with the signal present in the lower left corner. A) To generate a response at each location (x_i), the ideal observer performs a cross-correlation of the stimulus (a_i) with the ideal template, which in Gaussian noise is the difference between the signal and the no signal patterns ($S_1 - S_0$). B) The ideal observer computes the probability of target presence at each location, given all the responses (the likelihoods, $l_i = p(\mathbf{x}|S_1,i)$). Then the ideal observer calculates the posterior probabilities of signal presence at each location ($p(S_{1,i}|\mathbf{x})$) by weighting the likelihoods (l_i) with the prior probability of target presence, or the overall cue validity (w_i). C) For the yes/no (perceptual) task (lower left), the ideal observer calculates the likelihood ratio of the posterior probability of signal presence over the posterior probability of signal absence. This ratio is compared to a criterion (crit). Values equal to or above the criterion lead to a Yes response, and values below the criterion lead to a No response. D) For the localization (saccadic) task (lower right), the location with the maximum weighted likelihood is chosen as the signal location. Modifications to the ideal observer for fits to human performance are noted in red. For the fits of the ideal observer predictions to human performance, d' was allowed to vary. This is equivalent to adding internal Gaussian noise to the responses at each location ($\mathbf{e_i}$). Also, for the yes/no (perceptual) task, the criteria (crit) for each set size were varied.

The model calculates the probability of signal presence at each location given all the responses, or the likelihoods ($p(\mathbf{x}|S_1,i)$). Then (as an expression of Bayes' theorem) the ideal observer finds the posterior probability of signal presence at each location i, given the responses ($p(S_{1,i}|\mathbf{x})$), by weighting the likelihoods by the prior probability of signal presence at that location (w_i) or the cue validity (across both signal present and signal absent trials) at that location. If no cue is present

at a location, the prior probability is equal to zero. For this study, the prior probability was 0.50 at the primary cue location and 0.50/(M-1) at each secondary cue location. Thus, for the ideal observer the difference between a visual search task and a cueing task is simply (and completely determined by) the difference in the weighting of the likelihoods.

For the yes/no decision (upper box), the ideal observer computes the likelihood ratio of the summed weighted likelihoods of target presence over the posterior probability of target absence ($p(S_0|\mathbf{x})$). If the ratio is above an optimal criterion value, then the ideal observer responds Yes; otherwise, it responds No. For the localization task (lower box), the ideal observer chooses the maximum value amongst the weighted likelihoods as the signal location. Note that for the localization task, the weighted likelihood can be simplified mathematically to an additive bias of the logarithm of the prior probability summed to the logarithm of the likelihood (this simplification is not possible in the yes/no task).

For the fits to the human observers, the ideal observer was modified in two ways (see items in red in Figure 2). First, d' was varied to find the best fit to the overall performance of the human observer. This is equivalent to the addition of internal noise to the responses of the ideal observer ($\mathbf{e}_i$). Also, in the yes/no perceptual tasks, the criteria for each set size were allowed to vary (see Shimozaki, Eckstein, & Abbey, 2003), rather than assuming an optimal decision criterion. Also, to illustrate cueing effects, the ideal observer was compared to a suboptimal unweighted model; this model shares the structural components of the ideal observer, except that the weights for all locations were equal. This model removes the use of the primary vs. secondary cue information from the ideal observer, and thus can be used to assess the use of cues. Also, it is equivalent to the ideal observer in a standard visual search task that has no differential cues.

Methods

Four observers (MG – male, 22 years; ML – female, 22 years; SS – male, 42 years, first author; WS, 23 years, second author) participated in a yes/no cued contrast discrimination visual search task with effective set sizes of 2, 3, 5, and 8 (see Figure 1, set sizes 2 and 8 shown). The observers judged upon the presence or absence of a small 2D Gaussian contrast increment signal ($\sigma = 11'$) that was present on 50% of the trials at one of eight locations 6.0° from the center. Stimuli were presented on a grey background with a mean luminance of 25.0 cd/m² . Prior to the stimulus display, a cueing display appeared for 500 milliseconds. The cueing display had

two types of cues, a primary cue (black 2.5° square, 5.86 cd/m²) and secondary cues (black circle, diameter 2.5°, 5.86 cd/m²) appearing at the potential signal locations. The primary cue always had a conditional 50% validity; in other words, if the signal appeared, it would appear at the primary cued location 50% of the time. The number of secondary cues was 1, 2, 4, or 7, depending on the condition, and the conditional validity across all secondary cues was 50%. Therefore, the conditional validity of each individual secondary cue was 50%, 25%, 12.5%, or 7.1% (50%/7), and the effective set sizes were the number of secondary cues plus one (the primary cue), or 2, 3, 5, and 8. This cueing method has been shown to be effective in manipulating the relevant set size to the cued locations (Palmer, 1995; Palmer, Ames, & Lindsey, 1993), particularly for simple nonlinguistic signals, such as the Gaussians used here. As there were half signal present and half signal absent trials, the overall cue validities were half the conditional cue validities.

A 2D Gaussian +7.81% contrast pedestal (same size as the signal) appeared at each location in Gaussian white noise ($\sigma = 2.93$ cd/m²), whether the location was cued or not. The signal contrast was +6.25% above the pedestal, except for ML, who performed with a contrast of +8.59%. During pilot studies it was found that ML performed worse than the other observers at the lower contrast, and therefore her contrast was made higher to compensate. The ideal observer Signal-to-Noise Ratios (*SNR*'s) are defined as

$$SNR = \frac{\sqrt{(\mathbf{S}_1 - \mathbf{S}_0)^t (\mathbf{S}_1 - \mathbf{S}_0)}}{\sigma_{pixel}}, \qquad (1)$$

for a given pixel image noise (σ_{pixel}), and with $\mathbf{S}_1$ and $\mathbf{S}_0$ representing the signal and pedestal, respectively, as column vectors, and t representing the transpose (of the vector $(\mathbf{S}_1 - \mathbf{S}_0)$). The Signal-to-Noise Ratios for the lower and higher (for ML) signal contrasts were 3.78 and 5.18, respectively. Four small tick marks indicated the possible signal location to reduce location uncertainty, and the locations were equally spaced, with locations at the major axes (top, bottom, left, and right) and at the four 45° oblique intervals.

There were two stimulus duration conditions, long and short. The long duration was 1 second and was run first. In this condition we measured the perceptual yes/no decision and also the first saccadic localization decision, or in other words, the location closest to the landing point of the first saccade after the stimulus display appeared (see details below). The short duration was determined by the first saccadic latencies measured in the long duration condition (by each individual observer and set size), minus 80 milliseconds. As mentioned earlier, the goal of the short duration was to match the processing time of the perceptual decision

with the first saccadic decision of the long duration, and 80 milliseconds was chosen to account for the *dead time* latency between the motor command to make a saccade and saccade initiation (Becker, 1991; Caspi, Beutter, & Eckstein, 2004). The short duration was chosen to not allow time for saccades; thus, only the perceptual yes/no decision was measured in this condition.

Observers performed the task on a chinrest to reduce motion artifacts, and each observer performed in 600 trials for each stimulus duration (long and short) and set size (2, 3, 5, and 8). (Note that the number of trials was larger than that for a typical eye-tracking study because of the model fitting involved.) At the start of each trial, observers were advised to maintain fixation on the center cross until the stimulus display appeared, with verification by eye tracking of fixation within 1° of the cross during the cueing display. With the long stimulus duration, observers were advised to move their eyes freely after the appearance of the stimulus display; with the short duration, observers were advised to maintain fixation during the stimulus display.

After completion of the long duration trials, data were analyzed offline to detect the first saccades occurring after the appearance of the stimulus display (and disappearance of the cue display). The restrictions on the categorization of first saccades were that they were the first saccades further than 2.35° from the center and within 120 to 900 milliseconds of stimulus appearance; these restrictions led to a rejection of 1.09% of the trials across all observers. The potential signal location closest to the first saccadic endpoint was taken as the localization decision for that trial to be analyzed further (Findlay, 1997; Eckstein, Beutter, & Stone, 2001; Beutter, Eckstein, & Stone, 2003).

Apparatus for experiments

Stimuli were displayed on a computer monitor (42.2 by 31.7 cm, Image Systems, monochrome, Minnetonka, MN) viewed at 50 cm at 1024 × 768 pixel resolution so that each pixel subtended 0.045° visual angle. Luminance and color were calibrated with the Easy Cal (Pantone, NJ) photometer and software. Eye position was monitored through the left eye only with an infrared tracking system (250 Hz, Eyelink I, SMI/SR Research Ltd., Osgoode, ON, Canada). Calibrations (on a 9-point grid) were performed every 100 trials, and there was a drift correction at the start of each trial when the observers fixated the center of the screen. Tracker error measured immediately after calibration at the beginning of each 100-trial session had a mean of 0.470° ($SE = 0.015$°) across all observers (MG: mean error = 0.365°, $SE = 0.021$°; ML: mean error = 0.525°, $SE = 0.031$°; SS: mean error = 0.516°, SE

$= 0.031°$; WS: mean error $= 0.478°$, $SE = 0.028°$). Saccades were detected offline with software provided by SMI/SR Research (Osgoode, ON, Canada) when both eye velocity and acceleration exceeded a threshold (velocity – 35 °/s; acceleration – 9500 °/s²).

Model predictions and fits

Validity for all results are stated in terms of the primary cue, so that *valid* refers to the primary cue being valid (signal appeared at the primary cue location) and *invalid* refers to the primary cue being invalid (signal appeared at one of the secondary cue locations).

Predictions for the models' performances (see Appendix A) were estimated through Monte Carlo simulations with 50,000 trials (which was judged to be a reasonable number to minimize the error in estimating the models' performance, see also Shimozaki, 2010) for each individual set of parameters. These predictions were compared to human performance using the Root Mean Square Error of Approximation (RMSEA), a standard statistic for assessing model fits based on the χ^2 statistic (Browne & Cudeck, 1992; McCallum, Browne, & Sugawara, 1996; Steiger, 1990). With N = sample size,

$$RMSEA = \sqrt{\frac{\left(\frac{\chi^2}{df} - 1\right)}{(N-1)}}. \tag{2}$$

With the RMSEA, values less than 0.05 indicate good fits, and values larger than 0.10 indicate poor fits. This statistic has been used instead of a simple χ^2 statistic, as χ^2 is heavily biased towards significance for larger sample sizes (greater than 200). Confidence intervals for the RMSEA can be calculated based upon the noncentral χ^2 distribution (see Appendix B for details). Based on the calculation in Appendix B, 90% confidence intervals were found for the RMSEAs, which were then used in two possible tests. First, the upper bound of this interval could have been compared to 0.05; if the upper bound was below 0.05, then it could be concluded that the fit was *good* with 95% confidence. Second, the lower bound could have been compared to 0.10; if the lower bound was above 0.10, then it could be concluded that the fit was *poor* with 95% confidence. (Browne & Cudeck, 1992; McCallum, Browne, & Sugawara, 1996).

Fits were performed across all four set sizes, and separately for each observer. For the yes/no task, fits were done on the hits and misses for the valid trials (one degree of freedom), the hits and misses for the invalid trials (one degree of freedom), and the false alarms and correct rejections for the signal absent trials (one degree of freedom), giving three degrees of freedom for each set size, and $3 \times 4 = 12$ degrees of

freedom for each observer's data set. The free parameters of the modified ideal observer and the unweighted model (ideal except for equal weights at all cued locations) were the overall d' of the observer and the four criteria, one for each set size (see red items in Figure 2) resulting in $12 - 5 = 7$ degrees of freedom for these fits. Adjusting the d' of the ideal observer and the unweighted model to match the human observer performance was equivalent to adding internal noise to the responses of the ideal observer or the unweighted model.

For the localization task, fits were performed assuming no fixations to uncued locations (this point will be discussed later). Thus, for the valid signal present trials there were both the correct and incorrect localizations (one degree of freedom). For the invalid signal trials there were the correct responses, the incorrect responses to the primary cue, and the incorrect responses to the secondary cue for the invalid trials (except for set size 2, as there was no possibility for incorrect responses to the secondary cue). Thus, with respect to the invalid signal trials there were two degrees of freedom, except for set size 2 having one degree of freedom. For the signal absent trials, there were the responses to the primary cue or the secondary cue, and thus one degree of freedom. Overall, for each set size there were four degrees of freedom $(1 + 2 + 1)$, except for set size 2 (with $df = 3$), and the total number of degrees of freedom was 3 (for set size 2) $+ 4 + 4 + 4 = 15$. There was one free parameter for the modified ideal observer and the unweighted model, the d' of the human observer, giving 15 - 1 = 14 degrees of freedom for the localization fits. All fits of the human data with the models were performed with the RMSEA transform of the standard χ^2 statistic (Equation 2).

Results

The results are divided into two main sections, the model simulation results and the human observer results. For the model simulation results, the behavior of the ideal observer and the unweighted model is assessed across set size and also across different levels of performance (d'). For both the yes/no task (presented first) and the localization task (presented second) both the ideal observer and the unweighted model exhibit set size effects, as demonstrated in previous studies of visual search using SDT models (Palmer, 1995; Palmer, Verghese, & Pavel, 2000; Shaw, 1980, 1982, 1984; Verghese, 2001). For both tasks the ideal observer also exhibits cueing effects, as demonstrated in previous studies (Droll, Abbey, & Eckstein, 2009; Eckstein, Shimozaki, & Abbey, 2002; Shimozaki, Eckstein, & Abbey, 2003). With respect to d', the ideal

observer predicts variable cueing effects as a function of d'. In particular, for the yes/no task cueing effects are small for low and high d's and larger for intermediate d's; this is consistent with a previous study on the ideal observer and the cueing task (Shimozaki, Eckstein, & Abbey, 2003).

The results for the human observer results are presented with the perceptual yes/no tasks first (the long duration followed by the short duration). Those results indicate generally good fits for the ideal observer, and somewhat worse fits for the unweighted model. The results for the saccadic decision localization task are presented last. For this task, there were a large number of saccadic decisions to uncued locations (neither primary nor secondary), for which neither the ideal observer nor the unweighted model can account. Even with the removal of these uncued saccadic decisions, the fits to the ideal observer were poor (the fits for the unweighted model were somewhat better, in this case). However, there was evidence of the observers using the primary cue. In particular, when assessing the saccadic decisions in the signal absent trials (and thus not confounded with signal presence), three of four observers had saccades to the primary cue location greater than chance ($1/M$, where $M =$ number of total cued locations).

Results, model simulations

Yes/no task (perception)

Figures 3 and 4 summarize the results for the ideal observer in the yes/no task used to model the perceptual decision results. The gold symbols and lines indicate the ideal observer predictions, and the blue symbols and lines indicate the predictions for the case in which each location is equally weighted (unweighted). The unweighted model would be ideal in a standard visual search experiment in which the signal can appear in all locations equally and no differential cues are given. However, for the current task the model is suboptimal in that it ignores the cue information. Thus, in general the comparison between the ideal observer and the equally weighted model demonstrates the difference in performance when both having and using the cue information.

Figure 3 gives the model results for the valid and invalid hit rates (correctly saying "yes" when the signal was present) and the false alarm rates (incorrectly saying "yes" when the signal was not present) for $d' = 1.0, 2.0,$ and 3.0. Note that for the unweighted model the valid and invalid hit rates were the same, as expected from the equal weights (no cueing effect). For the ideal observer, the valid hit rates were greater than
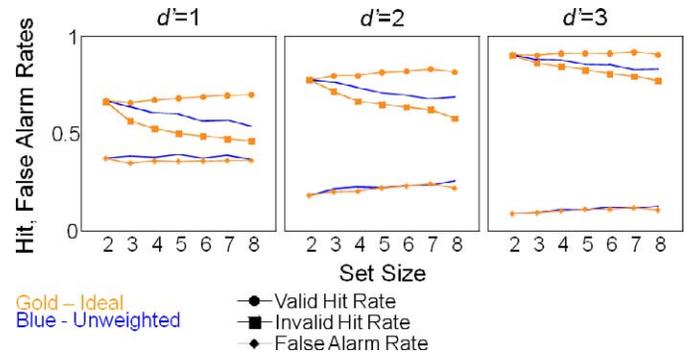

Figure 3. Ideal observer predictions for hit and false alarm rates for the yes/no detection task (perceptual decisions) for $d' = 1.0, 2.0, 3.0$. Gold – ideal observer. Blue – unweighted (equal weights for cued and uncued). Circles – valid (relative to the primary cue) hit rates. Squares – invalid (relative to the primary cue) hit rates. Diamonds – false alarm rates.

the invalid hit rates, indicating a cueing effect, and this difference increases with increasing set size. Note that for set size $= 2$ the valid and invalid hit rates were equivalent, as both the primary and the single secondary cue are 50% valid in this case. The false alarm rates for the ideal observer and the unweighted models were nearly the same.

Figure 4A summarizes the overall proportion correct (PC) across all trials as a function of set size for $d' = 1.0, 2.0,$ and 3.0. Both models show the characteristic set size effect, with decreasing performance as set size increases. Note that proportion correct is slightly greater for the ideal observer; this indicates the benefit in using the cue information. For this arrangement of cue validities, there is no benefit at set size 2 (50% valid), and the benefit increases as the set size increases and the primary cue increases validity compared to each individual secondary cue location (e.g., 50% vs. $50/7 = 7.14\%$ for set size 8). Increasing the validity of the primary cue would also increase the benefit of using the cue information (Vincent, 2011b).

Figure 4B summarizes the cueing effects for the ideal observer as a function of set size, expressed as the difference between the valid hit rate and the invalid hit rate. The left graph gives cueing effects for $d' = 0.5, 1.0,$ and 1.5 and the right graphs gives cueing effects for $d' = 1.5, 2.0, 2.5, 3.0,$ and 3.5. The cueing effects increase with set size, due to the difference in validity between the primary cue and the individual secondary cues increasing with increasing set size. Also, for the range of d's presented here, the cueing effects first increase with increasing d' up to $d' = 1.5$ (left graph), and then decrease for d's greater than 1.5 (right graph) (also see Shimozaki, Eckstein, & Abbey, 2003). This function of cueing effects with d' is due to two factors. At low d's, performance with both valid and invalid cues are near chance levels, leading to small cueing effects; at high
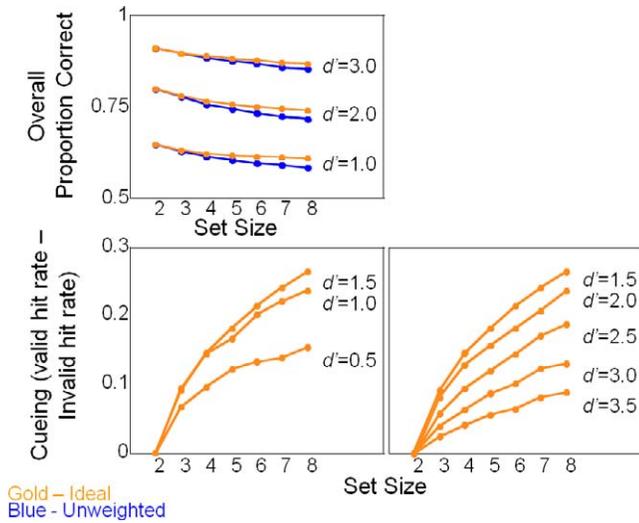
Figure 4. A. Ideal observer predictions for Proportion Correct (PC) for the yes/no detection task (perceptual decisions), $d' = 1.0$, 2.0, 3.0. Gold – ideal observer. Blue – Unweighted (equal weights for cued and uncued locations). B. Ideal observer predictions for cueing effects (valid hit rate - invalid hit rate) for the yes/no detection task (perceptual decisions). Left: $d' = 0.5$, 1.0, 1.5. Right: $d' = 1.5$, 2.0, 2.5, 3.0, 3.5.

d's, performance with invalid cues increases with increases in d' and ceiling effects consequently cause less of a cueing effect.

Localization task (saccade)

Figures 5, 6, and 7 summarize the results for the ideal observer in the localization task used to model the first saccadic decision results. As before, the ideal observer is shown in gold and the unweighted model is in blue. In Figures 5 and 6, only trials in which the signal was present (half of all the trials) are considered,
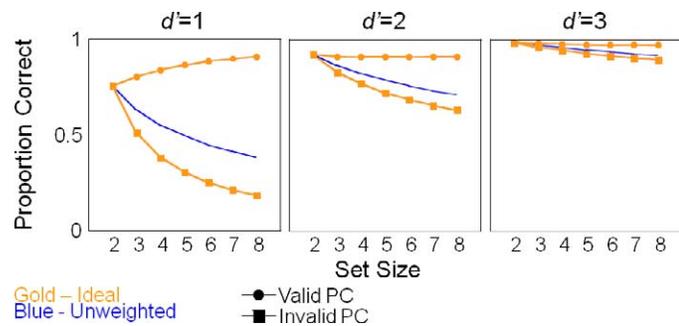

Figure 5. Ideal observer predictions for Proportion Correct for valid and invalid cues for the localization task (first saccadic decisions) for $d' = 1.0$, 2.0, 3.0. Gold – ideal observer. Blue – Unweighted (equal weights for cued and uncued locations). Circles – valid (relative to the primary cue) percent correct. Squares – invalid (relative to the primary cue) percent correct.
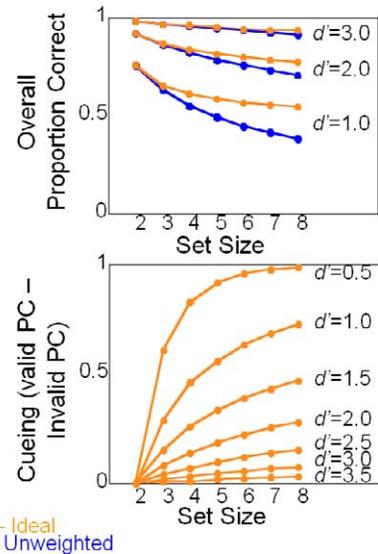

Figure 6. A. Ideal observer predictions for overall Proportion Correct for the localization task (first saccadic decisions), $d' = 1.0$, 2.0, 3.0. Gold – ideal observer. Blue – Unweighted (equal weights for cued and uncued locations). B. Ideal observer predictions for the cueing effects (valid PC - invalid PC) for the localization task (first saccadic decisions), $d' = 0.5$, 1.0, 1.5, 2.0, 2.5, 3.0, 3.5.

and the saccadic localization decisions were compared to the signal locations. Note that the signal present condition on its own is equivalent to a standard M-AFC task, and thus these figures also describe the ideal observer and unweighted model behavior for an M-AFC task with this cue validity arrangement. Figures 5 and 6 are analogous to Figures 3 and 4 for the yes/no task, with Figure 5 presenting the proportion correct (PC) for the valid and invalid trials ($d' = 1.0$, 2.0, 3.0), Figure 6A presenting the overall proportion correct ($d' = 1.0$, 2.0, 3.0), and Figure 6B presenting the cueing effects, expressed as the difference between the valid proportion correct and the invalid proportion correct ($d' = 0.5$, 1.0, 1.5, 2.0, 2.5, 3.0, 3.5). The results summarized in Figures 5 and 6A were similar to the results in Figures 3 and 4. Figure 5 shows a cueing effect in which the valid proportion correct was greater than the invalid proportion correct for the ideal observer, except for set size 2, and that the difference between the valid and invalid proportion correct values increased with set size. Figure 6A indicates that both the ideal observer and the unweighted (equal weight) model had set size effects (decreasing proportion correct with increasing set size). Also, the proportion correct for the ideal observer was greater than that for the unweighted model, indicating the benefit in using the cue information. Figure 6B shows that the cueing effects decreased with increasing d' for the range of d's in this study. Note that this pattern differs from that for the yes/no task, and reflects the difference in the two tasks (yes/no vs. localizations). At low d's, and thus a

lack of perceptual evidence, the localization decisions essentially follow the cue and favor the primary cue location. At high d's, ceiling effects for performance in the invalid trials lead to decreased cueing effects.

To summarize, set size effects for the ideal observer and the unweighted model are shown in Figure 4A for the yes/no task and in Figure 6A for the localization task. Cueing effects for the ideal observer are shown in Figure 4B for the yes/no task and Figure 6B for the localization task. Also evident in Figures 4B and 6B is the dependence of the cueing effects upon d' for the two tasks. For the yes/no task, cueing effects rise and then fall with increasing d' (Shimozaki, Eckstein, & Abbey, 2003), and for the localization task, cueing effects decrease with increasing d'.

Choices for nontarget locations in target absent and invalid cue trials

Figure 7 summarizes the ideal observer predictions for nontarget localization decisions for the invalid and target absent trials. Figure 7A and 7B give the predicted nontarget localization rates in the invalid trials (the signal appears at a secondary cue location). These decisions represent errors in the task, and there were two types, choosing the primary cue location (p(primary), 7A) and choosing an incorrect secondary cue location (p(incorrect secondary), 7B). Note that for set size = 2, p(incorrect secondary) = 0, as there was no incorrect secondary cue location. As expected, the error rates decreased with increasing d', as indicated by the decrease of both p(primary) and p(incorrect secondary) with d', except for $d' = 0$. In the case of $d' = 0$, the ideal observer always chose the primary cue location, except for set size = 2, in which the primary and secondary cues had equal cue validity. Again, this was due to the fact that decisions were driven by the cue information (following the primary cue) at low discriminabilities. The decrease of p(primary) in Figure 7A with increasing d' also partly reflects the decreased effect of cues with increasing d' shown in Figure 6B. Finally, the rates of p(primary) and p(incorrect secondary) increased with set size, as expected from the set size effects shown in Figure 6A.

The present task is somewhat different from typical localization tasks in that predictions can be made for localization decisions with no signal to localize, the signal absent trials of this task. Figure 7C and 7D summarize the ideal observer and unweighted predictions for these localization decisions; in these cases, there was no correct response, and categorizing responses as correct and incorrect was not applicable. Figure 7C gives the predicted probabilities of choosing the primary cue location (p(primary)) and Figure 7D gives the predicted probabilities of choosing any secondary cue location (p(secondary)), or 1 - (p(prima-
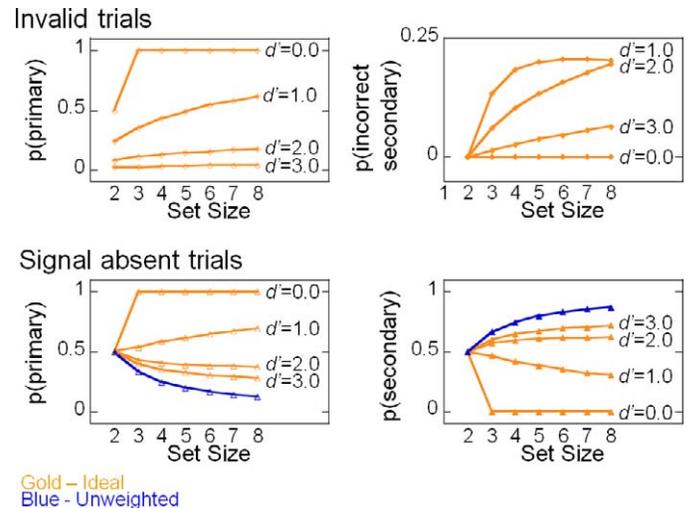

Figure 7. Ideal observer predictions for the probability of first saccades to nontarget locations in the localization task. Gold – ideal observer. Blue – Unweighted (equal weights for cued and uncued locations). A. Probability of saccades to primary cue (p(primary)), invalid trials, $d' = 0.0, 1.0, 2.0, 3.0$. B. Probability of saccades to incorrect secondary cue (p(incorrect secondary)), invalid trials, $d' = 0.0, 1.0, 2.0, 3.0$. C. Probability of saccades to primary cue (p(primary)), signal absent trials, $d' = 0.0, 1.0, 2.0, 3.0$. D. Probability of saccades to secondary cue (p(secondary)), signal absent trials, $d' = 0.0, 1.0, 2.0, 3.0$.

ry)). For all d's at set size = 2, the probability of choosing the primary or secondary cue is 0.50, as the primary and secondary cues have equal cue validity. Without a signal present, the unweighted model chooses a location randomly; thus, its probability of choosing the primary cue location in the signal absent trials was 1/set size (1/M). As expected from the weighting of the primary cue location, the ideal observer chose the primary cue location more frequently than the unweighted model. As in the earlier cases, the cue validity had a smaller effect as d' increased. For example, with $d' = 0$ the ideal observer always chose the primary cue location, except for set size = 2. As discriminability increases, the dependence upon the primary cue decreased.

Results, human observers

Saccade latencies

Table 2 gives the mean saccade latencies of the 4 observers in the long duration (1 second) task. These values, minus 80 milliseconds for motor programming, were used for the short stimulus durations. No consistent set size effects were found. SS and WS had positive correlations of saccade latency with set size (from the Fisher z-transformation [Fisher, 1915], SS: $r = 0.193$, $p <$

Setsize	MG mean	SE	ML mean	SE	SS mean	SE	WS mean	SE
2	250.09	2.63	350.67	5.00	199.79	2.29	257.28	3.11
3	244.62	2.76	316.83	4.06	201.77	2.44	265.51	3.56
5	258.76	3.97	275.92	3.50	211.52	3.52	276.80	3.94
8	253.73	4.08	292.95	4.17	231.68	3.44	287.52	4.27

Table 2. Saccade latencies with the long (1 s) stimulus duration.

.0001; WS: $r = 0.128$, $p < .0001$), ML had a significant negative correlation ($r = -0.202$, $p < .0001$), and MG had no significant correlation ($r = 0.034$, $p < .108$).

Perceptual yes/no decisions and comparison to ideal observer

Perceptual decisions, long (1 second, multiple fixations)

Figure 8 and Table 3 summarize the human perceptual yes/no responses in the long (1 second) duration and their fits to the modified ideal observer (left) and the unweighted model (right). In Figure 8, the human observer results are in black, the ideal observer fits are in gold, and the unweighted model fits are in blue. As shown in Table 3, the RMSEAs for the ideal observer across all four observers ranged from 0.0000 to 0.0275, below the value of 0.05 that indicates a good fit. Also, the upper bounds of the 90% confidence intervals for the RMSEAs were below 0.05 (ranging from 0.0289 to 0.0453), indicating that the fits were good with 95% confidence. Specifically, the components of the ideal observer predictions with respect to set size (Figure 3) that were similar to the human performances were increasing false alarm rates, decreasing invalid hit rates, and the relatively unchanged

valid hit rates. Note that ML had a larger fitted d', most likely due to the larger contrast difference in her studies. The fits for the unweighted model had higher RMSEAs (except for ML), with RMSEAs ranging from 0.0257 to 0.0441. Also, only the upper bound of the RMSEA confidence interval for one observer (ML, 0.0437) was below 0.05, with the other three falling slightly above the 0.05 criterion (0.0560 to 0.0602) and thus not indicating good fits with 95% confidence. The difference in fits for the two models is evident in the difference in the valid and invalid hit rates for the human observers (except for ML).

Perceptual decisions, short (saccade latency – 80 milliseconds, single fixation)

Figure 9 and Table 4 summarize the human perceptual yes/no responses for the short duration condition (matched to the first saccade latencies in the long condition, minus 80 milliseconds). The fits for the modified ideal observer were somewhat poorer than those for the long duration but were still good. The RMSEAs ranged from 0.0181 to 0.0246, with the upper bounds of the 90% confidence intervals under the value

Figure 8. Valid hit rates, invalid hit rates, and false alarm rates for the yes/no perceptual decisions in the long (1 s) task, compared to the modified ideal observer (left panel) and the unweighted model (right panel). Circles – valid (relative to the primary cue) hit rate. Squares – invalid (relative to the primary cue) hit rate. Diamonds – false alarm rate. Black – human observer results. Gold – modified ideal observer. Blue – unweighted model. Note that the valid and invalid hit rates are the same for the unweighted model.

	MG	ML	SS	WS
a) Ideal observer				
d'	1.94	2.48	1.78	1.94
log criterion (set size = 2)	0.43	−0.51	−0.35	−0.17
log criterion (set size = 3)	−0.05	−0.17	−0.07	−0.19
log criterion (set size = 5)	−0.08	−0.04	−0.16	−0.06
log criterion (set size = 8)	−0.08	−0.44	−0.26	−0.28
$\chi^2(7)$	5.294	19.74	4.545	7.357
RMSEA	0.0000	0.0275	0.0000	0.0046
RMSEA, lower bound, 90% confidence	0.0000	0.0222	0.0000	0.0046
RMSEA, upper bound, 90% confidence	0.0289	0.0453	0.0289	0.0297

Table 3a. Fits of the modified ideal observer to the yes/no perceptual task, long duration. RMSEA - Root Mean Square Error of Approximation. RSSEA < .05 indicates a good model fit.

of 0.05 (ranging from 0.0375 to 0.0427), indicating that all four fits were good with 95% confidence. The fitted d''s were somewhat less than those for the long duration, as expected, with ML again having the highest d'. Observer SS had a larger drop in d' than the other observers, probably due to his shorter saccade latencies and therefore stimulus durations. As with the long durations, the fits for the unweighted model showed higher RMSEAs than those for the ideal observer (with RMSEAs ranging from 0.0299 to 0.0654). Two of the four observers had upper bounds of the 90% confidence intervals below 0.05 (ML, 0.0473; SS, 0.0488) indicating good fits with 95% confidence. Again the difference in the fits between two models is evident in the difference between the valid and invalid hit rates for the human observers.

Saccade localization decisions

Saccadic decisions to uncued locations

For the analysis of the saccadic localization decisions (of the first saccade), a criterion of saccades of 4° to 8° from central fixation was used. This represented a distance of 2° or less from the centers of the stimulus locations (6°) and encompassed the regions including the cues (square sides and circle diameters = 2.5°). Results did not differ qualitatively with the original criterion using saccades greater than or equal to 2.35°. It was found that there were a large number of initial saccadic decisions to uncued locations (neither primary nor secondary cues). Table 5 summarizes the proportion of these first fixations to uncued locations for each observer and Figure 10 gives scatterplots of representative cue configurations for set sizes 2, 3, and 5 in signal absent trials (and thus without the influence of location of the signal). Note that there were no uncued locations for set size 8. By each uncued location (and excluding set size 8), there were consistently about 6% of all initial saccades to each uncued location across all observers and set sizes (mean = 6.24%, $SE = 0.17\%$).

Model fits, excluding saccadic decisions to uncued locations

Neither the modified ideal observer nor the unweighted model predicts localization decisions to any uncued location, and thus they would not be able to represent these fixations. A further analysis was done removing these fixations and then fitting to the two

	MG	ML	SS	WS
b) Unweighted model	MG	ML	SS	WS
d'	2.00	2.54	1.84	2.00
log criterion (set size = 2)	0.82	−0.16	0.02	0.18
log criterion (set size = 3)	0.64	−0.34	−0.16	0.00
log criterion (set size = 5)	0.90	0.86	0.80	0.88
log criterion (set size = 8)	1.14	0.80	1.00	0.98
$\chi^2(7)$	33.29	18.10	39.65	34.74
RMSEA	0.0396	0.0257	0.0441	0.0406
RMSEA, lower bound, 90% confidence	0.0319	0.0208	0.0359	0.0329
RMSEA, upper bound, 90% confidence	0.0560	0.0437	0.0602	0.0570

Table 3b. Fits of the modified unweighted model to the yes/no perceptual task, long duration. RMSEA - Root Mean Square Error of Approximation. RSSEA < .05 indicates a good model fit.
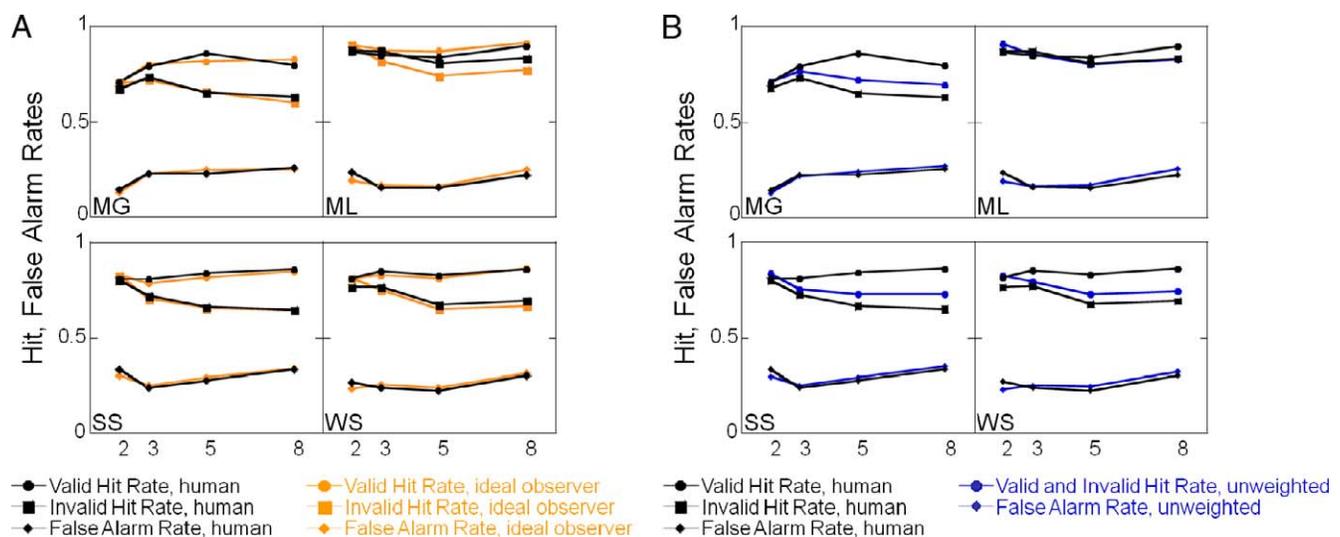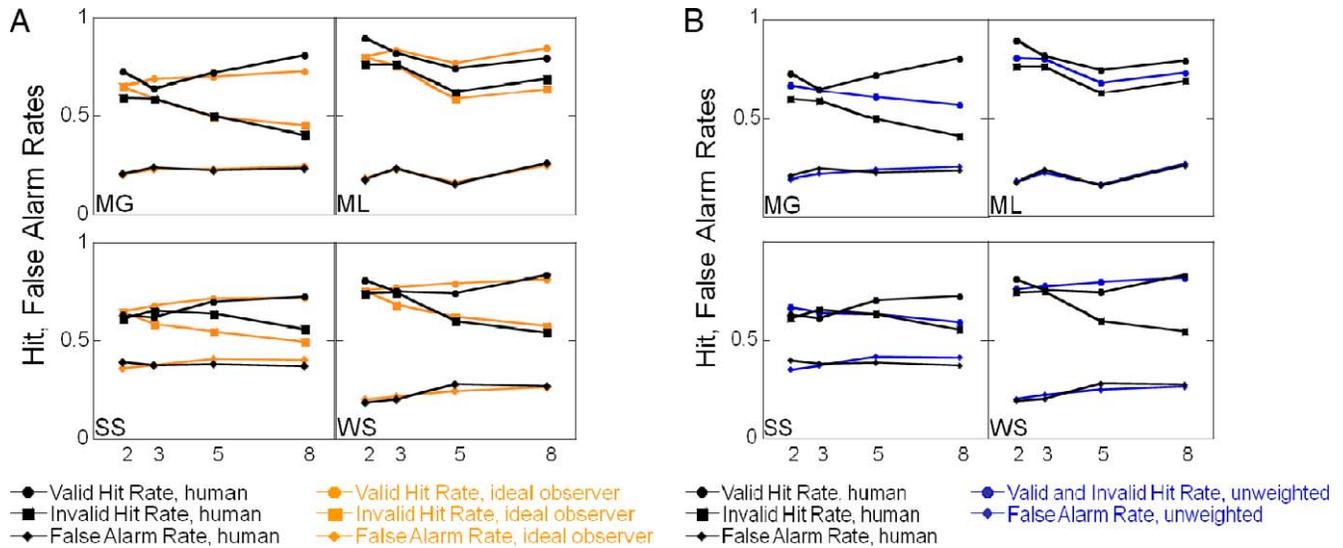
Figure 9. Valid hit rates, invalid hit rates, and false alarm rates for the yes/no perceptual decisions in the short (saccade latency – 80 ms) task, compared to the modified ideal observer (left panel) and the unweighted model (right panel). Circles – valid (relative to the primary cue) hit rate. Squares – invalid (relative to the primary cue) hit rate. Diamonds – false alarm rate. Black – human observer results. Gold – modified ideal observer. Blue – unweighted model. Note that the valid and invalid hit rates are the same for the unweighted model.

models; Figures 11 and 12 and Table 6 summarize these findings. Note that the time for this decision is the latency for the first saccade in this condition and varies from trial to trial. Figure 11 summarizes the results for the valid and invalid proportion correct in the signal present trials; Figure 12 summarizes the results of localization decisions to the primary cue when the signal did not appear at the primary cue. As before, the human observer results are in black, the ideal observer fits are in gold (left), and the unweighted model fits are in blue (right). From Table 6, it is clear that the fits to the modified ideal observer were generally poor, even without the fixations to the uncued locations. The RMSEAs ranged from 0.1395 to 0.2301, and the lower bound of the RSMEA 90% confidence intervals were above 0.10 (ranging from 0.1309 to 0.2209), the criterion for a poor fit, thus indicating that the fits were poor with 95% confidence. The fits to the

unweighted model were generally not as poor (except for SS), with RMSEAs ranging from 0.0000 to 0.1758, and with two fits having upper bounds within 0.05 (MG, 0.0488; ML, 0.0302), indicating good fits. Note, however, that these do not indicate good fits overall, as the saccadic decisions to the uncued locations were not included. When the unweighted model was fit with the uncued location saccadic decisions included (with an allowance of 5% for uncued location saccadic decisions), as expected the fits were poor for MG ($\chi^2(30) = 2208$; RMSEA = 0.1783; 90% RMSEA confidence, 0.1725 to 0.1851) and ML ($\chi^2(30) = 1205$; RMSEA = 0.1290; 90% RMSEA confidence, 0.1235 to 0.1359).

The main difficulty for the ideal observer shown in Figure 11 is that human observers did not have the magnitude of cueing effects predicted by the ideal observer, with the possible exception of SS. The difficulty may be characterized as the valid proportion

	MG	ML	SS	WS
a) Ideal observer				
d'	1.52	2.06	0.96	1.82
log criterion (set size = 2)	0.23	−0.01	−0.01	0.07
log criterion (set size = 3)	0.15	−0.17	−0.03	0.03
log criterion (set size = 5)	0.16	0.26	−0.06	−0.02
log criterion (set size = 8)	0.10	−0.14	−0.06	−0.06
$\chi^2(7)$	15.01	16.91	17.16	12.49
RMSEA	0.0218	0.0243	0.0246	0.0181
RMSEA, lower bound, 90% confidence	0.0183	0.0199	0.0201	0.0161
RMSEA, upper bound, 90% confidence	0.0405	0.0425	0.0427	0.0375

Table 4a. Fits of the modified ideal observer to the yes/no perceptual task, short duration. RMSEA - Root Mean Square Error of Approximation. RMSEA < .05 indicates a good model fit.

	MG	ML	SS	WS
b) Unweighted model	MG	ML	SS	WS
d'	1.60	2.14	1.06	1.86
log criterion (set size = 2)	0.64	0.36	0.36	0.44
log criterion (set size = 3)	0.46	0.18	0.18	0.26
log criterion (set size = 5)	1.06	1.18	0.86	0.90
log criterion (set size = 8)	1.32	1.06	1.16	1.18
$\chi^2(7)$	78.76	22.04	23.79	41.81
RMSEA	0.0654	0.0299	0.0316	0.0455
RMSEA, lower bound, 90% confidence	0.0556	0.0240	0.0253	0.0372
RMSEA, upper bound, 90% confidence	0.0805	0.0473	0.0488	0.0616

Table 4b. Fits of the modified unweighted model to the yes/no perceptual task, short duration. RMSEA - Root Mean Square Error of Approximation. RMSEA < .05 indicates a good model fit.

correct for humans having large set size effects, or decreases in the valid proportion correct with set size, while the ideal observer predicted small increases in valid proportion correct with set size. As a consequence, the cueing effects of the human observers were much less than the ideal observer predictions.

Note that the d's and χ^2s are the same for Figures 11 and 12, as the data represented across both figures were fit simultaneously to the modified ideal observer and the unweighted model. The diamonds indicate the rates of erroneously choosing the primary cue location in the invalid trials, p(primary|invalid) (Figure 7A summarizes the ideal observer predictions for p(primary|invalid)). The triangles indicate the rates of choosing the primary cue location in the signal absent trials, p(primary|absent), which cannot be coded as correct or incorrect (Figure 7C summarizes the ideal observer predictions for p(primary| absent)). As with the valid and invalid proportion correct values, the human performance for localizing the primary cue location in these conditions was poorly fit to the modified ideal observer. The ideal observer predicted that p(primary|invalid) increases monotonically with set size, while p(primary|absent) remains relatively constant at 0.50. These trends were opposite the general trends of the human observers, who tended to show monotonic decreases of p(primary|invalid) and p(primary|absent) with set size. The exception was SS, who showed an inverted U function with set size peaking at set size 3. Also, the ideal observer predicted that p(primary|absent) would be consistently larger than p(primary|invalid), whereas for the human observers p(primary|absent) and p(primary-invalid) were nearly equivalent, with the exception of WS.

	MG	ML	SS	WS
Set size 2	0.430	0.412	0.336	0.368
Set size 3	0.338	0.266	0.279	0.301
Set size 5	0.200	0.176	0.199	0.186
Set size 8	0.000	0.000	0.000	0.000

Table 5. Proportion of fixations to uncued locations.

Analysis of the use of the primary cue

To assess whether observers used the primary cue information relative to the secondary cue in their saccadic decisions or a cueing effect, two analyses were performed (summarized in Table 7). The first analysis considered only the signal present trials; this analysis compared the accuracy of the saccadic decisions (proportion correct) in the valid and invalid trials. It was found that one observer, SS, had significantly larger valid PCs than invalid PCs (Table 7a). The second analysis considered only the signal absent trials; this analysis assessed whether the probabilities of saccadic decisions to the primary cue (p(primary|absent)) were greater than the probability of a random decision ($1/M$). It was found that all observers except ML did show a greater probability
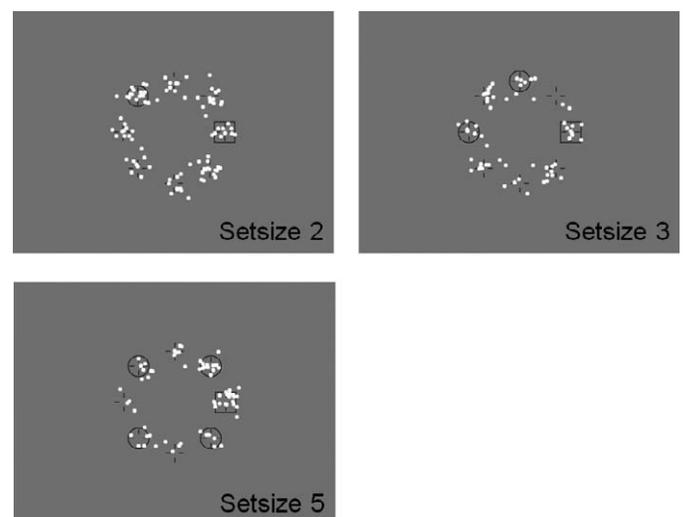

Figure 10. Scatterplots of the initial fixations (first saccadic decisions) in the long duration task for target absent trials and representative cue configurations, collapsed over observers. Fixations include cue configurations that match the canonical cue configuration in the Figure (with the primary cue in the far right location) after rotation and/or mirror reversal. Eccentricity of the possible signal locations = 6°.
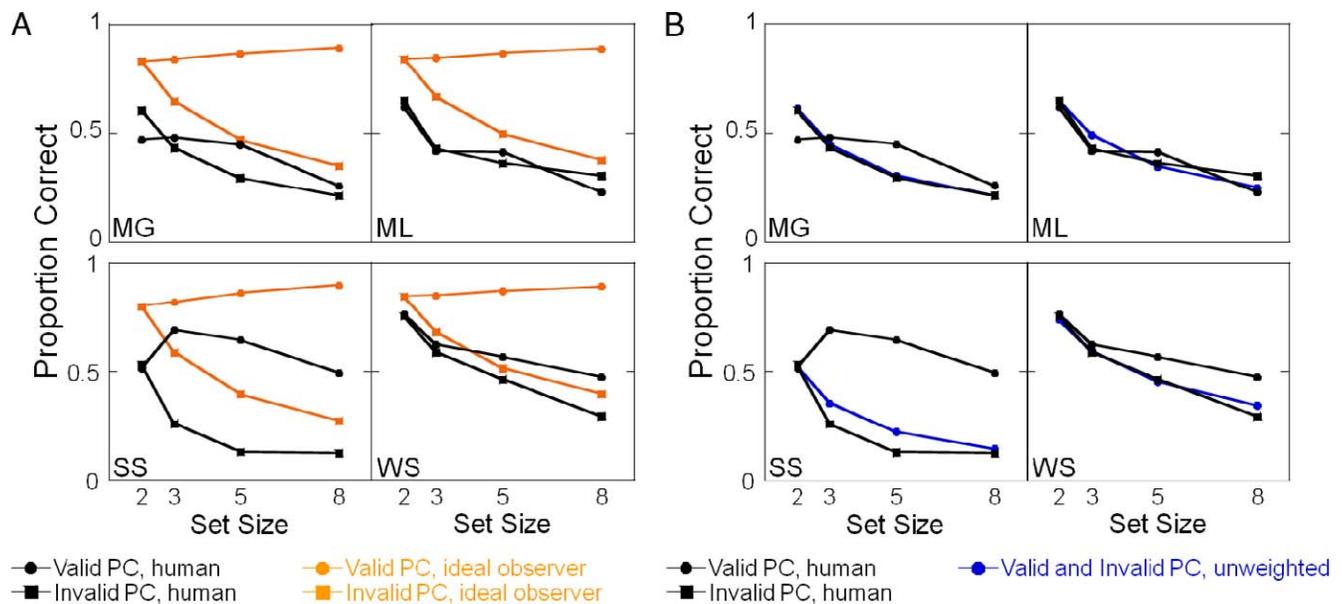
Figure 11. Proportion correct for localization of the first saccade for the target present trials in the long (1 s) task, compared to the modified ideal observer (left panel) and the unweighted model (right panel). Circles – valid (relative to the primary cue) trials. Squares – invalid (relative to the primary cue) trials. Black – human observer results. Gold – modified ideal observer. Blue – unweighted model. Note that the valid and invalid proportion corrects (PC) are the same for the unweighted model.

than chance to make a saccadic decision to the primary cue. Thus, although the observers' data were poorly fit to the modified ideal observer, and in particular the predicted size of the cueing effects (Figure 11), all observers except ML showed evidence of using the primary cue for their saccadic decisions.

Discussion

Comments on the ideal observer

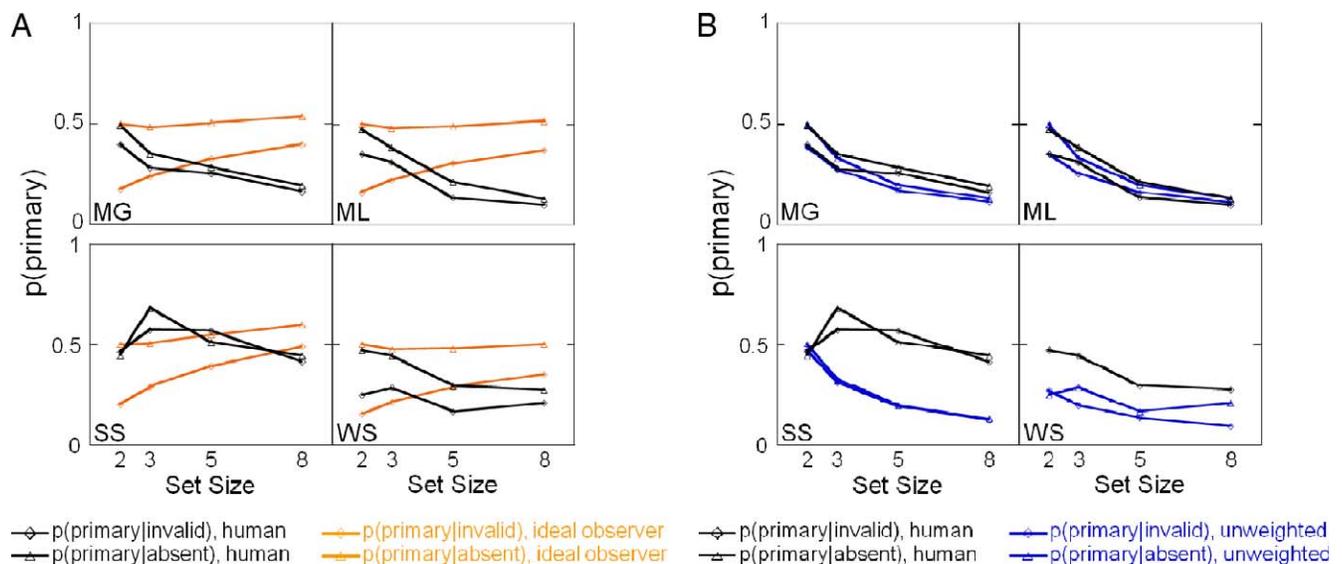We present an ideal observer analysis of visual search and cueing task that models set size and cueing

Figure 12. Probability of the first saccade to the primary cue location (p(primary)), compared to the modified ideal observer (left panel) and the unweighted model (right panel). Triangle – probability of first saccade to the primary cue location given a signal absent trial (p(primary|absent)). Diamond – probability of the first saccade to the primary cue location, given an invalid trial (p(primary|invalid)). Black – human observer results. Gold – best fitting ideal observer. Blue – unweighted model.

	MG	ML	SS	WS
a) Ideal Observer				
d'	1.34	1.40	1.18	1.44
$\chi^2(14)$	1,164	1,384	486.2	375.8
RMSEA	0.2185	0.2301	0.1395	0.1424
RMSEA, lower bound, 90% confidence	0.2091	0.2209	0.1309	0.1327
RMSEA, upper bound, 90% confidence	0.2302	0.2413	0.1519	0.1571

Table 6a. Fits of the modified ideal observer to the localization saccadic task in the long (1 s) duration condition, excluding the fixations to uncued locations. RMSEA - Root Mean Square Error of Approximation. RMSEA < .05 indicates a good model fit.

effects jointly as the result of a selective weighting mechanism. While mathematically straightforward, this is a potentially crucial aspect of an attentional model, as generally set size and cueing effects are treated separately and are not explicitly connected in attentional models. The experimental task was designed to incorporate both set size and cueing effects in the same study, and the results of the computer simulations indicated that the ideal observer predicted set size and cueing effects for this task within a single framework.

As stated in the Introduction, there are several cases that the ideal observer cannot predict, a priori: e.g., inhibition of return (reversed cueing effects with longer cue SOAs, e.g., Klein, 2000; Posner & Cohen, 1984), automatic vs. voluntary attention (e.g., Jonides, 1981; Müller & Rabbitt, 1989; Wright & Ward, 2008), anti-predictive cues (e.g., Posner, Cohen, & Rafal, 1982; Warner, Juola, & Koshino, 1990), and attentional capture (e.g., Folk, Remington, & Johnston, 1992, Experiment 3; Jonides, 1981, Experiment 2; Theeuwes, 1991). Also, the current study found that first saccadic decisions were fit poorly. Thus, clearly the ideal observer cannot be seen as a ubiquitous description of visual attention. However, the ideal observer does have the value of predicting optimal behavior for a particular task, and as such can provide an assessment of whether human performance is also optimal. Such a quantitative comparison would seem to have utility, particularly when the statistical structure of the task becomes more complex than those used in more typical visual search and cueing tasks, such as the task in this study. Another related (and perhaps understated)

utility is that, as the ideal observer is a parallel-noisy model, this comparison can provide a test of parallel vs. limited capacity models.

To review the main characteristics of the ideal observer for this task, the ideal observer predicted set size effects (in proportion correct) and increases in cueing effects as set size increased (for the cue validities in this study with the primary cue fixed at 50% validity). The increases in cueing effects were due to the decreasing validity at each secondary location $(1/(M-1))$ with increasing set size. Also, as a function of d', the cueing effects for the ideal observer first rose, starting from $d' = 0$, and then fell with increasing d'. This dependence of cueing effects upon d' agrees with an earlier study of an ideal observer analysis of cueing effects (Shimozaki, Eckstein, & Abbey, 2003).

Human observer perceptual decisions (yes/no)

With respect to the human observer results, the question we wished to address was whether the results were consistent with an optimal and purely selective weighting (parallel-noisy) description of attention. For the yes/no perceptual decisions, the answer was apparently *yes*. Across all observers, the ideal observer was a good fit for both the short (saccade latency – 80 milliseconds) and long (1 second) stimulus durations, with somewhat better fits for the longer durations. The poorer fits for the shorter stimulus durations was a rather surprising, a priori, as typically SDT/IO models have

	MG	ML	SS	WS
b) Unweighted Model				
d'	0.40	0.54	0.10	0.88
$\chi^2(14)$	37.67	11.58	763.2	85.04
RMSEA	0.0313	0.0000	0.1758	0.0631
RMSEA, lower bound, 90% confidence	0.0296	0.0000	0.1667	0.0569
RMSEA, upper bound, 90% confidence	0.0488	0.0302	0.1878	0.0805

Table 6b. Fits of the modified unweighted model to the localization saccadic task in the long (1 s) duration condition, excluding the fixations to uncued locations. RMSEA - Root Mean Square Error of Approximation. RMSEA < .05 indicates a good model fit.

	MG	ML	SS	WS
a) Valid PC vs. invalid PC				
$\chi^2(8)$	9.570	3.069	140.4	10.24
p	0.2965	0.9300	<.0001	0.2486
b) Primary|absent				
$\chi^2(4)$	21.55	3.034	475.2	56.21
p	0.0002	0.3803	<.0001	<.0001

Table 7. Assessing the use of the primary cue: a) Valid PC vs. invalid PC, testing whether proportion correct (PC) was greater for valid cues. b) Primary|absent, testing whether saccadic decisions to the primary cue in the signal absent trials was greater than chance (1/M).

been successfully applied to short stimulus durations used to avoid the confounding effects of foveation of possible target locations by saccades (e.g., Baldassi & Verghese, 2002; Dosher, Han, & Lu, 2004; Eckstein, 1998; Eckstein, Shimozaki, & Abbey, 2002; Eckstein et al., 2000; Kinchla, 1974; Palmer, 1995; Palmer, Ames, & Lindsey, 1993; Palmer, Verghese, & Pavel, 2000; Schoonveld, Shimozaki, & Eckstein, 2007; Shimozaki, Eckstein, & Abbey, 2003; Verghese, 2001). Thus, the good fit of the model to the longer stimulus durations with multiple saccades might be somewhat unexpected. During the multiple-fixation search, performance improvement with fewer cues (lower set sizes) was expected, due to both selective covert attention and the strategizing of eye movements to fixate on potential target locations. However, the effect of eye movements was not represented in the ideal observer models in this and previous studies, which were typically developed for single fixation search. Furthermore, a recent study has confirmed that contributions of foveation through saccades can result in human set size effects larger than that expected from a nonfoveated ideal observer, but explained by a foveated ideal searcher (Schoonveld & Eckstein, 2009).

A likely explanation for the present success of the (nonfoveated) ideal observer in accounting for set size effects in the multiple-fixation search is that the ability to detect the low-frequency Gaussian target in the current study is rather insensitive to retinal eccentricity. In such cases, one would expect that the effects of set size on multiple fixation perceptual decisions might be similar to those of single fixation searches. In addition, there have been previous examples in the literature of set size effects in perceptual decisions with unlimited time search in noise limited images that have been successfully modeled by an ideal observer, without explicitly considering the inhomogeneity of retinal processing (Burgess & Ghandeharian, 1984; Swensson & Judy, 1981; Eckstein & Whiting, 1996; Bochud, Abbey, & Eckstein, 2004).

Perhaps the slightly poorer fits to the short duration perceptual decisions reflect the statistical structure of the task. As mentioned above, this structure changed with set size and was somewhat more complex than most previous studies of visual search and cueing. Specifically, the combination of partially valid cues with set size had the particular property of changing the usefulness of the primary cue. For our task, at set size 2 the primary cue provided no information, and as set size increased the information provided by the cue increased. Thus, it is plausible that the human results reflect the fact that the longer stimulus durations allowed the observer to more effectively use the complex cue information.

Human observer saccadic decisions (localization)

For the human saccadic localization results, there was some evidence that observers did use the primary cue information (Table 7). This agrees with previous findings that saccadic decisions can be influenced by the probabilistic structure of the task (e.g., explicit cues) or the stimuli (e.g., the scene context) (e.g., Brockmole & Henderson, 2006; Droll, Abbey, & Eckstein, 2009; Eckstein, Dresher, & Shimozaki, 2006; Ehinger et al., 2009; Einhäuser, Rutishauser, & Koch, 2008; Malcolm & Henderson, 2010; Neider & Zelinsky, 2006; Torralba et al., 2006; Walthew & Gilchrist, 2006). However, it was apparent that human observers did not weight the cue information optimally and that the fits to the ideal observer were poor. These poor fits of the ideal observer to the human localization saccadic decisions might be due to several aspects of this study. First, an underlying assumption in this theoretical ideal observer analysis of the eye movement behavior is that the goal of the saccade is to fixate the target (saccadic targeting). However, it has been correctly pointed out by Najemnik and Geisler (2005) that the goal of the eye movement system is not to foveate the target but to maximize the collection of information subserving the perceptual decision. In many instances a model that tries to maximize the information gain through eye movements (ideal searcher) will make similar eye movements to a model that tries to foveate the target (maximum aposteriori probability, MAP; Beutter, Eckstein & Stone, 2003; Eckstein, Beutter, & Stone, 2001; Zhang & Eckstein, 2010). However, in other instances the two models will make different eye movement predictions (Zhang & Eckstein, 2010). In addition, when the ability to detect a target is relatively constant across retinal eccentricity and/or the observer has time to make many eye movements to foveate a large subset of target locations, there might be little added benefit to the final perceptual decision by adopting a strategy that biases the eye movements towards the highly probable target location. This situation might explain the apparent

suboptimal nature of saccadic decisions and also the fact that different observers seem to adopt different eye movement strategies, which arguably have little impact on the final perceptual decision.

Second, as mentioned above, the statistical structure of this task was somewhat more complex than previous studies of visual search and/or cueing. The randomization of the secondary cue location relative to the primary cue may have also made the task more complex for human observers. In particular, the human observers may have had difficulty in resolving the weighting of the cue information. It is possible that cues along a dimension other than shape, such as color (as shown by Droll, Abbey, & Eckstein, 2009), might have allowed for more guidance of saccades to the cued locations. Also, the study presented all the cues simultaneously, which is the standard methodology for cueing tasks and has been shown to be effective in determining the behavioral set size in visual search tasks (e.g., Palmer, 1995; Palmer, Ames, & Lindsey, 1993). However (as suggested by Greg Zelinsky, a reviewer), it is possible that a serial presentation of the cues would have been more effective. For example, presenting cues for all the relevant locations (primary and secondary) for that trial first, followed by the primary cue, might have allowed the observers to select the relevant locations more easily and might have reduced the number of saccadic decisions to the uncued locations.

Third, even though the short stimulus duration time was chosen to equate the display time for the short perceptual decision and the first saccade in the long duration, the response times for the two tasks differed. By definition the responses for the saccadic decisions were made within the saccadic latency, while the perceptual decisions were not under time constraints, allowing for more offline processing.

Conclusions

Two predominant paradigms to study visual attention are visual search and cueing tasks. The typical result in a visual search task is the set size effect, in which performance worsens with increasing number of items to search. The common result in a cueing task is the cueing effect, in which valid cues (a cue indicating the correct signal location) leads to better performance, compared to invalid cues (a cue indicating the incorrect signal location). Set size and cueing effects have been influential in the evidence for (and theories of) visual attention; however, the two effects generally have not been integrated well. An ideal observer model is presented for saccadic and perceptual decisions in a visual search task designed to incorporate set size and cueing effects. The ideal observer predicted both set size

and cueing effects through the weighting of information at each location by the prior probability of signal presence, or the cue validity. Thus, in the ideal observer set size and cueing effects may be described as a consequence of a single mechanism.

The human perceptual decisions were fit well by the predictions of a modified ideal observer, indicating that an optimal selective weighting (parallel-noisy) model was an appropriate description of these results. However, the results for the human saccadic decisions were not fit well. One possibility for the poor fits is the goal of the saccadic system expressed in this ideal observer model, to localize the target; this may have differed from the actual goal of the saccadic system, which might have been to maximize information accrual for the final perceptual decision (an ideal searcher).

Acknowledgments

References

Abbey, C. K., & Eckstein, M. P. (2002). Optimal shifted estimates of human-observer templates in two-alternative forced-choice experiments. *IEEE Transactions in Medical Imaging, 21*(5), 429–40. [PubMed]

Awh, E., & Pashler, H. (2000). Evidence for split attentional foci. *Journal of Experimental Psychology: Human Perception and Performance, 26*(2), 834–846. [PubMed]

Baldassi, S., & Verghese, P. (2002). Comparing integration rules in visual search. *Journal of Vision, 2*(8):3, 559–570, http://www.journalofvision.org/content/2/8/3, doi:10.1167/2.8.3. [PubMed] [Article]

Barlow, H. B. (1978). The efficiency of detecting changes in density in random dot patterns. *Vision Research, 18*(6), 637–650. [PubMed]

Becker, W. (1991). Saccades. In R. H. S. Carpenter (Ed.), *Eye movements, Volume 8, vision and visual dysfunction* (pp. 95–137). Boca Raton: CRC Press.

Beutter, B. R., Eckstein, M. P., & Stone, L. S. (2003).

Saccadic and perceptual performance in visual search tasks. I. Contrast detection and discrimination. *Journal of the Optical Society of America, A, 20*(7), 1341–55. [PubMed]

Bochud, F. O., Abbey, C. K., & Eckstein, M. P. (2003). Search for lesions in mammograms: Statistical characterization of observer responses. *Medical Physics, 31*(1), 24–36. [PubMed]

Briand, K. A., & Klein, R. M. (1987). Is Posner's "beam" the same as Treisman's "glue"?: On the relation between visual orienting and feature integration theory. *Journal of Experimental Psychology: Human Perception and Performance, 13*(2), 228–241. [PubMed]

Brockmole, J. R., & Henderson, J. M. (2006). Recognition and attention guidance during contextual cueing in real-world scenes: Evidence from eye movements. *Quarterly Journal of Experimental Psychology, 59*(7), 1177–87. [PubMed]

Browne, M. W., & Cudeck, R. (1992). Alternative ways of assessing model fit. *Sociological Methods of Research, 21*(2), 230–258.

Burgess, A. E., & Ghandeharian, H. (1984). Visual signal detection. II. Signal-location identification. *Journal of the Optical Society of America, A, 1*(8), 906–910. [PubMed]

Burgess, R. F., Wagner, R., Jennings, J., & Barlow, H. B. (1981). Efficiency of human visual signal discrimination. *Science, 214*(4516), 93–94. [PubMed]

Carrasco, M., Giordano, A. M., & McElree, B. (2006). Attention speeds processing across eccentricity: Feature and conjunction searches. *Vision Research, 46*(13), 2028–2040. [PubMed] [Article]

Carrasco, M., Ling, S., & Read, S. (2004). Attention alters appearance. *Nature Neuroscience, 7*(7), 308–313. [PubMed]

Caspi, A., Beutter, B. R., & Eckstein, M. P. (2004). The time course of visual information accrual guiding eye movement decisions. *Proceedings of the National Academy of Sciences, USA, 101*(35), 13086–13090. [PubMed] [Article]

Cave, K. R., & Wolfe, J. M. (1990). Modeling the role of parallel processing in visual search. *Cognitive Psychology, 22*(2), 225–271. [PubMed]

Chelazzi, L., Miller, E. K., Duncan, J., & Desimone, R. (1993). A neural basis for visual search in inferior temporal cortex. *Nature, 363*, 345–347. [PubMed]

Cohn, T. E., & Lasley, D. J. (1974). Detectability of a luminance increment: Effect of spatial uncertainty. *Journal of the Optical Society of America, 64*(12), 1715–1719. [PubMed]

Crowell, J. A., & Banks, M. S. (1996). Ideal observer for heading judgments. *Vision Research, 36*(3), 471–490. [PubMed]

Dayan, P., Kakade, S., & Montague, P. R. (2000). Learning and selective attention. *Nature Neuroscience, 3*(supplement), 1218–1223. [PubMed]

Desimone, R. (1996). Neural mechanisms for visual memory and their role in attention. *Proceedings of the National Academy of Sciences, USA, 93*(24), 13494–13499. [PubMed] [Article]

Desimone, R. (1998). Visual attention mediated by biased competition in extrastriate visual cortex. *Philosophical Transactions of the Royal Society of London, Series B, Biological Sciences, 353*(1373), 1245–1255. [PubMed] [Article]

Desimone, R., & Duncan, J. (1995). Neural mechanisms of selective visual attention. *Annual Review of Neuroscience, 18*(1), 193–222. [PubMed]

Dosher, B. A., Han, S., & Lu, Z.-L. (2004). Parallel processing in visual search asymmetry. *Journal of Experimental Psychology: Human Perception and Performance, 30*(1), 3–27. [PubMed]

Dosher, B. A., & Lu, Z.-L. (2000). Mechanisms of perceptual attention in precuing of location. *Vision Research, 40*(10), 1269–92. [PubMed]

Downing, C. J. (1988). Expectancy and visual-spatial attention: Effects on perceptual quality. *Journal of Experimental Psychology: Human Perception and Performance, 14*(2), 188–202. [PubMed]

Droll, J. A., Abbey, C. K., & Eckstein, M. P. (2009). Learning cue validity through performance feedback. *Journal of Vision, 9*(2):18, 1–22, http://www.journalofvision.org/content/9/2/18, doi:10.1167/9.2.18. [PubMed] [Article]

Duncan, J. (1998). Converging levels of analysis in the cognitive neuroscience of visual attention. *Philosophical Transactions of the Royal Society of London, Series B, Biological Sciences, 353*(1373), 1245–1255. [PubMed] [Article]

Eckstein, M. P. (1998). The lower efficiency for conjunctions is due to noise and not serial attentional processing. *Psychological Science, 9*(2), 111–118.

Eckstein, M. P., Abbey, C. K., Pham, B. T., & Shimozaki, S. S. (2004). Perceptual learning through optimization of attentional weighting: Human versus optimal Bayesian learner. *Journal of Vision, 4*(12):3, 1006–1019, http://www.journalofvision.org/content/4/12/3, doi:10.1167/4.12.3. [PubMed] [Article]

Eckstein, M. P., Beutter, B. R., & Stone, L. S. (2001). Quantifying the performance limits of human

saccadic targeting during visual search. *Perception, 30*(11), 1389–401. [PubMed]

Eckstein, M. P., Dresher, B. A., & Shimozaki, S. S. (2006). Attentional cues in real scenes, saccadic targeting, and Bayesian priors. *Psychological Science, 17*(11), 973–980. [PubMed]

Eckstein, M. P., Peterson, M. F., Pham, B. T., & Droll, J. A. (2009). Statistical decision theory to relate neurons to behavior in the study of covert visual attention. *Vision Research, 49*(10), 1097–1128. [PubMed]

Eckstein, M. P., Shimozaki, S. S., & Abbey, C. K. (2002). The footprints of visual attention in the Posner cueing paradigm revealed by classification images. *Journal of Vision, 2*(1):3, 25–45, http://www.journalofvision.org/content/2/1/3, doi:10.1167/2.1.3. [PubMed] [Article]

Eckstein, M. P., Thomas, J. P., Palmer, J., & Shimozaki, S. S. (2000). A signal detection model predicts the effects of set size on visual search accuracy for feature, conjunction, triple conjunction, and disjunction displays. *Perception & Psychophysics, 62*(3), 425–451. [PubMed]

Eckstein, M. P., & Whiting, J. S. (1996). Visual signal detection in structured backgrounds: I. Effect of number of possible spatial locations and signal contrast. *Journal of the Optical Society of America, A, 13*(9), 1777–1787. [PubMed]

Ehinger, K. A., Hidalgo-Sotelo, B., Torralba, A., & Oliva, A. (2009). Modeling search for people in 900 scenes: A combined source model of eye guidance. *Visual Cognition, 17*(6-7), 945–978. [PubMed] [Article]

Einhäuser, W., Rutishauser, U., & Koch, C. (2008). Task demands can immediately reverse the effects of sensory-driven saliency in complex visual stimuli. *Journal of Vision, 8*(2):2, 1–19, http://www.journalofvision.org/content/8/2/2, doi:10.1167/8.2.2. [PubMed] [Article]

Eriksen, C. W., & St. James, J. D. (1986). Visual attention within and around the field of focal attention: A zoom lens model. *Perception & Psychophysics, 40*(4), 225–240. [PubMed]

Eriksen, C. W., & Yeh, Y.-Y. (1985). Allocation of attention in the visual field. *Journal of Experimental Psychology: Human Perception and Performance, 11*(5), 583–597. [PubMed]

Findlay, J. M. (1997). Saccade target selection during visual search. *Vision Research, 37*(5), 617–31. [PubMed]

Fisher, R. A. (1915). Frequency distribution of the values of the correlation coefficient in samples of an indefinitely large population. *Biometrika (Biometrika Trust), 10*(4), 507–521.

Folk, C. L., Remington, R. W., & Johnston, J. C. (1992). Involuntary covert orienting is contingent on attentional control settings. *Journal of Experimental Psychology: Human Perception & Performance, 18*(4), 1030–1044. [PubMed]

Glimcher, P. W. (2003). The neurobiology of visual saccadic decision making. *Annual Review of Neuroscience, 26*(1), 133–179. [PubMed]

Gobell, J., & Carrasco, M. (2005). Attention alters the appearance of spatial frequency and gap size. *Psychological Science, 16*(8), 644–651. [PubMed]

Gold, J., Bennett, P. J., & Sekuler, A. B. (1999). Signal but not noise changes with perceptual learning. *Nature, 402*(6758), 176–178. [PubMed]

Golla, H., Ignashchenkova, A., Haarmeier, T., & Thier, P. (2004). Improvement of visual acuity by spatial cueing: A comparative study in human and non-human primates. *Vision Research, 44*(13), 1589–1600. [PubMed]

Green, D. M., & Swets, J. A. (1974). *Signal detection theory and psychophysics*. Melbourne, FL: Robert E. Kreiger Publishing Co., Inc.

Jonides, J. (1981). Voluntary versus automatic control over the mind's eye's movement. In J. B. Long & A. D. Baddeley (Eds.), *Attention and performance IX* (pp. 187–203). Hillsdale, NJ: Erlbaum.

Jonides, J. (1983). Further toward a model of the mind's eye's movement. *Bulletin of the Psychonomics Society, 21*(4), 247–250.

Kinchla, R. A. (1974). Detecting target elements in multi-element arrays: A confusability model. *Perception & Psychophysics, 15*(1), 149–158.

Kinchla, R. A. (1977). The role of structural redundancy in the perception of visual targets. *Perception & Psychophysics, 22*(1), 19–30.

Kinchla, R. A., Chen, Z., & Evert, D. (1995). Precue effects in visual search: Data or resource limited? *Perception & Psychophysics, 57*(4), 441–50. [PubMed]

Klein, R. M. (2000). Inhibition of return. *Trends in Cognitive Sciences, 4*(4), 138–47. [PubMed]

Legge, G. E., Klitz, T. S., & Tjan, B. S. (1997). Mr. Chips: An ideal-observer model of reading. *Psychological Review, 104*(3), 524–53. [PubMed]

Liu, Z., Knill, D. C., & Kersten, D. (1995). Object classification for human and ideal observers. *Vision Research, 35*(4), 549–568. [PubMed]

Lu, Z. L., & Dosher, B. A. (1998). External noise distinguishes attention mechanisms. *Vision Research, 38*(9), 1183–98. [PubMed]

Lu, Z. L., & Dosher, B. A. (2000a). Noise exclusion in spatial attention. *Psychological Science, 11*(2), 139–46. [PubMed]

Lu, Z. L., & Dosher, B. A. (2000b). Spatial attention: Different mechanisms for central and peripheral temporal precues? *Journal of Experimental Psychology: Human Perception and Performance, 26*(5), 1534–48. [PubMed]

Luck, S. J., Chelazzi, L., Hillyard, S. A., & Desimone, R. (1997). Neural mechanisms of spatial selective attention in areas V1, V2 and V4 of macaque visual cortex. *Journal of Neurophysiology, 77*(1), 24–42. [PubMed] [Article]

Ma, W. J., Navalpakkam, V., Beck, J. M., Berg, R., & Pouget, A. (2011). Behavior and neural basis of near-optimal visual search. *Nature Neuroscience, 14*(6), 783–790. [PubMed]

Malcolm, G. L., & Henderson, J. M. (2010). Combining top-down processes to guide eye movements during real-world scene search. *Journal of Vision, 10*(2):4, 1–11, http://www.journalofvision.org/content/10/2/4, doi:10.1167/10.2.4. [PubMed] [Article]

McCallum, R. C., Browne, M. W., & Sugawara, H. M. (1996). Power analysis and determination of sample size for covariance structure modeling. *Psychological Methods, 1*(2), 130–149.

McMains, S. A., & Somers, D. C. (2004). Multiple spotlights of attentional selection in human visual cortex. *Neuron, 42*(4), 677–686. [PubMed]

McMains, S. A., & Somers, D. C. (2005). Processing efficiency of divided spatial attention mechanisms in human visual cortex. *Journal of Neuroscience, 25*(41), 9444–9448. [PubMed]

Moran, J., & Desimone, R. (1985). Selective attention gates visual processing in the extrastriate cortex. *Science, 229*(4715), 782–784. [PubMed]

Müller, H. J., & Humphreys, G. W. (1991). Luminance-increment detection: Capacity-limited or not? *Journal of Experimental Psychology: Human Perception and Performance, 17*(1), 107–124. [PubMed]

Müller, M. M., Malinowski, P., Gruber, T., & Hillyard, S. A. (2003). Sustained division of the attentional spotlight. *Nature, 424*(6946), 309–312. [PubMed]

Müller, H. J., & Rabbitt, P. M. A. (1989). Reflexive and voluntary orienting of visual attention: Time course of activation and resistance to interruption. *Journal of Experimental Psychology: Human Perception and Performance, 15*(2), 315–330. [PubMed]

Murray, R. F., & Gold, J. M. (2004). Troubles with bubbles. *Vision Research, 44*(5), 461–470. [PubMed]

Najemnik, J., & Geisler, W. S. (2005). Optimal eye movement strategies in visual search. *Nature, 434*(7031), 387–391. [PubMed]

Neider, M. B., & Zelinsky, G. J. (2006). Scene context guides eye movements during visual search. *Vision Research, 46*(5), 614–621. [PubMed]

Palmer, J. (1995). Attention in visual search: Distinguishing four causes of set-size effects. *Current Directions in Psychological Science, 4*(4), 118–123.

Palmer, J., Ames, C. T., & Lindsey, D. T. (1993). Measuring the effect of attention on simple visual search. *Journal of Experimental Psychology: Human Perception and Performance, 19*(1), 108–130. [PubMed]

Palmer, J., Verghese, P., & Pavel, M. (2000). The psychophysics of visual search. *Vision Research, 40*(10), 1227–1268. [PubMed]

Pashler, H. E. (1998). *The psychology of attention.* Cambridge, Massachusetts: MIT Press.

Posner, M. I. (1980). Orienting of attention. *Quarterly Journal of Experimental Psychology, 32*(1), 3–25. [PubMed]

Posner, M. I., & Cohen, Y. (1984). Components of visual orienting. In H. Bouma & D. G. Bouwhuis (Eds.), *Attention and performance X* (pp. 531–56). Hillsdale, NJ: Erlbaum.

Posner, M. I., Cohen, Y., & Rafal, R. D. (1982). Neural systems control of spatial orienting. *Philosophical Transactions of the Royal Society B, 298*(1089), 187–198. [PubMed]

Prinzmetal, W., Ha, R., & Khani, A. (2010). Mechanisms of involuntary attention. *Journal of Experimental Psychology: Human Perception and Performance, 36*(2), 255–267. [PubMed]

Prinzmetal, W., Presti, D. E., & Posner, M. I. (1986). Does attention affect visual feature integration? *Journal of Experimental Psychology: Human Perception and Performance, 12*(3), 361–369. [PubMed]

Remington, R. W., Folk, C. L., & McLean, J. P. (2001). Contingent attentional capture or delayed allocation of attention? *Perception & Psychophysics, 63*(2), 298–307. [Article]

Schoonveld, W. A., Eckstein, M. P. (2009). Cueing effects for human and ideal searchers during multiple-fixation visual search. *Journal of Vision, 9*(8): 1192, http://www.journalofvision.org/content/9/8/1192, doi:10.1167/9.8.1192. [Abstract]

Schoonveld, W. A., Shimozaki, S. S., & Eckstein, M. P. (2007). Optimal and suboptimal models of single fixation oddity search predict a shallow set size function. *Journal of Vision, 7*(10):1, 1–16, http://

www.journalofvision.org/content/7/10/1, doi:10.1167/7.10.1. [PubMed] [Article]

Shaw, M. L. (1980). Identifying attentional and decision-making components in information processing. In R. S. Nickerson (Ed.), *Attention and performance, VIII* (pp. 277–296). Hillsdale, NJ: Lawrence Erlbaum Associates.

Shaw, M. L. (1982). Attending to multiple sources of information: 1. The integration of information in decision-making. *Cognitive Psychology, 14*(3), 353–409.

Shaw, M. L. (1984). Division of attention among spatial locations: A fundamental difference between detection of letters and detection of luminance increments. In H. Bouma & D. G. Bouwhuis (Eds.), *Attention and performance X* (pp. 109–121). Hillsdale, NJ: Erlbaum.

Shimozaki, S. S. (2010). Uncued and cued dynamics measured by response classification. *Journal of Vision, 10*(8):10, 1–27, http://www.journalofvision.org/content/10/8/10, doi:10.1167/10.8.10. [PubMed] [Article]

Shimozaki, S. S., Eckstein, M. P., & Abbey, C. K. (2003). Comparison of two weighted integration models for the cueing task: Linear and likelihood. *Journal of Vision, 3*(3):3, 209–229, http://www.journalofvision.org/content/3/3/3, doi:10.1167/3.3.3. [PubMed] [Article]

Shiu, L. P., & Pashler, H. (1994). Negligible effect of spatial precuing on identification of single digits. *Journal of Experimental Psychology: Human Perception and Performance, 20*(3), 1037–1064.

Shiu, L. P., & Pashler, H. (1995). Spatial attention and vernier acuity. *Vision Research, 35*(3), 337–43. [PubMed]

Smith, P. L. (1998). Attention and luminance detection: A quantitative analysis. *Journal of Experimental Psychology: Human Perception and Performance, 24*(1), 105–133.

Smith, P. L. (2000). Attention and luminance detection: Effects of cues, masks, and pedestals. *Journal of Experimental Psychology: Human Perception and Performance, 26*(4), 1401–20. [PubMed]

Sperling, G., & Dosher, B. A. (1986). Strategy and optimization in human information processing. In K. R. Boff, L. Kaufman, & J. P. Thomas (Eds.), *Handbook of perception and human performance: Volume 1* (pp. 2-1–2-65). New York: Wiley-Interscience.

Sperling, G., & Melchner, M. J. (1978a). The attention operating characteristic: Some examples from visual search. *Science, 202*(4365), 315–318. [Article]

Sperling, G., & Melchner, M. J. (1978b). Visual search, visual attention, and the attention operating characteristic. In J. Requin (Ed.), *Attention and performance VII* (pp. 675–686). Hillsdale, NJ: Erlbaum.

Spitzer, H., Desimone, R., & Moran, J. (1988). Increased attention enhances both behavioral and neuronal performance. *Science, 240*(4850), 338–340. [PubMed]

Steiger, J. H. (1990). A structural model evaluation and modification: An interval estimation approach. *Multivariate Behavioral Research, 25*(2), 173–180.

Swensson, R. G., & Judy, P. F. (1981). Detection of noisy visual targets: Model for the effects of spatial uncertainty and signal to noise ratio. *Perception & Psychophysics, 29*(6), 521–534. [PubMed]

Theeuwes, J. (1991). Exogenous and endogenous control of visual attention: The effect of visual onsets and offsets. *Perception & Psychophysics, 49*(1), 83–90. [PubMed]

Thornton, T. L., & Gilden, D. L. (2007). Parallel and serial processes in visual search. *Psychological Review, 114*(1), 71–103. [PubMed]

Tjan, B. S., Braje, W. L., Legge, G. E., & Kersten, D. (1995). Human efficiency for recognizing 3-D objects in luminance noise. *Vision Research, 35*(21), 3053–3069. [PubMed]

Torralba, A., Oliva, A., Castelhano, M. S., & Henderson, J. M. (2006). Contextual guidance of eye movements and attention in real world scenes: The role of global features in object search. *Psychological Review, 113*(4), 766–786. [PubMed]

Treisman, A., & Gelade, G. (1980). A feature-integration theory of attention. *Cognitive Psychology, 12*(1), 97–136. [PubMed]

Verghese, P. (2001). Visual search and attention: A signal detection theory approach. *Neuron, 31*(4), 523–35. [PubMed]

Vincent, B. T. (2011a). Search asymmetries: Parallel processing of uncertain sensory information. *Vision Research, 51*(15), 1741–50. [PubMed]

Vincent, B. T. (2011b). Covert visual search: Prior beliefs are optimally combined with sensory evidence. *Journal of Vision, 11*(13):25, 1–15, http://www.journalofvision.org/content/11/13/25, doi:10.1167/11.13.25. [PubMed] [Article]

Vincent, B. T., Baddeley, R. J., Troscianko, T., & Gilchrist, I. D. (2009). Optimal feature integration in visual search. *Journal of Vision, 9*(5):15, 1–11, http://www.journalofvision.org/content/9/5/15, doi:10.1167/9.5.15. [PubMed] [Article]

Walthew, C., & Gilchrist, I. D. (2006). Target location probability effects in visual search: An effect of

sequential dependencies. *Journal of Experimental Psychology, Human Perception and Performance, 32*(5), 1294–1301. [PubMed]

Warner, C. B., Juola, J., & Koshino, H. (1990). Voluntary allocation versus automatic capture of visual attention. *Perception & Psychophysics, 48*(3), 243–251. [PubMed]

Weiss, Y., & Adelson, E. H. (1998). *Slow and smooth: A Bayesian theory for the combination of local motion signals in human vision (A. I. Memo No. 1624)*. Cambridge, MA: MIT Press.

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

Wolfe, J. M. (2007). Guided Search 4.0: Current progress with a model of visual search. In W. Gray (Ed.), *Integrated models of cognitive systems* (pp. 99–119). New York: Oxford University Press.

Wolfe, J. M., Cave, K. R., & Franzel, S. L. (1989). Guided search: An alternative to the feature integration model for visual search. *Journal of Experimental Psychology: Human Perception and Performance, 15*(3), 419–433. [PubMed]

Wolfe, J. M., & Gancarz, G. (1996). Guided Search 3.0. In V. Lakshminarayanan (Ed.), *Basic and clinical applications of vision science* (pp. 189–192). Dordrecht, Netherlands: Kluwer Academic.

Wright, R. D., & Ward, L. M. (2008). Studying attention shifts with location cueing. *Orienting of attention* (pp. 15–36). Oxford: Oxford University Press.

Yeshurun, Y., & Carrasco, M. (1998). Attention improves or impairs visual performance by enhancing spatial resolution. *Nature, 396*(6706), 72–76. [PubMed]

Yeshurun, Y., & Carrasco, M. (1999). Spatial attention improves performance in spatial resolution tasks. *Vision Research, 39*(2), 293–306. [PubMed]

Yu, A. J., & Dayan, P. (2005a). Inference, attention, and decision in a Bayesian neural architecture. In L. K. Saul, Y. Weis, & L. Bottou (Eds.), *Advances in neural information processing systems, Vol. 17* (pp. 1577–1584). Cambridge, MA: MIT Press.

Yu, A. J., & Dayan, P. (2005b). Uncertainty, neuromodulation, and attention. *Neuron, 46*(4), 681–692. [PubMed]

Zhang, S., & Eckstein, M. P. (2010). Evolution and optimality of similar neural mechanisms for perception and action during search. *Public Library of Science Computational Biology, 6*(9):e1000930. [Pubmed] [Article]

Appendix A

Ideal observer model

The basis of the ideal observer model for this task may be found in Green and Swets (1974) (see also Abbey & Eckstein, 2002; Barlow, 1978; Cohn & Lasley, 1974). Signal detection theory and ideal observer analyses of visual search may be found in Kinchla, (1974), Shaw (1980, 1982, 1984), Palmer (Palmer, 1995; Palmer, Ames, & Lindsey, 1993; Palmer, Verghese, & Pavel, 2000), Eckstein, (Eckstein, 1998; Eckstein, Thomas, Palmer, & Shimozaki, 2000), Verghese (2001), and Baldassi and Verghese (2002). Signal detection theory and ideal observer analyses of the cueing task may be found in Kinchla, Chen & Evert, (1995), Eckstein, Shimozaki, & Abbey (2002), and Shimozaki, Eckstein, & Abbey (2003). Two tasks are presented, the yes/no detection task (used for the perceptual decisions) and the localization task (used for saccadic decisions). Note that the modeling for the localization task with the target present is equivalent to forced-choice tasks (M-AFC) for these cueing conditions.

The task of the observer is to judge either the presence (yes/no detection) or location (localization) of a single *signal* pattern (S_1) amongst other *no signal* patterns (S_0). At each location i (of M possible locations), a stimulus ($\mathbf{a}_i$) appears, comprised of either S_0 or S_1 in a field of Gaussian pixel image noise with $\mu = 0$ and $\sigma = \sigma_{\text{pixel}}$. Assuming that 2D spatial profiles are represented as column vectors and $\mathbf{e}_i$ represents the image noise at location i,

$$\mathbf{a_i} = \mathbf{S_0} + \mathbf{e_i}, \text{ or}$$

$$\mathbf{a_i} = \mathbf{S_1} + \mathbf{e_i}. \tag{A1}$$

In a yes/no task, a signal absent trial has S_0 at all locations, and a signal present trial has S_1 at one location and S_0 at the rest of the locations. A trial in a localization task has S_1 at one location and S_0 at the rest of the locations.

The ideal observer generates a response (x_i) by cross-correlating the stimulus at location i ($\mathbf{a}_i$) with the ideal template. In Gaussian noise, the ideal template is equal to the difference between the signal and the no signal patterns (without noise), so that

$$x_i = (\mathbf{S_1} - \mathbf{S_0})^t \mathbf{a}_i, \tag{A2}$$

where the superscript t indicates the transpose of the template vector.

The responses (x_i) are Gaussian distributed and therefore may be described as two normalized Gaussian distributions, one for responses to S_1, and one for responses to S_0. Typically, the mean of the responses to S_0 is set to zero and the mean of the responses to S_1 is set to d'. If we define

$$g(x) = \frac{1}{\sqrt{2\pi}} e^{\left(-\frac{1}{2}x^2\right)}, \tag{A3}$$

then

$$p(x_i \mid S_{0,i}) = g(x_i) = \frac{1}{\sqrt{2\pi}} e^{\left(-\frac{1}{2}x^2\right)}, \tag{A4}$$

and

$$p(x_i \mid S_{1,i}) = g(x_i - d') = \frac{1}{\sqrt{2\pi}} e^{\left(-\frac{1}{2}x^2 - d'\right)}. \tag{A5}$$

At each location i, the likelihoods (l_i) are calculated, or the probabilities of the responses at all M locations ($\mathbf{x} = [x_1, x_2, \ldots, x_M]$, given the signal at that location, ($p(\mathbf{x}|S_{1,i})$).

By independence,

$$l_i = p(\mathbf{x}|S_{1,i}) = p(x_i|S_{1,i}) \prod_{j=1, j \neq i}^{M} p(x_j|S_{0,j}) \tag{A6}$$

and substituting the Gaussian assumption,

$$l_i = g(x_i - d') \prod_{j=1, j \neq i}^{M} g(x_j). \tag{A7}$$

The posterior probability of $p(S_{1,i}|\mathbf{x})$ (the presence of S_1 at location i, given $\mathbf{x}$) is calculated through Bayes' rule. Each likelihood is weighted by the prior probability of signal presence ($p(S_{1,i})$), or the cue validity, at that location. If we define $w_i = p(S_{1,i})$, then

$$p(S_{1,i}| \mathbf{x}) = p(S_{1,i})p(\mathbf{x}| S_{1,i}) = w_i l_i. \tag{A8}$$

If the signal cannot appear at a given location, a possibility in the searches of 2, 3, or 5 in this task, the cue validity is zero. Note that for the yes/no task, w_i is the overall cue validity over both signal present and signal absent trials.

For the yes/no task, the likelihood ratio of the posterior probability of target presence (at any of the M locations) over the posterior probability of target absence is calculated, so that

$$Likelihood\ ratio = \frac{p(S_1|\mathbf{x})}{p(S_0|\mathbf{x})} = \frac{\sum_{i=1}^{M} p(S_{1,i}|\mathbf{x})}{p(S_0|\mathbf{x})}. \tag{A9}$$

By substituting A9 into A10 we have

$$Likelihood\ ratio = \frac{\sum_{i=1}^{M} w_i l_i}{p(S_0|\mathbf{x})}. \tag{A10}$$

Similar to the posterior probability of target presence, the posterior probability of target absence is

$$p(S_0| \mathbf{x}) = p(S_0)p(\mathbf{x}| S_0), \tag{A11}$$

where

$$p(\mathbf{x}|S_0) = \prod_{i=1}^{M} p(x_i|S_{0,i}) = \prod_{i=1}^{M} g(x_i). \tag{A12}$$

By substituting A12 into A11 we have

$$Likelihood\ ratio = \frac{\sum_{i=1}^{M} w_i l_l}{p(S_0)p(\mathbf{x}|S_0)}. \tag{A13}$$

The likelihood ratio is compared to a criterion; ratios larger than the criterion lead to *yes* responses, and all other values lead to *no* responses. The optimal criterion is equal to the equal posterior probabilities of target presence and target absence, or 1.0.

For the localization task, the location with the maximum posterior probability of target presence, or equivalently, the maximum weighted likelihood value, is chosen as the signal location.

$$\begin{aligned} \max\Big(p(S_{1,1}| \mathbf{x}), p(S_{1,2}| \mathbf{x}), \ldots p(S_{1,M}| \mathbf{x})\Big) \\ = \max(w_1 l_1, w_2 l_2, \ldots w_m l_m) \end{aligned} \tag{A14}$$

The ideal observer predictions were compared to an unweighted model, identical to the ideal observer, except that all the weights were equal ($w_i = 1/M$ for all i). This model is the ideal observer for the typical visual search task that has the same cue validities at each location. Alternatively, this model can be considered to be ideal, except for the use of the cue information. Comparisons of the ideal observer to this model assessed the cueing effects for the ideal observer. Lastly, the unweighted model for localizations in the target present trials is equivalent to the ideal observer model for standard M-AFC tasks (in which the probability of signal presence for each location/alternative is the same).

Appendix B

As stated in the text, the Root Mean Square Error of Approximation (RMSEA, Browne & Cudeck, 1992; McCallum, Browne, & Sugawara, 1996; Steiger, 1990) has been used as a fitting statistic, instead of a simple χ^2 statistic because χ^2 is heavily biased towards significance for larger sample sizes (greater than 200). RMSEA values less than 0.05 indicate good fits, and values larger than 0.10 indicate poor fits. Confidence intervals for the RMSEA can be calculated based upon the noncentral χ^2

distribution, which has two parameters, df (degrees of freedom) and λ (the noncentrality parameter), with $\lambda = \max(0, \chi^2 - df)$. If $\lambda = 0$, then the central χ^2 distribution is described, or that used for the standard χ^2 statistic. The probability distribution function for the noncentral χ^2 distribution is equal to

$$f(x|df,\lambda) = \sum_{i=0}^{\infty} \frac{e^{-\lambda/2}(\lambda/2)^i}{i!} \chi^2_{df+2i}(x), \qquad (B1)$$

with $\chi^2_{df+2i}(x)$ equal to the probability distribution function for the central (standard) χ^2 distribution with degrees of freedom $= df + 2i$. If we define $F(x)$ as the cumulative distribution function of the noncentral χ^2 distribution, $F(x)$ is equal to

$$F(x|df,\lambda) = \sum_{i=0}^{\infty} \frac{e^{-\lambda/2}(\lambda/2)^i}{i!} \mathrm{p}\left(\chi^2_{df+2i}(x) \leq x\right)$$
$$(B2)$$

where $p(\chi^2_{df+2i}(x) \leq x)$ is the probability of $\chi^2_{df+2i}(x) \leq x$, or the central (standard) cumulative probability

function of χ^2 with degrees of freedom $= df + 2i$. The inverse of $F(x)$ is evaluated for probabilities 0.05 and 0.95 (for 90% confidence intervals) to find the λ's defining the lower and upper bounds of the confidence interval, $\widehat{\lambda_L}$ and $\widehat{\lambda_U}$. The lower and upper bounds of 90% confidence intervals for the RMSEA are given as

$$\mathrm{RMSEA, \ lower \ bound} = \sqrt{\frac{\widehat{\lambda_L}}{Ndf}}, \qquad (B3)$$

and

$$\mathrm{RMSEA, \ upper \ bound} = \sqrt{\frac{\widehat{\lambda_U}}{Ndf}}. \qquad (B4)$$

The lower and upper bounds then can be used to assess the model fits. RMSEAs with upper bounds less than 0.05 represent good fits with 95% confidence; RMSEAs with lower bounds greater than 0.10 represent poor fits with 95% confidence (Browne & Cudeck, 1992; McCallum, Browne, & Sugawara, 1996).