Generating a taxonomy of spatially cued attention for visual discrimination: effects of judgment precision and set size on attention

Richard Hetley · Barbara Anne Dosher · Zhong-Lin Lu

Abstract Attention precues improve the performance of perceptual tasks in many but not all circumstances. These spatial attention effects may depend upon display set size or workload, and have been variously attributed to external noise filtering, stimulus enhancement, contrast gain, or response gain, or to uncertainty or other decision effects. In this study, we document systematically different effects of spatial attention in low- and high-precision judgments, with and without external noise, and in different set sizes in order to contribute to the development of a taxonomy of spatial attention. An elaborated perceptual template model (ePTM) provides an integrated account of a complex set of effects of spatial attention with just two attention factors: a set-size dependent exclusion or filtering of external noise and a narrowing of the perceptual template to focus on the signal stimulus. These results are related to the previous literature by classifying the judgment precision and presence of external noise masks in those experiments, suggesting a taxonomy of spatially cued attention in discrimination accuracy.

Keywords Attention · Judgment precision · External noise filtering

Introduction

Spatial attention may deploy visual processing resources to regions in space or to objects, usually leading to more accurate visual judgments. Spatial attention refers to orienting attention—usually by a pre-cue or other goal-related selection—to process a given location in space or the object in that location. The mechanisms by which attention improves visual performance have been the focus of intense and sustained study. The importance of attention for perception was recognized by the early sensory physiologists and psychologists, with a history that dates back more than 100 years (e.g., James, 1890; Pillsbury, 1908; Titchener, 1908; Wundt, 1902). Selective attention to a location in space, or to an object, has been studied with controlled experimentation since the 1970s (Posner, 1980; Sperling & Melchner, 1978; Treisman & Gelade, 1980; see Itti et al., 2005, for a selected review). However, the effects of spatial attention can vary significantly.

Attention to a location in space can, in certain circumstances, improve performance accuracy or response time relative to unattended locations or objects (e.g., Bashinski & Bacharach, 1980; Downing, 1988; Duncan, 1984; Han, Dosher, & Lu, 2003; Nissen, 1985; Posner, 1978; Posner, 1980; Shiffrin & Czerwinski, 1988; Sperling & Dosher, 1986). However, in other cases performance accuracy in attended and unattended conditions is essentially identical (Dosher & Lu, 2000b; Lu & Dosher, 2000; Shiu & Pashler, 1994a; Smith, 2000; Solomon, 2004). In some cases, performance accuracy differences in attended and unattended conditions (when they occur) have been attributed to structural factors such as decision uncertainty. Decision uncertainty refers to situations in which performance is compromised by multiple sources of false alarms in the decision process while perception is unchanged (Eckstein et al., 2000; Palmer et al., 1993; Shaw & Shaw, 1977). Related explanations apply to altered weights on the elements in the display, or to altered biases toward responses (Bundesen, 1990; Logan, 2002).

An essential research question is: what are the task and stimulus circumstances in which spatially cued attention

R. Hetley · B. A. Dosher (✉)
Department of Cognitive Sciences, University of California, Irvine, CA 92697-5100, USA
e-mail: bdosher@uci.edu

Z.-L. Lu
Department of Psychology, The Ohio State University, Columbus, OH 43210-1351, USA

improves the accuracy of performance without structural uncertainty? The current paper seeks to contribute to our understanding of the mechanisms by which such attention operates by identifying key factors that determine when and how attention is important, and identifying the mechanisms by which it operates. We evaluate the mechanisms of attention in key situations that have not received extensive experimental investigation in order to further develop a taxonomy or systematization of when and how spatially cued attention is important in performance.

We investigated the important stimulus and task factors in spatially cued attention through assays that measure the effects of spatially cued attention while varying the required judgment precision, visual workload, and stimulus contrasts, with and without external noise masking. Figure 1 illustrates the four major task and stimulus factors manipulated here, including the contrast of the signal stimulus (a), the presence of external noise (b), the precision of the required judgment (c), and the set size or workload demands of the task (d). In the current study, contrast is varied in multiple steps

spanning a full psychometric function from chance to maximum accuracy, the external noise manipulation uses an end-point manipulation comparing effects of attention in zero noise and the highest external noise conditions (Dosher & Lu, 2000b), workload is manipulated by set sizes of 2, 4, and 8, and performance is contrasted for orthogonal and very similar orientation discrimination. These stimulus and task manipulations are designed to include a wide range of contexts in which attention might be measured. Attention is manipulated by a precue that appears 170 ms prior to the signal stimuli, and compared to a cue that appears simultaneous with the signal stimuli. The observer knows exactly which location is being queried, which eliminates structural uncertainty about the target location.

We examine spatially cued attention within the context of a theoretical framework that has identified two dominant mechanisms of visual attention. The perceptual template model (PTM), developed through research on spatial cuing (Lu & Dosher, 1998, 2008; Dosher & Lu, 2000b) and perceptual learning (Dosher & Lu, 1998), is a model

Fig. 1 a–d Sample manipulations of the major stimulus and task factors in which attention is tested. The target or signal stimulus is an oriented Gabor (windowed sinewave). a Contrast of the Gabor signal is varied from low (*bottom*) to high (*top*); these tests have no external noise. Contrast is varied to span the psychometric function. b The contrast in the external noise is varied from zero (*top*) to high (*bottom*), holding signal contrast constant at a relatively high value. The current experiment tested zero and high external noise. c The precision of the required judgment, varied from low (*top*) to high (*bottom*). The current experiment tested low precision as 20° tilt left or right of vertical (40° total difference) and high precision as 4° left or right of vertical (8° total difference). d Set size or workload was manipulated by the number of locations at the same eccentricity. The current experiment tested 2, 4, and 8 locations, where a single target location was precued in the attended location, or marked simultaneously in the unattended condition
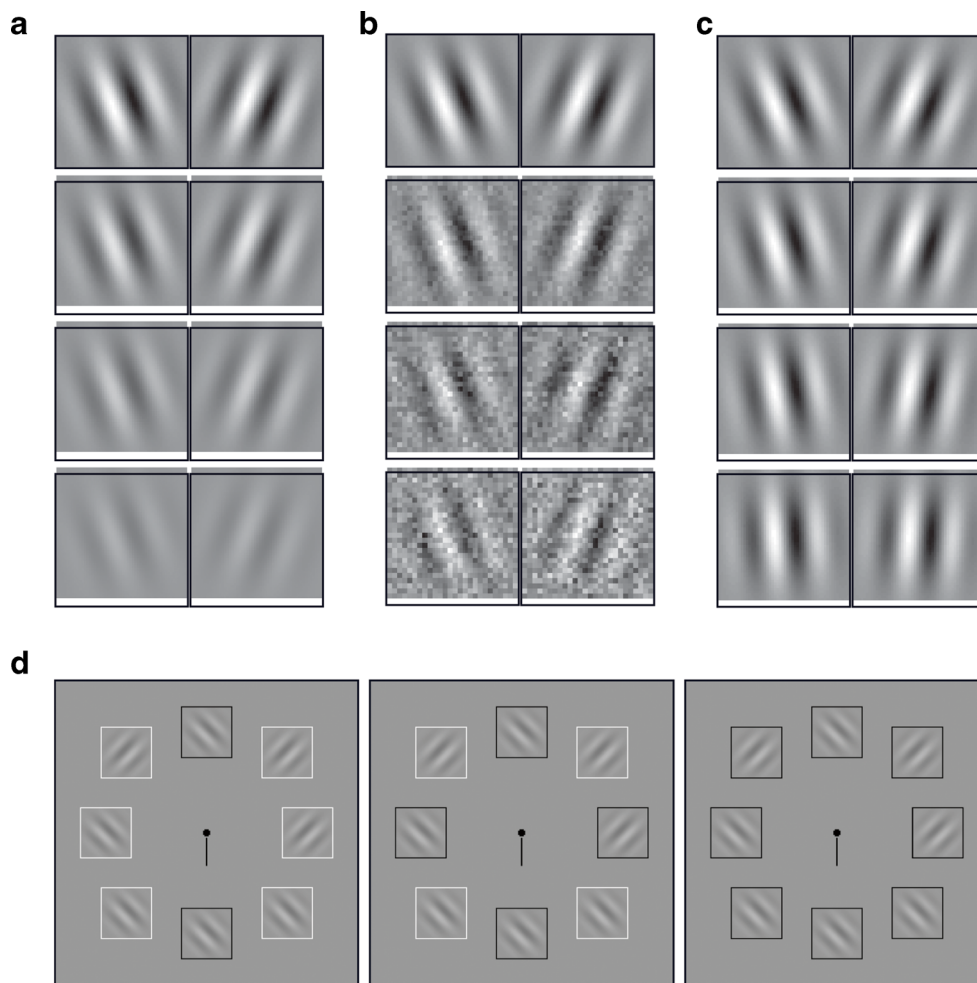
of the observer's behavior that incorporates external stimulus qualities, internal noise limits of the observer, and effects of attention to account for task performance. Over many studies, we and others have observed two primary mechanisms of visual attention: stimulus enhancement and external noise exclusion (Dosher & Lu, 2000a, b; Ling & Carrasco, 2006a; Lu & Dosher, 1998, 2000; Lu et al., 2000, 2002; Smith, 2000; Smith & Wolfgang, 2007). External noise refers to masking noise or non-signal elements presented in the external stimulus (see Fig. 1b). Internal noise refers to variability and inefficiency in the response of the visual system of the observer to an external stimulus. It represents noisiness or inefficiencies in internal processes. External noise exclusion refers to improvements (i.e., improvements due to attention) in filtering of external noise in the stimulus, while stimulus enhancement refers to a relative improvement of signal to (internal) noise that occurs in the absence of external noise. Of these, external noise filtering seems to be a dominant mechanism (see Dosher & Lu, 2013, for a review).

A perceptual template model of spatial attention

The spatial attention effects in our experiment were analyzed within the theoretical framework of the perceptual template model, specifically the elaborated PTM (ePTM). The model provides a framework for understanding the mechanisms by which attention has an effect on performance. The original PTM (as with other observer models) was developed to account for discriminability, d', for low-precision judgments (Lu & Dosher, 1998; Dosher & Lu, 2000a, b). Low precision judgments require discrimination or identification of very dissimilar stimuli. For example, Dosher and Lu (2000a, b) tested discrimination for four stimuli with orientations or tilts 45° away from each other, where each of four possible stimuli plausibly stimulated just one perceptual template. Jeon et al. (2009) manipulated precision of the judgment (Fig. 1c) and derived the elaborated perceptual template model (ePTM) to allow the target image and distractor image to be more similar, thereby stimulating "each other's" template. In Jeon et al. (2009), observers identified Gabors as oriented top right or left in different judgment precisions (±3°, ±6°, ±15°, and ±45° from vertical) in separate mini-blocks. Here, we extend the ePTM to incorporate attention effects, by analogy to the mechanisms of the original PTM (Lu & Dosher, 1998; Dosher & Lu, 1998), and show the predicted effects on psychometric functions and threshold-versus-contrast functions of manipulations like attention that may change the state of the observer by several different mechanisms.

The perceptual template model has five major components: the perceptual template(s), a nonlinear transducer function, multiplicative internal noise, additive internal noise, and a decision process (see Fig. 2a). A perceptual template is essentially a filter tuned to a signal stimulus for the task. Although the template filter spans all dimensions of the stimulus, it is illustrative to focus on its tuning in the dimension of the task discrimination. In this paper, targets differ in orientation, so a good example of a perceptual template is an orientation filter defined by its center orientation and bandwidth, and shaped as a Gaussian with maximum gain at its center (see below) (Fig. 2b).

In the ePTM with two-alternative identification, the decision depends upon the difference between the responses of the two templates tuned for the two to-be-identified targets to the test stimulus relative to the total limiting noises. Performance accuracy in the ePTM is described by:

$$d' = \frac{(\beta_M c)^\gamma - (\beta_U c)^\gamma}{\sqrt{A_f^2 N_{ext}^{2\gamma} + N_m^2 \left(A_f^2 N_{ext}^{2\gamma} + \frac{(\beta_M c)^{2\gamma} + (\beta_U c)^{2\gamma}}{2} \right) + A_a^2 N_a^2}}$$

(1)

The stimulus is defined by its contrast, c, and amount of (external) noise, N_{ext}, both manipulated by the experimenter. The parameters β_M and β_U are the gains of the matched and un-matched perceptual templates to the test signal stimulus, respectively. For example, if the task is to discriminate ±12° stimuli, and a +12° stimulus is presented, then β_M is the gain of the +12° template to the (matched) stimulus and β_U is the gain of the –12° template to the (unmatched) +12° stimulus. The ePTM defaults to the original PTM for low-precision judgments, as the other template is more separated—and β_U approaches 0. The visual system's response is nonlinear, which is expressed as raising the input to a power γ. Within the visual system are sources of multiplicative internal noise, N_m, and additive internal noise, N_a, that limit discrimination (Lu & Dosher, 2008; Jeon et al., 2009). Limitations in human performance are modeled as equivalent internal noises. Multiplicative noise is a noise source with amplitude proportional to the average amplitude of the output response of the perceptual template; it depends upon the contrast energy of the signal and the external noise in the stimulus and is associated with Weber-like behavior. Additive internal noise is a noise source whose variance does not depend upon the output of the template and limits absolute discrimination.

Two mechanisms of attention, originally modeled within the PTM, are attention factors for external noise exclusion (A_f) and attention factors for stimulus enhancement (A_a). External noise exclusion improves performance through improved filtering and therefore a lesser impact of external noise. Stimulus enhancement improves performance by amplifying input stimuli or (mathematically) equivalently relative reduction of internal additive noise (Dosher & Lu, 2000b). In this

application, we set the attention factors to 1 in the attended conditions, and estimate attention multipliers greater than 1 in unattended conditions ($A_f > 1$ and $A_a > 1$).[1] The effect of inattention is cast as an increased susceptibility to external noise and to internal additive noise. Stimulus enhancement can only improve performance in low external noise, as accuracy is then limited by internal noise relative to stimulus gain. External noise exclusion can improve performance only when there are higher levels of external noise.

As to-be-discriminated stimuli become more similar—the judgments becoming more precise—the difference between β_M and β_U is reduced as the unmatched stimulus approaches the 'shoulder' of the template. To formulate this in the model, we assume that perceptual templates have tuning with standard deviation σ. The gain to a stimulus in the matched template is β_M; the gain to a stimulus in the unmatched template, β_U, is related to the angular difference between the stimulus and the template center, θ, relative to the standard deviation, σ:

$$\beta_U = \beta_M \left(\frac{g(\theta \,|\, 0, \ \sigma)}{g(0 \,|\, 0, \ \sigma)} \right), \tag{2}$$

where $g(x|\mu, \ \sigma)$ is the probability density function of the Gaussian distribution at the value x.

Attention may sharpen the tuning—decrease the bandwidth—of the perceptual template ($\sigma_A < \sigma_U$) (Dosher & Lu, 2000a, b; Lu & Dosher, 1998; see also Lee et al., 1999). If attention does sharpen template tuning and the judgment precision is high, then reducing β_U by attention would increase the numerator of d' and increase the asymptotic level of accuracy. On the other hand, if the judgment precision is very low, then sharpening template tuning (reducing β_U) will have no effect on asymptotic level of accuracy— β_U is close to 0 in either the attended or the unattended condition. The same change in template tuning may occur in either case, but it is made visible at the asymptote only in the high precision judgment while it is invisible in low precision judgments (see Fig. 2b for illustrations). These asymptotic differences, when they occur, will be visible in both high and in low external noise tests. This same sharpening of the template is usually also associated with improvement in exclusion of external noise by the narrower template. External noise

filtering is estimated separately because it reflects filtering in all stimulus dimensions of the template. If there are effects at asymptote, in most scenarios there is an effect of external noise exclusion as well.

Figure 3 shows different signature patterns of attention in the ePTM for high-precision and low-precision judgments in which the template is narrowed with attention, as well as external noise exclusion and stimulus enhancement mechanisms. The model explains asymptotic effects with high-precision judgments. The model then provides a framework describing and systematizing the pattern of attention mechanisms corresponding with the many reported effects in the literature.

Visual spatial attention

In this section, we consider some of the key prior literature on the functions and mechanisms of spatial attention in visual discrimination. Some of these experiments and corresponding effects are summarized in Table 1. Columns in the table indicate whether the experiment included masking or external visual noise, the precision of the tested judgment, and the workload used in the experiment (number of screen locations or stimuli displayed on any given trial), central or peripheral precuing. Other columns provide a classification of the nature of the possible attention effects, and whether spatial uncertainty could have influenced the results (or was eliminated procedurally or by uncertainty computations).

External noise exclusion

A number of prior studies have pointed to the importance of external noise exclusion as a primary or dominant effect of spatial cuing of attention (see Dosher & Lu, 2013, for a review). External noise exclusion has its signature effect in high external noise, where external noise is the key limiting factor, and better filtering of external noise improves performance. Stimulus enhancement has its signature effect in low external noise, where internal noises characteristic of the observer limit performance. High precision judgments may also reveal asymptotic effects, so attention effects in either high or low noise require more careful assessment (see below, and ePTM predictions).

Dosher and Lu (Dosher & Lu 2000a, b; Lu & Dosher, 2000; see also Gould, Wolfgang, & Smith, 2007; Cheal & Lyon, 1991) argued that external noise exclusion or filtering was the main mechanism of attention. They measured contrast psychometric functions, and the corresponding threshold contrasts, for judgments of the orientation of a target Gabor in external noise of varying strengths. Attention was manipulated by central or endogenous precue validity. There were no detectable attention effects on threshold when there was no or very little external noise, whether the cues were valid or invalid, so long as spatial uncertainty was controlled. In general, studies with external noise

---

[1] In other related applications of the PTM (i.e., Dosher & Lu, 2000a), attention multipliers have used the opposite convention with the unattended conditions set to 1, and A_f and A_a less than 1 in attended conditions. We chose to reverse the convention here to capture the observation that a precue may equate the performance in the attended location regardless of set size (Dosher & Lu, 2000b). For any given set size condition, the selection of the baseline is arbitrary; when considered together, setting the attended condition to 1 provides the constraint of equivalent attended performance.
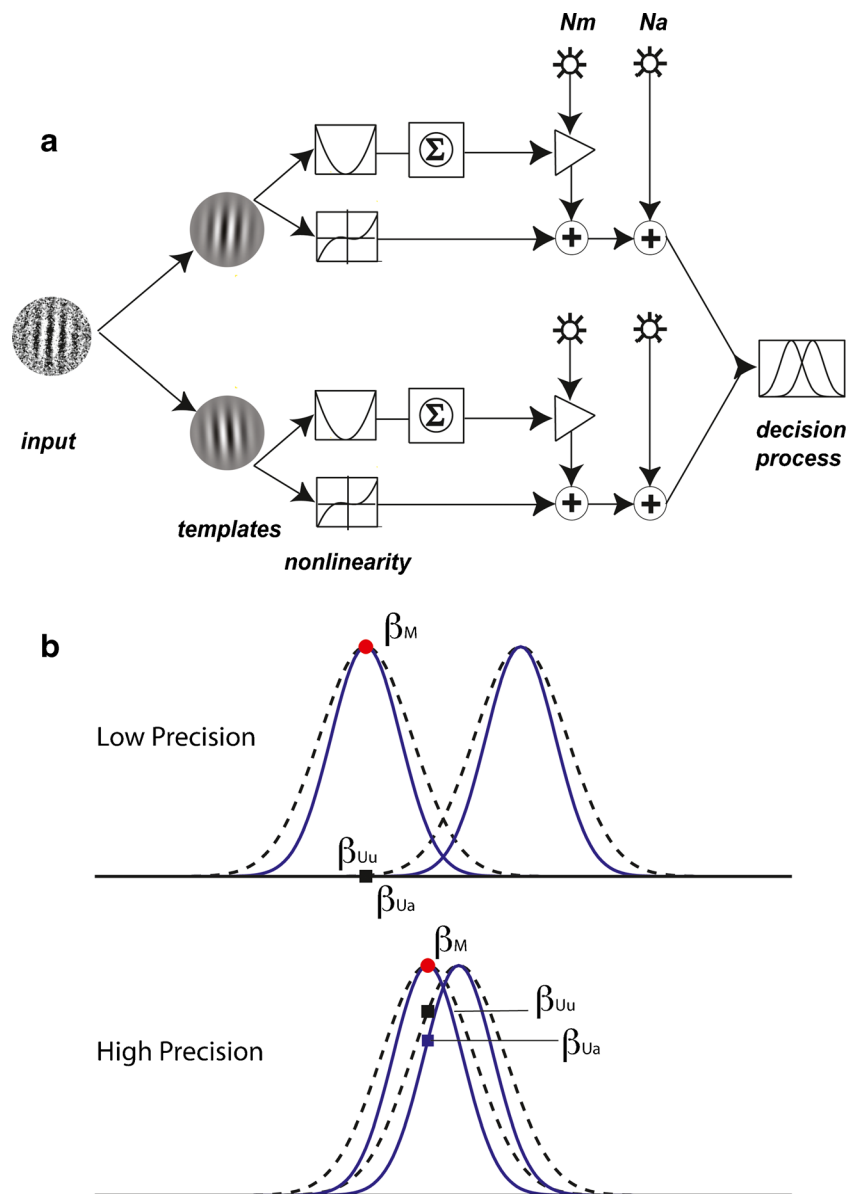
Fig. 2 a,b An illustration of the perceptual template model, and of the perceptual templates for judgments of different precision with attention narrowing the templates. **a** The perceptual template model including two templates for discrimination. The stimulus is compared with each template, followed by nonlinearity and contrast gain control paths, internal multiplicative noise and internal additive noise. The output of two templates is compared to yield a decision variable. **b** Judgments for left-right discrimination matched to low (*top*), and high (*bottom*) precision judgments, such as orientation judgments. The *red circle* marks the response of a left-tilted target stimulus to its matched perceptual template for each judgment precision (β_M), and the *dark squares* mark the response(s) of the paired template for a right-tilted target to the unmatched left-tilted stimulus (β_{Uu} or β_{Ua}, for unattended or attended conditions). The difference between the responses of the two templates to the test stimulus, modulated by contrast and non-linearity, controls the numerator of the perceptual template model equation and is the major factor in constraining discrimination at different judgment precisions. If attention narrows the templates (*dashed* versus *solid lines*), this has essentially no effect on β_U for very low precision tasks (as it is zero in either case), but will affect it in intermediate and high precision tasks—leading to asymptotic changes at high contrast

find external noise exclusion whether cues are central (e.g., Dosher & Lu, 2000a, 2000b; Lu & Doshe, 2000; Lu et al., 2002) or peripheral (e.g., Baldassi & Burr, 2000; Liu et al., 2009c; Lu & Dosher, 2000; Smith & Wolfgang, 2007). Often, so long as decision uncertainty has been eliminated by simultaneous report cues, attended and unattended conditions either converge at high contrast or, at worst, the convergence is ambiguous (because it would occur at more than 100 % contrast) but is well fit by converging psychometric functions.

An important but orthogonal distinction in external noise exclusion contrasts external noise that is added to the stimulus as integrated noise (either simultaneously or temporally integrated by rapid interleaving in time) and pattern post-masking that
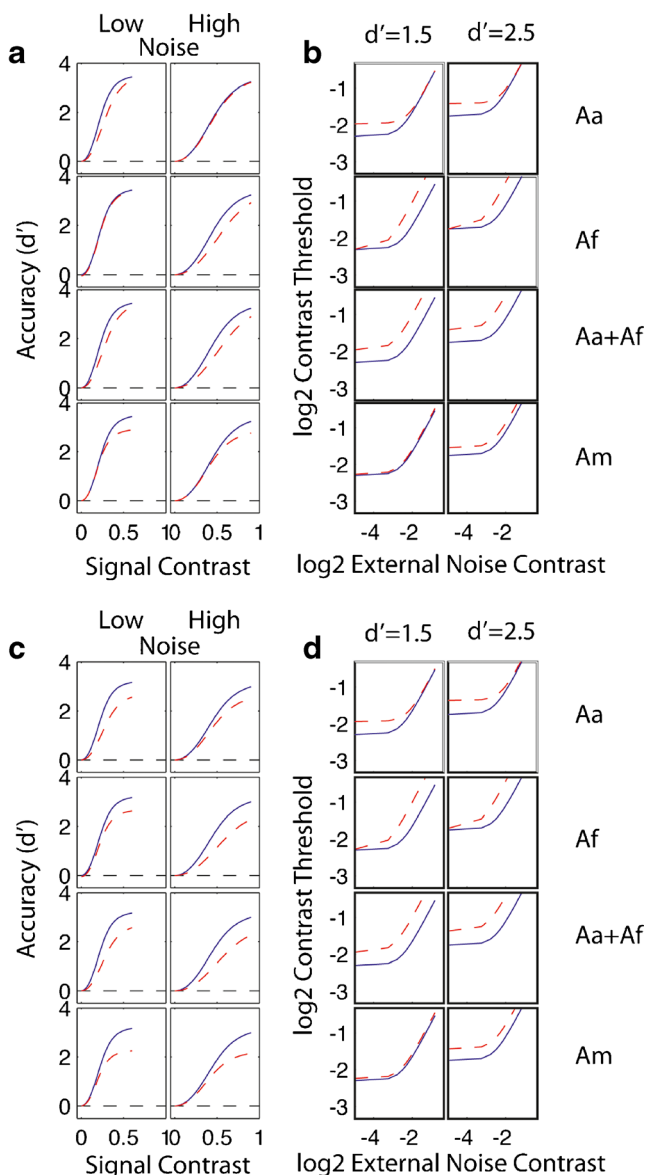
Fig. 3 Signatures of attention mechanisms for the elaborated perceptual template model (ePTM) showing stimulus enhancement (A_a), external noise exclusion (A_f), a mixture of both ($A_a + A_f$), and multiplicative noise reduction (A_m) for orthogonal stimuli (low-precision judgments) (**a**–**b**) and similar stimuli (high-precision judgments) (**c**–**d**). Predictions are shown for psychometric functions in low and high external noise displays (**a**, **c**) and for threshold versus contrast (TvC) functions at two criterion accuracies of $d' = 1.5$ and 2 (**b**, **d**). *Solid blue lines* Attended conditions, *red dashed lines* unattended conditions. Parameter values $N_m = 0.3$, $N_a = 0.03$, $\gamma = 2$, $\beta = 1.1$, $\beta_{uA} = 0.3$, $\beta_{uU} = 0.5$, $A_{fU} = 1.6$, $A_{aU} = 1.6$, $A_{mU} = 1.2$

occurs at some point after the stimulus display and interrupts processing. The original applications of the PTM are focused on external noise that is integrated with the target stimulus, and reflects filtering in the stimulus domain (i.e., Baldassi & Burr, 2000; Dosher & Lu, 2000a, 2000b; Lu & Dosher, 2000; Lu et al., 2002). Poststimulus masking reflects a different kind of filtering in the time domain (i.e., Smith & Wolfgang, 2007; Smith, Ratcliff, & Wolfgang, 2004). The distinction between the two

kinds of noise manipulation is indicated in Table 1. Our focus is on external noise and external noise exclusion, although in many cases qualitative results parallel those of postmasking. We return to this issue in the discussion.

Stimulus enhancement

Dosher and Lu (2000a, b) used endogenous or central cues (pointer cues at or near the fixation) and found no evidence of attention effects in the absence of external noise. Others have used exogenous or peripheral cues (close to the test stimuli) and find attention effects on performance when cues are peripheral absent external noise (e.g., Cameron et al., 2002; Carrasco et al., 2000). Lu and Dosher (2000) manipulated whether cues were central or peripheral within a single test paradigm. Consistent with Dosher and Lu (2000b), they found that central precuing improved accuracy only in high noise through external noise exclusion. Peripheral precuing, however, improved performance in all conditions, suggesting that peripheral or exogenous cuing invoked both stimulus enhancement and external noise exclusion.

Gould et al. (2007) argued that some spatial attention cuing effects in the absence of external noise or postmasks even in peripheral cuing situations should be attributed to uncertainty rather than stimulus enhancement (an effect of attention on perception). With dim images that appear on a neutral gray background, the location of the target stimulus is not obvious, and so information from multiple locations in the display might impact performance due to decision uncertainty. Smith and colleagues argued that once spatial uncertainty is minimized, attention effects occur only in the presence of a post-stimulus mask (e.g., Smith et al., 2010), or in the presence of external noise (Liu et al., 2009c; Smith & Wolfgang, 2007). These claims are related to our reports that external noise exclusion is the primary mechanism of endogenous cuing (without stimulus enhancement) when spatial uncertainty is eliminated (Dosher & Lu, 2000a; Lu & Dosher, 2000). The Smith claims extend to peripheral precuing of spatial attention; they attributed all of the prior effects of spatially oriented attention under these circumstances and absent noise to unsolved uncertainty confounds. Note, however, that uncertainty cannot account for the effects of peripherally cued attention in the absence of external noise reported in Lu and Dosher (2000).

Ling and Carrasco (2006a) also explicitly manipulated cue type and proposed a different interpretation. In displays with no external noise, they found attention improved performance in both central and peripheral cuing, but reported that attention also had an effect on asymptotic performance when using peripheral cuing, an asymptotic increase that they associated with response gain (see below). Ling and Carrasco (2006a, b), and Pestilli et al. (2007) tested attention with higher-precision judgments

Table 1 Literature summarized by major manipulations and effects. Manipulations in experiments: *Precision* Angles between targets as a number of degrees. *Cues: C* Central, *P* peripheral, *B* both. *External noise* (or masks): *0* No external noise, *N* high external noise, *V* variable external noise (including 0 and high), *B* both (0 and high external noise only), *PM* postmask. *Cued/locations* (on the display): # of locations/# of targets. *Decision*: probable, minimized, eliminated. Effects on performance data (results): *A* Asymptotic, *SE* stimulus enhancement (in low external noise), *ENE* external noise exclusion, *UNC* uncertainty (Yes, Probable, No). The presence of possible uncertainty contaminates, and so reduces the certainty of, the interpretation of other attention effects

Source	Precision	Cues	External noise	Cued/locations	Decision	A	SE	ENE	UNC
Carrasco, Talgar, and Cameron (2001)	4°	P	0	8/1	Yes	N/A	Y?	N/A	Y
Pestilli et al. (2007)	5°	P	0	2 / 2	Eliminated (delayed)	Y	Y?	N/A	N?
Ling and Carrasco (2006b)	6°	C	0	4 / 1	Eliminated	N/A	Y/N adapt state)	N/A	N
Ling and Carrasco (2006a)	8°	P/C	0	8 / 1	Probable @ low contrast	N-C Y-P	Y? Y?	N/A	P
Pestilli and Carrasco (2005)	8°	P	0	2	Probable (4°, 9°)	N/A	Y?	N/A	P
Baldassi and Burr (2000)	16°	P	N	1,4,8 /*	Yes	N/A	N/A	Y	Y
Carrasco et al. (2001)	30° 15°	P		1, 4, 8	Yes	N/A	Y?	N/A	Y
Lu and Dosher (1998)	24°	B	V (N)	2 / 2	Eliminated	N	Y	N	N
Cameron et al. (2002)	30°	P	0	8 / 1	Probable @ low contrast)	N	Y?	N/A	P
Dosher and Lu (2000a)	45°	C	V (N)	4 / 4	Eliminated	N	N	Y	N
Gould et al. (2007)	90°	P	0	3 / 1	Manipulated	N	N	N/A	Y
Liu et al. (2009c)	90°	P	B PM	3 / 1	Manipulated		Y	Y	Y
Smith et al. (2010)	90°	P	N, PM	3 / 1	Eliminated	N	N-0 Y-N	N/A	N
Smith and Wolfgang (2007)	90°	P	N (& post masks)	3 / 1	Minimized	N	N/A	Y	N
Lu et al. (2002)	90°	C	B	4 1-4	Eliminated	N	N	Y	N
Dosher and Lu (2000b)	90°	C	B	2, 4, 8/1 2, 4, 8/1	Eliminated	N	N	Y	N
Lu and Dosher (2000)	90°	P/C	V	4 / 1	Eliminated	N	N-C Y-P	Y	N
Smith et al. (2004)	90°	P	B, PM	3/1	Eliminated (pedestal)	N	(0)	N	N
Carrasco et al. (2000)	90°	P	0 N (E4)	2	Yes (location) (spatial frequency)	N/A	Y?	Y	Y Y(E4)
Carrasco et al. (2001)		P		8/1 (alone or with distractors)	Probable	N/A	Y?	N/A	Y

(<8° orientation differences) and showed effects of attention in clear displays with peripheral cues. However, their experiments might reflect both attention and uncertainty effects in the lowest contrast conditions.

A reasonable summary appears to be that stimulus enhancement is generally not a factor in central or endogenous precuing; it may sometimes occur in peripheral or exogenous precuing although this is under contention.

Asymptotic effects

Asymptotes, or performance in the saturating contrast region of psychometric functions, are often not assayed—for example, in experiments measuring only thresholds. When asymptotes can be measured convincingly, they have been of great recent interest. For example, Pestilli et al. (2007) and Herrmann et al. (2010) argued that performance at asymptote may allow classification of an attention effect that occurs by contrast gain or response gain, by analogy to the contrast-response functions for a neuron (see Reynolds & Heeger, 2009). Contrast gain is a leftward shift of the contrast-response function of a neuron, while response gain is an upward shift, i.e., an asymptotic change. Hermann et al. argued that response gain (a shift up for the entire psychometric function) occurs when the attention field is small relative to the stimuli; they claimed that contrast gain occurs when stimuli are small relative to the attention field. They found

the same pattern of results regardless of whether cues were central or peripheral. Both of these papers used relatively high precision tasks in their experiments.

Note, however, that behavioral performance reflects the signal and the noise properties of internal responses that determine the discriminability of targets, not simply activity as in the response of neurons. An asymptotic change of neuronal response functions may or may not lead to an asymptotic change in psychometric functions. In particular, if neuronal responses become more noisy as they increase, then the increase in noise may vitiate the increase in response and eliminate asymptotic effects. Furthermore, effects of attention on asymptotic performance accuracy (discriminability) at high contrast have a special significance within the framework of the ePTM model. As described above, they reflect a change in the response of the template due to attention that can only easily be revealed in high precision judgments.

Spatial uncertainty

In many studies with spatial cuing, the observer does not know which location in a display contains the target until or unless a report cue appears. One experimental manipulation of attention varies whether the report cue is a precue or a simultaneous cue to the target, with the precue giving the observer lead time to direct attention to that location (e.g., Cheal & Lyon, 1992; Lu & Dosher, 2000). Another alternative is to have a separate precue and report cue, and vary whether the precue is valid (e.g., Dosher & Lu, 2000a; Liu et al., 2009b). In either of these cases, uncertainty about the spatial location of the target is eliminated by a report cue, and so decision uncertainty is not an alternative explanation for attention effects.

Decision uncertainty occurs not due to a change in the perceptual processing of the stimulus, but rather due to the inclusion of more locations in the decision thus allowing more potential sources of false alarm errors. One of the standard methods of studying spatial attention leaves open uncertainty as a contributor to attention effects. In this method, there is only a precue (with no report cue) and the precue gives spatial information or not at all, either validly indicating the target's upcoming location or remaining neutral (e.g., Ling & Carrasco, 2006a). Uncertainty calculations can place boundary conditions on the size of decision effects (Palmer, 1994; Eckstein et al., 2000). Possible uncertainty effects intrinsically make some designs more difficult to interpret. To make things more complicated, when only a single target is presented (i.e., Ling & Carrasco, 2006a; Cameron et al., 2002), uncertainty may be eliminated by the targets themselves at the higher contrast levels of psychometric functions while it remains at lower contrasts.

Set size

The magnitude of attention effects may depend on set size or workload. A valid precue can restrict attention to a single target regardless of set size; but without a cue, attention spreads across all possible locations for the target, so the costs for being unattended increase with set size. The benefit associated with external noise exclusion in Dosher & Lu (2000b) was correspondingly greater as set size increased through two, four, and eight elements.[2] The costs of misdirected attention on psychometric functions, and correspondingly on threshold contrast, increased with set size for invalid cues in high external noise, indicating attention effects of external noise exclusion. However, when cues were valid and attention was therefore directed to the target, there were no detectable set size effects on threshold in high external noise. Attention and judgment were restricted to the target location.

Judgment precision

Precision of the required judgment, controlled by the magnitude of the difference (or conversely, the similarity) between to-be-identified stimuli, is not a common manipulation in the attention cuing literature. In fact tested judgment precision has often been low, with the stimuli to be discriminated relatively dissimilar. Most of the studies cited above (see Table 1) involve judgment between Gabor patches, lines, or rotated T characters that are very different, often with 90° angular difference between alternatives (Carrasco et al., 2000; Cheal & Lyon, 1991; Gould et al., 2007; Liu et al., 2009a, b, c; Lu & Dosher, 2000; Lu et al., 2002; Smith et al., 2010; Smith & Wolfgang, 2007). Identifications are rarely as precise as 30° (e.g., Cameron et al., 2002), and Dosher and Lu (2000b) noted that a difference near 45° (for their Gabor stimuli) is enough for each target to stimulate predominately just one of the templates or channels tuned to the two tilts.

Attention studies that have used high-precision tasks include Baldassi and Burr (2000), Ling and Carrasco (2006a), Ling and Carrasco (2006b), Liu et al. (2009b), Pestilli et al. (2009), and Pestilli et al. (2007), with the images to be discriminated differing by from 5° to 16°. Attention effects occur variously in these conditions, but precision is rarely a manipulated factor in the experiments. Liu et al.'s (2009b) study of object attention (not spatially cued orienting)

---

[2] Palmer (1994) and Palmer et al. (1993) distinguished between *display set size* which is the number of stimuli physically presented, and *relevant set size* where the participant is validly cued to a subset of the presented stimuli, such as with black or white cues for relevant or irrelevant locations. Their experiments suggested that both forms of set size lead to similar effects on threshold performance, and, although the two manipulations are often equivalent, they argued for using relevant set size to control sensory effects that could obscure the contribution of attention.

is an exception; greater effects of attention were found with higher precision judgments. The contrast gain versus response gain distinction was developed through experiments with both high-precision (5°; Pestilli et al., 2007) and low-precision (60°; Herrmann et al., 2010) judgments, with judgment precision itself having no role in the hypothesis.

In summary (see Table 1), visual spatial attention studies show effects of attention expressing a mechanism of external noise exclusion (whether cues are central or peripheral), and sometimes via stimulus enhancement. Most studies have used low-precision tasks (45° or more difference between to-be-discriminated stimuli). Those with higher precision find some of these same effects. There is also evidence of further effects on asymptotic performance (Ling & Carrasco, 2006a; Pestilli et al., 2007); however, spatial uncertainty (Gould et al., 2007) or judgment precision (Liu et al., 2009a, b) may have influenced the results. In those few studies that manipulated set size or workload, performance losses for unattended stimuli increase with workload, even when uncertainty is controlled with a report cue (Dosher & Lu, 2000b). In short, the full pattern of effects of spatially cued orienting of attention, and their interactions with judgment precision, are not specified by the prior literature—although the importance of external noise exclusion is highly suggestive.

The current study

The current study measures the effects of central (endogenous) attention on contrast psychometric functions in an orientation discrimination task for all of these factors in order to determine the mechanisms by which attention operated: attention (precues versus simultaneous cues), external noise (none or high), set size or workload (relevant set size 2, 4, and 8), and judgment precision (low at ±20° and high at ±4°) to determine the full taxonomy of attention effects in spatial cuing. Cues are always valid; uncertainty is eliminated by either the precue or simultaneous cue since the observer always knows the target location to be reported, while the precue allows deployment of attention in advance of the stimulus.

In many ways, it is surprising that no single study has previously assayed all of these important factors at the same time. Although we might predict some of the results from the prior literature, in many cases—such as precision—the manipulation has rarely occurred within the same study. Set size or load manipulations have not been tested with high precision judgments. This provides an opportunity to examine the mechanisms of spatially cued attention within the systematic framework of the elaborated perceptual template model (ePTM) and begins to formulate an understanding of which

attention mechanisms are operable under which circumstances.

Methods

Observers

Five observers were recruited by fliers and were paid US $ 10 an hour. All observers had normal or corrected-to-normal vision.

Apparatus

A computer running Mac OS 9.2.2 and Matlab 5.2.1 displayed images on a ViewSonic Graphics Series G225f monitor, combining two output channels to create 12.6 bit grayscale images (Pelli & Zhang, 1991). Minimum and maximum luminance were 0.01 and 98.9 cd/m^2. The monitor maintained a background luminance of 53.2 cd/m^2 and had a refresh rate of 60 Hz. Experiments were performed in a darkened room with the participant using a chin rest 60.8 cm away from the monitor.

Experimental design

Independent variables included attention condition, external noise contrast, stimulus contrast, set size (workload), and precision of discrimination. Attention (attended or unattended) was manipulated by either a precue or a simultaneous cue. Both of these cues were central, reflecting endogenous attention. External noise contrast was zero or high. Stimulus contrast was selected from six values for each external noise condition as described below. Set size was selected from three levels of relevant set sizes (Palmer, 1994; Palmer et al., 1993). Precision was low or high, corresponding with different angular differences for the discrimination between Gabor stimuli tilted left/right of vertical. Experimental trials were blocked by precision. This allowed the observers to know which patterns were to be discriminated.

Stimuli and procedure

The participant initiated a session with a key press on the keyboard. Trials were blocked by precision to allow the participant to maintain a single set of perceptual templates at any one time. The participant was informed of the precision at the start of each block of trials by the text "large tilt" (low precision) or "small tilt" (high precision). Low precision meant 20° tilt left or right of vertical (40° total difference) and high precision meant 4° (8° total). Precision alternated across all blocks and
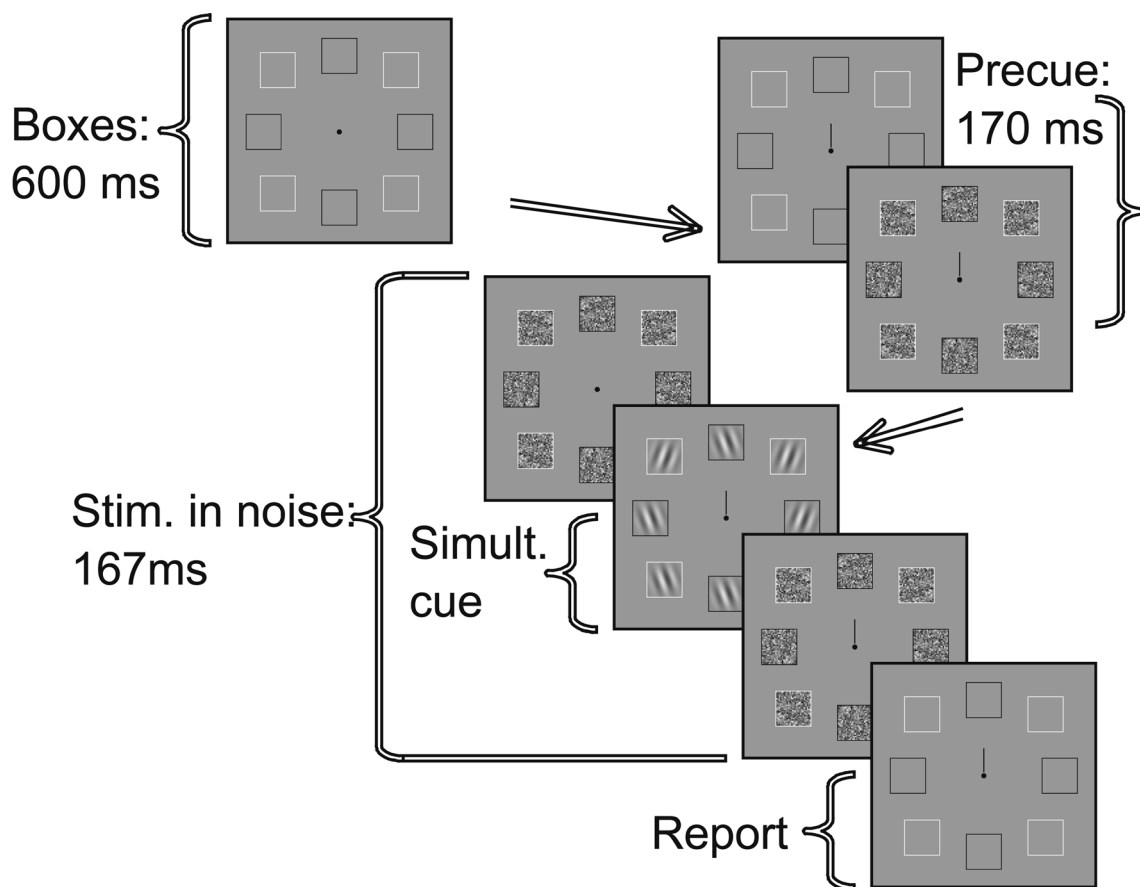
Fig. 4 Time course and sample layouts of trials with a pre-cue or a simultaneous cue, shown for set size 4 marked by the black boxes, and with high external noise. In low noise, the blank background gray was displayed within each box instead of the noise images

sessions. Example stimuli, the layout, and the procedure are shown in Figure 4.

On each trial, a fixation point appeared at the center of the screen, surrounded by eight empty $2.47° × 2.47°$ boxes on a ring of radius 6.85°. The boxes were spaced equally from each other and outlined either in black (minimum screen value) or white (maximum screen value) to establish the relevant set size for that trial: 2, 4, or 8. For some participants white was the relevant cue, and for others black was the relevant cue (the latter after Palmer, 1994). No difference was observed in results based on which outline style was used. The participant paid attention to the relevant boxes while maintaining fixation; fixation was encouraged by having the set size 2 boxes be arrayed in a randomly-selected opposing pair of locations, and set size 4 boxes arrayed in a randomly selected X or cross. The use of 100 % valid precues or simultaneous cues minimized spatial uncertainty at the decision stage as an alternate explanation for attention effects (Gould et al., 2007) or as a variable that would control attention effects (Herrmann et al., 2010).

The participant had 600 ms to observe the set size layout and fixation display. Then, on trials with a precue,

a spoke appeared next to the fixation point 170 ms before the stimuli appeared and indicated which box would contain the target. Then stimulus animations appeared in all the boxes, with Gabor stimuli presented within a sequence of random external noise. The animation was 167 ms long with the Gabor stimuli occurring 67 ms into this span. The 170-ms cue lead time was counted to the onset of Gabor stimuli. This is less than the 250 ms necessary for a saccade to be initiated (e.g., Carpenter, 1988; Mayfrank et al., 1987), so eye movements to the target were counterproductive and unlikely.

On trials with a simultaneous cue, the spoke appeared at the onset of the signal stimulus frame, 67 ms into the animation. On both types of trial, the boxes and spoke cue remained on the screen during and after stimulus presentation. The target only appeared within a cued box, so the cues were never invalid.

The stimulus animation consisted of two frames each of two patterns of external noise, two of a Gabor stimulus, then two more frames each of two more external noise patterns. This gave the visual impression of a Gabor within external noise due to temporal summation. The

luminance of pixels at each (x,y) location in a Gabor was determined through the equation

$$l(x,y) = l_0 \left(1.0 + c\sin(2\pi f(x\cos\theta + y\sin\theta))\exp\left(\frac{-x^2 + y^2}{2\sigma^2}\right)\right),$$
(3)

where l is the luminance, l_0 is the background luminance, c is the Gabor contrast as discussed below, f is the spatial frequency of 1.13 cycles per degree, θ is the tilt as discussed below, and $\sigma = 0.642°$ is the standard deviation of the Gaussian window of the Gabor. The tilt was the amount away from vertical either clockwise ("right") or counterclockwise ("left"), with the target image tilting in either direction half the time, and each distractor image tilting randomly in either direction. External noise was displayed in an area of the same size as a Gabor filled with noise elements that were 2×2 pixels in dimension. The contrast of each 2-pixel noise element was randomly sampled from a Gaussian distribution with a mean of 0 and a standard deviation as discussed below. The interior of the boxes reverted to uniform gray immediately after the animation.

Contrast was determined as Michelson contrast (Michelson, 1927, p 40). The two levels of external noise contrast were zero and high, with a standard deviation of 33 % of the maximum display contrast. Each level of external noise was tested with six levels of stimulus contrast, chosen during development of the experiment to span a wide range of judgment accuracy. For 0 % external noise, these were linearly spaced between 0.02 and 0.09; for 33 % external noise, 0.05 and 0.75.

The target tilt and target position were manipulated so that conditions were evenly distributed across the experiment. For observer comfort, session length was kept short (under an hour). All factors other than judgment precision (which was blocked) were randomized. Checks for bias to respond preferentially to any target positions were performed between sessions. All analyses pool across target positions.

The participant's task was to report via a key press whether the target was tilted clockwise (a right hand response) or counterclockwise (a left hand response). A feedback beep was given for each correct response. After each response, the computer prepared images for the next trial, which took around 1 s. Blocks contained 36 trials, and after each one a message appeared on the screen informing the participant of the total number of trials completed and what precision level would appear in the next block. The participant was allowed to rest as needed and resume the session with a keypress. There were 1,152 trials in a session, divided into 32 blocks. After three practice sessions, each participant performed eight experimental sessions.

Analysis

The dependent variable was participant performance accuracy as measured by either proportion correct or d' values. Analysis of variance as well as nested Weibull model fits were performed on proportion correct, where proportion was calculated for each combination of attention condition, external noise contrast, stimulus contrast, set size, and precision, pooling across target positions. Analyses of proportion correct assessed the significance of the effects of these manipulations on the accuracy of performance. An empirical d' value was also calculated based on signal detection theory and these were the basis for analysis and fit by the ePTM model. The d' values are derived from and monotonic with proportion correct, using the correction for proportions near 0 or 1 by adding or subtracting $1/(2n)$ (Macmillan & Creelman, 2004). Over 8 experimental sessions, d' and proportion correct in each test condition are based on 64 trials. Standard deviations for d' data were estimated by randomly sampling from a binomial distribution.

The ePTM model was fit to the d' data with signal stimulus contrast, c, and amount of (external) noise, N_{ext}, as manipulated factors, and other PTM parameters estimated from the data. The Matlab function *fminsearch* was used to minimize the least squared error (LSE) between the model predictions and the data, and generate an r^2 value. Separate fits involved different saturation of parameters. Basic parameters included system parameters N_m, N_a and γ, the gain of the matching template β_M, and template bandwidth σ. Additional parameters included attention multipliers or template bandwidths to account for attention effects. Parameter saturation, or the number of parameters required to account for all attention effects, was systematically compared: a fit could include both A_f and A_a, only A_f, only A_a, or none of the terms. A second question was whether separate attention terms were needed for each relevant set size or one attention term for all three set sizes. A third question was whether the fits were improved by separate σ terms for attended and unattended conditions (used to compute β_U from β_M, and equivalent to estimating different β_U for attended and unattended cases). The significant parameters in the different model variants provide an alternative set of tests for effects based on the d' data.

The r^2 values for the fits were compared by F tests to determine if the inclusion of terms significantly improved the fit by nested model tests (Wichmann & Hill, 2001; Lu & Dosher, 2013). We compared fits in nested model lattices with a varying number of A_f terms: either 0 terms, 1 term for all conditions, or three separate terms for the three set sizes. We did a similar test with A_a. We also tested varying σ terms: either 1 term for all conditions, or two separate terms for the two attention (cuing) conditions. The P-values within a single type of comparison were combined
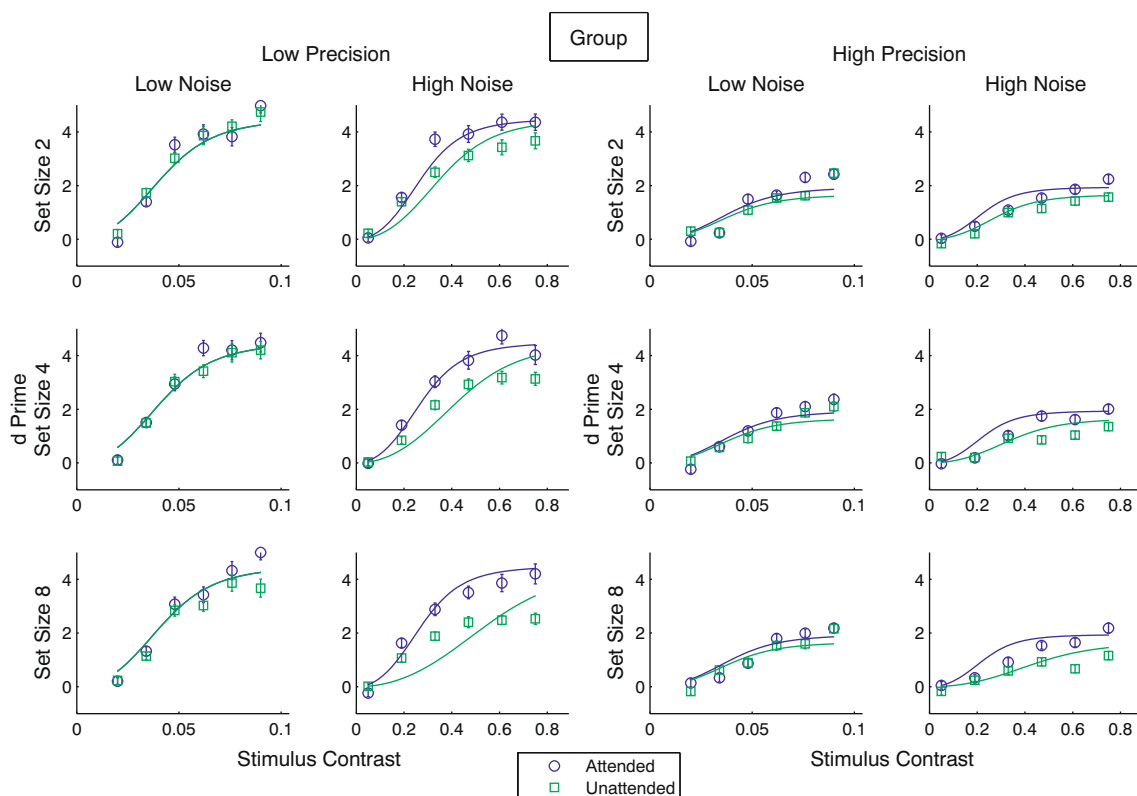
Fig. 5 Data and best fit for the mean across all five participants. The fit parameters for the elaborated perceptual template model are given in Table 2, and include external noise exclusion (A_f terms) and template narrowing (σ terms)

across participants using Fisher's χ^2 to judge effects across the whole group. The Fisher's (1925)

$$\chi^2_{2k} = -2 \sum_{i=1}^{k} \ln(p_i) \ , \ \text{with degrees of freedom } 2k.$$

Results

Figure 5 shows the d' data and the best fit for the aggregate data, and Fig. 6 shows the data for individual participants. Smooth curves are the best fits of the ePTM. All conditions for each participant or for the aggregate data were fit simultaneously and share basic ePTM parameters. Table 2 lists the estimated parameters for the best-fitting ePTM, plus nested ePTM model test results, for all participants and for the aggregate data. Each observer provides an independent replication of the effects, and another replication occurs in the aggregate data.

The overall pattern of discrimination performance includes several different effects, showing reduced discrimination for high-precision judgments, effects of attention due to external noise exclusion restricted to high noise, asymptotic effects of attention for high-precision judgments, and increasing inattention losses with increasing set size or workload. The ePTM model does a remarkable

job of predicting this complex pattern with a relatively compact parameter set.

However, before considering the results in the context of the ePTM, we provide some information about effect significance of the experimental variables (attention, external noise contrast, stimulus contrast, set size, and precision) in the proportion correct data using analysis of variance, or comparisons of psychometric functions using nested Weibull tests. The observed d', a monotonic transformation of the proportion correct based on signal detection theory, was also analyzed with analysis of variance. These analyses document the significance of the effects of the experimental manipulations without reference to the observer model. We expected to find significant effects of precision, set size, attention, and contrast level within each external noise condition. External noise might or might not be significant here because different and compensatory contrasts were used in zero and high external noise to span the full psychometric function in each case.

An analysis of variance on percent correct with attention, precision, set size, external noise, and contrast (all factors within subject) found significant effects of precision [$F(1,4) = 387.81$, $P < 0.0001$], attention [$F(1,4) = 55.03$, $P < 0.001$], set size, [$F(2, 8) = 10.82$, $P < 0.005$], external noise [$F(1, 4) = 19.72$, $P < 0.01$], and contrast, [$F(5,20) = 617.16$, $p < 0.0001$], the interaction of precision
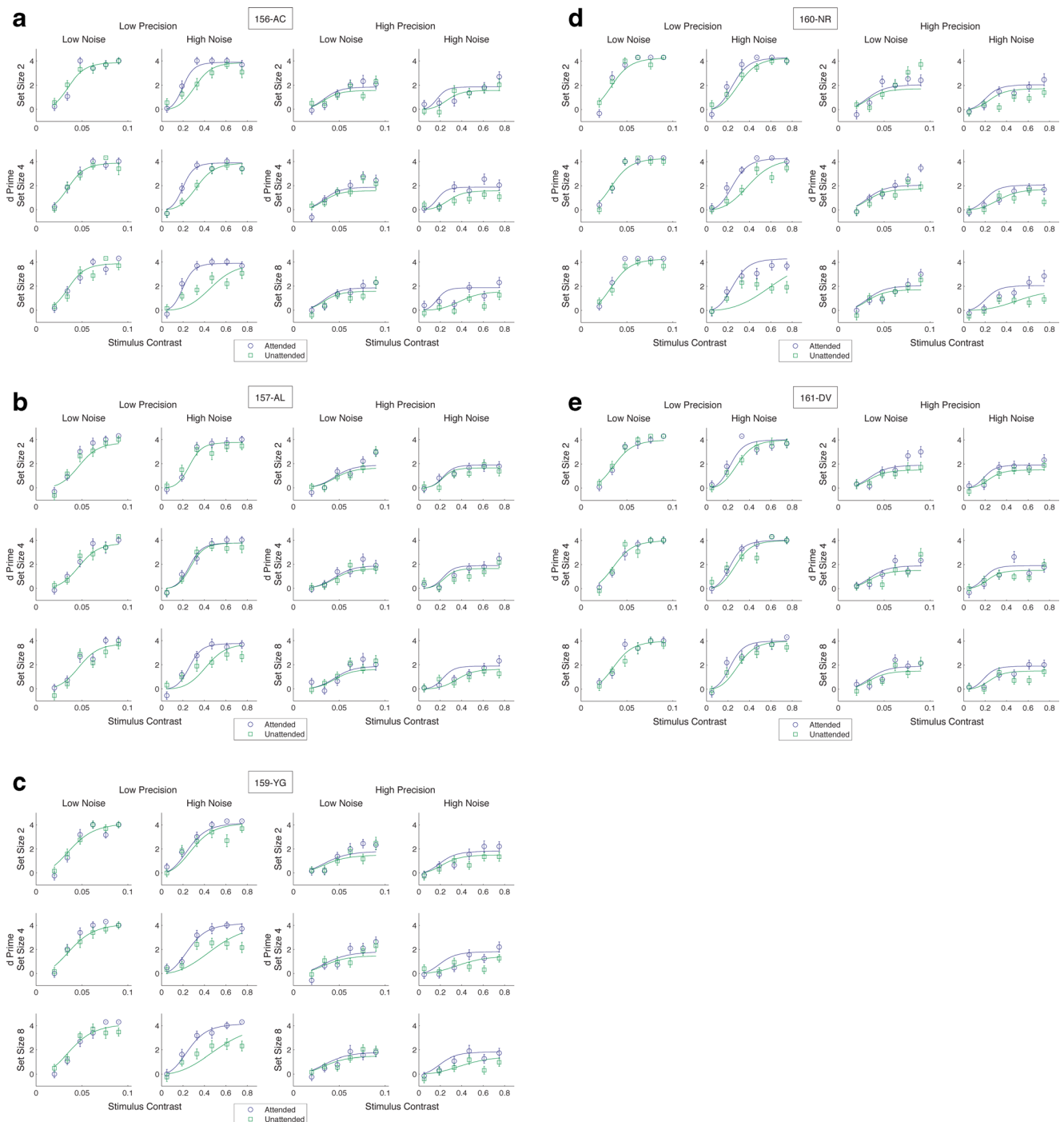
Fig. 6 Data and best fit for each participant, with estimated parameters in Table 2

and attention [$F(1,4) = 13.28$, $P < 0.02$], set size and external noise [$F(2,8) = 6.36$, $P < 0.02$], attention and external noise [$F(1,4) = 10.62$, $P < 0.03$], as well as other interactions. Analyses of variance were also carried out separately for low noise and high noise stimuli since contrast within external noise may not have been matched exactly in relation to their respective psychometric functions; the pattern of effects are equivalent to the combined

analysis. (In low noise: there were significant effects of precision [$F(1,4) = 910.41$, $P < 0.0001$], attention [$F(1,4) = 41.37$, $P < 0.003$], and contrast, [$F(5,20) = 504.26$, $P < 0.0001$], the interaction of precision and attention [$F(1,4) = 4.25$, $P < 0.02$], as well as interactions of precision and of attention with contrast, but a non-significant effect of set size, [$F(2, 8) = 2.88$, $P \approx 0.11$]. In high external noise: there were significant effects of precision [$F(1,4) = 191.35$, $P <$

Table 2 The parameters for one fit of the elaborated perceptual template model (ePTM) for each participant, plus nested ePTM model test results on R^2 values. The selected fit includes three A_f terms and two σ terms, as this was predominately the best fit. The β_U term is determined by using β_M along with the angular difference between the templates (either 8° or 40°) and their standard deviation, σ. The subscript on the σ terms indicates the attention (cuing) condition. The extra subscript on the A_f terms indicates the relevant set size. A_a terms are not listed (and are set to 1) because allowing them to vary did not significantly improve any fit. Tests are described in text

Parameters	Observers					
	156-AC	157-AL	159-YG	160-NR	161-DV	Group
N_m	0.3626	0.3748	0.3370	0.3280	0.3515	0.3142
N_a	0.0005	0.0002	0.0026	0.0007	0.0007	0.0022
γ	2.7089	3.0535	2.0076	2.3757	2.5111	2.0675
β_M	2.2587	1.6627	2.0442	1.9627	2.0744	1.9932
σ_{Precue}	10.7039	11.0532	9.7648	10.0362	10.3554	9.974
$\sigma_{Simultaneous\ cue}$	11.8621	12.0488	10.9075	11.1401	11.8708	10.904
$A_{f\,2}$	3.3092	1.0000	1.3182	1.5571	1.8201	1.7053
$A_{f\,4}$	3.8197	1.1816	3.6324	3.0151	1.5960	2.4670
$A_{f\,8}$	9.6140	4.1835	4.1074	8.5539	1.9686	4.1423
LSE	28.6434	27.7766	31.7631	42.0045	27.2230	20.1548
R^2	0.8957	0.8968	0.8847	0.8742	0.9043	0.9322
Tests						
3 A_f vs. 0 A_f (3,135)	16.1361**	4.3169**	10.3816**	11.9475**	2.3511	18.2522**
3 A_a vs. 0 A_a (3,135)	0.2555	0.1197	0.0000	0.0566	0.3150	0.5739
3 A_f vs. 1 A_f (2,135)	4.2713*	5.9520**	7.0252**	9.7118**	0.1411	7.8650**
2 σ vs. 1 σ (1,135)	3.8830	2.6163	3.1613	3.1121	7.6176**	3.7832
Fisher's χ^2 for σ						20.5704**

* $P < 0.05$, ** $P < 0.01$

0.0002], attention [$F(1,4) = 30.59$, $P < 0.005$], set size, [$F(2, 8) = 10.46$, $P < 0.005$], and contrast, [$F(5,20) = 473.69$, $P < 0.0001$], and a number of interactions, including the interaction of precision, attention, and contrast [$F(5,20) = 8.59$, $P < 0.0002$].) Analysis of variance on the d' values yielded essentially equivalent results; the analysis of variance on the proportion correct data is slightly more conservative.

In our design, each observer also provides an independent replication of the experiment, which provides direct evidence of the reliability of the results. The analyses of variance on individual data supported the aggregate findings and patterns of significance: The effect of judgment precision is systematic and large [$F(1,10) = 232.5$, 339.43, 585.61, 428.43, 619.40 for the different observers respectively for analysis of variance on proportion correct,[3] all $P < 0.01$; and 1,197.7, $P \ll 0.001$ for

(average) aggregate data]. Attended and unattended conditions differed significantly [$F(1,10) = 13.87$, 9.87, 23.18, 29.36, 15.44 for the different observers, all $P < 0.01$; and 51.21, $P \ll 0.001$ for aggregate data]. Attention effects also interacted for most observers either with external noise, or with external noise and set size (see graphs of individual data in Fig. 6). Of the five observers, three of the five also showed either significant 2-way interactions of attention with external noise ($P < 0.008$ in aggregate data) or 3-way interactions with external noise and set size ($P < 0.006$ in aggregate data), or both. As described above, the large effects of external noise were compensated by large differences in contrast between the zero and high external noise conditions, so direct comparisons are not interpretable. Individual observer analyses of variance were also performed separately in low and high noise, and the patterns of significance are consistent with the same conclusions. Finally, the individual observer analyses of variance were performed on d' data. F-values were in general higher, and P-values smaller, but the patterns were the same. Overall, then, essentially all of the manipulations had some significant effect on performance either as main effects or as interactions with external noise. However, as is visible in the data, attention has its most reliable effects in high external noise and large set size.

---

[3] Within-observer analysis of variance tests were performed up to four-way interactions, with the five-way interactions of contrast, attention, set size, external noise, and judgment precision used as the error terms using the Matlab function *anovan*. The analysis of the 144 observed proportions for each observer was partitioned into the grand mean plus 10, 34, 52, and 47 degrees of freedom in main effects, two-way, three-way and four-way interactions, and 10 degrees of freedom in five-way interactions. The corresponding analyses of variances for low and high external noise separately were partitioned similarly.

If precues focus attention on the single item, then performance on this item should not depend upon set size, and this pattern is observed: the performance in the precued or attended conditions were statistically identical for the different set sizes in both precision conditions (all $P > 0.05$) by nested Weibull tests on the proportion correct psychometric functions. The unattended (simultaneous) cue condition differed in high external noise with low-precision judgments [$F(3,13) = 13.0379$, $P = 0.0008$] and high-precision judgments [$F(3,13) = 5.0887$, $P = 0.0233$]. Validly cued performance did not depend upon set size—but the damage for invalid cues did.

Remarkably, this complex pattern of data is quantitatively and qualitatively very well fit with the ePTM model with only a few variable terms for the attention effects, with estimated parameter values shown in Table 2. Each column represents an independent replication for each observer of the experiment and model tests. We analyzed the ePTM by comparing a lattice of nested tests for models with different numbers of parameters for each observer, and for the average observer.

Attention has its primary effect in high external noise or external noise exclusion—with higher susceptibility to high external noise in unattended conditions as the set size increases, which was seen in the increasing A_f factor with set size. The effects of attention in high external noise captured by A_f were significant for four out of five participants and the aggregate data ($P \ll 0.01$). The F values in Table 2 are for our nested tests comparing more and less saturated ePTM models: for aggregate data, comparing three A_f terms (one for each display size or workload) to no attention terms (no attention effect) [$F(3, 135) = 18.2522$, $P \ll 0.01$]. Attention multipliers in low noise (A_a) were not significant by nested model tests (all could be set to 1), indicating no stimulus enhancement effects. In no cases did A_a terms significantly improve fits: for aggregate data, comparing three A_a terms to no attention terms at all [$F(3, 135) = 0.5739$, $P = 0.633$]. Nor did adding A_a terms to A_f terms improve the model fit: for aggregate data, comparing the fit with three A_f terms and three A_a terms to the fit with only A_f terms [$F(3, 132) = 1.6147$, $P = 0.1890$]. Thus, external noise exclusion is the dominant effect of attention in these circumstances, with little or no evidence for stimulus enhancement. The attention effect occurs predominantly at higher set sizes; using separate A_f terms for each set size significantly improved fits over using a single A_f term [$F[2, 135] = 7.8650$, $P = 0.0006$; $P < 0.05$ for four of five observers]. This shows a dependency on workload, with larger attention factors estimated in Table 2 for larger set sizes. The attention multipliers range from 1.7 for set size 2 to 4.1 for set size 8 for the group data, reflecting substantial effects of attention on external noise exclusion even in set size 2, but extremely large ones in set size 8.

The attended and unattended data (precue versus simultaneous cue) appear to be rising toward different asymptotes in

the high-precision condition. Using two σ terms instead of one significantly improves ePTM fits by allowing the asymptote to differ primarily for high-precision judgments (see Fig. 2). A template is more narrowly tuned around the signal stimulus when σ is smaller. This translates to higher β_U values for responses of the unmatched template in unattended conditions and smaller β_U values in attended conditions. In contrast, attention effects on template bandwidth σ have essentially no effect (no asymptotic differences) for low-precision cases where the unmatched template is so far away from the stimulus that $\beta_U \approx 0$ for both attended and unattended conditions (corresponding with the original PTM for near-orthogonal stimuli) (see Fig. 2b). For the aggregate data, comparing two σ terms to one σ term was significant [$F(1, 135) = 3.7832$, $P = 0.051$; Fisher's χ^2 value that combines the P-values across the five individual participant tests is also significant with $\chi^2(df = 8) = 20.5704$, $P = 0.0084$]. The attended condition is estimated to have a more narrowly tuned template (smaller σ) than the unattended condition, as expected, with values of 9.97 and 10.94 respectively—a decrease in bandwidth for the attended conditions of about 10 %. We tested whether using separate σ terms for each set size in the unattended data significantly improved the ePTM fits; it did not, although the effect itself is modest which makes it more difficult to measure differences. Note that, although the overall performance levels are quite different, the same attention multipliers provided an excellent account of the effects of attention in both low- and high-precision conditions.

The quality-of-fit of the best-fitting ePTM model was quite good. The r^2 of the best-fitting model was 0.932 for average group data and between 0.872 to 0.904 for individual data. These are high r^2 values, especially given the restricted range of the high precision psychometric functions.[4] The model accounts for all the effects, including the differences between the high asymptotes of the low precision judgments and the much lower asymptotic accuracies of the high precision judgments. We are unaware of competing quantitative models that naturally account for the overall patterns of data. Although there are some cases where the data seem to depart from the model predictions (i.e., set size 8 high external noise unattended), comparative model fits did not support a more complex model conclusion.

Our set size manipulation is what Palmer (1994) and Palmer et al. (1993) described as relevant set size. We ran four other participants (results are not reported in detail here) through another version of this experiment, identical except for the use of display set size instead of relevant set size, and found no difference in the results. This supports the observations of

---

[4] The appearance of deviations between the model and data, especially in high precision tests where asymptotes are consistent with normal data variability; the same deviations on a curve with high asymptotes appear smaller.

Palmer and colleagues that the two methods of manipulating set size are equivalent. It also implies that visual interactions or masking were not important factors in the large set size displays here.

Overall, then, the very complex set of data on the role of endogenously or centrally cued attention is quantitatively described by the ePTM with attention narrowing the tuning of the perceptual template slightly and with associated effects on external noise exclusion in both low- and high-precision judgments that depend upon set size or workload. Attention affected bandwidth by about 10 % and the impact of external noise in set size 8 was about twice that in set size 2—where attention reduced external noise by about 40 %. These results are consistent with the prior literature (as detailed in the discussion), but go beyond it to identify an articulated pattern of attention effects across judgment precision and external noise masking conditions.

Discussion

We performed this experiment to extend our understanding of the circumstances in which attention improves performance, and build towards a taxonomy of spatially cued attention and its effects on performance accuracy. Specifically, we measured the effect of attention in a visual identification task with varying levels of external noise, workload, and precision in a wide range of stimulus contrast conditions. To our knowledge, direct manipulation of judgment precision and its interaction with spatial attention and workload, within a single design that allows direct comparisons, has not been reported previously. A complex set of results is well described using the elaborated perceptual template model (ePTM; Jeon et al., 2009), extended to incorporate different possible mechanisms of attention (Liu et al., 2009a, b).

Attention effects for central cuing restricted to high external noise conditions are consistent with the original reports that tested low-precision judgments (Dosher & Lu, 2000a; Lu & Dosher, 2000). The increasing performance losses in larger set size displays for unattended conditions is also consistent with previously reported set size effects of attention in low-precision judgments (Dosher & Lu, 2000b), as well as with cross-experiment comparisons in which higher set sizes tend to lead to larger attention effects. Attention effects with low-precision judgments and central cuing tend to converge at the highest contrasts (Dosher & Lu, 2000a, b; Lu & Dosher, 2000)—a pattern that, when combined with an attention effect at lower contrasts, is sometimes associated with "contrast gain" (Ling & Carrasco, 2006a). Effects of attention on the high asymptote of the psychometric function have been reported previously (Ling & Carrasco, 2006a, b; Pestilli et al., 2007). They occurred in relatively high-precision judgments (Table 1). Interactions of attention effects with judgment

precision have also been reported in dual-object attention manipulations (Liu et al., 2009a, b, c).

Other studies have examined the effects of attention in high-precision judgments (Ling & Carrasco, 2006a) and in low precision (Herrmann et al., 2010) in different experimental contexts, but may not fully control uncertainty. Here we explicitly compared the effects of attention in low- and high-precision judgments in a fully matched experiment. Decision uncertainty is eliminated with 100 % valid cues to report location.

The ePTM gives a good account for the data, as seen in Figs. 5 and 6, and Table 2. A_f parameters, with a separate A_f term for each set size, account for external noise exclusion and workload effects. Separate σ terms for the attended and unattended condition, which differed by about 10 % in the current study, account for the asymptotic effect associated with attention primarily in the high-precision judgments. Attention sharpens tuning of the perceptual templates, with effects on asymptotic performance that are visible in high-precision judgments but that have little effect on asymptotic performance in low-precision judgments, as predicted by the ePTM framework.

In the model, stimuli are compared to perceptual templates for the to-be-discriminated stimuli. Their standard deviation σ or bandwidth determines the difference between β_U (for the un-matching template) and β_M (for the matching template). If the two possible states of a target are very similar, e.g., the pattern orientations differ by only 8°, then both will have similar gain of response; narrowing the template in these conditions results in a change at asymptotic performance. Narrowing the template is less important at lower precision, such as our ±20° condition, where either σ is consistent with little overlap in the templates for the two stimuli. Matched templates for Gabor stimuli near 45° away from each other may essentially respond to one template (Dosher & Lu, 2000b). This effect of attention on the asymptotic performance in high-precision judgments is compatible with the observations of Liu et al. (2009b) for dual-object dual-report effects in object attention.

Carrasco and colleagues reported asymptotic effects in high-precision judgments in the absence of external noise or post-masks (e.g., Ling & Carrasco, 2006a; Pestilli et al., 2007; Herrmann et al., 2010) for peripheral precues; they interpreted the results in terms of both contrast gain and response gain.[5] Contrast gain and response gain are concepts borrowed from

---

[5] Our experimental circumstances are somewhat similar to those used by Herrmann et al. to "shrink the attention field," i.e., stable locations for stimuli; yet we found that the asymptotic effect depended on the required precision of the judgment and occurred with central precues. These authors have not suggested that precision would compel a change in attention field, so the distinction of contrast gain versus response gain proposed by those researchers does not obviously describe our results.

neural responses where they refer to the level of firing or level of neural activity. Increased neural activity translates into performance improvements only if increased firing is larger than corresponding increases in noise or variability in firing. Contrast gain and response gain must be translated through a model to predict psychometric function improvements. The ePTM—essentially a signal detection or signal-to-noise analysis—provides a model-based analysis of the effects of attention on the psychometric function curves where the dependent measure is performance accuracy. The ePTM model associates asymptotic effects that elsewhere have been labeled response gain with changes in the tuning of the template(s) around the signal stimuli. Attention improvements in zero or low noise tests have a pattern elsewhere labeled contrast gain, and attention effects on external noise exclusion may also show a similar pattern in psychometric functions.

In sum, the elaborated perceptual template model fit all the effects of attention in this visual discrimination task by using a compact set of parameters. The results show an attention effect of external noise exclusion when using central or endogenous cues, in both the low-precision and high-precision task. Workload effects also occurred in both low and high precision. In addition, we found effects of attention on asymptotic performance in high precision, which we modeled as narrowing the perceptual template in attended conditions. These effects, some reported individually in previous experiments, were all measureable in our study using joint manipulations of external noise, set size, and precision.

A summary of the results of this experiment, and those of other experiments in the literature, are summarized in Table 3. The primary effect of spatial attention is mediated by external noise exclusion with a magnitude that depends upon set size. These effects of external noise exclusion occur at both levels of precision, however in high precision template tuning also is visible in different performance levels at asymptotic contrast levels. Consistent with previous experiments using low

precision tests, we found no evidence for stimulus enhancement in central cuing.

We chose to test the ePTM using central precues because the model predicted a complex yet bounded pattern of attention effects, while peripheral precuing is expected to show attention effects everywhere. Still, one could extend the current study by using peripheral or exogenous cues. We would expect to find a similar pattern of attention in exogenous cuing—with a remaining ambiguity concerning whether stimulus enhancement occurs. This would require another very data intensive experimental protocol. We would predict similar results, including an attention effect of external noise exclusion in high noise, and retuning of the perceptual template in high precision. Based on the results of Liu et al. (2009a) in object attention and Lu and Dosher (2000) in spatial attention, it seems possible that peripheral precues may lead to an additional effect of stimulus enhancement. Whether stimulus enhancement, or effects in clear displays in the absence or noise (or postmasks) occurs reliably with exogenous precues is a matter for further investigation.

Our findings, together with an analysis of the ePTM model, contribute to our understanding of the taxonomy of attention that specifies the circumstances in which spatial attention has important effects, and their mechanisms of operation. These findings related to effects of spatial attention on the accuracy of performance. Spatially oriented attention may alter response times—but these effects may occur either with or without effects on accuracy of performance (Smith et al., 2004), and may reflect uncertainty or biases in response selection and variability in salience as well as improvements in discriminability of performance. Smith and colleagues (Smith et al., 2004) applied a random walk model of response times and accuracy to account for the effects of attention on performance in the presence or absence of postmasks that alter the temporal course of processing. The model estimates

Table 3 Towards a taxonomy of spatially oriented attention. External noise exclusion occurs in high external noise or masked conditions. Stimulus enhancement occurs in low or zero external noise conditions. Stimulus enhancement may occur in some circumstances for peripheral precuing

Conditions			Effects		
Cue type	Set size or workload	Judgment precision	Asymptotic accuracy	Stimulus enhancement	External noise exclusion
Endogenous	Low	Low	No	No	Yes
		High	Yes	No	Yes
	High	Low	No	No	Yes
		High	Yes	No	Yes
Exogenous	Low	Low	No	Sometimes	Yes
		High	Yes	Sometimes	Yes
	High	Low	No	Sometimes	Yes
		High	Yes	Sometimes	Yes

different drift rates to account for the effects of external (or integrated) noise.

In contrast, the ePTM is designed to prove a linkage that systematizes the interlocked effects of target contrast, discrimination precision, and external noise contrast over a wide range of conditions with a few parameters. Understanding the mechanisms and circumstances in which attention alters the ability to discriminate with the ePTM is a first step towards a broad understanding of the wider effects of attention.

Another goal of subsequent analysis is to create a bridge between the observed effects of spatially cued attention, which generally specifies one location of attention focus, and the broader effects of attention in other paradigms such as visual search on the one hand, and divided or object attention on the other. Spatial uncertainty is a powerful functional mechanism that controls overall accuracy in visual search (Dosher et al., 2004, 2010; Eckstein, 1998; Eckstein et al., 2000; Morgan et al., 2010; Palmer et al., 1993; Sperling & Dosher, 1986; but see Wolfe, 1994, 2003; Wolfe et al., 1992). Effects of attention over and above uncertainty in visual search could provide evidence of attention effects on the quality of the perceptual representation. Ongoing research in our laboratories is studying visual search in the external noise situations in which external noise exclusion or filtering occurs in spatially cued attention experiments to see whether these effects, in addition to uncertainty effects, extend to visual search situations (Hetley et al., 2010; Baek et al., 2011). Preliminary evidence suggests that the dominance of uncertainty effects in visual search as compared to external noise filtering may depend upon whether a small number of templates create a possible strategy in visual search. Further work will be necessary to clarify whether the preliminary taxonomy of spatially cued attention is extensible to these other attention effects.

References

Baek, J., Zhao, Y., Lu, Z.-L., & Dosher, B. (2011). Visual attention inspatial cuing and visual search. *Journal of Vision, 11*(11), 162. doi:10.1167/11.11.162 (Abstract)

Baldassi, S., & Burr, D. C. (2000). Feature-based integration of orientation signals in visual search. *Vision Research, 40,* 1293–1300.

Bashinski, H. S., & Bacharach, V. R. (1980). Enhancement of perceptual sensitivity as the result of selectively attending to spatial locations. *Perception & Psychophysics, 28*(3), 241–248.

Bundesen, C. (1990). A theory of visual attention. *Psychological Review, 97,* 523–547.

Cameron, E. L., Tai, J. C., & Carrasco, M. (2002). Covert attention affects the psychometric function of contrast sensitivity. *Vision Research, 42,* 949–967.

Carpenter, R. H. S. (1988). *Movements of the eyes*. London: Pion.

Carrasco, M., Penpeci-Talgar, C., & Eckstein, M. (2000). Spatial covert attention increases contrast sensitivity across the CSF: Support for signal enhancement. *Vision Research, 40,* 1203–1215.

Carrasco, M., Talgar, C. P., & Cameron, E. L. (2001). Characterizing visual performance elds: Effects of transient covert attention, spatial frequency, eccentricity, task and set size. *Spatial Vision, 15*(1), 61–75.

Cheal, M., & Lyon, D. (1991). Central and peripheral precuing of forced-choice discrimination. *Quarterly Journal of Experimental Psychology: Human Experimental Psychology, 43A,* 859–880.

Cheal, M., & Lyon, D. R. (1992). Benefits from attention depend on the target type in location-precued discrimination. *Acta Psychologica, 81*(3), 243–267.

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.

Dosher, B. A., Han, S., & Lu, Z. L. (2010). Information-limited parallel processing in difficult heterogeneous covert visual search. *Journal of Experimental Psychology: Human Perception and Performance, 36*(5), 1128.

Dosher, B. A., & Lu, Z.-L. (1998). Perceptual learning reflects external noise filtering and internal noise reduction through channel reweighting. *Proceedings of the National Academy of Sciences of the United States of America, 95,* 13988–13993.

Dosher, B. A., & Lu, Z.-L. (2000a). Noise exclusion in spatial attention. *Psychological Science, 11*(2), 139–146.

Dosher, B. A., & Lu, Z.-L. (2000b). Mechanisms of perceptual attention in precuing of location. *Vision Research, 40,* 1269–1292.

Dosher, B. A., & Lu, Z.-L. (2013). Mechanisms of visual attention. In C. Chubb, B. Dosher, Z.-L. Lu, & R. Shiffrin (Eds.), *Frontiers in Human Information Processing*. American Psychological Association.

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.

Duncan, J. (1984). Selective attention and the organization of visual information. *Journal of Experimental Psychology: General, 113*(4), 501–517.

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

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.

Fisher, R. A. (1925). *Statistical methods for research workers*. Edinburgh: Oliver & Boyd.

Gould, I. C., Wolfgang, B. J., & Smith, P. L. (2007). Spatial uncertainty explains exogenous and endogenous attentional cuing effects in visual signal detection. *Journal of Vision, 7,* 1–17.

Han, S., Dosher, B. A., & Lu, Z.-L. (2003). Object attention revisited: Identifying mechanisms and boundary conditions. *Psychological Science, 14*(6), 598–604.

Herrmann, K., Montaser-Kouhsari, L., Carrasco, M., & Heeger, D. J. (2010). When size matters: Attention affects performance by contrast or response gain. *Nature Neuroscience, 13,* 1554–1559.

Hetley, R., Dosher, B. A., & Lu, Z.-L. (2010). Attention and uncertainty limit visual search in noisy conditions. *Journal of Vision, 10*(7), 227. doi:10.1167/10.7.227. (Abstract)

Itti, L., Rees, G., & Tsotsos, J. K. (Eds.). (2005). *Neurobiology of attention*. San Diego: Elsevier.

James, W. (1890). *The principles of psychology*. New York: Dover.

Jeon, S.-T., Lu, Z.-L., & Dosher, B. A. (2009). Characterizing perceptual performance at multiple discrimination precisions in external noise. *Journal of the Optical Society of America A, 26*(11), B43–B58.

Lee, D. K., Itti, L., Koch, C., & Braun, J. (1999). Attention activates winner-take-all competition among visual filters. *Nature Neuroscience, 2*(4), 375–381.

Ling, S., & Carrasco, M. (2006a). Sustained and transient covert attention enhance the signal via different contrast response functions. *Vision Research, 46,* 1210–1220.

Ling, S., & Carrasco, M. (2006b). When sustained attention impairs perception. *Nature Neuroscience, 9,* 1243–1245.

Liu, S.-H., Dosher, B. A., & Lu, Z.-L. (2009a). Spatially cued visual attention for precise discriminations may narrow the template as well as excluding external noise: An elaborated perceptual template model. *Journal of Vision, 9*(8), 197. http://www.journalofvision.org/content/9/8/197 (Abstract Only).

Liu, S.-H., Dosher, B. A., & Lu, Z.-L. (2009b). The role of judgment frames and task precision in object attention: Reduced template sharpness limits dual-object performance. *Vision Research, 49,* 1336–1351.

Liu, C. C., Wolfgang, B. J., & Smith, P. L. (2009c). Attentional mechanisms in simple visual detection: A speed-accuracy trade-off analysis. *Journal of Experimental Psychology: Human Perception and Performance, 35,* 1329–1345.

Logan, G. D. (2002). An instance theory of attention and memory. *Psychological Review, 109,* 376–400.

Lu, Z.-L., & Dosher, B. A. (1998). External noise distinguishes attention mechanisms. *Vision Research, 38,* 1183–1198.

Lu, Z.-L., & Dosher, B. A. (2000). Spatial attention: Different mechanisms for central and peripheral temporal precues? *Journal of Experimental Psychology: Human Perception and Performance, 26*(5), 1534–1548.

Lu, Z. L., & Dosher, B. A. (2008). Characterizing observers using external noise and observer models: Assessing internal representations with external noise. *Psychological Review, 115*(1), 44.

Lu, Z.-L., & Dosher, B. A. (2013). *Visual psychophysics: From laboratory to theory.* Cambridge, MA: MIT Press.

Lu, Z. L., Liu, C. Q., & Dosher, B. A. (2000). Attention mechanisms for multi-location first-and second-order motion perception. *Vision Research, 40*(2), 173–186.

Lu, Z.-L., Lesmes, L. A., & Dosher, B. A. (2002). Spatial attention excludes external noise at the target location. *Journal of Vision, 2,* 312–323.

Macmillan, N. A., & Creelman, C. D. (2004). *Detection theory: A user's guide.* Psychology Press.

Mayfrank, L., Kimmig, H., & Fischer, B. (1987). The role of attention in the preparation of visually guided saccadic eye movements in man. In J. K. O'Regan & A. Levy-Schoen (Eds.), *Eye movements: From physiology to cognition* (pp. 37–45). New York: North-Holland.

Michelson, A. A. (1927). *Studies in optics.* Chicago, IL: University of Chicago Press.

Morgan, M. J., Ward, R. M., & Castet, E. (2010). Visual search for a tilted target: Tests of spatial uncertainty models. *The Quarterly Journal of Experimental Psychology Section A: Human Experimental Psychology, 51*(2), 347–370.

Nissen, M. J. (1985). Accessing features and objects: Is location special? In M. I. Posner & O. S. M. Marin (Eds.), *Attention and performance XI* (pp. 205–219). Hillsdale, NJ: Erlbaum.

Palmer, J. (1994). Set-size effects in visual search: The effect of attention is independent of the stimulus for simple tasks. *Vision Research, 34,* 1703–1721.

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,* 108–130.

Pelli, D. G., & Zhang, L. (1991). Accurate control of contrast on microcomputer displays. *Vision Research, 31,* 1337–1350.

Pestilli, F., & Carrasco, M. (2005). Attention enhances contrast sensitivity at cued and impairs it at uncued locations. *Vision Research, 45*(14), 1867–1875.

Pestilli, F., Ling, S., & Carrasco, M. (2009). A population-coding model of attention's influence on contrast response: Estimating neural effects from psychophysical data. *Vision Research, 49,* 1144–1153.

Pestilli, F., Viera, G., & Carrasco, M. (2007). How do attention and adaptation affect contrast sensitivity? *Journal of Vision, 7,* 1–12.

Pillsbury, W. B. (1908). *Attention.* New York: MacMillan.

Posner, M. I. (1978). *Chronometric explorations of mind.* Hillsdale, NJ: Erlbaum.

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

Reynolds, J. H., & Heeger, D. J. (2009). The normalization model of attention. *Neuron, 61,* 168–185.

Shaw, M. L., & Shaw, P. (1977). Optimal allocation of cognitive resources to spatial locations. *Journal of Experimental Psychology: Human Perception and Performance, 3*(2), 201–211.

Shiffrin, R. M., & Czerwinski, M. P. (1988). A model of automatic attention attraction when mapping is partially consistent. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 14,* 562–569.

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*(5), 1037–1054.

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.

Smith, P. L., Ellis, R., Sewell, D. K., & Wolfgang, B. J. (2010). Cued detection with compound integration-interruption masks reveals multiple attentional mechanisms. *Journal of Vision, 10,* 1–28.

Smith, P. L., Ratcliff, R., & Wolfgang, B. J. (2004). Attention orienting and the time course of perceptual decisions: Response time distributions with masked and unmasked displays. *Vision Research, 44*(12), 1297–1320.

Smith, P. L., & Wolfgang, B. J. (2007). Attentional mechanisms in visual signal detection: The effects of simultaneous and delayed noise and pattern masks. *Perception & Psychophysics, 69*(7), 1093–1104.

Solomon, J. A. (2004). The effect of spatial cues on visual sensitivity. *Vision Research, 44*(12), 1209–1216.

Sperling, G., & Dosher, B. A. (1986). Strategy and optimization in human information processing. In K. Boff, L. Kaufman, & J. Thomas (Eds.), *Handbook of perception and performance* (Vol. 1). New York: Wiley.

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

Titchener, E. B. (1908). *Lectures on the elementary psychology of feeling and attention.* New York: MacMillan.

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

Wichmann, F. A., & Hill, N. J. (2001). The psychometric function I: Fitting, sampling and goodness-of-fit. *Perception & Psychophysics, 63*(8), 1293–1313.

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

Wolfe, J. M. (2003). Moving towards solutions to some enduring controversies in visual search. *Trends in Cognitive Sciences, 7*(2), 70–76.

Wolfe, J. M., Friedman-Hill, S. R., Stewart, M. I., & O'Connell, K. M. (1992). The role of categorization in visual search for orientation. *Journal of Experimental Psychology: Human Perception and Performance, 18,* 34–49.

Wundt, W. (1902). *Grundzüge der Physiologischen Psychologie.* Leipzig: Wilhelm Engelmann.