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The spatial window of the perceptual template and endogenous attention

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Abstract

One primary function of spatial attention is to exclude external noise [e.g., Psychol. Sci. 11(2) (2000) 139], especially in the region of the target stimulus [J. Vis. 2(4) (2000) 312]. What is not known is the spatial profile of external noise exclusion in the vicinity of the target and how this depends upon attention. The spatial region around an oriented Gabor target was segmented into four concentric rings (R1–R4). Psychometric functions were measured for orientation discrimination with external random Gaussian noise in all combinations of rings (e.g., R1 alone; R1 + R2; etc.). Regions with larger impact on performance are weighted more heavily in the perceptual template. In an orientation discrimination task in periphery the effective noise regions aligned closely with the high contrast regions of the target Gabor, with attention reducing the effective noise across the spatial template. The combined effects of external noise regions were well-modeled by a (non-linear) perceptual template model (PTM) [Vis. Res. 38(9) (1998) 1183]. In another experiment in attended fovea, the results were similar to those in periphery, but exhibited additional ability to selectively weight clear spatial regions.

Keywords: Spatial attention; Masking; Observer models

1. Attention and spatial selection

1.1. Overview

Perception of objects in the visual field requires the integration of visual input from spatial regions incorporating that object. Optimizing the spatial region of analysis may depend upon attention (Posner, 1980; Sperling & Weichselgartner, 1995). In this study we measure the spatial window of the perceptual template by evaluating the impact of high contrast external noise (masking) in distinct spatial sub-regions in and around an oriented Gabor target stimulus. If a spatial region has low weight in the perceptual template for discrimination, then noise in that region should have little or no effect on performance. The effect of endogenous attention on the spatial profile is investigated using central pre-cuing in multi-element peripheral displays. The spatial profile is also measured for a single (attended) object in the fovea. A perceptual template model (PTM) (Lu & Dosher, 1998) of the human observer estimated the spatial weights within each region under different attention conditions, and successfully accounted for performance as a non-linear function of the weighted sum of the impacts of individual regions.

1.2. Noise exclusion in spatial attention

Spatial attention—cuing the target region in advance of the stimulus—significantly improves perceptual performance relative to un-cued or mis-cued attention in many perceptual tasks (Cheal & Lyon, 1991; Dosher & Lu, 2000c; Egly & Homa, 1991; Eriksen & Hoffman, 1972; Henderson, 1991; Lu & Dosher, 2000; Lyon, 1990; Posner, 1980). Spatial attention (pre-cuing), when it has an effect on performance, increases accuracy for a given signal stimulus contrast or, equivalently, decreases the contrast necessary to achieve a threshold accuracy. The

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previous literature shows that attention or cuing effects are largely restricted to more challenging visual tasks with multi-element displays and masked or high-noise conditions (Dosher & Lu, 2000b; Shiu & Pashler, 1994). External noise (masking) reveals the importance of attention in excluding external noise (Dosher & Lu, 2000a, 2000b; Lu & Dosher, 1998, 2000). A perceptual template model (PTM) (Dosher & Lu, 1998, 2000c; Lu & Dosher, 1998) has been used to model perceptual performance and also to distinguish different functions or mechanisms of attention.

Although attention can in some circumstances improve performance in the absence of external noise or masks (*stimulus enhancement*), especially when peripheral pre-cues are used, *external noise exclusion* (Dosher & Lu, 2000c) is the major effect of both peripheral (exogenous) and central (endogenous) pre-cuing (Lu & Dosher, 2000). Several authors (Henderson, 1991; Shiu & Pashler, 1994) have speculated that attention functions to eliminate the effects of masks in distal non-target locations. [1] However, comparison of a large number of mask and target conditions (Lu, Lesmes, & Dosher, 2002) indicated that—although the existence of potential competing locations is crucial—the effect of attention does not depend upon the content (noise or potential target) in those non-target locations. Only the content of the target region is relevant, so that attention serves to reduce the effect of noise in that region. However, these investigations did not provide a measurement of the spatial window of the perceptual template near the target stimulus, or the possible dependence of this window upon attention.

In classic views, spatial attention serves to focus information uptake in space (and in time) (LaBerge, 1995; Posner, 1980; Sperling & Weichselgartner, 1995; Treisman & Gelade, 1980). And spatial attention improves the exclusion of external noise (Dosher & Lu, 2000c; Lu & Dosher, 1998). The expectation is that spatial pre-cuing may effectively narrow the spatial tuning around the signal stimulus, while absence of spatial pre-cuing may lead to a more diffuse spatial tuning. This view predicts that attention should narrow the spatial profile of the template.

The spatial profile of the template was recently measured using a reverse correlation (classification image) method for contrast increment detection (Eckstein, Shimozaki, & Abbey, 2002) in a simple 2-location cuing ("Posner") paradigm (Posner, 1980). The spatial profile approximately matched the Gaussian blob stimulus in both cue conditions about equally. However, performance in this 2-location Posner paradigm reflected a change in criteria or information weighting, not in sensitivity or information coding (Eckstein et al., 2002; see also Sperling & Dosher, 1986). This result does not dismiss the possibility that attention might alter the shape of the spatial profile in cases where attention does alter sensitivity. In this paper, we consider a multi-location (6-location) pre-cuing paradigm that is known to engage true attention effects upon discrimination accuracy and not merely changes in criteria or statistical uncertainty (Dosher & Lu, 2000c). [2]

1.3. External noise, spatial masking, and lateral interactions

Extraneous noise or masks superimposed over a stimulus reduces performance in perceptual tasks (Breitmeyer, 1984; Francis, 2003). Our external noise manipulations (Dosher & Lu, 2000c; Lu & Dosher, 1998) inject visual noise in spatial and temporal proximity to the signal stimulus. The mask in classical integration masking (Enns & Di Lollo, 1997; Francis, 2003) studies usually (1) is of moderately high contrast, (2) spatially covers beyond the signal stimulus, and (3) is in close temporal proximity to the signal stimulus. Extraneous noise or patterned stimuli appearing adjacent to a stimulus may also impact performance through a variety of mechanisms, including lateral interactions (Cannon & Fullenkamp, 1991; Polat & Sagi, 1993; Yu, Klein, & Levi, 2002) or crowding (Chung, Levi, & Legge, 2001; Eriksen, 1995; He, Cavanaugh, & Intriligator, 1996; Parkes, Lund, Angelucci, Solomon, & Morgan, 2001). Thus, a priori, external noise masks might impact performance either due to superimposition or due to contiguity with the signal stimulus. External noise directly overlapping the critical regions of the signal stimulus and external noise adjacent to the signal stimulus may, possibly to different degrees, influence perceptual performance.

2. Perceptual template model

The impact of external noise and of attention is understood within a perceptual template model (PTM) of the observer (Lu & Dosher, 1999). The PTM models the observer as an ideal detector with inefficiencies due to perceptual coding or processing limitations. The PTM consists of a perceptual template adapted to the stimuli in the task, a non-linear transducer function, and two internal noises reflecting processing inefficiencies: additive internal noise (that determines absolute

[1] The plausibility of this conclusion reflected the uncertainty about the target location in the Shiu and Pashler (1994) experiments. Structural uncertainty is eliminated in the current and previous designs (e.g., Dosher & Lu, 2000a) by the presence of a report cue for target location.

[2] The "attention" effects in the Posner paradigm are often attributed to alteration of decision weighting with identical perception (Sperling & Dosher, 1986).

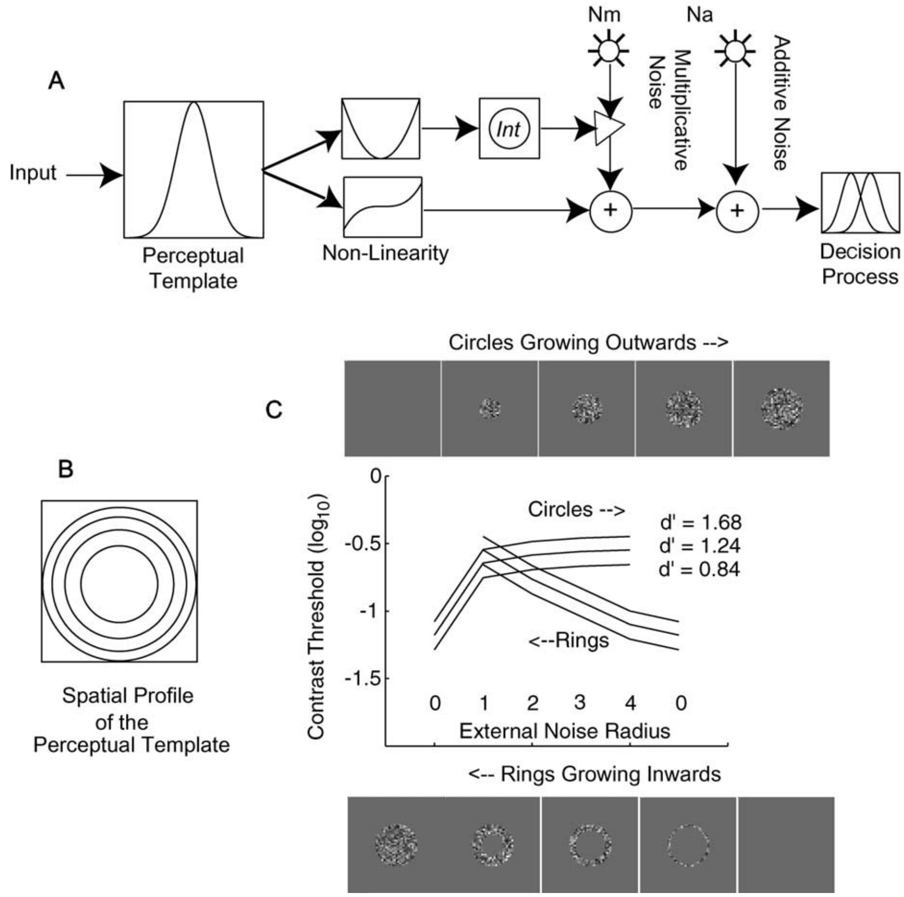

Fig. 1. Schematic of the perceptual template model (PTM) and predicted thresholds patterns of different external noise conditions. (A) The PTM includes a perceptual template tuned to the signal stimulus, a transduction non-linearity, multiplicative internal noise, additive internal noise, and a decision process. (B) The spatial profile of the spatial template (x, y) with the boundary radii for the four external noise rings. (C) Contrast threshold performance ($\log_{10}$) for three performance criteria for the PTM showing increasing thresholds for increasing noise conditions: circles of growing radius, and annuli (rings) growing inwards.

threshold) and multiplicative noise (internal noise that increases with the level of the stimulus) (see Fig. 1).

As an observer model, the level of perceptual performance in detection or discrimination tasks is described by the discrimination d', which reflects the fundamental signal and noise limitations of the observer system: $d' = \frac{S}{N}$, where S is the magnitude of the signal information and N is the variance of the noise. In the PTM, derived elsewhere (Dosher & Lu, 1999, 2000c; Lu & Dosher, 1998, 1999), the fundamental signal detection function is:

$$d' = \frac{(\beta c)^{\gamma}}{\sqrt{N_{\text{ext}}^{2\gamma} + N_{\text{mult}}^2((\beta c)^{2\gamma} + N_{\text{ext}}^{2\gamma}) + N_{\text{add}}^2}}.$$

In this equation, β is the gain of the perceptual template for the signal stimulus, γ captures the non-linear gain of the system (expressed as a power), N_{ext}^2 is the variance (power) of the external noise, N_{mult}^2 is the proportional constant characterizing equivalent internal multiplicative noise and N_{add}^2 is the variance of the equivalent internal additive noise. This model can be rewritten to express the contrast threshold for a given d':

$$c_{\tau} = \frac{1}{\beta}\left[\frac{(1 + N_{\text{mult}}^2)(N_{\text{ext}})^{2\gamma} + (N_{\text{add}}^2)}{1/d'^2 - N_{\text{m}}^2}\right]^{\frac{1}{2\gamma}}.$$

In prior applications, the overall scaled strength of the signal was quantified by the match of the target stimulus to the template multiplied by its contrast, βc. The overall external noise N_{ext}^2 was set as equal to the variance of the pixel noise distribution. However, the purpose of the current study is to estimate the contribution from each of several distinct spatial regions on perceptual performance, which requires the estimation of the impact of signal and of noise in separate sub-regions. When simple spatial integration occurs [3], the

[3] "Simple spatial integration" (specified by this equation) specifies no interactions or context dependence of the impact of each external noise sub-region. Context-dependent interactions are considered in the foveal data.

total effective external noise controlling the perceptual decision is defined as the weighted sum of the external noise in each tested spatial region (in this case, spatial ring):

$$N_{\text{ext}}^2 = \sum_{i=1}^{K} w_i^2 N_i^2 \quad \left(\ni \sum_{i=1}^{K} w_i^2 = 1 \right),$$

where i is the index on the regions, K is the total number of regions, and $w_i^2 N_i^2$ represents the weighted noise from region i. Similarly, the total effective signal is defined as the sum of the effect in each spatial region:

$$\beta c = \left(\alpha \sum_{i=1}^{K} w_i \widehat{c}_i \right) c,$$

where $w_i \widehat{c}_i c$ is the weighted contrast of the signal stimulus in each region, and α is a scaling factor that reflects the gain of the system on the signal stimulus and $\widehat{c}_i$ is the normalized (proportion) of signal contrast within each spatial region. [4] The weights on the spatial regions, then, provide a (quantized) estimate of the spatial profile of the perceptual template.

Attention may operate in one or more distinct ways within the perceptual template model. (1) Attention may improve performance by *external noise exclusion*—accomplished by retuning of the perceptual template. This operates only when there is external noise to exclude. Two aspects or kinds of retuning can be distinguished. One type reflects changes in the spatial profile of the template, where the weights in both the attended (w_i') and unattended (w_i) conditions are normalized to 1 ($\sum_{i=1}^{K} w_i^2 = 1 \quad or \quad \sum_{i=1}^{K} w_i'^2 = 1$). External noise exclusion is improved to the extent that the weights on spatial regions with high signal to noise ratio are increased and those with low signal to noise ratio are decreased. The other type of external noise exclusion allows for an additional overall reduction in external noise (relative to signal) by a factor A_f ($0 \leqslant A_f \leqslant 1$), reflecting changes in the perceptual template in dimensions other than spatial selection. (2) Attention may amplify or enhance the stimulus. *Stimulus enhancement* (or, equivalently, additive internal noise reduction) is captured by A_a ($0 \leqslant A_a \leqslant 1$), a multiplicative factor applied to N_a, and is observed only in low noise, or near absolute threshold. Previous research suggests that we will not observe this factor in a central (endogenous) attention task. (3) Attention may *reduce internal multiplicative noise* by a factor A_m ($0 \leqslant A_m \leqslant 1$), which acts to reduce N_m, or attention may alter performance by modifying transduction non-linearity γ. These factors jointly determine the "gain control" properties of the system and are closely specified by requiring the model to fit threshold data for three different criterion levels of performance (Dosher & Lu, 1999, 2000b; Lu & Dosher, 1999).

[4] In the term (βc), β represents the match of the target stimulus and the template times a scaling factor. The parameter α in this equation makes this scaling factor explicit.

3. Experiment 1: attention and the spatial window of the template in periphery

3.1. Purpose

Experiment 1 evaluates the spatial window of information integration in visual periphery and the effect of spatial attention upon this profile. Attention is important within the context of multiple-stimulus displays, where pre-cuing attention improves the exclusion of external noise (Dosher & Lu, 2000c; Lu & Dosher, 2000; Lu et al., 2002). Observers were asked to report the orientation of one of six peripheral targets. In the attended condition, the target was cued prior to presentation. In the unattended condition, the target was indicated by a simultaneous report cue. If attention assists in tuning the spatial window, then spatial selection might be more closely tuned to the signal stimulus, and the impact of external noise may be restricted to smaller regions. Lacking a pre-cue, spatial selection may be more diffuse. The evaluation of thresholds at three criterion performance levels specifies the system non-linearities within the PTM (Lu & Dosher, 1999).

3.2. Method

3.2.1. Apparatus

Visual stimuli were presented on a Nanao Technology FlexScan-6600 monitor with a P4 phosphor, a refresh rate of 120 frames/sec and a luminance range from 1 to 50 cd/m^2 (background = 25 cd/m^2). The display was controlled with a 7300 Macintosh computer using the PsychToolbox (Brainard, 1997) and Matlab (Mathworks, 1998). A special circuit (Brainard, 1997) combined two 8-bit output channels of the video card and divided the full luminance range of the monitor into 6144 distinct gray levels (12.6 bits), gamma corrected using a psychophysical procedure. Observers viewed the displays binocularly with natural pupil at a viewing distance of approximately 70 cm in a dimly lit room.

3.2.2. Stimuli and displays

The signal stimuli were windowed oriented sinewaves, or Gabor patches (see Fig. 2A):

$$l(x,y) = l_0 \left(1.0 + c \sin(2\pi f (x\cos\theta + y\sin\theta)) \times \exp\left(-\frac{x^2+y^2}{2\sigma^2} \right) \right). \tag{1}$$

The Gabors were tilted at four angles relative to the vertical, or $\theta = 22.5°$, $67.5°$, $102.5°$, or $157.5°$. The fre-

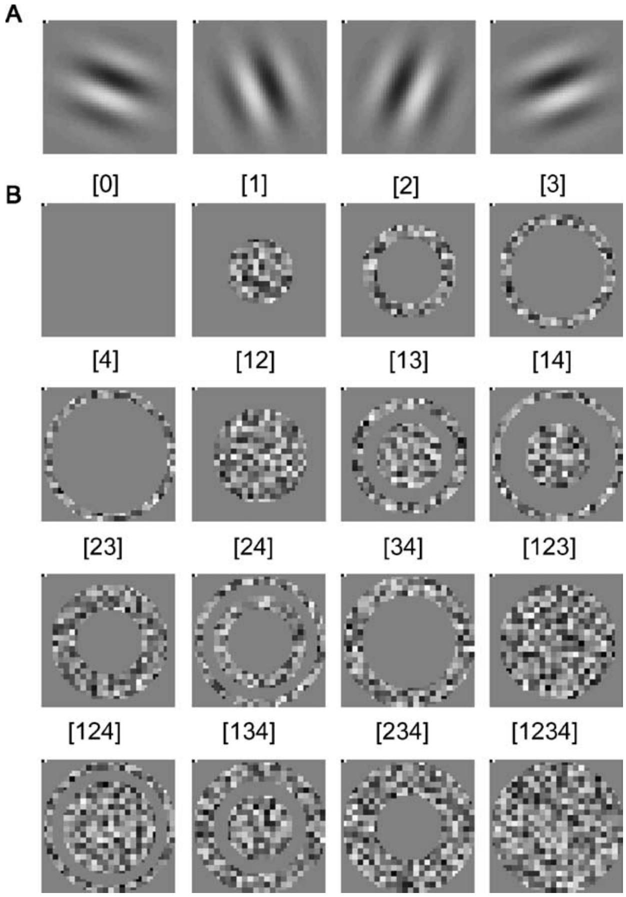

Fig. 2. Examples of stimuli used in the experiment. (A) The four oriented Gabor stimuli to be identified as tilted top far left, top near left, top near right, and top far right. The contrast is increased for illustrative purposes. The signal stimuli shown are the frequency used in Experiment 2. (B) The 16 external noise conditions, consisting of all possible combinations of rings R1, R2, R3, and R4.

quency of the Gabor was $f = 1.33$ cycles/deg (1/16 pixels), and the spatial window of the Gabor had $\sigma = 0.39°$ (9 pixels). Mean luminance, l_0, was 25 cd/m^2. The contrast of the Gabor, c, took on seven values for each condition, selected from pilot data to estimate a psychometric function. Six 48×48 pixel Gabor stimuli, with orientation chosen randomly with replacement, were displayed equidistantly around an annulus with 6.16° eccentricity.

External noise stimuli were created as follows: Noise elements consisted of 2×2 pixel patches ($0.083° \times 0.083°$) in a 108×108 pixel image, where the contrast of each noise patch was drawn from a Gaussian distribution of contrasts with mean 0 and standard deviation 0.32 relative to the achievable contrast range of ±1.0. Each 108×108 noise image in the display was independently sampled, and then spatially masked consistent with the external noise condition by setting noise pixel contrasts to 0 (background luminance l_0) or to the random noise contrast depending upon the assignment of that pixel to a high noise or no-noise spatial region. The spatial region in and around the oriented Gabor target was divided into four concentric rings, R1 – R4, at radii of 12, 17, 21, or 24 pixels from the center of the Gabor, e.g., R1 = a circle with radius $r \leqslant 12$ pixels, R2 = a ring with $12 < r \leqslant 17$ pixels, etc. These radii approximately equated the number of pixels in each region, with 437, 452, 480, 420 pixels, respectively.

3.2.3. Design and procedure

There were two attention conditions, in which the report location was either pre-cued or cued simultaneously. There were 16 external noise conditions defined by the combination of rings of external noise. The central circle (0.5°, 12 pixel radius) is denoted R1, while the region demarked by the next radius (0.708°, 17 pixels) and ring 1 is denoted as R2, etc. The 16 conditions consist of the set [R1, R2, R3, R4, R1 + R2, R1 + R3, R1 + R4, R2 + R3, R2 + R4, R3 + R4, R1 + R2 + R3, R1 + R2 + R4, R1 + R3 + R4, R2 + R3 + R4, R1 + R2 + R3 + R4, R0 (no noise)] (see Fig. 2B). This set of conditions provides checks on the combination rules in integration of input from the noise regions. Seven Gabor contrast levels were tested for each external noise condition, selected to span a psychometric function; attended and unattended conditions for a given external noise condition were tested with the same set of signal contrasts.

Each 672-trial session tested 16 external noise conditions × 2 attention conditions × 7 contrast conditions. In attended trials, a fixation square and edge markers for each of the six stimulus locations appeared for 600 ms, followed by an arrow pre-cue for 150 ms, followed by six locations of external noise images for 33.3 ms, six locations of Gabor signals for 16.7 ms, six locations of external noise images for 33.3 ms, and the report arrow until response. In unattended trials, an uninformative fixation box appears instead of the pre-cue and an arrow report cue appeared simultaneously with the Gabor stimulus image. The orientation of the Gabor stimulus was indicated on the keyboard ("d" = top tilted far left, "f" = near left, "j" = near right, "k" = far right). Correct responses were indicated by a system beep as feedback (high tone for correct, low tone for incorrect).

3.2.4. Observers

Six observers with normal or corrected-to-normal vision participated in the experiment. These observers participated in 14 experimental sessions plus a practice session for pay, yielding 9408 trials per observer, or 42 trials per point on the psychometric functions.

3.2.5. Analyses

The observed psychometric functions (probability correct for seven contrast levels) for each condition were fit with a Weibull function: $P(c) = 0.5 + (\max - 0.5)(1 - 2^{-(c/\alpha)^{\eta}})$ (Wichmann & Hill, 2001) using standard gradient descent methods implemented in Matlab (The

Mathworks, 1998, Inc.) and a maximum likelihood criterion. Threshold contrast values at three correct performance levels of 0.50, 0.625, and 0.75 (corresponding to d' values of 0.84, 1.24, 1.68) were interpolated from the Weibull functions.

The perceptual template model (PTM) (Lu & Dosher, 1999) was fit to 96 thresholds (2 attention × 16 external noise × 3 performance criteria) by gradient descent methods implemented in Matlab. The *N observed* contrast thresholds, $\log(c^{\text{observed}})$, were compared with the predicted (PTM model) contrast thresholds, $\log(c_\tau^{\text{theory}})$ or with the corresponding mean threshold, $\log(c^{\text{mean}})$. The best-fitting PTM parameter set was found that minimized the sum of squared errors,

$$\mathrm{SSE} = \sum_{i=1}^{N}[\log(c_i^{\text{observed}}) - \log(c_i^{\text{theory}})]^2.$$

The quality of the best fitting PTM model was summarized by:

$$r^2 = 1 - \frac{\sum_{i=1}^{N}(\log(c_i^{\text{observed}}) - \log(c_i^{\text{theory}}))^2}{\sum_{i=1}^{N}(\log(c_i^{\text{observed}}) - \log(c^{\text{mean}}))^2},$$

the proportion of variance accounted for by the model. Versions of the model with different numbers of parameters are statistically compared, when one model is nested inside another. The *reduced* model is nested within the *fuller* (superset) models by constraining some parameters to be equal or not to vary with condition. The k_{reduced} and k_{fuller} are the number of model parameters. An alternative test, the likelihood test comparing a "fuller" and a nested "reduced" model is $\lambda = (\mathrm{RSE}_{\text{full}}/\mathrm{RSE}_{\text{reduced}})^{N/2}$. Corresponding to this, $-2\ln\lambda = N\ln(\mathrm{RSE}_{\text{reduced}}/\mathrm{RSE}_{\text{full}})$ is distributed as χ^2 with degrees of freedom $(k_{\text{full}} - k_{\text{reduced}})$, where RSE is the residual squared error, or $(1 - r^2)$ for the model (Boraviak, 1989).

3.3. Results

3.3.1. Psychometric functions and measured thresholds

Weibull functions were fit to the 32 psychometric functions of each observer. [5] Observed thresholds at criterion performance levels of 50%, 62.5%, and 75% were interpolated using the Weibull from the psychometric functions for each observer. Average threshold data were computed by averaging estimated thresholds over observers. Fig. 3 shows the average thresholds in the unattended (3A) and attended (3C) conditions for the 62.5% criterion (see explanation for the layout below). The thresholds for the 50% criterion and the 75% criterion, omitted for brevity, showed very similar patterns, but were systematically shifted lower and higher, respectively, as expected. The average data were representative of individual observer data (available from the authors). Fig. 3 also shows the corresponding best model fits to that data (3B and 3D). The tests of the PTM model are considered below in Section 3.3.2.

The threshold data have been graphed in a "tree" layout so as to reveal the relationships between the different conditions. There are three general qualitative phenomena expressed in these data. First, the pattern of contrast thresholds over external noise conditions exhibits strong regularities across the threshold tree. The single-noise ring conditions (bottom contour of the tree, heavy line), [R0 → R1 → R2 → R3 → R4], provide a first-order estimate of the spatial weights on the four external noise rings. External noise in ring 1 has the greatest impact on threshold, while noise in rings 2–4 alone has successively less impact on threshold. Expanding circles of noise (upper contour of the tree) [R0 → R1 → R1 + R2 → R1 + R2 + R3 → R1 + R2 + R3 + R4] reveal a saturating impact of external noise added in the outer rings. The remaining intermediate combinations are regularly arrayed in expected locations between these two contours. To illustrate the regularity in the thresholds as a function of external noise levels, the thresholds for the outward growing subset (*circles*) {R0 → R1 → R1 + R2 → R1 + R2 + R3 → R1 + R2 + R3 + R4} and for an inward growing subset (*rings*) {R0 → R4 → R3 + R4 → R2 + R3 + R4 → R1 + R2 + R3 + R4}, at each of three criterion thresholds, are shown in Fig. 4A for the unattended and the attended conditions, respectively (smooth curves are model fits, see below).

Second, the contrast threshold levels of the unattended, simultaneous cuing trials were higher than those of the attended, pre-cued conditions in the high external noise conditions. This demonstrates a benefit of attention associated with external noise exclusion, consistent with previous findings (Dosher & Lu, 2000c; Lu & Dosher, 2000). The reduction in contrast thresholds due to attention are shown directly in Fig. 4B, where $\log_{10}$ thresholds for the attended condition are plotted against those of the unattended condition (left)—values below the diagonal reflect improvements due to attention. There is a concentration of below-diagonal values in the high external noise conditions, as seen in the histogram of ($\log_{10}$) threshold differences (unattended–attended) in Fig. 4C. The large effect of attention in high-noise conditions, and reduced or eliminated effect in lower noise conditions is characteristic of external noise exclusion.

Third, the pattern of the threshold trees is shifted to higher contrast threshold levels as the criterion accuracy

[5] Consistent with previous observations (Cameron, Tai, & Carrasco, 2002; Dosher & Lu, 2000c; Lu & Dosher, 2000), the attention conditions did not produce different psychometric slopes, and allowing independent slopes did not improve the quality of the Weibull fits ($p > 0.10$). In a very small number of cases it was necessary to constrain the slope of the Weibull function to achieve a fit that was consistent with other similar conditions; this reflected a non-optimal selection of contrasts and variability in the observed percent correct.

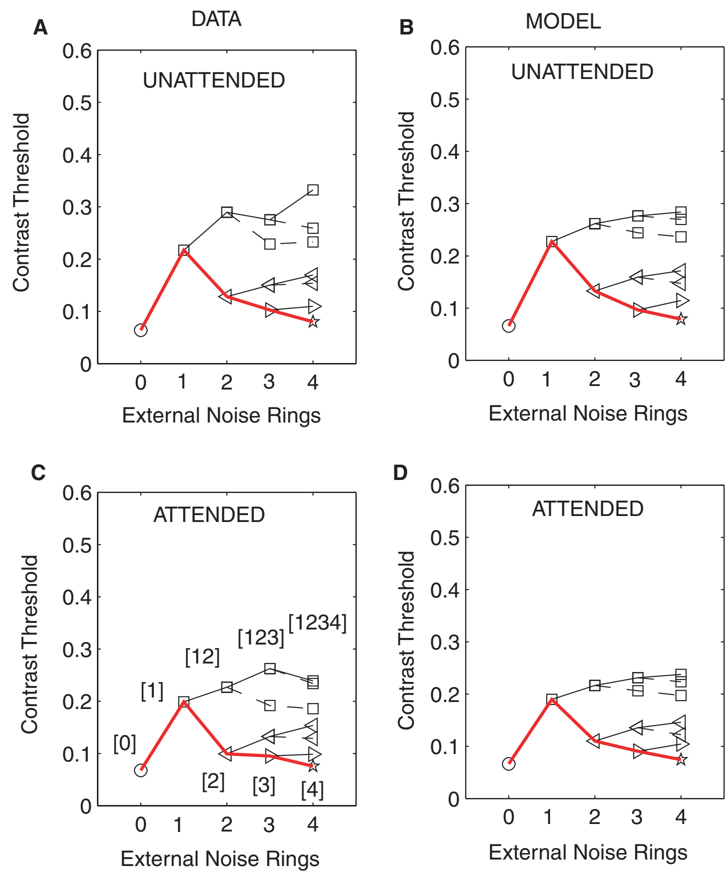

Fig. 3. Contrast thresholds "trees" are shown for 16 external noise conditions for the 62.5% criterion, corresponding to 1.24 d', for the average data in the unattended (A) and for the attended (C) condition. The corresponding best fitting model predictions for the average data (parameters in Table 2) are shown in (B) and (D). The layout of the threshold "tree" (e.g., [1] = Ring 1 external noise alone; [124] = Ring 1 + 2 + 4 external noise; etc.) is labeled in C.

increases, while the pattern is essentially replicated. Again, the effect of criterion is seen for a subset of the 16 conditions in Fig. 4A.

3.3.2. PTM model

Several variants of the PTM model were fit to the 96 threshold contrasts for 50%, 62.5%, and 75% correct (corresponding to 0.84 1.24 1.68 d', respectively) for 16 different external noise conditions in each of two attention conditions for the average data and for each observer. The fullest (most saturated) model (Model A) accommodates four kinds of attention effects—external noise exclusion in two forms (spatial and general), stimulus enhancement, and internal multiplicative noise reduction and estimates the spatial profile of the perceptual template as weights on the four measured spatial rings. This model includes three independent spatial weights applied to signal and noise in each ring in the unattended condition (the fourth determined by normalization $\sum_{i=1}^{4} w_{i,\mathrm{U}}^2 = 1$) and three independent spatial weights in the attended condition (the fourth determined by normalization $\sum_{i=1}^{4} w_{i,\mathrm{A}}^2 = 1$). That is, $w_{i,\mathrm{U}}$ (or $w_{i,\mathrm{A}}$) is applied to the contrast of signal within ring i (the proportion of signal contrast within each ring, $\widehat{c}_i$, was computed as the normalized RMS contrast in the pixels of each "ring"), and $w_{i,\mathrm{U}}^2$ (or $w_{i,\mathrm{A}}^2$) is applied to the external noise in each ring (which is 0 if there is no noise in that ring for a particular stimulus). Further reduction of external noise by factor A_f^2 in the attended condition allows for the possibility that attention has eliminated external noise overall, in dimensions other than space. These seven parameters jointly characterize the spatial selection of the perceptual template and the external noise exclusion by attention. In the fullest model, there are two additional attention parameters: A_a allows for possible stimulus enhancement by attention (although we do not expect it with central cuing) and A_m, allows for possible reduction in multiplicative noise (although we do not expect it since it has not previously been observed). Finally, all variants of the PTM model have the following parameters that together set the general performance level and non-linearity of the system: N_add, estimates equivalent additive internal noise; N_mult estimates the equivalent multiplicative internal noise; α is a scaling factor on the gain of the signal, and power γ describes the non-linearity.

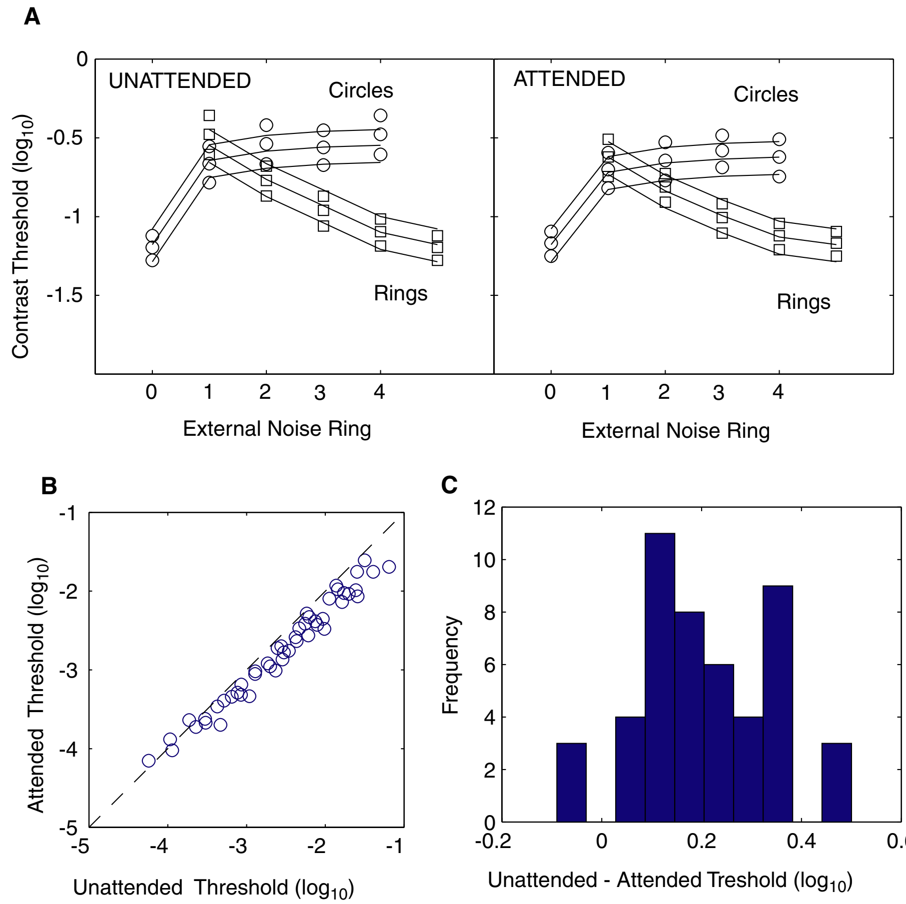

Fig. 4. Contrast threshold ($\log_{10}$) for unattended and attended conditions for different criteria and increasing noise conditions (A). Thresholds are shown at three criteria (lowest = 50%, intermediate = 62.5%, highest = 75%) for the circles of increasing radii external noise growing outward (external noise growing outward from left to right: [R0 →R1 →R1 + R2 →R1 + R2 + R3 →R1 + R2 + R3 + R4]), or for outer annuli increasing towards the center (external noise growing inward from right to left: [R0 →R4 →R3 + R4 →R2 + R3 + R4 →R1 + R2 + R3 + R4]). The smooth curves are the fit of the PTM model. (B) The attended ($\log_{10}$) contrast thresholds are plotted against the unattended thresholds for all external noise and criterion conditions; values below the diagonal represent lower thresholds for attended than for unattended conditions. (C) Histogram of the differences between ($\log_{10}$) contrast thresholds of unattended and attended conditions (positive values indicate improvements in threshold with attention).

Independent tests of the psychometric functions as well as nested model tests (see Section 3.2.5) indicated that the model could be simplified by setting certain parameters to be equal in the attended and unattended conditions. First, in zero noise, there was no discernable effect of attention on the psychometric functions ($p > 0.20$) (with the exception of observer KC, nested model test $F(1,36) = 20.1$, $p < 0.001$). That attention has little or no effect in zero or low noise in the case of central pre-cuing was also consistent with previous observations (Dosher & Lu, 2000a; Lu & Dosher, 2000). Second, the threshold ratio between attended and unattended conditions was statistically equivalent at the three threshold criterion levels (equivalent to an equal slope for attended and unattended psychometric functions (Dosher & Lu, 1999; Lu & Dosher, 1999)). The lack of a change of multiplicative noise ($A_m = 1$) and non-linearity ($\gamma = \gamma_A = \gamma_U$) with attention replicates prior findings in attention and perceptual learning studies using external noise (Dosher & Lu, 1998, 1999, 2000b, 2000c; Lu & Dosher, 2000; Lu et al., 2002). The simple level-shift relationship in (log) contrast threshold between conditions at the three criterion levels is the visually apparent property of the data. These independent assessments indicate that it should be possible to set $A_a = 1$ (with the exception of KC) and $A_m = 1$, reducing the model by two free parameters. This conclusion is verified by the nested model test (a form of maximum likelihood test based on the statistic λ and distributed as χ^2 (Boraviak, 1989)) [6] listed in Table 1 (Model A vs. B). The χ^2-values were very low for all but

[6] This maximum likelihood χ^2 statistic is similar to the nested-F test,

$$F = \frac{(\mathrm{SSE}_{\mathrm{reduced}} - \mathrm{SSE}_{\mathrm{fuller}})/(k_{\mathrm{fuller}} - k_{\mathrm{reduced}})}{(\mathrm{SSE}_{\mathrm{fuller}})/(N - \mathrm{fuller})},$$

df $= (k_{\mathrm{fuller}} - k_{\mathrm{reduced}})$, $(N - k_{\mathrm{fuller}})$, but is slightly less conservative. The p-values for the two tests are very similar.

Table 1
Four PTM models and nested model tests

Model	Statistic	Observers						
		AK	BM	CY	JW	KC	NC	AV
Model A	r^2	0.924	0.891	0.926	0.907	0.942	0.947	0.981
Model B	r^2	0.922	0.891	0.926	0.907	0.917	0.947	0.981
Model C	r^2	0.894	0.884	0.903	0.880	0.878	0.921	0.958
Model D	r^2	0.916	0.883	0.924	0.884	0.914	0.942	0.980
A vs. B	χ^2 (2)	3.05	0.00	0.00	0.00	14.92**	0.46	0.01
B vs. C	χ^2 (1)	27.01**	4.18*	25.06**	5.68*	35.21**	27.26**	73.67**
B vs. D	χ^2 (3)	5.41	5.91	1.35	20.77**	2.19	7.88*	2.55

Notes:
Model A parameters: $\langle N_m, N_a, \alpha, \gamma, A_a, A_m, A_f, w_{1,U}, w_{2,U}, w_{3,U}, w_{1,A}, w_{2,A}, w_{3,A}\rangle$.
Model B parameters: $\langle N_m, N_a, \alpha, \gamma, A_f, w_{1,U}, w_{2,U}, w_{3,U}, w_{1,A}, w_{2,A}, w_{3,A}\rangle$.
Model C parameters: $\langle N_m, N_a, \alpha, \gamma, w_{1,U}, w_{2,U}, w_{3,U}, w_{1,A}, w_{2,A}, w_{3,A}\rangle$.
Model D parameters: $\langle N_m, N_a, \alpha, \gamma, A_f, w_{1,U=A}, w_{2,U=A}, w_{3,U=A}\rangle$.
Symbols $^*p < 0.05$, $^{**}p < 0.01$.
The best fits for observer KC include A_a. Model B + A_a yields $r^2 = 0.942$; Model C + A_a yields $r^2 = 0.914$; Model D + A_a yields $r^2 = 0.937$; B + A_a vs. C + A_a yields $\chi^2(1) = 37.59$, $p < 0.001$; B + A_a vs. D + A_a yields $\chi^2(3) \approx 8.44$, $p < 0.05$.

KC (the χ^2 are near 0 for several of the subjects, reflecting the fact that A_a and A_m were estimated as 1 ± 0.03 when free to vary, and hence led to identical parameter solutions). Observer KC showed a small but statistically significant stimulus enhancement in zero and low noise.

The spatial profile of the perceptual template and the form of external noise exclusion are tested through the combined effect of the spatial ring weights and A_f. Several additional reduced models were examined. The model that allowed independent estimates of spatial profiles in the unattended and attended conditions (3 weights each), but assumed that the only mode of external noise exclusion is by spatial retuning (by setting $A_f = 1$), and assuming no further overall reduction in external noise, was easily rejected. Table 1 shows that eliminating A_f (Model B vs. C) noticeably reduced r^2, uniformly resulting in high χ^2 values (all $p < 0.0001$). Thus, the data demands an overall reduction in external noise relative to signal that does not result from a differential tuning in the spatial profiles.

Next, we evaluated whether the spatial profile differed significantly between the unattended and the attended conditions by constraining the 3 weights in the attended condition to be equal to those in the unattended condition. In this case, assuming that the spatial profile of the perceptual template was equivalent in the unattended and attended conditions did not lead to a significant reduction in fit for three of the observers, led to a marginal reduction in fit for one observer, and a significant reduction in fit for two other observers. The relevant χ^2 values are listed in Table 1 (B vs. D). Even in cases where the spatial profile did differ significantly between the unattended and attended condition, the estimated profiles are still quite similar.

Table 2
PTM model fits experiment 1

Parameter	Observers						
	AK	BM	CY	JW	KC	NC	Average
N_m^2	0.381	0.291	0.270	0.100	0.101	0.322	0.357
N_a^2	0.012	0.026	0.014	0.011	0.032	0.008	0.010
α	1.526	1.431	1.495	1.468	1.474	1.408	1.501
γ	1.481	1.432	1.514	1.985	1.370	1.941	1.809
A_a^2	1.000	1.000	1.000	1.000	0.500	1.000	1.000
$w_{1,U}^2$	0.599	0.787	0.649	0.471	0.678	0.616	0.640
$w_{2,U}^2$	0.263	0.130	0.172	0.255	0.211	0.215	0.210
$w_{3,U}^2$	0.084	0.083	0.113	0.185	0.071	0.092	0.100
$w_{1,A}^2$	0.539	0.740	0.621	0.549	0.681	0.674	0.635
$w_{2,A}^2$	0.248	0.096	0.214	0.227	0.160	0.170	0.197
$w_{3,A}^2$	0.110	0.102	0.108	0.156	0.112	0.118	0.113
A_f^2	0.606	0.769	0.661	0.902	0.603	0.747	0.690
r^2	0.922	0.891	0.925	0.906	0.942	0.947	0.981

Note: The best-fitting PTM (Model B) had 11 parameters (α, γ, N_a, N_m, A_f, 3 $w_{i,U}$ and 3 $w_{i,A}$, $A_a \equiv 1$). For observer KC, stimulus enhancement was significant and the 12-parameter model including A_a is listed. For observers AK, BM, and CY, an 8-parameter model with $w_{i,A}^2 = w_{i,U}^2$ was acceptable. For JW, KC, NC, the unattended and attended profile weights differed significantly.

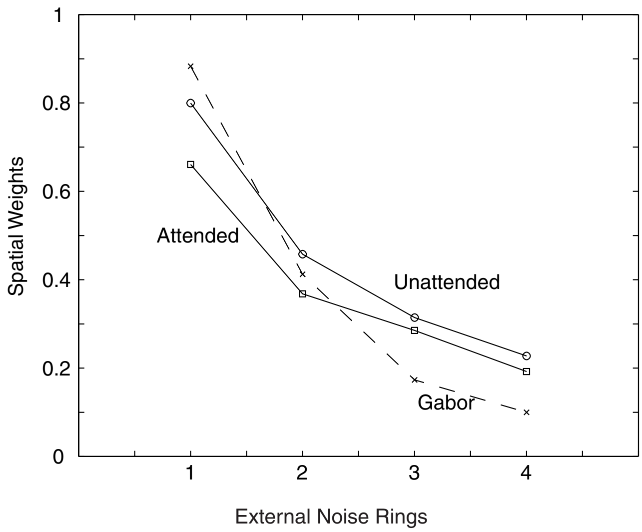

Fig. 5. Experiment 1's estimated weights (w_i) from the PTM model for each of the four rings of external noise. Also graphed is the proportion RMS contrast for each ring in the signal stimulus, $\left\lfloor\sqrt{\sum_{\forall i,j\,\text{in Ring}\,K}(l_{i,j}-l_0)^2}\Big/\sqrt{\sum_{\forall i,j\,\text{in Image}}(l_{i,j}-l_0)^2}\right\rfloor$. The spatial profile of both the attended and the unattended condition match the spatial profile of the stimulus.

The parameters of model B are listed in Table 2 (KC also includes the extra parameter A_a). The quality of fit, r^2, is quite good. The PTM model and the weighted spatial integration model of external noise impact were strongly supported. Fig. 5 shows the net effective weights for the average data—$w_{i,U}$ for the unattended condition and $A_f w_{i,A}$ for the attended condition. The general patterns and the estimated parameter values (Table 2) for the average and for individual observers are strongly related to the information in the Gabor signal, measured by the proportion of the total RMS contrast occurring within each ring

$$\left\lfloor\sqrt{\sum_{\forall i,j\text{ in Ring}\,K}(l_{i,j}-l_0)^2}\Bigg/\sqrt{\sum_{\forall i,j\text{ in Image}}(l_{i,j}-l_0)^2}\right\rfloor,$$

or $\widehat{c}_k$ for ring k.

The spatial profiles in the unattended and the attended conditions are similar to one another, but for three of the six observers there are small but significant alterations in the weight profile with attention. However, the larger factor in external noise exclusion is the overall reduction of noise that is not spatially selective, but instead reflects filtering in non-spatial dimensions, or uniformly improved external noise exclusion over the full spatial profile.

3.4. Discussion

This study asked: What is the spatial window of the perceptual template (e.g., spatial region of external noise integration) in periphery and does the optimality of this spatial window in periphery depend upon attention? The estimated spatial window of the perceptual template, as measured by the weights on concentric rings, is generally well-matched to the signal Gabor stimulus in both attended and in unattended conditions, although the spatial profile is somewhat improved by attention for three observers. Attention further reduces the weight on external noise in all spatial regions by a factor A_f, reflecting filtering in non-spatial dimensions. The composite effect of external noise in different ring combinations was very closely fit by the PTM with non-linear transduction and multiplicative noise.

4. Experiment 2: the spatial window of the perceptual template in fovea

4.1. Purpose

The purpose of Experiment 2 was to evaluate the spatial window of the perceptual template in a foveal task. Attention is not explicitly manipulated but, absent a secondary task, the foveal task probably functions as attentive viewing.

4.2. Method

4.2.1. Participants

Four observers with normal or corrected-to-normal vision participated in the experiment. These observers participated in 15–25 sessions for pay, yielding 6720–11,200 trials per observer, or 60–100 trials per point on the psychometric functions.

4.2.2. Stimuli, display and apparatus

The stimuli consisted of a single Gabor patch at the center of the screen. The specification of the Gabor stimuli was identical to Experiment 1, except that the viewing distance was 70 cm, the frequency was $f = 3.0$ cycles/deg (1/8 pixels), and the Gabor window was defined by $\sigma = 0.50°$ (12 pixels). Mean luminance, $l_0 = 25$ cd/m^2. Spatial "fixation" marks consisted of 5×1 pixel lines at the corners of a 64×64 region centered on fixation.

4.2.3. Design and procedure

The design of Experiment 2 was identical to Experiment 1 except that attention was not manipulated. Each session tested 448 trials (16 noise conditions $\times$ 7 contrasts $\times$ 4 target orientations). Each trial began with a fixation or position indicator displayed for 150 ms, a blank screen for 100 ms, a noise frame for 16.7 ms, signal frame for 16.7 ms, noise frame for 16.7 ms, followed by a blank screen until the observer responded.

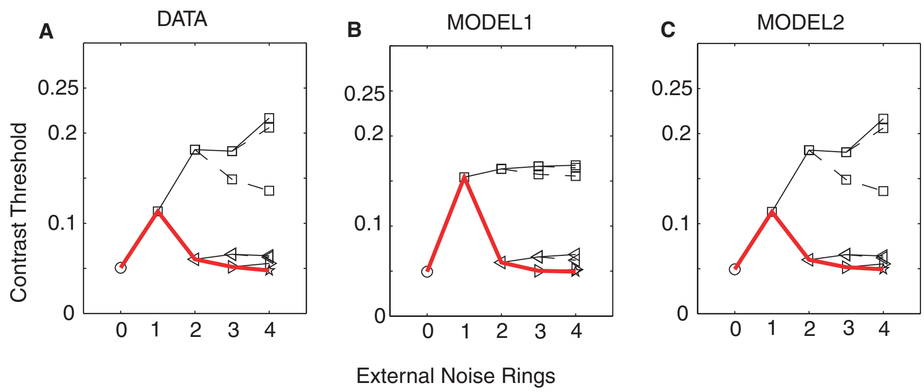

Fig. 6. Contrast thresholds "trees" for 16 external noise conditions at criterion accuracy of 62.5% (1.24 d') for the average data (A) and for two separate model fits (B and C) (see text).

4.3. Results

4.3.1. Psychometric functions and measured thresholds

Sixteen psychometric functions were measured for each of the five observers. Threshold contrasts at 50%, 62.5%, and 75% correct criteria were estimated using a fitted Weibull as the interpolation function. The thresholds for each of the 16 conditions, averaged over observers, are shown in Fig. 6A for criterion 62.5%. (The average is shown including all observers, including observer PK, who exhibited a significant non-monotonicity of thresholds involving Ring 2. The average excluding PK is similar, but less irregular, and more monotonic, and the conclusions are the same).

The single ring conditions provided a first-order measurement of the impact of external noise in each ring. As in the previous experiment, the pattern of single-ring thresholds (lower threshold contour) indicated highest weight on ring 1, and successively less weight on each more eccentric ring of external noise [R1 > R2 > R3 ⩾ R4 ⩾ R0 (null)]. Similarly, a pattern of increasing external noise conditions (upper threshold contour) showed a consistent increase in thresholds across conditions [R0 (null) → R1 → R1 + R2 → R1 + R2 + R3 → R1 + R2 + R3 + R4].

Certain aspects of the threshold pattern appear to be inconsistent with the weighted integration model of combined impact of multiple external noise rings. For example, rings 3 and 4 have very small impact in elevating contrast threshold above the zero noise condition. Yet adding rings 3 and 4 to rings 1 and 2 appears to have a quite noticeable impact on threshold performance. This point is considered further in the context of the PTM model. This may reflect an ability to carry out some context-dependent weighting or selective looking in noise-free regions of an individual display.

4.3.2. Spatial noise integration and the PTM

Since attention was not manipulated explicitly in the experiment, the PTM model is simplified to seven parameters: the scaling of gain of the template for the signal stimulus, α, non-linearity power γ, equivalent additive internal noise, N_a, and equivalent multiplicative internal noise N_m, and, finally, the integration weights w_i applied to each ring of external noise (3 independent weights, and the fourth constrained by the normalization $\sum_{i=1}^{4} w_i^2 = 1$). [7] This 7-parameter model was applied to the 48 measured contrast thresholds (16 noise ring conditions ×3 threshold criteria) for the average data and for each observer. The predictions of the weighted-sum version of the PTM model are graphed in Fig. 6B. Model parameters and r^2's are listed in Table 3.

This version of the PTM model, which assumes a simple spatial integration and weighted combination rule $\left(N_{\text{ext}}^2 = \sum_{i=1}^{K} w_i^2 N_i^2 \quad (\ni \sum_{i=1}^{K} w_i^2 = 1)\right)$, provides moderately good first-order fits to the threshold data ($r^2 = 0.949$ for the average data), as seen in the listed r^2's. These r^2 's reflect the ability of the PTM to account for the general ordering of external noise conditions and the systematic relationship of performance at three criterion levels (e.g., across the psychometric function). The profile of the spatial window of external noise integration—the relative weights on the four rings—is shown in Fig. 7. As indicated just below, this is at best an approximation, as the simple integration model does *not* provide a full account of the threshold data.

Unlike Experiment 1, there are systematic residual misfits of the simple integration PTM model to the data, especially in the higher noise conditions, as seen in the first set of model predictions in Fig. 6B. These deviations reflect inconsistencies between the small impact of certain rings of noise alone and their impact on performance when combined with other rings of noise. For example, external noise ring 4 has relatively high impact on threshold when added to rings 1–3 but an almost negligible impact on performance when alone. A version

[7] Normalizing to 1 rather than to A_f is equivalent. The value of A_f would not be constrained.

Table 3
Integration PTM model fits experiment 2

Parameter	Observers				
	AH	JM	PK	RT	Average
N_{mult}	0.472	0.437	0.375	0.417	0.434
N_{add}	0.005	0.004	0.006	0.002	0.003
α	2.446	2.550	3.451	2.055	2.463
γ	2.168	2.437	1.881	2.961	2.493
w_1^2	0.822	0.823	0.827	0.715	0.817
w_2^2	0.113	0.119	0.128	0.119	0.113
w_3^2	0.059	0.056	0.043	0.060	0.060
r^2	0.926	0.932	0.860	0.940	0.949

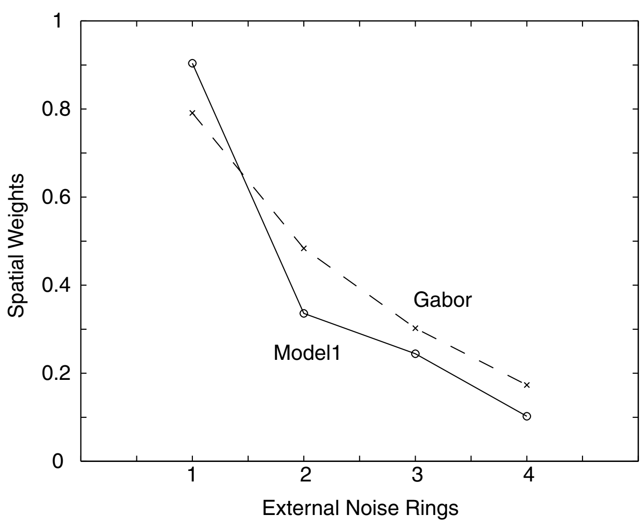

Fig. 7. Experiment 2's estimated weights (w_i) from the PTM (Model 1) for each of the four rings of external noise, along with the proportion RMS contrast for each ring in the signal stimulus.

of the PTM model with independent impact factors for all external noise condition was tested, requiring 14 impact weights for the 16 external noise conditions ($w_0 = 0$ for no noise, and $w_{16} = 1$ for the full noise condition). This is equivalent to the weighted sum model plus a context (interaction) term (off-looking term) for every external noise condition with multiple rings. This model continues to provide the core constraints of the PTM on the performance at different criterion levels (fitting 48 data points with 18 parameters). The predictions of this model are shown in Fig. 6C. The parameter values for the elaborated model with independent condition weights are shown in Table 4. The r^2's for the simple model is in Table 3, and the r^2's for the larger context model, as well as the maximum likelihood χ^2 (Boraviak, 1989) for the comparison of the fuller (with interaction) and reduced (original) models are listed in Table 4. In every case, the fuller model provided an improved ($p < 0.0001$) fit to the data.

This more complex pattern of impact of sub-regions of external noise may reflect some ability to selectively look at regions without noise in a particular trial—a ring

Table 4
Context PTM model fits experiment 2

Parameter	Observers				
	AH	JM	PK	RT	Average
N_{mult}	0.283	0.283	0.284	0.311	0.310
N_{add}	0.008	0.003	0.010	0.015	0.007
α	1.309	1.361	2.058	1.400	1.487
γ	1.727	2.159	1.537	1.952	1.941
w_1^2	0.235	0.267	0.217	0.344	0.268
w_2^2	0.039	0.048	0.048	0.095	0.055
w_3^2	0.029	0.000	0.031	0.000	0.022
w_4^2	0.000	0.000	0.028	0.000	0.000
w_{12}^2	0.651	0.565	0.916	0.764	0.703
w_{13}^2	0.419	0.503	0.512	0.455	0.470
w_{14}^2	0.367	0.284	0.422	0.519	0.393
w_{23}^2	0.050	0.056	0.071	0.136	0.075
w_{24}^2	0.046	0.038	0.061	0.121	0.063
w_{34}^2	0.026	0.099	0.039	0.095	0.039
w_{123}^2	0.977	0.766	0.275	0.663	0.685
w_{124}^2	0.814	0.797	1.000	0.860	0.905
w_{134}^2	0.512	0.370	0.963	0.571	0.600
w_{234}^2	0.062	0.049	0.042	0.134	0.070
R^2	0.989	0.998	0.968	0.989	0.998
χ^2 (11)	90.89	168.78	70.93	81.09	152.09

Note: Parameters for the PTM with an independent weight for each external noise condition. The impact of zero noise, $w_0^2 = 0$, and the impact of full noise $w_{1234}^2 = 1$ as a free scaling parameter. The χ^2-values are from the maximum likelihood nested test (see text) of this full context model compared to the simple integration PTM (Table 2); all $p < 0.0001$.

that by itself has little impact may be damaging if it now covers the last remaining region of signal. In fact, selective looking is more consistent with a sophisticated ideal-observer performance (Burgess, Wagner, Jennings, & Barlow, 1981). A sophisticated observer might be able, on each trial, to determine which pattern of external noise was present—the external noise is of high contrast and appears in clearly defined regions, and at fovea the observer often has a subjective sense of the external noise condition (e.g., central circle of external noise, outside ring of external noise). A sophisticated observer might further know the distribution of evidence in the signal stimulus (signal known). A sophisticated observer (signal known, external noise known) would then suit the weighting of information in each ring to the signal-to-noise ratio in each spatial sub-region.

4.4. Discussion

The spatial window of information integration in (attended) fovea, as in periphery, weights the central region of the Gabor more highly than more peripheral sub-regions. However, the threshold performance for ring combinations systematically deviate from weighted integration. There is less impact of external noise in any particular region if there is at least one high signal-to-noise region within a stimulus, which might be consistent with a sophisticated observer.

5. General discussion

5.1. Summary of results

The results and conclusions of the two experiments are several:

(1) The spatial window of external noise integration is closely matched to the spatial regions of high contrast in the signal stimulus, whether in periphery or in fovea.
(2) Attention eliminates external noise by (a) modest retuning of the spatial profile in three of six observers and by (b) an overall reduction in external noise due to filtering in non-spatial dimensions.
(3) In peripheral stimuli (Experiment 1), contrast threshold performance for all combinations of external noise regions follows a simple integration (weighted sum) rule of external noise combinations, subject to transducer non-linearities and multiplicative noise.
(4) In foveal stimuli (Experiment 2), there is evidence that observers are able to focus to some degree on clear regions of the stimulus.
(5) The perceptual template model (PTM)—a noisy observer model of perceptual performance—provides an excellent theoretical account of the regular relations between thresholds at three criterion performance levels.

5.2. Possible boundary conditions

The spatial window of the perceptual template in these tasks was generally closely aligned to the signal stimulus. Attention (pre-cuing) modestly retuned the spatial profile of the perceptual template relative to the unattended condition for three observers, and did not alter the spatial profile significantly for three others—although all observers showed a substantial improvement in performance associated with non-spatial filtering. This matching of the spatial window of the perceptual template to the signal stimulus may depend upon the simplicity of the spatial distribution of the signal stimulus, upon the location marking of the stimulus frame that reduces spatial uncertainty, and upon the relatively practiced state of the observers in this study. It is possible that in less well-practiced observers and tasks the spatial distribution of information integration in the unattended condition might prove to be much more diffuse than that of the attended condition. Prior claims of pre-cuing and focusing attention (LaBerge, 1995; Posner, 1980) were based on experiments that allowed statistical uncertainty (Palmer, 1994; Palmer, Ames, & Lindsey, 1993), while here we eliminate "structural uncertainty" by marking the target location by a report cue even in the unattended condition (Dosher & Lu, 2000b, 2000c). The pre-cue provides advance deployment of attention, but even in the simultaneous cue condition, the observer is not integrating information from all (peripheral) locations to determine both the identity and the location of the target.

5.3. Related evidence

A prior classification image study of the spatial template (Eckstein et al., 2002) reported that the spatial profile of the template did not depend upon cue validity in the 2-location Posner paradigm. This result confirmed the view (Sperling & Dosher, 1986) that the 2-location paradigm measures changes in decision criteria or weighting and not in sensitivity or early stimulus coding. Experiment 1 of the current study evaluated a multi-location cuing paradigm where, in contrast, the attention manipulation has a substantial impact upon sensitivity and measures the spatial profile of the perceptual template with external noise methods. We showed that the spatial profile of the perceptual template was similar to that of the signal stimulus in both attended and unattended conditions, that attention may slightly retune this spatial profile for some observers, and that additionally attention reduced external noise impact by retuning the template along non-spatial dimension(s).

5.4. Spatial masking and lateral interactions

In the current external noise study, the impact of external noise masks in the four distinct spatial subregions is closely tied to the spatial profile of the signal stimulus information. This suggests that effective external noise masking occurs primarily when the external noise mask directly stimulates the same spatial filters as the signal stimulus (Breitmeyer, 1984; Legge & Foley, 1980; Watson & Solomon, 1997).

A priori, external noise outside of the primary central spatial region of the Gabor patch could have had an impact on performance through some form of lateral interaction or lateral masking. The possibility of lateral effects was suggested by evidence for lateral interactions in related but distinct paradigms. For example, contrast patches at larger spatial distances from a central stimulus strongly impact perceived contrast of the center (Cannon & Fullenkamp, 1991). Spatial interactions of pattern surrounds can have significant impact on central stimuli (e.g., Yu et al., 2002). Powerful lateral crowding effects, in which a signal stimulus is surrounded by very similar lateral stimuli, make individual items difficult to access, but may leave the low-level coding of those stimuli intact (Parkes et al., 2001). Indeed, on the basis of these widely reported lateral effects, we had originally expected an impact upon orientation threshold from rings of external noise at greater distance from the center of the signal stimulus. We eliminated these more distant locations for external noise rings based on pretesting of the experiment.

In the current experiments, masking of identification performance primarily affected regions in space that directly overlap with the signal stimulus, similar to integration masking (Francis, 2003). The more peripheral rings of external noise had little impact on performance except when combined (non-linearly) with other high-noise regions. It may be that discrimination and identification operate differently from lateral effects on appearance measures such as perceived contrast. Lateral interaction effects can be fairly sharply tuned for spatial frequency and moderately tuned for orientation, and crowding depends upon similarity of feature content, while the energy in Gaussian (white) external noise is spread across spatial frequencies and orientations, rather than concentrated in very similar feature content.

5.5. PTM observer model

The perceptual template model (PTM) of the observer with a weighted spatial combination rule provided an excellent account of the pattern of thresholds of all the external noise conditions in attended and unattended peripheral conditions. The large set of conditions, consisting of all possible combinations of four different external noise rings, provided an extensive set of internal consistency checks on both the estimated impact of external noise in each spatial ring and of the combined impact. The combined impact reflected both the relative weight on the blocks combined, but also the non-linear consequences of that noise on gain control. The model also accounted for the systematic relationship between the thresholds at three different criteria—a proxy for the full psychometric function. The decomposition of the impact of external noise in the various sub-regions specifies the spatial window of the perceptual template. The PTM model provided an excellent account of attended and unattended peripheral stimuli, and a good a first-order account of the pattern of thresholds in the fovea. The foveal performance indicated systematic deviations possibly reflecting an additional ability to selectively weight spatial regions without external noise on a given trial.

5.6. External noise exclusion

The constancy of multiplicative noise factor ($A_m = 1$) with alteration in attention and the absence of an attention effect for central cuing in zero noise ($A_a = 1$) are both consistent with prior attention studies using the external noise plus attention (PTM) paradigm (Dosher & Lu, 2000b, 2000c; Lu & Dosher, 2000; Lu et al., 2002). This isolates the primary attention effect in the current paradigm as external noise exclusion (see also Dosher & Lu, 2000b, 2000c; Lu & Dosher, 2002). Whether attended or unattended, the relative profile or shape of the spatial window was reasonably well-matched to the signal. Modest but significant retuning of the spatial profile due to attention occurred in half of the observers, but spatial retuning either did not occur or was not significant in the other half. The largest effect of attention was to reduce the impact of external noise relative to signal by a multiplicative factor across the spatial window. In this experiment, the signal stimulus is narrow-band in spatial frequency and orientation (however the orientation alternatives span the full orientation space). In contrast, the external noise, or random Gaussian pixel noise, by definition has energy in all spatial frequencies and orientations. Attention apparently serves to reduce, or down-weight, the input from stimulus energy not relevant to the signal stimulus. The fact that attention had no measurable effect in zero or low noise is important because this rules out an increased response to the signal as the mechanism of the overall improvement in performance with attention not attributable to retuning of the spatial profile.

This account of external noise exclusion is consistent with a framework in which the stimulus is represented by units tuned to orientation and spatial frequency at different locations in space (spatial filters), and in which the inputs from the units carrying predominantly noise to a decision unit or units are down-weighted under attention. This is similar to a related account of performance improvements with perceptual learning (Dosher & Lu, 1998, 1999).

6. Conclusion

The spatial profile of influence of external noise—the template for external noise—is closely matched to the spatial profile of the signal stimulus. Spatial attention reduces the impact of external noise nearly uniformly across the relevant spatial regions of the stimulus.

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