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External Noise Distinguishes Attention Mechanisms

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We developed and tested a powerful method for identifying and characterizing the effect of attention on performance in visual tasks as due to signal enhancement, distractor exclusion, or internal noise suppression. Based on a noisy Perceptual Template Model (PTM) of a human observer, the method adds increasing amounts of external noise (white gaussian random noise) to the visual stimulus and observes the effect on performance of a perceptual task for attended and unattended stimuli. The three mechanisms of attention yield three "signature" patterns of performance. The general framework for characterizing the mechanisms of attention is used here to investigate the attentional mechanisms in a concurrent location-cued orientation discrimination task. Test stimuli—Gabor patches tilted slightly to the right or left—always appeared on both the left and the right of fixation, and varied independently. Observers were cued on each trial to attend to the left, the right, or evenly to both stimuli, and decide the direction of tilt of both test stimuli. For eight levels of added external noise and three attention conditions (attended, unattended, and equal), subjects' contrast threshold levels were determined. At low levels of external noise, attention affected threshold contrast: threshold contrasts for non-attended stimuli were systematically higher than for equal attention stimuli, which were, in turn, higher than for attended stimuli. Specifically, when the rms contrast of the external noise is below 10%, there is a consistent 17% elevation of contrast threshold from attended to unattended condition across all three subjects. For higher levels of external noise, attention conditions did not affect threshold contrast values at all. These strong results are characteristic of a signal enhancement, or equivalently, an internal additive noise reduction mechanism of attention.

Visual attention   Signal enhancement   Distractor exclusion   Internal noise suppression   Additive internal noise   Multiplicative internal noise   Equivalent internal noise   Perceptual template model   Concurrent paradigm

INTRODUCTION

For more than 100 years, selective attention has fascinated sensory physiologists and psychologists. Pioneer investigators, including Mach, Fechner, Wundt, Titchener and James (Fechner, 1860; James, 1890; Wundt, 1902; Pillsbury, 1908; Titchener, 1908), debated whether attention affects the perceived quality of objects, such as the brightness of a light patch, the loudness of a musical tone, the clarity of a visual pattern, or the vividness of a certain color. Much of this early work was introspective in character, and the views of these early theorists differed (James, 1890). Indeed, despite extensive subsequent research, we still have only the most rudimentary answer to the original question: Does attention affect the quality or strength of perception? It is very difficult to quantify or test the subjective appearance of perceived objects (but see Prinzmetal, Amiri & Allen, 1997). In this research we ask the somewhat more modest but substantially more tractable question of whether or not attention affects *performance* on perceptual tasks by a signal enhancement mechanism or by other means. Before describing our method for distinguishing mechanisms of attention, we briefly consider previous research in visual attention.

Attention to locations and features

Since the 1970s, selective attention has been the topic of intensive psychological research, much of which studied the consequences of attending to particular spatial locations and not to other spatial locations, or to particular features but not others. By cuing subjects to attend to a region of the visual field and varying the validity of the cues, it has been established that: (1) observers react faster to objects falling in the attended region than those in unattended regions (e.g., Eriksen & Hoffman, 1972; Posner, 1978, 1980; Nissen, 1985; Shiffrin, 1988; Sperling & Dosher, 1986); (2) observers

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are more accurate in classifying a stimulus in terms of brightness, orientation or form when it is in the attended region than when it is in the unattended region (e.g., Shaw & Shaw, 1977; Bashinski & Bacharach, 1980; Downing, 1988). By cuing subjects to stimulus features alone (independent of spatial location), it has been shown that: (3) observers react faster to a stimulus of an expected size than to an unexpected size (Larsen & Bundesen, 1978; Cave & Kosslyn, 1989); (4) observers detect a stimulus with an expected spatial frequency with higher accuracy than stimuli with an unexpected spatial frequency (Davis & Graham, 1981; Shulman & Wilson, 1987; Sperling, Wurst & Lu, 1993); and however (5) in certain situations, observers' performance on stimuli with the attended feature is not better than those with unattended features (Tsal & Lavie, 1988; Cave & Pashler, 1995; Shih & Sperling, 1996).

The theoretical interpretation of these empirical facts is less clear. In cases (1), (3) and (4), for example, it is often not possible to conclude immediately that attention has truly changed perceptual discriminability as opposed to changing criteria, or changing the decision structure of the task (see Sperling & Dosher, 1986 for a review of these issues, and Palmer, Ames & Lindsey, 1993 for a recent application). In case (2), sufficient experimental controls were provided to determine that perceptual discriminability improved in attended locations. However, these investigations tell us nothing about the specific attentional mechanism leading to the improved discriminability. Improvements in discrimination could be the result of perceptual enhancement (Prinzmetal *et al.*, 1997), or response competition (Pohlmann & Sorkin, 1976; Duncan, 1980, 1984), or of a number of other mechanisms.

Mechanisms of attention

In order to explain the various documented effects of selective attention in human information processing, researchers have proposed a number of possible mechanisms through which selective attention might operate: a filter (Broadbent, 1958), effort (Kahneman, 1973), resources (Shaw & Shaw, 1978), a control process of short-term memory (Shiffrin & Schneider, 1977), orienting (Posner, 1980), conjoining object features (Treisman & Gelade, 1980), a moving spotlight (Tsal, 1983), a gate (Reeves & Sperling, 1986), a zoom lens (Eriksen & St. James, 1986), and both a selective channel and a preparatory activity distribution (LaBerge & Brown, 1989). While these metaphoric models of attention make strong suggestions about how attention operates, and in certain cases even admit quantitative applications (Reeves & Sperling, 1986), we take an alternative approach.

We suggest a formal perceptual decision structure and develop and test models of attentional effects that focus on modulation of perceptual discriminability (signal and noise levels) in the cognitive processes. We outline three mechanisms of attention.

1. In signal enhancement, attention enhances the strength of the signal.
2. In distractor exclusion, attention narrows a filter (i.e., feature template) that is processing the stimulus so that distractors (or external noise) is differentially excluded.
3. In internal noise reduction, attending reduces internal noise associated with perceptual processing. (We will distinguish additive and multiplicative internal noise, explained below).

Evidence that may relate to these mechanisms has already been cited: in some cases, attention acts to increase the signal to noise ratio in perceptual processes (Bashinski & Bacharach, 1980; Downing, 1988), to exclude distractors (Davis & Graham, 1981; Shiu & Pashler, 1994), or to decrease variance in perceived quality of signal (Prinzmetal *et al.*, 1996). However, these suggestive results need to be studied systematically within a coherent theoretical framework, and with more powerful empirical methods.

We develop a novel paradigm which manipulates the stimulus through the addition of external noise, and the observer through attention instructions. Using newly developed mathematical predictions for the external noise plus attention paradigm, we can fully and quantitatively characterize the attentional mechanism(s) mediating performance under different attentional instructions for a wide range of particular perceptual tasks. Signal enhancement (or equivalently, additive internal noise reduction) is characterized by divergence between attentional conditions at low, but not high levels of external noise; distractor suppression is characterized by divergence between attentional conditions at high, but not low levels of external noise; and (multiplicative) internal noise reduction is characterized by divergence between attentional conditions at both low and high levels of external noise. Any attention effect must manifest itself either in the low noise region, the high noise region, or both the low and the high noise regions. Our model provides an explanation for each of these patterns, and in this sense fully characterizes attention effects.

In this article, we first develop the noisy Perceptual Template Model (PTM) and derive mathematical predictions for the performance of the model under each of the three attention mechanisms. We then apply the general method to the study of attention mechanisms in a location-cued orientation discrimination task.

THEORY

The Perceptual Template Model (PTM)

Internal noise

Perceptual processing by human observers, especially near threshold, is characterized by limits imposed by some combination of neural randomness, limitations of coarse coding of stimulus properties, loss during information transmission, etc. These various inefficiencies can be simply characterized in terms of the *equivalent* internal noise—the amount of random internal noise necessary to produce the degree of inefficiency in processing exhibited by the perceptual system. In

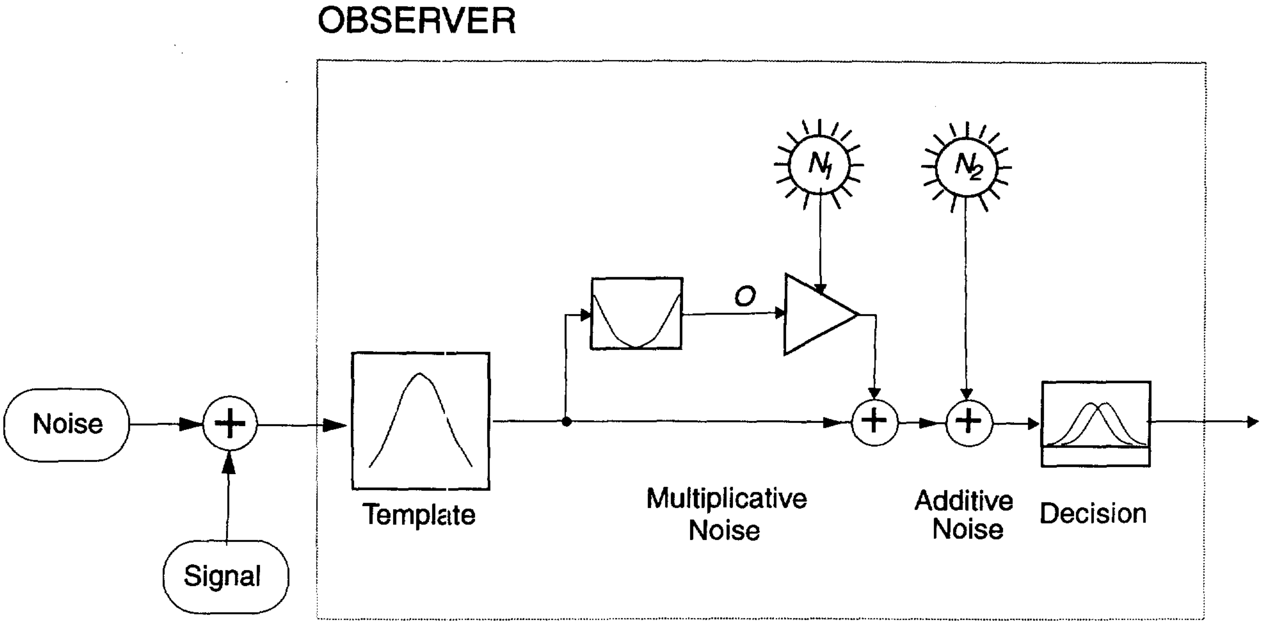

FIGURE 1. Noisy perceptual template model. It consists of four major components: (1) a perceptual template; (2) a multiplicative internal noise source, N_1; (3) an additive internal noise source, N_2; and (4) a decision process. The box with U-shaped function represents possibly non-linear full-wave rectification; the triangle denotes an amplifier which multiplies its two inputs to produce an output. A good example of a perceptual template is a spatial frequency filter *F(f)*, with a center frequency and a bandwidth such that a range of frequencies adjacent to the center frequency pass through with smaller gains. Limitations of human observers are modeled as equivalent internal noise. Multiplicative noise is an independent noise source whose amplitude is proportional to the (average) amplitude of the output from the perceptual template. Additive internal noise is another noise source whose amplitude does not vary with signal strength. Both multiplicative and additive noises are added to the output from template matching, and the noisy signal is submitted to a decision process. Depending on the task, the decision could reflect either detection or discrimination, and could take the form of either *N*-alternative forced choice or "yes"/"no" with confidence rating.

applications of signal detection theory to perception and to memory, for example, it is commonly understood that predicted performance depends critically on the variance of the noise distributions (Green & Swets, 1966), and that various processing inefficiencies such as criterion variability can be equivalently modeled by altering the variance of noise distributions (Wickelgren, 1968). Although modeling processor inefficiencies in terms of equivalent internal noise does not distinguish between various reasons for the inefficiency, it allows us to quantify perceptual loss with respect to performance losses arising from external noise, and further allows the comparison of different perceptual tasks.

External noise manipulations

External noise, also called "equivalent input noise", is frequently used in electrical engineering to measure the properties of noisy amplifiers (North, 1942; Friis, 1944; Mumford & Schelbe, 1968). The method has also been adopted by psychologists to study a wide range of perceptual processes (Fletcher, 1940; Barlow, 1956, 1957; Swets, Green & Tanner, 1962; Greis & Rohler, 1970; Pollehn & Roehrig, 1970; Carter & Henning, 1971; Stromeyer & Julesz, 1972; Harmon & Julesz, 1973; Pelli, 1981, 1990; Henning, Hertz & Hinton, 1981; Pavel, Sperling, Riedl & Vanderbeek, 1987; Riedl & Sperling, 1988; Parish & Sperling, 1991). The basic idea is to estimate the amount of internal noise and characteristics of the perceptual processes by studying how performance in some task is affected by experimenter-manipulated external noise.

Noisy perceptual template model

The external noise method is applied here to perceptual detection or perceptual discrimination tasks. Perceptual task performance is modeled as the combination of outputs from a perceptual process—a "template"—and (additive or multiplicative) internal noise sources. The noisy template model shown in Fig. 1 consists of (1) a perceptual template; (2) a multiplicative internal noise source;* (3) an additive internal noise source; and (4) a decision process. Consider each component in turn.

A perceptual template with certain tuning characteristics. The first component of the model is a

*Some authors in the equivalent noise literature (e.g., Pelli, 1981) did not include multiplicative noise in their models. In most cases, these authors considered only low contrast regions (<10%) or considered such restricted ranges of external noise levels that a distinction between additive and multiplicative noise was not warranted. However, multiplicative noise has been considered by numerous studies (e.g., Nachmias & Sansbury, 1974; Stromeyer & Klein, 1974; Legge & Foley, 1980; Burbeck & Kelly, 1981) and is absolutely necessary to account for our data (see section entitled "*Fitting the PTM models*" for a detailed discussion).

perceptual processor, termed a perceptual template. A good example of a perceptual template is a spatial frequency filter $F(f)$, with a center frequency and a bandwidth such that a range of frequencies adjacent to the center frequency pass through with smaller gains. A perceptual template might, however, be far more complex, for example, a template for an alphanumeric character. Because the ultimate goal of the PTM is to account for human decisions, we could cast the output of the perceptual template as a vector in decision space. In the experimental example we consider here, the decision axis is one-dimensional (1-D) so the outcome of perceptual processing may be coded as a scalar. Say that the gain (height) of the filter for a signal-valued stimulus is β. Then the output signal amplitude S for a signal stimulus of contrast c is:

$$S = \beta c. \tag{1}$$

External noise—noise added to the stimulus by the experimenter, like the stimulus, is processed through the perceptual template. If the external noise has a gaussian histogram, the output noise from the perceptual template also has a gaussian histogram; this is so because the template functions as an integrator. We label the standard deviation of the noise output from the perceptual template associated with the external noise N_{ext}. (In fact, the relationship between the weight given to a signal-valued stimulus, β, and the value of N_{ext} passed through the perceptual template or filter may be known only up to a constant. We characterize this as ΓN_{ext}, and further simplify the development by assuming $\Gamma = 1$, which is equivalent to an assumption that the integral of the gains for the attention-neutral perceptual template is normalized to 1.)

Multiplicative internal noise. Perceptual task performance (e.g., signal detection) is limited by properties of the stimulus (signal contrast, amount of external noise) and by properties of the human observer (randomness and inefficiencies of the processing). The human limits are modeled as equivalent *internal* noise. Internal noise is either multiplicative or additive. Multiplicative noise is a natural way of characterizing tasks in which, for example, perceived sensory variability, or perceived differences, are proportional to signal strength (Weber-law situations). Multiplicative noise is an independent noise source whose magnitude is a function of the contrast in the external stimulus, as processed through the perceptual template. Independent multiplicative noise is modeled as a gaussian random variable with mean 0 and standard deviation of N_1, multiplied by some measure of the output amplitude of the perceptual template. The measure of output amplitude of the perceptual template reflects the total contrast (power) ($\|.\|^2$) of the signal and the external noise, possibly raised to a power γ in order to account for saturating or compressive nonlinearities. Further, the multiplier on the multiplicative noise is a function of the output amplitude of the perceptual template integrated over some brief period of time and small area of space (locally space–time averaged). The exact nature of the space and time averaging might change the relative weight of the signal and external noise; however, this is equivalent to a change in the parameter β. Hence the standard deviation of the multiplicative noise N_{mul} is:

$$N_{\text{mul}} = N_1 \left(\sqrt{\beta^2 c^2 + N_{\text{ext}}^2} \right)^{\gamma}. \tag{2}$$

The formulation of multiplicative noise is mathematically equivalent to a theory of contrast gain control (e.g., Legge & Foley, 1980; Carlson & Klopfenstein, 1985; Sperling, 1989).*

Additive internal noise. Recall that human processing limits are modeled as equivalent *internal* noise, which may be either multiplicative or additive. In contrast with multiplicative internal noise, the amplitude of additive internal noise does not vary with signal strength. Independent additive noise is modeled as a gaussian random variable with mean 0 and standard deviation N_2. One could include internal additive noise early and/or late in the process. For brevity, Fig. 1 shows late additive noise because this is consistent with our subsequent data.

Decision process. Both multiplicative and additive noises are added to the output from template matching, and the *noisy* signal is submitted to a decision process. Depending on the task, the decision could reflect either detection or discrimination, and could take the form of either N-alternative forced choice or "yes"/"no" with confidence rating. These different tasks are modeled in detail elsewhere (see MacMillan & Creelman, 1991). Our development here is general, and focuses on the characteristic patterns of signal to noise ratios over manipulations of external noise and attention. The details of one specific application to a discrimination task are illustrated in the experimental application.

Threshold predictions for white gaussian external noise

In this section, we describe how an observer's perceptual threshold depends on the amplitude of the external noise added to the signal. In visual tasks, the signal and the noise are rendered as intensities (graylevels) of pixels on a screen. Figure 2(a) shows "white gaussian noise" samples of increasing amplitude, and Fig. 2(b) shows corresponding signal plus noise samples. In this example, the signal is a Gabor patch—a spatially windowed 1-D sine wave. "White gaussian noise" refers to noise whose pixel graylevels are jointly independent identically distributed gaussian random variables. In consequence, the pixel gray-level histogram is gaussian

*This form is related, but not identical to a development of properties of neural responses by Geisler and Albrecht (1995), in which the variance of a neural response is proportional to the mean response. Geisler and Albrecht's equations do not consider additive noise; and our multiplicative noise equation is somewhat simpler than theirs. However, the predictions are qualitatively similar.

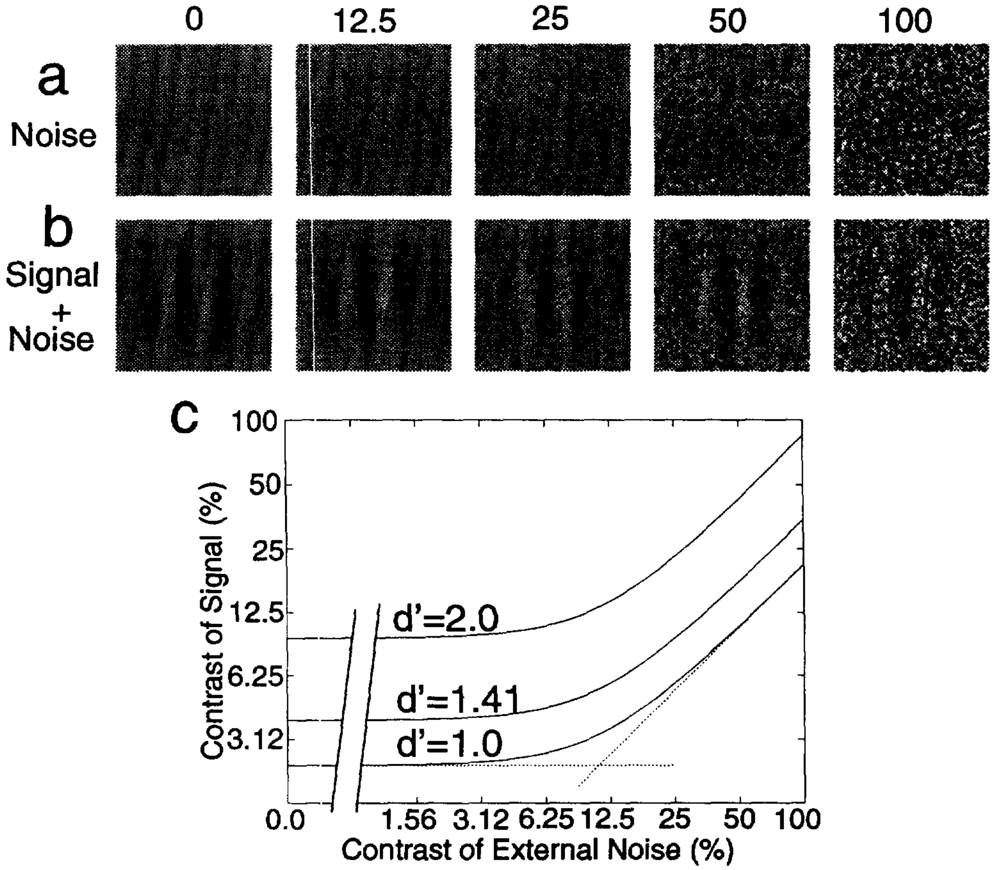

FIGURE 2. Contrast threshold of the noisy perceptual template model as a function of the contrast of the external noise for three different performance levels (d' = 1, 1.41, 2.0). (a) External gaussian white noise. From left to right, the contrast of the noise increases from 0 to 100%. (b) Signal + external noise. Different amount of external gaussian noise (a) is linearly superimposed on a Gabor with constant contrast. The detectability of the Gabor deteriorates with the amplitude of the added external noise. (c) Contrast threshold of the noisy perceptual template model as a function of the external noise amplitude for three d' levels. For each d' level, the contrast threshold is a constant when the amplitude of the external noise is small; it increases with the amplitude of the external noise at high noise amplitudes. In that range, external noise dominates internal noise; performance is mostly determined by the amount of external noise.

and it has equal Fourier energy at all the spatial frequencies.

Signal discriminability, d', is determined by the strength of the signal, S, and the standard deviation of the total noise (external and internal), σ_N:

$$d' = S/\sigma_{\mathrm{N}}. \tag{3}$$

The signal strength is determined by the template gain constant for the signal, β, and the signal contrast, c. Since all the noise sources (external, multiplicative, and additive noise) in the perceptual template model are independent (Legge & Foley, 1980; Carlson & Klopfenstein, 1985; Sperling, 1989) the total variance of the noise σ_{N}^2 is the sum of the variances of all the noise sources:

$$\begin{aligned}\sigma_{\mathrm{N}}^2 &= N_{\mathrm{ext}}^2 + N_{\mathrm{mul}}^2 + N_{\mathrm{add}}^2 \\ &= N_{\mathrm{ext}}^2 + N_1^2(\beta^2 c^2 + N_{\mathrm{ext}}^2)^\gamma + N_2^2. \end{aligned} \tag{4}$$

Combining these facts [equations (1, 3) and equation (4)]:

$$d' = \frac{\beta c}{\sqrt{N_{\mathrm{ext}}^2 + N_1^2(\beta^2 c^2 + N_{\mathrm{ext}}^2)^\gamma + N_2^2}}. \tag{5}$$

Each of the noise distributions is assumed to be gaussian, so that the sum of the noise distributions is also gaussian. This assumption is not critical to any of the development outlined above, but it does simplify the application to signal detection estimation—the gaussian noise distribution allows us to use the gaussian form of signal detection calculations (see the experiment for details).

An experiment might present a single fixed signal contrast and measure d' for various noise conditions. However, this procedure is too dependent on the tails of distributions to be usable over a full range of external noise levels. Instead, the contrast of the signal is manipulated to achieve a particular threshold level of d' (or, equivalently, 2 AFC percent correct) for each level of external noise. To simplify the current development, we restrict ourselves to situations where $\gamma = 1$, unless otherwise specified. (For the more general case where γ is different from 1, see the model-fitting section following the experiment. Additionally, the Appendix describes a numerical procedure developed to iteratively solve the equation for a threshold value of contrast c_τ for cases where $\gamma \neq 1$.)

For a fixed d', we can rearrange equation (5) to express the required threshold signal contrast c_τ as a function of the amount of external noise:

$$c_\tau = \sqrt{\frac{(1+N_1^2)N_{ext}^2 + N_2^2}{\beta^2(1/d'^2 - N_1^2)}}. \tag{6}$$

Figure 2(c) plots threshold contrast of the signal, c_τ, as a function of the contrast (variance) of the external noise N_{ext} at three fixed threshold levels ($d' = 1$, 1.41, 2) for a hypothetical case in which $\gamma = 1$, $N_1 = 0.45$, $N_2 = 0.0625$ and $\beta = 2.4$. It is convenient for this purpose to plot these on a log–log scale. Taking logs of equation (6) yields:

$$\log(c_\tau) = 1/2\log((1+N_1^2)N_{ext}^2 + N_2^2) - 1/2\log(1/d'^2 - N_1^2) - \log(\beta). \tag{7}$$

Such graphs possess a characteristic shape: (1) When the contrast (variance) of the external noise N_{ext} is very small, threshold signal contrast c_τ does not vary with the amount of external noise because internal noise N_2 dominates external noise. (2) When the contrast of external noise N_{ext} is very large, $\log(c_\tau)$ increases as a linear function of $\log(N_{ext})$ because external noise dominates internal noise. (3) When the external noise (N_{ext}) has intermediate contrast, there is a smooth transition from the region where internal noise is dominant to the region where external noise is dominant. Graphs of this kind are sometimes called threshold versus contrast, or TvC, graphs (e.g., Blakemore & Campbell, 1969).

Of course, in any real application, γ, N_1, N_2 and β are unknown quantities and must be determined from the experimental data. These values can be estimated from data such as that in Fig. 2(c) by non-linear estimation techniques.* The power of the external white gaussian noise manipulation is that it enables us to estimate the contributions of both kinds of internal noises, the multiplicative internal noise N_1 and the additive internal noise N_2. These internal noise estimates characterize the inefficiencies in the human processing system.

Attention Plus External Noise Manipulations

We are now able to turn to the main purpose of this development, which is a characterization of attention mechanisms. Theoretical predictions are developed for the performance of the perceptual template model (PTM) under both attention and external noise manipulations. We consider three classic proposed mechanisms of attention-signal enhancement, distractor exclusion, and internal noise reduction—and identify how each mechanism would operate under the PTM model. The signature performance patterns derived here for signal enhancement, distractor exclusion and noise suppression do not include consideration of uncertainty phenomena which would be relevant to certain tasks. In this paper, we choose a task which does not require uncertainty computations. Alternatively, one could correct for uncertainty effects to yield true d' measures, to which these signatures should apply.

Signal enhancement

One classic view (Wundt, 1902; see Prinzmetal *et al.*, 1997 for a review) is that attention somehow enhances the perceptual strength of the signal. In the context of the PTM, signal enhancement is operationalized as an attentionally manipulated increase (or decrease) of the gain on the output of the perceptual template [Fig. 3(a)]. (Since the output of the perceptual template depends on both the signal and the external noise, perhaps a better label for signal enhancement would be stimulus enhancement.) Attended regions might be enhanced by multiplying the output of the perceptual processors in those regions by a factor $A_1 > 1.0$, and unattended regions might be attenuated by multiplying the output by a factor $A_1 < 1.0$. Thus, attention "turns up the gain" in certain regions, and "turns down the gain" in others. Signal enhancement applies to the signal *and* to the external noise—both are amplified by a factor A_1.

In order to see the consequences of this for the relation between $\log(c_\tau)$ and $\log(N_{ext})$ in the simple case where $\gamma = 1$, we simply substitute A_1c for c and A_1N_{ext} for N_{ext} in equation (7), and find that:

$$\log(c) = 1/2\log((1+N_1^2)N_{ext}^2 + N_2^2/A_1^2) - 1/2\log(1/d'^2 - N_1^2) - \log(\beta). \tag{8}$$

(Notice that enhancing the signal by a factor of A_1 is mathematically equivalent to reducing the additive internal noise N_2 by a factor of $1/A_1$ if $\gamma = 1$.)

What is the signature of signal enhancement in performance? In Fig. 3(b), we plot $\log(c_\tau)$ vs $\log(N_{ext})$ at a fixed performance level ($d' = 1$) for three attention conditions (attended: $A_1 = 1.414$; equal attention: $A_1 = 1$; and unattended: $A_1 = 0.707$) in the hypothetical situation where $\gamma = 1$, $N_1 = 0.45$, $N_2 = 0.0625$, and $\beta = 2.4$. The signature feature of these curves is that they split at low external noise levels, and they overlap with each other at high external noise levels. Signal enhancement cannot improve performance in the region where external noise dominates because enhancement applies equally to the external noise and the signal. The parameters γ, N_1, N_2/A_1 and β can be estimated from experimental data for each attention condition. The size of the attention effect can be quantified in terms of the ratio of performance in the attended, unattended, and equal attention conditions.

To summarize, if attention enhances attended signals, it will only be effective when internal noise dominates external noise; when external noise is high (and where $\gamma = 1$), attention will neither improve nor damage performance.

Distractor exclusion

Another common view (e.g., Davis & Graham, 1981;

*Alternatively, simple equations can be derived which allow us to compute estimates of certain of these parameters from relations in the data. We do not develop the details here; measurements of thresholds at three different performance levels are required.

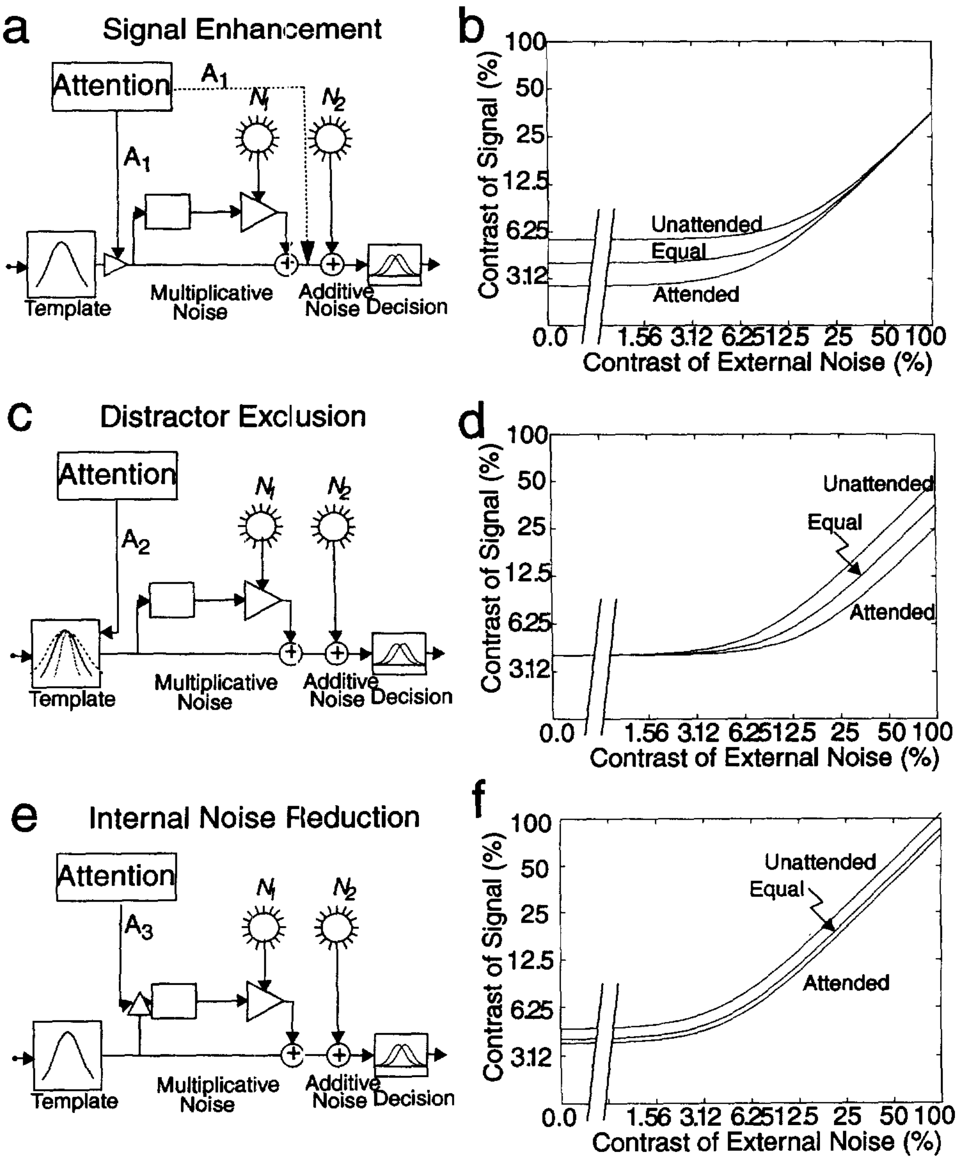

FIGURE 3. Three possible attention mechanisms and the performance of the noisy perceptual template model under each of the three possible mechanisms. (a) A PTM model in which attention operates via signal enhancement. (b) Prediction of performance of the model in (a): signal threshold of the PTM model vs external noise contrast. These curves split at low external noise levels, and they overlap with each other at high external noise levels. Signal enhancement can only improve performance in low external noise levels. (c) A PTM model in which attention operates via distractor exclusion. (d) Prediction of performance of the model in (d). The signature feature of these curves is that attention only modulates performance at high levels of external noise. (e) A PTM model in which attention operates via internal multiplicative noise reduction. (f) Prediction of performance of the model in (g). Attention affects performance at all levels of external noise, but increasingly so as external noise increases.

Shiu & Pashler, 1994) is that attention allows you to exclude distractors that differ along some significant dimension from the signal. We call this proposed mechanism "distractor exclusion". Distractor exclusion is operationalized within the PTM model as changing the tuning function of the perceptual template. If attending narrows the tuning function, noise, or distractors, may impact less on the output of the perceptual template. In Fig. 3(c), attention modulates the width of the perceptual template by multiplying the width of the function with $A_2 < 1.0$ in attended conditions and with $A_2 > 1.0$ in unattended conditions.*

Suppose that narrowing the tuning function changes the area under it by a factor of A_2. This would reduce the effective external noise by a factor of A_2, presumably without affecting the effective signal. In this case, the relation between $\log(c_\tau)$ and $\log(N_{\text{ext}})$ is derived from equation (7) by substituting A_2N_{ext} for N_{ext}:

$$\log(c_\tau) = 1/2\log((1+N_1^2)A_2^2N_{\text{ext}}^2+N_2^2) -1/2\log(1/d'^2-N_1^2)-\log(\beta). \quad (9)$$

What is the signature of distractor exclusion in

*Certain paradigms with filter shape changes may require changes in the gain of the signal, i.e., β, as well as filter width.

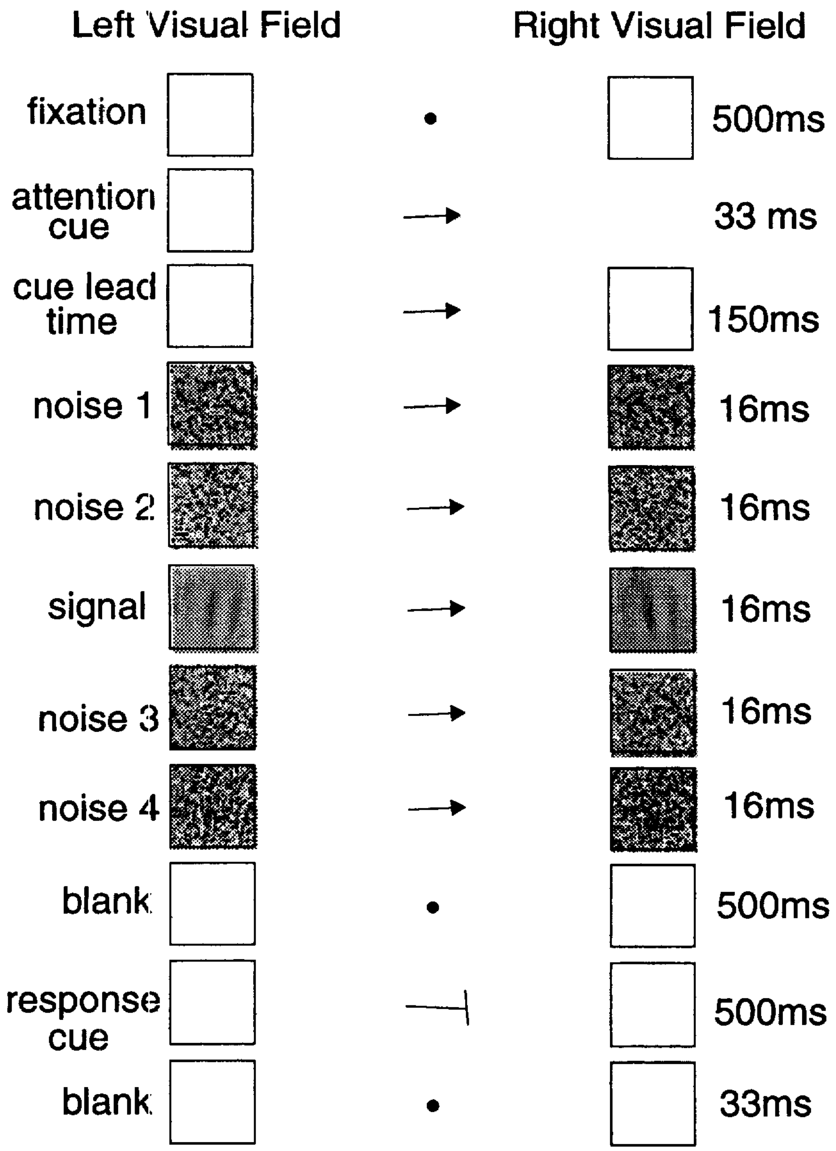

FIGURE 4. Experimental procedure. Following a subject keypress, a fixation display appears for 0.5 sec. The fixation display includes two square-frames, each displaced 3 deg to left or right of the central fixation point. Then the 33 msec attention cue replaces the fixation dot, instructing the observer to attend to the right (or left, or equally to both sides). The cue appears 150 msec prior to the stimulus. During this time period, the right square (or left, or both) blinks, creating a peripheral event at the attended location. The stimulus includes, in sequence, two noise frames, a signal frame, and two noise frames. All noise samples in each trial are independent samples with the same variance (contrast), as the signal frames on the left and right. Each frame appears for 16 msec, so the total time from the beginning of the attention cue to the end of the signal frame is only 233 msec; this precludes an eye movement to the attended location. After the stimulus sequence, the fixation display reappears for 500 msec, followed by a 500 msec response cue instructing the subject to report the orientation of first the right and then the left signal Gabor. The trial ends with the fixation display and auditory feedback for both left and right responses.

performance? In Fig. 3(d), we plot $\log(c_T)$ *vs* $\log(N_{ext})$ at a fixed performance level ($d' = 1$) for three attention conditions (attended: $A_2 = 0.707$; equal attention: $A_2 = 1$; and unattended: $A_2 = 1.414$) in the hypothetical situation where $\gamma = 1$, $N_1 = 0.45$, $N_2 = 0.0625$, and $\beta = 2.4$. The signature feature of these curves is that attention only modulates performance at high levels of external noise. Only when the external noise or distractors have a substantial effect on performance is reduction of that noise important. At low levels of external noise, internal noise dominates and template tuning does not impact on internal noise. Again, in an experiment, the parameters N_1, N_2, β and A_2 can be estimated from the data. The pattern of predictions holds even in cases where γ differs from 1.

To summarize, if attention changes the tuning of the perceptual template or perceptual processes, then attention can only modulate performance when external noise dominates internal noise.

Internal noise reduction

Another often suggested mechanism of attention involves the reduction of internal noise for the attended stimulus (e.g., LaBerge, 1995). As it happens, the reduction of additive noise is formally equivalent to the enhancement of signal [see equation (8)] in the special case where $\gamma = 1$. In this section we consider an attentional mechanism which modulates multiplicative internal noise by changing the gain on the independent multiplicative noise [Fig. 3(e)]. Changing the gain of the multiplicative noise by a factor of A_3 is equivalent to substituting A_3N_1 for N_1 in equation (8), to yield:

$$\log(c_\tau) = 1/2\log((1 + A_3^2N_1^2)N_{\text{ext}}^2 + N_2^2) - 1/2\log(1/d'^2 - A_3^2N_1^2) - \log(\beta). \quad (10)$$

The signature of an attentional modulation of multiplicative internal noise is shown in Fig. 3(f), where we plot $\log(c_\tau)$ vs $\log(N_{\text{ext}})$ at a fixed performance level ($d' = 1$) for three attention conditions (attended: $A_3 = 0.707$; equal attention: $A_3 = 1$; and unattended: $A_3 = 1.414$) in the hypothetical situation where $N_1 = 0.45$, $N_2 = 0.0625$, and $\beta = 2.4$. Attention affects performance at all levels of external noise. Generally, attention affects the high external noise regions somewhat more than low external noise regions. Furthermore, the magnitude of the attention effect depends on the particular d'. This feature distinguishes multiplicative noise reduction from a mixture of signal enhancement and distractor exclusion, where the magnitude of attention effect does not change with d'.

To summarize, if attention modulates multiplicative internal noise, it affects performance at all external noise levels, with slightly larger effects when external noise dominates internal noise.

EXPERIMENT

In this section, we apply the attention plus external noise paradigm to study attention mechanisms in a location-cued orientation discrimination task. The particular task was chosen because location cuing of orientation judgments is one of the few paradigms in the literature with clearly demonstrated attentional control over discriminability in a perceptual task (Downing, 1988).

We chose a concurrent design in which stimuli are independently varied at each stimulus location and the subject was required to make an independent response for every stimulus location. This has the advantage of avoiding statistical uncertainty issues in the decision process in compound paradigms, in which only one detection response is required in a trial involving multiple locations (see Sperling & Dosher, 1986; Dosher & Sperling, forthcoming, for reviews).

In this experiment, the display always consisted of a test stimulus on both the left and the right of fixation. Observers were cued on each trial to attend to the location on the left of fixation, the location on the right of fixation, or to attend evenly to both locations. The observers always report on both left and right. Each test stimulus was a Gabor test patch oriented slightly (top) to the right or (top) to the left, and the stimuli on the left and right of fixation vary independently. To this basic stimulus was added various amounts—from 0 to moderately high contrast—of random external noise. In the experiment, the threshold signal contrast level for each subject in performing the orientation discrimination task was determined for all combinations of attention conditions and external noise levels.

Method

Stimulus and display. The "signal" in the experiment consisted of Gabor patterns tilted either θ deg to the left or θ deg to the right of vertical (Fig. 4):

$$l(x,y) = l_0\left(1.0 + c\sin(2\pi f(x\cos(\theta) \pm y\sin(\theta))\exp\left(-\frac{x^2+y^2}{2\sigma^2}\right)\right) \quad (11)$$

For subject ZL, $\theta = 10$ deg; for subjects HS and EB, $\theta = 12$ deg. Each Gabor extended $1.5 \times 1.5\ \text{deg}^2$, with a center frequency $f = 2.5$ cycle/deg, and a standard deviation $\sigma = 0.6$ deg. The mean luminance l_0 is 169 cd/m^2. The maximum contrast of each Gabor varied so as to generate psychometric functions, at levels dependent upon the level of external noise. The center of the left/right Gabor is displaced 3 deg to the left/right of the fixation point.

The pixel gray-levels of each external noise frame were sampled from a gaussian distribution with a mean of 0 and a variance depending on the amount of external noise desired. Noise frames had the same size as that of the signal frames, with each pixel subtending $0.05 \times 0.05\ \text{deg}^2$ visual angle. To ensure that the external noise did conform to the gaussian distribution, the maximum standard deviation of the noise was kept below 33% maximum achievable contrast.

Apparatus. Both signal and noise frames were generated off-line using the HIPS image processing software (Landy, Cohen & Sperling, 1984a; Landy, Cohen & Sperling, 1984b) and displayed using a program based on a software package (Runtime Library for Psychology Experiments, 1988) on an IKEGAMI DM516H monochrome monitor driven by an AT-Vista video graphics board in an IBM 486PC computer. The monitor has a fast, white P4-type phosphor, and a 60 Hz refresh rate. While many monitors have pixel interactions so that the intensity of an isolated pair of adjacent intensified horizontal pixels is different from a pair of adjacent vertical pixels, the IKEGAMI DM516H monitor has a sufficiently extended temporal frequency response to reduce such interactions to insignificance. A special circuit that combines two graphics card output channels produces 4096 distinct gray levels (12 bits).

The luminance of the monitor was 12.1 cd/m^2 when every pixel was assigned the lowest gray level and 325 cd/m^2 when every pixel was given the greatest gray level. We chose the background luminance to be that value which, when it is assumed by every pixel, produces 0.5*(325 + 12.1) = 169 cd/m^2. A lookup table was generated by means of a psychophysical procedure that

TABLE 1. Estimated threshold values for the experiment

Noise	Attn	ZL α	ZL η	HS α	HS η	EB α	EB η
	attn	0.0286	3.21	0.0346	3.18	0.0384	2.85
0	eq	0.0337	3.39	0.0359	2.11	0.0400	3.44
	unat	0.0349	3.73	0.0413	2.91	0.0432	3.42
	attn	0.0279	2.99	0.0311	2.25	0.0387	4.19
0.021	eq	0.0311	3.39	0.0349	2.55	0.0400	2.51
	unat	0.0324	2.94	0.0416	3.71	0.0451	4.58
	attn	0.0298	2.05	0.0368	2.85	0.0384	2.52
0.041	eq	0.0327	2.31	0.0378	2.33	0.0448	3.04
	unat	0.0349	1.91	0.0397	2.85	0.0470	1.68
	attn	0.0314	2.48	0.0406	1.91	0.0425	2.77
0.082	eq	0.0343	1.91	0.0457	1.17	0.0454	2.07
	unat	0.0375	2.09	0.0495	1.58	0.0483	2.46
	attn	0.0502	1.88	0.0594	1.28	0.0552	1.72
0.123	eq	0.0508	1.67	0.0670	1.40	0.0568	1.44
	unat	0.0524	1.91	0.0714	2.22	0.0641	2.57
	attn	0.0683	1.92	0.100	1.90	0.0819	1.77
0.164	eq	0.0721	1.92	0.0994	1.84	0.0810	1.33
	unat	0.0730	2.49	0.102	2.24	0.0857	1.50
	attn	0.146	1.91	0.175	0.99	0.167	0.95
0.246	eq	0.140	1.33	0.178	0.62	0.168	1.67
	unat	0.146	1.80	0.179	1.24	0.172	1.88
	attn	0.219	2.86	0.308	0.81	0.306	1.05
0.328	eq	0.219	1.94	0.300	1.11	0.297	2.38
	unat	0.216	1.83	0.306	2.11	0.303	0.89

Note: the 10-point psychometric functions for each level of attention and of external noise were summarized with a Weibull function, where α estimates the 75% correct level of 2AFC performance, and η indexes the slope of the function.

linearly divided the whole luminance range into 256 gray levels. When extremely low contrasts were required by the experiment, a simpler lookup table was generated by linearly interpolating luminance levels around the background luminance (for contrasts less than 1%). All the displays were viewed binocularly with natural pupil at a viewing distance of 75 cm in a dimly lighted room (the average luminance in the room is approx. 10 cd/m^2). At this viewing distance, the monitor extended a 24 × 15 deg visual angle.

Design. Subjects' threshold signal contrasts were estimated for each attention condition and each external noise level. There were three attention (attended, equal attention, and unattended) and eight external noise level conditions (0, 0.02, 0.04, 0.08, 0.12, 0.16, 0.25, 0.33). The method of constant stimuli (Woodworth, 1938) with 10 different signal contrasts was used to generate psychometric functions at each of the 24 combinations of attention and external noise levels. There were at least 40 trials in each of the 240 conditions. All experimental conditions were intermixed in every session. Data were collected from each of three subjects in five sessions, each consisting of 960 trials and lasting approx. 1.5 hr.

Procedure. The display sequence of a typical trial is shown in Fig. 4. Following a subject keypress, a fixation display appears for 0.5 sec. The fixation display includes two square-frames, each displaced 3 deg to left or right of the central fixation point. Then the 33 msec attention cue replaces the fixation dot, instructing the observer to attend to the right (or left, or equally to both sides). The cue appears 150 msec prior to the stimulus. During this time period, the right square (or left, or both) blinks, creating a peripheral event* at the attended location (Yantis & Jonides, 1990). The stimulus includes, in sequence, two noise frames, a signal frame, and two noise frames. In this procedure, the noise is combined with the signal through temporal integration. All noise samples in each trial are independent samples with the same contrast (variance); the contrast levels of the signal frames on the left and right during a trial are also the same. Each frame appears for 16 msec, so the total time from the beginning of the attention cue to the end of the signal frame is only 233 msec; this precludes an eye movement to the attended location (Hallett, 1986). After the stimulus sequence, the fixation display reappears for 500 msec, followed by a 500 msec response cue instructing the subject to report the orientation of first the attended and then the unattended signal Gabor. The order of report was randomized in the equal attention condition. The trial ends with the fixation display and auditory feedback for both left and right responses.

Subjects. Two graduate students (SH and EB), naïve to the purposes of the experiments, and the first author (ZL) served as subjects in the experiment. All have corrected-to-normal vision.

Results

The two-alternative forced-choice (2AFC) percent correct for judgments of Gabor orientation on the left

*Further experiment suggested that this peripheral cue, when added to the central cue, did not have a substantial effect on subjects' performances.

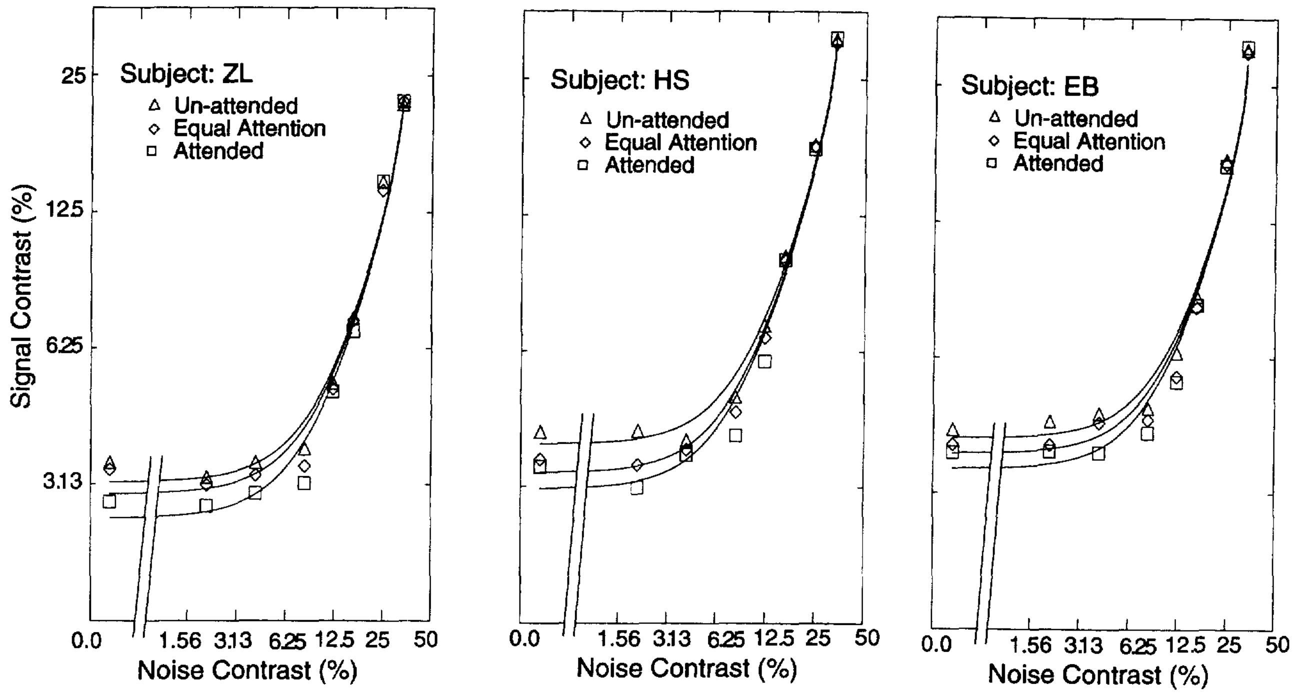

FIGURE 5. Threshold contrast (rms contrast of the Gabor) vs external noise level (rms contrast of the gaussian random noise) for three subjects each in three different attention conditions. The curves are generated from the best-fit PTM model with signal enhancement occurring after multiplicative noise. Attention affected threshold contrast only at low external noise levels. For higher levels of external noise, attention conditions did not affect threshold contrast values at all. Fitting PTM models to the data suggests that attention operates via signal enhancement after multiplicative noise, or equivalently, internal additive noise reduction.

and the right were tabulated. Data from attend-to-the-left and attend-to-the-right trials were collapsed and coded in terms of attended and unattended locations; the equal attention trials formed the third attention condition. These three attention conditions had been tested at 10 appropriate signal contrast levels at each of the eight external noise levels to yield 24 10-point psychometric functions.

In 2AFC paradigms such as this one, choosing a threshold value of percent correct is equivalent to choosing a threshold value for d' [see equation (6) and equation (7)] (MacMillan & Creelman, 1991). Threshold signal contrast (the rms contrast of the Gabor), c_T, yielding a threshold value of 75% correct performance level in 2AFC (equivalent to d' of 0.95) for orientation judgments was computed by fitting a Weibull function:

$$\text{Percent correct} = 1 - 0.5 \times 2^{-\left(\frac{c}{\alpha}\right)^{\eta}} \qquad (12)$$

to each of the 24 attention × external noise condition psychometric functions using a maximum likelihood procedure (Hays, 1981). In the Weibull, the parameter value α corresponds to the contrast yielding 75% correct performance, and the parameter value η indexes the slope of the function. Estimated values of α and η for all subjects and experimental conditions are summarized in Table 1.

Figure 5 plots the threshold signal contrast (α in the Weibull function, corresponding to 75% correct 2AFC performance) against external noise level (the rms contrast of the external noise) for each subject under all three attention conditions.

The pattern of results is quite obvious from Fig. 5: at low levels of external noise, attention affected threshold contrast-threshold contrasts for unattended stimuli were systematically higher than for equal attention stimuli, which were in turn higher than for attended stimuli. For higher levels of external noise, attention conditions did not affect threshold contrast values at all. This pattern held for all three subjects individually. These results qualitatively conform perfectly to the signature pattern for the signal enhancement (or, equivalently, internal additive noise reduction) mechanism of attention [see Fig. 3(a, b)].

The size of the attentional effect at low external noise levels (<10% rms contrast) can be expressed in several ways. For each of the three subjects, averaged over the low-noise region where attention operates, the attentional effect represents a 17% change in contrast threshold from attended to unattended conditions. This is equivalent to a 12% shift along a 2AFC psychometric function (50–100%) or 24% of the full psychometric function. The size of the effect is exactly in line with the prior effects on sensitivity (as distinct from bias) of attention to location. For example, the well-known sensitivity effect of attentional cuing of Bashinski and Bacharach (1980) was equivalent to 17% in 2AFC percent correct. The often-cited cuing effects of Downing (1988) were equivalent to 12–20% 2AFC percent correct, in a

TABLE 2. PTM Model with signal enhancement following multiplicative noise

Subject	Aattnd	Aeq	Anon	N1	N2	β	γ	r^2
ZL	1.12	1.00	0.948	0.939	0.115	4.81	1.17	0.9789
HS	1.08	1.00	0.879	0.942	0.098	3.62	1.16	0.9884
EB	1.07	1.00	0.936	0.952	0.128	4.69	1.12	0.9779

paradigm with far more attention competition for the memory supporting an extended response structure.

Fitting the PTM models

Although the qualitative pattern of these data is strong, we also quantitatively model the data using the PTM model. We focus on the signal enhancement variant of the PTM model, which yields the best qualitative and quantitative description of the pattern of attentional effects under different levels of external noise. A least-squares procedure was developed to fit the PTM model, with signal enhancement as the attentional mechanism, to the log threshold $\log(c_\tau)$ for each subject. This turned out to be non-trivial. It was necessary to develop and estimate parameters for the more complicated form of the PTM model with $\gamma > 1$.

Estimation procedure. Our estimation procedure was implemented in Matlab (The Mathworks, Inc.), and was applied separately to the data for each subject. (1) Computed $\log(c_\tau^{\text{theory}})$ from the PTM model with certain parameters for each attention and external noise contrast level; (2) computed the squared difference between the log threshold prediction from the model and the observed $sqdiff = (\log(c_\tau^{\text{theory}}) - \log(c_\tau))^2$ for each attention and external noise condition; (3) computed L: summation of *sqdiff* from all the attention and external noise conditions. (4) Used a gradient descending method to adjust the model parameters to find the minimum of L. (5) After obtaining the least L, computed the r^2 statistic to evaluate the goodness of model fit:

$$r^2 = 1.0 - \frac{\Sigma\left(\log(c_\tau^{\text{theory}}) - \log(c_\tau)\right)^2}{\Sigma(\log(c_\tau) - \text{mean}\ (\log(c_\tau)))^2} \qquad (13)$$

where Σ and *mean* () runs over all the data points for a particular subject.

A PTM model without multiplicative noise. In modeling signal contrast threshold as a function of external noise, certain authors (e.g., Pelli, 1981) in the equivalent noise literature consider only additive internal noise. While this model worked reasonably well in their limited problem domains, it is inadequate to account for our data.

The predicted relationship between signal contrast threshold vs external noise contrast in a PTM without multiplicative noise can be derived by simply setting N_1 to 0 in equation (8):

$$\log(c) = 1/2 \log\left(\frac{d'^2}{\beta^2}\left(N_{\text{ext}}^2 + N_2^2/A_1^2\right)\right). \qquad (14)$$

This model seriously misfits our data—although the model captures the generally increasing nature of the functions, there are substantial and systematic misfits over the entire range of noise values. Since this reduced model, excluding multiplicative noise, is nested within a fuller model, including both additive and multiplicative noise, the two can be statistically compared, and this oversimplified model can easily be rejected ($P < 0.0000001$). (The details appear below in the description of the fuller model and of nested model tests.)

Simple PTM model ($\gamma = 1$). We then fit the data with the simple PTM model ($\gamma = 1$) including both additive and multiplicative noises with a signal enhancement attention mechanism [equation (8)] to the data. Although the quality of fit as measured by r^2-values was reasonable ($r^2 = 0.9122, 0.9248, 0.8859$ for subjects ZL, HS and EB, respectively), there were serious systematic misfits of the data. Comparing the model predictions of $\log(c_\tau^{\text{theory}})$ to the observed $\log(c_\tau)$, it is apparent that the simple model misfits data in the high external noise region. The parameter γ determines the slopes of the TvC curves in the high external noise region. With $\gamma = 1$, the slope of this region should also be 1, yet these slopes are clearly significantly greater than 1 for all the subjects. A more general model with $\gamma > 1$ is necessary to fit the data.

PTM model with γ as a free parameter. For $\gamma > 1.0$—corresponding to slopes greater than 1.0 in the high external noise region—two different loci of signal enhancement (or additive noise reduction) must be considered. Signal enhancement (or additive noise reduction) might occur either before or after multiplicative noise. (These two loci generate mathematically equivalent c_τ vs N_{ext} relationships when $\gamma = 1$.)

Fortunately, we can easily reject a PTM model with signal enhancement before multiplicative noise because it makes a very counter-intuitive prediction that, at high external noise levels (in our experiment, for conditions with rms contrast >0.20), contrast thresholds for the unattended location should actually be smaller than for the attended location, although the reverse is true at low external noise levels.

Therefore, the discussion will be restricted to an analysis of the PTM model with signal enhancement after multiplicative noise. With this locus, the attentional gain A_1 is applied to everything before additive internal noise, including the signal S, the external noise N_{ext}, and multiplicative noise N_{mul}. Substituting A_1c for c in equation (1), A_1N_{ext} for N_{ext} and A_1N_{mul} in equation (4), we have:

$$d' = \frac{\beta A_1 c}{\sqrt{(A_1N_{\text{ext}})^2 + (A_1N_1)^{2*}(\beta^2c^2 + N_{\text{ext}}^2)^\gamma + N_2^2}}. \qquad (15)$$

Because it is not possible to solve this equation analytically for c_T, a numerical procedure was developed (Appendix I).

This model yielded a quite reasonable fit to all regions of the data. The resulting model parameters for each subject are listed in Table 2. The model predictions with fit parameters are shown as the solid lines with the data in Fig. 5. The model fits the data in the low and in the high external noise regions very well, as well as accommodating the substantial attentional effects in the low external noise region and the lack of attentional effects in the high external noise region.

The model slightly quantitatively misfits the data in the transitional region between the low and high external noise limbs. This is a consequence of slightly over-simplifying the mechanisms of contrast gain control by using a single γ to account for all contrast gain control non-linearities. More complex models of contrast gain control have been considered in order to account for the shape of individual TvC curves (Nachmias & Sansbury, 1974; Stromeyer & Klein, 1974; Legge & Foley, 1980; Burbeck & Kelly, 1981). Although more complex model variants might yield an improved fit to the exact shape of the TvC curves, the current model is more than adequate for our purpose of establishing the mechanism of attention, and estimating the size of the attentional effects.

Using the General PTM model with signal enhancement after multiplicative noise and $\gamma > 1$ as the fully saturated model, it was possible to apply an F test for nested (reduced) models to reject the Simple PTM model with $\gamma = 1$.

$$F(df_1, df_2) = \frac{\left(r^2_{\text{full}} - r^2_{\text{reduced}}\right)/df_1}{\left(1 - r^2_{\text{full}}\right)/df_2} \tag{16}$$

where $df_1 = k_{\text{full}} - k_{\text{reduced}}$, and $df_2 = N - k_{\text{full}} - 1$. The k's are the number of parameters in each model, and N is the number of predicted data points. In this case, $N = 24$, the number of parameters in the full $\gamma > 1$ model $k_{\text{full}} = 6$, the number of parameters in the reduced $\gamma = 1$ model $k_{\text{reduced}} = 5$. The r^2_{full} and r^2_{reduced} are taken from the General PTM model and the Simple PTM model fits, respectively. This test evaluates whether assuming that $\gamma = 1$ significantly damages the quality of the model fit. The values of $F(1,17)$ were 53.7, 93.2, and 70.8 for subjects ZL, HS and EB (all $P < 0.000005$). Hence, the Simple PTM model ($\gamma = 1$) can be rejected in favor of the General PTM model ($\gamma > 1$) with signal enhancement after multiplicative noise.

A comparable test comparing our General PTM model with the oversimplified, additive noise only, model also easily rejected that model (see the section "*PTM model without multiplicative noise*"). The values of $F(2,17)$ were 26.97, 46.60 and 35.38 for subjects ZL, HS and EB (all $P < 0.000001$).

PTM Model without attention effects. Quantitative application of the PTM model also allows the statistical evaluation of the attentional effects. In order to test whether there were significant attention effects, we estimated the model values N_l, N_2, β, γ from fitting the PTM model with signal enhancement after multiplicative noise to the data of each subject. The model was fit to the data in the lowest three external noise levels, where attention had an impact on performance. We compare the case where A_l for the attended location condition and for the non-attended location condition were allowed to vary to the case where all A_ls are set to 1. (A_l for the equal attention condition is set to 1 as a normalizing constant in all model fits.) For the data in the low noise region, the r^2s for the model with A_ls as free parameters are: 0.6519, 0.9999, and 0.7242 for subjects ZL, HS and EB; and the r^2s for the model with all A_ls set at one are: −0.2443, −0.3795 and −0.2475 for subjects ZL, HS and EB. (Again, negative r^2 indicate that the model is doing worse than simply assuming the mean of these data values.) The corresponding nested F tests allowed us to reject the hypothesis that attention had no impact on performance: $F(2,6) = 7.72$, 4127 and 10.57 ($P < 0.025$) for subjects ZL, HS, and EB.

The results of our quantitative treatment of the PTM model can be summarized as follows: attending to a location enhances the signal at that location, on average, by a factor of 1.09, while not attending to a location reduces the signal at that location, on average, by a factor of 0.92. Finally, attentional mediation of performance is accomplished via a mechanism of enhancement of the attended stimulus which occurs after multiplicative noise.

Discussion

In this location-cued orientation discrimination task, attending to a spatial location reduces the signal contrast levels needed to achieve threshold performance in that location, while not attending to a spatial location increases the signal contrast needed to achieve threshold performance in that location. Our results are consistent with prior demonstrations that location-cued attention alters discriminability of targets of varying orientations (e.g., Downing, 1988). While prior demonstrations of location-cued attention effects do not inform us as to the mechanism of attention, the external noise plus attention paradigm allowed the precise specification of the mechanism of attention in this case. Attention affected performance via signal enhancement (or, equivalently, additive internal noise reduction) which operated after the introduction of internal multiplicative noise.

We have chosen a concurrent (dual-task) paradigm in which two responses were requested from the subject on each trial. Some authors (Pohlmann & Sorkin, 1976; Duncan, 1980, 1984) have claimed that differential performance under different attentional conditions in dual task procedures might be due to response competition. Response competition cannot account for the attentional effects in our data. If attention mediated which response had priority in response competition, then our attentional effects should have been found equally across all external noise conditions. The reported attentional effect, which mediated performance only at low levels of external noise, is incompatible with response competition explanations.

The current experiment isolates the mechanism of attention for a particular location-cued orientation discrimination as signal enhancement. We make no claim about the generality of this particular result. Whether the same, or different attentional mechanism(s) operate in other task situations is a matter for empirical investigation. If signal enhancement is the primary mechanism of location-based attention, then we should expect to see similar results in a variety of location-cued attention tasks using the external noise plus attention paradigm. If the mechanism of location-based attention is more opportunistic, then we would expect to see different attention mechanisms utilized for different target tasks. Whether the same attentional mechanism or different attentional mechanisms apply in different task situations, the General PTM model (or a slightly elaborated version of it) should be useful in the quantification and classification of those attentional mechanisms.

GENERAL DISCUSSION

Generality and applicability of the external noise plus attention paradigm

In this paper, we developed the external noise plus attention paradigm within the Perceptual Template Model, generated clear theoretical predictions for three mechanisms of attention, and provided a strong example application of the method to a classic perceptual task. To our knowledge, the external noise plus attention paradigm provides the strongest and most precise test of mechanisms of attention currently available. The basic design is widely applicable to many perceptual decision tasks, ranging from detection of sine waves to visual identification of objects. It can be applied to both location-cued and to feature-cued attention paradigms. In fact, the only requirement for application is the availability of an appropriate external noise, which can be varied in strength over a suitably wide range.

For convenience, we chose an experimental paradigm which used a 2AFC concurrent task structure (Sperling & Dosher, 1986). The choice of a concurrent task structure eliminated the need to include statistical uncertainty calculations in the model. The choice of a 2AFC task simplified the calculation of d', as it allowed the criterion value to be specified in terms of a target percent correct. However, the model and attention plus external noise method is in no way restricted either to concurrent (dual) tasks, nor to 2AFC tasks. The model could be extended to compound tasks by consideration of the appropriate statistical uncertainty calculations (see below). The criterion d' could be related to any suitable detection or discrimination paradigm with the appropriate form of signal detection theory (SDT).

Other forms of external noise

The external noise plus attention paradigm described here used a form of external noise that is essentially masking noise. The theoretical and methodological development of the external noise plus attention paradigm is, however, extensible to external noise manipulations in which random variation is added to the dimension of discrimination only. These alternative noise manipulations would leave the display looking "clean", but introduce irrelevant variation to the signal itself. For example, if an observer is discriminating patch contrast as an increment or decrement, variation would be introduced into the size of the increment or decrement. External noise manipulations of this kind may be more consistent with the traditional form of certain perceptual tasks, such as visual search. The availability of both forms of external noise manipulation critically increases the applicability of our methods to a very wide range of perceptual domains. Although only masking noise was described in detail in the current paper, either form of external noise may be explicable using the PTM model.

The external noise plus attention method may also be complicated somewhat in order to further specify the nature of perceptual processing performed by the perceptual template. This requires the manipulation of the content of the external noise. For example, the determination of a threshold contrast c_T for different external noise conditions which vary in their bandpass characteristics can provide estimates of the bandwidth of the relevant perceptual template, or perceptual process. This form of external noise manipulation may be most interesting if "distractor exclusion" is identified as a significant attention mechanism in a standard, white external noise task. Extensions to filtered noise would serve to validate and quantify distractor exclusion mechanisms and to further specify the perceptual template.

Extension to visual search and other compound tasks

Further extensions of these methods to quite different, but classic attention paradigms are possible. As discussed above, a concurrent paradigm in which each possible signal requires a response eliminates the need for a complex model of the effects of statistical uncertainty. The interpretation of data from compound experiments requires the modeling of the noise sources in one vs several locations (or one vs several stimuli). Once uncertainty effects are corrected, the derived signature patterns for the three attention mechanisms (Fig. 3) apply just as well to true d' measures in compound tasks. Alternatively, one could generate new signature patterns which incorporate uncertainty effects directly.

On the other hand, the exact distribution of noise is critical in the process of correcting for uncertainty effects in a compound task. One example of a compound task is visual search. A great deal of modeling work on visual search (Shaw, 1980, 1982; Palmer *et al.*, 1993; Palmer, 1994, 1995; Pavel, 1993) is based on assumptions about the unknown distribution of noise. Different assumed noise distributions lead to different conclusions about whether attention affects perceptual quality. Once our methods are verified and the impact of noise in various domains is known, we can use those methods to identify regions in the target task in which a known external noise dominates internal noise. These conditions can be used in visual search and other compound tasks in order to form precise distribution-known tests of the competing search models (Pavel, 1993). We can make exact predictions from various search models to answer the question of whether limited resources determine performance.

Conclusion

The attention plus external noise paradigm and the Perceptual Template Model provide a general characterization of three mechanisms of attention: signal enhancement, distractor exclusion, and internal noise reduction. The method is extensible in a number of ways to related paradigms. The experiment demonstrates the strength of the approach in a classic location-cued orientation discrimination task. Attention in this task reduces threshold contrast in attended locations and increases threshold contrast in unattended locations by affecting signal enhancement, or equivalently, internal additive noise reduction. Conclusions regarding the generality of the empirical result await further experimentation.

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APPENDIX

In this Appendix, we explain the numerical procedure we developed to solve the following equation (A1) for the threshold contrast level c_τ in the general situation where $\gamma \neq 1$:

$$d'(c) = \frac{\beta c}{\sqrt{N_{\text{ext}}^2 + N_1^2(\beta^2 c^2 + N_{\text{ext}}^2)^\gamma + N_2^2}}. \tag{A1}$$

Because we expect γ to be not too different from 1.0, we first solve the equation with $\gamma = 1$, thus:

$$c_0 = \sqrt{\frac{(1 + N_1^2)N_{\text{ext}}^2 + N_2^2}{\beta^2(1/d'^2 - N_1^2)}}. \tag{6a}$$

Then, we use the following recursive procedure to find a better and better approximation of c_τ for the general case where $\gamma \neq 1$:

$$c_{k+1} = d'/\beta\sqrt{N_{\text{ext}}^2 + N_1^2(\beta^2 c_k^2 + N_{\text{ext}}^2)^\gamma + N_2^2}. \tag{A2}$$

The recursion stops when $(d'(c_{k-1}) - d'_{\text{threshold}})^2 < 0.00000001$. We set $c_\tau = c_{k+1}$.