Visual signal detection in structured backgrounds. II. Effects of contrast gain control, background variations, and white noise

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Studies of visual detection of a signal superimposed on one of two identical backgrounds show performance degradation when the background has high contrast and is similar in spatial frequency and/or orientation to the signal. To account for this finding, models include a contrast gain control mechanism that pools activity across spatial frequency, orientation and space to inhibit (divisively) the response of the receptor sensitive to the signal. In tasks in which the observer has to detect a known signal added to one of M different backgrounds due to added visual noise, the main sources of degradation are the stochastic noise in the image and the suboptimal visual processing. We investigate how these two sources of degradation (contrast gain control and variations in the background) interact in a task in which the signal is embedded in one of M locations in a complex spatially varying background (structured background). We use backgrounds extracted from patient digital medical images. To isolate effects of the fixed deterministic background (the contrast gain control) from the effects of the background variations, we conduct detection experiments with three different background conditions: (1) uniform background, (2) a repeated sample of structured background, and (3) different samples of structured background. Results show that human visual detection degrades from the uniform background condition to the repeated background condition and degrades even further in the different backgrounds condition. These results suggest that both the contrast gain control mechanism and the background random variations degrade human performance in detection of a signal in a complex, spatially varying background. A filter model and added white noise are used to generate estimates of sampling efficiencies, an equivalent internal noise, an equivalent contrast-gain-control-induced noise, and an equivalent noise due to the variations in the structured background. [S0740-3232(97)04209-9]

1. INTRODUCTION

Many studies have investigated detection of a briefly presented signal superimposed on one of two identical fixed backgrounds (often called the masks).[1,2] These experiments have been traditionally called masking experiments. In this paper we refer to these tasks as detection in a fixed deterministic background. A common finding in these tasks is that the contrast detection threshold first decreases (facilitation) and then increases as a function of the background contrast.[1,2] The signals and the backgrounds used are generally sinusoidal gratings or Gabor patches.[1,2] These experimental results have been modeled by a contrast gain control mechanism that has a nonlinear excitatory component and broadband inhibition that is pooled across spatial frequencies, space, and orientation.[2,3] In these models the performance degradation in the presence of a high-contrast background is due to the inhibitory (divisive normalization) effect of the background on the receptors responding to the signal. These models are similar to models used to fit recordings of simple-cell response in the cat striate cortex.[4,5] Similar models have also been applied to image discrimination of more complex images such as object detection in a fixed background[6] and quantification of the effect of image compression on image discrimination between an original image and a distorted image (after lossy compression).[7]

In many practical tasks, the observer has to find a target or an object in a complex, spatially varying background. In such conditions, unlike detection in fixed backgrounds, the observer has to evaluate locations with different backgrounds. In addition, unlike the traditional fixed background experiments, the observer may have unlimited time to decide about the signal location or presence.

Many studies have investigated detection of a known signal in simple random backgrounds (stochastic noise).[8–13] Most of these studies have been performed with computer-generated, Gaussian, spatially uncorrelated (white) noise.[8,9,14] Recent studies have investigated detection in more complex random backgrounds, such as backgrounds with random inhomogeneities (lumpy backgrounds)[10,13] and filtered noise.[12] Models based on statistical decision theory have been used to model human performance in these tasks. The model observer uses prior knowledge about the signal and noise ensemble statistics to evaluate the hypothesis of signal presence.[8–13] In these models performance is degraded by the stochastic image noise and by the observer's suboptimal classification rules. Most of these models do not include a source of degradation that is due to the deterministic presence of the background (contrast gain control mechanism). The omission of this source of degradation in the models might be justified on the grounds that in most of the fixed background experiments the signal is presented very briefly (30–70 ms) and that the masking effect might be negligible in free viewing conditions. However, Burgess conducted human detection performance in a two-alternative forced-choice experiment with two identical samples of white noise and unlimited viewing time and found performance (d') improvement by a factor of 1.63 over the condition with different samples of white noise.[14] Based on these and other experiments, he concluded that the external white noise induced an additional uncorrelated internal noise that was approximately 0.6–0.8 times the external added white noise.[14]

Our goal in this paper is to examine both the deterministic effects of high-contrast backgrounds (contrast gain control mechanism) and the effects of random variation in the background when the observer has unlimited time to detect a target among different samples of a complex background. Determining the main sources of performance degradation will help develop human detection models for these tasks. These models could be used for task-performance-based image quality evaluation as well as display optimization (e.g., image compression, image enhancement, and reconstruction).

The backgrounds used in this paper were samples extracted from patients' digital x-ray coronary angiograms. They provide complex backgrounds that include many anatomical features, such as other arterial segments, lung tissue, and other features, that are not relevant to the task at hand. The medical image backgrounds should increase the applicability and relevance of our results to medical image applications. Many studies have investigated human visual detection and identification of signals in simple computer-generated noise, such as Gaussian spatially uncorrelated noise that approximates image noise of quantum origin.[8,9,14] However, natural medical image backgrounds not only include quantum noise but also include other anatomical structures in the image that are not relevant to the detection task. The development and testing of psychophysical models for the detection of abnormalities in natural medical images is a high-priority goal in the field of medical image perception.[15]

Previously we created test images that combine real structured backgrounds from x-ray coronary angiograms with computer-simulated signals to evaluate the effects of image processing techniques such as image compression,[16] image enhancement,[17] and feature motion stabilization[18] and to investigate the effect of the number of possible signal locations and signal contrast on performance.[19]

We use a four-alternative forced-choice task in which the observer has to detect the signal in one of four spatial locations. To isolate the effects of a fixed background from the effect of random variations in the backgrounds we include three different types of background experimental condition: (1) uniform gray background, (2) one structured background repeated in all four locations, and (3) different structured backgrounds in each of the four locations.

In the first condition, the background had a uniform luminance (left-hand image in Fig. 1). In the second condition, a different structured background was sampled on each trial and was used for all four possible locations (middle image in Fig. 1). In the third condition, different samples of structured background were used for each of the possible signal locations and trials (right-hand image in Fig. 1). Performance degradation from the uniform gray background to the repeated structured background condition can be attributed to the presence of the fixed deterministic background. In this paper this degradation is interpreted as the effect of a contrast gain control mechanism. Performance degradation from the repeated background condition to the different backgrounds condition is interpreted as the effect of the random variations across background samples.

For each condition we use five levels of signal contrast to investigate the effect of signal strength. For each background condition we investigate five conditions with different amounts of added random white visual noise (Gaussian distributed). These conditions enable us to use a method introduced by Pelli[20] to estimate three noise sources: a constant equivalent internal noise, an equivalent contrast gain control noise, and an equivalent background random variation noise. Each of the noise measures can be interpreted as the amount of white noise that needs to be added to the stimulus to produce a performance degradation equivalent to that produced by the corresponding source of performance degradation (internal noise, contrast gain control mechanism, or random

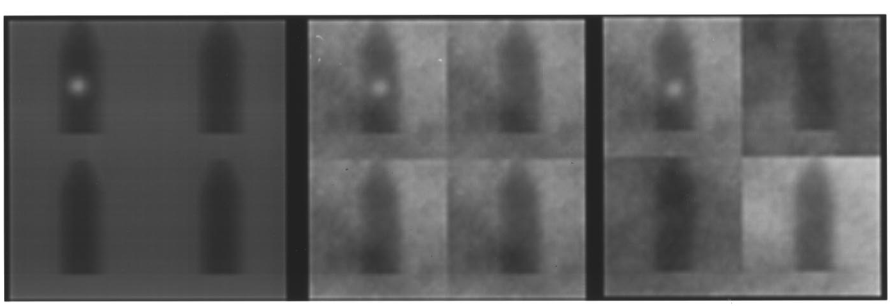

Fig. 1. Images used in a four-alternative forced-choice detection task in which the observer had to indicate the signal location among four possible locations. The signal was always embedded at the horizontal and vertical center in one of the four simulated arteries (lower-contrast bars in the image). The study included three experimental background conditions: (1) uniform gray background (left-hand image); (2) repeated structured background condition in which the same sample of background was used for each of the four possible locations (middle image); (3) different structured background condition in which a different random sample of background from a population of backgrounds was used for each of the four possible locations (right-hand image). The displayed photograph was scaled for presentation purposes.

variations across backgrounds). Before describing the psychophysical experiments in detail we discuss the ideal observer and human models for three background conditions with added white noise.

2. THEORY

A. Detection in White Noise

1. Ideal Observer

The best expected performance in a noise-limited task is that of the ideal Bayesian observer.[21] Ideal observer performance has been compared with human performance in a variety of visual tasks.[22–25] The ideal observer computes the likelihood of the signal given the data at each possible location and chooses the location with the highest *a posteriori* likelihood.[21] For the case of a signal embedded in Gaussian white noise with equal probability of appearance in one of M locations, the ideal observer needs only to correlate the data with a template that matches the signal (matched filter) at the M possible signal locations.[25] The ideal observer then chooses the location that elicited the highest output correlation. Given that the output correlation to the signal plus noise and the noise are Gaussian distributed with equal variance, then performance can be measured as

$$d' = \frac{\lambda_s - \lambda_n}{\sigma_\lambda}, \tag{1}$$

where λ_s is the mean output correlation to the signal plus noise, λ_n is the mean output correlation to noise only, and σ_λ is the standard deviation of the output correlation (assumed to be equal for signal plus noise and noise only). For the ideal observer it can be shown that d'_{ideal}, referred to as the signal-to-noise ratio, can be expressed in terms of the square root of the energy and the spectral noise density[25]:

$$\text{SNR} = \sqrt{\frac{E}{N_0}}. \tag{2}$$

E is the signal contrast energy defined as

$$E = \iint S^2(x, y)\mathrm{d}x\mathrm{d}y, \tag{3}$$

where $S(x, y)$ is the signal intensity profile and N_0 in Eq. (2) is the noise spectral density. When the white noise consists of discrete samples and the sampling distance (pixel width) is defined as unity, then N_0 is the pixel noise variance.

We can relate the signal-to-noise ratio to percent correct performance by calculating the probability of the signal response taking a value x and the cumulative probability of the remaining $M - 1$ responses to the noise-only locations taking a value less than x[26]:

$$\text{Pc}(M, d') = \int_{-\infty}^{+\infty} g(x - d')G^{M-1}(x)\mathrm{d}x, \tag{4}$$

where

$$g(x) = \sqrt{\frac{1}{2\pi}}\exp\left[-\frac{x^2}{2}\right],$$

$$G(x) = \int_{-\infty}^{x} g(y)\mathrm{d}y.$$

2. Human Observer

Human visual performance detection and identification of a known signal in white spatial noise has been successfully modeled as a suboptimal Bayesian observer.[8,9,14,23–25] The idea of modeling human performance in terms of a suboptimal matched filter observer is not incompatible with the notion of a multichannel visual system. Models that have initial multichannel processing followed by a Bayesian or suboptimal Bayesian observer have been proposed.[12,17] However, the human observer has a number of sources of limitations: a constant additive internal noise,[9] another additive internal noise component proportional to the external noise,[14] suboptimal sampling efficiency,[9,24,27] and unavoidable intrinsic uncertainty.[23,24,28] Internal noise arises from the noise in the neural firing of cells[29] as well as from fluctuations in the decision criteria used by observers.[30] Pelli proposed a method to measure the amount of constant internal as equivalent internal noise, which is the amount of added external white noise needed to degrade performance by an amount equivalent to the internal noise.[20] Sampling efficiency refers to the observer's inability to perfectly match his or her filter to the signal profile or to integrate over the entire signal area. The index of detectability for the human observer modeled as a suboptimal matched filter with a source of internal noise is given by[27]

$$d' = \delta\sqrt{E}, \quad \text{where } \delta = \sqrt{\frac{J_{\text{ub}}}{{\sigma_i}^2 + {\sigma_e}^2}}, \tag{5}$$

and J_{ub} is the sampling efficiency (the subscript refers to uniform background), ${\sigma_i}^2$ is the equivalent internal noise, and ${\sigma_e}^2$ is the external white-noise variance. Equation (5) predicts a linear relationship between the signal contrast or square-root signal contrast energy and d'. However, experiments on detection of signals in the presence and the absence of external noise show a nonlinear relationship between the signal contrast and d'.[31,32] One interpretation for this result is that there is a nonlinear transducer function acting on the physical signal strength to produce the response within the observer.[31,32] A different account of the nonlinearity between signal contrast and d' is based on stimulus uncertainty in the decision process.[28] In this model the observer is uncertain about some aspect of the signal and therefore not only monitors the M task-relevant decision variables but also monitors U-irrelevant decision variables, where U is referred to as the uncertainty number. This uncertainty in the decision process produces a nonlinearity in the psychometric function (d' versus signal contrast); however, it will not affect the slope of the function at higher signal contrast levels.[28] In this paper we take this second approach and use stimulus uncertainty to model departures from the linear relationship between d' and signal contrast. In our specific model of stimulus uncertainty, each of the M signal locations has associated with it U additional irrelevant, statistically independent decision variables. The observer is assumed to monitor the decision variable responding to the signal, the $M - 1$ noise decision variables, and UM irrelevant decision variables and chooses the location with the maximum response. The observer will then respond to the signal location if either the response to the signal or any one of the U-irrelevant decision variables associated with the signal location takes a larger value than the $(M - 1)U$ decision variables associated with the nonsignal locations. The maximum rule adopted here is not the optimal Bayesian rule in the case of uncertainty but approximates it in many cases.[28] Pelli[28] suggests the use of the Weibull function to fit psychometric functions and provides a table to compare the obtained parameter fits for these functions with an associated uncertainty number. Instead of using these functions, we choose to fit our data with the exact uncertainty prediction [Eq. (6)].

Percent correct for the maximum rule in the presence of uncertainty can be calculated to be

$$\mathrm{Pc}(M, U, d') = \int_{-\infty}^{+\infty} g(x - d')[G(x)]^{[M(1+U)-1]} + Ug(x)[G(x)]^{[M(1+U)-2]}G(x - d')\mathrm{d}x, \tag{6}$$

where M is the number of possible signal locations in the task (relevant decision variables), U is the uncertainty number corresponding to the irrelevant decision variables per location monitored by the observer, d' is defined as the distance in standard deviation units between the signal and noise distributions [Eq. (5)], and $g(x)$ and $G(x)$ are as previously defined [Eq. (4)]. Equation (6) assumes that the internal responses have Gaussian distributions. Burgess has confirmed that the Gaussian assumption can successfully predict human performance in detecting a disk at one of M locations in spatially uncorrelated Gaussian noise.[33]

Unlike previous methods[8,20] used to estimate the sampling efficiency and equivalent constant internal noise [Eq. (5)], Eq. (6) allows effects of uncertainty to be separated from sampling efficiency and internal noise.

B. Detection in White Noise with Deterministic Background

1. Ideal Observer

The ideal observer strategy for signal detection in one of M locations consisting of white Gaussian noise and a repeated background remains the same as with a uniform background. Since the M backgrounds are the same across the M locations, the matched filter output at the different locations will have the same filtered background constant added, and performance will not be affected. Performance for the ideal observer in this condition is described by the equations used for the detection of a signal in white noise with a uniform background.

2. Human Observer

Unlike the ideal observer, a fixed high-contrast background does degrade human performance in detecting a signal. For example, Legge and Foley[1] measured detection of a sine-wave grating superimposed on a background (mask) sine-wave grating with varying spatial frequency. Their high-contrast results showed a threshold elevation for a range of masker frequencies within an octave around the target frequency. Burgess[34] found that the detectability of a disk in white noise was reduced in a sinusoidal and a square-wave background as compared with a uniform background. The effect of a high-contrast background has been modeled by a contrast gain control mechanism that normalizes (divisively) the response of the mechanism sensitive to the signal.[2,3] Foley[2] pointed out that the response strength of the Legge–Foley model could be interpreted as a signal-to-noise ratio (difference in the mean response to the signal plus background and background-only divided by the standard deviation of the response). This interpretation assumes that after the nonlinearity there is a unit additive internal noise variance that is constant for all background contrast. Ahumada[35] and Legge *et al.*[27] have shown that a nonlinearity with constant internal noise can be equally well modeled by a constant signal response and a stimulus-dependent internal noise. In the present context, the contrast normalization with constant internal noise can be equally well modeled by an additional nonconstant noise source in the decision variable that is determined by the background. We shall refer to this source of noise as the contrast-gain-control-induced noise. If we assume that the constant internal noise is independent of the noise induced by the presence of the deterministic background (contrast gain control), then d', the index of detectability for human visual performance in the presence of the deterministic same-structured background and added external white noise, is given by

$$d' = \delta\sqrt{E}, \quad \text{where } \delta = \left(\frac{J_{\mathrm{sb}}}{{\sigma_i}^2 + {\sigma_e}^2 + {\sigma_{\mathrm{cgc}}}^2}\right)^{1/2} \tag{7}$$

and J_{sb} is the sampling efficiency in the presence of the deterministic same background, ${\sigma_i}^2$ is the equivalent constant internal noise, ${\sigma_{\mathrm{cgc}}}^2$ is the equivalent contrast gain control noise, and ${\sigma_e}^2$ is the external white-noise variance. Modeling the effect of the presence of a deterministic structured background on performance in terms of an additional induced noise component is not a new method. Burgess and Colborne[14] used this method to model the effect of a fixed deterministic white-noise background. The equivalent contrast gain control noise (${\sigma_{\mathrm{cgc}}}^2$) should be interpreted as the amount of white noise that needs to be added on a uniform background to degrade performance as much as the effect of the deterministic background (contrast gain control). An assumption made in our working model is that the sampling efficiency with a deterministic background (J_{sb}) does not change as a function of external noise. This assumption requires that the observer use the same effective filter across all levels of added white noise. However, as we discuss in Section 5, the fixed filter assumption might be violated for many reasons.

A final step in the model is to obtain percent correct performance from d' by using Eq. (6) to allow for possible sources of stimulus uncertainty, based on a Gaussian distribution assumption. This is reasonable if the decision variable statistics are dominated by the statistics of the added Gaussian-distributed external white noise. However, if the deterministic background induces a source of variability that is not Gaussian distributed, then the Gaussian internal response might be violated.

C. Detection in White Noise with Background with Random Variations

1. Ideal Observer

In filtered noise backgrounds, the ideal observer strategy is to compare the data with a template (filter) that compensates for the noise spatial correlations.[11] This filter can also be described as the product, in the frequency domain, of the matched filter and a prewhitening filter that removes the noise correlations.[11] Predicting ideal observer performance for detection in complex backgrounds with random inhomogeneities (lumpy backgrounds) or real patient structured backgrounds would involve the use of nonlinear procedures.[10,13] Because of the mathematical complexity of the ideal observer in these cases, investigators have compared linear models with human performance.

2. Linear Models and Human Observer

In linear models, the observer correlates a template (filter) with the data at the possible signal locations and chooses the location that elicits that largest response. The models differ in the prior knowledge that they use and in their information constraints in constructing the filter. The optimum linear observer, the Hotelling observer[10–12] calculates the best possible linear filter based on the known signal shape and on the ensemble statistics of the background (variance covariance matrix). Others[36–38] have used Hotelling observers with the addition of a channel mechanism and front-end limitations[37] that constrain the possible amount of noise decorrelation by the observer. Another proposed model is the nonprewhitening matched filter model that uses knowledge about the signal but ignores the background correlations.[10–13] Burgess proposed a modified nonprewhitening matched filter model that incorporates a front-end eye filter to account for the contrast sensitivity function.[13] In all these models the source of the performance degradation is the random background variations, which cause random variations in the model's output from location to location. There is still no consensus about which of these models predicts human performance the best.

In this paper we do not assess performance of these operational models for particular filters. Our interest is to quantify the relative effects of the contrast gain control mechanism and the random background variations on human performance. Therefore we adopt an expression for performance similar to the expressions used for the detection of a signal in white noise and in white noise with a fixed deterministic background. In doing so, we implicitly assume that the observer uses the same linear filter for varying levels of added external noise. If an observer uses a fixed linear filter for the different levels of the added external white noise (holding the contrast of the different structured backgrounds constant), d' will be related to the external noise variance as follows[39]:

$$d' = \delta\sqrt{E}, \quad \text{where}$$

$$\delta = \left(\frac{j_{\mathrm{rb}}}{{\sigma_e}^2 + {\sigma_i}^2 + {\sigma_{\mathrm{cgc}}}^2 + {\sigma_{\mathrm{rbv}}}^2}\right)^{1/2}, \tag{8}$$

where J_{rb} is the sampling efficiency in the presence of random background variations, ${\sigma_i}^2$ is the equivalent internal noise, ${\sigma_{\mathrm{cgc}}}^2$ is the equivalent contrast gain control noise, ${\sigma_{\mathrm{rbv}}}^2$ is the equivalent random background variation noise, and ${\sigma_e}^2$ is the external white-noise variance. The equivalent random background variation noise, ${\sigma_{\mathrm{rbv}}}^2$, is interpreted as the amount of added white noise needed to degrade performance as much as the random variations in the structured background. Note that the standard interpretation of the sampling efficiency as the correlation between the human effective filter and the ideal observer filter or the matched filter does not hold for the present case. In this case j_{rb} is simply a constant that relates d' to the square-root signal contrast energy. The exact shape of the linear filter used by the observer will affect the sampling efficiency, j_{rb}; however, it will not change the relationship between d' and the external white-noise variance as long as the observer always uses the same filter as the added external white-noise level varies. The plausibility of the fixed filter assumption is addressed in Section 3.

To compute percent correct performance from d' in the different structured background condition, we again use Eq. (6), which requires that the internal responses to the varying structured backgrounds be Gaussian distributed. This assumption has been investigated by measurement of detection performance in structured backgrounds as a function of the number of possible locations. Eckstein and Whiting[19] found that the Gaussian assumption is reasonable for such complex backgrounds and successfully predicts the effect of the number of possible locations on performance.

3. METHODS

A. Generation of Test Images

The experimental image generation procedure was designed to approximate the x-ray image generation process by use of real backgrounds from x-ray coronary angiograms and simulated arterial segments and signals.[19] Arterial segments are generated by mathematical projection of a three-dimensional right-circular cylinder with a diameter of 3.0 mm (10 pixels) onto the patient structured background. One calculates the individual pixel intensity value by assuming that the cylindrical segments were filled with x-ray-absorbing iodinated contrast material with an attenuation coefficient of 0.10/mm. The signal was a hemiellipsoidal filling defect embedded within one of the three arterial segments. The two-dimensional projection of the lesion (signal) appears as a brighter disk. The disk is blurred with a Gaussian point-spread function with a standard deviation of 0.30 mm. A detailed discussion of the test image generation has been presented previously.[19] For the specific experiments in this paper, we generated three types of image sets (Fig. 1): (1) uniform gray background, (2) repeated structured background, and (3) different structured background. For the uniform gray background condition the mean luminance level of the background was manipulated from trial to trial to match the mean gray level of the structured backgrounds in the repeated structured background condition. Since the external white noise is additive, the rms noise contrast, which is defined as the ratio of the noise standard deviation and the mean background luminance, changes with background luminance. The reported rms noise contrast values are for the average background luminance.

In the repeated structured background condition, one sample from 400 possible structured background samples was randomly chosen and was used as a background for the four possible signal locations.[19] In the different background condition, four different samples of structured background were sampled without replacement for each of the four possible signal locations. The test images were 128×128 pixel images subtending a visual angle of 4.15×4.15 deg.

Signal energies in the resulting images were calculated by use of Eq. (3). The average white-noise rms contrast values were 0, 0.071, 0.125, 0.18, and 0.25. The squared rms noise values can be transformed to spectral densities by multiplication by the pixel area, 1.14×10^{-3} deg^2. The resulting noise spectral densities (in deg^2) are 5.75×10^{-6}, 1.785×10^{-5}, 3.95×10^{-5}, and 7.13×10^{-5}.

B. Psychophysical Studies

The two naïve observers participated in the study after approximately 100 trials of training for each condition. For each of the three background conditions there were five different levels of additive white noise. The study therefore contained a total of 3 (background conditions) × 5 (added-noise conditions) conditions. Observers participated in seven sessions of 150 trials for each experimental condition. Each session had 30 trials at each of five levels of signal contrast. The observer selected a position by clicking on its location with the mouse. The images were presented on a GMA201 19-in. high-resolution monochrome Tektronix gray-scale monitor driven by an 8-bit image buffer. Video display luminance was measured with an IL 180 photometer system (International Light, Inc., Newburyport, Mass.). The mean luminance of the test images was 5.5 cd/m^2, which corresponds to a gray level of 128. Viewing was binocular from a distance of approximately 50 cm. Observers had unlimited time to reach a decision.

4. RESULTS

Percent correct performance was computed separately for each session and each signal contrast level. Performance was then averaged across sessions (within each experimental condition) for each observer. Percent correct was converted into $d'(M = 4, U = 0)$ [with Eq. (4)], the distance in standard deviation units between the noise and the signal internal response distributions, assuming no stimulus uncertainty ($U = 0$). This is a customary way of plotting performance.[8,14,28] Figures 2 and 3 show performance, $d'(M = 4, U = 0)$ as a function of square-root signal contrast energy (which is linear with signal contrast) for each of the experimental conditions. Error bars represent 95% confidence intervals computed by propagation of the binomial variance of percent correct to d' by the method of partial derivatives.

A. Statistical Efficiency

The statistical efficiency for a given task is a measure of the relative performance of the human observer with respect to the ideal Bayesian observer. For our models it can be measured by the squared ratio of the index of detectability for the human and the ideal observer $(d'_{\text{human}}/d'_{\text{ideal}})^2$.[22,24,25] The statistical efficiencies ranged from approximately 10% to 30% for the uniform background condition and from 6% to 25% for the repeated structured background condition, depending on the level of external noise and signal contrast. No statistical efficiencies are reported for the different structured background conditions because of the complexity of the calculation for the ideal observer in such a case (see Subsection 2.C.2 for more details).

B. Psychometric Function Slope and Uncertainty Number

Psychometric functions [Eq. (6)] were estimated with two free parameters: δ and U (the uncertainty number), and two known parameters: the number of possible locations, M, and the square root of the signal contrast ($\sqrt{E}$). The parameter δ controls the slope of the function at high signal contrast levels (linear portion of the psychometric function). The uncertainty number, U, produces a nonlinearity at low signal contrasts and produces positive shifts in the positive x direction for the upper portion of the psychometric function without altering its slope. Separate fits were done for each background and added-noise condition by use of a χ^2 criterion based on the binomial variance of percent correct. Table 1 shows the best-fit parameters for both observers for each of the experimental conditions. For both observers, the slope of the psychometric function decreased as the added white external noise increased, for all three background conditions (Table 1). The slopes show a decrease from the uniform gray background to the repeated structured background to the different structured backgrounds, an effect that disappears as the added white noise increases. For the repeated structured background and different structured background conditions, there was a tendency for the uncertainty number to increase with added external noise (Table 1). For the uniform background the 0.071 and 0.125 noise rms contrast resulted in nonzero uncertainty numbers for both observers.

The percent correct model predictions [from Eq. (6)] were then converted to $d'(M = 4, U = 0)$ with Eq. (4) to plot them in the same units as the data (solid curves in

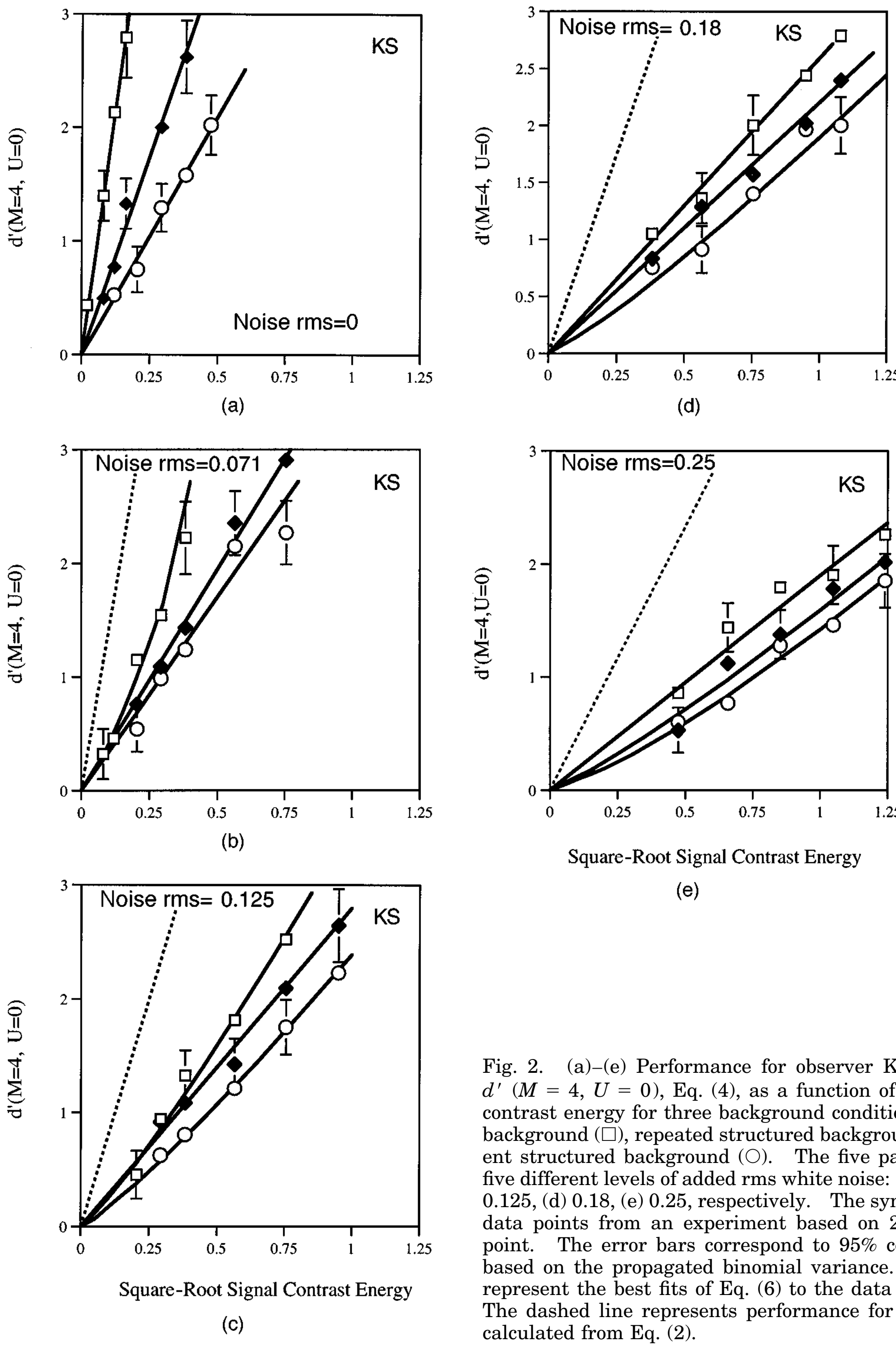

Fig. 2. (a)–(e) Performance for observer KS as measured by d' ($M = 4$, $U = 0$), Eq. (4), as a function of square-root signal contrast energy for three background conditions: uniform gray background (□), repeated structured background (♦), and different structured background (○). The five panels correspond to five different levels of added rms white noise: (a) 0, (b) 0.071, (c) 0.125, (d) 0.18, (e) 0.25, respectively. The symbols correspond to data points from an experiment based on 210 trials per data point. The error bars correspond to 95% confidence intervals based on the propagated binomial variance. The solid curves represent the best fits of Eq. (6) to the data for each condition. The dashed line represents performance for the ideal observer calculated from Eq. (2).

Figs. 2 and 3). Uncertainty in these plots results in shifts along the positive x axis of the upper linear portion of the function.

C. Sampling Efficiencies, Equivalent Internal Noise, Equivalent Contrast Gain Control Noise, Equivalent Background Variation Noise

Figure 4 shows the slope of the psychometric function as a function of the added white noise for the three background conditions. A fit to the slope as a function of added white noise was done by simultaneously fitting of the data with Eq. (5) for the uniform gray background condition, with Eq. (7) for the same structured background condition, and with Eq. (8) for the different structured background condition with six free parameters: sampling efficiency in the uniform background condition (J_{ub}), sampling efficiency in the same structured background condition (J_{sb}), sampling efficiency in the different structured background condition (J_{rb}), equivalent internal noise (σ_i^2), equivalent contrast gain control noise (σ_{cgc}^2), and equivalent background variation noise (σ_{rbv}^2). The fit was based on a mean-square error criterion between the model prediction and the measured psychometric function slopes (δ).

A χ^2 criterion on the predicted percent correct was not used because the numerical evaluation of the integral in Eq. (6) on each iteration of the fit would have resulted in extremely long durations for the iterative computer fits. Tables 2 and 3 list the best-fitting parameters for both observers. We calculated a χ^2 goodness-of-fit measure by first calculating the predicted percent correct with the best-fit parameters, using Eq. (6), and then dividing the mean-square error by the expected binomial variance in the data (Tables 2 and 3). The solid curves in Fig. 4 are the predictions of the best-fit model to the slopes given in Table 1.

5. DISCUSSION

A. Uniform Background

The statistical efficiency for the uniform background condition for both observers ranged from ~10% to ~30%, depending on the external noise level and signal contrast.

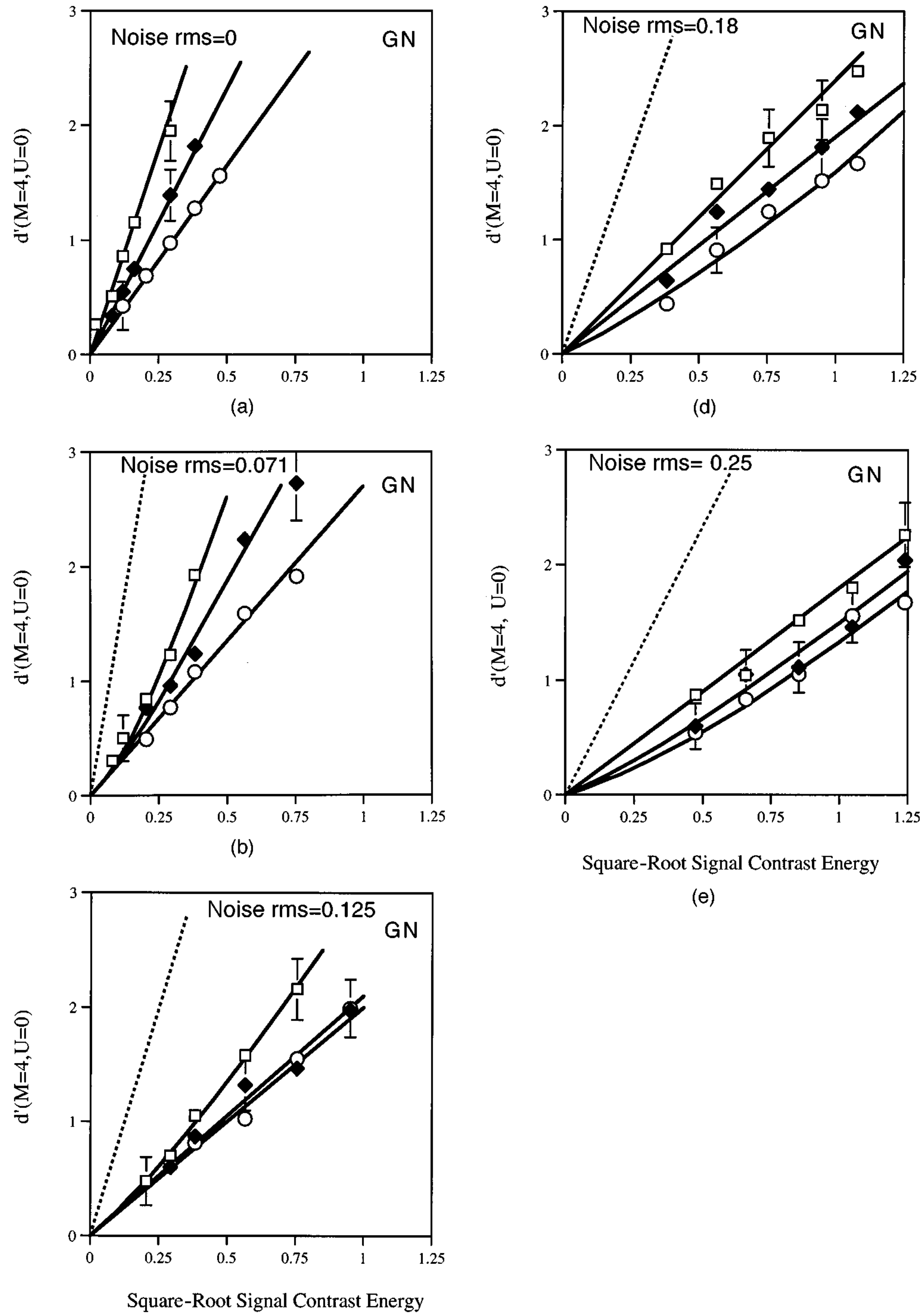

Fig. 3. Same as Fig. 2, but for observer GN.

Table 1. Best Fits to the Individual Psychometric Functions by Use of Eq. (6), Which Allows for Possible Signal Uncertainty[a]

	Noise rms				
	0	0.071	0.125	0.18	0.25
Observer KS					
Uniform background	$\delta = 17.6$, $U = 0$	$\delta = 7.1$, $U = 2$	$\delta = 3.8$, $U = 1$	$\delta = 2.6$, $U = 0$	$\delta = 1.95$, $U = 0$
Same structured background	$\delta = 7.0$, $U = 0$	$\delta = 3.9$, $U = 0$	$\delta = 2.8$, $U = 0$	$\delta = 2.23$, $U = 0$	$\delta = 1.92$, $U = 1$
Different structured background	$\delta = 4.2$, $U = 0$	$\delta = 3.4$, $U = 0$	$\delta = 2.7$, $U = 1$	$\delta = 2.2$, $U = 1$	$\delta = 1.94$, $U = 2$
Observer GN					
Uniform background	$\delta = 7.2$, $U = 0$	$\delta = 6.5$, $U = 1$	$\delta = 3.3$, $U = 1$	$\delta = 2.4$, $U = 0$	$\delta = 1.83$, $U = 0$
Same structured background	$\delta = 4.7$, $U = 0$	$\delta = 4.3$, $U = 1$	$\delta = 2.1$, $U = 0$	$\delta = 1.89$, $U = 0$	$\delta = 1.81$, $U = 1$
Different structured background	$\delta = 3.31$, $U = 0$	$\delta = 2.7$, $U = 0$	$\delta = 2.0$, $U = 0$	$\delta = 1.9$, $U = 1$	$\delta = 1.79$, $U = 2$

[a] There are two free parameters: the slope of the function (δ), and the uncertainty number U.

An increase in statistical efficiency with external added-white-noise level is expected, since the relative contribution of the internal noise should decrease with increasing external noise. An increase in statistical efficiency with increasing signal contrast is expected when there is stimulus uncertainty, since stimulus uncertainty affects low signal contrasts more than high signal contrasts.

The obtained statistical efficiencies are somewhat smaller than those obtained by Burgess and Colborne[14] (40%) but are larger than those obtained by Myers *et al.*[11] (12%) for a similar target.

The proportionality between d' and signal contrast for the case of a uniform background without noise differs from the common result of a nonlinear accelerating function for the detection of sinusoidal gratings.[31] Perhaps the projected simulated arterial segments containing the signals act as pedestals. Studies have shown that the presence of a pedestal that is identical to the signal (contrast discrimination task) reduces the effect of uncertainty and will produce a linear d' versus signal contrast function.[24,28,31] If the pedestal reduces the effect of uncertainty, then one might expect that increasing the additive white noise for a fixed pedestal contrast might increase the effect of uncertainty. The U estimates do not show a clear trend (see Table 1). The linear shape of the psychometric function could also be attributed to the difference between the disk signals used in this study and the sinusoidal or Gabor signals of the other studies.[14,24,25] For aperiodic signals such as disks and Gaussian blobs, d' versus signal contrast functions in the presence of noise are close to linear (with a 0 x intercept).[14,25,40] However, the psychometric functions for periodic signals such as sinusoidal and Gabor signals show a more pronounced nonlinearity.[24,25,40] The nonlinearity increases with the center spatial frequency of the signal.[40]

The equivalent internal noise is the amount of external noise that needs to be added to the image to produce a degradation in detection performance equivalent to the effect of the internal noise.[28] The estimated values of internal noise in absolute units for both observers were slightly larger than values of internal noise (approxi-

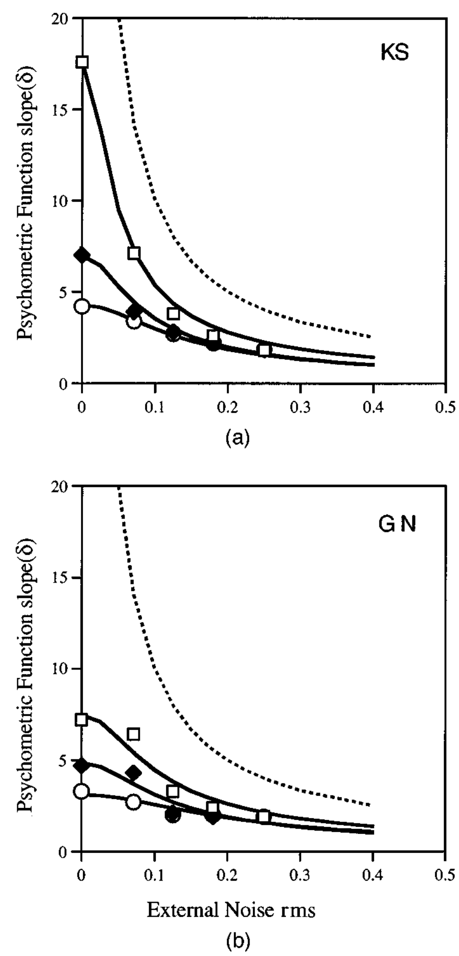

Fig. 4. Slope of psychometric functions for (a) observer KS and (b) observer GN as a function of the external noise rms for the three background conditions: uniform background (□), repeated structured background (♦), and different structured background (○). The solid curves correspond to the simultaneous fit of Eqs. (5), (7), and (8) for the corresponding background conditions with six free parameters: three sampling efficiencies, equivalent internal noise, equivalent contrast gain control noise, and equivalent background variation noise. The dotted curve corresponds to the ideal observer performance in white noise.

mately 1×10^{-6} deg^2) obtained by Pelli's analysis of other data sets with similar mean luminance levels.[20]

B. Effect of a Deterministic Structured Background

Comparisons between observer performance in the uniform gray background condition and the repeated structured background condition indicate the effect of the deterministic structured background on human performance. The results show that, for both observers (Figs. 2 and 3), performance for the repeated background condition was degraded with respect to the uniform gray background for all levels of added white noise. In the absence of added white noise, the slope of the psychometric function was reduced by a factor of 2.51 for observer KS and by a factor of 1.53 for observer GN. Our high-contrast deterministic complex background degrades performance despite the unlimited decision time.

The effect of the deterministic structured background on human performance is independent of the signal contrast level [the effect on d' as given by Eq. (7) is independent of the signal contrast]. In our model, departures from this prediction are interpreted as differential stimulus uncertainty across conditions. Other interpretations might be possible. In the repeated background, the statistical efficiency dropped for both observers from 10% to 1%, depending on the white-noise level. The effect of the deterministic background on performance decreased with increasing levels of added white noise.

Performance degradation from a deterministic background has been explained by a contrast gain control mechanism that normalizes the response of the mechanisms responding to the signal.[2–5] We represent the effect of the contrast gain control mechanism by an induced noise component in the decision variable. Ahumada[35] and Legge *et al.*[27] have shown that a model with a response nonlinearity with constant internal noise is equivalent to a model with a linear response and a signal-dependent noise. The noise component induced by the presence of the structured background is a function of the background contrast; however, we did not manipulate the rms contrast of the structured background in these experiments. The equivalent contrast gain control noise is the amount of external noise added to the image needed to degrade performance by the same amount as the degradation due to the contrast gain control. The estimates of the rms equivalent contrast gain control noise were similar for both observers (0.049 for observer KS, and 0.04 for observer GN); however, the measured and predicted performance degradation due to the contrast gain control noise was larger for observer KS. This is because the ratio of the contrast gain control noise to the internal noise is greater for observer KS ($\sigma_i = 0.032$) than for observer GN ($\sigma_i = 0.074$). The estimated sampling efficiency in the presence of the structured background was smaller than the sampling efficiency in the uniform background. However, for observer KS, constraining the sampling efficiencies to be equal, did not degrade the fit (Table 2).

A strong assumption in our working model is that the sampling efficiency does not change as a function of increasing added white noise. This assumption requires that the human observer use the same filter for the different relative amounts of added white noise and structured background. This would be expected if the noise induced by the contrast gain control was also white. The optimal strategy would remain the same irrespective of the relative amounts of added white noise and structured background. However, if the noise induced by the contrast gain control mechanism is not white, then the optimal strategy changes as a function of the added-white-noise level, since the effective power spectrum changes. When the white noise dominates the contrast-gain-control-induced noise the optimal strategy would be matched filtering. But when the contrast-gain-control-induced noise dominates the white noise the optimal strategy involves prewhitening prior to the matched filtering. However, observers might be able to adjust the filtering strategy, depending on the relative amounts of added white noise and structured background.

Our analysis quantifies the effect of the deterministic structured background averaged across many samples. To predict the specific effect of an individual sample of structured background on signal detection, a detailed model of contrast gain control could be used. However, directly applying current contrast gain control models[2,3] to predict the effect of deterministic backgrounds in tasks with unlimited decision time is not straightforward. Some of the current contrast gain control models have been fitted to data for presentation times of ~30 ms[2]. The applicability of these results to experiments in which the observer has unlimited time to perform the task is unknown. Some recent experiments have shown that the presentation times will change the effect of the background on the signal's threshold. Ross *et al.*[41] presented the background and signal for 2 s and found lower effects of the mask than were found by Foley.[2] Foley[42] has also performed experiments with a stimulus presentation of 100 ms (versus 33 ms), finding that the orientation bandwidth of the inhibitory pooling mechanism decreases with the extended presentation time.

Another potential complexity is that familiarity with the background will decrease the effect of the background on the contrast threshold of the signal. Ahumada *et al.*[43] compared a condition in which a different white-noise background sample was added on each trial with a second condition in which the same noise sample was used throughout the blocks of trials. Masking was reduced with the familiar background. Smith and Swift[44] have also shown that background familiarity will reduce the performance degradation due to the background. Contrast gain control cannot account for this difference. The effect of an unfamiliar background is not the result of just a hard-wired mechanism (contrast gain control). Its prediction requires understanding the decision strategy of the observers.

C. Effect of Structured Background Variations

Differences between the repeated background condition and the different background condition indicate the effect of background variations, across backgrounds, on performance. For both observers, performance in the different structured background was poorer than in the repeated background condition. Without white noise [Figs. 2(a) and 3(a)] the slope of the psychometric functions (and therefore d') was reduced by approximately one third from the repeated structured background to the different structured background. This result is similar to the decrease in performance measured by Burgess and Colborne from a two-alternative forced-choice disk detection for repeated samples of white noise to different samples of external noise (a factor-of-1.59 reduction).[14] For observer GN the reduction factor is comparable with that for the contrast gain control mechanism. For observer KS reduction in the slope from background variations is somewhat smaller than the contrast gain control reduction. Our result shows that interlocation random variation in the background can be a significant source of performance degradation in detection in a complex spatially varying background. The estimated values for the equivalent background variation noise were of larger magnitude than the equivalent internal noise and the equivalent contrast gain control (see Tables 2 and 3). The estimated sampling efficiency for the case of different structured background conditions was similar to the sampling efficiency in the same structured background and somewhat smaller than the uniform background condition. How-

Table 2. Best Fits to the Variation of the Psychometric Slope (δ) as a Function of the External Added White Noise, Obtained by Use of Eq. (5) for Uniform Background Condition, Eq. (7) for the Repeated Structured Background Condition, and Eq. (8) for the Different Structured Background Condition (Observer KS)[a]

Parameter	Best Fit	Constraint	df	χ^2/df
Sampling efficiency (uniform, J_{ub})	0.316	No constraints	54	3.67
Sampling efficiency (same structured background, J_{sb})	0.166	$J_{\mathrm{ub}} = J_{\mathrm{sb}} = J_{\mathrm{rb}}$	2	−1.65[b]
Sampling efficiency (different structured background, J_{rb})	0.166	$J_{\mathrm{sb}} = J_{\mathrm{rb}}$	1	−4.03[b]
Equivalent internal noise[c]	${\sigma_i}^2 = 0.032^2$			
Equivalent contrast gain control noise	${\sigma_{\mathrm{cgc}}}^2 = 0.049^2$	${\sigma_{\mathrm{cgc}}}^2 = 0$	1	178.7
Equivalent background variation noise	${\sigma_{\mathrm{rbv}}}^2 = 0.075^2$	${\sigma_{\mathrm{rbv}}}^2 = 0$	1	248.8

[a] There were six free parameters: the equivalent internal noise, the equivalent contrast gain control noise, the equivalent background variation noise, and three corresponding sampling efficiencies. The third column describes fits with additional constraints. The fourth column has the degrees of freedom for the test. The fifth column has the goodness-of-fit measure, χ^2/df.

[b] The negative χ^2 values for the constraints on sampling efficiencies are caused by the fact that the parameter fits were performed on the psychometric function slopes by use of a rms error criterion and not based on a χ^2 criterion (see Section 3 for more information).

[c] To obtain the noise spectral density of the equivalent internal noise in degrees squared, one must multiply the equivalent noise by the constant 1.14×10^{-3} deg^2/pixel^2.

Table 3. Same as Table 2, but for Observer GN

Parameter	Best Fit	Constraint	df	χ^2/df
Sampling efficiency (uniform, J_{ub})	0.308	No constraints	54	5.2
Sampling efficiency (same structured background, J_{sb})	0.166	$J_{\mathrm{ub}} = J_{\mathrm{sb}} = J_{\mathrm{rb}}$	2	9.0
Sampling efficiency (different structured background, J_{rb})	0.2083	$J_{\mathrm{sb}} = J_{\mathrm{rb}}$	1	18.00
Equivalent internal noise[a]	${\sigma_i}^2 = 0.074^2$			
Equivalent contrast gain control noise	${\sigma_{\mathrm{cgc}}}^2 = 0.04^2$	${\sigma_{\mathrm{cgc}}}^2 = 0$	1	27.2
Equivalent background variation noise	${\sigma_{\mathrm{rbv}}}^2 = 0.12^2$	${\sigma_{\mathrm{rbv}}}^2 = 0$	1	56.07

[a] To obtain the noise spectral density of the equivalent internal noise in degrees squared, one must multiply the equivalent noise by the constant 1.14×10^{-3} deg^2/pixel^2.

ever, a fit that kept the sampling efficiency constant across conditions did not improve the fit for GN but did for KS.

A main assumption of our model is that the sampling efficiency remains constant as a function of the added white noise in the image. The assumption would hold if the observer used the same filter for all rms white-noise levels (fixed filter assumption).[39] This assumption would be violated if the observer tried to optimize its filter as a function of the relative amount of white noise and interlocation random variation in the background. At relative high levels of white noise a matched filter would be close to optimal, while at low levels of white noise a filter that attempts to decorrelate the combined noise would perform better (e.g., Hotelling[10,11] and channelized Hotelling[36–38] models). Several experiments on detection in filtered noise and backgrounds with random inhomogeneities have yielded results consistent with the adaptive filtering by human observers.[10] However, Burgess showed that a fixed matched filter with a front eye filter (modified nonprewhitening matched filter) can also account for human detection in backgrounds with random inhomogeneities.[13] Recently, Burgess presented new experiments on detection in backgrounds with two noise components (a white-noise component and a low-pass-filtered noise), showing that humans can perform adaptive filtering (partial prewhitening).[39] Together, these results[10,13,39] suggest that future work should test the fixed filter assumption for the case of structured backgrounds and white noise used in our experiments.

D. Effect of Additive White Noise

For both observers the relative effects of the fixed deterministic same background condition (contrast gain control) and the different background condition (random variations) on performance were reduced with increasing added white noise. In our model, when the white-noise level is high, it dominates the variability in the decision variable. In this case, an induced noise from the deterministic fixed background or a noise source from random variations in the background will have a relatively small effect.

On a uniform background, d' is related to the rms contrast white noise as described by Eq. (5) (the energy threshold is linear with the noise spectral density). This relationship is supported by detection and contrast discrimination experiments by Burgess *et al.*,[8] Pelli,[20] and others (e.g., Nagaraja[45]). For the deterministic structured background and the different structured background conditions we assumed that the mathematical relationship between d' and the squared rms noise was unaffected (except for the sampling efficiency). This assumption would hold if the observer used the same filter for the different rms added-white-noise conditions. However, if the fixed filter assumption does not hold, then departures from Eqs. (7) and (8) might arise.[39]

In our treatment we have assumed that the degrading effect of white noise is from its variability from location to location. However, the white noise will also affect performance through the contrast gain control mechanism. Experiments by Burgess[14] that measured detection in a two-alternative forced choice with the same sample of white noise versus different samples of white noise showed that there is an induced white-noise component proportional to the added external white noise, with the random variability being the larger source of degradation. Ahumada *et al.*[43] used a temporal two-interval forced choice in the presence of a complex background (airport runway) and found that detection performance was the same regardless of whether the samples of white noise in the two intervals were the same or different. The apparently higher level of internal noise in the results obtained by Ahumada *et al.* should be, in part, a result of the background (airport runway) and, in part, a result of decision variability, since Burgess presented the images simultaneously, while Ahumada *et al.* presented them sequentially through time.

Our analysis cannot distinguish whether the white-noise degradation is from the random variations in the white noise or whether it is from an induced noise component (contrast gain control). Future research could test this hypothesis by comparing performance in a condition in which the different locations have the same sample of white noise plus the structured background with performance in a condition in which the different locations have different samples of white noise plus the structured background.

E. Impact on the Development of Computer Observer Models for Automated Evaluation of Task-Performance Medical Image Quality

Objective measures of medical image quality can be measured in terms of performance in tasks that are relevant to visual clinical diagnosis.[46] Evaluation of medical image quality through psychophysical studies can be time consuming. For optimization of image processing techniques with a large number of parameters, psychophysical studies may simply not be feasible. One goal has thus been to develop models that can accurately predict human performance as a function of basic image properties such as signal contrast and image processing and acquisition techniques. This model could potentially be used for automated evaluation and optimization of image quality.[46,47] A number of linear models have been used in recent years to predict human performance, including the nonprewhitening matched filter and modified nonprewhitening matched filter, Hotelling, and channelized Hotelling models.[10–13,17,36–38,47] The source of degradation in these models is the random variation in the backgrounds and the observer's suboptimal processing of the data. Possible limitations in the processing of the data could be through an eye filter,[13] a number of narrow-band channels that reduce the effective information available to the observer,[36–38] or an inability to use the noise ensemble statistics to undo the correlations in the noise.[10,11,13] None of these models includes a source of performance degradation associated with a fixed background; they predict no performance degradation from the uniform gray background condition to the repeated background condition. However, our results show that the deterministic background contributes approximately as much to performance degradation as do the random variations in the complex background. Models developed to predict human performance in visual detection in medical image noise require a source of degradation from a fixed deterministic background.

F. Assumptions, Limitations, and Future Directions

The main limitation in the current treatment is the assumption that the observer uses the same effective filter (fixed filter assumption) as a function of the relative amounts of added white noise and structured background (in both the same and different structured background conditions). This assumption will produce the relationship between d' and the added-white-noise spectral noise density implicit in Eqs. (7) and (8). We have discussed the possible violations of this assumption in Subsections 5.C–5.E for the cases of the same structured background and the different structured background conditions. Future research needs to rigorously test the fixed filter assumption and investigate how operational models that use a fixed filter (nonprewhitening and modified nonprewhitening matched filter) or an adaptive effective filter (Hotelling, channelized Hotelling models) may account for observer performance in structured backgrounds with different degrees of additive white noise.

6. CONCLUSIONS

We have investigated how two sources of performance degradation in human visual signal detection (the presence of a deterministic high-contrast background and random variations in the background) contribute to the detection of a signal in a spatially varying complex background (structured backgrounds). The performance degradation caused by a fixed deterministic background (contrast gain control) was approximately equal to that caused by the random variations in the background. Models for human visual detection in spatially varying complex backgrounds require both a contrast gain control mechanism and decision strategies that use prior knowledge about the signal and/or background statistics.

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