Zero-dimensional noise: The best mask you never saw

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The transmission of weak signals through the visual system is limited by internal noise. Its level can be estimated by adding external noise, which increases the variance within the detecting mechanism, causing masking. But experiments with white noise fail to meet three predictions: (a) noise has too small an influence on the slope of the psychometric function, (b) masking occurs even when the noise sample is identical in each two-alternative forced-choice (2AFC) interval, and (c) double-pass consistency is too low. We show that much of the energy of 2D white noise masks extends well beyond the pass-band of plausible detecting mechanisms and that this suppresses signal activity. These problems are avoided by restricting the external noise energy to the target mechanisms by introducing a pedestal with a mean contrast of 0% and independent contrast jitter in each 2AFC interval (termed zero-dimensional [0D] noise). We compared the jitter condition to masking from 2D white noise in double-pass masking and (novel) contrast matching experiments. Zero-dimensional noise produced the strongest masking, greatest double-pass consistency, and no suppression of perceived contrast, consistent with a noisy ideal observer. Deviations from this behavior for 2D white noise were explained by cross-channel suppression with no need to appeal to induced internal noise or uncertainty. We conclude that (a) results from previous experiments using white pixel noise should be re-evaluated and (b) 0D noise provides a cleaner method for investigating internal variability than pixel noise. Ironically then, the best external noise stimulus does not look noisy.

Keywords: noise masking, contrast detection, gain control, suppression, human vision

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Introduction

In human vision, detection thresholds for simple targets such as sine wave gratings increase when white pixel noise is added to the display (Lu & Dosher, 2008; Pelli, 1985). The classical explanation for this noise-masking effect (the noisy ideal observer model) is that the external pixel noise contributes to the variance of the observer's internal response to the target. When the external noise approaches or exceeds the observer's internal (neural) noise, sensitivity to the target declines and masking occurs.

It is therefore possible to estimate the magnitude of internal noise in units of the external noise (Pelli & Farell, 1999). The "equivalent input noise" level is the point at which the noise mask raises the contrast detection threshold by a factor of $\sqrt{2}$ (for a linear observer), because the external noise has doubled the total variance, and is usually estimated by model fitting to contrast masking functions. This equivalent noise paradigm has received widespread use in studies comparing basic experimental manipulations (Allard & Faubert, 2006; Gold, Bennett, & Sekuler, 1999; Goris, Zaenen, & Wagemans, 2008; Henning & Wichmann, 2007; Kersten, 1984; Lu & Dosher, 2008; Neri, 2010; Pelli, 1981) and those investigating clinical conditions (Huang, Tao, Zhou, & Lu, 2007; Levi, Klein, & Chen, 2007, 2008; Pardhan, Gilchrist, Elliott, & Beh, 1996; Xu, Lu, Qiu, & Zhou, 2006).

However, human observers are not linear systems. For example, it is well established that there is mutual suppression between spatiotemporally tuned channels in primary visual cortex (Bonds, 1989; Carandini & Heeger, 1994; Heeger, 1992; Morrone, Burr, & Maffei, 1982). These "gain control" effects produce threshold elevation from (deterministic) grating masks, even those with very different spatial properties from the target (Brouwer & Heeger, 2011; Eckstein, Ahumada, & Watson, 1997; Foley, 1994; Meese & Holmes, 2007). It seems likely that noise masks will also induce this type of suppression (which is usually modeled as a divisive process [Foley, 1994; Heeger, 1992]), because much of the energy of a typical noise mask will fall outside the pass-band of the channels used to detect the target.

We demonstrate this by filtering many samples of 2D white pixel noise (low-pass filtered and spatially

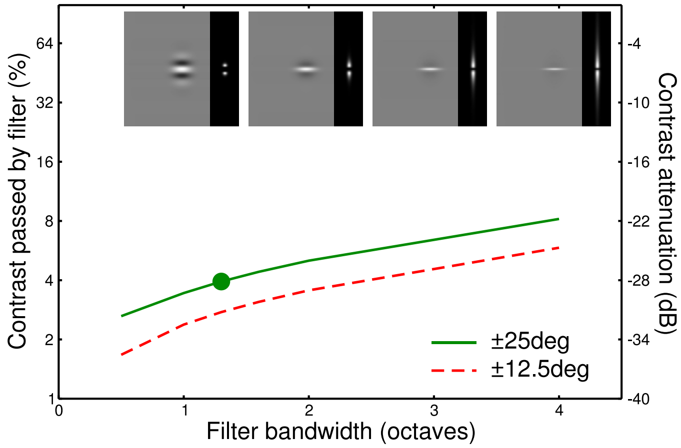

Figure 1. Contrast attenuation for 2D white noise stimuli following bandpass filtering. Results are the average of 1,000 noise samples (created as described in the Methods section) and refer to changes in RMS contrast. Filters were Cartesian separable log-Gabors (Meese, 2010) with center orientation and spatial frequency of 90° and 4.25 c/image, respectively. (Note that we use c/image rather than c/deg because the images in these simulations were never displayed in an experiment.) The orientation and spatial frequency bandwidths of the example filters (upper insets) are ±25°, and 1, 2, 3, or 4 octaves, respectively, from left to right. The simulations sampled the range more finely than this (solid green curve) and also for an orientation bandwidth of ±12.5° (red dashed curve). The section to the right of each example filter is the Fourier transform of that filter. The green circular symbol indicates the log-Gabor used as the target stimulus in later experiments.

windowed, as described in the Methods section) with oriented log-Gabor filters of various bandwidths. We found that 92%–98% of the noise contrast was excluded by the filtering (see Figure 1 and its caption for details). This suggests that white pixel noise might produce very little within-channel variance and that, instead, the masking it causes might be due to suppression from cross-channel interactions.

To better understand the processes involved in noise masking, we first formalize the two very different processes previously described. The models in this section are canonical and could be implemented as stochastic or deterministic models, operating on numeric contrast values or full images. In the noisy ideal observer model, the response is given by: $resp_{NIO} = C + G_\sigma$, where C is the contrast response of a linear filter sufficiently broad to respond to the target and the external noise, and G_σ is zero-mean Gaussian noise with standard deviation, σ, representing the internal noise of the observer. In the gain control model, there is a nonlinear contrast transducer and suppression of the target mechanisms from adjacent channels (Foley, 1994; Hansen & Hess, 2012; Heeger, 1992) with superimposed receptive fields. The response of this model is given by: $resp_{GCM} = (C^p / (Z + C^q + X)) + G_\sigma$, where X represents the pooled and weighted activity in adjacent (nontarget) channels, Z is a constant (e.g., $Z = 1$), and the exponents p and q typically have values of 2.4 and 2, respectively (Legge & Foley, 1980). In realistic situations, the external noise will contribute to the variance at the decision variable in this model, just as it does in the noisy ideal observer model. However, we find it most instructive to begin by excluding this contribution to masking from the model (by setting C to the target contrast) so that we can consider the effects of signal suppression in isolation (we revoke this exclusion in the Discussion). Thus, in the noisy ideal observer model, noise masking derives entirely from an injection of external noise into the detecting mechanism, whereas in our stripped-down gain control model here, it derives entirely from cross-channel suppression.

We compare the behavior of the two models above in four main experiments designed to reveal the relative contributions of within-channel noise and cross-channel suppression for white noise masks. Each experiment (described in the Results section) was performed for (a) conventional spatially two-dimensional (2D) static white pixel noise (Figure 2e) and (b) a novel type of noise involving a cosine-phase pedestal matched to the log-Gabor target (Figure 2c). The mean contrast of the pedestal was 0%, but it was jittered on an interval-by-interval basis (in two-interval forced-choice [2IFC]) using values drawn from a normal (Gaussian) distribution. Negative contrasts were expressed by changing the phase of the pedestal to negative cosine phase. Because this type of noise has neither spatial nor temporal dimensions (these parameters are defined by the target; the noise is merely a signed level of contrast), we refer to it as zero-dimensional (0D) noise.

The 0D noise condition fulfills the crucial requirement of standard noise-masking experiments; there should be a random component of activity in the detecting mechanisms across trials and across each interval within each 2IFC trial. Furthermore, because 0D noise is concentrated entirely within the pass-band of the detecting mechanism, there should be no contamination from cross-channel suppression. (A similar approach has been used for luminance [Cohn, 1976; Lasley & Cohn, 1981; Neri, 2010] but not previously for contrast-defined targets.) Our results tend toward the noisy ideal observer model for 0D noise and the gain control model for 2D noise. By comparing the results across the noise conditions, we were able to demonstrate a strong contribution to masking from suppression (contrast gain control) made by conventional white noise masks. This influence is probably greater than many previous studies have credited.

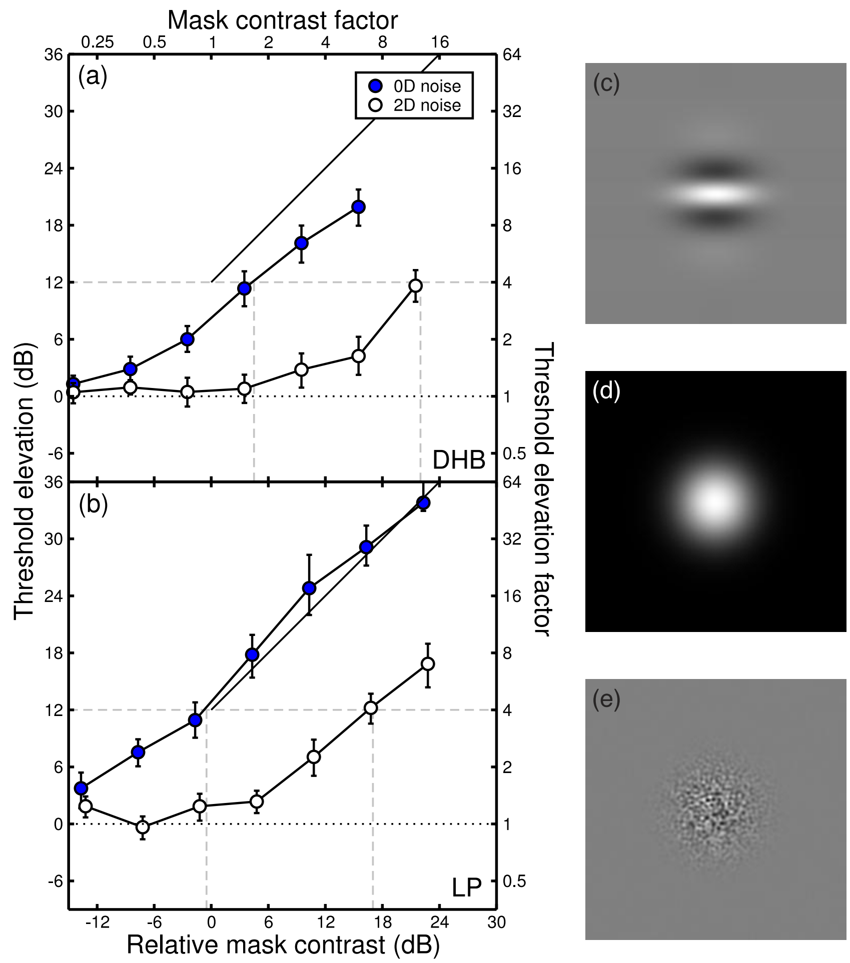

Figure 2. Noise-masking results (preliminary experiment) for two observers (top and bottom) and example stimuli. (a, b) Results are plotted as functions of relative mask contrast (e.g., they are scaled by the detection thresholds for the masks). The diagonal lines have unit slope for reference, and error bars give 95% confidence intervals obtained by bootstrap resampling. The intersections of the horizontal and vertical dashed lines indicate the mask contrasts that produced equal levels of threshold elevation (12 dB), used in subsequent experiments. (c) Log-Gabor target. (d) The Gaussian envelope used to window the noise (see Methods). (e) An example of windowed 2D white noise.

Methods

Apparatus and stimuli

Stimuli were presented on an Iiyama VisionMaster Pro 510 using a BITS++ box (Cambridge Research Systems Ltd., Kent, UK) controlled by an Apple Macintosh computer. We used elements of the Psychophysics Toolbox software (Brainard, 1997; Pelli, 1997) to control the stimulus display. The monitor was gamma corrected, had a mean luminance of 50 cd/m^2, and was viewed at a distance of 114 cm. At this distance, 1 degree of visual angle occupied 60 pixels on the monitor.

The target in all experiments was a horizontal 1 c/deg Cartesian separable log-Gabor patch (Meese, 2010) with bandwidths of 1.3 octaves and $\pm 25°$ in polar coordinates (see Figure 2c). The target was luminance-balanced and always in positive cosine phase with a bright bar in the center flanked by two dark bars. These bandwidths were chosen so that the spatial extent of the target was approximately equal in all directions. We then used an isotropic 2D Gaussian of the same spatial extent (Figure 2d) to window the 2D noise mask stimuli (full-width at half-height of 1 degree). The 2D white noise mask (Figure 2e) was generated from Gaussian pixel noise, which was low-pass filtered in the Fourier domain at 15 c/deg using a cosine ramp. The low-pass filtering removed frequencies which would be largely invisible to the observer at the displayed mask contrasts and concentrated the mask energy within a 4-octave range of the target frequency. All stimuli were static, having no temporal modulation besides their onset and offset.

We report contrast throughout in decibels (dB), defined as $20*log_{10}(C)$, where C is the nominal contrast in linear units. For the target stimulus, this was the root mean square (RMS) contrast of the target waveform (i.e., the standard deviation of luminance over space). For the 2D noise masks, nominal contrast was the RMS contrast over space (e.g., Moulden, Kingdom, & Gatley, 1990; Peli, 1997). For the 0D noise masks (contrast jitter of a pedestal with 0% mean contrast), nominal contrast was the RMS contrast across multiple presentations. Put another way, it was the standard deviation of the zero-mean Gaussian noise source that determined the discrete contrast of each noise mask. Note that, for a single pixel in the center of the display, the luminance variation across trials was the same for 0D and 2D noise masks of equal nominal contrasts. (This would not be the case had we used an alternative metric, such as spectral density, to characterize the 2D noise.)

Observers

Two observers completed all experiments. They were the first author (DHB) and a postgraduate student (LP). Both were emmetropic and psychophysically experienced, but only DHB was aware of the purpose of the experiments.

Procedure

All experiments used a temporal 2AFC design with each interval indicated by an auditory beep. All stimuli appeared in the center of the display inside a quad of fixation points placed at a radius of 1 degree. The stimulus duration was 100 ms, with a 400-ms interstimulus interval. Observers responded using the buttons of a mouse to indicate which interval they believed contained the target. There was no feedback in any experiment. This was because, in some conditions (particularly the 0D noise conditions), it was possible that the interval containing the target had a lower physical contrast, or was of the opposite polarity, to that in the null interval. Feedback in this situation would be confusing to the observer, so we removed it for all conditions.

Detection thresholds with each type of noise mask were measured at seven mask contrasts to produce masking functions. Each threshold was estimated using a pair of three-down, one-up staircases, each of which terminated after the lesser of 70 trials or 12 reversals. Staircase pairs for each condition were collected individually, taking around 2 to 3 minutes each, and observers were informed of the masking condition before each session began. The entire set of masking conditions was repeated four times. Baseline detection thresholds for the targets without a mask were measured four times per repetition of the mask conditions (i.e., 16 measurements in total). Data were pooled across the multiple repetitions, and thresholds were estimated (at 81.6% correct) by fitting a Weibull function to the psychometric data (e.g., the percentage of correct responses at each target contrast level).

The masking functions were used to estimate the mask contrasts that would produce an equal amount of threshold elevation (around 12 dB) for each mask condition. These mask contrasts were used in all subsequent experiments. To assess the slope of the psychometric function, double-pass consistency, and twin masking, full psychometric functions were measured at nine target contrast levels using the method of constant stimuli (MCS). This was completed in 20 blocks of 90 trials per condition, producing psychometric functions each derived from 1,800 trials. The second halves of the MCS experiments (i.e., the final 10 blocks) were exact replications of the first halves in terms of the noise samples used, the ordering of trials and blocks, and the target interval in each trial. This allowed double-pass consistency scores to be calculated by comparing trial-by-trial responses across the first and second halves of the experiments. The "twin" conditions of Experiment 3 were run in a similar manner, except that the noise mask was the same in both intervals of a trial (though it differed between trials).

In the final experiment, observers compared the perceived contrast of a masked target to a matching stimulus without a mask. The task was to indicate which target appeared higher in contrast. The target and matching waveforms were identical, but the target contrast was fixed and the matching contrast was determined by a one-down, one-up staircase (Meese, 1995) using a step size of 1.5 dB. The staircase converged on the 50% point of the psychometric function (the point of subjective equality [PSE]), which was estimated by fitting a cumulative log-Gaussian function.

Results

Preliminary experiment: Equating the level of masking for two different types of external noise

We first measured contrast-masking functions for two observers using 2D pixel noise and 0D jitter noise. As shown in Figure 2, all functions increased monotonically with mask contrast and had a slope around unity (on log-log contrast axes) at higher mask contrasts. Overall, 0D noise (filled blue symbols) produced much stronger masking than 2D white noise (open symbols). This result held when the abscissa was normalized to the detection threshold of each mask (as shown here) and also when expressed as absolute contrast (not shown). Although we do not know the precise bandwidths of the detecting mechanisms or the weight of suppression from the gain pool, it is not surprising that the 0D noise is the more potent mask because it injects more variance into the detecting mechanism than does the more broadband 2D noise.

The main purpose of this experiment was to use the noise-masking functions to find mask contrasts for each type of noise that would produce approximately equal amounts of threshold elevation (around 12 dB; a factor of 4). These mask contrasts—given by the intersections of the horizontal and vertical dashed lines in Figure 2—were then used in the four main experiments. For both observers, the contrast of the 2D noise needed to be 18 dB (eight times) higher than that of the 0D noise to produce similar levels of threshold elevation.

Experiment 1: Birdsall linearization

Psychometric slopes (i.e., the slope of the function relating proportion of correct responses to target contrast) for contrast detection are usually described as steep in the absence of external noise, with the slope (β) parameter of a fitted cumulative Weibull distribution having typical values of around 3–4 (Mayer & Tyler, 1986; Meese, Georgeson, & Baker, 2006). This steepness has been attributed to nonlinear signal transduction (Foley & Legge, 1981; Nachmias & Sansbury, 1974), mechanism uncertainty (Pelli, 1985), or a mixture of the two (Meese & Summers, 2009). Strong external noise injected into the detecting mechanism should remove the effects of invertable transduction nonlinearities within the system. This is known as Birdsall linearization (Klein & Levi, 2009), deriving from Birdsall's theorem (Lasley & Cohn, 1981), and occurs because the ordinal values of responses at the decision variable cannot be rearranged by invertible nonlinear transduction after the limiting noise. This means that external noise should neutralize any such nonlinearities once it dominates the internal noise. This will reduce the psychometric slope to $\beta \sim$ 1.3 in Weibull slope units (Klein & Levi, 2009; Lasley & Cohn, 1981; Pelli, 1985; Tyler & Chen, 2000) (equivalent to the d' slope of unity that is characteristic of a linear system, hence the "linearization" terminology). On the other hand, a pure gain control account of masking predicts no change in the psychometric slope because divisive suppression does not affect the form of contrast transduction (Meese & Baker, 2009; Meese, Challinor, & Summers, 2008). We measured psychometric slopes using the method of constant stimuli with 1,800 trials per psychometric function. For each observer, the psychometric slope at detection threshold (i.e., no noise) was around β = 3.5, consistent with estimates from previous studies (Dao, Lu, & Dosher, 2006; Dosher & Lu, 2000; Eckstein et al., 1997; Goris et al., 2008; Harwerth & Smith, 2000; Henning, Bird, & Wichmann, 2002; Henning & Wichmann, 2007; Kersten, 1984; Legge, Kersten, & Burgess, 1987; Lesmes, Jeon, Lu, & Dosher, 2006; Levi et al., 2008; Lu & Dosher, 1999, 2008; Pelli, 1981; Smithson, Henning, MacLeod, & Stockman, 2009; Thomas, 1985; Xu et al., 2006) (see the distribution on the lower axis of Figure 3a) and much steeper than the linear prediction of β = 1.3. This steep slope was effectively linearized by 0D noise for both observers (DHB, $\beta = 1.28$; LP, $\beta = 1.47$). For observer DHB, 2D noise also linearized the slope ($\beta = 1.22$), whereas linearization was only partial for LP ($\beta = 1.82$).

Variability in this type of analysis has been found before. Therefore, to draw a clearer picture of the relation between external noise and the slope of the psychometric function, we considered our findings in the context of 17 other studies that provided related information. This is summarized by the scatterplot in Figure 3a, where the slopes of the psychometric functions measured in the presence of the highest level of external noise used in each study are plotted against equivalent slopes measured at detection threshold (without external noise). If external noise did not affect psychometric slope, the results should be distributed evenly about the purple diagonal line of unity. This is not the case, with the majority of points lying below the line, indicating that external noise did reduce the slope of the psychometric function. The geometric means across studies supported this observation with $\beta = 3.03$ at detection threshold reducing to β = 2.02 in the presence of noise. However, in most studies, linearization was not complete because the external noise did not cause the points to drop as low as β = 1.3 (the orange horizontal line in Figure 3a).

Figure 3b shows the same results as in Figure 3a but replotted in terms of the dimensionality of the noise mask used in each study (see figure caption for details), including the results from the present study (red circles). As the dimensionality increases, Birdsall linearization is found less frequently (more points tend to be higher than β = 1.3). In sum, although there is some evidence for Birdsall linearization, it is far from a universal finding (as discussed elsewhere [Klein & Levi, 2009]) and is rarely observed for noise masks where the variance is distributed along several dimensions. Taken together, these results indicate that, as the dimensionality of the noise increases, the influence of externally invoked variability in the detecting mechanism tends to decrease (though the variability in Figure 3 does suggest that other factors might also be involved).

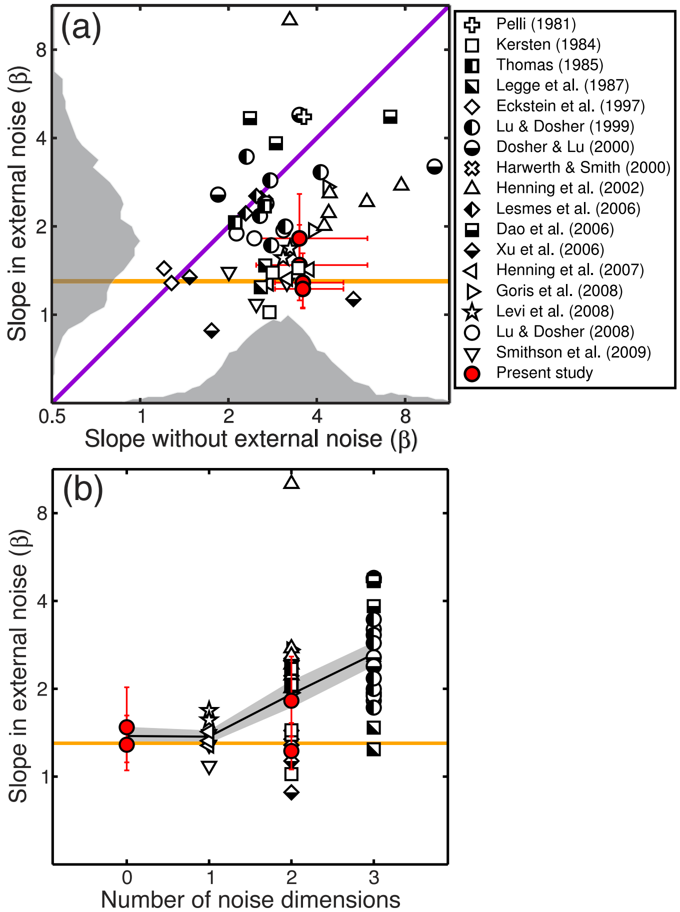

Figure 3. Slopes of the psychometric function (Weibull β), with and without external noise, from 18 studies (Dao et al., 2006; Dosher & Lu, 2000; Eckstein et al., 1997; Goris et al., 2008; Harwerth & Smith, 2000; Henning et al., 2002; Henning & Wichmann, 2007; Kersten, 1984; Legge et al., 1987; Lesmes et al., 2006; Levi et al., 2008; Lu & Dosher, 1999, 2008; Pelli, 1981; Smithson et al., 2009; Thomas, 1985; Xu et al., 2006) on noise masking, including Experiment 1 here. Symbols indicate the study, as shown in the legend. (In some cases, it was necessary to extract data on proportion correct from published figures [using computer software] and fit them with Weibull functions to derive estimates of β ourselves.) The shaded areas in (a) are histograms showing the distributions of β values from the 18 studies (note that the peak of each of these is at $\beta > 1.3$). Panel (b) shows the ordinate data replotted as a function of the number of noise dimensions. Dynamic 2D noise, which varies in time, spatial frequency, and orientation, can be considered to have three dimensions. Lower dimensional noise varies in only a subset of these dimensions. The black curve and shaded region show the mean and $\pm 1SE$. Error bars on the red symbols are 95% confidence intervals obtained by bootstrap resampling.

Thus, we might expect that the internal variability produced by external noise becomes less relevant to noise masking as the dimensionality of the noise increases. We provide more direct evidence for this with the next experiment.

Experiment 2: Response consistency

A second expectation of injecting external noise into the detecting mechanism is that an observer's responses should become highly consistent when trials are replicated using identical samples of noise. This can be assessed using a "double-pass" paradigm (Burgess & Colborne, 1988) where a precise sequence of experimental trials is repeated a second time (i.e., the same noise samples are used on each pass). Consistency of responses across the two passes should be high in the presence of strong external noise, even when response *accuracy* is near chance (e.g., 50% correct for 2AFC). This is the prediction of the noisy ideal observer model, shown by the curves in Figure 4 for varying levels of influence from the external noise (see legend). This includes the situation where there is no influence from the external noise (black curve), which is also the prediction for the gain control model, and for contrast detection in the absence of a noise mask (Klein & Levi, 2009) under either model. In these cases, the agreement across repeated trials is purely a function of performance.

In the experiment, the 0D noise condition (filled blue symbols) produced very high levels of response consistency, even at low levels of performance, and was close to the predictions of the noisy ideal observer model where external noise was two to four times higher than the internal noise. In contrast, the 2D noise condition (open white symbols) produced much lower consistency, implying approximately equal contributions from internal and external noise. This difference across noise types is remarkable as the two different masks elevated detection thresholds by approximately the same amount (recall the preliminary experiment). This shift of the 2D results from the 0D results and toward the prediction by the gain control model (black curves) is strong evidence that the different types of external noise invoke different processes of masking. Previous studies have also reported low double-pass performance in 2D (or 3D) noise (Burgess & Colborne, 1988; Hayes & Merigan, 2007; Levi et al., 2007; Lu & Dosher, 2008; Neri, 2010), but have not compared this with 0D noise or the predictions of a gain control model.

Experiment 3: Twin masking

In the previous experiments, a different sample of noise was used in each 2IFC interval. In noise-masking studies, this is known as the "random" configuration (Ahumada & Beard, 1997; Watson, Borthwick, & Taylor, 1997), and it produces strong masking in each of our models. However, when the same sample of noise is used in each of the 2IFC intervals (known as the "twin" configuration [Watson et al., 1997]), masking should be

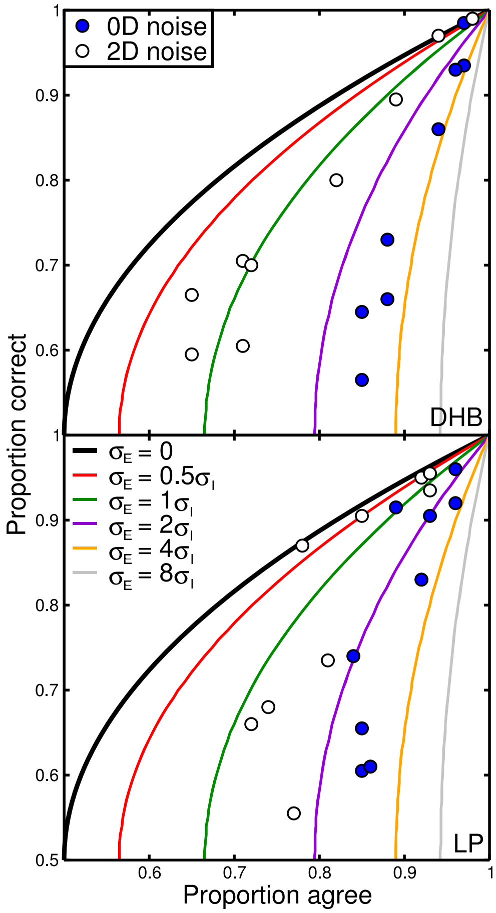

Figure 4. Double-pass consistency results (Experiment 2) for two observers (different panels) for 0D (blue symbols) and 2D (white symbols) noise masks. The curves are predictions (obtained by stochastic simulation [Klein & Levi, 2009]) of the noisy ideal observer model for different ratios of external:internal noise (given by the legend in the lower panel, where σ_E is external noise and σI is internal noise). The black curve ($\sigma_E = 0$) is also the prediction of the gain control model and applies to all situations where there is no external noise (e.g., baseline detection thresholds) (Klein & Levi, 2009).

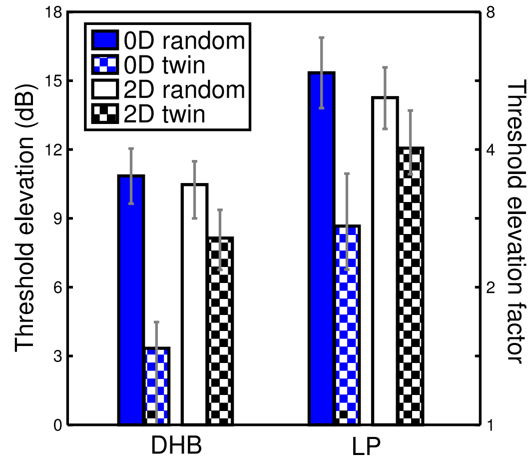

Figure 5. Random and twin noise configuration results (Experiment 3) for two observers (left and right). Bars show threshold elevation for 0D and 2D noise masks using each type of noise configuration (see legend). Empirical thresholds were determined using the method of constant stimuli with 1,800 trials per condition. The noisy ideal observer model predicts that threshold elevation should be 0 dB for the twin conditions (checked bars). The gain control model predicts that the level of masking should be the same for the random and twin conditions. Deviations from these predictions are discussed in the main text. Error bars show bootstrapped 95% confidence intervals.

abolished for the noisy ideal observer. This is because the external noise affects the internal responses in each 2IFC interval equally, and so it does not contribute to the difference in activation between intervals. In the gain control model, the similarity of the mask shown in the null interval is immaterial because all of the threshold elevation is due to suppression of the target by the mask in the target interval. Therefore, the gain control model predicts that the level of masking should be the same for the random and twin configurations.

We found that the random configuration produced threshold elevation of similar strength for the 0D and 2D random masks (Figure 5; solid bars) as to be expected for the mask levels chosen after the preliminary experiment. For the 2D noise condition (black and white checks), masking changed very little in the twin configuration (a mean reduction of 2.27 dB) consistent with previous reports (Ahumada & Beard, 1997; Watson et al., 1997). We attribute this small departure from the gain control prediction (of no effect) to the variability injected into the detecting mechanism by the external 2D noise, which is not part of our stripped-down model but is consistent with the results from Experiment 2. For the 0D noise condition (blue and white checks), the reduction in masking was much greater (7.10 dB). However, even for 0D noise, masking was not abolished. We attribute this residual effect to the compressive contrast response function (Legge & Foley, 1980) which derives from a within-mechanism contribution from the contrast gain pool in contemporary models of masking (Foley, 1994) and would produce pedestal masking (Bowen, 1997; Foley & Chen, 1999; Legge & Foley, 1980) for sufficiently high samples of noise. We have confirmed the plausibility of this in further model simulations (not shown).

In sum, the results of Experiment 3 tended towards the noisy ideal observer model for the 0D noise and towards the gain control model for the 2D noise, just like in Experiment 2. Departures from this were the same for both observers, and were predicted by the differences from our stripped down gain control model that we might expect the real visual system to possess.

Experiment 4: Contrast matching

Our fourth and final experiment concerns the perceived contrast of a grating target embedded in noise. Over many trials, the injection of external noise into the target mechanism should increase the variance but not the mean of the internal response distribution, and so the overall perceived level of contrast should not change (orange line in Figure 6). For the contrast gain control model, however, the effects of suppression would reduce the mean activity, and so perceived contrast should be attenuated (purple graded shading in Figure 6). Note that, for this model, the level of masking depends on the details of the suppressive weights in the gain pool. Because we have no independent measures of these, we show the predicted effects of masking as graded shading (becoming more severe as the weights increase). We tested these predictions by adjusting the contrast of a stimulus without noise (perceived contrast) to match that of an identical stimulus embedded in noise (physical contrast).

The results of this experiment are clear. There was no change in perceived contrast for targets embedded in 0D noise (blue symbols), consistent with the noisy ideal observer model. However, substantial attenuation, sometimes exceeding 6 dB (a factor of 2), was evident for the 2D noise mask (white symbols) for both observers and as predicted by the gain control model. This is a similar result to the suppressive effects of cross-oriented grating masks on perceived target contrast reported previously (Meese & Hess, 2004).

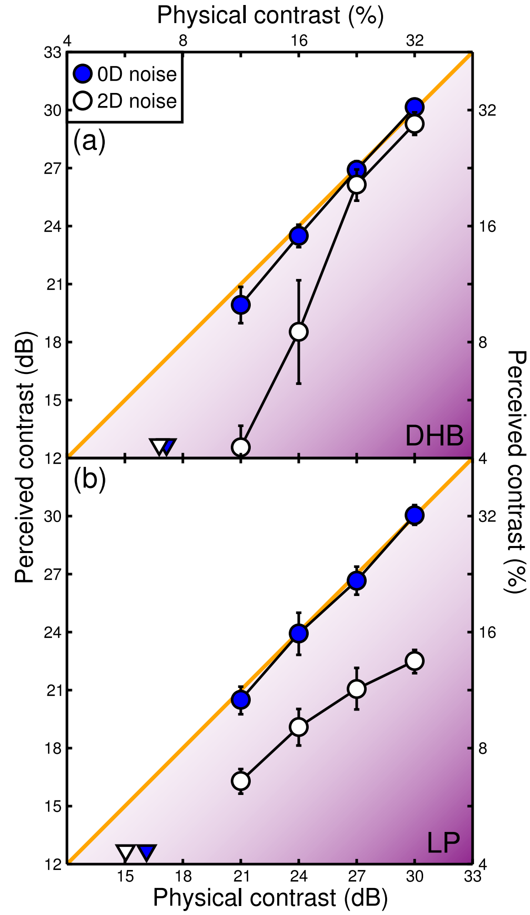

Figure 6. Perceived contrast in noise (Experiment 4) for two observers (top and bottom). The physical target contrast is plotted along the abscissa and the perceived (matching) contrast along the ordinate. If a mask had no effect on perceived contrast, the results should fall on the diagonal orange line. Results falling below this line (in the purple graded shading) indicate that perceived contrast was attenuated by the mask with darker shading corresponding to stronger attenuation. Error bars show 95% confidence intervals obtained by bootstrap resampling. Triangles placed on the *x*-axis indicate (masked) contrast detection thresholds for each condition for the same mask contrast as was used in the matching one.

Discussion

Across four experiments, 0D noise behaved exactly as external noise is expected to behave. It produced strong threshold elevation, a linear psychometric function, high double-pass consistency, weak twin masking, and no change in perceived contrast. This is consistent with the noisy ideal observer model. However, the results were very different when we used 2D pixel noise, which (a) produced weaker masking, (b) did not always linearize the slope of the psychometric function (consistent with 17 previous studies), (c) had low double-pass consistency, (d) produced strong twin masking, and (e) attenuated perceived contrast. All of these behaviors are consistent with the gain control model. However, we are not proposing that the visual system literally switches between different processes of masking depending on the type of noise. Rather, by reprieving the inevitable component of variance from external noise in the gain control model (this was excluded in the Introduction), we propose that all of the results are consistent with that single model. For example, it will behave in a similar way to the noisy ideal model for 0D noise, as all of the noise energy is directed to the decision variable. However, for 2D noise, spatiotemporal filtering means that much less of the noise energy arrives at the decision variable (e.g., see results and discussion of Experiment 3), and the suppressive component of masking is significant.

The implication is that suppression has contaminated previous studies of external noise. As these effects are rarely acknowledged, this brings most previous conclusions about equivalent noise into question. In extreme cases, experiments might be measuring variations in the level of suppression rather than internal noise, for example in amblyopia (Huang et al., 2007).

We propose that 0D noise offers a cleaner method for assessing the factors limiting human performance because an estimate using this method will be a single number that describes the standard deviation of the noise within the detecting mechanism(s). This avoids the ambiguity involved from estimates using 2D (or 1D) noise which depend on the variance and the bandwidth of the detecting mechanism, the strength of suppression from other mechanisms, and the spectral characteristics of the noise. For example, the equivalent noise for 2D white noise will be very different from the equivalent noise for 1D pink noise, and neither will provide a direct estimate of the internal variability within the detection mechanism(s).

It is possible that observers adopt different detection strategies for detecting targets in 0D noise and 2D noise. For example, the 0D noise pedestal helps to identify the target mechanism whereas the 2D noise pedestal does not. Nonetheless, our point is that any change in strategy would be prompted by the activity in the extraneous mechanisms in the 2D case. This is consistent with our general point that contrast sensitivity in 2D noise depends on processes other than the injection of external noise into the detecting mechanism. Certainly, any difference in strategy cannot be prompted by what happens in the detecting mechanism (which is what noise-masking studies allege to investigate) because the distribution of responses is the same zero mean Gaussian (e.g., evenly split across positive and negative) for both noise types.

Induced noise and induced uncertainty

There are at least three alternatives to suppression from contrast gain control that also predict steep psychometric slopes and (in two cases) low double-pass consistency in noise. The first of these assumes that external noise masks induce additional internal noise at a late stage (Burgess & Colborne, 1988; Eckstein et al., 1997; Lu & Dosher, 2008). This reduces the effective ratio of external:internal noise, ameliorating the Birdsall linearization effect (and so psychometric functions remain steep in noise) and decreasing double-pass consistency (Burgess & Colborne, 1988). The perceptual template model of Lu and Dosher (1999) includes an explicit pathway for induced noise to imbue their model with these properties.

Alternatively, pixel noise masks might activate additional detecting mechanisms that compete with the target mechanisms for access to the decision variable. This account is related to the uncertainty model of detection (Pelli, 1985; Tyler & Chen, 2000) in which steep psychometric functions in the absence of external noise are due to competition amongst many noisy mechanisms (instead of a static nonlinearity). If adding external noise induces additional uncertainty (or distraction [Kontsevich & Tyler, 1999]), psychometric slopes would remain steep instead of being linearized. However, induced uncertainty is not expected to reduce double-pass consistency (and does not appear to do so empirically; see Figure 2e of Neri, 2010), unless the activities within the irrelevant mechanisms that drive decision-making are uncorrelated across repeated presentations of the same noise stimulus.

A related possibility suggested to us by Neri (personal communication, August 7, 2012) is that the observer sums local filter responses across the stimulus in each interval, but that the small proportion of mechanisms that are selected for summation are done so at random on each interval. This is a form of induced uncertainty, where the uncertainty applies to the summation process. In this model, double-pass consistency is expected to be less for 2D noise than 0D noise (consistent with our results) because its component of random selection will be influenced much more by the spatial variation of 2D noise than 0D noise.

Thus, induced noise and both versions of induced uncertainty can produce some effects that are similar to those from contrast gain control, despite the large conceptual distinctions between them. In principle, any combination of these processes might have been a factor in our experiments. However, induced uncertainty and noise cannot influence perceived contrast because the mean activity in the target mechanism is not affected. As a consequence, although induced uncertainty and noise may well be contributing factors in noise masking, they are neither necessary nor sufficient to explain all of the results here.

Reinterpretation of previous studies

Our finding that 2D white noise masking might derive primarily from suppression makes sense of some inconsistencies in the literature. As shown in Figure 3, Birdsall linearization occurs only partially for many studies (Klein & Levi, 2009). The group of studies that show consistent linearization are those in which the noise is 1D, presumably because they have the greatest concentration of mask energy within the detecting mechanism (i.e., they are most similar to our 0D noise).

Several studies by Lu and Dosher (Dao et al., 2006; Dosher & Lu, 2000; Lu & Dosher, 1999, 2008) show very little evidence of Birdsall linearization (black and white half-filled circles and low-filled squares in Figure 3). These studies used spatially 2D noise in a rapid temporal sequence (mask-test-mask or mask-mask-test-mask-mask, with each frame lasting at most 33.3 ms). Previous work (Cass & Alais, 2006; Meese & Baker, 2009; Meese & Holmes, 2007) has shown that (all else being equal) more transient masks produce the strongest cross-channel effects, so this choice of masking regime may have inadvertently favored suppressive processes. This would also explain why Lu and Dosher (2008) report low double-pass consistency, even at high mask contrasts.

Burgess, Li, and Abbey (1997) measured noise-masking functions for various low-pass filtered noise masks. Whereas noise-masking functions typically have unit slope, theirs became shallower with increasing difference between the spatial scales of the background and target. In the present context, this is easily explained as a cross-channel suppressive effect for which unit slope is not predicted (Meese & Holmes, 2002). A more recent study (Henning & Wichmann, 2007) showed that notch filtered noise—with little or no energy within 1.5 octaves of the target—reduced the level of facilitation in the dipper function for contrast discrimination. This is not readily explained by suppressive processes alone and remains a challenge for future models. It seems likely that multiple mechanisms are required to explain this effect (Goris, Wichmann, & Henning, 2009) and that contrast integration might also be involved (Meese & Summers, 2007).

Conclusions

We asked why masking from 2D pixel noise fails to behave according to theory. Taken together, the evidence from four experiments led us to conclude that 2D noise masks have a substantial suppressive influence (Hansen & Hess, 2012) on the neural representation of the target. This means that they might be unsuitable for some applications of noise masking. We propose that 0D noise (contrast jitter of a 0% mean contrast pedestal) provides a more direct method of injecting external noise into the detecting mechanisms. It is unaffected by suppression and behaves like ideal noise in all of our experiments.

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