Measurement and modeling of adaptation to noise in images

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Abstract — Webster[1] has proposed "that adaptation increases the salience of novel stimuli by partially discounting the ambient background." This is an excellent, concise, description of the purpose and function of chromatic adaptation in image-reproduction applications. However, Webster was not limiting this proposal to just chromatic adaptation, but rather using it as a general description for all forms of perceptual adaptation. Demonstrations of adaptation to other properties of image displays such as motion, blur, and spatial frequency led the authors to ponder the question of whether observers might adapt to the noise structure in images to enhance the novel stimuli — the systematic image content. This phenomenon, noise adaptation in images, was easily demonstrated, but apparently has not been carefully studied in the past. Psychophysical measurements of noise adaptation in color image perception is described and mathematical prediction of the effect is explored. The results illustrate the hypothesized pattern-dependent adaptation and its prediction through adaptation of a 2-D contrast-sensitivity function in an image-appearance-model-based difference metric.

Keywords — *Noise adaption, spatial-frequency adaption, image quality, psycophysics, image-appearance models.*

1 Introduction

Spatial frequency, or pattern, adaptation has been recognized for over 30 years and used as evidence for the existence of spatial-frequency- and orientation-tuned mechanisms in the human-visual system.[2] Figure 1 shows a typical demonstration of spatial-frequency adaptation. After gazing at the bar on the left side of Fig. 1 for 15–30 sec, the identical patterns on the right side appear to shift in spatial frequency in directions opposite the adapting stimuli.

Webster and co-workers[1,3,4] have expanded the exploration of spatial-frequency adaptation to the study of adaptation to complex spatial stimuli such as image blur, face expression, and face recognition. Figure 2 recreates one of Webster's demonstrations of blur adaptation. After gazing at the bar between the upper images for 15–30 sec, the bottom two images, which are physically identical, will appear significantly different. The image on the left will appear more blurred after adaptation to a sharp image while the image on the right will appear sharper after adaptation to a blurry image. This effect can also be seen in the form of simultaneous contrast whereby an image will appear sharper if surrounded by blurry images.

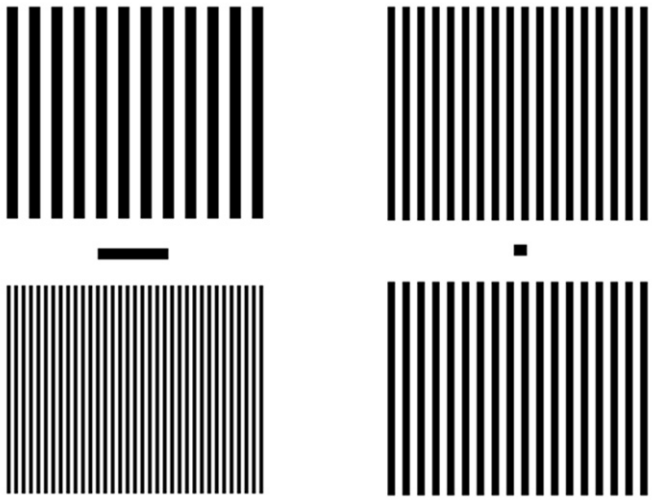

FIGURE 1 — Demonstration of spatial-frequency adaptation.

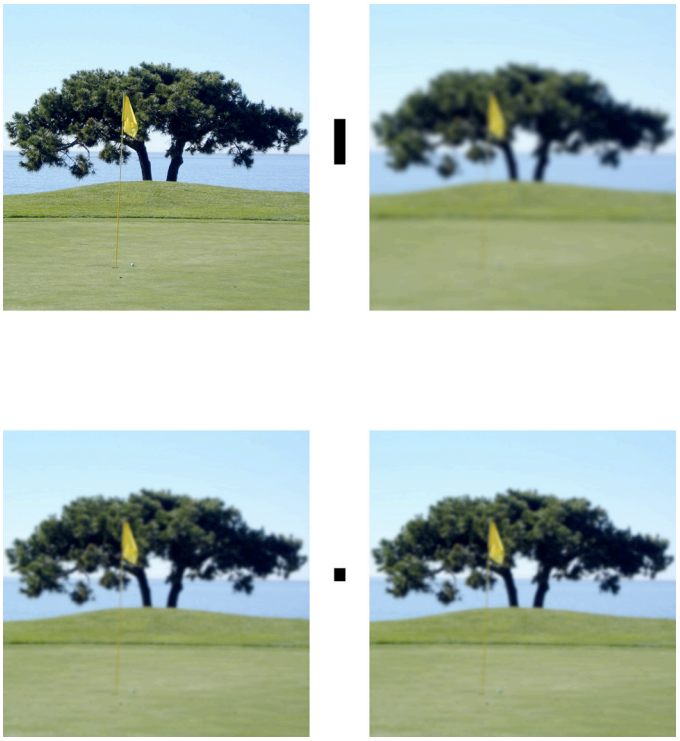

FIGURE 2 — Demonstration of adaptation to image blur.

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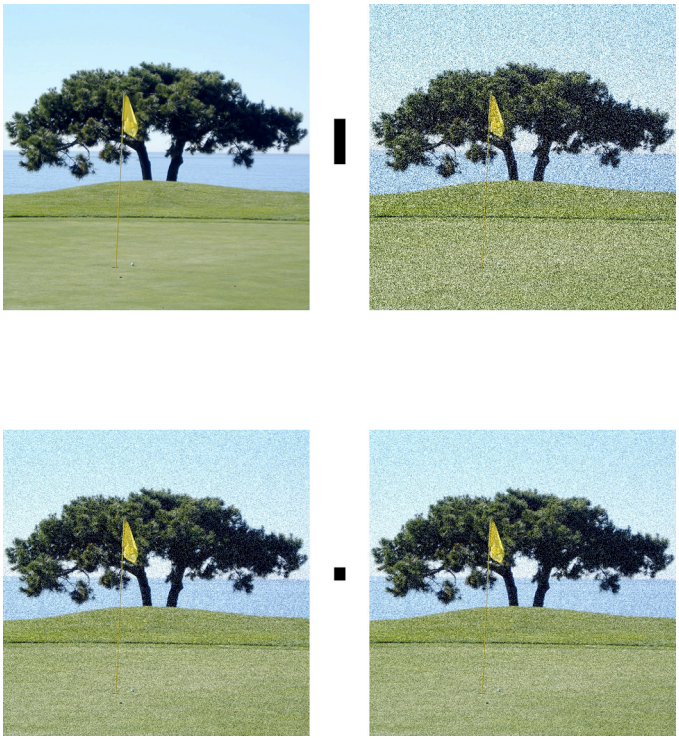


FIGURE 3 — Demonstration of adaptation to image noise.

Webster's observations of adaptation in natural images led the authors to hypothesize that the human-visual system might be capable of adapting to noise content in images, effectively enhancing the perception of image content while minimizing the perception of artifacts introduced by imaging systems. Quantitative knowledge of such adaptation effects is critical for the development of accurate image-quality metrics.

A visual demonstration of noise adaptation in images is easily created as illustrated in Fig. 3. Adaptation to the images at the top will result in the lower-left image appearing noisier than the lower-right image despite being physically identical. A literature review has, to date, uncovered no previous research on this phenomenon. However, studies on closely related adaptation effects can be found.

Webster and Mollon[5] measured contrast adaptation in natural images, illustrating that the visual system does adapt to the range of color and lightness information in a scene. This adaptation could be considered similar to automatic gamut mapping in the visual system. In other words, the widely varying range of colors and luminances encountered in the world are mapped to relatively constant perceptions of scene object colors. While these results suggest the possibility of adapting to the noise contrast in an image, they did not explicitly explore noise adaptation. Field and Brady[6] describe an approach to perception based on the content of natural scenes that is easily extensible to the concept of adaptation to the noise in an image. Other researchers have explored related forms of adaptation, but not specifically image noise. Clifford and Weston[7] studied adaptation to glass patterns, essentially noise with some correlated structure. Anderson and Wilson[8] described complex spatial-frequency adaptation to identity elements in faces. Artal *et al.*[9] have shown that neural mechanisms, presumably long-term adaptation, are capable of compensating for optical aberrations in observers' eyes. Finally, Durgin *et al.*[10,11] have shown adaptation to natural and artificial texture. This and related work comes closest to measuring noise adaptation, however, texture adaptation is an examination of noise adaptation in the absence of other content while noise adaptation refers to adaptation to spatially varying stimuli in the presence of some other signal that would not be considered noise. The current work aims to examine the perception of the remaining image content after noise adaptation.

2 Experimental

The experiment began with the hypothesis that adaptation to spatially structured noise would decrease the sensitivity (raise the threshold) of observers to similar noise within an image. Furthermore, it was hypothesized that adapting noise of one structure (*e.g.,* vertically oriented) would have little or no effect on the sensitivity to noise of a completely different structure (*e.g.,* horizontally oriented). A simple psychophysical experiment was designed and implemented to test these hypotheses.

Observers were presented with images intermittently placed on an adapting background. Three types of adapting backgrounds were used (see Fig. 4), 2-D random, horizontal, and vertical white noise with uniform luminance distribution. Noise was created at the pixel level (*i.e.,* each pixel with different noise amounts) with 2-D noise being variable in all pixels and horizontal and vertical noise being variable along one-pixel-wide lines across the image. Additionally, a uniform gray adapting background was used for a baseline adaptation. Each adapting background was used with Michelson contrast levels of 0.094, 0.189, 0.281, and 0.375 (Fig. 4). The adapting backgrounds filled the experimental display, a carefully characterized 23-in. Apple Cinema HD display viewed from 1 m. The display (1920 × 1200 pixels)

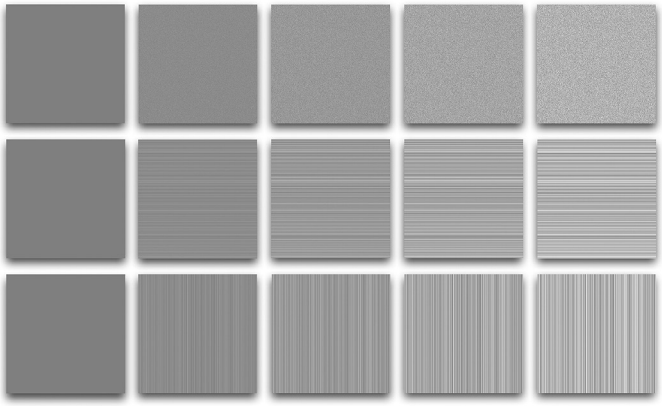


FIGURE 4 — Adapting backgrounds ranging from uniform (left) to 37.5% contrast (right) for random, horizontal, and vertical white noise.

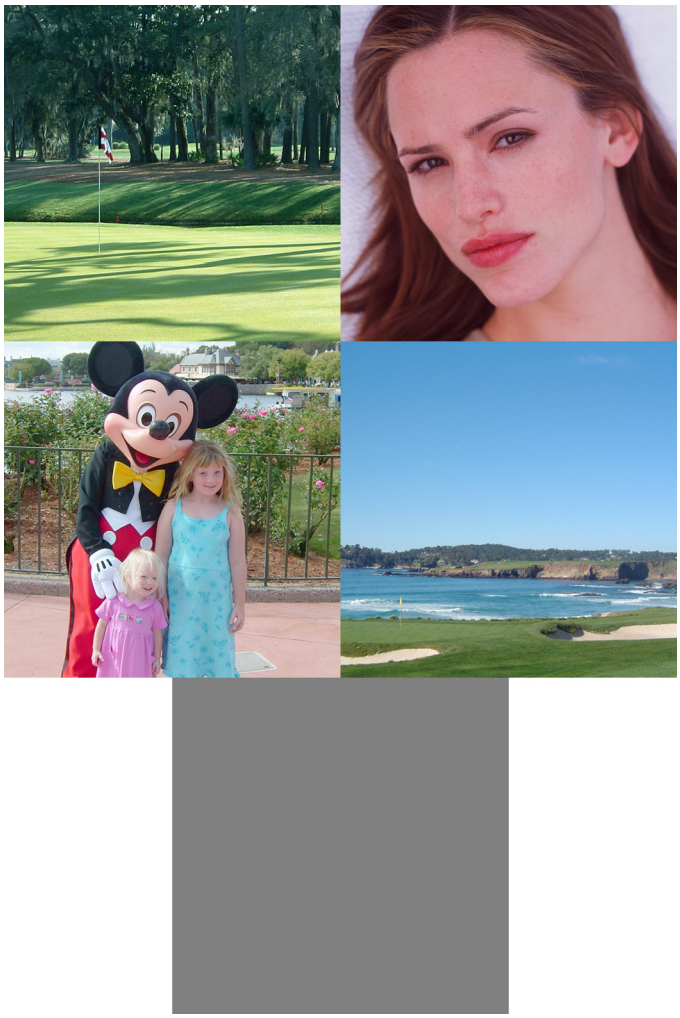


FIGURE 5 — Five images used for measurement of sensitivity to added noise (random, horizontal, and vertical). These images are referred to as Harbor, Jennifer, Mickey, Pebble, and Uniform (right-to-left, top-to-bottom).

subtended 28 × 17° of visual field with an addressability of 68 pixels/deg. The maximum display luminance was 320 cd/m^2 with a white-point chromaticity approximating CIE Illuminant D65. The adapting backgrounds were achromatic of middle lightness with a mean luminance of 20% of the display white (*i.e.*, 64 cd/m^2).

Visual sensitivity to each of the three types of noise (random, horizontal, and vertical) was measured using the method of adjustment. These measurements were completed using five different images, shown in Fig. 5, upon which the noise was added. Note that the noise was defined as positive and negative numbers about a mean background, and it was these signed numbers that were added to the images. These images include four pictorial scenes and a uniform gray (equal to the adapting background mean luminance, approximately middle gray, and 128 digital counts on a Macintosh display). The images were each 512 × 512 pixels, or 7.5 × 7.5° of viewing angle.

The test images were presented together with an original image having no added noise. The images were

FIGURE 6 — Example stimulus with the reference image on the left, test image with horizontal noise on the right, and adapting background with vertical noise.

presented for 1 sec followed by 4 sec in which only the adapting background was present. This cycle was repeated while the observers adjusted the noise contrast of the right image until it was just identifiable. Specifically, observers were asked to adjust the noise contrast until they could just discriminate which of the three types of noise was being added to the image. These contrast discrimination thresholds (called visible contrast in the plotted results) were obtained for each combination of image content, background-noise type, background-noise contrast, and image-noise type. Observers could adjust the noise contrast in either direction above and below their ultimate threshold selection. The range of noise adjustment was from zero contrast (no noise) to the maximum displayable which was well above threshold for most viewing conditions. There were a total of 195 threshold settings for a full experimental session. Observers could complete a session in about 2 hours. Once observers set the image-noise level to the

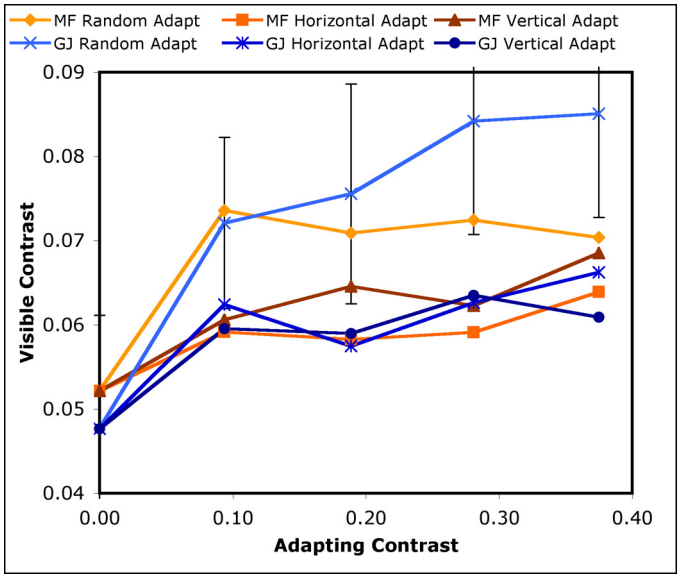
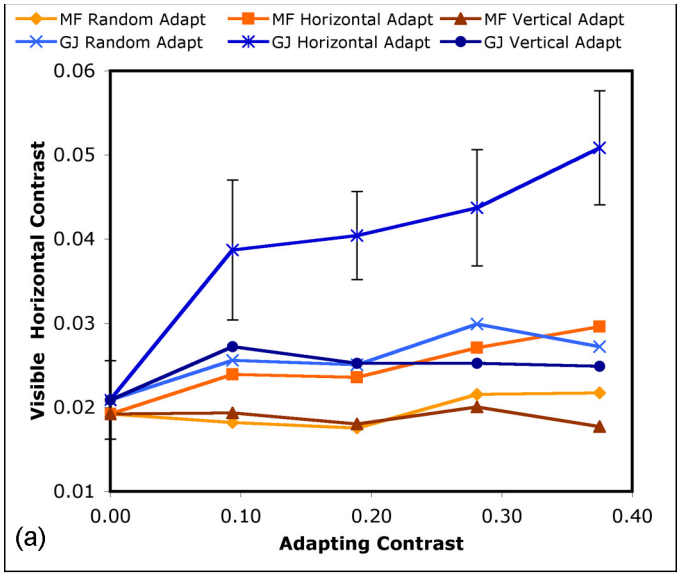


FIGURE 7 — Random-noise visibility for all adapting conditions.



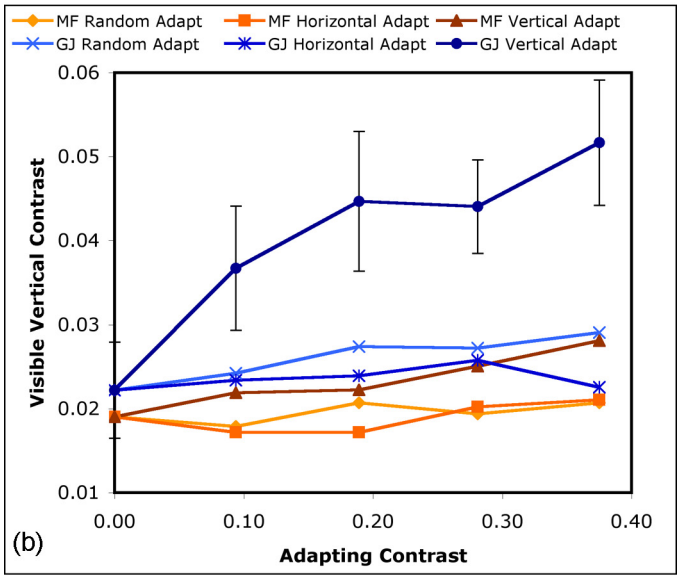


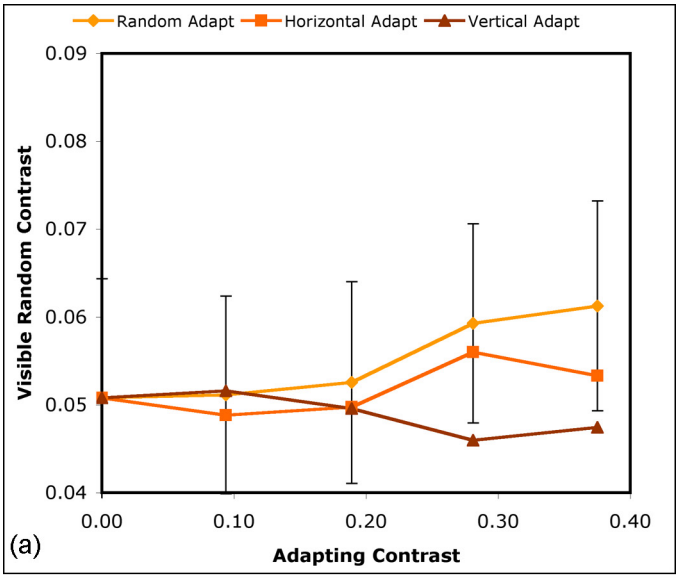
FIGURE 8 — Horizontal (a) and (b) vertical noise visibility.

criterion contrast, they pressed a button and a new trial began. Trials were completely randomized in all experimental variables. Figure 6 shows an example stimulus configuration with vertical noise in the adapting background and horizontal noise (clearly above the threshold setting) in the test image.

Two observers, MF and GJ, the authors, performed the experiment five times each to collect precise data on two observers and assess intra-observer variability. An additional 10 observers completed the experiment once each to verify the effect and to estimate inter-observer variability. All observers had normal or corrected-to-normal visual acuity and normal color vision. Data for two observers were discarded because the available range of noise was not sufficient for them in multiple trials. Thus, the reported inter-observer data are for a total of 10 observers.

3 Results

Figure 7 shows the visibility of random noise (observers MF and GJ) as a function of adapting background contrast averaged over all images for each adapting condition. Example 95% error bars are presented on one curve, the magnitude of which would be similar for the other data sets. While the error bars appear large relative to the adaptation effect, most of the variability is due to image-dependent changes in the threshold. Only about 1/3 of the error is associated with random noise (see Fig. 10). The adaptation effect is statistically significant for each viewing situation. The results show that for both observers random noise in the adapting field elevates the threshold for random noise in the image and the effect increases with adapting contrast. Horizontal and vertical adapting noise also elevate the thresholds, but to a



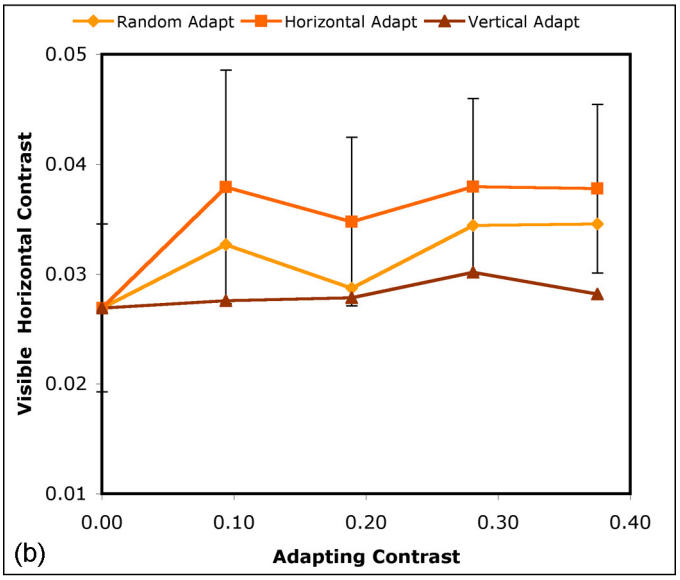


FIGURE 9 – (a) Random, (b) horizontal, and (c) vertical noise visibility for 10 observers.

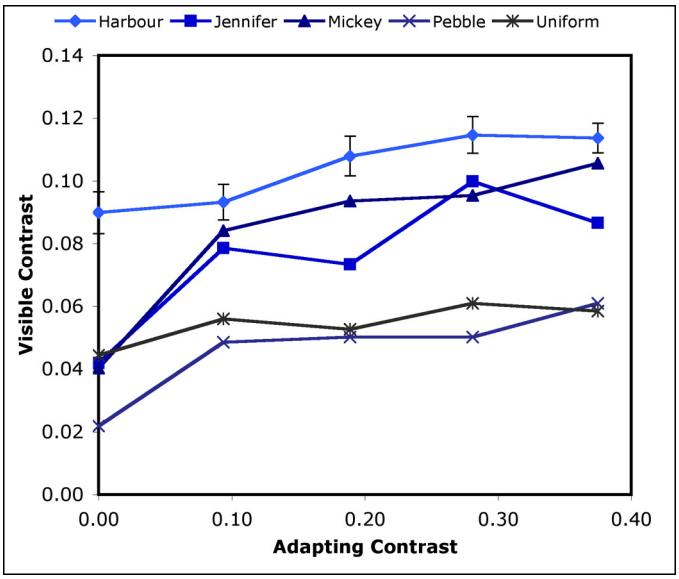


FIGURE 10 — Image dependence for random-noise visibility on random-noise-adapting backgrounds for observer GJ.

lesser extent as would be expected since those adapting stimuli only depress one dimension of the 2-D contrast-sensitivity function according to the accepted understanding of human-visual processing that relies on separate spatial-frequency and orientation channels. Observer GJ generally shows higher thresholds (possibly a criterion effect in the method of adjustment) and larger adaptation effects.

Figure 8 shows similar results for the visibility of horizontal and vertical image noise. The results are consistent with the thresholds for vertical noise elevated when adapting to vertical noise and vice versa. There is no effect of horizontal noise adaptation on the visibility of vertical noise or of vertical noise adaptation on the visibility of horizontal noise (expected because adaptation and detection are in different orientation-selective mechanisms). There was also little effect of adaptation to random noise on the perception of vertical or horizontal noise.

Figure 9 shows analogous results for the average response of 10 observers. Again, example error bars are presented that include uncertainty due to inter-observer variation and image dependence. Most of the variability, about 2/3, is due to image dependency, and again the adaptation trends are statistically significant for each individual image and are present for all observers. Examination of the three plots in Fig. 9 illustrates that the threshold is most elevated for the type of noise present in the adapting background as expected. Note how the order of the three curves changes in each of the three plots in Fig. 9.

Figure 10 explores image dependency. For simplicity, the results are shown for one observer (GJ) and only for random-noise visibility with random-adapting noise. The general trends are similar for other situations. Observer GJ was chosen due to higher thresholds and larger adaptation effects than observer MF and to use an observer with multiple trials. Example error bars illustrate the magnitude of intra-observer variability for the five replicate trials. Clearly, this is much smaller than the overall uncertainty illustrated in Fig. 7 and supports the statement that most of the uncertainty illustrated in Fig. 7 is due to image dependence.

Several observations can be made regarding the results in Fig. 10. Regardless of adaptation, noise visibility is a function of image content. This can be explained by masking and adaptation to the spatial-frequency content of the image itself. Johnson and Fairchild[12] have previously observed and modeled this effect. Random noise is most perceptible on the Uniform and Pebble images. The Pebble image has a large expanse of nearly uniform sky. The visibility of noise is lowest on the Harbor image. Several observers reported difficulty detecting the random noise on this image. In the foreground of the Harbor image is closely mown grass that has an appearance similar to random noise, and the background has a large amount of high-frequency high-contrast content. All of this image content serves to mask the noise and cause spatial-frequency adaptation at all frequencies. The other two images had intermediate levels of intrinsic "noise" in the image content. The results in Fig. 10 also illustrate that there is a systematic noise-contrast adaptation effect regardless of image content.

4 Modeling

Concepts of spatial-frequency adaptation, masking, and contrast sensitivity have long been used in various models of visual function and image quality. For example, Watson and Solomon[13] present a model that incorporates contrast gain control and pattern masking in multiple mechanisms tuned to various spatial frequencies and orientations. Such a model, perhaps with some tuning and calibration, should be capable of predicting the effects observed in this research.

Ferwerda *et al.*[14,15] have created and extended such models for practical application in image rendering and reproduction. In particular, they proposed a multi-channel model for contrast masking that could be used for rendering synthetic images.[15] Ultimately, this work was combined and extended with color-appearance modeling to create an overall multi-scale observer model capable of predicting appearance and threshold data.[16] Similar to the Watson and Solomon[13] model, the Pattanaik *et al.*[16] model should be capable of predicting the observed results, at least qualitatively.

However, it is likely that a simpler approach, utilizing a 2-D contrast-sensitivity function without explicit channels, might well be adequate and more efficient. Fairchild and Johnson[17] have explained the motivation for and formulated such a model. Johnson and Fairchild[12] further explain their modular image-difference metric that incorporates spatial-frequency-and orientation-dependent contrast adaptation without the need for explicit channels. This model, now part of the iCAM image-appearance model,[17] was evaluated for its capability to predict the noise adaptation observed in this work.

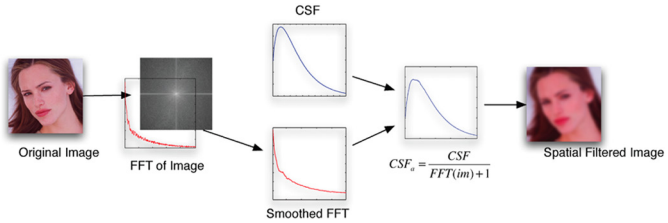


FIGURE 11 — Flow chart of model processing steps for spatial-frequency adaptation to an image.

The model processes for spatial-frequency adaptation and for simulating the experimental data are illustrated in Figs. 11 and 12, respectively. The adaptation process (Fig. 11) is to compute the 2-D FFT of the image to determine the spatial frequency and orientation content for adaptation. This FFT of the image is then blurred using a two-dimensional Gaussian convolution kernel of width 11. This width was chosen simply as a compromise between computational efficiency and accuracy in approximating a Gaussian function, other widths could be used. In essence, this can be considered multiplying the original image by a Gaussian envelope in the spatial domain. The extent of the Gaussian kernel should be a function of both the viewing distance and image size. For this particular experiment, with an image size of 512 × 512 pixels and a viewing distance corresponding to 42 pixels/degree of visual angle, the blurring is approximately 2° in the frequency domain. The effect of this blurring is to simulate the influence of discrete spatial-frequency and orientation channels adapting to a band of frequencies and orientations without actually implementing a multi-channel model. It is mathematically identical with having a different spatial-frequency channel for each pixel in the FFT image. The smoothed 2-D adapting image FFT is then used to modulate via division of the 2-D CSF used in the model to predict visibility of various image elements. The CSF used for this modeling is a version of that described by Movshon and Kiorpes[18] and modified by Johnson and Fairchild.[12] This was further modified by first subtracting the image mean and applying the CSF as a frequency filter with the following parameters in Eq. (1): $a = 0.63$, $b = 0.085$, $c = 0.616$. This filter goes to zero at the dc component, which is why the mean was first subtracted from the image. The mean is then added back to the image after the filtering is performed:

$$\mathrm{csf}(f) = a \cdot f^{c} \cdot e^{-b \cdot f}. \tag{1}$$

The model was used to predict simulated experimental data following the process in Fig. 12. The smoothed FFT of the adapting image was computed as a weighted sum of the image plus noise and the adapting noise background. The weighting was in the ratio 1:4 matching the duration of exposure to the background and the image in the psychophysical experiment [Adapting Image = (Image with Noise + 4 × Background Image)/5]. The image, spatially filtered with the adapted 2-D CSF, was then compared with the original noise-free image filtered with a CSF that was

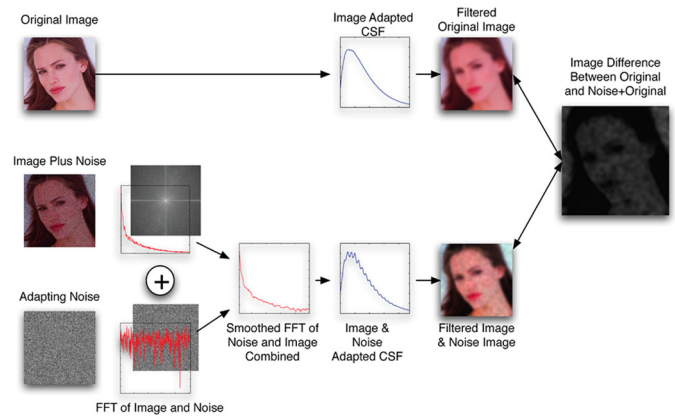


FIGURE 12 — Flow chart of modeling steps to compute predicted effects of adaptation to noise backgrounds.

adapted only with the image itself. The two filtered images were compared and an iCAM image difference was computed. The process was repeated with the noise level in the test image adjusted until a criterion image difference was reached. In this manner, the image-difference calculation was used to simulate the behavior of an actual observer. In the experiment, the observer would adjust the amount of noise present in the image until it was just noticeable. Computationally, the model would predict the overall perceived difference between the images, and if it was below a certain "threshold," that more noise would be added to the test image and the model would predict the overall image difference again. This can be considered a brute-force approach to a linear optimization to determine the amount of noise necessary to achieve a certain overall image difference.

The model was evaluated by having it act as a virtual observer for the experiment. The criterion contrast threshold was arbitrarily set at a mean image difference, ΔIm, of 2.0 units (this could be scaled/calibrated to better match the observed magnitudes, but that would not change the predicted adaptation trends). For each viewing condition, noise contrast was added until the model predicted the criterion threshold. The model predicts spatial-frequency adaptation by normalizing its 2-D CSF by the Fourier transform of the spatial adapting stimulus. In other words, the CSF is divided by the spatial-frequency content of the adapting image in order to compute an effective post-adaptation CSF. Normally, the adapting image is the image itself, but for this experiment the adapting image was taken to be a weighted average of the adapting background (80%) and the image (20%). These proportions were selected to match the time-integrated presentation of the background and image. Figure 13 shows the predicted noise-contrast thresholds, averaged across the five images, for random, horizontal, and vertical noise and each of the three adapting conditions. The predicted trends are similar to those observed in the psychophysical results. The contrast values differ, but this is simply a matter of calibrating the threshold value and degree of adaptation. Figure 14 shows the model image dependence for random noise with random adaptation. This does not

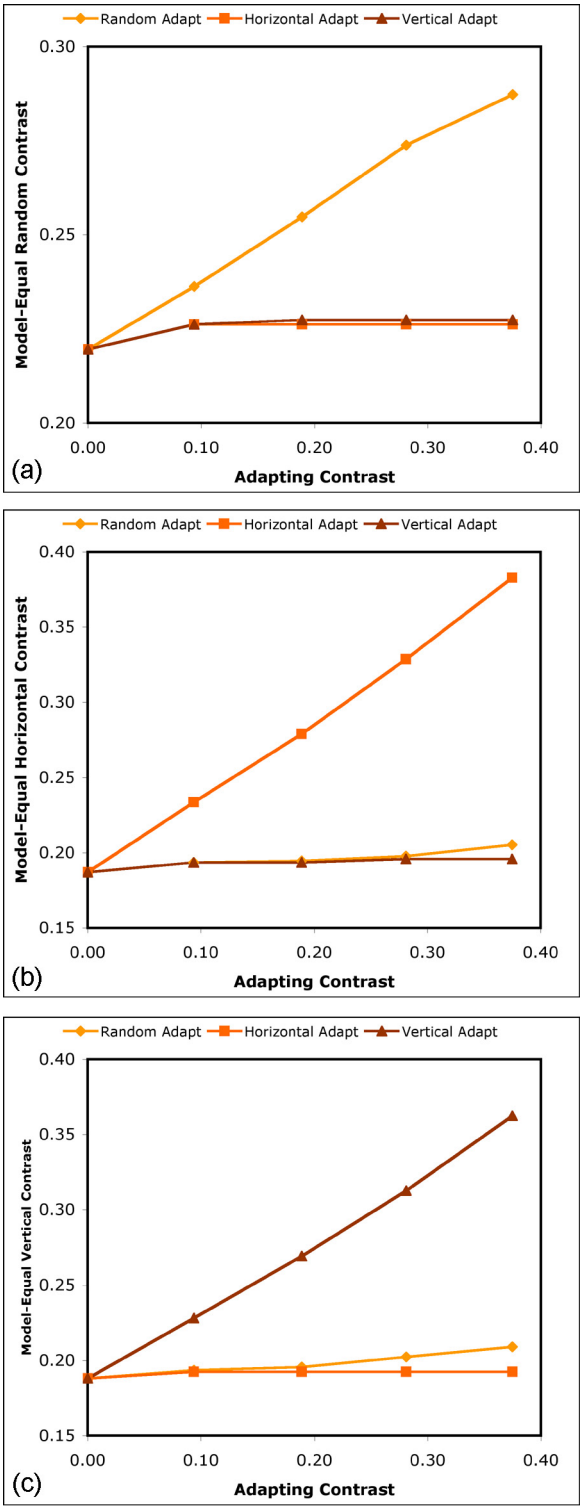


FIGURE 13 — Model predictions for (a) random, (b) horizontal, and (c) vertical noise visibility.

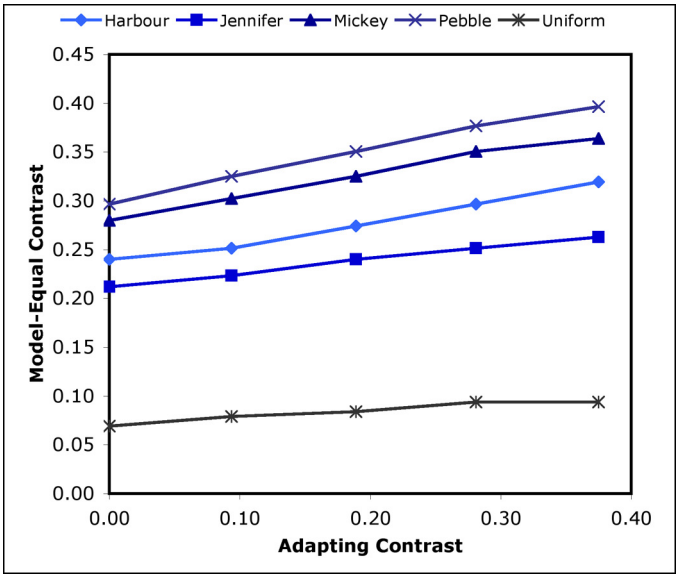


FIGURE 14 — Model predictions of image dependence for random-noise visibility on random-noise-adapting backgrounds.

match the observed results, but Fig. 14 does illustrate the image dependence of the model due to inherent noise masking and adaptation to the images themselves. As expected, the thresholds are lowest for the uniform background, but the predicted threshold for the Pebble image is surprisingly high. This could be due to using the mean ΔIm rather than a 95th percentile or similar statistic. While the model predicts the general trends of the observed results, this analysis has suggested areas for improving the model. It is worth noting that a model without spatial-frequency or orientation channels is fully capable of predicting effects often thought to require such channels. This is due simply to the use of a 2-D CSF and frequency and orientation specific adaptation.

5 Discussion

Visual adaptation to spatially structured noise was psychophysically measured through decreases in the sensitivity to similar noise presented in pictorial images. While this type of adaptation is conceptually easily related to spatial-frequency adaptation, it apparently has not been previously measured or modeled in image quality or vision research. The effect of noise adaptation on noise thresholds, and thus perceived image quality, was easily modeled using a simplified version of a previously published image-difference metric.[17] The key feature of the adaptation model is a divisive normalization of the 2-D CSF by the frequency content of the adapting image while retaining the mean image information constant. This model will be further developed and refined.

The practical meaning of this phenomenon for imaging science is that artifacts present in imaging systems are likely to be less visible than would be predicted by vision, or image quality, models that do not incorporate spatial-frequency adaptation to the image. For example, artifacts in raster displays become less apparent, halftone patterns are less perceptible than would be expected, and random image noise is less objectionable than often predicted. It also suggests that viewing conditions can be manipulated to minimize the perceptibility of artifacts. The experimental, and model, results suggest that overall apparent image contrast

would appear lower if an image was presented on a background of high-contrast random noise as compared with the presentation on a uniform background. This simultaneous contrast effect on contrast is indeed easily observed. This lends credence to the practice of viewing images on uniform gray backgrounds when critical image-quality judgements are being made.

Observations of visual adaptation such as these typically lead to speculation regarding the physiological locus of adaptation in the human-visual system. Wainwright *et al.*[19] have proposed a theoretical model of divisive contrast normalization in the visual cortex that serves contrast adaptation in a way completely consistent with the observed results. Müller *et al.*[20] have found cortical neurons with rapid and highly tuned contrast adaptation properties. They struggled to find a visual purpose for such adaptation, but the properties of those cells are similar to the observed results. While it is doubtful that the human-visual system evolved to minimize the perception of image noise, it is easy to imagine situations in nature that would benefit from such adaptation. For example, seeing objects through falling rain, snow, or fog would benefit greatly from noise and contrast adaptation. Gallant[21] has speculated on the importance and function of such mechanisms for vision in natural scenes. As suggested by a reviewer of this paper, a primary ecological purpose of vision is to distinguish objects from their backgrounds, especially to identify potential sources of food or danger against textured backgrounds. In such cases, the reduced sensitivity to the fixed background noise through adaptation would be a great asset.

Finally, an important result of this work is the successful modeling of a complex spatial-adaptation phenomenon with a very simply model, normalization of the 2-D CSF to the adapting stimulus. While it might seem remarkable that such adaptation can be effectively modeled without spatial-frequency and orientation channels, the reality is that the model is essentially using a very large number of channels. This is similar to predicting the effects of chromatic adaptation by normalizing spectra instead of cone responses. While either model would work, spectral normalization seems inordinately complex. This is true for chromatic adaptation since the color channels are relatively well understood and spectral information for entire scenes is rarely available. However, it might not be similar overkill for spatial-frequency adaptation. One reason is that spatial and orientation channels are not nearly so well-defined or understood as chromatic channels. A second is that the full spatial-frequency content of a scene is readily available to the visual system. It is not at all unreasonable to imagine very large numbers of spatial frequency and orientation "channels," each tuned rather selectively, and each adapting independently, to produce the net effect of normalization of the CSF to fairly distinct bands of spatial frequency and orientation as originally observed by Blakemore and Campbell.[2] Indeed, Watson and Ahumada[22] have recently explored the importance of various components in spatial-vision models for prediction of the ModelFest data and found that models without explicitly defined spatial-frequency channels can perform quite well. It should also be noted that others have recently shown that multi-channel models are helpful for predicting some perceived changes in images.[23] However, it is possible that an adaptation model could produce similar results. Thus, the model as described in this paper is consistent with the visual function and of great potential applicability in image-quality measurement.

6 Conclusion

This research has quantified visual adaptation to image noise directly analogous to chromatic adaptation to the image white point and shown how it can be modeled through gain control of a 2-D contrast sensitivity function (akin to von Kries normalization of chromatic signals). Such adaptation enhances the salience of important image features: namely, the objects in a scene. This phenomenon allows imaging-systems engineers to get away with slightly more artifacts in imaging systems (such as halftone patterns, random noise, compression artifacts, *etc.*) since the visual system naturally masks signals that are relatively constant in a system to facilitate perception of the novel image content. This assistance by the human-visual system is similar to the blessing of metamerism that allows color reproduction to be accomplished with just three image channels.

Appendix

MATLAB code segments for implementation of the noise adaptation model described in this paper are presented below.

```
% Simple Matlab code to perform
% spatial frequency adaptation
%
% The variable adaptField represents
% the adapting stimulus: in this experiment
% it was (4*noise + image)/5

% calculate the 2D power spectrum of adapting
% stimulus

sfAdapt = abs(real(fft2(adaptField))) ;
% set the DC component to be zero

sfAdapt(1,1) = 0 ;

% normalize to "contrast" units by dividing by
% the total number of pixels in the adapting
% field, where xSize and ySize are the image
% dimensions

sfAdapt = sfAdapt/(xSize+ySize) ;

% Get a 2D convolution kernel to "blur" the
% FFT

h = fspecial('gaussian', 11,3) ;
```

```
% Apply the convolution kernel. Note we use
% The image processing toolbox here, but the
% same could be done with Matlab's conv2
sfAdapt = imfilter(sfAdapt, h) ;

% renormalize the DC
sfAdapt(1,1) = 0 ;

% now calculate the adapting CSF

adapt_csf = csf./(sfAdapt+1) ;
```

Acknowledgments

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