Uniform Apparent Contrast Noise: A Picture of the Noise of the Visual Contrast Detection System

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July 1984
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Introduction

We have generated pictures which are samples of random contrast noise. The noise spectrum in a region of the picture varies with the distance from the region to the center. At each distance the noise spectrum is inversely proportional to the human spatial frequency contrast sensitivity function at the corresponding eccentricity. When an observer fixates the center of the picture from the appropriate distance the noise appears to have equal contrast at each spatial frequency and location. If contrast thresholds are set by internal noise, then this picture represents that noise.

There is evidence that contrast sensitivity functions at different eccentricities differ only by a scale factor along the spatial frequency dimension. This means that such pictures can be generated by passing "white" noise through a space-invariant filter and then stretching the output by the appropriate space-varying magnification factor. The filter shape will be the inverse of the contrast sensitivity function at the fovea. The parameters for the filter and the magnification factor were taken from a model of spatial contrast vision devised by Watson (ref. 1).

The pictures summarize a noisy linear model of detection and discrimination of contrast signals by referring the internal noise of the model to the domain of the input picture. The detectability of an arbitrary pattern can be estimated by computing its ideal detectability in samples of the noise. Since unlimited inspection of contrast targets in noise leads to near ideal detection performance (Burgess et al., (ref. 2)), the absolute detectability of a low-contrast target in a particular retinal position for a brief duration can be estimated by adding a sample of noise to the target and trying to detect the target visually with no constraints on the viewing conditions.
The Picture

If one views figure 1 from a distance where it subtends four degrees of visual angle and fixates the center, the contrast variations in different regions of the picture should look roughly equal because they are all about the same level above threshold in log units. Both the contrast in spatial regions varying in eccentricity from the center and the contrast in different spatial frequency bands in each region have been made proportional to the threshold for detecting small contrast variations at that eccentricity and in that spatial frequency band. There is evidence that as actual contrast increases, there is a greater increase in apparent contrast for spatial frequencies with higher contrast thresholds (Georgeson and Sullivan, ref. 3), so the perceptual uniformity should be best close to threshold.

Figure 1. A picture of the noise of the contrast detection system referred to its input.

The perceptual uniformity was not the original goal in generating the picture. The original goal was to make a picture of noise equivalent to that visual system noise which limits our ability to detect spatial contrast signals. In engineering language, we wanted to make a picture representing the noise of the spatial contrast detection system referred to its input. Pelli (ref. 4) has discussed temporal and spatial characteristics of this noise. Here we are concerned only with the spatial aspects of the noise which limits the detection of a brief (approximately one sec, with smooth onset and offset) presentation of a static, low-contrast signal.
Although the concept of referring the performance-limiting noise of a system to its input is common in engineering, it is not often encountered in perception. The advantage of reporting unidimensional absolute (or difference) thresholds in stimulus units was seen as soon as quantitative measurements of thresholds were attempted. This is equivalent to referring the noise of the observer back to the input. Consider these three statements about an observer's ability to detect brightness differences:

(1) The observer has a brightness difference threshold of 0.1 log units.

(2) The observer has $d'=1$ when the brightness difference is 0.1 log units.

(3) The observer's noise referred to the input has a standard deviation of 0.1 log units.

These three statements ascribe equivalent ability to the observer. Statements like (2) are currently the most popular formal expressions of thresholds. They result from models of the detection process in which the presentation of a stimulus value results in an internal random variable whose variability limits detection performance. Referring the noise to the input is just transforming the internal random variable back into the stimulus dimension. The appropriate transformation is the inverse of the transformation which computes the mean of the internal distribution from the value of the stimulus.

In the case of multidimensional stimuli, the equivalent noise at the input will have a multivariate distribution in the dimensions of the stimulus. For the case of visual contrast detection for arbitrary targets, the stimulus can be regarded as a multidimensional stimulus with the contrast of each pixel being a dimension. The input equivalent noise will then be a multivariate distribution giving the probability that the pixels will jointly take on particular contrast values. The construction of the input equivalent noise for contrast detection is just the construction of a sample from that distribution. The theory behind the construction of the picture of the equivalent noise is outlined and the actual construction method is described.
The Theory

The basis for the construction of the picture of equivalent noise is the signal-specified-exactly version of a model of visual contrast detection which has been shown to accurately predict a range of human contrast detection data by Watson (ref. 1) and Watson and Ahumada (ref. 7). In this model, contrast variations activate linear feature sensors whose receptive fields are similar to those of simple cortical cells. Noise is present at the output of these feature sensors. Both the filtering action of the feature sensors and the noise at their outputs restrict the ability of the model to detect low-contrast signals. The noisy output of the sensors is then combined linearly into a single number by the ideal decision mechanism, which then compares the number with a criterion do determine the response. Here we derive the equivalent input noise for this model. If this noise is added to any contrast signal and the sum is presented to an ideal observer, the performance level of the observer will be equivalent to that of the ideal observer looking at the noisy feature-sensor outputs. The equivalent noise thus reflects both the filtering and the noisy aspects of the model.

Before showing the results for this model, we describe an apparently more general class of models for which the method is appropriate. The early stages of the visual system are organized in layers, so it would be convenient to model the visual system as a series of layers of processing. Figure 2 illustrates a general multilayer model for spatial contrast detection. A signal enters and is processed by a series of K layers. The spatial contrast signal is represented by a column vector S consisting of N contrast values, one for each pixel in the signal picture.

\[ S = \left( s_i \right), \quad i = 1, N. \] (1)

Figure 2. A multilayer model for contrast detection.
Pictures (spatial contrast signals) are usually represented as rectangular arrays, but for our purposes it is more convenient to place the rows end to end and regard a picture as a long row vector. In our actual computations, the picture resolution is 256 by 256 pixels, so that N is 65,536. Each layer is represented as a noisy linear operator. For example, the first layer might represent the receptors, with the linear operator representing the optical point spread function, and the noise a combination of photon and transducer noise. In figure 2 the top boxes represent the linear operators, which are just matrices of coefficients.

\[ A_k = (a_{kij}), k = 1, K; i = 1, N_{k-1}; j = 1, N_k \]  

(2)

is the kth operator, where \( a_{kij} \) is the weighting that the jth output of the kth operator gives to its ith input and

\[ N_0 = N. \]  

(3)

If the first layer represented the receptors, \( a_{lij} \) would reflect assumed to be Gaussian with a mean vector of zero and an arbitrary covariance matrix.

\[ R_k = (r_{kij}), k = 1, K; i, j = 1, N_k \]  

(4)

is the kth covariance matrix, giving the covariance between the noise added to the ith and jth output variables at the kth stage. Returning to the receptor layer example, the off-diagonal elements of the noise covariance matrix would be zero to represent the independence of photon and receptor noise between two different receptors and the diagonal elements would have the variances of the outputs of the receptors. The output of the last stage goes to an ideal classifier, which, for the case of detecting the presence or absence of a single pattern, is a simple linear classifier.

How reasonable are the above assumptions when the visual system is known to have nonlinear response functions and to have noise sources which are usually characterized as approximately Poisson, where the variance is a function of the signal strength? This is only a model for the detection of small contrast signals. Only the small signal response of the system has to be linear and the noise is assumed to be dominated by the noise generated by the background level itself. The ideal observer assumption can be regarded as a convenient way of describing the consequences of computing the noise of the system referred to its input.
Mathematically, the multiple layers can be represented by a single layer whose linear operator $A$ is the product of the previous operators,

$$A = A_1A_2 \ldots A_K,$$  \hspace{1cm} (5)

and whose noise distribution is computable from the noises and operators of the multiple layer model. If the noise of the different layers is independent, the covariance matrix $R$ for the equivalent single layer is given by

$$R = R_K + A_K^{\top}uT_{R_{K-1}}A + \ldots + H_k^{\top}uT_{R_k}H_k + \ldots + H_1^{\top}uT_{R_1}H_1,$$  \hspace{1cm} (6)

where

$$H_k = A_{k+1}A_{k+2} \ldots A_K.$$  \hspace{1cm} (7)

Figure 3 illustrates this simplification. The two models are the same from the point of view of the ideal observer. In either case its inputs are normally distributed with mean $SA$ and covariance matrix $R$.

Figure 3. A single layer model for contrast detection.

The performance level of the ideal observer as a function of the contrast signal $S$ can be specified in terms of the hit rate and the false alarm rate by the measure $d'$ given by
\[ d'(S) = z(\text{Prob}\{D|\text{Signal}=S\}) - z(\text{Prob}\{D|\text{Signal}=0\}), \]  

where \( D \) is the observer's response that a signal was present and \( z \) is the functional inverse of the standard normal cumulative distribution function. The equation for the performance level of the ideal observer for the above models is given by

\[ d'(S) = S A R^{-1} A^{T} S^{T}. \]

The derivation of this equation can be found in standard texts such as Anderson (ref. 6, chapt. 12).

**Figure 4.** A single layer model for contrast detection whose noise is "white".

This model can be further simplified to a model with the same performance function, but with a simplified noise structure. In this new case, the noise added to each linear filter unit's output is an independent standardized \( z \) score with zero mean and unit variance. The operator in this new model, then, accounts for the effects of both the operators and the noises of the previous models. This version of the model is illustrated in figure 4, where it is called the "white" noise model because independent, identically distributed normal variates arranged in a rectangular array generate a picture in which all spatial frequencies have equal expected contrast energy. The equation for the linear operator \( C \) in this case in terms of the operator and noise of the previous model is given by
\[ C = A B^{-1}, \]  
(10) 

where \( B \) is a matrix of factor loadings of \( R \), that is 
\[ R = B^T B. \]  
(11) 

Since this model is a special case of the previous one, the identity of performance can be verified by substituting \( C \) for \( A \) and the identity matrix \( I \) for \( R \) in equation 9.

![Figure 5. The input equivalent noise model for contrast detection.](image)

Figure 5 illustrates another model with the same performance function, but with no linear operator. In this version, the noise is in the same domain as the signal. Samples of the noise are pictures and the variances and correlations of the pixel values have all the information in the original operators and noises relevant to detection. The equation of the covariance matrix for the equivalent input noise in terms of the linear operator of the "white" noise model is simply 
\[ R_E = (C C^T)^{-1}. \]  
(12) 

The identity of the performance function can be verified by substituting the identity matrix \( I \) for \( A \) and \( R_E \) for \( R \) in equation 9. The noise in this model is the noise of the previous models referred to the input picture domain.
The model developed by Watson (ref. 1) has the form of the "white" noise model. The values for the matrix C are available in the paper by Watson and Ahumada (ref. 5). Figure 6 illustrates a way of computing the equivalent noise when C is known. In this figure, the noise starts as independent z scores and then is "back projected" through an operator D which is the reverse (transpose) of the operator for the standard noise model multiplied by an inverse gain factor correction; that is,

\[ D = C^T (C C^T)^{-1}. \]  

The factor after the transpose is called an inverse gain factor correction because in the case that C is an orthogonal transformation, it is a diagonal matrix containing the inverses of the squared lengths of the rows of C. In general, it also corrects for the correlations among the rows of C.

The Calculation Method

The initial idea for calculating the noise was just to use the transpose of C on "white" noise to obtain the picture. We realized that we had to correct for the gain factors, but we had not yet derived Equation 12 so we were not aware of the appropriate way to correct for the correlations. We generated low resolution pictures (64 x 64 pixels) using this method and described it in the ARVO abstract (Ahumada and Watson, (ref. 7)).
Since the model is not spatially homogeneous, we could not see any simple way to derive the gain factor correction matrix. However, the model is approximately a spatially homogeneous model preceded by a nonhomogeneous magnification function. That is, the linear dimensions of the linear feature detectors of the model are scaled by a factor

$$s = 1 + ce,$$

where $e$ is the eccentricity in degrees of the center of the response area from the center of the fovea and the constant $c$ is estimated to be about $0.023 \text{ (mrad)}^{-1} (0.4 \text{ (deg.)}^{-1})$. The linear dimensions of the detectors are thus doubled at an eccentricity of 44 mrad (2.5 deg.). The response areas of the detectors at the fovea range from about 0.7 mrad (0.04 deg.) to 91 mrad (5.2 deg.) in octave steps. For all but the largest layers, the outputs of the detectors can be accurately approximated by first stretching the picture with a magnification function which is inversely proportional to that of equation 13, and then filtering with detectors whose response areas are independent of retinal eccentricity. This spatially homogeneous model can be represented by its response in the spatial frequency domain. Neglecting the presumably small effects of the actual spatial position and orientation of the output features, the spatially homogeneous model can be approximated by a model which has uniform orientation and phase response, but with a spatial frequency amplitude response matched to that of the central fovea.

Figure 7. "White" noise. The contrast value of each pixel is approximately normally distributed and independent of all other values.
Figures 7, 8, and 9 illustrate the actual calculations performed by the computer programs, whose listings appear in the appendix. All these programs were written in Fortran and were run under the RT-11 operating system on an LSI-11/23 processor. In addition to the program listings, the appendix also contains the operating system commands and program parameters used to create the actual files of data displayed in the figures. Like figure 1, figures 7 and 9 were photographed from the monitor of our raster graphics display.

Figure 7 shows the "white" noise with which we started. It was generated by the program FNOIS, which computes an approximately normally distributed value for each pixel by adding 12 uniformly distributed pseudorandom numbers. We then transformed this picture into the spatial frequency domain using a floating point two-dimensional FFT program, FFFT. Next, the noise in the transform domain was multiplied by the inverse of an approximation to the spatial spectral sensitivity of the fovea. The sensitivity function used is given by

\[ s(f) = \exp\left(-\left(\frac{f}{14.}\right)^2\right) - 0.9 \exp\left(-\left(\frac{f}{1.0}\right)^2\right), \]  

(15)

where \( f \) is the spatial frequency in cycles per degree. This function is plotted in figure 8A. The amplitude of the noise in the frequency domain was multiplied by the factor \( a(f) \) given by

\[ a(f) = \frac{s(32)}{s(f)}, \quad f < 32 \]

\[ = 0, \quad f \geq 32. \]  

(16)

This function is plotted in figure 8B. Since the 256 pixels across a picture are assumed to span 4 degrees of visual angle, frequencies in either the horizontal or vertical directions are limited to 32 cycles per degree. Higher frequencies do occur in diagonal directions, since the spatial frequency is given by

\[ f = \left( f_x^2 + f_y^2 \right)^{1/2}, \]  

(17)

in terms of the frequencies in the \( x \) and \( y \) directions alone. The amplitude of the noise at these frequencies was limited so that essentially invisible noise power at these frequencies would not use up the small dynamic range of the output, which was limited to 8 bits. The frequency domain filtering was done by the program FDOGM.
Figure 8. (A) The model's contrast sensitivity at zero eccentricity as a function of spatial frequency. (B) The amplitude factor of the filter used to make the homogeneous filtered noise from the white noise.

Figure 9 shows the result of transforming the filtered noise back into the spatial domain. As figure 8B indicates, this is essentially high-pass noise. We expected it to be more like band-reject noise because the spatial frequency sensitivity function is usually plotted in logarithmic frequency co-ordinates and the sensitivity function looks reasonably symmetric in these co-ordinates.

Finally, the noise of figure 1 was obtained from the noise shown in figure 9 by stretching the noise according to the inverse of the cortical magnification factor. Using the subscript 1 for the spatially homogeneous input picture and the subscript 2 for the stretched output picture, the intensity $I$ for the output is just copied from a corresponding intensity in the input, that is

$$I_2(x_2, y_2) = I_1(x_1, y_1).$$

(18)
Figure 9. The spatially homogeneous filtered noise.

The input co-ordinates in degrees of visual angle corresponding to an output were found by

\[ x_1 = m \cdot x_2 \quad \text{and} \quad y_1 = m \cdot y_2, \]  

(19)

where the inverse expansion factor \( m \) is given by

\[ m = \frac{\ln(1 + cr_2)}{cr_2}, \]  

(20)

where \( r_2 \) is the length of \((x_2, y_2)\), that is

\[ r_2 = (x_2^2 + y_2^2)^{1/2}. \]  

(21)

The constant \( c \) is the parameter in the inverse local cortical magnification function in Watson's model (ref. 1) given by

\[ M(e) = \frac{1}{1 + ce}, \]  

(22)

which is just the multiplicative inverse of equation 13. Equation 20 is just the integral of this local magnification function along the radius to the point. The inverse of the constant \( c \) is the eccentricity in degrees at which the inverse
local cortical magnification function has dropped to a value of one half. We set this value to 44 mrad (2.5 deg.), which corresponds to a value of 0.023 (mrad)$^{-1}$ (0.4 (deg.)$^{-1}$) for c.

There is an additional complexity in the program BCRMG which stretched figure 9 to obtain figure 1. The co-ordinates for a point in the input corresponding to a point in the output do not usually fall exactly on a point in the input. The output in the general case has to be interpolated from the surrounding points. In this case we used a four by four interpolation function which is the product of the sinc function in each direction, with the amplitude of the interpolation normalized to correct for the fact that the sinc function was only computed at the four closest values in each direction.

Summary

To summarize, the noise of figure 1 is perceptually homogeneous in the spatial and spatial frequency domains. Except for a contrast gain factor, it represents in a single picture the spatial contrast detection ability of the visual system. It is a picture of the noise of the visual contrast detection system in a useful sense. Once any signal is added to the noise the result can be inspected at any magnification, gain, or for any length of time to see whether the signal is "visible".
This appendix contains the Fortran IV source code listings of the programs used to create the figures, preceded by a list of the required RT-ll system commands and program control parameters.

! RT-ll system commands and program parameters
! Device m: should be fastest device available
! (we used a ramdisk device driver).
create m:image.flo[1024]
r fnois
create image.byt[128]
r fb
28.0,0.0
copy image.byt noise.byt
! figure 7 in file noise.byt
r fft
0
r fdogm
r fft
-1
r fb
100.0,0.0
copy image.byt noidog.byt
! figure 9 in file noidog.byt
copy image.byt m:input.byt
r bcrmg
! figure 1 in file image.byt

program fnois
! This program fills the file M:IMAGE.FLO with 256 times 256 floating point numbers which are approximately independent, normally distributed values with a mean of 0.0 and a standard deviation of 1.0. These numbers are followed by an equal number of zeros in anticipation of a complex fft.

real z, row(256)
crow, column dimensions
n= 256
open( unit=1, name= 'M:IMAGE.FLO', type='OLD',
& access= 'DIRECT', recordsize= n)
c random seeds
iran= 0
jran= 0
c do rows
    do 6 j=1, n
c do columns
    do 7 i=1, n
    z= 0.
    do 10 k= 1, 12
10  z = z + ran(iran, jran)
    row(i) = z - 6.0
7  continue

   jl = j
   write(1'jl) (row(i), i = 1, n)
   type *, j, row(1), row(n)
6  continue
c do zeros
   do 8 i = 1, n
8  row(i) = 0.0
   do 9 j = 1, n
9   jl = j + n
    write(1'jl) (row(i), i = 1, n)
   stop
end

program fb
c Converts floating input of n records of length n,
c to byte output (-128 to 127) using scale factors input
c from the terminal. Scale factors are obtained from
c program frang.
c
   real c(256)
   byte a(256)
   integer ia
   n = 256
open( unit= 1, name= 'M:IMAGE.FLO', type= 'OLD',
     & access= 'DIRECT', recordsize= n)
nd4 = n/4
open( unit= 2, name= 'IMAGE.BYT', type= 'OLD',
     & access= 'DIRECT', recordsize= nd4)
type*, ' scale factor, offset ?'
accept*, scale, offset
do 7 j = 1, n
   jl = j
   read(1'jl) (c(i), i = 1, n)
   do 8 i = 1, n
5   fa = scale*c(i)+offset
   if ( fa .lt. 0. ) fa = fa - 1.
      a(i) = fa
8  continue
   write(2'jl) (a(i), i = 1, n)
   type*, ' row ', jl
7  continue
   stop
end
program frang
  c Finds the maximum and minimum values in a complex image.
  c
  real c(256), d(256)
n= 256
open( unit=1, name= 'M:IMAGE.FLO', type= 'OLD',
& access= 'DIRECT', recordsize= n)
cmax=-10000000.
cmin= 10000000.
dmax=cmax
dmin=cmin
do 7 j= 1, n
  jl= j
  jml= jl+256
read (l'jl) ( c(i), i= 1, n)
read(l'jml) (d(i), i= 1, n)
do 8 i= 1, n
cmax=amax1(cmax,c(i))
dmax=amax1(dmax,d(i))
cmin=amin1(cmin,c(i))
dmin=amin1(dmin,d(i))
8 continue
type*, ' row ',jl
7 continue
type*, ' cmax,cmin,dmax,dmin=',cmax,cmin,dmax,dmin
stop
end

program fft
  c Two-dimensional complex floating point fft.
  c Inverse flag is 0 for direct, nonzero for inverse.
  c Calls one-dimensional subroutine:
  c    fft( n, c, d, costab, invers)
  c Output is written over input file, M:IMAGE.FLO
  c
  real c(256), d(256), costab(65)
real cbuf(8,256), dbuf(8,256)
n= 256
n2= n*2
lbuf= 8
open( unit=1, name= 'M:IMAGE.FLO', type= 'OLD',
& access= 'DIRECT', recordsize= n)
pi = 3.1415927
twopi = 2. * pi
type*, ' non-zero entry for inverse ?'
accept 100, invers
100 format(i10)
  if( invers .ne. 0 ) inverse= -1
c fill cosine table
do 10 i= 1, n/4 +1
10 costab(i) = cos( twopi*(i-l)/n )
c type*, ( costab(i), i= 1, n/4 +1)
c do row transforms first
   do 1 j= 1, n
      j1= j
      jml= j1+ n
      read(l'j1) (c(i), i = 1, n)
      read(l'jml) (d(i), i = 1, n)
      call fft( n, c, d, costab, invers)
      j2= j
      jml2= j2+ n
      write(l'j2) (c(i), i = 1, n)
      write(l'jml2) (d(i), i = 1, n)
      type *, ' row ', j
   1 continue
   close(unit=1)
c do columns
   nbuf= n/lbuf
   open( unit=1, name= 'M:IMAGE.FLO', type= 'OLD',
     & access= 'DIRECT', recordsize= lbuf)
   nrec= n*(n/lbuf)
   do 6 il = 1, nbuf
      ibuf = il
      do 9 j= 1, n
         jl = ibuf
         ibuf = ibuf + nbuf
         jml = jl + nrec
         read(l'jl) (cbuf(i,j), i= 1, lbuf)
         read(l'jml) (dbuf(i,j), i= 1, lbuf)
      9 continue
      do 11 i2 = 1, lbuf
         do 7 j= 1, n
            c(j) = cbuf(i2,j)
            d(j) = dbuf(i2,j)
         7 continue
         call fft( n, c, d, costab, invers)
         do 8 j= 1, n
            cbuf(i2,j)= c(j)
            dbuf(i2,j)= d(j)
         8 continue
         icol= i2+ lbuf*(il-1)
         type *, ' col ', icol
      11 continue
   6 continue
stop
end
program fdogm

c Multiplies the amplitudes of a complex frequency domain image by an amplitude response having the form of the inverse of the difference of two Gaussians.
c The 256 pixels are assumed to subtend 4 degrees of visual angle.
c Spatial frequencies above 32 cycles per degree are given an amplitude of zero.

c real c, d
real crow(256), drow(256)
real gl(256), g2(256)
n= 256
open( unit= 1, name= 'M:IMAGE.FLO', type= 'OLD',
& access= 'DIRECT', recordsize= n)
nd2= n/2
nd2pl= nd2+1
c Difference of Gaussian parameters: ampl, spread1, amp2, spread2
are respectively, a1, bl, a2, b2.
a1= 1.
a2= .9.
b1= 10.*4.
b2= 0.7*4.
x= 3.5*b1
nx= min0( nd2pl, nx)
c= -0.5/(bl*bl)
do 10 i= 1, nx
10 gl(i)= a1*exp(c*x*x)
if(nx .ge. nd2pl) go to 14
do 11 i=nx+1,nd2pl
11 gl(i)= 0.
14 continue
nx= 3.5*b2
nx= min0( nd2pl, nx)
c= -0.5/(b2*b2)
do 12 i= 1, nx
12 g2(i)= a2*exp(c*x*x)
if(nx .ge. nd2pl) go to 15
do 13 i= nx+1,nd2pl
13 g2(i)= 0.
15 continue
nx= min0( 32, nd2pl)
dogmin= a1*a1*exp(-.5*(32/10.)*x*x)
type*, dogmin
c do rows
do 6 j= 1, n
19
iy = j
if ( iy .gt. nd2p1) iy = n-iy+2
factor = dogmin/( gl(ix)*gl(iy)-g2(ix)*g2(iy) )
if(factor.gt.1.) factor = 0.
crow(i)=factor*crow(i)
drow(i)=factor*drow(i)
continue
jl = j
write(l'jl) (crow(i), i= 1, n)
jl = j+n
write(l'jl) (drow(i), i= 1, n)
type*, 'row ', j
continue
stop
end

program bcrmg
 c This program generates a picture in IMAGE.BYT
 c by sampling and interpolation from M:INPUT.BYT
 c according to the linear approximation to the cortical
 c magnification factor.
c A sinc function is used for the interpolation, with a gain
 c correction factor to compensate for amplitude variations
 c caused by truncation of the sinc function.
c
byte row2(256), bufl(256,4)
real w(201)
real cor(100)
n = 256
nd4 = n/4
open( unit= 1, name= 'M:INPUT.BYT', recordsize= nd4, & access= 'DIRECT', type= 'OLD')
open( unit= 2, name= 'IMAGE.BYT', recordsize= nd4, & access= 'DIRECT', type= 'OLD')
pi = 3.1415927
twopi = 2. * pi
c Sinc weighting function.
do 200 i= 2, 201
   il=i-1
200   w(i)=sin(pi*il/100.)/(pi*il/100.)
   w(1)=1.
c Amplitude correction.
do 300 i= 1, 100
300   cor(i)=1.0/(w(i)+w(i+100)+w(102-i)+w(202-i))
c viewing distance in pixels so 1 pixel is 1/64 degree
  vdist=57*64
c coefficient of magnification factor in pixels
  c= 0.4 * 57. / vdist
  ci= 1. / c
  lower and upper ranges of output pixel ranges
  n12 = 1
  nu2 = n
c input and output magnification center coordinates
  no2 = ( nu2 + n12 ) / 2
origin = no2
jold= -1

c For each output row
do 10 j2 = n12 , nu2
c For each output column
do 1 i2 = n12 , nu2
di = i2 - no2
dj = j2 - no2
r2 = sqrt ( di * di + dj * dj )
if ( r2 .eq. 0. ) goto 2
r1 = ci * alog ( 1. + c * r2 )
ratio = r1 / r2

2 ratio = 0.
3  x1 = ratio * di + origin
   y1 = ratio * dj + origin
   il = x1
   jl = y1
   idx= int((x1-il)*100.)+1
   idy= int((y1-jl)*100.)+1
   wx2= w(idx)
   wy2= w(idy)
   wx1= w(100+idx)
   wy1= w(100+idy)
   wx3= w(102-idx)
   wy3= w(102-idy)
   wx4= w(202-idx)
   wy4= w(202-idy)
   ilpl = il + 1
   jlpl = jl + 1
   ilml = il - 1
   jlml = jl - 1
   ilp2 = il + 2
   jlp2 = jl + 2
   jrecl= jlml
   if(jlml .eq. jold) goto 9
   jold= jlml
do 8 j= 1, 4
read(l'jrecl) ( bufl(i,j), i=1,n )
8 jrecl= jrecl+1
9 continue
all = bufl( ilml, 1)
al2 = bufl( ilml, 2)
al3 = bufl( ilml, 3)
al4 = bufl( ilml, 4)
a21 = bufl( il, 1)
a22 = bufl( il, 2)
a23 = bufl( il, 3)
a24 = bufl( il, 4)
a31 = bufl( ilpl, 1)
a32 = bufl( ilpl, 2)
a33 = bufl( ilpl, 3)
a34 = bufl( ilpl, 4)
a41 = bufl( ilp2, 1)
a42 = buf1( ilp2, 2)
a43 = buf1( ilp2, 3)
a44 = buf1( ilp2, 4)
ave = wx1*(wyl*a11+wy2*a12+wy3*a13+wy4*a14)
    & +wx2*(wyl*a21+wy2*a22+wy3*a23+wy4*a24)
    & +wx3*(wyl*a31+wy2*a32+wy3*a33+wy4*a34)
    & +wx4*(wyl*a41+wy2*a42+wy3*a43+wy4*a44)
row2(i2) = ave*cor(idx)*cor(idy)
1 continue
jrec= j2
write(2'jrec) (row2(i), i= 1, n)
type*, 'row ', jrec
10 continue
stop
end

REFERENCES

We have generated a picture which is a sample of random contrast noise. The noise amplitude spectrum in each region of the picture is inversely proportional to spatial frequency contrast sensitivity for that region, assuming the observer fixates the center of the picture and is the appropriate distance from it. In this case, the picture appears to have approximately the same contrast everywhere.

To the extent that contrast detection thresholds are determined by visual system noise, this picture can be regarded as a picture of the noise of that system.

There is evidence that, at different eccentricities, contrast sensitivity functions differ only by a magnification factor. The picture was generated by filtering a sample of "white" noise with a filter whose frequency response is inversely proportional to foveal contrast sensitivity. It was then stretched by a space-varying magnification function.

The picture summarizes a noise linear model of detection and discrimination of contrast signals by referring the model noise to the input picture domain.