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

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UNIFORM APPARENT CONTRAST NOISE:

A PICTURE OF THE NOISE OF THE VISUAL CONTRAST DETECTION SYSTEM

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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.

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.
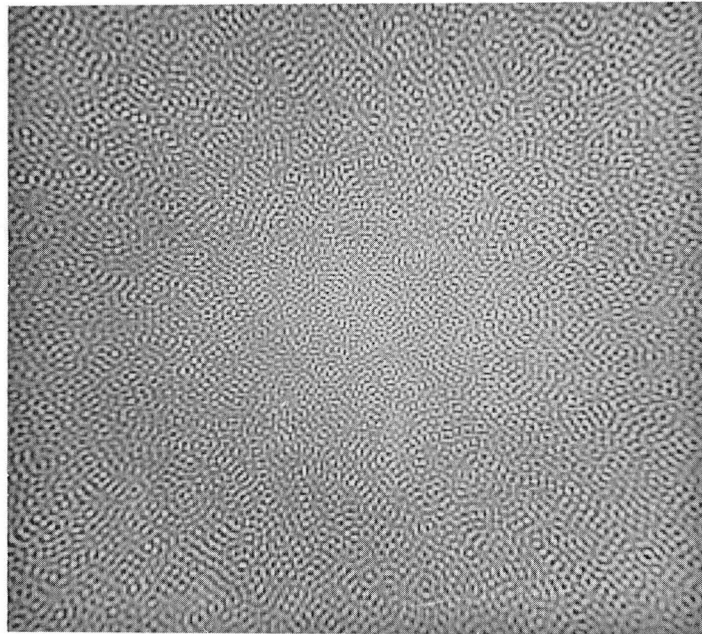

Figure 1. A picture of the noise of the contrast detection system referred to its input.

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 charcteristics 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.
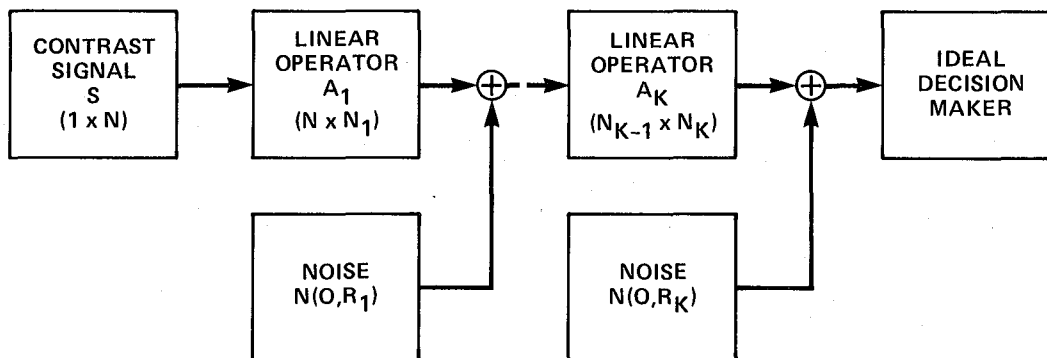
$$S = (\ s_i\ ),\ i = 1,\ N. \tag{1}$$

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.

$$A_k = (\ a_{kij}\ ), \quad k = 1,\ K;\ i = 1,\ N_{k-1};\ j = 1,\ N_k \tag{2}$$

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

$$N_0 = N. \tag{3}$$

If the first layer represented the receptors, a_{1ij} would reflect assumed to be Gaussian with a mean vector of zero and an arbitrary covariance matrix.

$$R_k = (\ r_{kij}\ ), \quad k = 1,\ K;\ i,\ j = 1,\ N_k \tag{4}$$

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,

$$A = A_1 A_2 \ldots A_K, \tag{5}$$

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

$$R = R_K + A_K \backslash uT R_{K-1} A + \ldots + H_k \backslash uT R_k H_k + \ldots + H_1 \backslash uT R_1 H_1, \tag{6}$$

where

$$H_k = A_{k+1} A_{k+2} \ldots A_K. \tag{7}$$

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.
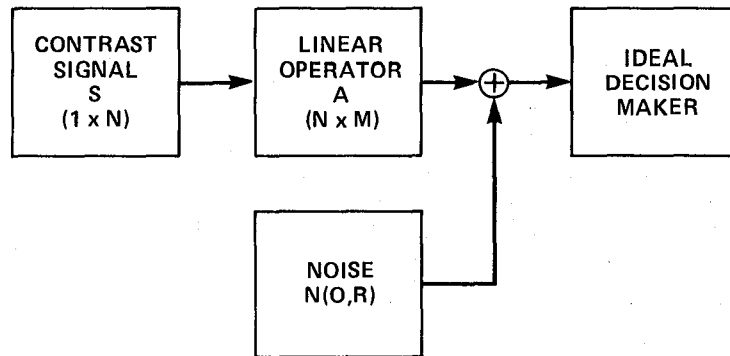

Figure 3. A single layer model for contrast detection.

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

$$d'(S) = z(\text{Prob}\{D|\text{Signal}=S\}) - z(\text{Prob}\{D|\text{Signal}=0\}), \qquad (8)$$

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

$$d'(S) = S \, A \, R^{-1} A^T S^T. \qquad (9)$$

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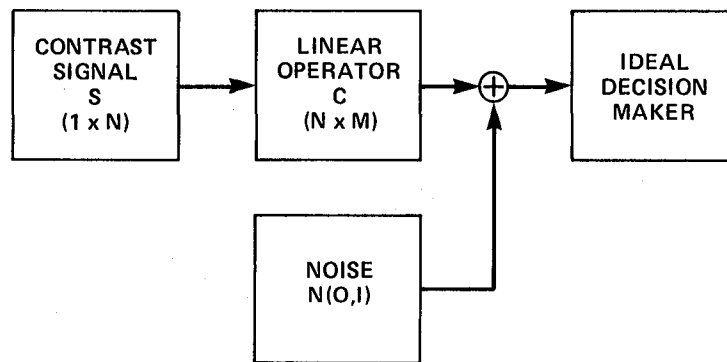such as Anderson (ref. 6, chapt. 12).

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

$$C = A \, B^{-1}, \tag{10}$$

where B is a matrix of factor loadings of R, that is

$$R = B^T B. \tag{11}$$

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.

```
┌─────────────┐            ┌─────────────┐
│  CONTRAST   │            │   IDEAL     │
│   SIGNAL    │──→ ⊕ ──→   │  DECISION   │
│     S       │            │   MAKER     │
│   (1 x N)   │            │             │
└─────────────┘     ↑      └─────────────┘
                    │
┌─────────────┐     │
│    NOISE    │     │
│  N(O,R_E)   │─────┘
│             │
└─────────────┘
```
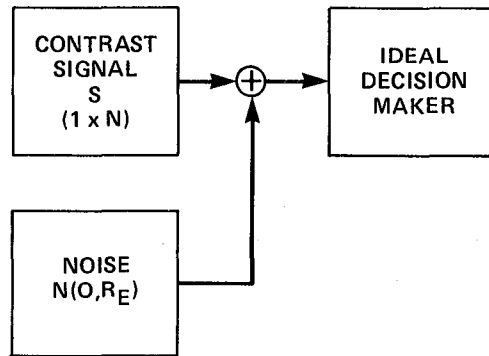
Figure 5. The input equivalent noise model for contrast detection.

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

$$R_E = (C \, C^T)^{-1}. \tag{12}$$

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.
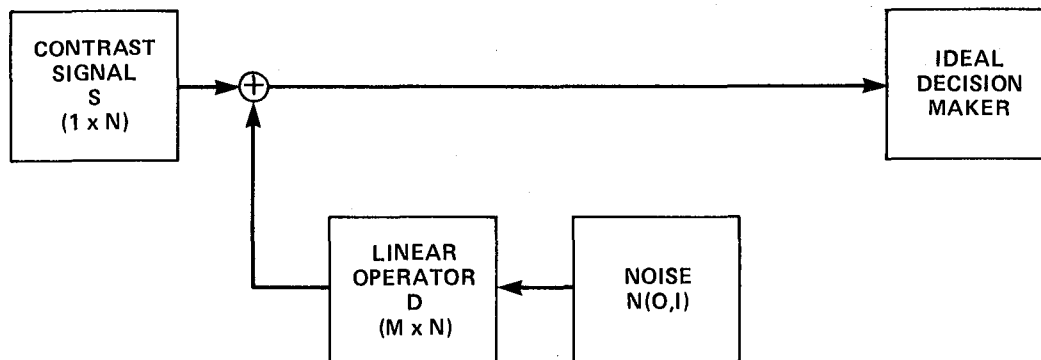
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Figure 6. The input equivalent model with "back-projected"
"white" noise.

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,

$$D = C^T (C \ C^T)^{-1}. \tag{13}$$

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

$$s = 1 + ce ,\qquad(14)$$

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 $(mrad)^{-1}$ (0.4 $(deg.)^{-1}$). 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
presumeably 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
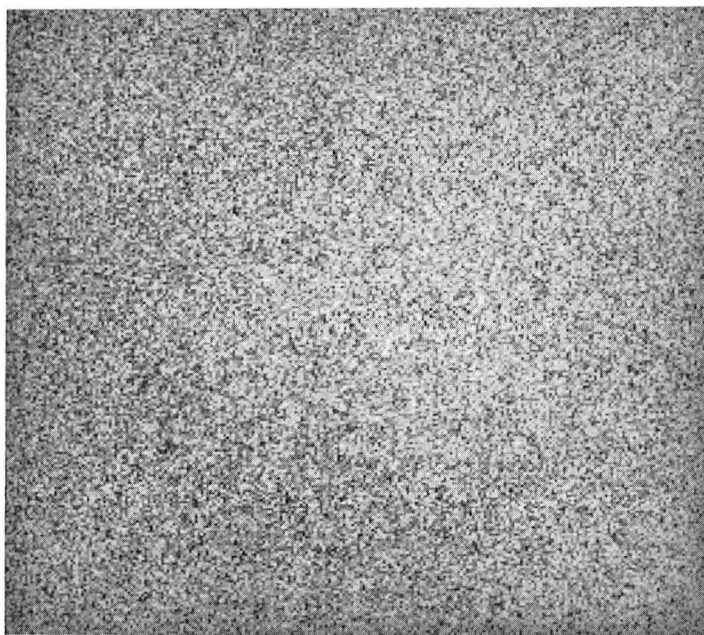amplitude response matched to that of the central fovea.

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

$$s(f) = \exp(-(f/14.)^2) - 0.9 \exp(-(f/1.0)^2), \tag{15}$$

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

$$a(f) = s(32)/s(f), \quad f < 32$$

$$= 0, \quad f > \text{or} = 32. \tag{16}$$

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

$$f = (f_x^2 + f_y^2)^{1/2}, \tag{17}$$

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.
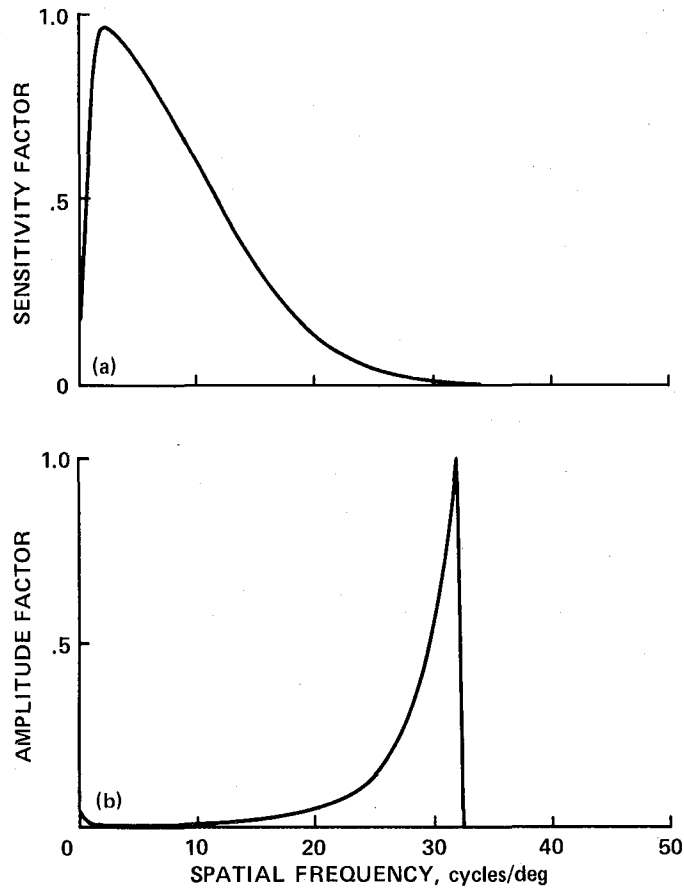
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Figure 8. (A) The model's contrast sensitivity at zero
eccentricity as a function of spatial frequency. (B) The
amplitude factor of the filter used to make the homogeneous
filtered noise from the white noise.

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

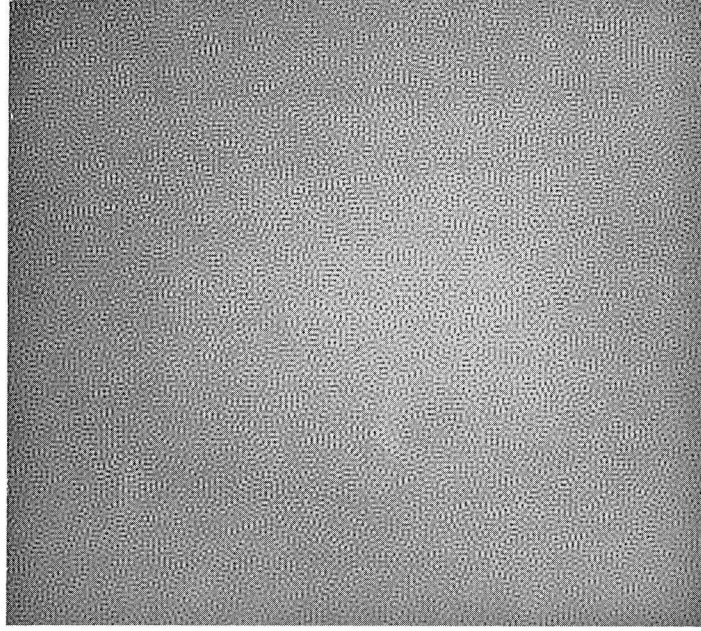$$I_2(x_2,y_2) = I_1(x_1,y_1).$$

(18)

Figure 9. The spatially homogeneous filtered noise.

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

$$x_1 = m\ x_2 \quad \text{and} \quad y_1 = m\ y_2, \tag{19}$$

where the inverse expansion factor m is given by

$$m = \ln(\ 1 + cr_2)/cr_2, \tag{20}$$

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

$$r_2 = (\ x_2{}^2 + y_2{}^2)^{1/2}. \tag{21}$$

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

$$M(e) = 1/(1+ce), \tag{22}$$

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

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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".

APPENDIX

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-11 system commands and program control parameters.


```
! RT-11 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 ffft
0
r fdogm
r ffft
-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
c This program fills the file M:IMAGE.FLO with 256 times 256
c floating point numbers which are approximately independent,
c normally distributed values with a mean of 0.0 and a
c standard deviation of 1.0.  These numbers are followed by an
c equal number of zeros in anticipation of a complex fft.
c
      real z, row(256)
c row, 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


   j1= j
   write(1'j1) (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
   j1= j + n
9  write(1'j1) (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
   j1= j
   read(1'j1) (c(i), i=1, n)
   do 8 i= 1, n
   fa = scale*c(i)+offset
   if ( fa .lt. 0. ) fa = fa - 1.
   a(i) = fa
8  continue
   write(2'j1) (a(i), i=1, n)
   type*, ' row ', j1
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(1'jl) (c(i), i= 1, n)
      read(1'jml)(d(i), i= 1, n)
      do 8 i= 1, n
      cmax=amaxl(cmax,c(i))
      dmax=amaxl(dmax,d(i))
      cmin=aminl(cmin,c(i))
      dmin=aminl(dmin,d(i))
8     continue
      type*, ' row ',jl
7     continue
      type*, ' cmax,cmin,dmax,dmin=',cmax,cmin,dmax,dmin
      stop
      end



      program ffft
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-1)/n )
c    type*, ( costab(i), i= 1, n/4 +1)
```

```
c do row transforms first
      do 1 j= 1, n
      j1= j
      jm1= j1+ n
      read(1'j1) (c(i), i= 1, n)
      read(1'jm1) (d(i), i=1, n)
      call fft( n, c, d, costab, invers)
      j2= j
      jm2= j2+ n
      write(1'j2) (c(i), i = 1, n)
      write(1'jm2) (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
      j1 = ibuf
      ibuf = ibuf + nbuf
      jm1 = j1 + nrec
      read(1'j1) (cbuf(i,j), i= 1, lbuf)
      read(1'jm1) (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
      ibuf= il
      do 12 j= 1, n
      j1= ibuf
      ibuf= ibuf + nbuf
      jm1= j1 + nrec
      write(1'j1) (cbuf(i,j), i= 1, lbuf)
      write(1'jm1) (dbuf(i,j), i=1, lbuf)
12    continue
6     continue
      stop
      end
```

```fortran
      program fdogm
c Multiplies the amplitudes of a complex frequency domain
c image by an amplitude response having the form of the
c 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
c an amplitude of zero.
c
      real c, d
      real crow(256), drow(256)
      real g1( 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,spreadl,amp2,spread2
c are respectively, a1, b1, a2, b2.
      a1=1.
      a2=.9
      b1= 10.*4.
      b2= 0.7*4.
      nx= 3.5*b1
      nx=min0( nd2pl, nx)
      c= -0.5/(b1*b1)
      do 10 i= 1, nx
      x=i-1
10    g1(i)= a1*exp(c*x*x)
      if(nx .ge. nd2pl) goto 14
      do 11 i=nx+1,nd2pl
11    g1(i)= 0.
14    continue
      nx= 3.5*b2
      nx=min0( nd2pl, nx)
      c= -0.5/(b2*b2)
      do 12 i= 1, nx
      x=i-1
12    g2(i)= a2*exp(c*x*x)
      if(nx .ge. nd2pl) goto 15
      do 13 i= nx+1,nd2pl
13    g2(i)=0.
15    continue
      nx= min0( 32, nd2pl)
      dogmin= a1*a1*exp(-.5*(32/10.)**2)
      type* , dogmin
c do rows
      do 6 j=1, n
      j1= j
      read(1'j1) (crow(i), i=1, n)
      j1= j+ n
      read(1'j1) (drow(i), i=1, n)
c do columns
      do 7 i= 1, n
      ix=i
      if( ix .gt. nd2pl) ix= n-ix+2
```

```
      iy= j
      if( iy .gt. nd2pl) iy= n-iy+2
      factor= dogmin/( gl(ix)*gl(iy)-g2(ix)*g2(iy) )
      if(factor.gt.1.) factor= 0.
8     crow(i)=factor*crow(i)
      drow(i)=factor*drow(i)
7     continue
      jl= j
      write(1'jl) (crow(i), i= 1, n)
      jl= j + n
      write(1'jl) (drow(i), i= 1, n)
      type*, ' row ', j
6     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
c lower and upper ranges of output pixel ranges
      nl2 = 1
      nu2 = n
c input and output magnification center coordinates
      no2 = ( nu2 + nl2 ) / 2
```

```fortran
      origin = no2
      jold= -1
c For each output row
      do 10 j2 = nl2 , nu2
c For each output column
      do 1  i2 = nl2 , nu2
      di = i2 - no2
      dj = j2 - no2
      r2 = sqrt ( di * di + dj * dj )
      if ( r2 .eq. 0. ) goto 2
      rl = ci * alog ( 1. + c * r2 )
      ratio = rl / r2
      goto 3
2     ratio = 0.
3         xl = ratio * di + origin
      yl = ratio * dj + origin
      il = xl
      jl = yl
      idx= int((xl-il)*100.)+1
      idy= int((yl-jl)*100.)+1
      wx2= w(idx)
      wy2= w(idy)
      wxl= w(100+idx)
      wyl= 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(1'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)
```

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```
       a42 = bufl( ilp2, 2)
       a43 = bufl( ilp2, 3)
       a44 = bufl( ilp2, 4)
       ave = wx1*(wy1*a11+wy2*a12+wy3*a13+wy4*a14)
     &     +wx2*(wy1*a21+wy2*a22+wy3*a23+wy4*a24)
     &     +wx3*(wy1*a31+wy2*a32+wy3*a33+wy4*a34)
     &     +wx4*(wy1*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
```

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15. Supplementary Notes

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16. Abstract

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.

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