Camera Simulation for Predicting Information Metrics and Machine Vision Performance

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We present a new set of camera performance metrics, based on information theory, that are superior to traditional metrics such as *MTF* (*SFR*) and noise or Signal-to-Noise Ratio (*SNR*) for predicting Machine Vision/Artificial Intelligence (MV/AI) system performance.

We describe a new image sensor noise model, and show how it's used with Imatest's camera/ISP simulator, *Simatest*, to

- **predict imaging system performance, and**
- **allow camera systems to be soft-prototyped.**

Outline of the presentation

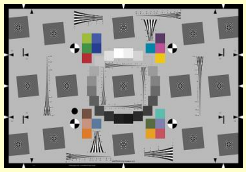
- My background — photography & engineering
- Introduction to information theory and metrics
  - Calculating information capacity, *C*, in the presence of a signal
  - Information metrics (related to *C*), including - *NPS*, *NEQ*, *SNRi* (metric for object detection),
  - Matched filters to optimize object and edge detection (brief)
- Information-based Dynamic Range using & low-light performance from the new InfoDR chart.
- Image sensor noise model based on Photon Transfer Curve (PTC) or EMVA 1288
- *Simatest*: ISP/Camera simulator (lens, sensor, ISP)
- Demonstration if time & setup allows

"Green is for geeks" boxes contain equations or technical details you don't need to follow during the presentation, but you may want to review later.

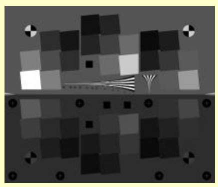
Measurement and simulation

Image quality measurements

Spatial detail (full image)

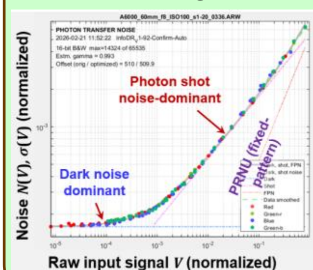


Tonal detail (near image center)



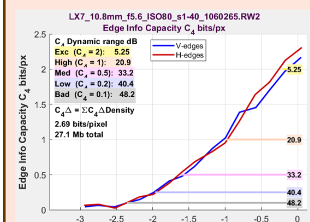
Key results: Information capacity and related metrics

Image sensor noise model for simulation from raw images



Simatest camera simulation:

Create image, lens losses, noise, ISP



C_4 information capacity vs. exposure

My background

- Grew up in Rochester, NY. “Kodak city” Frequently visited George Eastman House (museum). Fascinated by both the fine prints and the cameras.
- Interest in photography started around age 12. Dissatisfied with sharpness of cameras I could afford.
- Summer job University of Rochester Institute of Optics, 1961. MTF curves.
- Master’s degree in physics; 34 year career in magnetic recording technology; Similar math (FFTs...) to imaging.
- Lifelong interest in Photography. Mastered darkroom printing; had occasional shows.
- Launched normankoren.com (images and technical tutorials) in 2000, which led to founding *Imatest* in 2003 for measuring lens and camera quality.

How I became acquainted with information theory

I worked at Kodak San Diego from 1985-1998. During that time I frequently visited UCSD Center for Magnetic Recording Research (CMRR), where I became acquainted with infor-mation theory.

CMRR (now, Center for Media and Recording Reasearch) produced the video, which I highly recommend.

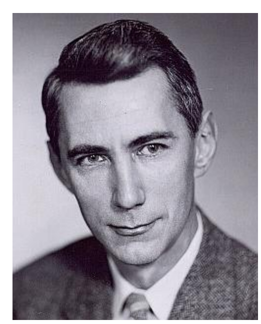
[Claude Shannon – Father of the Information Age](www.youtube.com/watch?v=z2Whj_nL-x8).

I enjoy the intersection of science and art.

Claude Shannon - Father of the Information Age

www.youtube.com/watch?v=z2Whj_nL-x8

Introduction to Information theory



Developed by Claude Shannon at Bell Labs in 1948-9.

Information is the amount by which the outcome of an event or a measurement reduces uncertainty.

Widely used in electronic communications, where channels are characterized by information capacity C in bits/second, which is the maximum rate information can be transmitted without error.

Images are communication channels where C has units of bits/pixel or bits/image.

***Imatest* has developed a method to conveniently calculate C by measuring signal power, $S(f)$, and noise power, $N(f)$, at the *same* location in slanted edge test patterns.**

C_4, which is measured directly from ISO-standard 4:1 contrast slanted edges, is of special interest. It is the amount of information a 4:1 contrast object — typical for several applications — can convey. It's closely related to its detectability.

What is information?

***Information*, defined by Claude Shannon in his classic 1948 and 1949 papers, is a measure of the resolution of uncertainty**, i.e., how much is learned from the outcome of a measurement. It is the basis of all electronic communication.

For a system with n possible states, s_1, …, s_n, with probabilities $p(s_1)$, …, $p(s_n)$, information can be represented as ***entropy***,

$$H(S) = \sum_{i=1}^{n} p(s_i) \log_2(1/p(s_i)) = -\sum_{i=1}^{n} p(s_i) \log_2(p(s_i))$$

Example 1: a "fair" coin flip. $p_1 = p_2 = 1/n = 0.5$; H = entropy = .5 + .5 (information gained from the flip) = 1 "bit".

When one outcome is more probable than the other, the information gained in the trial is ***lower***. For example,

Example 2: For $p_1 = 0.95$; $p_2 = 0.05$, H = 0.95*0.074+.05*4.322 = 0.286.

More on information

When $H < 1$, data can be ***encoded*** for efficient transmission. Coding is a key aspect of information theory — integral to data compression (PNG, JPEG, etc.)

The number of states n is closely related to the Signal-to-Noise Ratio (S/N or SNR) of a continuous system.

Electronic channels — including cameras — are communication channels that can be characterized by a **channel information capacity, C** (the maximum rate that information that can be transmitted without error), which has units of bits/pixel or bits/image.

C is calculated from the **Shannon-Hartley equation** (next page), which uses

- frequency-dependent signal power $S(f)$ (which includes MTF),
- Noise power N or NPS(f)

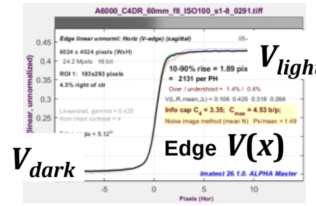
The challenge: How to conveniently obtain $S(f)$, N or $NPS(f)$.

The key performance indicators for MV/AI systems are closely related to C.

Shannon-Hartley equation for C_4

4:1 contrast edges are specified by ISO 12233 and widely used for practical measurements.

$S(f) = \left(\left(V_{light} - V_{dark}\right) SFR(f)\right)^2/12$ **is the mean signal power of the edge, $V(x)$: includes sharpness ($SFR(f)$).**



$$C_4 = \int_0^W \log_2\left(1 + \frac{S(f)}{NPS(f)}\right) df$$

$NPS(f)$ is the Noise Power Spectrum, from the noise image

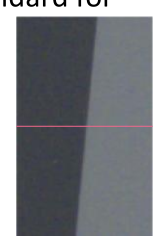
W is always the Nyquist frequency, 0.5 C/P.

C_4, the information that can be conveyed in a 4:1 contrast object, is a *complete* pixel-level performance metric that combines *partial* metrics: signal power, $S(f)$, sharpness, $SFR(f)$, and noise. $NPS(f)$.

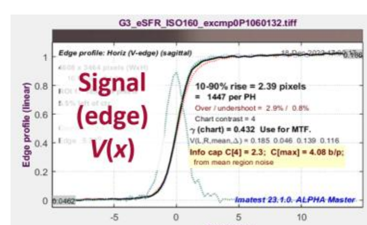
The key to conveniently calculating C is to measure Signal S(f) and noise NPS(f) at the *same* location

Slanted edge calculation

The widely used **slanted edge** test pattern— a part of the **ISO 12233** standard for image sharpness — is fast and compact enough to map MTF over an entire image. The **ISO 12233** algorithm



- Linearizes the image,
- Finds the center of each scan line,
- Fits the centers to a polynomial,
- Adds each shifted scan line to one of four bins to obtain a 4x oversampled averaged edge, **Amplitude (voltage) =** $V(x) = \mu_s(x)$, shown on the right, is used to calculate *MTF* and information metrics. ***MTF*** **=** $|\mathrm{FFT}(dV(x)/dx)|$



Binning effectively reduces noise by $\sqrt{\text{samples in each bin.}}$

Best results are obtained when edge ROI length ≥ 100 pixels. [e.g., 100 pixels in 4 bins (≅25 per bin), reduces noise by $\sqrt{25} \approx 5$.]

The key to conveniently calculating information metrics is to ***measure signal (SFR or MTF) and noise in the same location***.

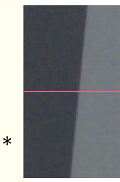
Measuring noise, $N(x)$, from the slanted edge

Information capacity, $C_{EdgeVar}$, is calculated with the spatially dependent noise power, $N(x)$ (the *edge variance*), measured at the *same location* as the signal,

Sum the *squares* of each scan line to find the edge variance

$$\sigma_s^2(x) = N(x) \text{ (the noise power).}$$

Spatially dependent noise power $N(x) = \sigma_s^2(x) = \frac{1}{L}\sum_{l=0}^{L-1} y_l^2(x) - \mu_s^2(x)$ *

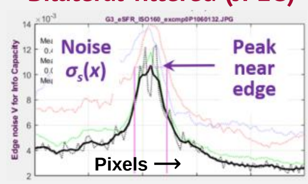


***$N(x)$ is the sum of the squares minus the square of the sum, all divided by the number of points L.**

Examples of Noise amplitude $\sigma_s(x) = \sqrt{N(x)}$, which was not previously visible.

Uniformly-processed

Bilateral-filtered (JPEG)



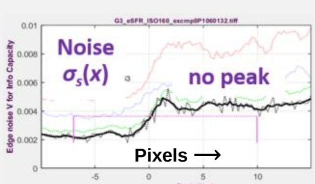
$N(x)$ can look *very* different for different types of image processing

(same image capture)

Noise power N for calculating information capacity, C

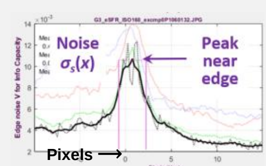
<u>N must be calculated where *SFR* (*MTF*) is measured for accurate results</u>

Noise to enter into Shannon-Hartley eq. depends on the image processing.



Noise amplitude $\sigma_s(x) = \sqrt{N(x)}$

Processing type (minimal/uniform or bilateral filtered) can be determined from
1. knowledge of image processing, or
2. Absence or presence of a peak in $N(x)$



Little or no noise peak.

<u>Minimal or uniform processing</u>

Use the mean of the noise power for C,

$$N = \text{mean}(N(x))$$

A better method for C is available.

Distinct noise peak.

<u>Nonuniform processing (bilateral filtered)</u>

Use the peak (smoothed) noise power for C,

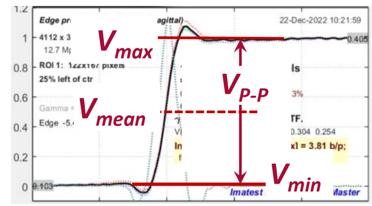
$$N = N_{peak\text{-}smooth}$$

***MTF* does *<u>not</u>* represent texture.**

Signal power for calculating C

The **mean signal power**, $S_{mean}(f)$ must be entered into the Shannon-Hartley equation in addition to **noise power** N to calculate information capacity, C.

The measured signal from the slanted-edge, typically with 4:1 contrast. has a Peak-to-Peak amplitude, $V_{P\text{-}P} = V_{max} - V_{min}$.



$$\textbf{Mean signal power } S_{mean}(f) = \left(V_{p-p}\, MTF(f)\right)^2/12$$

The frequency-dependence of $S_{mean}(f)$ comes from $MTF(f)$. Division by 12 gives the mean power for uniformly-distributed data over $V_{P\text{-}P}$, which maximizes C.

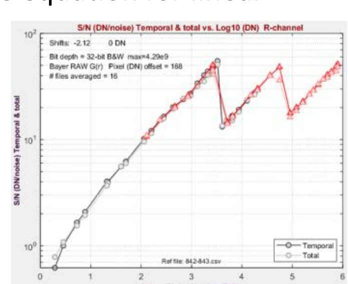
Signal power , $S_{mean}(f)$, is a strong function of exposure and chart contrast (the ISO 12233 standard 4:1 contrast is strongly recommended for *MTF* measurements).

Calculating information capacity C_4 and C_{max}

For most applications, we prefer C_4, measured from ISO 12233-standard 4:1 contrast slanted edges, which are relatively immune to saturation (for good exposures) and have good SNR. C_4 is a strong function of exposure, making it useful for measuring performance over a wide range of illumination, including low light.

Because C_4 varies with exposure, we developed a more stable metric, ***Maximum information capacity, C_{max}***, by extrapolating $V_{p\text{-}p}$ to $V_{max} = 1$ (or the maximum for the camera) and adjusting the noise, which follows a simple equation for linear sensors.

$$N(V) = k_0 + k_1 V$$



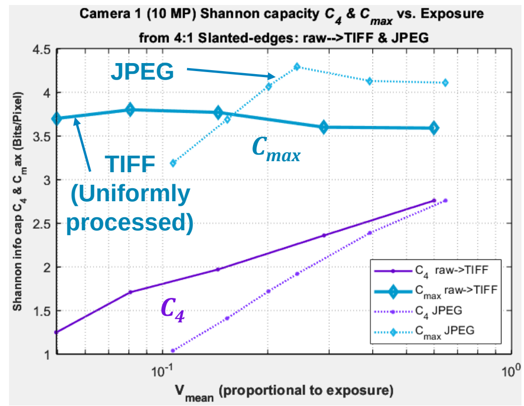
Because C_{max} is difficult to calculate for HDR sensors, which have irregular $N(V)$ response (shown on the right), and is not useful for low-light, we have de-emphasized it.

Measuring information capacity C_n and C_{max}

C_4, which is a function of exposure and chart contrast ratio *n*, and *maximum information capacity*, C_{max}, are shown on the right.

C_{max} (upper plots) is a stable measurement, nearly independent of exposure, that can be used as a single number to characterize a camera's potential. Care is required in when calculating C_{max}.

C_4 (lower plots) is useful for characterizing camera performance as a function of exposure, especially low light.



C_4 and C_{max} characterize the *potential* performance of a camera system.

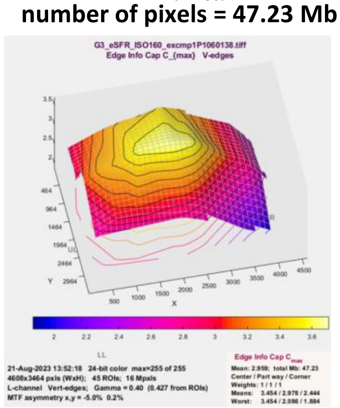
We will discuss object and edge detection metrics, which are also impacted by image processing.

Information capacity displays

The 3D plot can show C_4 or C_{max} mapped over the image.

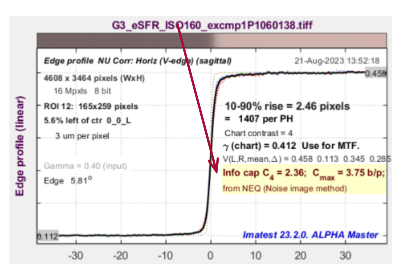
Mean(C_{max}) = 2.96 b/p.

Total info capacity $C_{maxTotal}$ = mean(C_{max}) * number of pixels = 47.23 Mb



C_4 and C_{max} are displayed in the Edge/MTF plot.

Information capacities C_4 = 2.36 b/p; C_{max} = 3.75 b/p.

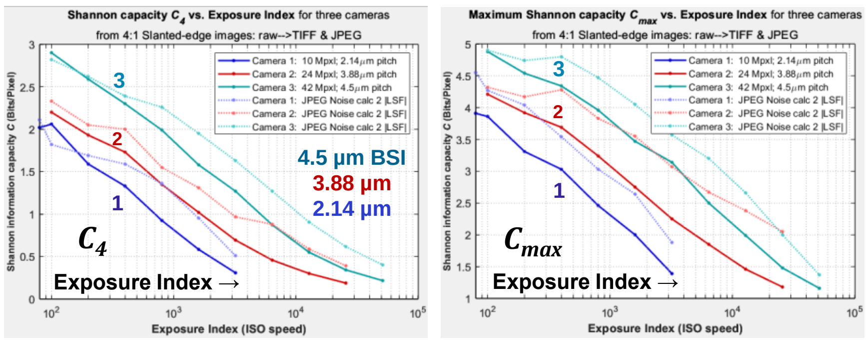


C_4 and C_{max} results for three cameras

Sensors: 4.5 µm BSI, 3.88 µm, 2.14 µm

C_4 and C_{max} decrease with Exposure Index (EI, also called ISO speed), which

- is proportional to analog gain,
- Is inversely proportional to total exposure (or illumination), and
- increases with pixel size.

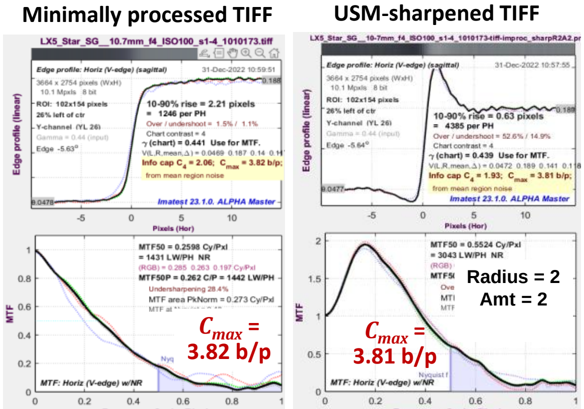


C_{max} is larger than C_4 by roughly 2 bits/pixel.

Sharpening and information capacity

Uniform Sharpening has little effect on C because it boosts the high frequency signal and noise by the same amount.

Minimally processed TIFF **USM-sharpened TIFF**



More generally,

C is unaffected by linear, reversable image processing.

For this reason, it is not useful for finding optimum image processing.

The image information metrics, to be described in the following slides (*SNRi* and *Edge location σ*)

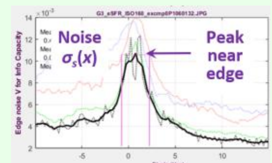
- **measure how well objects and edges are detected, and**
- **are sensitive to image processing,**

The noise image method:
calculated for uniformly processed images

The calculation of C so far, which is based on the spatially dependent noise power, $N(x) = \sigma_s^2(x)$, is called the *Edge Variance method*.

$C_{EdgeVar}$ is approximate because it omits the Noise Power Spectrum, $NPS(f)$.

$NPS(f)$ cannot be measured accurately for bilateral-filtered images, because they are *nonuniformly* processed, i.e., *lowpass-filtered* to reduce noise in much of the ROI, but sharpened near edges where MTF is calculated.



The *Noise Image method*, which is only valid for minimally or uniformly processed images, results in a more accurate value of C, and enables the image information metrics, NEQ, $SNRi$, *Edge Location* σ, and more.

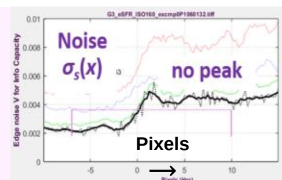
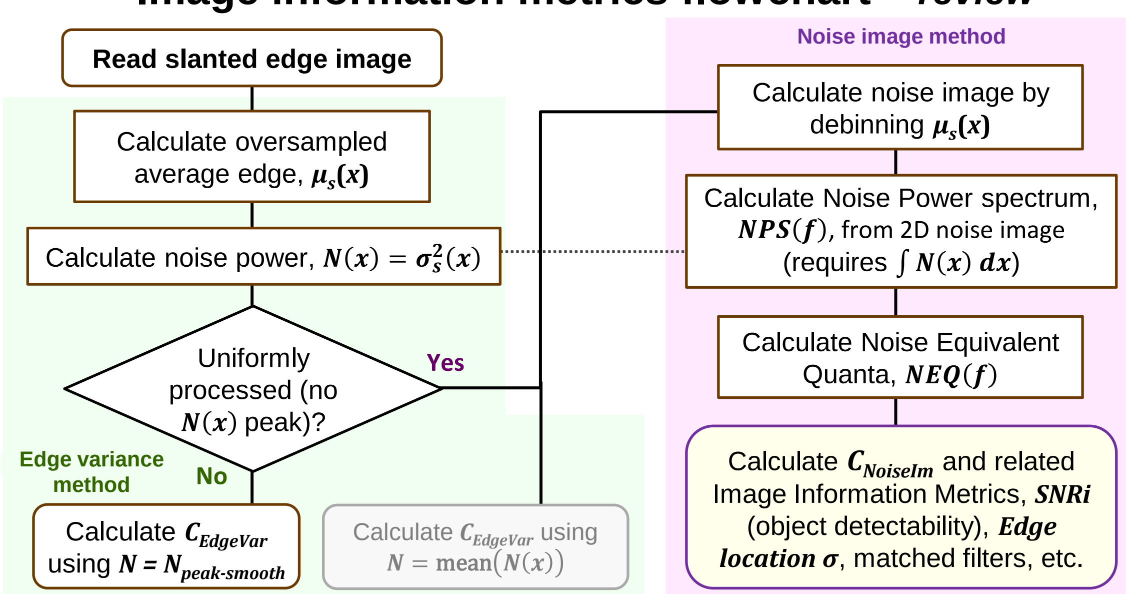


Image information metrics flowchart – *review*



The noise image enables the calculation of the Noise Power spectrum, $NPS(f)$, and the Image information metrics

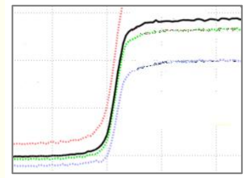
To obtain the noise image

Note that the averaged oversampled image consists of four interleaves from the original bins of the ISO 12233 calculation.

De-bin the image by moving the low-noise contents of each interleave back to its original locations.

The de-binned image (2) has much lower noise than the original (1).

Noise image (3) = original image (1) – de-binned image (2).



Micro 4/3 camera @ ISO 12800

(1) Original | **(2) De-binned** | **(3) Noise image = original – de-binned**

The noise image is shown lightened.

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Noise Power (Wiener) Spectrum $NPS(f)$

The initial calculation of information capacity, $C_{EdgeVar}$, is based on the assumption that noise power, N, is white, i.e., it has no frequency dependence.

C can be calculated with greater accuracy from the noise image, which enables the noise power spectrum, $NPS(f)$, to be calculated for the integral form of the Shannon-Hartley equation.

$$C_{NoiseIm} = \int_0^W \log_2\left(1 + \frac{S(f)}{NPS(f)}\right) df$$

***W* is bandwidth ≡ 0.5 C/P (f_{Nyq}), *S* is mean signal power.**

To calculate $NPS(f)$, start by calculating the magnitude of the 2-dimensional (2D) Fourier transform (FFT) for each channel of the noise image, then transform the 2D spectrum into 1D for use in the Shannon-Hartley equation

[Full details in the Appendix, in the **"green for geeks (best read offline)"** area.

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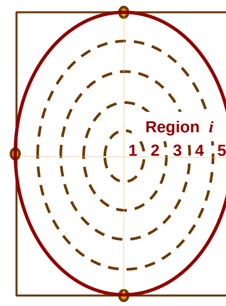
1D Noise Power spectrum *NPS*(*f*)

- The 2D FFT is divided into n_{rad} regions with $f_i = 0$ shifted to the center.
- For region i, the initial (unnormalized) $NPS_{i\_mean}(f_i)$, is the mean noise power of the n_i points.

$$NPS_{i\_mean}(f_i) = \left[\sum_{k=1}^{n_i} DN^2\right]/n_i \quad \text{where } f_i = 0.5(i-0.5)/n_{rads}$$



- Because this procedure does not maintain the invariance in energy between the spatial and frequency domains implied by Parseval's theorem, ***NPS*(*f*) must be normalized so that**

$$\int NPS(f)\,df = \int N(x)\,dx\,; \qquad NPS(f) = \frac{NPS_{i\_mean}(f)\ \int N(x)\,dx}{\int NPS_{i\_mean}(f)\,df}$$

Normalizing the noise power *NPS*(*f*) to the mean edge variance *N*(*x*) or N_{NI} removes the effect of the *M* scan lines, i.e.,

Image information metrics are not affected by ROI size *(as long as it's not too small)*.

1D Noise Power (Wiener) Spectrum *NPS*(*f*)

NPS*(*f*)** is calculated in one dimension to have the same scaling (normalization) as the signal ***S. [Recall, signal and noise were measured at the same location.]

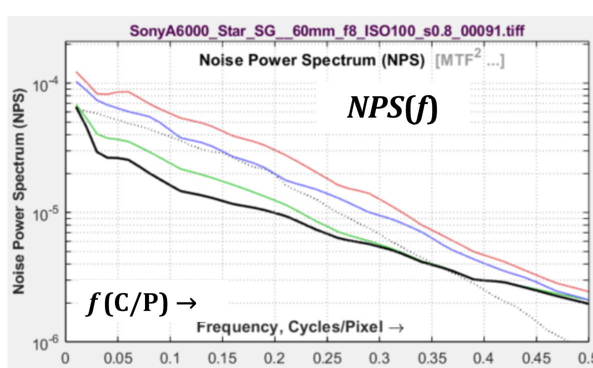
The noise amplitude (voltage) spectrum is $N_V(f) = \sqrt{NPS(f)}$

$NPS(f)$ is a part of the kernel (the defining factor) of the image information metrics to be introduced,

$$K(f) = MTF^2(f)/NPS(f)$$

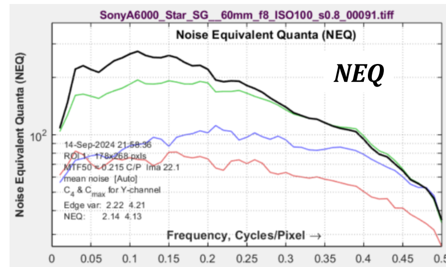
***K*(*f*)** is proportional to ***NEQ*(*f*)** (next slide)

The noise power for the Y channel is lower that for the uncorrelated R, G, B channels because is a derived channel: Y ≅ 0.21*R + 0.72*G + 0.07*B



Noise Equivalent Quanta $NEQ(f)$

$NEQ(f)$ is a frequency-dependent Signal-to-Noise (power) Ratio, equivalent to the number of quanta that would generate the measured SNR when photon shot noise is dominant. Used in medical imaging.



$$NEQ(f) = \frac{V_{mean}^2 \, MTF^2(f)}{NPS(f)} = V_{mean}^2 \, K(f)$$

$K(f) = MTF^2(f)/NPS(f)$ **is the *kernel* (the defining factor) of the image information metrics to be introduced.**

$NEQ(f)$ and $K(f)$ are not affected by uniform, linear, reversible filtering, such as most sharpening and lowpass filtering, because they affect $MTF^2(f)$ and $NPS(f)$ identically.

Calculations related to $NEQ(f)$

Information capacity can be calculated from $NEQ(f)$ by substituting $V_{P-P}^2/12$ (for a uniform distribution) for V_{mean}^2. This is the accurate ***noise image calculation***.

$$C_{NoiseIm} = \int_0^{f_{Nyq}} log_2\left(1 + \frac{V_{P-P}^2 \, MTF^2(f)}{12 \, NPS(f)}\right) df$$

$C_{NoiseIm}$ can be thought of as a summary metric for $NEQ(f)$.

Results are close to $C_{EdgeVar}$, but more accurate because $C_{NoiseIm}$ includes the noise spectrum.

Channel		R	G	B	Y
Info capacity C_{Max}(EdgeVar)	=	3.52	4.1	3.75	4.21
Info capacity C_4(EdgeVar)	=	1.61	2.12	1.71	2.22
Info capacity C_{Max}(NEQ)	=	3.45	4.04	3.7	4.13
Info capacity C_4(NEQ)	=	1.54	2.06	1.66	2.14

(for the 24MP Micro Four-Thirds camera).

Detective Quantum Efficiency, $DQE(f)$, is the ratio of $NEQ(f)$ (the number of quanta equivalent to the measured SNR) to the mean number of incident quanta. It has maximum value of 1.

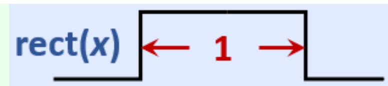
$$DQE(f) = \frac{NEQ(f)}{\bar{q}}$$

Under development.

Ideal Observer Signal-to-Noise Ratio *SNRi* (1)

SNRi* is metric for the detectability of *objects, calculated for $w \times kw$ rectangles.

For $g(x, y) = V_{P-P} \cdot \text{rect}(x/w) \cdot \text{rect}(y/kw)$,



The Fourier transform of $g(x, y)$ is

$$FFT\big(g(x,y)\big) = G\big(f_x, f_y\big) = kw^2 V_{P-P} \frac{\sin(\pi w f_x)}{\pi w f_x} \frac{\sin\big(\pi k w f_y\big)}{\pi k w f_y}$$

$$SNRi^2 = \int_0^{f_{yNyq}} \int_0^{f_{xNyq}} |G\big(f_x, f_y\big)|^2 \, K(f) \; df_x \, df_y \quad \text{where } f = \sqrt{f_x^2 + f_y^2}$$

The numerical calculation (for reference) is $SNRi^2 = \Delta f_x \, \Delta f_y \, \sum_{i=1}^{N_x} \sum_{j=1}^{N_y} \frac{SFR^2(i,j)\, G^2(i,j)}{NPS(i,j)}$

Since Parseval's theorem states that the integrals of a Fourier Transform pair must be equal,

$$\int_{-\infty}^{\infty} |r(x)|^2 dx = \int_{-\infty}^{\infty} |R(\omega)|^2 d\omega = \int_{-\infty}^{\infty} |R(2\pi f)|^2 df,$$

***SNRI*^{2}** is the total noise-whitened (S/N) energy of the object in the spatial domain.

Ideal Observer Signal-to-Noise Ratio *SNRi* (2)

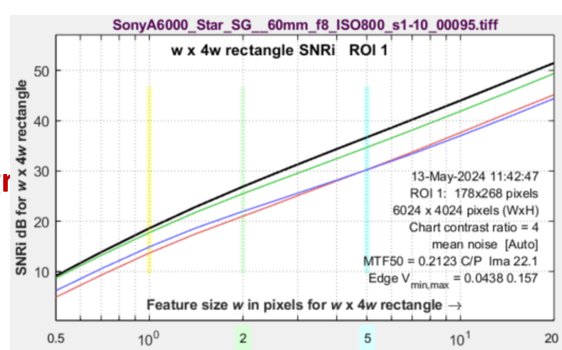
SNRi was retrieved by Paul Kane from ICRU Report 54 (an obscure medical imaging document that correlates *SNRi* with Bayesian detection statistics).

In spatial domain, *SNRi*^{2} is the total energy of the noise-whitened object *S/N*: related to *object visibility*.

***SNRi* is proportional to the Michelson contrast of the chart, $((lt\text{–}dk)/(lt\text{+}dk))$** (0.6 for 4:1 contrast ratio).

It is affected by filtering (Image Signal processing).

***SNRi* plots can be difficult to interpret because they strongly increase with *w*.**



***Feature size w* in pixels →**

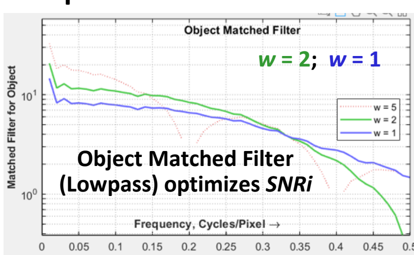
Optimum equalization: the matched filter

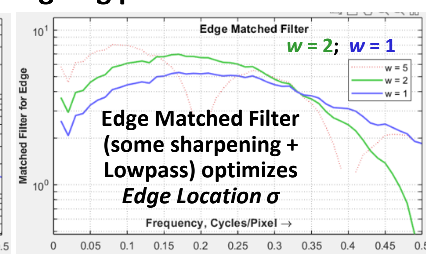
A *matched filter* optimizes object or edge detection performance for a specific system. Originally developed for radar. Filter rolloff is based on the spectrum of the object (measured in the system). Described in ICRU Report 54.

Matched filters optimize a single metric: *SNRi* or ***Location σ*** for a specific object width ***w***.

If the matched filter transfer function (below) is known, it can be approximated by a standard lowpass filter (Bessel, Butterworth, etc.), and, if needed, sharpening filter. The filter must perform well for a variety of conditions, including interference from neighboring objects. This requires a tradeoff (not severe).

Best practices are needed for designing practical matched filters.



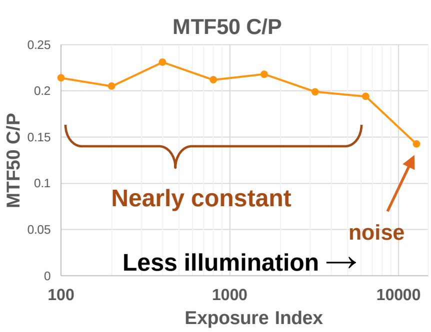


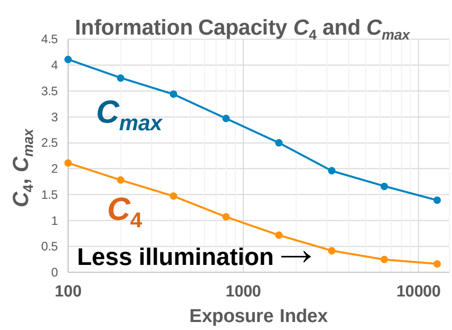
Example 1a: Exposure Index

24 MP Micro Four-Thirds mirrorless camera

Vary Exposure Index (EI; proportional to analog gain) from 100 to 12800.

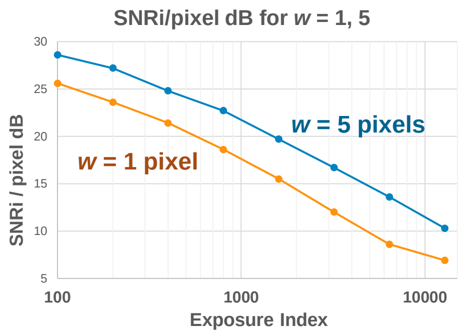
With auto-exposure, increasing EI reduces the light reaching the sensor, but keeps the image Digital Numbers (DNs) relatively constant.

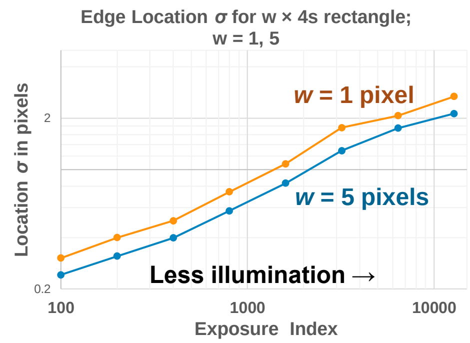




Example 1b: Exposure Index

24 MP Micro Four-Thirds mirrorless camera, EI 100-12800



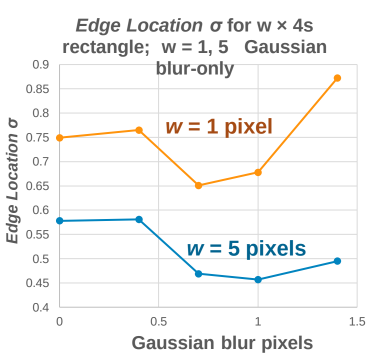


As expected, performance improves with more illumination (lower EI).

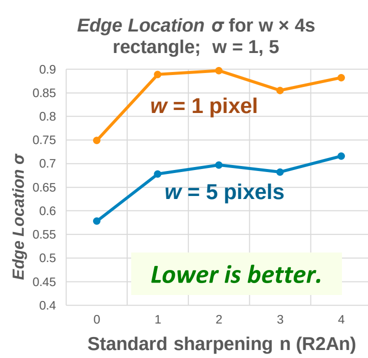
Example 2: Image processing

24 MP Micro Four-Thirds mirrorless camera, EI 800

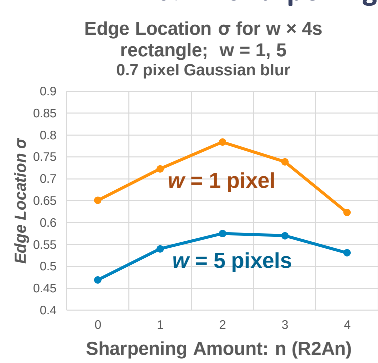
Gaussian blur (LPF)



Sharpening-only



LPF 0.7 + Sharpening



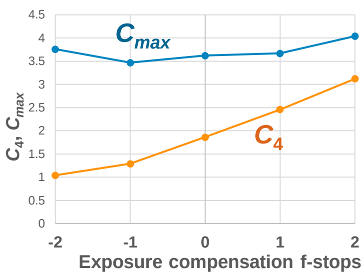
Lowpass filtering (Gaussian blur = 0.7 & 1) makes some improvement. Sharpening-only causes some degradation. LPF + Sharpening shows no clear trend.

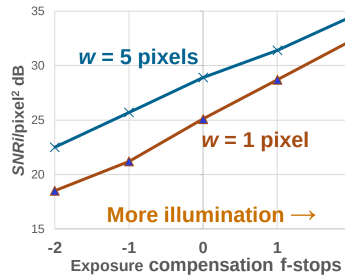
The effects of image processing are not dramatic, perhaps because the original edge was very high quality.

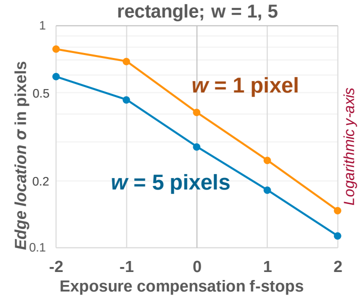
Example 3: Exposure compensation

16MP Micro Four-Thirds mirrorless camera. EI 160, f/5.6

Exposure compensation from -2 to 2 f-stops (dark to light).
Each step of 1 f-stop doubles the illumination, improving the performance.







Exposure compensation
from -2 to 2 f-stops
(dark to light)

-2 

G3_eSFR_ISO160_excmp-2P1060134.tiff

0 

G3_eSFR_ISO160_excmp0P1060137.tiff

+2 

G3_eSFR_ISO160_excmp2P1060139.tiff

Information metrics summary 1

Information capacity C_4

- can be conveniently calculated using tricks for measuring signal power ***S(f)*** and noise power spectral density (***NPS(f)***) at the same location in 4:1 contrast slanted edges.
- is not affected by reversable linear image processing (with no nulls at $f < f_{Nyquist}$). In particular, it is not improved by sharpening.

Signal averaging — N identical images can be averaged to improve the consistency (Signal-to-Noise Ratio) of the results, which is improved by $\sqrt{N}$ (3 dB for every doubling of N).

ISO 23654 standard — We are working on incorporating the new metrics into **ISO 23654, Photography — Digital cameras — Image Information Metrics**. We encourage participation; there is a lot of work ahead. The equations and algorithms are public and not proprietary. ETA November 2028

Information metrics summary 2

Image information capacity, C, quantifies the *potential* performance of a camera, and is not affected by reversable image processing.

Object and edge detection metrics, $SNRi$ and $Edge\ location\ \sigma$ (which has some unresolved scaling issues) are affected by image processing. We have shown how to design matched filters to optimize these parameters (which requires a tradeoff).

Once the required value of C has been determined, a camera can be selected with the *minimum* number of pixels to accomplish the task, and then image processing (filtering) can be designed. *With experience*, this should

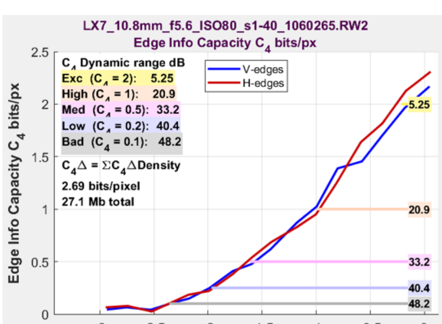
- **Minimize power consumption, and**
- **Minimize cost**
- **Maximize speed**

In addition to the slanted-edge, C can also be calculated from Siemens star and Dead Leaves (Spilled Coins) test charts.

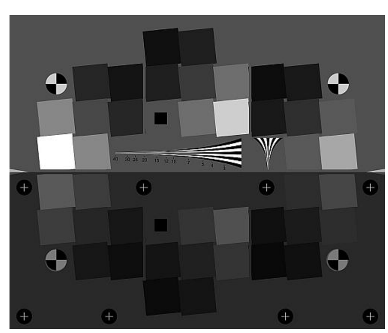
Information-based Dynamic Range

Measuring camera performance over a wide range of illumination from a single image

We present the new InfoDR chart that can measure C_4 — the information capacity in a 4:1 object measured from a 4:1 slanted edge — over a wide range of exposure from a single image. *This cannot be done with current test charts.*



C_4 as a function of exposure

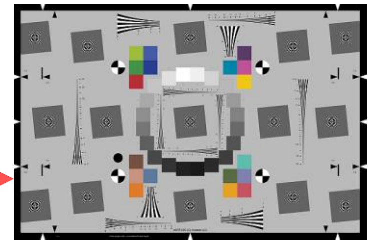


the new InfoDR chart

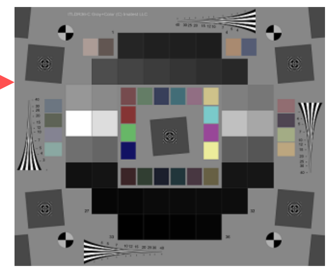
Spatial vs. tonal detail

Two types of chart are currently in widespread use.

<u>Charts with high spatial detail</u> Sharpness and C_4 — the information capacity of 4:1 contrast objects measured from widely-used 4:1 edges — can be measured at only one illumination level.



<u>Charts with high tonal detail</u> Traditional Dynamic Range based on Signal-to-Noise Ratio (SNR), but not C_4, can be measured from flat patches on High Dynamic Range (HDR) test charts, usually near the center of the image.



The InfoDR chart can be used to measure C_4 over a wide exposure range from a single image.

The Information-based Dynamic Range (InfoDR) test chart: building blocks

<u>The InfoDR chart contains</u>

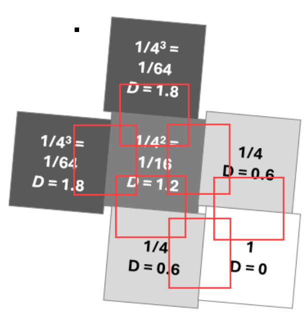
a large number near-vertical and near-horizontal 4:1 contrast (ΔDensity = ΔD = 0.6) slanted edges in a compact arrangement so SFR doesn't vary by much in the active area.

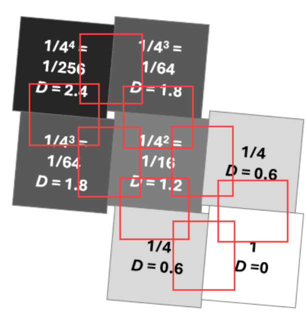
smaller density steps than 0.6 (ΔD = 0.15, 0.2, or 0.3) in the final chart, where neighboring groups of patches are offset.

<u>Basic building blocks (patch groups)</u>

Each square differs from its neighbors by ΔD = 0.6 (4:1 contrast). Groups of {1,2,1,2} patches of the same Density.

.

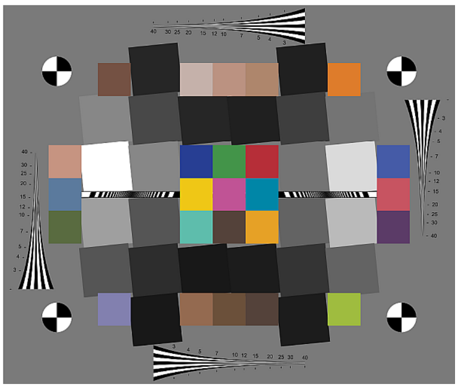




Constructing the InfoDR test chart

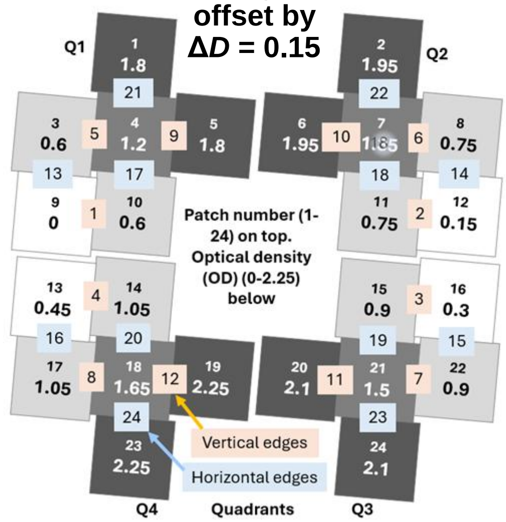
Four groups of squares are combined for the final (reflective) chart design.

Each group is offset from its neighbors by Δ*D* = 0.15.



Final design

Schematic: 4 groups, each offset by Δ*D* = 0.15



Two-layer film InfoDR test chart

for Dynamic Range measurements

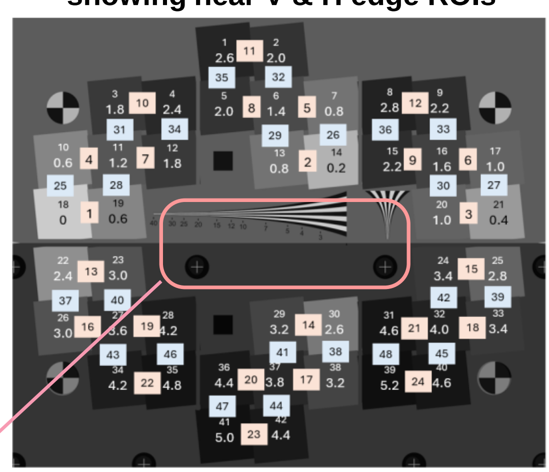
Six groups of squares; each offset from its neighbors by Δ*D* = 0.20. 2nd layer with D = 2.4 on bottom.

42 patches; D_{max} = 5.2 (104 dB);

48 (V & H) edges; Edge *D*-range = 4.6 (92 dB).

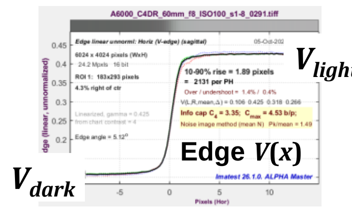
Patches analyzed sequentially from light to dark: last good MTF is kept when SNR becomes too low to measure MTF.

Schematic: 6 groups offset by ΔD = 0.20, showing near V & H edge ROIs



V2 (modified) design leaves open space near the chart center where reflections are worst.

Edge contrast adjustment for calculating C_4



4:1 contrast is the nominal value for calculating C_4.

But transmissive film charts can vary enough so that individually-measured reference files are supplied with each chart. Contrast can differ from 4:1.

The edge density increment is $\Delta D_i = D_j - D_k$ for adjacent patches j and k. Contrast ratio is $10^{\Delta D_i}$.

To correctly calculate C_4 for each edge i, replace $\Delta V_i = (V_{light} - V_{dark})$ with

$$\Delta V_{i-corrected} = \Delta V_i \; 10^{(\text{mean}(\Delta D) - \Delta D_i)}$$

Where mean(ΔD) ≅ 0.6 .

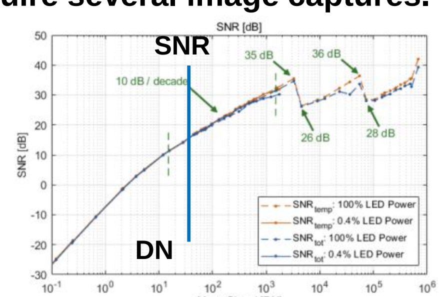
Alternative InfoDR (C_2) test chart

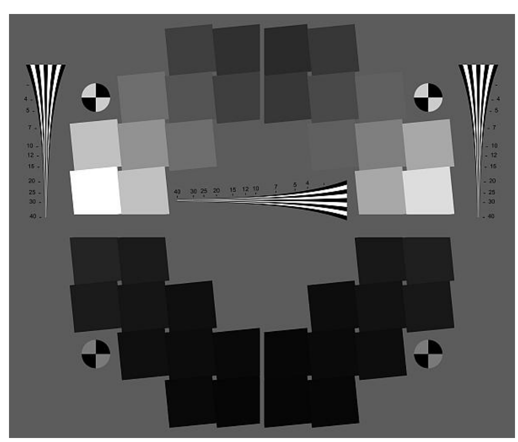
(*design – not yet built*)

For examining anomalies near steps in HDR sensor behavior

Measures C_2 over a wide tonal range: 75 dB in steps of 3 dB (0.15 OD) (not quite HDR).

Same analysis as C_4 charts, but may require several image captures.

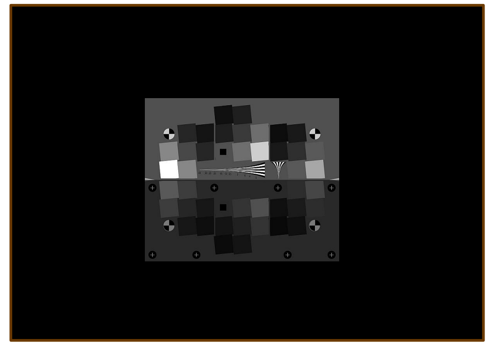




Suggested by Uwe Artmann

Using the InfoDR test chart

The active area of the chart are should ***NOT*** fill the frame — it should be near the center, where SFR is relatively consistent. 600 vertical pixels are sufficient.



The chart *must* be in good focus (unlike traditional SNR-based DR measurements).

Measure and enter the lightbox luminance in candelas/meter^2 , lens aperture A (f-number) and shutter speed t (seconds) to get absolute light level readings.

Photograph the chart in a dark environment.

Save raw files (if possible) and convert to RGB with minimal processing.

Enter the (individually-measured) density reference file into the program.

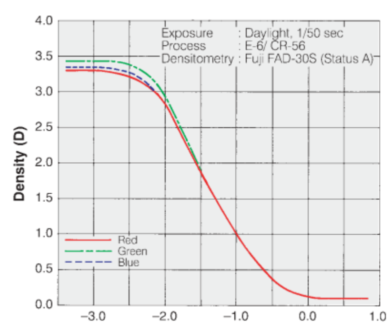
Light measurement

Use a luminance meter pointed at the lightbox to measure lightbox luminance, L_{source}, in cd/m^2.

Patch luminance is $L_{patch} = L_{source}\ 10^{-Dpatch}$, where D_{patch} is the patch density from the density reference file.

The x-axis selections for the C_4 plot:

- **three *relative* measurements: Log$_{10}$ exposure (-Density), Exposure dB, and F-stops (EV) and**
- **three *absolute* measurements: Luminance cd/m^2 @ patch (L_{patch}), *H* = Exposure in Lux-sec @ sensor, and Log$_{10}$(*H*), where $H \cong 0.65\ L\ t/A^2$ from ISO 12232:2019, Annex B.**



Film characteristic curve with x-axis, Exposure [log$_{10}$*H* (lux-seconds)]

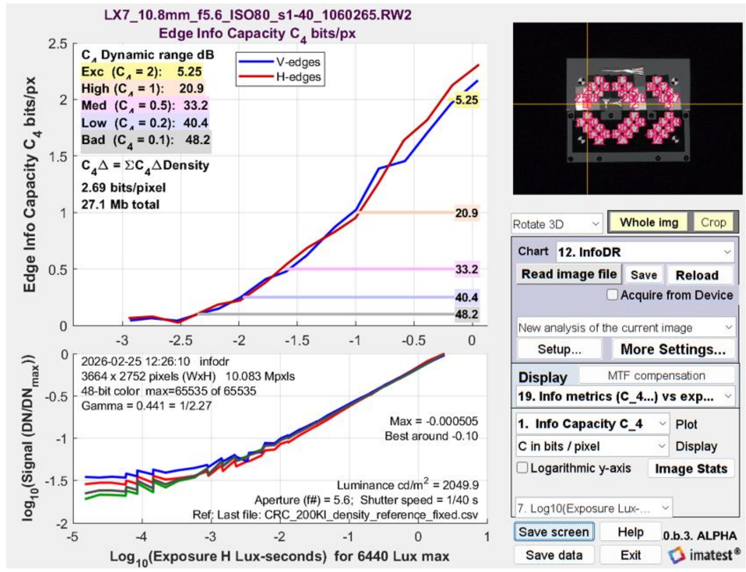
C_4 vs. Exposure ($\log_{10}(H)$): the key InfoDR result

Upper

C_4 plot, showing Dynamic Range and a new heuristic figure of merit, $C_4\Delta$

Lower

OECF (tonal response): Log(DN) vs. exposure

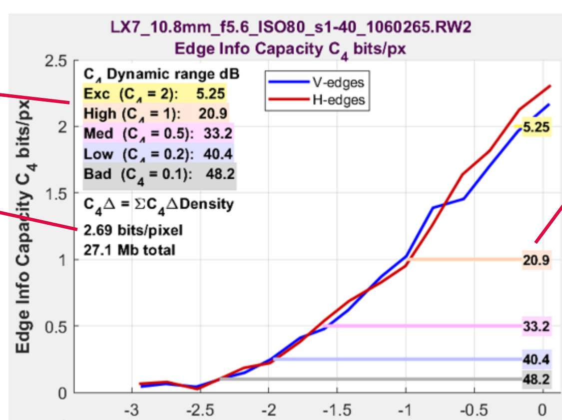


C_4 vs. Exposure ($\log_{10}(H)$) : the key InfoDR result

The C_4 curve (similar for Vertical and Horizontal edges) is the best metric of pixel-level performance, especially at low light levels.

Dynamic Range values

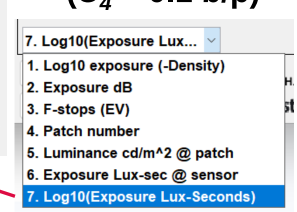
Preliminary heuristic Figure of Merit: $C_4\Delta$ is the area under the C_4 curve, where the x-axis has $\log_{10}$ units (same as Optical Density)



Log10(Exposure H Lux-seconds)

Dynamic Range bars and values:

Excellent (C_4 = 2 b/p) through Bad (C_4 = 0.1 b/p)



Tonal response ($\log_{10}(DN/DN_{max})$ vs. Exposure)

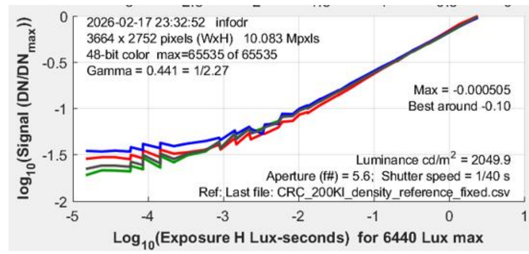
Tonal response is calculated from patches. Also available with traditional Dynamic Range measurements.

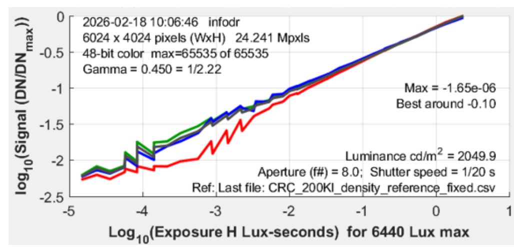
Bumps from stray light (?)

For raw-converted files with a straight gamma curve (Adobe RGB, *not* sRGB, which has a linear section),

$$D_{min} = \min(\log_{10}(DN/DN_{max}))$$

is a meaningful metric for veiling glare from stray light.





Upper: compact camera with 3:1 zoom lens. $D_{min} \cong 1.6$

Lower: APS-C camera with prime macro lens. D_{min} = 2.2

$\log_{10}$(Exposure *H* Lux-seconds)

Results: Compact 3:1 zoom camera

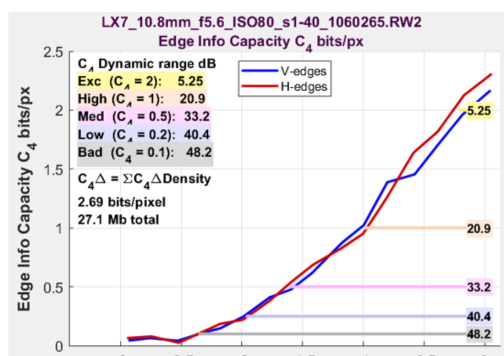
Compact camera with Leica-branded 3:1 zoom, f/5.6, 2.14 µm pixels, 10 Mp

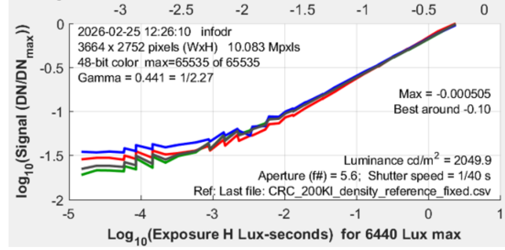
$C_4\Delta$ = 2.74 bits/px = 27.6 Mb total

High, Low *DR* (dB) = 21.3, 39.7 dB

D_{min} = -1.6 average

Note that although the plot has the same shape as the previous camera, the x and y-axis scales are different.





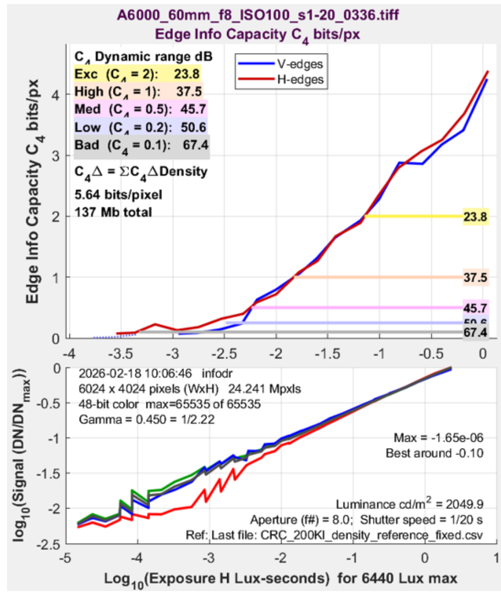
Results: APS-C camera with prime macro lens

APS-C camera with Canon 60mm f/2.8 prime macro, f/8, 3.88 µm pixels, 24 Mp

$C_4\Delta$ = 5.64 bits/px = 137 Mb total

High, Low *DR* (dB) = 23.8, 45.7 dB

D_{min} = -2.2 (excellent)



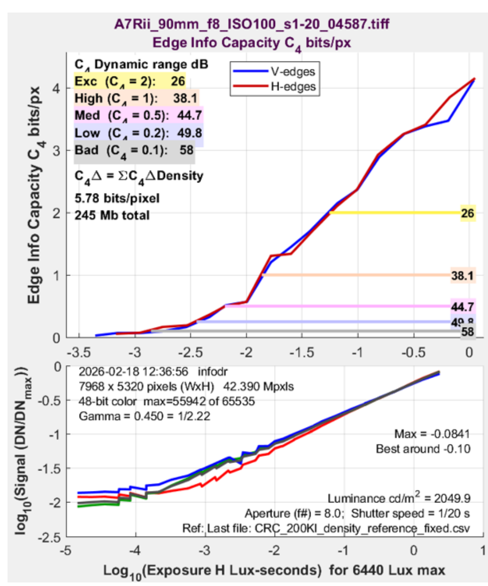
Results: Full-frame camera with prime macro lens

Premium full-frame camera with Sony 90mm f/2.8 prime macro, f/8, 3.88 µm pixels, 42.4 Mp

$C_4\Delta$ = 5.78 bits/px = 245 Mb total

High, Low *DR* (dB) = 26, 49.8 dB

D_{min} = -2 (very good)



Results: Pixel 8 Pro camera phone

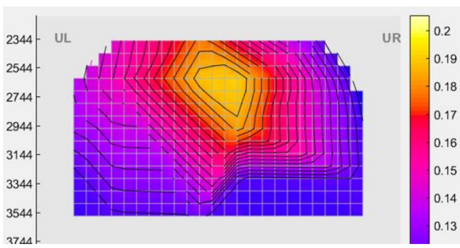
Pixel 8 Pro camera, 1.2 µm pixels, 50 Mp

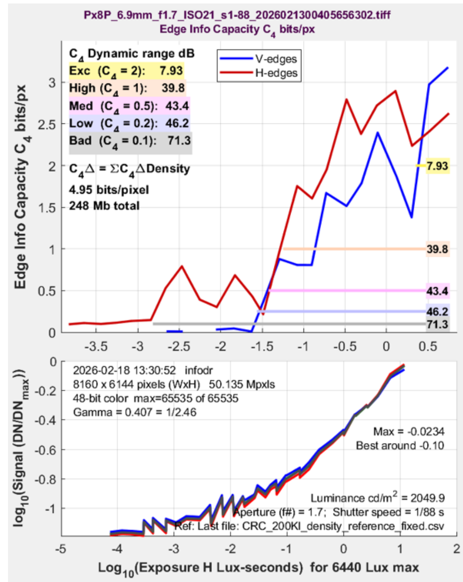
$C_4\Delta$ = 4.95 bits/px = 248 Mb total

High, Low *DR* (dB) = 39.8, 46.2 dB

D_{min} = -1.2 (issues with stray light)

The rough C_4 response was caused by SFR falloff from the image center.





Results: iPhone 15

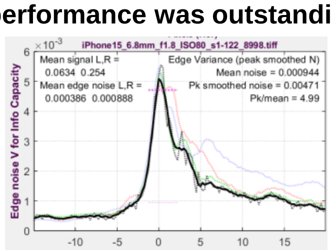
Camera phone, f/1.8 1.22 µm pixels, 48.8 Mp

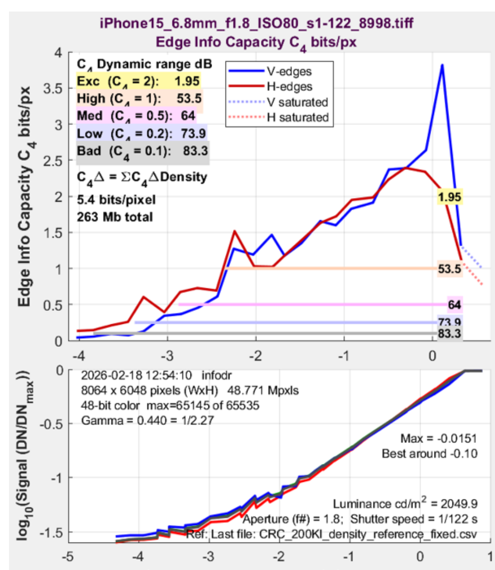
$C_4\Delta$ = 5. 4 bits/px = 263 Mb total

High, Low *DR* (dB) = 53.6, 73.9 dB

D_{min} = -1.6

There appeared to be noise reduction in the raw images, evidenced by the peak in the spatial noise — not seen in other raw images. Even with noise derived from peak, performance was outstanding.



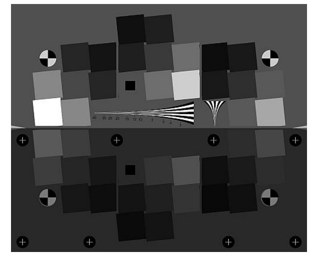


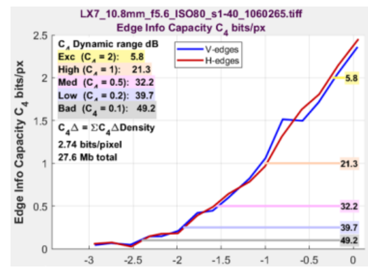
InfoDR Summary

We have developed the new InfoDR test chart with a compact design that measures C_4 information capacity (for 4:1 contrast objects) over a wide range of exposures.

- **valuable for measuring low light performance**
- **more meaningful results than standard Dynamic Range measurements.**

Although It has excellent *tonal* detail (ΔDensity = 0.2 = 4 dB over a 92 dB range), a chart with more *spatial* detail, such as Checkerboard, eSFR, or SFRplus, should be also be measured for a more complete camera characterization.





Key result: C_4 vs. Exposure H

Image Sensor Noise model and Simatest Image System Simulator

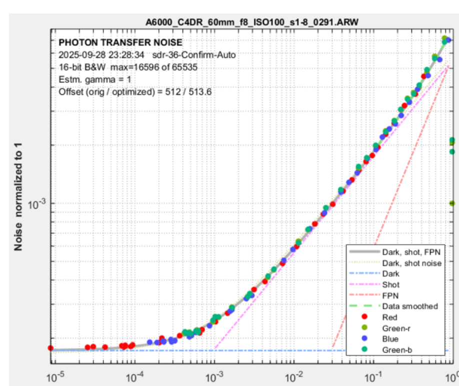
Introduction to Simatest camera simulator

Finding the Image sensor noise model from

- **A. Photon Transfer Curve (PTC), measured from a raw (undemosaiced) image of an InfoDR or 36-patch HDR test chart**
- **B. EMVA 1288 results**

Running Simatest

Simatest results



Photon transfer curve (PTC)

Simatest Camera performance simulator

Generate Input image (test chart): same resolution as image sensor

Lens effects: from lens design program or measurement

Simatest

Image sensor noise model: from Photon Transfer Curve or EMVA 1288

ISP: Image Signal Processing: sharpening, bilateral filtering, color correction, *much* more…

Display results: standard and information-based metrics

The effects of illumination level, lens, sensor, and ISP on results, including information metrics, can be predicted and displayed.

Simatest — Camera/Image Signal Processing (ISP) simulator

Calculate image sensor noise model and relative RGB sensitivity from raw grayscale image or EMVA 1288 parameters

Input images

- Raw or minimally-processed camera image
- Simulated image
- Simulated image run through lens design program (degraded sharpness, etc.)

Physical properties

Simulated blur (MTF)

Simulated image sensor noise model

Simatest

Simulated Image Signal Processing (ISP)

Adjustments
Mosaic/Demosaic
Exposure/gain
Gamma
RGB balance, AWB
Monochrome
Invert
Cos^4 lens shading
Fog

Degradations
Noise
Filter (LPF)

Enhancements
CCM (color matrix)
Tone mapping
Sharpening
Bilateral filter

Visual assessment | Color/Tone PTC, SNR, … | Rescharts (MTF (SFR), Image Information metrics…) | Misc. analysis

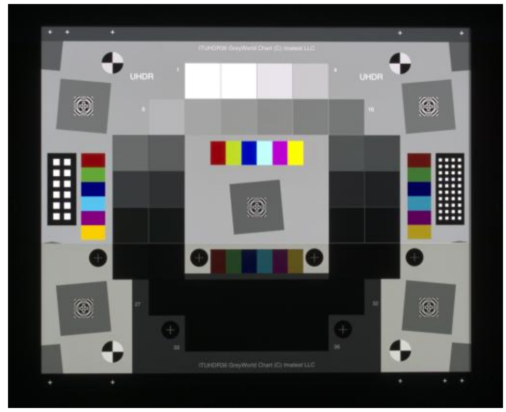
Note: Simulated or acquired Test Chart images are especially valuable, but any image can be used.

Obtaining the Photon Transfer Curve (PTC)

Raw (undemosaiced and unprocessed) images have a remarkable property.

The noise in each patch is a function of the mean digital number (DN), independent of color.

This allows the PTC — a plot of noise as a function of exposure (–chart density) to be measured from a raw image of a High Dynamic Range (HDR) test chart, such as the InfoDR chart or the 36-patch DR chart shown in RGB on the right.



HDR chart image (RGB)

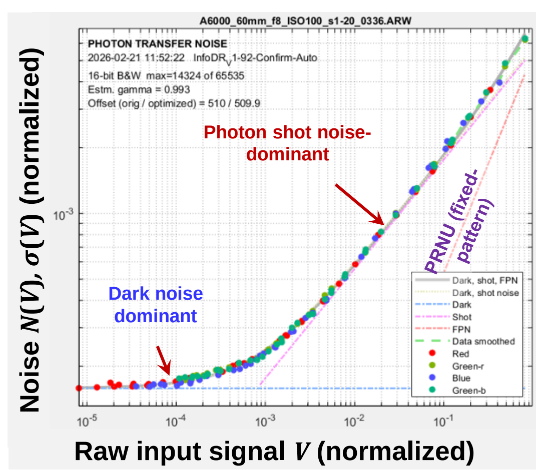
The PTC can be used to derive an *image sensor noise model* that can predict camera performance under a wide variety of conditions

Structure of the Photon Transfer Curve

The PTC — Plot of noise as a function of exposure V (–chart density) combines *three* noise sources.

- **Dark noise k_{Ndark} (fixed)**
- **Photon shot noise $k_{Nshot}\sqrt{V}$: increases with $\sqrt{V}$**
- **Photo Response NonUniformity $k_{PRNU}V$ increases with V.**

$$\sigma(V) = \sqrt{k_{Ndark}^2 + k_{Nshot}^2 V + k_{PRNU}^2 V^2}$$



The heart of the noise model is the three coefficients, k. But before we calculate them, we need to deal with the *signal offset*, DN_{off}, if present.

Photon Transfer Curve – Digital Number Offset

"Raw" images often contain an offset, DN_{off}, (frequently unknown) that must be removed to obtain a correct PTC.

For a chart where the mean (input) *DN* of each patch is V_{input},

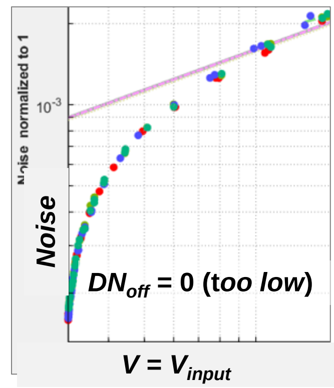
$V = V_{input} - DN_{off}$ should be used to calculate the PTC.

If DN_{off} is known, *use it!* But if DN_{off} is unknown. it can be estimated as DN_{offEst}.

If DN_{offEst} is too high, i.e., if $DN_{offEst} > V_{min}$, some values of $V < 0$, and data will be lost.

If DN_{offEst} is too low (right), the dark noise-dominant region (x-axis) is compressed, and dark noise cannot be obtained.

We have developed an algorithm for finding DN_{offEst} that works well for a wide range of linear cameras.



Estimating the Digital Number Offset, DN_{off}, for the PTC

Let D_{chart} be the set of measured patch densities for the test chart (supplied in a file for film or photomask dynamic range charts). The minimum and maximum values are D_{min} and D_{max}, and the range is $D_{range} = D_{max}\text{-}D_{min}$.

The Luminance ratio of the chart is $L_{ratio} = 10^{Drange} = 10^{Dmax}/10^{Dmin}$.

Let the mean input Digital Numbers for each patch be $DN = V_{input}$, with minimum and maximum values, V_{min} and V_{max}.

The signal V for calculating the PTC is $V = V_{input} - DN_{off}$.

The goal is to find the value of DN_{off} that makes the x-axis signal ratio identical to the luminance ratio.

$$(V_{max} - DN_{off})/(V_{min} - DN_{off}) = \min(L_{ratio}, 10^5) = L_{rTarget}$$

Solving, $$DN_{off} = (V_{max} - V_{min} L_{rTarget})/(1 - L_{rTarget})$$

This gives a reliable estimate of k_{Ndark}, k_{Nshot}, and k_{PRNU}, even though the x-axis (V) may be a little off in the dark (no signal) region.

Finding the PTC coefficients by optimization

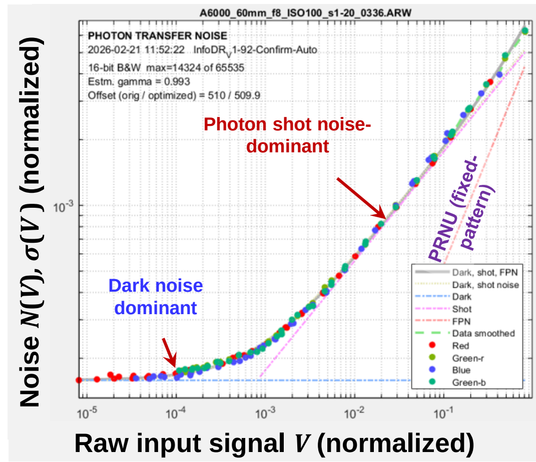
Input data for calculating the PTC consists of the measured patch noise for all channels, $N(V)$, as a function of the mean (corrected) Digital Number ($DN = V$), shown as colored dots, ● ● ● ●).

The Levenberg-Marquardt optimizer finds the values of k that minimizes

$$Error = (N^2(V) - \sigma^2(V))/N^2(V)$$

where

$$\sigma(V) = \sqrt{k^2_{Ndark} + k^2_{Nshot}V + k^2_{PRNU}V^2}$$



Division by $N^2(V)$ is critical to obtaining good results. Without it, large values of N have excessive weight, and k^2_{Ndark} cannot be accurately estimated.

PTC from the 36-patch Dynamic Range chart

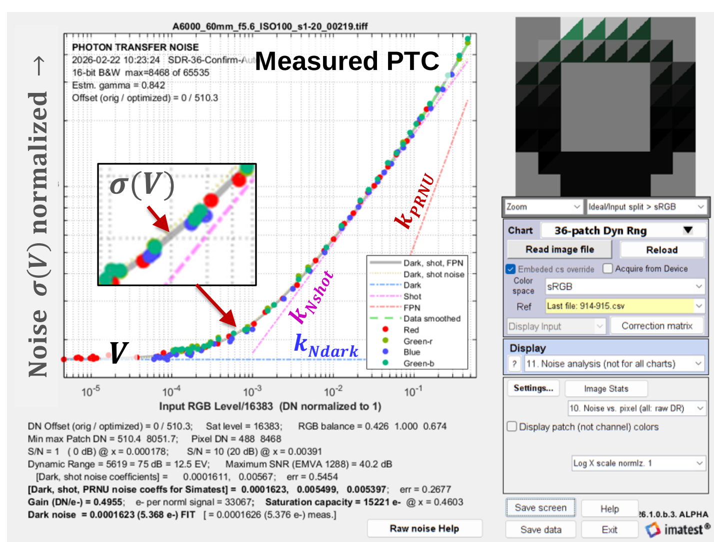
For the camera under test (24MP APS-C; pixel pitch = 3.9 μm)

k_{Ndark} = 0.0001623
Dark noise (total)

k_{Nshot} = 0.005499
Photon shot noise

k_{PRNU} = 0.005397
PRNU fixed-pattern noise

Gain (DN/e-) & RGB balance (0.426 1 0.674)also important



Photon Transfer Curve (PTC) & results

PTC from new InfoDR chart (for comparison)

Taken about three months after the DR36 image. Same camera.

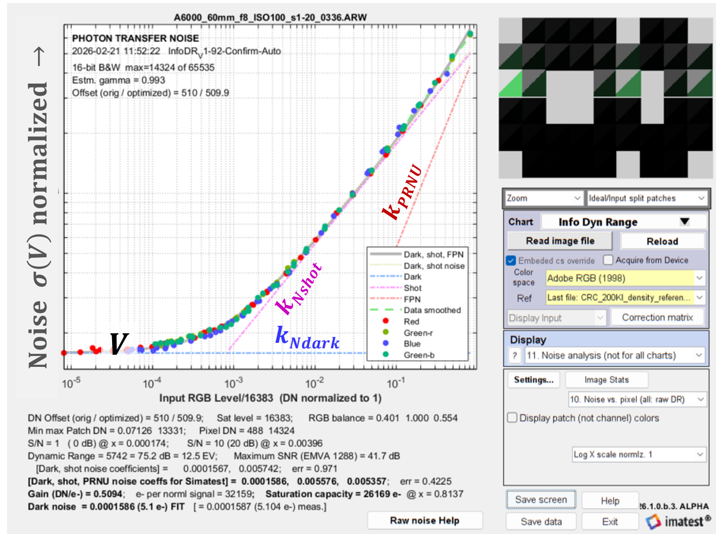
k_{Ndark} **= 0.0001568 Dark noise (total) — Slightly lower:** ***tempera-ture-sensitive*** (was 0.0001623)

k_{Nshot} **= 0.005576 Photon shot noise — Close** (was 0.005499)

k_{PRNU} **= 0.005367 PRNU fixed-pattern noise** (was 0.005397)

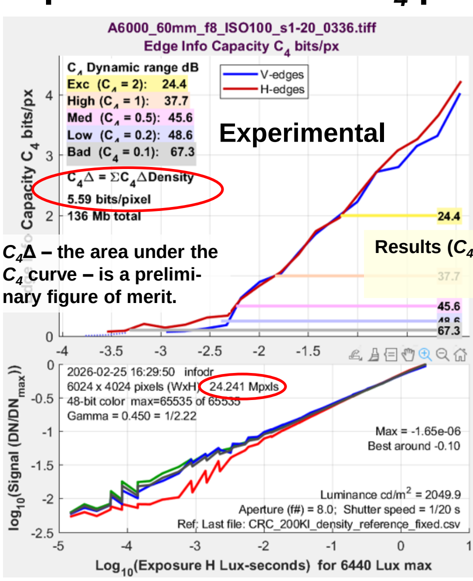
RGB **= (0.401 1 0.554)**

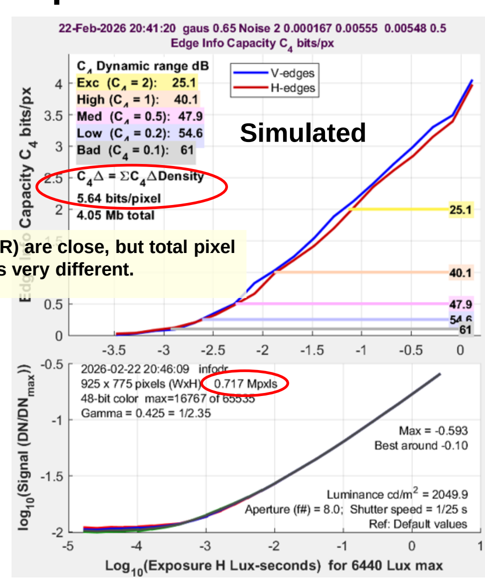
Results are virtually identical, even though the charts are different.



Photon Transfer Curve (PTC) & results

Comparison of InfoDR C_4 plots: Experimental and Simulated



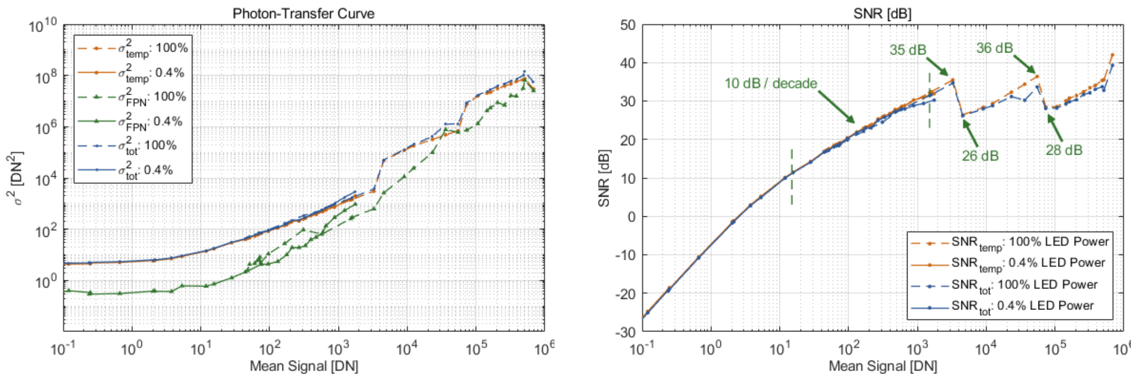


$C_4\Delta$ – the area under the C_4 curve – is a prelimi-nary figure of merit.

Results ($C_4\Delta$ & DR) are close, but total pixel size is very different.

Unfinished work: modeling High Dynamic Range (HDR) sensors

SNR Curves: PTC and SNR Curves



from IEEE P2020 Noise Metrics – A Review
Orit Skorka and Paul Romanczyk (2022)

HDR sensors have steps in noise and SNR.

Key EMVA 1288/ISO 24942 measurements

The key EMVA 1288 results needed to model noise are

Measurement	EMVA symbol	Units
Temporal dark noise	σ_d *or* σ_{Dark}	e-
Dark Signal Nonuniformity DSNU	$DSNU_{ISO}$	e-
Dark current (noise)	μ_C *or* i_{Dark}	e-/s
(Photon shot noise = $\sqrt{K/DN_{max}}$)		
Photo Response Nonuniformity PRNU	$PRNU_{ISO}$	%
Gain (DN/e-)	K	DN/e-
Saturation capacity	$\mu_{e.sat}$	e-
From ISO 24942, section 15.2 and Annex A or EMVA 12288 4.0, section G.		

DN = Digital Number; e- = electrons; s = exposure time (seconds)

EMVA 1288 measurements for the noise model

For DN = Digital Number and e- = electrons, and s = exposure time, where

V = normalized amplitude $= DN/DN_{max}$ where

DN_{max} is the maximum DN for the system, typically $2^{N\text{-}1}$ for bit depth = N,

The key EMVA 1288 measurements for Simatest input are

$$k_{NDark} = \text{total dark noise} = \sqrt{\sigma_d^2 + DSNU^2 + (i_{Dark}\, s)^2} \times \text{Gain}(V/e-)$$

$$k_{Nshot} = \text{photon shot noise} = \sqrt{\frac{\text{Gain}(DN/e-)}{DN_{max}}} = \sqrt{\frac{K}{DN_{max}}}$$

$$k_{PRNU} = \text{PRNU Fixed Pattern noise} = PRNU(\%)/100$$

www.imatest.com/imaging/image-sensor-noise/#emva

EMVA 1288 vs. Imatest PTC measurements — summary

EMVA 1288 measurements are

- well-established and documented: ISO 24942 standard.
- highly accurate and detailed: temporal noise and fixed pattern noise (DSNU, PRNU) sources are kept separate. Valuable for image sensor designers.
- time-consuming to acquire. 30+ images of a dark field and a flat field (around ½ saturation) are required.

The Imatest Photon Transfer Curve (PTC) method is

- new and somewhat unfamiliar (though the PTC has been around for a while).
- a subset of EMVA 1288 with less detail. Fixed pattern and temporal dark noise are combined, BUT it is sufficient for modeling camera performance.
- fast and convenient. One or at most two images are required.

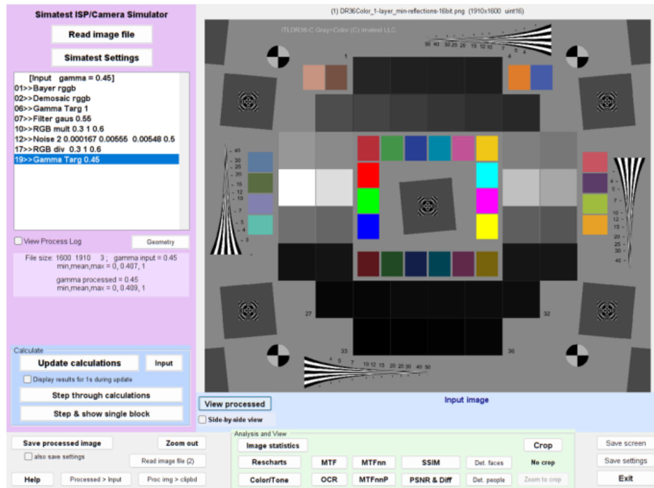
EITHER measurement provides input for Simatest simulations.

Running Simatest - preparation

Characterize the image sensor noise (obtain the key parameters, k_{Ndark}, k_{Nshot}, k_{DSNU}, etc.) with a Photon Transfer Curve or from EMVA 1288 results .

Ideal test chart images can be created with Imatest's Test Charts module. Blur can be simulated

- **with a Simatest gaussian filter to duplicate measured MTF50 or**
- **by running the image through a lens design utility such as Keysight's CODE V 2D Image Simulation (IMS) or Zemax OpticStudio.**



New DR test chart designed to minimize ghost images

Running Simatest

Open Simatest.

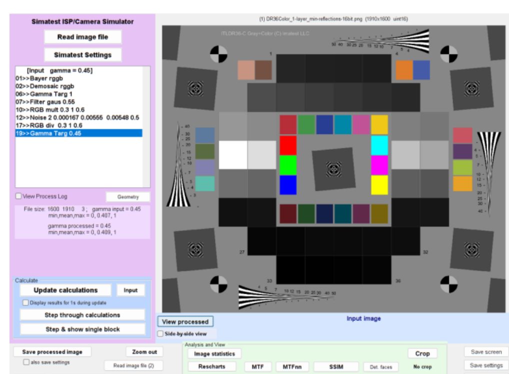
Open the test chart image: ideal or degraded (previous slide). An HDR chart witha grayscale at least one slanted edge recommended.

Enter the key parameters in the settings window (next slide), then update the calcu-lation.

You can use a variety of settings to

- **Simulate the PTC by converting the image into pseudo-raw, or**
- **Simulate the camera for normal operation, including low light.**

Open the simulated image in an Imatest analysis module (Color/Tone or Rescharts) to measure performance.



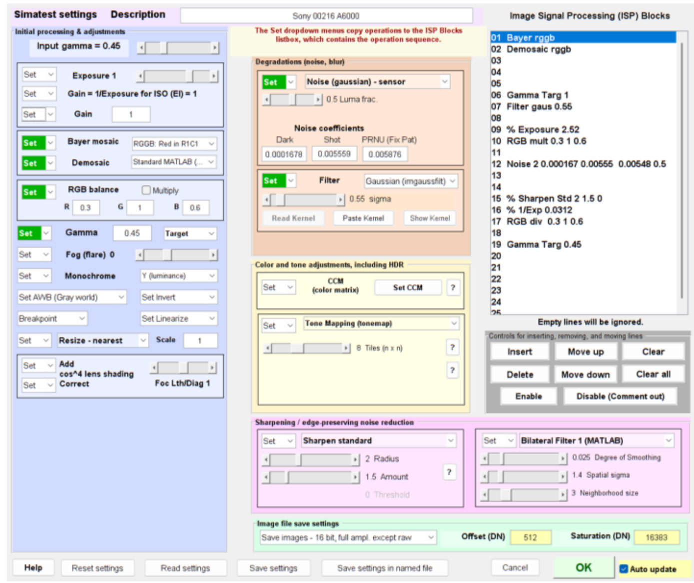
New DR test chart designed to minimize ghost images

Simatest settings

Settings are located in most of the Settings window, except for the upper right Image Signal Processing (ISP) Blocks section, which shows the selected blocks.

The contents of the ISP Blocks box can be edited (moved, deleted, disabled, etc.) using the buttons below the window.

The OK button near the bottom-right saves and closes the Settings window. Calculations are updated if Auto update is checked.



Changing Simatest settings

To change a setting

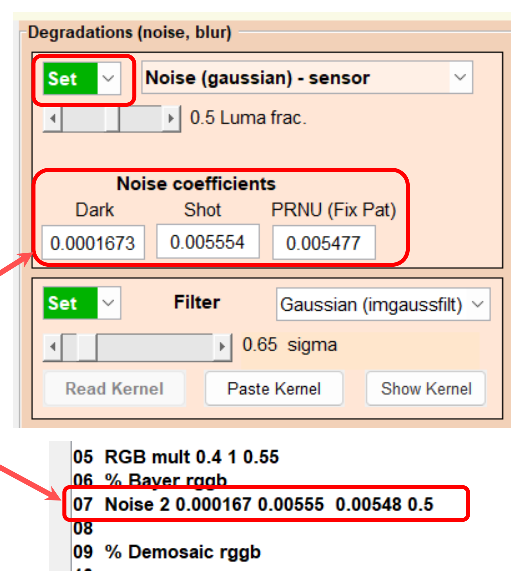
Choose a processing block, then adjust its parameters.

Use the Set dropdown menu to copy it to a line in the ISP blocks box (right, last slide). (Empty lines & comments (%) are ignored.)

For example, to enter noise coefficients, k_{Ndark}, k_{Nshot}, and k_{DSNU}, enter the values into the windows for the Dark, Shot, and PRNU Noise coefficients shown on the right.

Then select a line (07 in this case) in the Set drop-down to copy the settings. Results on lower right.

Pressing OK updates the Simatest calculations if Auto update is checked. Calculations can also be updated from the main Simatest window.



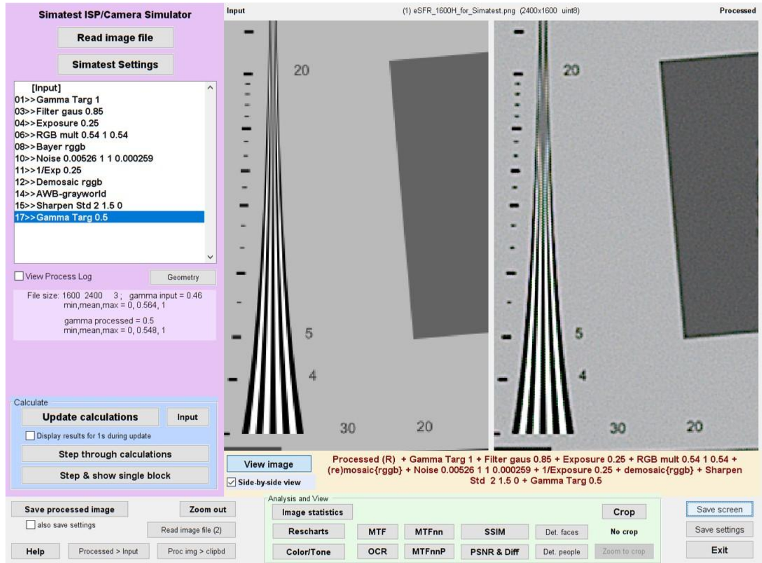
Simatest — Results: Side-by-side view

The original simulated image is on the left.

The processed image with blur, noise, sharpe-ning, etc., is on the right.

Processing steps are displayed on the left.

Buttons on the bottom let you select the results display or send results to *Imatest* modules for further analysis.



Simulated PTC using measured *k*-parameters

Read an <u>ideal</u> image in Simatest.

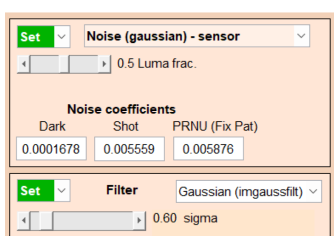
Enter parameters obtained by analyzing the raw HDR chart.

k_{Ndark}, k_{Nshot}, k_{DSNU}

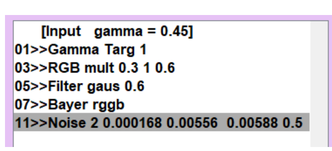
Gain (DN/e-)

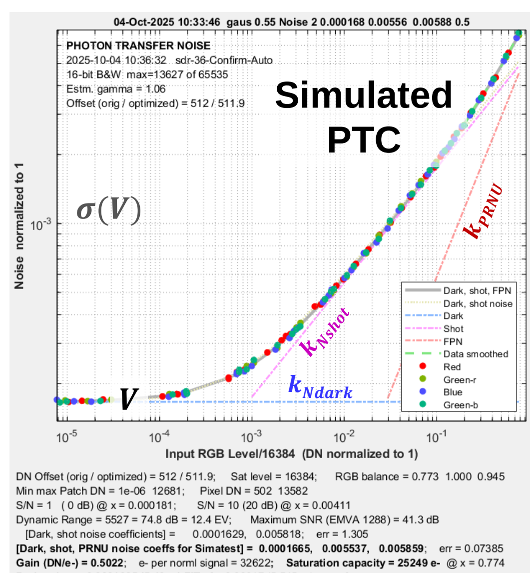
RGB balance

Noise and filter settings



Simatest process-sing steps

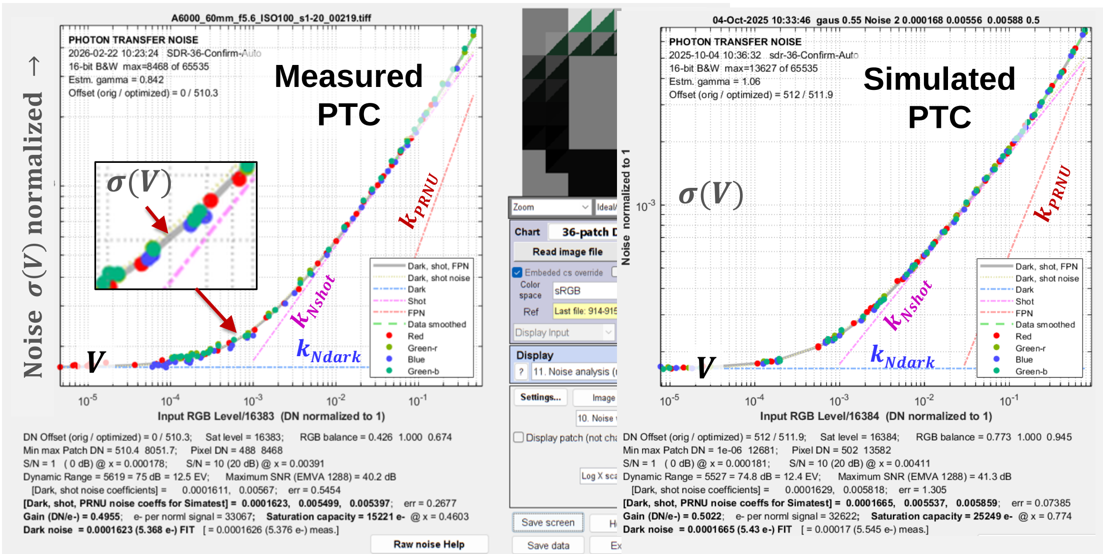




Convert the RGB image to pseudo-raw (Bayer rggb).

Open Color/Tone to obtain the PTC (right).

Measured and simulated PTC: side-by-side



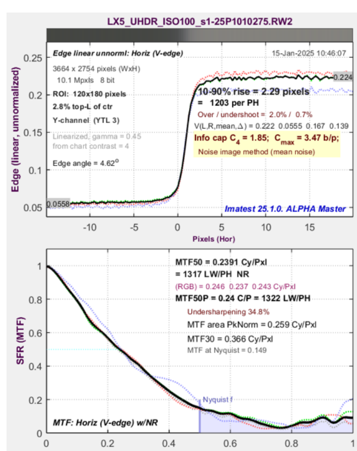
Photon Transfer Curves (PTCs)

Simatest results: acquired vs. simulated image

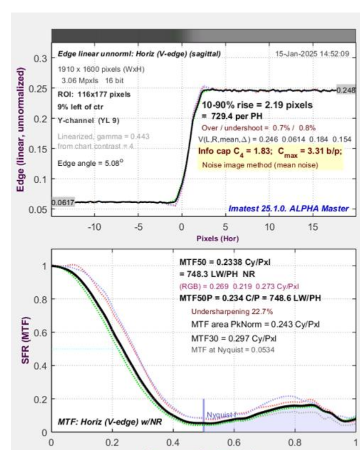
Edge rise distance,
MTF50,
Information capacity
are similar

The shapes of the MTF curves are somewhat different.

Simatest is well-suited for designing ISP pipelines and evaluating their performance, including image information metrics.



Acquired image (demosaiced raw with minimal processing)



Simulated image: Noise model from undemosaiced raw image. Mosaicing/demosaicing applied. Filter blur set to match MTF50.

www.imatest.com/imaging/Simatest-overview/

Simulating low light (high ISO speed) performance

Simulated image started with an ideal edge.

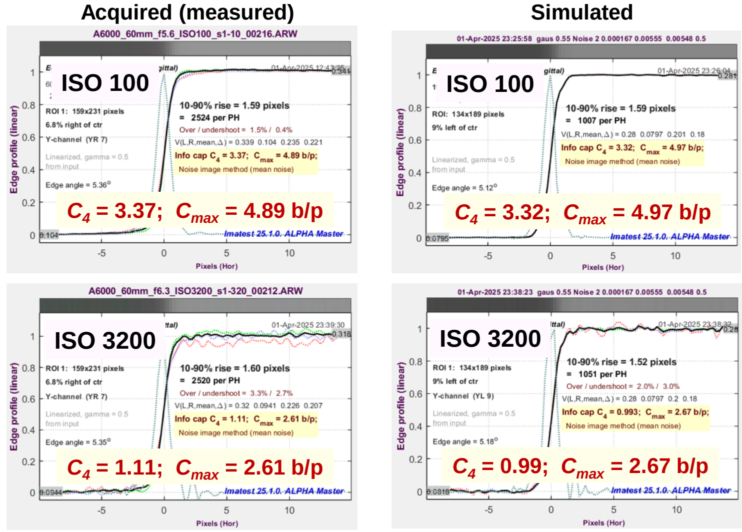
Blur was to match MTF50 for simulated and acquired images.

Noise model was calculated from a raw acquired image at ISO 100.

High ISO speed (low light) was simulated by attenuating the signal, adding the modeled noise, then restoring the signal.

Simatest can predict system performance for a wide variety of conditions, including low light and ISP tuning.

Acquired (measured) | Simulated



www.imatest.com/imaging/Simatest-overview/

Simatest Imatest's Camera/ISP simulator — Summary

Simatest simulates camera and ISP performance over a wide range of conditions:

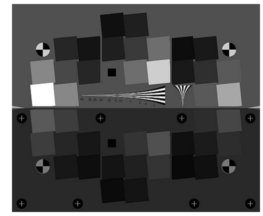
- Apply blur from lens design programs of add gaussian blur to ideal images to match measurements.
- Sophisticated image sensor noise model
- A large number of ISP operations can be applied in arbitrary order.
- Results can be displayed in Imatest modules, including Photon Transfer Curves, low light performance, and information metrics.

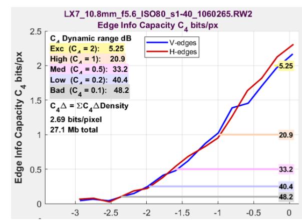
Simatest enables soft prototyping of camera systems, saving development time and money.

Short course — Summary

We have

- Reviewed information theory and showed how key metrics, especially C_4 — the amount of information that can be conveyed in a 4:1 contrast object, is calculated from slanted edges,
- Introduced the InfoDR test chart, for measuring Dynamic Range and low-light performance based on Information Capacity,
- Introduced the Photon Transfer Function-based Image sensor noise model,
- Described Simatest, Imatest's camera simulator, which uses the noise model to predict camera performance over a wide range of illumination.





Validating the information metrics 1

imatest.com/2025/04/validating-information-metrics-correlation-with-object-detection/

We have started working with Prof. Brian Deegan of the University of Galway, Ireland.

His group is working on correlating detection confidence with metrics including MTF50 and information capacity.

Using the picture on the right, with four groups of differently sized pedestrians, his group measured machine vision detection confidence as a function of various measured results with degraded contrast, blur, and gaussian noise.

Validating the information metrics 2

In both plots the image has been degraded with

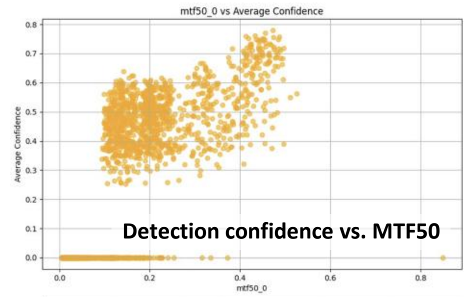
- **Gaussian blur**
- **Poisson noise**
- **Reduced contrast**

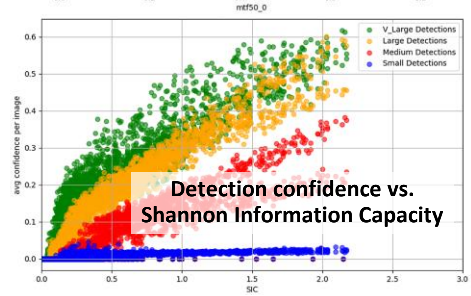
Upper plot: Detection confidence vs. MTF50 for large figures. No trend is visible.

Lower plot: Detection confidence vs. Shannon Information Capacity (SIC) for all four figure sizes. Result is a function of SIC and figure size.

More work is needed.

The results may be plotted as a single curve – a function of SNRi for object size a fraction of the total figure size (for heads, feet, etc.)





Thank you.

Documentation is linked from

image information metrics **Simatest** **InfoDR**

www.imatest.com/solutions/image-information-metrics/

www.imatest.com/imaging/simatest-overview/

Appendix: Calculation details

with “green for geeks” background in some

- **Converting 2D to 1D noise**
- **ROI size**

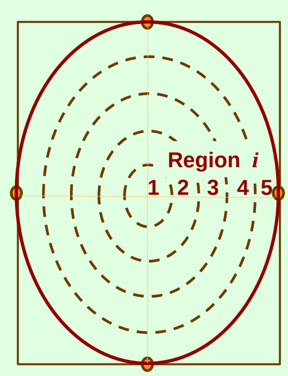
- **Removed slides (many redundant; would make presentation too long)**

Noise Power (Wiener) Spectrum $NPS(f)$ 2D → 1D

(Contents of green boxes are highly mathematical (“for geeks”). Best read offline)

To convert the 2D Fourier Transform (FFT) of the noise image into 1D.

- Shift the 2D |FFT| so that $f = 0$ at the center of the 2D FFT array (MATLAB fftshift). Each point in this array is represented by a Digital Number, *DN*.
- Divide the 2D FFT array into n_{rads} annular regions (between 4 and 20), depending on the minimum size of the array.
- n_{rads} is a tradeoff between noise and frequency discrimination: a small frequency increment (large n_{rads}) may result in excessive noise. For minimum ROI size n_{Rmn} (pixels), n_{rads} = 4 for n_{Rmn}, < 16; 4+round((n_{Rmn}-16)/7) for 16 ≤ n_{Rmn} ≤ 128; 20 for n_{Rmn} > 128.
- Noting that the outer (**dark red**) ellipse is at the Nyquist frequency, $f_{Nyq} = 0.5$ C/P, the mean frequency of region i is $f_i = 0.5(i - 0.5)/n_{rads}$; $\Delta f = 0.5/n_{rads}$. [$n_{rads} = 5$ in the image on the right.]



Converting $NPS(f)$ from 2D → 1D (continued)

(Geek alert — best read offline)

- In region i, the initial (unnormalized) Noise Power Spectrum, $NPS_{i\_mean}(f_i)$, is the mean noise power of the n_i points. [Exclude DC component: work needed.]

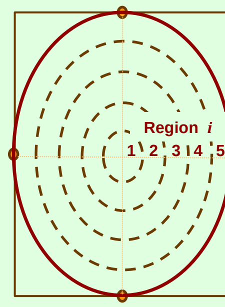
$$NPS_{i\_mean}(f_i) = \left[\sum_{k=1}^{n_i} DN^2\right] / n_i \quad \text{where } f_i = 0.5(i-0.5)/n_{rads}$$

- Because this procedure does not maintain the invariance in energy between the spatial and frequency domains implied by Parseval's theorem, **$NPS(f)$ must be normalized so that**

$$\int NPS(f)\, df = \int N(x)\, dx$$

$$NPS(f) = \frac{NPS_{i\_mean}(f) \int N(x)\, dx}{\int NPS_{i\_mean}(f)\, df}$$

Note that $NPS(f)$ is independent of the scaling of DN (and $NPS_{i\_mean}(f_i)$)



Effect of ROI size on measured noise

(Geek alert — best read offline, after the class)

- The mean noise power of the noise image N_{NI} is different from the noise power N_P of the input image because the noise power N_{DI} of the de-interleaved image is nonzero for finite ROI size.
- For M scan lines total, each of the four interleaves is the mean of $\cong M/4$ lines.
- The noise power of each interleave, and hence the de-interleaved image is $N_{DI} = N_P/(M/4) = 4N_P/M$.
- When the de-interleaved image is subtracted from the original image to obtain the noise image, the noise powers ***add***. Therefore the corrected noise image power is $N_{NI} = N_P/(1+4/M)$. For large M, $N_{NI} \cong N_P$.
- **Normalizing the noise power to the mean edge variance $N(x)$ or N_{NI} removes the effect of the M scan lines.**

$$NPS(f) = \frac{NPS_{i\_mean}(f) \int N(x)\, dx}{\int NPS_{i\_mean}(f)\, df}$$

Image information metrics are not affected by ROI size. ☺

Edge SNRi (There are some questions about scaling.)

Odd impulse pair ← *w* →

$$I_I(x/w) = \frac{1}{2}\left[\delta\left(x+\frac{w}{2}\right) - \delta\left(x-\frac{w}{2}\right)\right]$$

***Edge SNRi*, is new metric for the detectability of *edge location or object shape*.**

Similar to *SNRi*, with the object replaced by the edges (the gradient of the object), which forms ***Line Spread Function doublets*** (pairs opposite-polarity δ-functions spaced by *w*).

$$\Delta h(x,y) = V_{P-P} \cdot I_I(x/w) \cdot I_I(y/kw);$$

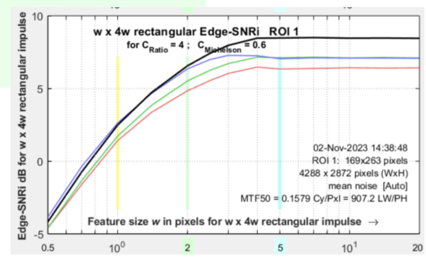
$$FFT(\Delta h(x,y)) = H(f_x, f_y) = \pi^2 f_x\, f_y\, G(f_x, f_y) = 2\, V_{P-P} \sin(\pi w f_x) \sin(\pi k w f_y)$$

$$Edge\ SNRi^2 = \iint \left|H(f_x, f_y)\right|^2 K(f)\ df_x\, df_y$$

***Edge location σ* (next slide), derived from *Edge SNRi*, is a promising metric for evaluating system performance.**

In spatial domain, *Edge SNRi²* is the energy of the LSF doublets.

Affected by filtering (ISP).



***Feature size w* in pixels →**

Edge location σ (standard deviation)

Edge location *σ* (standard deviation of edge or object location) is metric for the detectability of *edge location or object shape*.

Odd impulse pair ← *w* →

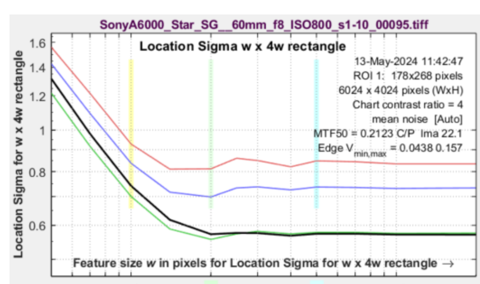
$$I_I(x/w) = \frac{1}{2}\left[\delta\left(x+\frac{w}{2}\right) - \delta\left(x-\frac{w}{2}\right)\right]$$

$$\boldsymbol{Edge\ Location\ \sigma = \frac{1}{Edge\ SNRi}}$$

Edge location *σ* has units of **pixels** (but can be converted to distance, angle, etc.).

A candidate for our preferred metric for evaluating system performance.

Affected by filtering (ISP). Can be used to design matched filters to optimize location (shape) detection.



***Feature size w* in pixels →**

Work is needed on its scaling and interpretation.

To do

- **Verify the correlation between image information metrics and Machine Vision/AI performance: accuracy, speed, and power consumption.**
- Determine the best practices for designing practical ***matched filters***, which must trade off optimization for different measurements and object sizes?

Questions to be answered

- Does information capacity, C, correlate with visual quality?
- Does C indicate how much the image can be sharpened without excessively boosting noise (based on perceptual estimation)?
- Concerns about $Edge\ Location\ \sigma = 1/Edge\ SNRi$ (scaling and interpretation)?
- Is there an advantage to working with YUV (or YC_bC_r) color space or raw images?