# Lecture 11: Noise and Color Sensing

### Yuhao Zhu

http://yuhaozhu.com <u>yzhu@rochester.edu</u>

### CSC 292/572, Fall 2022 **Mobile Visual Computing**



### Logistics

WA 1 grades are posted.

- The link is on the assignment page
- Can work in groups of 2

### Project idea document is posted. Feel free to work on your own idea too.

• Submit a one-page proposal describing what you want to work on by Oct. 26, 11:30 AM.



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https://medium.com/storm-shelter/the-importance-of-film-grain-255f0246cd64 5



### Noise

Without noise, raw pixel value is proportional to light luminance

ignore ADC quantization error, which itself also introduces noise

Two forms of noise:

- **Temporal Noise**; does vary from capture to capture

Temporal noise:

- Charge domain noise: the number of collected charges (electrons) is noisy
- Voltage domain noise: the voltage reading (converted from charges) is noisy

Any amplification (gain) amplifies the noise accumulated before the gain.

• Fixed Pattern Noise; doesn't vary from capture to capture but varies from pixel to pixel



# Temporal Noises and SNR



### **Temporal Noise**

Varies from shot to shot, but could be observed from neighboring pixels in one shot if scene has relatively uniform luminance.

- Charge-domain noise: the noise is represented in the collected charges • Photon Shot Noise: due to random arrival of photons.
  - Dark Current Noise (electronic shot noise): random arrival of (temperature-dependent) thermal generation of electrons even without any incident photons.

Voltage-domain noise: noise in circuits that convert charges to voltage; represented in the voltage measurement

- a.k.a. **Read Noise** (as the noise is generated in the process of reading the charges)



# **Observing Temporal Noise Spatially**

- Technically, temporal noise should be observed by comparing consecutive frames, which requires taking multiple frames.
- But if the scene has ~uniform illumination we can observe temporal noise **spatially** by analyzing pixels in a single image.
  - Think of M pixels in an image as taking M captures at a single pixel
- Or, for a real scene which is unlikely uniformly illuminated, we can analyze *neighboring* pixels, which likely are similarly illuminated.
  - such as the example on the next slide



# Photon Shot Noise Example



### Photon shot noise is less significant with longer exposure time (or equivalently brighter scenes)

https://en.wikipedia.org/wiki/Shot\_noise 10



### **Photon Shot Noise**

Photon emission is a random process. A light source with constant power **on average** emits the same amount of photons per second, but in any given constant period, the **absolute** amount of photons emitted will vary.

The relative deviation away from average is less significant for bright scenes (lots of photons on average) and is more significant for dark scenes (few photons on average).



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### Photon Shot Noise Example



Histogram of raw pixel value distribution in an image of sky (Canon 1D3, green channel).

http://theory.uchicago.edu/~ejm/pix/20d/tests/noise/ 12





## **Modeling Photon Shot Noise**

The distribution of the number of photoe the **Poisson distribution**.

The probability that  $\mathbf{k}$  photons actually arrive at a pixel when on average  $\boldsymbol{\lambda}$ photons arrive (per unit time).

$$p(k;\lambda) = \frac{\lambda^k \times e^{-\lambda}}{k!}$$

### The distribution of the number of photons received by a pixel is governed by





## Signal to Noise Ratio (SNR)

Signal: mean value Noise: Std. of value **SNR** = Signal / Noise





# Signal to Noise Ratio (SNR)

Signal: mean value

Noise: Std. of value

For a Poisson distribution:

- Mean  $\mu$  is  $\lambda$
- Variance is  $\lambda$
- Standard deviation  $\sigma$  is sqrt( $\lambda$ )





https://en.wikipedia.org/wiki/Shot\_noise 15



# Signal to Noise Ratio (SNR)

Signal: mean value

Noise: Std. of value

For a Poisson distribution:

- Mean  $\mu$  is  $\lambda$
- Variance is  $\lambda$
- Standard deviation  $\sigma$  is sqrt( $\lambda$ )

$$SNR = \frac{\mu}{\sigma} = \sqrt{\lambda}$$





https://en.wikipedia.org/wiki/Shot\_noise 15



When a pixel receives more photons (e.g., brighter scene, bigger pixel, longer exposure), the SNR is higher, i.e., less noisy.

# $SNR = \frac{\mu}{\sigma} = \sqrt{\lambda}$





When a pixel receives more photons (e.g., brighter scene, bigger pixel, longer exposure), the SNR is higher, i.e., less noisy.







 $SNR = \frac{\mu}{\sigma} = \sqrt{\lambda}$ 

https://www.flir.com/discover/iis/machine-vision/how-to-evaluate-camera-sensitivity 16





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https://www.flir.com/discover/iis/machine-vision/how-to-evaluate-camera-sensitivity 16





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https://www.flir.com/discover/iis/machine-vision/how-to-evaluate-camera-sensitivity 16





## **Dark Current Noise (Electronic Shot Noise)**

As temperature increases, electrons are dislodged even without any incident photon (unless sensor cooled to absolute zero temperature).

Dark current adds a pedestal offset to the actual electron read-out. But the offset is not constant across time — hence "noise".

• If the offset was constant, the readings would still be incorrect but won't constitute noise (since the offset is not random).





## **Dark Current Noise (Electronic Shot Noise)**

- Dark current  $I_d$  represents the average (expected value) # of dark electrons/ sec/pixel, which follows Poisson distribution (similar to photon shot noise).
- Over an exposure time t, average # of electrons (collected at each pixel) contributed by dark current is  $I_d \times t$ .
- So the dark current **noise** is **sqrt (I**<sub>d</sub> × t)
  - because dark current follows Poisson distribution
  - I<sub>d</sub> increases with the temperature
  - therefore dark current noise increases with temperature and **t**. • I<sub>d</sub> is also spatially non-uniform: a source of FPN.



### "Hot" Pixels From Dark Current Noise

### 15s exposure time

### 30s exposure time

Usually dark current noise is negligible, since dark current is very low (e.g., 50 e<sup>-</sup>/s; c.f., full well capacity > 10ke<sup>-</sup>), but can be significant if long exposure time is required, e.g., astrophysical imaging.





### **Cooling in James Webber Space Telescope**





### Passive cooling: sunshield to cool three of the four cameras (37 K)

https://webb.nasa.gov/content/observatory/sunshield.html 20





### **Cooling in James Webber Space Telescope**



Active cooling: cryocooler (7 K)

https://webb.nasa.gov/content/about/innovations/cryocooler.html 21



### **Read Noise**

The circuits that covert photons to digital values suffer voltage fluctuation • Remember eventually we read the voltage, not the photon count, so voltage fluctuation

- in the circuit introduces noise.

Read noise can be both positive and negative, since voltage fluctuation can be both positive and negative.

Read noise is modeled as a **0-mean Gaussian distribution**.

• Could be thermal-induced (Johnson–Nyquist noise, which is fundamental to all circuits and is called kTC noise when manifested on capacitors), <u>1/f noise</u>, or <u>burst noise</u>. Sources: various amplifiers (e.g., FD, SF, other gain controls), ADC (with additional

quantization errors), reset (of FD; can be suppressed by CDS), CDS circuit itself, etc.



## **Estimating Read Noise**

noise source is read noise (ignore FPN for now).



### Could be measured by reading a bias frame, which is an image captured at dark (lens cap on or shutter closed) with 0 exposure time (or use highest possible shutter speed), i.e., no light gets to the photodiodes and dark current is negligible, so the major

Raw pixel value histogram of Canon 1D3 at ISO 800.

\* Again, read noise should technically be observed temporally, but since scene is uniform (dark), noise across pixels spatially equates temporal noise, i.e., standard deviation of pixel values is the  $\sigma$  of read noise.





# **Three Slight Issues**

# First, signal voltage could be negative (recall: read noise is a zero-mean



Gaussian), which will be clipped to 0 by the ADC, contaminating analysis. • A bias voltage is usually added to the signal voltage (e.g., in the previous slide). The bias is one reason why dark frame pixels are not zero (even without any noise present).

> Pixel histogram at different illumination levels of Nikon D300, which doesn't add ADC bias.

> > http://theory.uchicago.edu/~ejm/pix/20d/tests/noise/ 24







# **Three Slight Issues**

First, signal voltage could be negative (recall: read noise is a zero-mean Gaussian), which will be clipped to 0 by the ADC, contaminating analysis.

• A bias voltage is usually added to the signal voltage (e.g., in the previous slide). The bias is one reason why dark frame pixels are not zero (even without any noise present).

• <u>Black level raw value</u> is stored as metadata (part of EXIF tag) of a raw image. It can be read through raw processing APIs (e.g., rawPy) and must be subtracted from the raw value of each pixel by the raw image signal processing pipeline (usually called black-level correction/compensation). We will see this in the ISP programming assignment.









# **Three Slight Issues**

- First, signal voltage could be negative (recall: read noise is a zero-mean Gaussian), which will be clipped to 0 by the ADC, contaminating analysis.
- Second, the read noise distribution should be measured for each ISO setting, which affects gains, which amplify noise.
- Third, it also assumes that no FPN is present, which is not true.
  - We will later see a more sophisticated method to estimate read noise isolated from FPN.





Reset noise: V<sub>reset</sub> is not the same for each capture, usually thermal induced.

Eliminate reset noise by reading  $V_{reset}$  and  $V_{transfer}$  and taking the delta; this is what Correlated Double Sampling does, among other things (in a few slides).

Without CDS, we read only  $V_{transfer}$  and the ADC circuit needs to be designed with a fixed, offline-determined  $V_{reset}$  in mind, introducing reset noise.



# Gains and ISO



# Signal Gain: ISO

### A scaling factor (gain) applied to the actual measured voltage of a pixel.

- Each camera has a base ISO value (e.g., ISO 400). Doubling ISO effectively doubles the measured voltage — equivalent to doubling exposure time.
- ISO is informally called camera sensitivity, but don't confuse it with the spectral sensitivity of the sensor.

### Why use ISO gain?

- Boost image brightness at low light: increasing effective exposure time without increasing the actual exposure time
- Reduce the exposure time, which reduces motion blur (if one were to increase the exposure time) and increases the frame rate
- **Big caveat**: shorter exposure time also reduces the SNR: noisy photo!





ISO 200





### ISO 400

ISO 800

### ISO 1600

https://photographylife.com/what-is-iso-in-photography 30



### ISO 800 and 1/2000s exposure



### ISO 1800 and 60s exposure on Pentax KP

https://photographylife.com/what-is-iso-in-photography 31







### Noise From High ISO



https://www.exposureguide.com/iso-sensitivity/


### **Noise From High ISO**



### Camera+2 app on iPhone



https://iphonephotographyschool.com/iphone-camera-controls/ 33





### Where to Apply ISO Gain?

### **Column amplifiers**



Assim Boukhayma Noise CMOS Image Sensors, Ultra Low

https://www.edmundoptics.com/knowledge-center/application-notes/imaging/understanding-camera-sensors-for-machine-vision-application



One single amplifier at the end



### Where to Apply ISO Gain?

### **Column amplifiers**



Applying the gain to the signal applies the gain to the noise too! Applying the gain early before much noise trickles in helps SNR.

- It's common to use column-level amplification. Some cameras have digital gains (post ADC).
- We could also use an <u>in-pixel amplifier</u>.
- ISO gain circuity is usually called Adaptive Gain Control (AGC) or Programmable Gain Amplifier (PGA).







# **Apply ISO Gain After ADC**

quantization artifact (contouring).



https://www.researchgate.net/figure/left-Input-image-quantized-to-16-levels-color-input-image-that-shows-visible-contouring\_fig1\_228982458

### Applying ISO gains after ADC quantization, i.e., digital gain, magnifies the

Before quantization: 3.4, 4.1 After quantization: 3, 4 Increasing ISO by 10X: 30, 40







### Gain Blocks

- Photon to electron conversion in PD
- electron charge to voltage conversion in FD
- SF in read-out
- other amplifiers (e.g., for ISO control)
- ADC, etc.



 $S_{out} = GS_{in}$  $\sigma_{out} = G\sigma_{in}$ 

Many blocks in signal chain can be seen as applying gains even though their goals are not to amplify signals.

- Photodiodes apply a photon to electron conversion; unit of gain is photon/electron.
- FD converts charges to voltage, and has a conversion gain with a unit of Volt/electron.
- ADCs convert voltages to raw pixel values, a.k.a., ADUs (analog-to-digital units) or DNs (data numbers). ADC gains have units of ADU/volt.

They also amplify noises.





### **ADC Gain**



ADC gain is technically non-linear,

https://www.allaboutcircuits.com/technical-articles/adc-offset-and-gain-error-specifications/





### **ADC Quantization Error**



Figure 4. Analog input, digital output and LSB error waveforms.

Digital Image Processing 5e, Bernd Jähne https://www.ti.com/lit/eb/slyy192/slyy192.pdf?ts=1672692692703

### ADC quantization error can be modeled as a "noise" source too.

• All voltages **v** within a LSB are replaced with the same level  $V_d$ .

Assuming analog values are uniformly distributed, the variance introduced by quantization is:

$$\sigma_{ADC-q}^{2} = \int_{V_{d} - \frac{1}{2}\Delta V_{\text{LSB}}}^{V_{d} + \frac{1}{2}\Delta V_{\text{LSB}}} (v - V_{d})^{2} \frac{1}{\Delta V_{\text{LSB}}} dv = \frac{1}{12}\Delta V_{\text{LSB}}$$







### **Other ADC Noises/Errors**

Offset error and gain error are fixed for an ADC and can be compensated once characterized. They are technically errors, not noises, just like quantization errors, but can be modeled as noises. Usually in modeling we lump all ADC noise sources together as a single ADC noise.









Noise Propagation



# **Noise Amplification in the Signal Chain**

- Photon to electron conversion in PD
- electron charge to voltage conversion in FD
- SF in read-out
- other amplifiers (e.g., for ISO control)
- ADC, etc.



$$S_{out} = GS_{in}$$
  
 $\sigma_{out} = G\sigma_{in}$ 

Recall that scaling a random variable by a constant scales the variance by the square of that constant.

- $Var(a X) = a^2Var(X)$
- $\sigma(a X) = a \sigma(X)$

Amplifying a signal amplifies the noise as well; SNR is unchanged (assuming the block has no inherent noise)!





# Noise Amplification in the Signal Chain

- Photon to electron conversion in PD
- electron charge to voltage conversion in FD
- SF in read-out
- other amplifiers (e.g., for ISO control)
- ADC, etc.



$$S_{out} = GS_{in}$$
$$\sigma_{out} = \sqrt{G^2 \sigma_{in}^2 + \sigma_b^2}$$

Each block in the signal processing chain introduces noises, which can be modeled as **independent** random variables. The variance of their sum is the sum of their variances.

• Var(X+Y) = Var(X) + Var(Y)

In general, SNR is worsened by the signal processing chain.





 $S_{out} = QE \times G_{read} \times S_{in}$ 

 $read \sigma_{photon}^2 +$  $\sigma_{out}$ 

\* assuming no noise in photon to electron conversion

$$G_{read}^2 \sigma_{dark-current}^2 + \sigma_{read}^2$$



### Apply Gains Earlier Improves SNR





$$\rightarrow \text{Output} \\ S_{\text{out}} \qquad \sigma_{out} = \sqrt{G_a^2(\sigma_{in}^2 + \sigma_b^2) + \sigma_b^2}$$

$$\sigma_{\text{out}} \qquad \sigma_{out} \qquad \sigma_{o$$







$$S = S_{in}G_1G_2 = S_{in}G$$
  

$$\sigma = (\sigma_{in}^2G_1^2 + \sigma_1^2)G_2^2 + \sigma_2^2 = \sigma_{in}^2G_1^2G_2^2 + \sigma_2^2$$

$$\sigma = (\sigma_{in}^2 G_1^2 + \sigma_1^2) G_2^2 + \sigma_2^2 = \sigma_{in}^2 G_1^2 G_2^2 + \sigma_1^2 G_2^2 + \sigma_2^2 = \sigma_{in}^2 (G_1 G_2)^2 + \sigma^2$$

$$= \int \begin{cases} G = G_1 G_2 \\ \sigma = \sqrt{\sigma_1^2 G_2^2 + \sigma_2^2} \end{cases} \quad \text{If three gains are combined:} \quad \begin{cases} G = G_1 G_2 G_3 \\ \sigma = \sqrt{\sigma_1^2 G_2^2 G_3^2 + \sigma_2^2} \end{cases} \quad \text{If three gains are combined:} \quad \begin{cases} G = \sqrt{\sigma_1^2 G_2^2 G_3^2 + \sigma_2^2 G_3^2 + \sigma_2^2} \end{bmatrix}$$





If the read-out chain consists of FD, SF, and an Adaptive Gain Control (e.g., column-level amp):

$$\begin{cases} S_{out} = QE \times G_{read} \times S_{in} \\ \sigma_{out} = \sqrt{QE^2 G_{read}^2 \sigma_{photon}^2 + G_{read}^2 \sigma_{dark-current}^2 + \sigma_{read}^2} \end{cases} \begin{cases} G_{read} = G_{FD} G_{SF} G_{AGC} \\ \sigma_{read} = \sqrt{\sigma_{FD}^2 G_{SF}^2 G_{AGC}^2 + \sigma_{SF}^2 G_$$

\* assuming no noise in photon to electron conversion





**SNR and Input- vs. Output-Referred Noise**  $QE \times G_{read} \times S_{in}$ SNR = $\sqrt{QE^2G_{read}^2\sigma_{photon}^2 + G_{read}^2\sigma_{dark-current}^2 + \sigma_{read}^2}$ S<sub>in</sub>  $\sqrt{\sigma_{photon}^2 + \sigma_{dark-current}^2/QE^2 + \sigma_{read}^2/QE^2/G_{read}^2}$  $QE \times S_{in}$  $\sqrt{QE^2\sigma_{photon}^2 + \sigma_{dark-current}^2 + \sigma_{read}^2/G_{read}^2}$ 



Sometimes input-referred noise is also expressed in electron counts





### **SNR vs. Exposure Time**



 $QE \times S_{in}$  $\sqrt{QE^2\sigma_{photon}^2 + \sigma_{dark-current}^2 + \sigma_{read}^2/G_{read}^2}$ Exposure  $P \times QE \times t$ time

Dark current: # of electrons/sec/pixel



### **SNR Examples**



https://andor.oxinst.com/learning/view/article/ccd-signal-to-noise-ratio 50





### A Sensor Model with Temporal Noise

$$Q(x, y) = \int_{t} \int_{\lambda} \int_{y}^{y+\nu} \int_{x}^{x+u} (Y(x, y, y)) dx$$
$$\Delta V(x, y) = \frac{Q(x, y)}{C} G + \eta_{read}$$
$$Gain (SF, I)$$

 $n(x, y) = \left\lfloor \frac{\Delta V(x, y)}{V_{max}} (2^N - 1) \right\rfloor$ Raw pixel value Max voltage correspondingto max raw value

# of incident photons at pixel (x, y); varies with  $\lambda$  and t. Subject to photon-shot noise.



ISO gain, etc.)



# **Fixed Pattern** Noise



# Fixed Pattern Noise (FPN): Spatial Non-Uniformity

Better be called spatial non-uniformity; due to manufacturing variation of circuity components across pixels, columns, etc. The variation is spatially different ("noise") but doesn't vary with shots ("fixed").

Two FPN components:

- Dark signal non-uniformity (**DSNU**): non-uniformity without illumination
- Photo response non-uniformity (**PRNU**): non-uniformity under illumination

FPN can be removed/reduced by subtracting the pattern (at each exposure time, illumination level, and/or ISO setting) if the pattern is known offline. • ISO setting affects gains, which amplify noise.



# **Two Components of DSNU**

**DCNU** (dark current non-uniformity):

current of each pixel, which can be seen as the pattern of DCNU.

### The effects of DCNU:

- increase with exposure time
- unaffected by irradiance

- Illumination level
- increase with ISO setting

• Think of DCNU as the fact that each pixel has a different (but fixed) mean dark current. Since actual dark current is inherently temporally varying, the effect of DCNU is not a constant voltage offset, but we can average multiple frames to get the average dark



# **Two Components of DSNU**

**SONU** (spatial offset non-uniformity):

- Many circuit blocks add a voltage offset/bias (e.g., in-pixel amplifiers/column ADC) or inherently introduce a voltage offset (e.g., charge injection on FD after PD to FD transfer). The offset voltage, while a constant for a pixel/column, varies across pixels. Think of SONU as adding a constant voltage offset to each pixel/column.

### The effects of SONU:

- unaffected by exposure time
- unaffected by irradiance
- increase with ISO setting

Illumination level



### **DSNU Pattern (Dark Frame) Examples**

DSNU pattern under an exposure time T and ISO setting is obtained by averaging multiple dark frames.



https://www.photometrics.com/learn/advanced-imaging/pattern-noise-dsnu-and-prnu http://theory.uchicago.edu/~ejm/pix/20d/tests/noise/







# **Removing DSNU Using Dark-Frame Subtraction**

Capture N dark frames, each captured at dark (with lens cap on; 0 incident photon) with an exposure time T and an ISO setting.

Average the N dark frames to obtain an averaged dark frame at <T, ISO>.

For an actual capture with <T, ISO>, subtract the corresponding averaged dark trame.

A raw Canon 20D image @ ISO 800 & 1ms exposure



http://theory.uchicago.edu/~ejm/pix/20d/tests/noise/







# **Removing DSNU Using Dark-Frame Subtraction**

Capture N dark frames, each captured at dark (with lens cap on; 0 incident photon) with an exposure time T and an ISO setting.

Average the N dark frames to obtain an averaged dark frame at <T, ISO>.

For an actual capture with <T, ISO>, subtract the corresponding averaged dark trame.

The calibrated image after dark-frame subtraction



http://theory.uchicago.edu/~ejm/pix/20d/tests/noise/









### PRNU

### Think of/model PRNU as gain variations across pixels/columns.

capacitances and transistors at each pixel/column, etc.).

### The effects of PRNU:

- increase with exposure time
- increase with irradiance
- increase with ISO setting

• Under illumination, electrical output given the same amount of incident photons isn't uniform across pixels/columns (e.g., variation in full well capacity, quantum efficiency,

Illumination level



### **Noise Amplification With PRNU**

- Photon to electron conversion in PD
- electron charge to voltage conversion in FD
- SF in read-out
- other amplifiers (e.g., for ISO control)
- ADC, etc.



Ignoring second-order terms:

$$\sigma_{out} = \sqrt{G^2 \sigma_{in}^2 + S_{in}^2 \sigma_G^2 + \sigma_b^2}$$

 $Var(XY) = Var(X)Var(Y) + Var(X)(E(Y))^{2} + Var(Y)(E(X))^{2} \approx Var(X)(E(Y))^{2} + Var(Y)(E(X))^{2}$ 





### **A Sensor Model with Temporal Noise and FPN**



The output voltage of an arbitrary pixel in an arbitrary  $(((X_{N_{sig}}^t X_{G_{QE}}^s + X_{N_{dc}}^t) X_{G_{FD}}^s + X_{V_{read-FD}}^t) X_{G_{SF}}^s + X_{V_{read-FD}}^t)$ 

Photon shot n

Temporal noise (expressed as random variables (r.v.) whose values Dark current n vary across captures) Read n

FPN (expressed as r.v. whose valuesPIare fixed across frames but varyscacross pixels; \*see caveats next slide)DC





### **A Note About Probabilistic Sensor Modeling**

It's correct to model temporal noises using random variables. When calculate the mean and std across pixels (under uniform illumination) or frames, the goal is to use the sample mean/std to approximate the expected value/std of the underlying distribution, which is what we care about.

It's technically **incorrect** to model FPN of a given sensor using random variables. It's true that there probably is an underlying distribution of pixel manufacturing variations (which could be Gaussian), but the spatial distribution on a given sensor is fixed once manufactured, which gives a distribution of samples.

a particular sensor, not the expected value of the FD gain for a given manufacturing facility.

Also note that the spatial distribution on a given sensor is most likely not perfectly Gaussian, although close; see <a href="https://www.emva.org/wp-content/uploads/EMVA1288General\_4.0Release.pdf">https://www.emva.org/wp-content/uploads/EMVA1288General\_4.0Release.pdf</a>, Figure 13.

• Importantly, when we calculate mean/std of spatial non-uniformities over pixels, we are calculating the sample mean/std, which are indeed what we care about, because they are statistics specific to the sensor of interest. We are *not* using sample mean/std to approximate population mean/std (i.e., underlying distribution). For instance, G<sub>FD</sub> represents the sample mean of FD gain across the pixels on



# **Reducing FPN Using CDS**

subtracts the two.

CDS can also suppress:

- reset noise (part of thermal-induced read noise).
- some read noise (the 1/f part, which is correlated between the two samples).

The SONU portion of FPN can be eliminated by <u>Correlated Double Sampling</u> (CDS), which, for each pixel during each capture, reads twice — first the reset voltage and second the actual voltage signal under exposure — and then

CDS can't remove PRNU/DCNU, because the effects of dark current and gain variations are not simply adding a constant voltage offset to each reading.





### **CDS Circuits**

Usually sits right before column ADC

• Therefore after FD, SF, and column amp.

Two implementations:

- two sampling caps for reset and signal, and then ADC takes differential input.
- one sampling cap, and the subtraction happens on that cap by sequentially sampling the reset and signal; then ADC takes the subtraction result as input.



Ultra Low Noise CMOS Image Sensors, Assim Boukhayma. Chapter 2.5.1







First sample:

$$((X_{N_{rst}}G_{FD} + X_{V_{read-FD}})G_{SF} + X_{V_{read-SF}} + V_{pix-offset})G_{AGC} + X_{V_{read-AGC}} + V_{col-offset})G_{AGC} + X_{V_{read-AGC}} + V_{col-offset})G_{AGC} + V_{Col-offset}$$

**Second sample** (*subtract* N<sub>sig</sub> and N<sub>dc</sub> because charge transfer *discharges* FD):  $(((X_{N_{rst}} - X_{N_{sig}}G_{QE} - X_{N_{dc}})G_{FD} + Y_{V_{read-FD}})G_{SF} + Y_{V_{read}})G_{SF} + Y_{V_{read}})G_{SF}$ 

For a specific pixel only temporal noises need to be considered

$$\begin{cases} X_{N_{sig}} \sim \text{Poisson}(\mu = N_{sig}, \sigma = \sigma_{sig} = \sqrt{N_{sig}}) \\ X_{N_{dc}} \sim \text{Poisson}(\mu = N_{dc}, \sigma = \sigma_{dc} = \sqrt{N_{dc}}) \\ X_{N_{rst}} \sim N(\mu = N_{rst} = V_{rst}C_{FD}, \sigma = \sigma_{rst}) \end{cases} \begin{cases} X_{V_{read-FD}}, Y_{V_{read-FD}} \sim N(\mu = 0, \sigma = \sigma_{V_{read-FD}}) \\ X_{V_{read-AGC}}, Y_{V_{read-AGC}} \sim N(\mu = 0, \sigma = \sigma_{V_{read-FD}}) \\ X_{V_{read-AGC}}, Y_{V_{read-AGC}} \sim N(\mu = 0, \sigma = \sigma_{V_{read-FD}}) \end{cases}$$

$$(A_{ad-SF} + V_{pix-offset})G_{AGC} + Y_{V_{read-AGC}} + V_{col-offset} + Y_{V_{read-CDS}}$$







First sample:

 $((X_{N_{rst}}G_{FD} + X_{V_{read-FD}})G_{SF} + X_{V_{read-SF}} + V_{pix-offset})G_{AC}$ 

**Second sample** (*subtract* N<sub>sig</sub> and N<sub>dc</sub> because charge transfer *discharges* FD):  $(((X_{N_{rst}} - X_{N_{sig}}G_{QE} - X_{N_{dc}})G_{FD} + Y_{V_{read-FD}})G_{SF} + Y_{V_{read-FD}})G_{SF} + Y_{V_{read-FD}})G_{SF}$ 

After subtraction:

$$(((X_{N_{sig}}G_{QE} + X_{N_{dc}})G_{FD} + X_{V_{read-FD}} - Y_{V_{read-FD}})G_{SF} + X_{V_{read-SF}} - Y_{V_{read-SF}})G_{AGC} + X_{V_{read-AGC}} - Y_{V_{read-AGC}} - Y_{V_{read-AGC}} - Y_{V_{read-AGC}} - Y_{V_{read-AGC}})G_{AGC} + X_{V_{read-AGC}} - Y_{V_{read-AGC}} - Y_{V_{read-AGC}} - Y_{V_{read-AGC}})G_{AGC} + X_{V_{read-AGC}} - Y_{V_{read-AGC}} - Y_{V_{read-AGC}}$$

- **Retained**: PRNU/DCNU, other temporal noise (in fact, variance of non-reset/non-1/f read noise is doubled)
- Introduced: read noise of the CDS circuitry itself

$$_{GC} + X_{V_{read-AGC}} + V_{col-offset}$$

$$+ V_{pix-offset})G_{AGC} + Y_{V_{read-AGC}} + V_{col-offset} + Y_{V_{read-AGC}}$$

**Eliminated**: the offset portion of FPN, reset noise (kTC-induced), and some amount of read noise (1/f component)





# Signal Processing For Noise Removal/Estimation



### **Recovering Noise-Free Images**



1. Under the same illumination level D, take N captures and average them pixel-wise; this effectively calculates the expected value of a composite random variable for each pixel:

 $E[((X_{N_{sig}}^{t}G_{QE}^{p} + X_{N_{dc}}^{t})G_{pix}^{p} + X_{V_{read-pix}}^{t} + V_{pix-ofs}^{p})G_{AGC}^{p} + X_{V_{re}}^{t}]$ 

$$\begin{cases} X_{N_{sig}}^{t} \sim \text{Poisson}(\mu = N_{sig}, \sigma = \sigma_{sig} = \sqrt{N_{sig}}) \\ X_{N_{dc}}^{t} \sim \text{Poisson}(\mu = N_{dc}^{p}, \sigma = \sigma_{dc} = \sqrt{N_{dc}^{p}}) \\ X_{V_{read-FD/read-SF/read-AGC}}^{t} \sim N(\mu = 0, \sigma = \sigma_{V_{read-FD/read-SF/read-AGC}}) \end{cases}$$

$$_{ead-AGC} + V^{p}_{col-ofs}] = ((N_{sig}G^{p}_{QE} + N^{p}_{dc})G^{p}_{pix} + V^{p}_{pix-ofs})G^{p}_{AGC} + V^{p}_{col-ofs})G^{p}_{AGC} + V^{p}_{col-ofs}$$

^p terms are pixel-specific constants

$$E[XY] = E[X]E[Y]$$

[E[X + Y] = E[X] + E[Y]]








1. Under the same illumination level D, take N captures and average them pixel-wise; this effectively calculates the expected value of a composite random variable for each pixel:

composite random variable:

$$E[((N_{sig}X_{G_{QE}}^{s} + X_{N_{dc}}^{s})X_{G_{pix}}^{s} + X_{V_{pix-ofs}}^{s})X_{G_{AGC}}^{s} + X_{V_{col-ofs}}^{s}] = ((N_{Sig}X_{G_{QE}/pix/AGC}^{s}) - N(\mu = G_{QE/pix/AGC}, \sigma = \sigma_{G_{QE/pix/AGC}}))$$

$$\begin{cases}
X_{G_{QE/pix/AGC}}^{s} \sim N(\mu = G_{QE/pix/AGC}, \sigma = \sigma_{G_{QE/pix/AGC}}), \sigma = \sigma_{V_{pix-ofs/col-ofs}}, \sigma = \sigma_{N_{dc}})
\end{cases}$$

 $E[((X_{N_{sig}}^{t}G_{OE}^{p} + X_{N_{dc}}^{t})G_{pix}^{p} + X_{V_{read-pix}}^{t} + V_{pix-ofs}^{p})G_{AGC}^{p} + X_{V_{read-AGC}}^{t} + V_{col-ofs}^{p}] = ((N_{sig}G_{QE}^{p} + N_{dc}^{p})G_{pix}^{p} + V_{pix-ofs}^{p})G_{AGC}^{p} + V_{col-ofs}^{p})G_{AGC}^{p} + V_{col-ofs}^{p}]$ 2. Average across all the pixels in the averaged frame obtained before. This effectively calculates the expected value of a

 $V_{sig}G_{OE} + N_{dc})G_{pix} + V_{pix-ofs})G_{AGC} + V_{col-ofs}$ 













1. Under the same illumination level D, take N captures and average them pixel-wise; this effectively calculates the expected value of a composite random variable for each pixel:

 $E[((X_{N_{sig}}^{t}G_{OE}^{p} + X_{N_{dc}}^{t})G_{pix}^{p} + X_{V_{read-pix}}^{t} + V_{pix-ofs}^{p})G_{AGC}^{p} + X_{V_{read-AGC}}^{t} + V_{col-ofs}^{p}] = ((N_{sig}G_{OE}^{p} + N_{dc}^{p})G_{pix}^{p} + V_{pix-ofs}^{p})G_{AGC}^{p} + V_{col-ofs}^{p}]$ 2. Average across all the pixels in the averaged frame obtained before. This effectively calculates the expected value of a

composite random variable:

 $E[((N_{sig}X_{G_{OE}}^{s} + X_{N_{dc}}^{s})X_{G_{pix}}^{s} + X_{V_{pix-ofs}}^{s})X_{G_{AGC}}^{s} + X_{V_{col-ofs}}^{s}] = ((N_{sig}G_{QE} + N_{dc})G_{pix} + V_{pix-ofs})G_{AGC} + V_{col-ofs})G_{AGC} + V_{col-ofs})G_{AG$ 

3. We subtract the two above arithmetically, we get the expected value of FPN at D for a pixel:

 $FPN = ((N_{sig}G_{QE}^{p} + N_{dc}^{p})G_{pix}^{p} + V_{pix-ofs}^{p})G_{AGC}^{p} + V_{col-ofs}^{p} - ((N_{sig}G_{QE} + N_{dc})G_{pix} + V_{pix-ofs})G_{AGC} - V_{col-ofs}$ 









4. We take a capture of a scene of interest, and for a pixel whose illumination level is D, we subtract its voltage reading (a composite random variable itself) with the FPN at D corresponding to that pixel (we do this subtraction for all pixels):

 $V^{p} = ((X^{t}_{N_{sio}}G^{p}_{OE} + X^{t}_{N_{dc}})G^{p}_{pix} + X^{t}_{V_{read-pix}} + V^{p}_{pix-ofs})G^{p}_{AGC} + X^{t}_{V}$  $= ((X_{N_{sio}}^{t}G_{OE}^{p} + X_{N_{dc}}^{t})G_{pix}^{p} + X_{V_{read-pix}}^{t} + V_{pix-ofs}^{p})G_{AGC}^{p} + X_{V_{read-pix}}^{t}$  $-((N_{sig}G^{p}_{OE} + N^{p}_{dc})G^{p}_{pix} + V^{p}_{pix-ofs})G^{p}_{AGC} - V^{p}_{col-ofs} + (($  $= (X_{N_{sig}}^{t} - N_{sig})G_{OE}^{p}G_{pix}^{p}G_{AGC}^{p} + (X_{N_{dc}}^{t} - N_{dc}^{p})G_{pix}^{p}G_{AGC}^{p} +$ + $((N_{sig}G_{OE} + N_{dc})G_{pix} + V_{pix-ofs})G_{AGC} + V_{col-ofs})$ 

Given this, there are a few interesting conclusions we can draw. 4.1: the expected value of each so-calculated pixel is the true signal of that pixel, which means if we average over many frames, we will get a completely noise-free image.

 $E[V^{p}] = ((N_{sig}G_{OE} + N_{dc})G_{pix} + V_{pix-ofs})G_{AGC} + V_{col-ofs}$ procedure, the constant voltage offsets will be eliminated, but dark current offset is still there.

$$T_{V_{read}-AGC}^{t} + V_{col-ofs}^{p} - FPN$$

$$T_{V_{read}-AGC}^{t} + V_{col-ofs}^{p}$$

$$T_{V_{read}-AGC}^{t} + V_{col-ofs}^{p}$$

$$T_{V_{read}-pix}^{t} G_{AGC}^{p} + N_{dc} G_{pix}^{t} + V_{pix-ofs} G_{AGC}^{t} + V_{col-ofs}$$

$$T_{V_{read-pix}}^{t} G_{AGC}^{p} + X_{V_{read}-AGC}^{t}$$

The dark current offset and pixel/column voltage offsets are still there, but they are constant across pixels (hence not noise). Consequently, the black level voltage won't be 0. If the sensor first performs CDS before going through our subtraction



4.2: each pixel itself, without averaging across frames, has a noise of the following form. We can see that the SONU is gone, but the PRNU and DSNU, although fixed for the pixel, is still there in addition to temporal noises. So the effect is similar to using CDS (which removes 1/f read noise and amplifies other read noises; see before).

 $Var[V^{p}] = Var[(X_{N_{sig}}^{t} - N_{sig})G_{OE}^{p}G_{pix}^{p}G_{AGC}^{p} + (X_{N_{dc}}^{t} - N_{dc}^{p})$  $= \sigma_{sig}^{2} (G_{OE}^{p} G_{pix}^{p} G_{AGC}^{p})^{2} + N_{dc}^{p} (G_{pix}^{p} G_{AGC}^{p})^{2} + \sigma_{V_{red}}^{2}$ 

4.3: if we want to show the noise both spatially and temporally (i.e., capture both FPN and temporal noises), then the voltage value at each pixel is expresses as a random variable below:

 $(X_{N_{sig}}^{t} - N_{sig})X_{G_{OE}}^{s}X_{G_{nix}}^{s}X_{G_{AGC}}^{s} + (X_{N_{dc}}^{t} - N_{dc}^{p})X_{G_{nix}}^{s}X_{G_{AGC}}^{s} + X_{C_{AGC}}^{s}$ 

The variance of this random variable is:

$$Var = (\sigma_{sig}^2 G_{QE}^2 G_{pix}^2 + \sigma_{sig}^2 \sigma_{G_{QE}}^2 G_{G_{pix}}^2 + \sigma_{sig}^2 G_{QE}^2 \sigma_{G_{pix}}^2 + \sigma_{sig}^2 \sigma_{G_{QE}}^2 \sigma_{G_{pix}}^2 + N_{dc}^p \sigma_{G_{pix}}^2 + N_{dc}^p G_{pix}^2 + \sigma_{read-AGC}^2)G_{AGC}^2 + \sigma_{read-AGC}^2$$

$$\approx (\sigma_{sig}^2 G_{QE}^2 G_{pix}^2 + N_{dc}^p G_{pix}^2 + \sigma_{read-FD}^2)G_{AGC}^2 + \sigma_{read-AGC}^2$$

We can see that when omitting high-order terms, the noise is the same as that without any FPN. So in general we can say that the so-obtained image is FPN-free. Alternatively, we can say that given a uniform illumination D, the pixel value differences in the image are due only to temporal noises.

$$G_{pix}^{p}G_{AGC}^{p} + X_{V_{read-pix}}^{t}G_{AGC}^{p} + X_{V_{read-AGC}}^{t}]$$

$$(G_{AGC}^{p})^{2} + \sigma_{V_{read-AGC}}^{2}$$

$$X_{V_{read-pix}}^{t} X_{G_{AGC}}^{s} + X_{V_{read-AGC}}^{t} \qquad Var(X_{1}X_{2}\cdots X_{n}) = \prod_{i=1}^{n} (\sigma_{i}^{2} + \mu_{i}^{2}) - \prod_{i=1}^{n} (\sigma_{i}^$$







#### **Dark-Frame Subtraction to Remove DSNU**



1. Under the same illumination level D, take N captures and average them pixel-wise; this effectively calculates the expected value of a composite random variable for each pixel:

 $E[((X_{N_{sig}}^{t}G_{OE}^{p} + X_{N_{dc}}^{t})G_{pix}^{p} + X_{V_{read-pix}}^{t} + V_{pix-ofs}^{p})G_{AGC}^{p} + X_{V_{re}}^{t}]$ 

When the illumination is 0, the frame is called a *dark frame*. After averaging above what we get is essentially a DSNU pattern (including both DCNU and SONU) under a given exposure time. Figure 3 of this article obtains the DSNU pattern under an 1ms exposure time by averaging 16 dark frames.

 $(N^{p}_{dc}G^{p}_{pix} + V^{p}_{pix-ofs})G^{p}_{AGC} + V^{p}_{col-ofs}$ 

If the exposure time is set to 0, each capture is called a *bias frame*. Figure 2 of this article is obtained by averaging 100 bias frames. In an averaged bias frame, the voltage reading of each pixel is (no dark current):

 $V^p_{pix-ofs}G^p_{AGC} + V^p_{col-ofs}$ 

$$_{ead-AGC} + V^{p}_{col-ofs}] = ((N_{sig}G^{p}_{QE} + N^{p}_{dc})G^{p}_{pix} + V^{p}_{pix-ofs})G^{p}_{AGC} + V^{p}_{col-ofs})G^{p}_{AGC} + V^{p}_{CO} + V$$





-ofs

#### **Dark-Frame Subtraction to Remove DSNU**

2. We take a capture of a scene of interest with an exposure time T, and subtract, pixel-wise, the averaged dark frame obtained at T. The voltage reading of each pixel is a random variable:

$$V^{p} = ((X_{N_{sig}}^{t}G_{QE}^{p} + X_{N_{dc}}^{t})G_{pix}^{p} + X_{V_{read-pix}}^{t} + V_{pix-ofs}^{p})G_{AGC}^{p} + X_{V_{read-AGC}}^{t} + V_{col-ofs}^{p} - (N_{dc}^{p}G_{pix}^{p} + V_{pix-ofs}^{p})G_{AGC}^{p} - V_{col-ofs}^{p})$$

$$= X_{N_{sig}}^{t}G_{QE}^{p}G_{pix}^{p}G_{AGC}^{p} + (X_{N_{dc}}^{t} - N_{dc}^{p})G_{pix}^{p}G_{AGC}^{p} + X_{V_{read-pix}}^{t}G_{AGC}^{p} + X_{V_{read-AGC}}^{t})$$

The expected value of this random variable (which can be approximated by averaging multiple frames) is the true signal without dark current and voltage offsets, but PRNU is still there. In other words, the noise in the frame is due only to PRNU.

#### $E[V^p] = N_{sig}G^p_{OE}G^p_{pix}G^p_{AGC}$

It's called <u>dark-frame subtraction</u>, which eliminates dark current noise and SONU. In astrophotography, it's called <u>dark</u> <u>current and bias correction</u> (bias being the constant voltage offsets in our language). Note that it removes the impact of dark current altogether (both DCNU and the shot noise of dark current). That's why it's often used in astrophotography, where the exposure time is usually excessively long.

Two things need to be noted. First, the dark frame to be subtracted must be taken under the same exposure time as the intended capture. Second, dark-frame subtraction does not eliminate FPN (which is a common misconception in online articles) because PRNU is still there.





## **Noise Analyses Using Dark Frames and Bias Frames**

Here are a few interesting things we can do now that we have dark and bias frames. 1: If we subtract an averaged bias frame from a single bias frame and plot the pixel value histogram (or plot the histogram) over multiple frames), what we get is the output-referred read noise distribution of the sensor.

Alternatively, we could also just plot the histogram of a single bias frame, in which case we will see a Gaussian with a nonzero mean, where the mean is due to the constant pixel/column voltage biases, but the distribution still shows read noise.



 $(X_{V_{read-pix}}^{t} + V_{pix-ofs}^{p})G_{AGC}^{p} + X_{V_{read-AGC}}^{t} + V_{col-ofs}^{p} - (V_{pix-ofs}^{p}G_{AGC}^{p} + V_{col-ofs}^{p}) = X_{V_{read-pix}}^{t}G_{AGC}^{p} + X_{V_{read-AGC}}^{t}$ 

• Gaussian read noise distribution measured in raw values of a single bias frame for the Olympus E-M1 at a selection of high ISO settings.

• The distributions are centered at the DN = 256, which shows the bias offset added by the sensor (ADC bias or other pixel/column offsets). Without no bias/offset, the negative values will be clipped to 0.

• The std increases with the ISO setting, because the ISO setting dictates the gain, which amplifies the variance (noise).

 Strictly speaking, the distribution is not purely from read noise, as PRNU/ SONU are still there. Subtracting the averaged bias frame eliminates SONU.



#### **Noise Analyses Using Dark Frames and Bias Frames**

2: If we subtract an averaged bias frame from an averaged dark frame, what we get is the dark current component of each pixel or, more specifically, the expected value of output-referred dark current-induced voltage of a pixel:

 $(N^{p}_{dc}G^{p}_{pix} + V^{p}_{pix-ofs})G^{p}_{AGC} + V^{p}_{col-ofs} - (V^{p}_{pix-ofs}G^{p}_{AGC} + V^{p}_{col-ofs}) = N^{p}_{dc}G^{p}_{pix}G^{p}_{AGC}$ 

3: Take a look at the expected value of a pixel after dark-frame subtraction (i.e., averaging over multiple frames with dark frame subtraction), what we get is the PRNU distribution of the sensor, because the noise in the frame is due only to PRNU.

 $E[V^p] = N_{sig}G^p_{OE}G^p_{pix}G^p_{AGC}$ 

We can see that the affect of PRNU is dependent on the illumination level (incident irradiance and exposure time).





#### **Flat-Field Correction to Remove Noise**

- 1. Take a raw capture of a scene of interest
- 2. Obtain an averaged dark frame
- 3. Obtain an averaged <u>flat-field frame</u>, i.e., averaging frames under uniform illumination
- 4. Obtain dark noise and bias-corrected flat-field frame
- 5. Calculate the pixel average of the corrected flat-field frame  $m = N_{sig}G_{OE}G_{pix}G_{AGC}$
- 6. Obtain dark noise and bias-corrected raw frame  $R D = X_{N_{sig}}^t G_{OE}^p G_{pix}^p G_{AGC}^p + (X_{N_{dc}}^t N_{dc}^p) G_{pix}^p G_{AGC}^p + X_{V_{read-pix}}^t G_{AGC}^p + X_{V_{read-AGC}}^t + X_{V_{read-AGC$
- 7. Calculate the final, calibrate image. After frame averaging, the only noise is photon shot noise
  - $\frac{(R-D)m}{F-D} = \frac{X_{N_{sig}}^{t}G_{QE}^{p}G_{pix}^{p}G_{AGC}^{p} + (X_{N_{dc}}^{t} N_{dc}^{p})G_{pix}^{p}G_{AGC}^{p} + X_{V_{read-pix}}^{t}G_{AGC}^{p} + X_{V_{read-AGC}}^{t} \times N_{sig}G_{QE}G_{pix}G_{AGC}}{N_{sig}G_{QE}^{p}G_{pix}^{p}G_{AGC}^{p}}$  $= X_{N_{sig}}^{t}G_{QE}G_{pix}G_{AGC} + (X_{N_{dc}}^{t} - N_{dc}^{p})\frac{G_{QE}}{G_{QE}^{p}}G_{pix}G_{AGC} + X_{V_{read-pix}}^{t}\frac{G_{QE}G_{pix}}{G_{QE}^{p}G_{pix}^{p}}G_{AGC} + X_{V_{read-AGC}}^{t}\frac{G_{QE}G_{pix}G_{AGC}}{G_{QE}^{p}G_{pix}^{p}G_{AGC}}$  $E[\frac{(R-D)m}{F-D}] = X_{N_{sig}}^t G_{QE} G_{pix} G_{AGC}$

 $R = ((X_{N_{sig}}^{t}G_{OE}^{p} + X_{N_{dc}}^{t})G_{pix}^{p} + X_{V_{read-pix}}^{t} + V_{pix-ofs}^{p})G_{AGC}^{p} + X_{V_{read-AGC}}^{t} + V_{col-ofs}^{p})$  $D = (N^p_{dc}G^p_{pix} + V^p_{pix-ofs})G^p_{AGC} + V^p_{col-ofs}$ 

 $F = ((N_{sig}G^p_{OE} + N^p_{dc})G^p_{pix} + V^p_{pix-ofs})G^p_{AGC} + V^p_{col-ofs})$ 

$$F - D = N_{sig} G^p_{QE} G^p_{pix} G^p_{AGC}$$

\* See <u>flat-field images</u> taken by the telescope at the Mees Observatory 76







Described by Emil Martinec here, which is very similar to the EMVA Standard 1288 (Release 4.0), which is a black-box model that doesn't specify the exact analytical form of the noise being measured, which we show here. Ignore dark current and DCNU. 1. Take two captures under uniform illumination D; voltages of the same pixel in the two images:

 $(X_{N_{sio}}^{\iota}G_{OE}^{\rho}G_{pix}^{\rho} + X_{V_{read-nix}}^{\iota} + V_{pix-ofs}^{\rho})G_{AGC}^{\rho} + X_{V_{read-AGC}}^{\iota} + V_{col}^{\rho}$  $(Y_{N_{sig}}^{t}G_{OE}^{p}G_{pix}^{p}+Y_{V_{read-pix}}^{t}+V_{pix-ofs}^{p})G_{AGC}^{p}+Y_{V_{read-AGC}}^{t}+V_{col}^{p}$ 

2. Subtract the two images pixel-wise; each pixel is expressed as:

 $((X_{N_{sig}}^{t} - Y_{N_{sig}}^{t})G_{OE}^{p}G_{pix}^{p} + (X_{V_{read-pix}}^{t} - Y_{V_{read-pix}}^{t}))G_{AGC}^{p} + (X_{V_{read-AGC}}^{t} - Y_{V_{read-AGC}}^{t})$ 

3. Now we want to calculate the variance across all pixels in this residual image, in which case FPN terms become random variables. So the voltage of each pixel in the residual image is expressed as a new random variable:

$$((X_{N_{sig}}^{t} - Y_{N_{sig}}^{t})X_{G_{QE}}^{s}X_{G_{pix}}^{s} + (X_{V_{read-pix}}^{t} - Y_{V_{read-pix}}^{t}))X_{G_{AGC}}^{s} + (X_{V_{read-pix}}^{s})X_{G_{AGC}}^{s} + (X_{V_{read-pix}}^{s})X_{G_{QE/pix/AGC}}^{s} \sim N(\mu = G_{QE/pix/AGC}, \ \sigma = \sigma_{G_{QE/pix/AGC}})$$

Note that it's incorrect to use the following random variable, which assumes we sample both temporally AND spatially before subtraction; instead, we sample temporally, subtract, and then sample spatially.

 $(X_{N_{sig}}^{t}X_{G_{OE}}^{s}X_{G_{pix}}^{s} + X_{V_{read-pix}}^{t} + V_{pix-ofs}^{p})X_{G_{AGC}}^{s} + X_{V_{read-AGC}}^{\iota} + V_{col-c}^{p}$ 

$$\begin{cases} Dl - ofs \\ N_{sig}, Y_{N_{sig}}^{t}, Y_{N_{sig}}^{t} \sim \text{Poisson}(\mu = N_{sig}, \sigma = \sigma_{sig} = \sqrt{N_{sig}}) \\ X_{V_{read-FD/read-SF/read-AGC}}^{t}, Y_{V_{read-FD/read-SF/read-AGC}}^{t} \sim N(\mu = 0, \sigma = \sigma_{V_{read-FD/read-SF/read-SF/read-SF/read-AGC}) \end{cases}$$

 $X_{V_{read-AGC}}^{t} - Y_{V_{read-AGC}}^{t})$ 

$$O_{ofs} - ((Y_{N_{sig}}^{t}X_{G_{QE}}^{s}X_{G_{pix}}^{s} + Y_{V_{read-pix}}^{t} + V_{pix-ofs}^{p})X_{G_{AGC}}^{s} + Y_{V_{read-AGC}}^{t} + V_{col}^{p}$$







4. Now calculate the variance across N pixels. Assuming N is sufficiently large, the sample variance approaches the population variance, which is expressed as:

 $Var[((X_{N_{sig}}^{t} - Y_{N_{sig}}^{t})X_{G_{OE}}^{s}X_{G_{pix}}^{s} + (X_{V_{read-pix}}^{t} - Y_{V_{read-pix}}^{t}))X_{G_{AGC}}^{s}$ 

5. Ignore high-order terms, the variance turns out to be exactly the output-referred temporal noise without any FPN:

 $\approx (2\sigma_{sig}^2 G_{OE}^2 G_{pix}^2 + 2\sigma_{read-pix}^2)G_{AGC}^2 + 2\sigma_{read-AGC}^2$  $= 2\sigma_{output-referred-temporal-noise}^{2}$ 

It is worth noting that this methodology to estimate temporal noise is almost exactly the same as that used in the <u>EMVA</u> Standard 1288 (see Equation 18) with one caveat: the EMVA standard also subtracts the difference of the mean values of the two images, which in the ideal case should be exactly the same. The standard does this correction to give "an unbiased estimate even if the mean values are slightly different by a temporal noise source that causes all pixels to fluctuate in sync."

$$\left[ + \left( X_{V_{read}-AGC}^t - Y_{V_{read}-AGC}^t \right) \right]$$

$$Var(X - Y) = Var(X) + Var(Y)$$

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6. Look at the temporal noise expression, we can see that the temporal noise scales linearly with the illumination level ( $N_{siq}$ ) and has a constant intercept, which is the read noise.

 $\sigma_{output-referred-temporal-noise}^{2} \approx \sigma_{sig}^{2} G_{QE}^{2} G_{pix}^{2} G_{AGC}^{2} + \sigma_{read-pix}^{2} G_{AGC}^{2} + \sigma_{read-AGC}^{2}$ 

Output-referred photon shot noise; increases linearly Output-referred read noise; a constant with  $\sigma^{2}_{sig} = N_{sig}$ , which is the incident photon count w.r.t. to incident photon count

But ultimately what we can measure is in ADU/DN, so we have to consider ADC and its gain, in which case the output-referred temporal noise, now in the unit of ADU/DN, is expressed as:

 $= N_{sig}G_{QE}^2G_{pix}^2G_{AGC}^2G_{ADC}^2 + \sigma_{read}^2 = (N_{sig}G_{QE}G_{pix}G_{AGC}G_{ADC})G_{QE}G_{pix}G_{AGC}G_{ADC} + \sigma_{read}^2$ 

 $= N_{ADU}G + \sigma_{read}^2$ 

 $= N_{sig}G_{OE}^2G_{pix}^2G_{AGC}^2 + \sigma_{read}^2$ 

 $\sigma_{output-referred-temporal-noise}^{2} \approx \sigma_{sig}^{2} G_{QE}^{2} G_{pix}^{2} G_{AGC}^{2} G_{ADC}^{2} + (\sigma_{read-pix}^{2} G_{AGC}^{2} G_{ADC}^{2} + \sigma_{read-AGC}^{2} G_{ADC}^{2} + \sigma_{read-AGC}^{2} G_{ADC}^{2} + \sigma_{ADC}^{2})$ 

 $N_{sig} \mathbf{G} = N_{ADU}$  **G**; unit is ADU/photon







To estimate the read noise, we regress a linear function of output-referred temporal noise vs. ADU under different illumination levels. The ADU is calculated by first adding the two frames together, calculating the mean raw value, and divide that by two.

The intercept of the linear function is the best-fit read noise. The slope of the linear function has a unit of ADU/photon, i.e., how many ADUs are increased for one photon, which is sometimes called the "conversion factor" and is proportional to the ISO and inversely proportional to the overall gain (how many incident photons are needed to increase ADU by 1).

Note that  $N_{sig} G = N_{ADU}$  is true only when all noises are eliminated. This is not achieved in what's described above, which includes the voltage offset (below), and that's why Martinec's article says we need to subtract the bias when calculating NADU.

$$N_{sig}G + V_{pix-ofs}G_{AGC}G_{ADC} + V_{col-ofs}G_{ADC}$$

 $= N_{ADU}G + \sigma_{read}^2$ 

 $\sigma_{output-referred-temporal-noise}^{2} \approx N_{sig}G_{QE}^{2}G_{pix}^{2}G_{AGC}^{2}G_{ADC}^{2} + \sigma_{read}^{2} = (N_{sig}G_{QE}G_{pix}G_{AGC}G_{ADC})G_{QE}G_{pix}G_{AGC}G_{ADC} + \sigma_{read}^{2}$ 

 $N_{sig} \mathbf{G} = N_{ADU}$  **G**; unit is ADU/photon





7: To calculate FPN, take a capture and calculate its the pixel variance, and subtract the temporal noise calculated before. Intuitively, the capture has FPN+temporal noise, from which we subtract the temporal noise. What we are calculating is:

$$Var\{(Z_{N_{sig}}^{t}Z_{G_{QE}}^{s}Z_{G_{pix}}^{s} + Z_{V_{read-pix}}^{t} + Z_{V_{pix-q5}}^{s})Z_{G_{AGC}}^{s} + Z_{V_{read-AGC}}^{t} + Z_{V_{col-of5}}^{s}\} - \frac{Var[((X_{N_{sig}}^{t} - Y_{N_{sig}}^{t})X_{G_{QE}}^{s}X_{G_{pix}}^{s} + (X_{V_{read-pix}}^{t} - Y_{V_{read-pix}}^{t})X_{G_{AGC}}^{s} + (X_{V_{read-AGC}}^{t} - Y_{V_{read-AGC}}^{t}) - \frac{2}{2}$$

$$= N_{sig}^{2}\sigma^{2}(Z_{G_{QE}}^{s}Z_{G_{pix}}^{s}Z_{G_{AGC}}^{s}) + \sigma^{2}(Z_{pix-ofs}^{s}Z_{G_{AGC}}^{s}) + \sigma^{2}_{col-of5}$$
In fact, we get the overall output-referred FPN, not just PRNU as the article describes, and the results are exact, i.e., no omission of high-order terms.
$$\begin{cases} Z_{N_{sig}}^{t} \sim Poisson(\mu = N_{sig}, \sigma = \sigma_{sig} = \sqrt{N_{sig}}) \\ Z_{V_{read-FD/read-SF/read-AGC}}^{t} \sim N(\mu = 0, \sigma = \sigma_{V_{read-FD/read-SF/read-AGC}}) \\ X_{G_{QED/pis/AGC}}^{s} \sim N(\mu = G_{QE/pix/AGC}, \sigma = \sigma_{G_{QE/pis/AGC}}) \\ X_{V_{pix-ofs/col-ofs}}^{s} \sim N(\mu = V_{pix-ofs/col-ofs}, \sigma = \sigma_{V_{pix-ofs/col-ofs}}) \end{cases}$$

This method to estimate FPN is exactly the same as that used in the <u>EMVA Standard 1288</u> (see Equations 16, 17, 18, 27). We can report the FPN directly using the std (e<sup>-</sup> for input-referred noise or mV for output-referred noise) or as the ratio of std/ full-well capacity or std/voltage swing, which then is a % number.

 $\sqrt{N_{sig}^2 \sigma^2 (Z_{G_{QE}}^s Z_{G_{pix}}^s Z_{G_{AGC}}^s) + \sigma^2 (Z_{pix-ofs}^s Z_{G_{AGC}}^s) + \sigma_{col-ofs}^2}$ FPN = - $FWC \times G_{Pix}G_{AGC}$ 







#### **Another FPN Estimation**

1. Under the same illumination level D, take N captures and average them pixel-wise; this effectively calculates the expected value of a composite random variable for each pixel:

 $E[((X_{N_{sig}}^{t}G_{OE}^{p} + X_{N_{dc}}^{t})G_{pix}^{p} + X_{V_{read-pix}}^{t} + V_{pix-ofs}^{p})G_{AGC}^{p} + X_{V_{re}}^{t}]$ 

2. Calculate the standard deviation/variance across all the M pixels in the averaged frame obtained before. Given that M and N are sufficiently large, this effectively calculates the standard deviation/variance of a composite random variable:

 $Var[((N_{sig}X_{G_{OE}}^{s} + X_{N_{dc}}^{s})X_{G_{nix}}^{s} + X_{V_{nix-ofs}}^{s})X_{G_{AGC}}^{s} + X_{V_{col-ofs}}^{s}]$  $= N_{sig}^{2} \sigma^{2} (X_{G_{OF}}^{s} X_{G_{niv}}^{s} X_{G_{AGC}}^{s}) + \sigma^{2} (X_{N_{dc}}^{s} X_{G_{niv}}^{s} X_{G_{AGC}}^{s}) + \sigma^{2} (X_{V_{niv-ofs}}^{s} X_{G_{AGC}}^{s}) + \sigma^{2} (X_{V_{ni-ofs}}^{s}) + \sigma$ 

This is the same procedure as a method described in <u>EMVA Standard 1288</u> (see Equations 28). The standard isn't very clear about the difference in applicability of the two methods (subtracting two images vs. averaging over multiple images).

$$_{ead-AGC} + V^{p}_{col-ofs}] = ((N_{sig}G^{p}_{QE} + N^{p}_{dc})G^{p}_{pix} + V^{p}_{pix-ofs})G^{p}_{AGC} + V^{p}_{col-ofs})G^{p}_{AGC} + V^{p}_{col-ofs}$$

$$\begin{cases} X_{G_{QE/FD/SF/AGC}}^{s} \sim N(\mu = G_{QE/FD/SF/AGC}, \sigma = \sigma_{G_{QE/FD/SF}}, S) + \sigma_{V_{pix-ofs/col-ofs}}^{2} \sim N(\mu = V_{pix-ofs/col-ofs}, \sigma = \sigma_{V_{pix-ofs/col-ofs}}, S) \\ X_{N_{dc}}^{s} \sim N(\mu = N_{dc}, \sigma = \sigma_{N_{dc}}) \end{cases}$$











Dynamic Range



sense the brightness and the darkest points of a scene.

**DR** is a single number characterizing the ability of a camera to simultaneously



# $DR = \frac{Maximal\ signal}{Noise\ floor} = \frac{Full\ well\ capacity}{\sigma_{read}}$

**DR** is a single number characterizing the ability of a camera to simultaneously sense the brightness and the darkest points of a scene.



 $DR = \frac{Maximal\ signal}{Noise\ floor} = \frac{Full\ well\ capacity}{\sigma_{read}}$ 

# of electrons sensed in the dark, i.e., when no incident photon

**DR** is a single number characterizing the ability of a camera to simultaneously sense the brightness and the darkest points of a scene.

 $\sigma_{read}$ 



 $DR = \frac{Maximal\ signal}{Noise\ floor} = \frac{Full\ well\ capacity}{\sigma_{read}}$ 

# of electrons sensed in the dark, i.e., when no incident photon

sense the brightness and the darkest points of a scene.





 $\sigma_{read}$ 

# **DR** is a single number characterizing the ability of a camera to simultaneously



The max signal record when a pixel is saturated  $DR = \frac{Maximal\ signal}{Noise\ floor} = \frac{Full\ well\ capacity}{\sigma_{read}}$  $\sigma_{read}$ Std. of read noise

# of electrons sensed in the dark, i.e., when no incident photon

sense the brightness and the darkest points of a scene.

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The max signal record when a pixel is saturated  $DR = \frac{Maximal\ signal}{Noise\ floor} = \frac{Full\ well\ capacity}{\sigma_{read}}$  $\sigma_{read}$  . Std. of read noise # of electrons sensed in the dark,

i.e., when no incident photon

**DR** is a single number characterizing the ability of a camera to simultaneously sense the brightness and the darkest points of a scene.

Ideally: maximal signal is full-well capacity; minimal signal: 0



 $DR = \frac{Maximal\ signal}{Noise\ floor} = \frac{Full\ well\ capacity}{\sigma_{read}}$ # of electrons sensed in the dark,

i.e., when no incident photon

sense the brightness and the darkest points of a scene.

Ideally: maximal signal is full-well capacity; minimal signal: 0

Bigger sensors improve DR, as we saw before.





- **DR** is a single number characterizing the ability of a camera to simultaneously



## **Dynamic Range and Signal to Noise Ratio**

High DR doesn't mean less noisy.

**DR** is a single number characterizing the ability of a camera to simultaneously sense the brightness and the darkest points of a scene.

**SNR** varies with light levels. At a given light level, the SNR characterizes "how noisy" the image it.

Higher light level leads to higher SNR.



Consider only photon shot noise and read noise and ignore dark-current noise here.

Image Sensor and Signal Processing for Digital Still Cameras, 2006. Junichi Nakamura





#### **DR and SNR Units**

Often DR and SNR are expressed in decibel or "stop".

 $SNR_{dB} = 20log_{10}(SNR)$ 

 $DR_{dB} = 20log_{10}(DR)$ 

 $SNR_{stop} = log_2(SNR)$ 

 $DR_{stop} = log_2(DR)$ 

https://en.wikipedia.org/wiki/Dynamic\_range

Factor (power)	Decibels	Stops
1	0	
2	3.01	
3.16	5	1.
4	6.02	
5	6.99	2.
8	9.03	
10	10	3.
16	12.0	
20	13.0	4.
31.6	15	4.
32	15.1	
50	17.0	5.
100	20	6.
1000	30	9.
1024	30.1	
10000	40	13
100000	50	16
100000	60	19
1048576	60.2	
10000000	80	26
1073741824	90.3	
100000000	100	33





## **Typical Dynamic Range**

Input "device": (maximal signal/noise floor)

- Smartphone camera: 10 stops (iPhone 11)
- DSLR: 14.8 stops (Sony A7R4)

• Human eyes: 10-14 stops (instantaneous, i.e., when the pupil size doesn't change)



### **Dynamic Range of "Output Devices"**

DR of light-emitting output "devices" is defined slightly differently.



## **Dynamic Range of "Output Devices"**

DR of light-emitting output "devices" is defined slightly differently.

DR = highest illumination/lowest illumination

- Natural scenes: ~20 stops (measurement)
- Typical Display: ~10 stops (LG 27UK850); of course every display you buy touts HDR...
- HDR Display: 14.2 stops (UHD Alliance Certified HDR LCD display)
- Paper: 6-8 stops (typical value); related to pigment density



#### **Output "Device" Illumination**







#### Natural Scenes Have High Dynamic Range



Range of Visible Luminance in Candellas per Meter Squared (cd/m<sup>2</sup>) Log Scale

#### Rendering the Print: the Art of Photography





#### **The Problem**







#### Rendering the Print: the Art of Photography 91



#### **Two Related Tasks in Sensor Signal Processing**



**1. HDR Imaging:** how to capture an HDR scene with a lower DR capturing device. Limited by the camera.

2. Tone Mapping: how to display HDR images on lower DR display devices. Limited by the display medium.





# Color Sensing



#### Goal of Color Sensing



https://9to5mac.com/2017/12/07/iphone-flikr-most-used-camera/ https://www.eyeworld.org/research-finds-human-visual-cortex-continues-development-mid-30s



#### Goal of Color Sensing



https://9to5mac.com/2017/12/07/iphone-flikr-most-used-camera/ https://www.eyeworld.org/research-finds-human-visual-cortex-continues-development-mid-30s

What if this is not true? Metamers in human vision would **not** be metamers in camera vision: colors appearing different to your eyes would look the same in photos and vise versa.





#### **How to Sense Color?**

- How do humans sensor color? We have three types of cones, each has a different **spectral sensitivity** to light.
  - Light spectrum gets transformed to three numbers (L, M, S cone responses, or equivalently the tristimulus values in a color space).

Cameras also need to somehow generate three numbers from light too.

The three values should ideally be the same as the LMS cone responses. • Or can be converted to tristumulus values in one of the known color spaces.

Principle of **univariance**: once a photon is converted to an electron, we lose wavelength/color information (there is no red electron vs. blue electron).




https://www.cs.rochester.edu/courses/572/colorvis/camcolor.html



Effectively we need to have three kinds of sensors, each has a unique spectral sensitivity function (SSF).

SSF(λ): generated electrical energy per unit incident light energy at a given  $\lambda$ .





https://www.cs.rochester.edu/courses/572/colorvis/camcolor.html



#### How should SSFs look like?

- Ideally: each sensor's SSF mimics LMS and XYZ, since CMFs in other color space usually involve negative values that are physically unrealizable.
- **Reality**: hard to be exact. SSF depends on lots of things (sensor quantum efficiency, microlens, filters, manufacturability, etc.).







#### https://www.cs.rochester.edu/courses/572/colorvis/camcolor.html





https://www.cs.rochester.edu/courses/572/colorvis/camcolor.html





### **Astrophysical Imaging Uses More Filters**

Spectral transmittance of the five filters in the first SDSS camera





https://www.asahi-spectra.com/opticalfilters/sdss.html 100



#### An image from SDSS (False Colors)

https://www.iac.es/en/projects/sloan-digital-sky-survey-iii-sdss 101



# Realizing "Three Kinds of Sensors"



#### Take Three Separate Shots and Combined Them



https://www.loc.gov/exhibits/empire/making.html http://www.cs.cmu.edu/afs/cs.cmu.edu/academic/class/15463-f11/www/proj1/www/machongm/ 103





1906 by Dr. Adolf Miethe

Sergey Prokudin-Gorsky (1836 — 1944)





#### **Use Three Sensors**

Use three sensors



Figure 14.3 (a) Three-sensor camera. (b) Sequential colour camera.

#### Similar to "three shots" (previous slide)

The Manual of Photography and Digital Imaging 10ed, Allen and Triantaphillidou 104



#### **Use Three Sensors**

Use three sensors



Figure 14.3 (a) Three-sensor camera. (b) Sequential colour camera.

https://pro.sony/ue\_US/products/handheld-camcorders/pxw-x180





### **Multi-Chip Sensing in Astrophysics**





https://www.asahi-spectra.com/opticalfilters/sdss.asp

https://www.sdss.org/dr16/imaging/imaging\_basics/ 106



### Vertical Stacking

### Longer-wavelength light penetrates deeper into silicon.



https://www.dpreview.com/articles/1431165397/sigma-dp3-merrill-foveon-75mm-equivalent 107

### **Color Filtering Array**



https://en.wikipedia.org/wiki/Bayer\_filter 108









#### https://pixelcraft.photo.blog/2019/12/18/the-bayer-filter/ 109

### **Color Filtering Array**

the percentage of photons that can get through at each wavelength.



## Each filter has a unique spectral transmittance function, which characterizes



#### **Filters Dim Lights**







### **Reading Sensor Specification: ONSemi NOII4SM6600A**



#### Monochromatic sensor

#### **ELECTRO OPTICAL SPECIFICATIONS**

Parameter	Specification
FPN (local)	<0.20%, 2 LSB10
PRNU (local)	<1.5%
Conversion Gain	43 μV/e⁻
Output Signal Amplitude	0.6 V
Saturation Charge	21500 e⁻
Sensitivity (peak)	411 V.m <sup>2</sup> /W.s 4.83 V/lux.s
Sensitivity (visible)	328 V.m <sup>2</sup> /W.s 2.01 V/lux.s
Peak QE * FF Peak Spectral Response	25% 0.13 A/W
Fill Factor	35%
Dark Current	3.37 mV/s 78 e-/s
Dark Signal Non Uniformity	8.28 mV/s 191 e-/s
Temporal Noise	24 RMS e-
Signal/Noise Ratio	895:1 (40 dB)
Dynamic Range	59 dB
Spectral Sensitivity Range	400 - 1000 nm
Optical Cross Talk	15% 4%
Power Dissipation	225 mW



#### **Reading Sensor Specification: ONSemi KAF-8300**

#### A RGB sensor



Figure 2. Block Diagram (Color)

**Table 6. SPECIFICATIONS** 

Description	Symbol	Min.	Nom.	Max.	Unit
ALL DEVICES					
Minimum Column	MinColumn	575	_	_	mV
Linear Saturation Signal	N <sub>e</sub> - <sub>SAT</sub>	25.5	_	_	ke⁻
Charge to Voltage Conversion	Q–V	22.5	23.0	_	μV/e
Linearity Error	LeLow10 LeLow33 LeHigh	-10 -10 -10	- - -	10 10 10	%
Dark Signal (Active Area Pixels)	AA_DarkSig	_	_	200	e⁻/s
Dark Signal (Dark Reference Pixels)	DR_DarkSig	_	_	200	e⁻/s
Readout Cycle Dark Signal	Dark_Read	-	-	15	mV/s
Flush Cycle Dark Signal	Dark_Flush	_	43	90	mV/s
Dark Signal Non-Uniformity	DSNU DSNU_Step DSNU_H	- - -	1.30 0.14 0.40	3.0 0.5 1.0	mV p-
Dark Signal Doubling Temperature	ΔΤ	-	5.8	-	°C
Dark Reference Difference, Active Area	DarkStep	-3.5	0.15	3.5	mV
Total Noise	Dfld_noi	-	-	1.08	mV
Total Sensor Noise	N	_	16	_	e⁻ rm
Linear Dynamic Range	DR	_	64.4	_	dB
Horizontal Charge Transfer Efficiency	HCTE	0.999990	0.999995	_	%
Vertical Charge Transfer Efficiency	VCTE	0.999997	0.999999	-	%
Blooming Protection	X_b	1,000	-	-	x E <sub>SA</sub>
Vertical Bloom on Transfer	VBloomF	-20	-	20	mV
Horizontal Crosstalk	H_Xtalk	-20	_	20	mV
Horizontal Overclock Noise	Hoclk_noi	0	-	1.08	mV
Output Amplifier Bandwidth	f <sub>-3dB</sub>	88	_	159	MHz
Output Impedance, Amplifier	R <sub>OUT</sub>	100	_	180	Ω
Hclk Feedthru	V <sub>HFT</sub>	-	-	70	mV
Reset Feedthru	V <sub>RFT</sub>	500	710	1,000	mV

1 Active (CTE Mc 3 Dark Dummy 4 Blue Pixel Buffe 16 Active Buffer V1 V2 2504 Act LODT LODB - H1 H2 16 Active Buff 4 Blue Pixel Bu 8 Dark Dumm 12 Dark 6 Dark Dumm



#### **Reading Sensor Specification: ONSemi KAF-8300**

1 Active (CTE Mc 3 Dark Dummy 4 Blue Pixel Buffe 16 Active Buffer

> V1 V2

2504

Act

LODT LODB

- H1 H2

16 Active Buff

4 Blue Pixel Bu

8 Dark Dumm

6 Dark Dumm

12 Dark

#### A RGB sensor



Figure 2. Block Diagram (Color)

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ALL DEVICES					
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Charge to Voltage Conversion	Q–V	22.5	23.0	_	μV/e
Linearity Error	LeLow10 LeLow33 LeHigh	-10 -10 -10	- - -	10 10 10	%
Dark Signal (Active Area Pixels)	AA_DarkSig	_	_	200	e⁻/s
Dark Sig				200	e⁻/s
Readou Dark curre	nt halves	as the	Э	15	mV/s
Flush C temperature	drons h	v 5 8°	<u> </u>	90	mV/s
Dark Sig	DSNU_Step DSNU_H		0.14 0.40	3.0 0.5 1.0	mV p-
Dark Signal Doubling Temperature	ΔΤ	_	5.8	_	°C
Dark Reference Difference, Active Area	DarkStep	-3.5	0.15	3.5	mV
Total Noise	Dfld_noi	_	_	1.08	mV
Total Noise Total Sensor Noise	Dfld_noi N	-	- 16	1.08 -	mV e⁻ rma
Total Noise Total Sensor Noise Linear Dynamic Range	Dfld_noi N DR	- - -	- 16 64.4	1.08 _ _	mV e⁻ rma dB
Total NoiseTotal Sensor NoiseLinear Dynamic RangeHorizontal Charge Transfer Efficiency	Dfld_noi N DR HCTE	- - 0.999990	- 16 64.4 0.999995	1.08 _ _ _	mV e⁻ rm dB %
Total NoiseTotal Sensor NoiseLinear Dynamic RangeHorizontal Charge Transfer EfficiencyVertical Charge Transfer Efficiency	Dfld_noi N DR HCTE VCTE	- - 0.999990 0.999997	- 16 64.4 0.999995 0.999999	1.08 - - -	mV e⁻ rm dB %
Total NoiseTotal Sensor NoiseLinear Dynamic RangeHorizontal Charge Transfer EfficiencyVertical Charge Transfer EfficiencyBlooming Protection	Dfld_noi N DR HCTE VCTE X_b	- - 0.999990 0.999997 1,000	- 16 64.4 0.999995 0.999999	1.08 - - - - -	mV e⁻ rm dB % % x E <sub>SA</sub>
Total NoiseTotal Sensor NoiseLinear Dynamic RangeHorizontal Charge Transfer EfficiencyVertical Charge Transfer EfficiencyBlooming ProtectionVertical Bloom on Transfer	Dfld_noi N DR HCTE VCTE X_b VBloomF	- - 0.999990 0.999997 1,000 -20	- 16 64.4 0.999995 0.999999 - -	1.08 - - - - 20	mV e⁻ rm dB % % x E <sub>SA</sub> mV
Total NoiseTotal Sensor NoiseLinear Dynamic RangeHorizontal Charge Transfer EfficiencyVertical Charge Transfer EfficiencyBlooming ProtectionVertical Bloom on TransferHorizontal Crosstalk	Dfld_noi N DR HCTE VCTE X_b VBloomF H_Xtalk	- - 0.999990 0.999997 1,000 -20 -20	- 16 64.4 0.999995 0.999999 - - - -	1.08 - - - 20 20	mV e⁻ rm dB % % x E <sub>SA</sub> mV mV
Total NoiseTotal Sensor NoiseLinear Dynamic RangeHorizontal Charge Transfer EfficiencyVertical Charge Transfer EfficiencyBlooming ProtectionVertical Bloom on TransferHorizontal CrosstalkHorizontal Overclock Noise	Dfld_noi N DR HCTE VCTE X_b VBloomF H_Xtalk Hoclk_noi	- - 0.999990 0.999997 1,000 -20 -20 0	- 16 64.4 0.999995 0.999999 - - - - -	1.08 - - - - 20 20 1.08	mV e⁻ rm dB % % x E <sub>SA</sub> mV mV mV
Total NoiseTotal Sensor NoiseLinear Dynamic RangeHorizontal Charge Transfer EfficiencyVertical Charge Transfer EfficiencyBlooming ProtectionVertical Bloom on TransferHorizontal CrosstalkHorizontal Overclock NoiseOutput Amplifier Bandwidth	Dfld_noi N DR HCTE VCTE X_b VBloomF H_Xtalk Hoclk_noi f_3dB	- - 0.999990 0.999997 1,000 -20 -20 0 88	- 16 64.4 0.999995 0.999999 - - - - - -	1.08 - - - - 20 20 1.08 159	mV e⁻ rm dB % % x E <sub>SA</sub> mV mV mV
Total NoiseTotal Sensor NoiseLinear Dynamic RangeHorizontal Charge Transfer EfficiencyVertical Charge Transfer EfficiencyBlooming ProtectionVertical Bloom on TransferHorizontal CrosstalkHorizontal Overclock NoiseOutput Amplifier BandwidthOutput Impedance, Amplifier	Dfld_noi N DR HCTE VCTE X_b VBloomF H_Xtalk Hoclk_noi f_3dB R <sub>OUT</sub>	- - 0.999990 0.999997 1,000 -20 -20 0 88 100	- 16 64.4 0.9999995 0.9999999 - - - - - - - - - -	1.08 - - - - 20 20 1.08 159 180	mV e <sup>-</sup> rm dB % % x E <sub>SA</sub> mV mV mV mV
Total NoiseTotal Sensor NoiseLinear Dynamic RangeHorizontal Charge Transfer EfficiencyVertical Charge Transfer EfficiencyBlooming ProtectionVertical Bloom on TransferHorizontal CrosstalkHorizontal Overclock NoiseOutput Amplifier BandwidthOutput Impedance, AmplifierHclk Feedthru	Dfld_noi N DR HCTE VCTE X_b VBloomF H_Xtalk Hoclk_noi f_3dB R <sub>OUT</sub> V <sub>HFT</sub>	- - 0.999990 0.999997 1,000 -20 -20 0 88 100 -	- 16 64.4 0.9999995 0.9999999	1.08 - - - 20 20 1.08 159 180 70	mV e <sup>-</sup> rm dB % % x E <sub>SA</sub> mV mV mV mV MHz Ω mV



### **Reading Sensor Specification: ONSemi KAF-8300**

#### The two green filters have slightly different spectral sensitivities!



KAF-8300 Quantum Efficiency

Figure 7. Typical Quantum Efficiency (Color Version)

Having microlenses improves spectral sensitivities because the FF improves!

**KAF-8300 Quantum Efficiency** 

Figure 8. Typical Quantum Efficiency (All Monochrome Versions)

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### **Reading Sensor Specification: Teledyne Prime-95B**

Being a scientific image sensor, the noise performance is much better

Specifications	Camera Performance	Camera Performance		
Sensor	GPixel GSense 144 BSI CMOS Ge	GPixel GSense 144 BSI CMOS Gen IV, Grade 1 in imaging area		
Active Array Size	1200 x 1200 pixels (1.44 Megapix	1200 x 1200 pixels (1.44 Megapixel)		
Pixel Area	11µm x 11µm (121µm²)			
Sensor Area	13.2mm x 13.2mm 18.7mm diagonal			
Peak QE%	>95%			
Read Noise	1.6e- (Median) 1.8e- (RMS)			
Full-Well Capacity	80,000e- (Combined Gain) 10,000e- (High Gain)			
Dynamic Range	50,000:1 (Combined Gain)			
Bit Depth	16-bit (Combined Gain) 12-bit (High Gain)			
Readout Mode	Rolling Shutter Effective Global Shutter			
Binning	2x2 (on FPGA)			
Linearity	>99.5%			
Cooling Performance	Sensor Temperature	Dark Current		
Air Cooled	-20°C @ 25°C Ambient	0.55e-/pixel/second		
Liquid Cooled	-25°C a 25°C Ambient	0.3e-/pixel/second		



