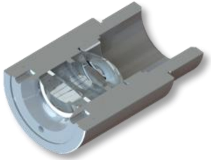

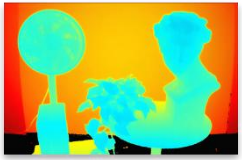

GAMES 204

Computational Imaging

Lecture 10: Image Noise Formation

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点昀技术（Point Spread Technology）

Today's Topic

- Sensor Noise Formation
- Signal-to-Noise Ratio (SNR)
- Noise Calibration
- Optimal Weights for HDR Merging

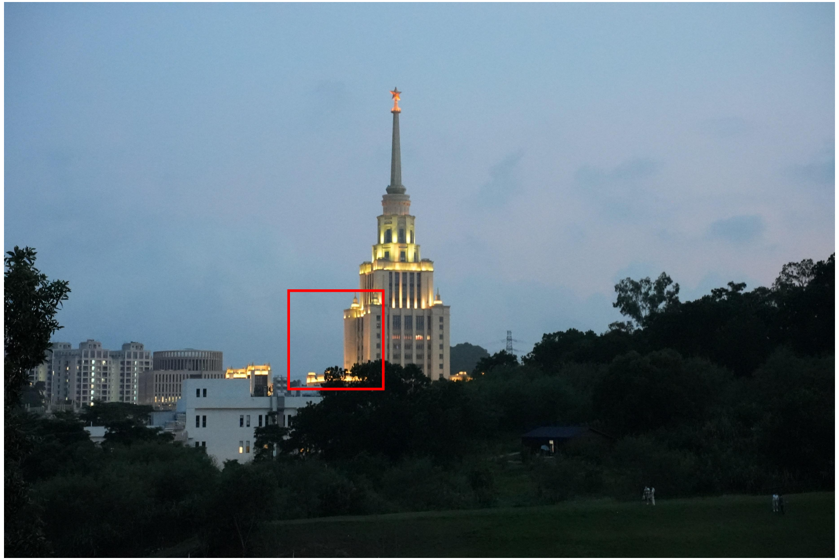
Sensor Noise

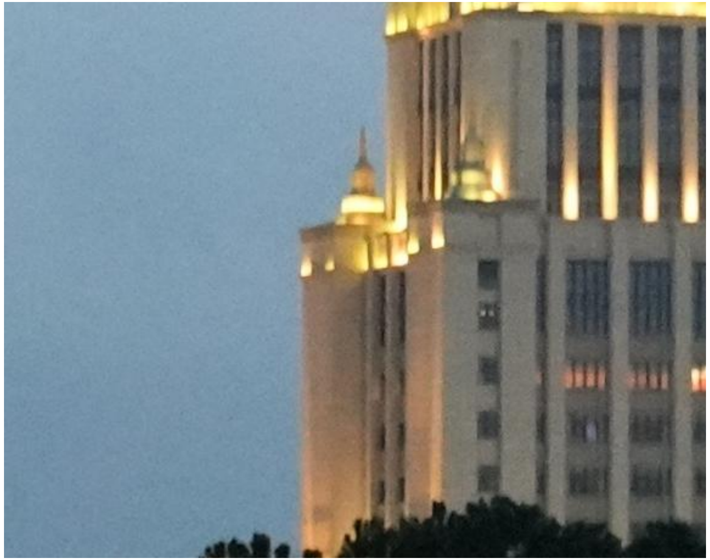
We will only consider per-pixel noise.

We will not consider cross-pixel noise effects (blooming, smearing, cross-talk, and so on).

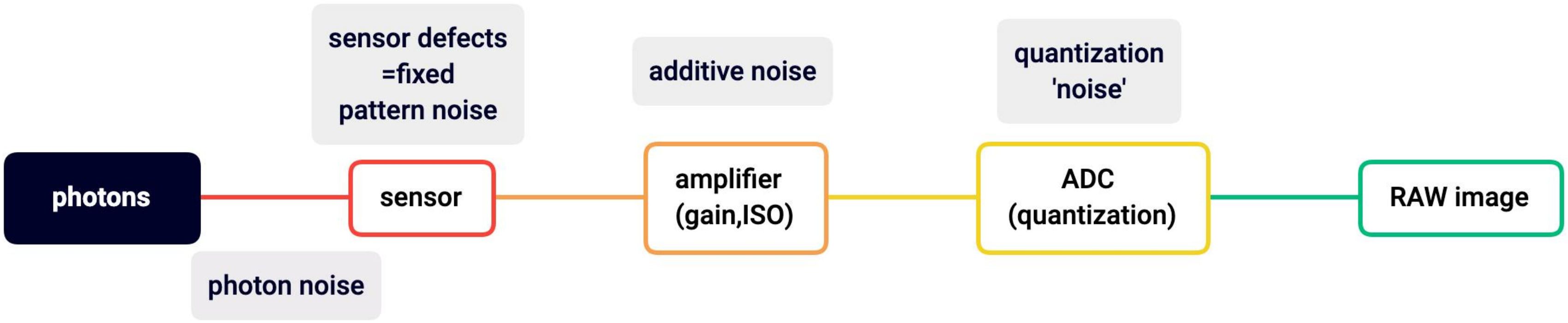
Noise in Images

Results in “grainy” appearance.



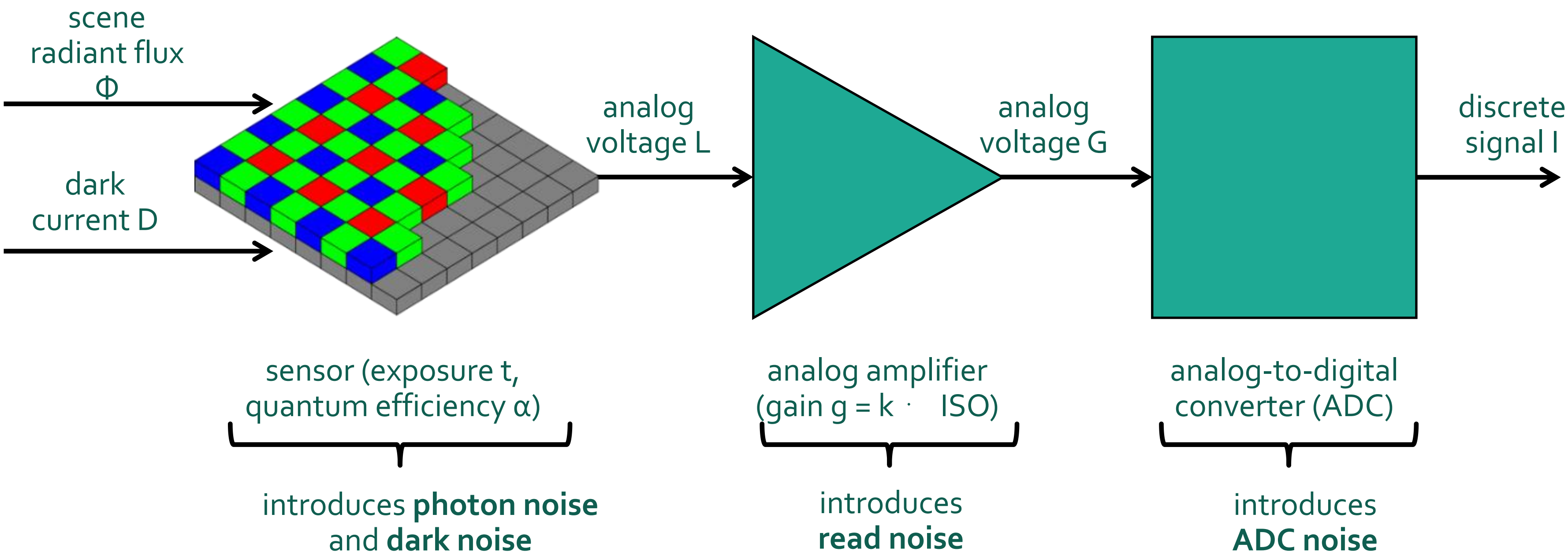


Recall:Photons to RAW Image



The Noisy Image Formation

Ignore saturation (a clipping operation) here.

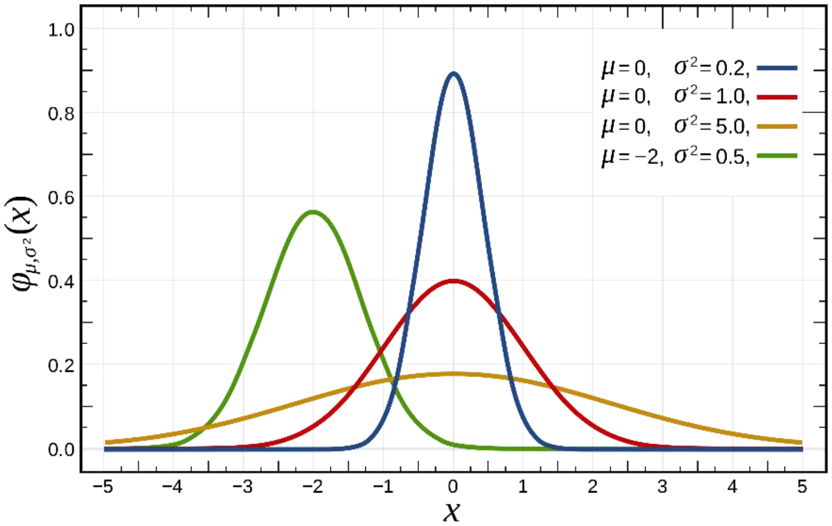


Background: Normal Distribution

- Continuous or discrete probability distribution?
  - Continuous.
- How many parameters does it depend on?
  - Two , the *mean* μ and the standard deviation σ.
- What is its probability distribution function?

$$n \sim \mathrm{Normal}(\mu, \sigma) \Leftrightarrow p(n = x; \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

- What are its mean and variance?
  - Mean: $\mu(n) = \mu$, Variance: $\sigma(n)^2 = \sigma^2$



- What is the distribution of the sum of two independent Normal random variables?

$$n_1 \sim \mathrm{Normal}(0, \sigma_1), n_2 \sim \mathrm{Normal}(0, \sigma_2) \Rightarrow n_1 + n_2 \sim \mathrm{Normal}\left(0, \sqrt{\sigma_1^2 + \sigma_2^2}\right)$$

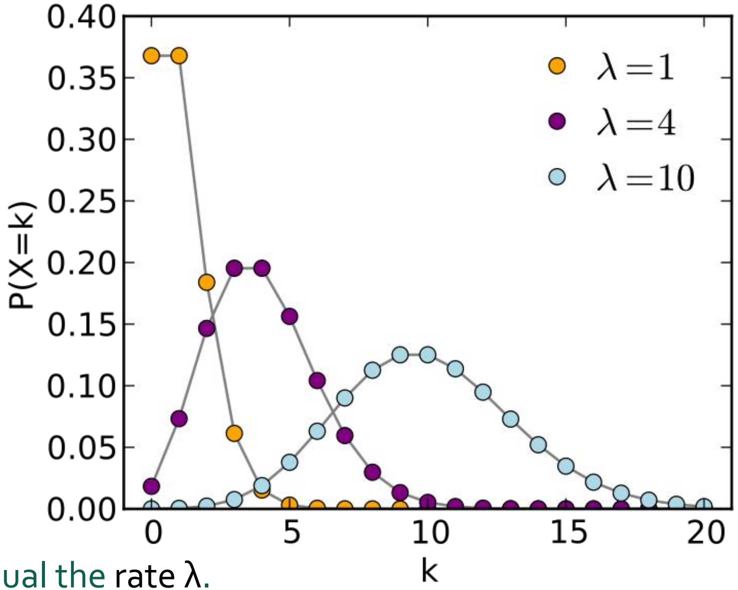
Background: Poisson Distribution

- Continuous or Discrete probability distribution?
  - Discrete .
- How many parameters does it depend on?
  - One, the *rate* λ.
- What is its probability mass function?

$$N \sim \text{Poisson}(\lambda) \Leftrightarrow P(N = k; \lambda) = \frac{\lambda^k e^{-\lambda}}{k!}$$

- What are its mean and variance?
  - Mean: $\mu(N) = \lambda$, Variance: $\sigma(N)^2 = \lambda$

The mean and variance of a Poisson random variable both equal the rate λ.



- What is the distribution of the +/- of two independent Poisson random variables?

$$N_1 \sim \text{Poisson}(\lambda_1), N_2 \sim \text{Poisson}(\lambda_2) \Rightarrow N_1 + N_2 \sim \text{Poisson}(\lambda_1 + \lambda_2)$$

$$\text{Skellam Distribution: } N_1 - N_2 \sim p(k; \lambda_1, \lambda_2) = \Pr\{\mathrm{K} = \mathrm{k}\} = e^{-(\lambda_1+\lambda_2)}\left(\frac{\lambda_1}{\lambda_2}\right)^{k/2} I_k(2\sqrt{\lambda_1 \lambda_2})$$

Where $I_k(z)$ is the modified *Bessel funtion* of the first kind.

Photon Noise

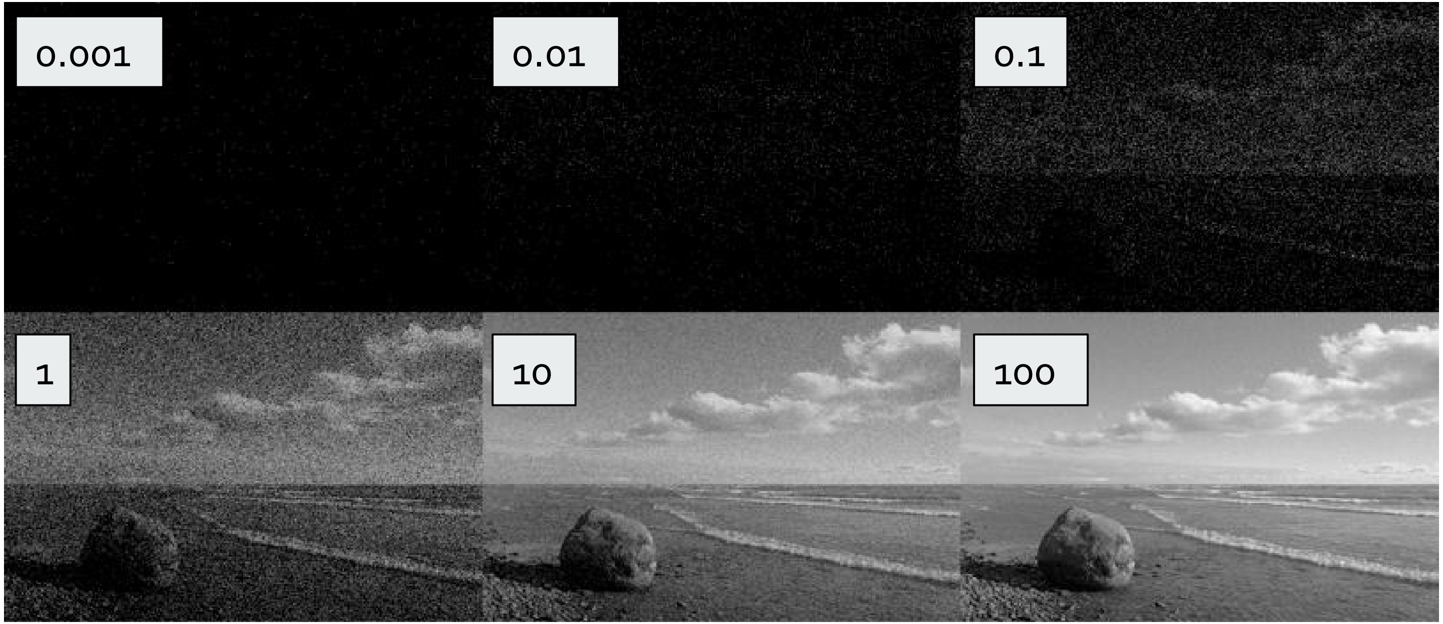
A consequence of the discrete (quantum) nature of light.

- Photon detections are independent random events.
- Total number of detections is Poisson distributed.
- Also known as shot noise and Schott noise.

photon noise depends on scene **flux** and **exposure**

$$N_{detections} \sim Poisson[t \cdot \boxed{\alpha \cdot \Phi}]$$

simulated mean #photons/pixel



Dark Noise

A consequence of "phantom detections" by the sensor.

- Electrons are randomly released without any photons.
- Total number of detections is Poisson distributed.
- Increases *exponentially* with sensor temperature (+6°C ≈ doubling).

dark noise depends on **exposure** but *not* on scene

$$N_{detections} \sim \text{Poisson}[\boxed{t \cdot D}]$$

Can you think of examples when dark noise is important?

- Very long exposures (astrophotography, pinhole camera).

Ideas to mitigate dark noise?

- Cool the sensor.

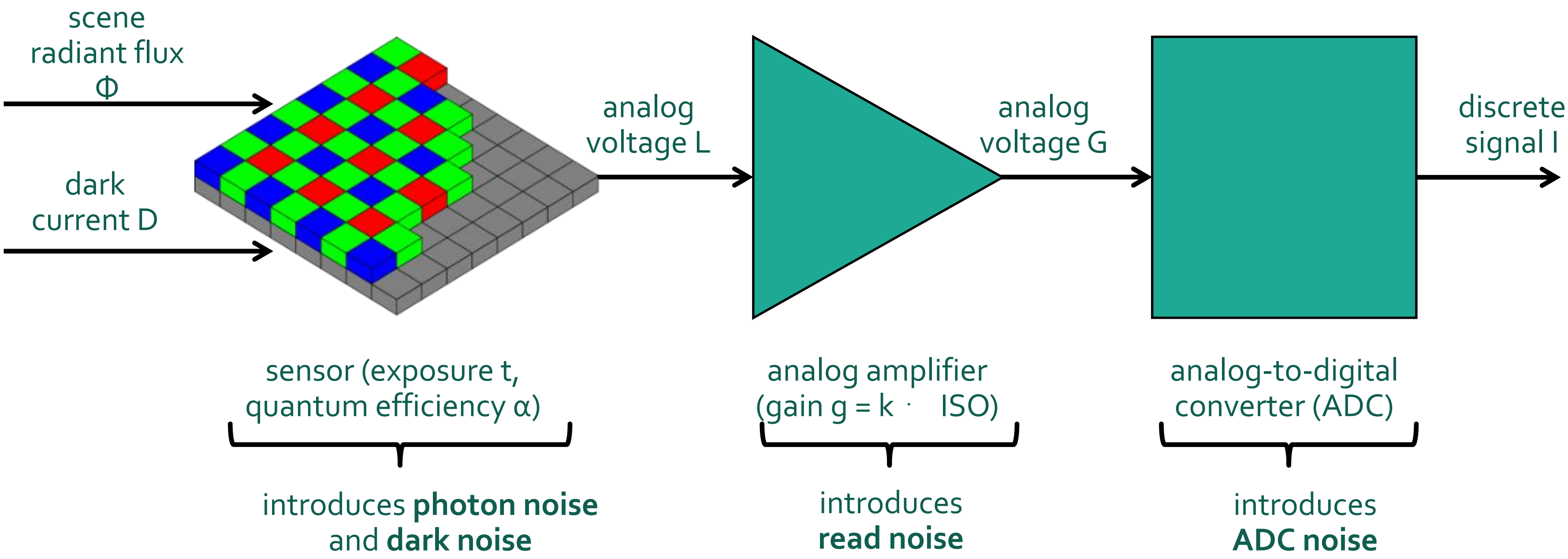
Passive and TE-Cooled Scientific CCD Cameras

Fundamental Question

Why are photon noise and dark noise Poisson random variables?

The Noisy Image Formation

- What is the distribution of the sensor readout L?



The Distribution of The Sensor Readout

- We know that the sensor readout is the sum of all released electrons:

$$L = N_{\text{photon\_detections}} + N_{\text{phantom\_detections}}$$

- What is the distribution of photon detections?

$$N_{\text{photon\_detections}} \sim \text{Poisson}(t \cdot \alpha \cdot \Phi)$$

- What is the distribution of phantom detections?

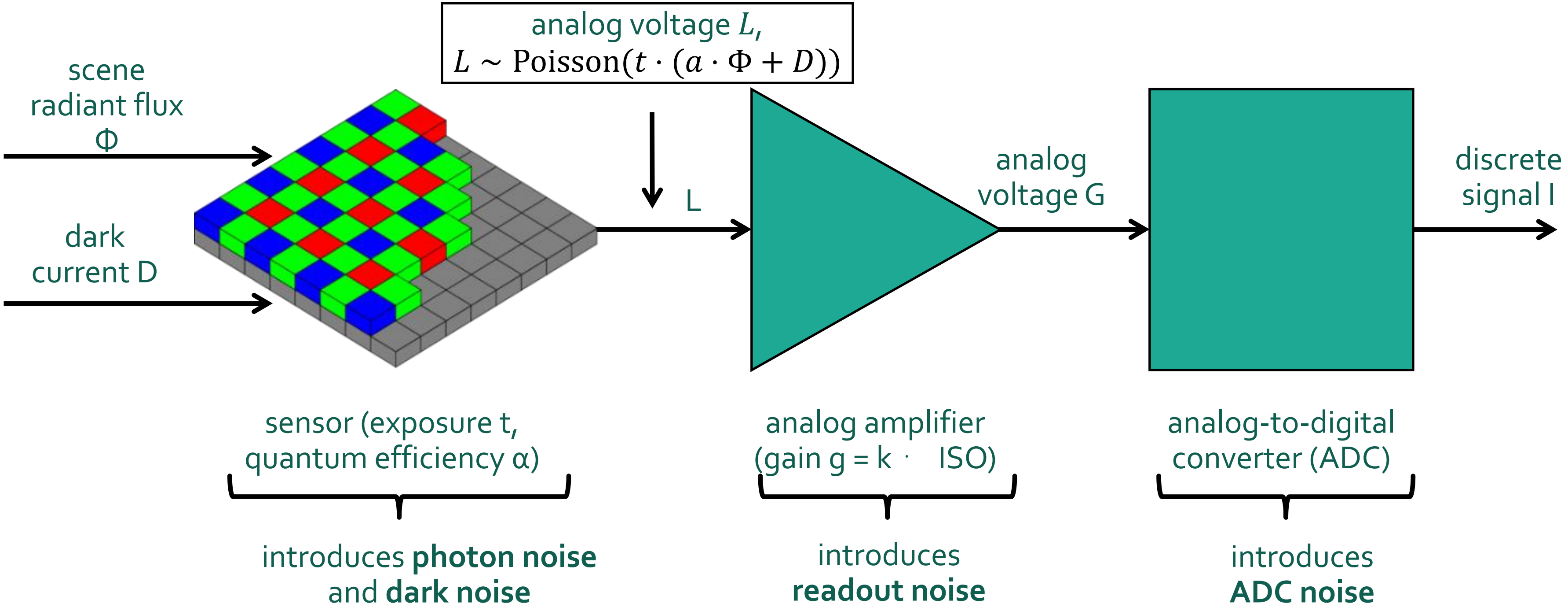
$$N_{\text{phantom\_detections}} \sim \text{Poisson}(t \cdot D)$$

- What is the distribution of the sensor readout?

$$L \sim \text{Poisson}(t \cdot (a \cdot \Phi + D))$$

The Noisy Image Formation

- What is the distribution of the sensor readout L?



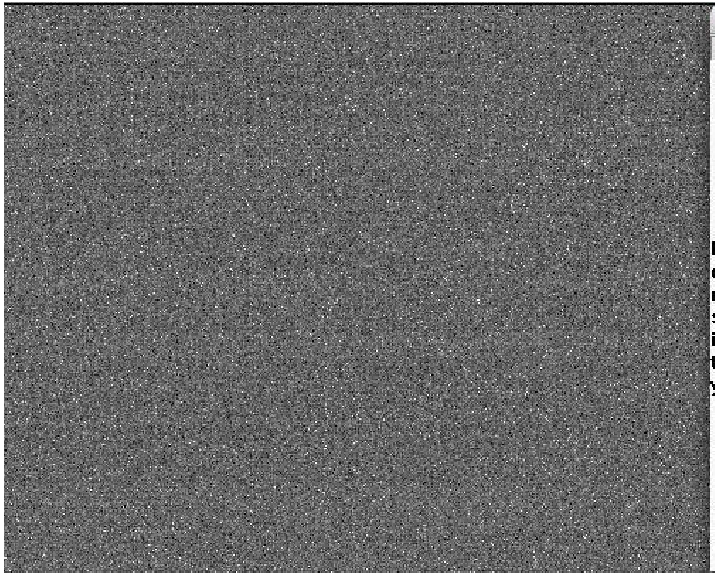
Read and ADC noise

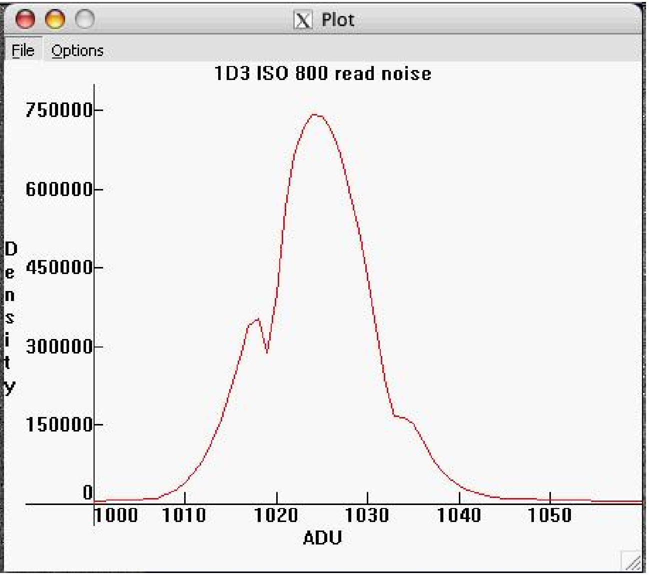
A consequence of random voltage fluctuations before and after amplifier.

- Both are independent of **scene** and **exposure**.
- Both are **normally** (zero-mean Guassian) distributed.
- ADC noise includes quantization errors.

$$n_{read} \sim \text{Normal}(0, \sigma_{read})$$
$$n_{ADC} \sim \text{Normal}(0, \sigma_{ADC})$$

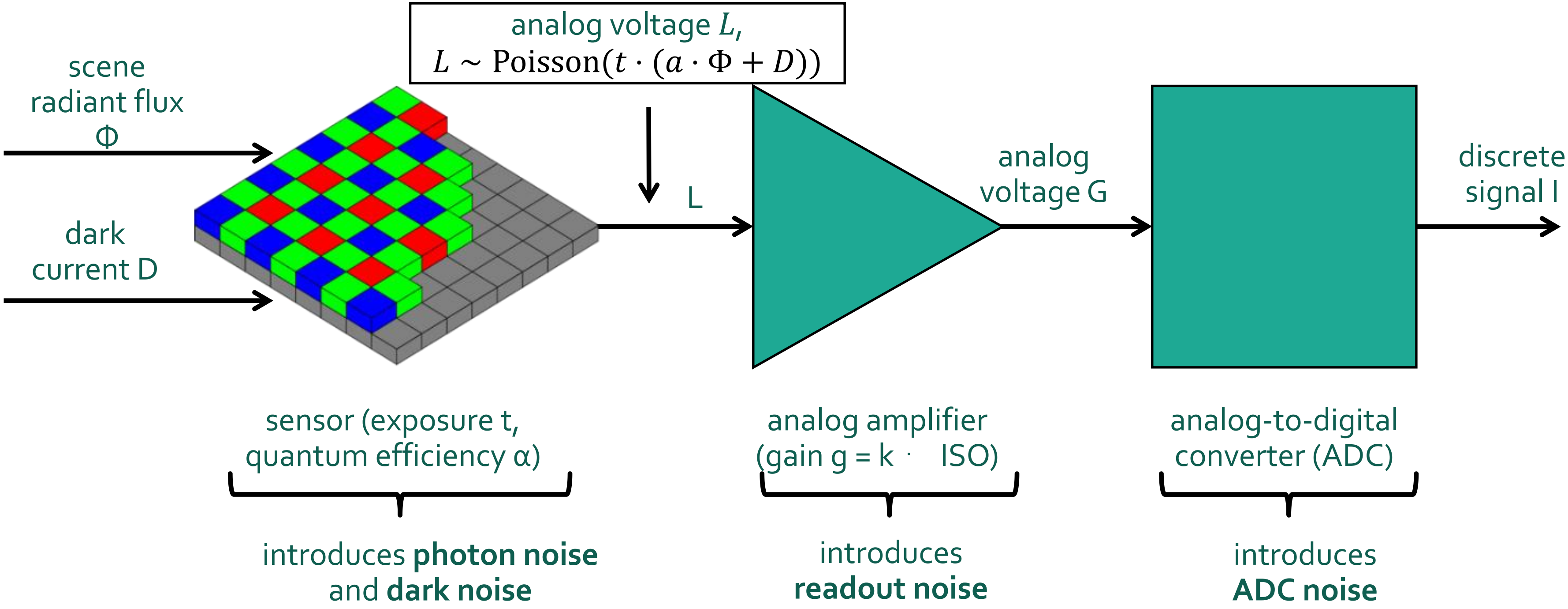
Very important for **dark pixels**.





The Noisy Image Formation

➢ How can we express the voltage G and discrete intensity I?



Expressions for the Amplifier and ADC Outputs

Both read noise and ADC noise are *additive* and *zero-mean.*

- How can we express the output of the amplifier?

$$G = L \cdot g + n_{\text{read}} \cdot g \longleftarrow$$

ISO-dependent gain

- How can we express the output of the ADC?

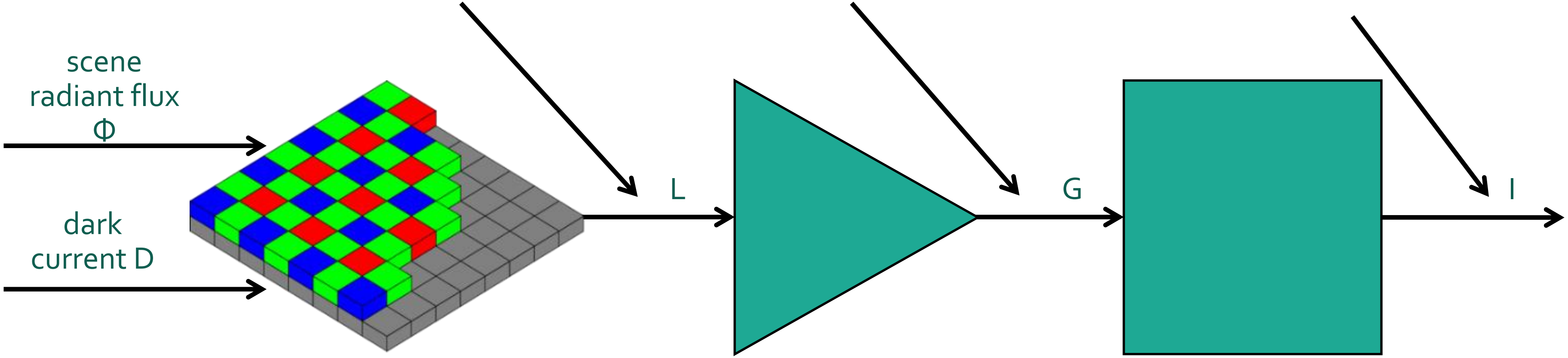
$$I = G + n_{\text{ADC}}$$

The Noisy Image Formation

analog voltage L,
$L \sim \mathrm{Poisson}(t \cdot (a \cdot \Phi + D))$

analog voltage $G = L \cdot g + n_{\mathrm{read}} \cdot g$
$n_{\mathrm{read}} \sim \mathrm{Normal}(0, \sigma_{\mathrm{read}})$

discrete signal $I = G + n_{\mathrm{ADC}}$
$n_{\mathrm{ADC}} \sim \mathrm{Normal}(0, \sigma_{\mathrm{ADC}})$



sensor (exposure t, quantum efficiency α)
introduces **photon noise** and **dark noise**

analog amplifier (gain g = k · ISO)
introduces **readout noise**

analog-to-digital converter (ADC)
introduces **ADC noise**

Putting it All Together

- Without saturation, the digital intensity equals:

$$I = L \cdot g + n_{\text{read}} \cdot g + n_{\text{ADC}}$$

where

$$L \sim \text{Poisson}\big(t \cdot (a \cdot \Phi + D)\big)$$
$$n_{\text{read}} \sim \text{Normal}(0, \sigma_{\text{read}})$$
$$n_{\text{ADC}} \sim \text{Normal}(0, \sigma_{\text{ADC}})$$

- What is the mean of the digital intensity (assuming no saturation)?

$$\begin{aligned} E(I) &= E(L \cdot g) + E(n_{\text{read}} \cdot g) + E(n_{\text{ADC}}) \\ &= t \cdot (a \cdot \Phi + D) \cdot g \end{aligned}$$

- What is the variance of the digital intensity (assuming no saturation)?

$$\begin{aligned} \sigma(I)^2 &= \sigma(L \cdot g)^2 + \sigma(n_{\text{read}} \cdot g)^2 + \sigma(n_{\text{ADC}})^2 \\ &= t \cdot (a \cdot \Phi + D) \cdot g^2 + \sigma_{\text{read}}^2 \cdot g^2 + \sigma_{\text{ADC}}^2 \end{aligned}$$

Compute Mean and Variance in Practice?

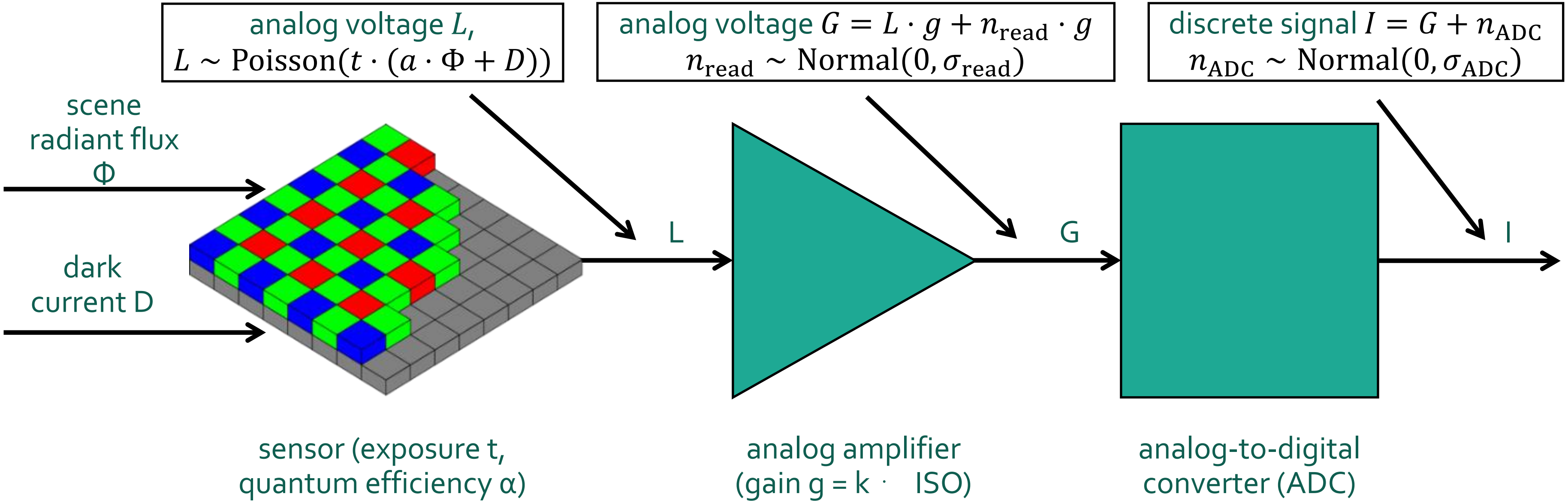
- Mean: capture multiple *linear* images with identical settings and average.

$$\bar{I} = \frac{1}{N}\sum_{n=1}^{N} I_n \xrightarrow{N\to\infty} E(I)$$

- Variance: capture multiple *linear* images with identical settings and form variance estimator.

$$\bar{\Sigma} = \frac{1}{N-1}\sum_{n=1}^{N} (I_n - \bar{I})^2 \xrightarrow{N\to\infty} \sigma(I)^2$$

The Noisy Image Formation



discrete image intensity (with saturation):

$$I = \min\left(L \cdot g + n_{\text{read}} \cdot g + n_{\text{ADC}}, I_{\max}\right)$$

saturation level

intensity mean and variance (without saturation):

$$E(I) = t \cdot (a \cdot \Phi + D) \cdot g$$

$$\sigma(I)^2 = t \cdot (a \cdot \Phi + D) \cdot g^2 + \sigma_{\text{read}}^2 \cdot g^2 + \sigma_{\text{ADC}}^2$$

Affine Noise Model

- Combine read and ADC noise into a single *additive* noise term:

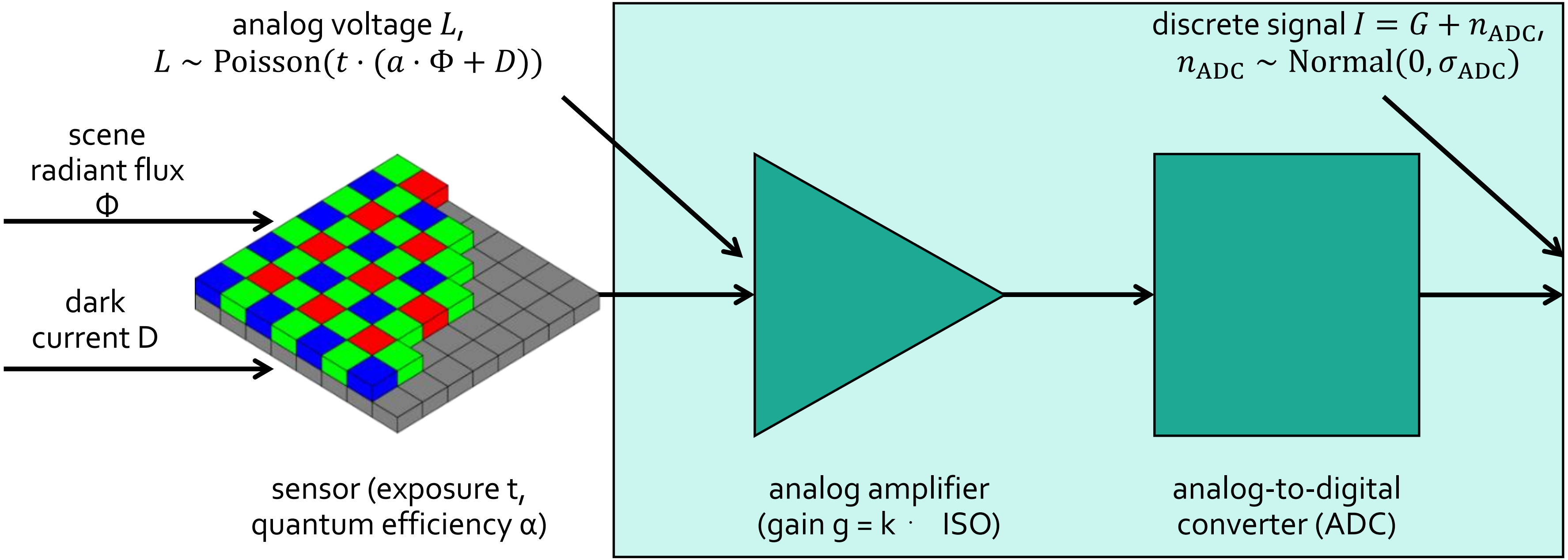
$$I = L \cdot g + n_{\text{add}}$$

where $$n_{\text{add}} = n_{\text{read}} \cdot g + n_{\text{ADC}}$$

- What is the distribution of the additive noise term?
  - Sum of two independent, normal random variables.

$$n_{\text{add}} \sim \text{Normal}(0, \sqrt{\sigma_{\text{read}}^2 \cdot g^2 + \sigma_{\text{ADC}}^2})$$

The noisy image formation process



discrete image intensity (with saturation):

$$I = \min\left(L \cdot g + n_{\text{read}} \cdot g + n_{\text{ADC}}, I_{\max}\right)$$

intensity mean and variance (without saturation):

$$E(I) = t \cdot (a \cdot \Phi + D) \cdot g$$

$$\sigma(I)^2 = t \cdot (a \cdot \Phi + D) \cdot g^2 + \sigma_{\text{read}}^2 \cdot g^2 + \sigma_{\text{ADC}}^2$$

Some Observations

Is image intensity an ***unbiased*** estimator of (scaled) scene radiant flux?

- No, because of dark noise (term $t \cdot D \cdot g$ in the mean).
- Averaging multiple images cancels out read and ADC noise, but *not* dark noise.

When are photon noise and additive noise dominant?

- Bright scenes: Photon noise .
- Dark scenes: Additive noise.

Can we ever completely remove noise?

- We cannot eliminate photon noise.
- Super-sensitive detectors have pure Poisson photon noise.

single-photon avalanche photodiode (SPAD) array

Summary: Noise Regimes

regime	dominant noise	notes
bright pixels	photon noise	scene-dependent
dark pixels	read and ADC noise	scene-independent
low ISO	ADC noise	post-gain
high ISO	photon and read noise	pre-gain
long exposures	dark noise	thermal dependence

discrete image intensity (with saturation):

$$I = \min\left(L \cdot g + n_{\mathrm{read}} \cdot g + n_{\mathrm{ADC}}, I_{\max}\right)$$

intensity mean and variance (without saturation):

$$E(I) = t \cdot (a \cdot \Phi + D) \cdot g$$

$$\sigma(I)^2 = t \cdot (a \cdot \Phi + D) \cdot g^2 + \sigma_{\mathrm{read}}^2 \cdot g^2 + \sigma_{\mathrm{ADC}}^2$$

Signal-to-Noise Ratio (SNR)

Paraxial Focusing

- Variance is an *absolute* measure of the (squared) magnitude of noise:

$$\sigma(I)^2 = E\left(\left(I - E(I)\right)^2\right) = E(I^2) - E(I)^2$$

- Signal-to-noise ratio (SNR) is a *relative* measure of the (inverse squared) magnitude of noise:

$$\mathrm{SNR} = \frac{E(I)^2}{\sigma(I)^2}$$

When noise *decreases*:

- The variance decreases.
- The SNR increases.

The Case of Sensor Noise

Assuming for simplicity that *there is no dark current*:

$$\mathrm{SNR} = \frac{(t \cdot a \cdot \Phi \cdot g)^2}{t \cdot a \cdot \Phi \cdot g^2 + \sigma_{\mathrm{read}}^2 \cdot g^2 + \sigma_{\mathrm{ADC}}^2} \qquad \sigma(I)^2 = t \cdot a \cdot \Phi \cdot g^2 + \sigma_{\mathrm{read}}^2 \cdot g^2 + \sigma_{\mathrm{ADC}}^2$$

What happens when the exposure time or flux are very large?

- We can ignore additive (read and ADC) noise terms.

photon-noise-limited case

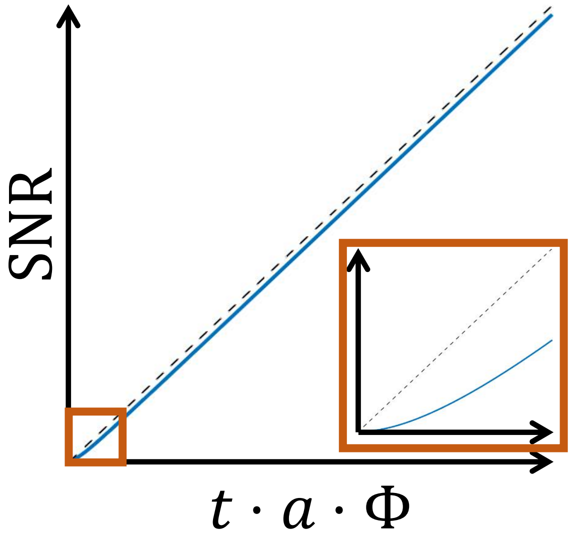
$$\mathrm{SNR} = \frac{(t \cdot a \cdot \Phi \cdot g)^2}{t \cdot a \cdot \Phi \cdot g^2} = t \cdot a \cdot \Phi \qquad \sigma(I)^2 = t \cdot a \cdot \Phi \cdot g^2$$

What happens when the flux or exposure time are very small?

- We can ignore scene-dependent noise terms.

additive-noise-limited case

$$\mathrm{SNR} = \frac{(t \cdot a \cdot \Phi \cdot g)^2}{\sigma_{\mathrm{read}}^2 \cdot g^2 + \sigma_{\mathrm{ADC}}^2} \qquad \sigma(I)^2 = \sigma_{\mathrm{read}}^2 \cdot g^2 + \sigma_{\mathrm{ADC}}^2$$



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Popular Questions

Is **One long exposure** or **Multiple short exposures** better? (no saturation, RAW images)

- One long exposure is better, because additive noise is only added once.
- Multiple short exposures is worse, because the result (after summing all images) will have additive noise variance increased by number of exposures.

Is it better to increase the **exposure**, the **ISO**, or **brighten digitally**?

(no motion blur/saturation, RAW images)

- Increasing the exposure is the best, as it increases Poisson noise but leaves read noise and ADC noise fixed.
- Increasing the ISO is the second best, as it increases Poisson noise and read noise, but leaves ADC noise fixed.
- Brightening digitally is the worst, as it increases all three types of noise.

Is it better to **downsample digitally**, or use a sensor with **fewer pixels**? (the total photosensitive area remains the same, the per-pixel additive noise remains the same, and no saturation)

- Fewer pixels is better, as it increases the Poisson, but leaves additive noise fixed.
- Downsampling digitally is worse, as it increases both the Poisson noise and additive noise.

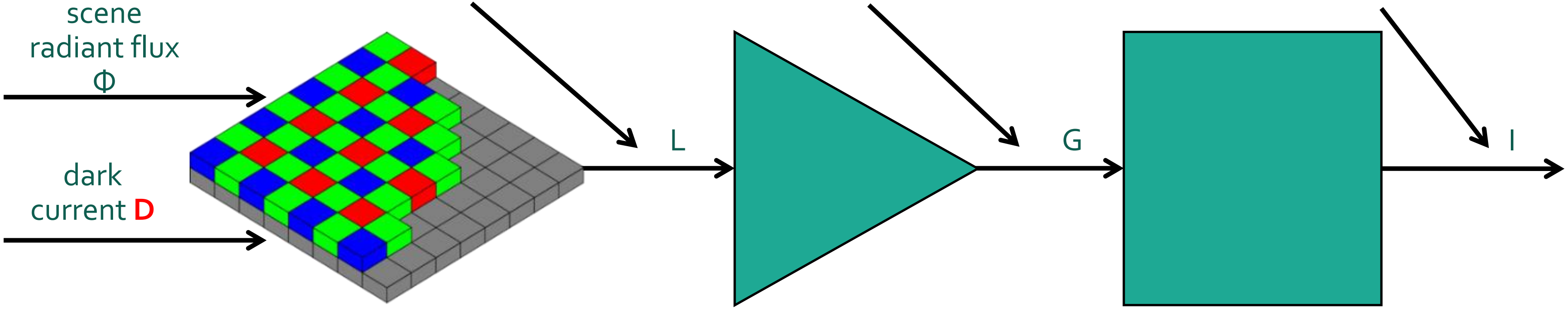
Noise Calibration

How to Estimate the Various Parameters?

analog voltage L, $L \sim \mathrm{Poisson}(t \cdot (a \cdot \Phi + D))$

analog voltage $G = L \cdot g + n_{\mathrm{read}} \cdot g$, $n_{\mathrm{read}} \sim \mathrm{Normal}(0, \boldsymbol{\sigma}_{\mathbf{read}})$

discrete signal $I = G + n_{\mathrm{ADC}}$, $n_{\mathrm{ADC}} \sim \mathrm{Normal}(0, \boldsymbol{\sigma}_{\mathbf{ADC}})$



sensor (exposure t, quantum efficiency α)

analog amplifier (gain g = **k** · ISO)

analog-to-digital converter (ADC)

discrete image intensity (with saturation):

$$I = \min\left(L \cdot g + n_{\mathrm{read}} \cdot g + n_{\mathrm{ADC}}, I_{\max}\right)$$

saturation level

intensity mean and variance (without saturation):

$$E(I) = t \cdot (a \cdot \Phi + D) \cdot g$$

$$\sigma(I)^2 = t \cdot (a \cdot \Phi + D) \cdot g^2 + \sigma_{\mathrm{read}}^2 \cdot g^2 + \sigma_{\mathrm{ADC}}^2$$

Estimating the Dark Current

Can you think of a procedure for estimating the **dark current D**?

- Capture **multiple images** with the sensor completely blocked and average to form the ***dark** frame*.

Why is the dark frame a valid estimator of the dark current D?

- By blocking the sensor, we effectively set $\Phi = 0$.
- Average intensity becomes:

$$E(I) = t \cdot (a \cdot 0 + D) \cdot g = t \cdot D \cdot g$$

- The dark frame needs to be computed separately for each ISO setting, unless we can also calibrate the gain g.

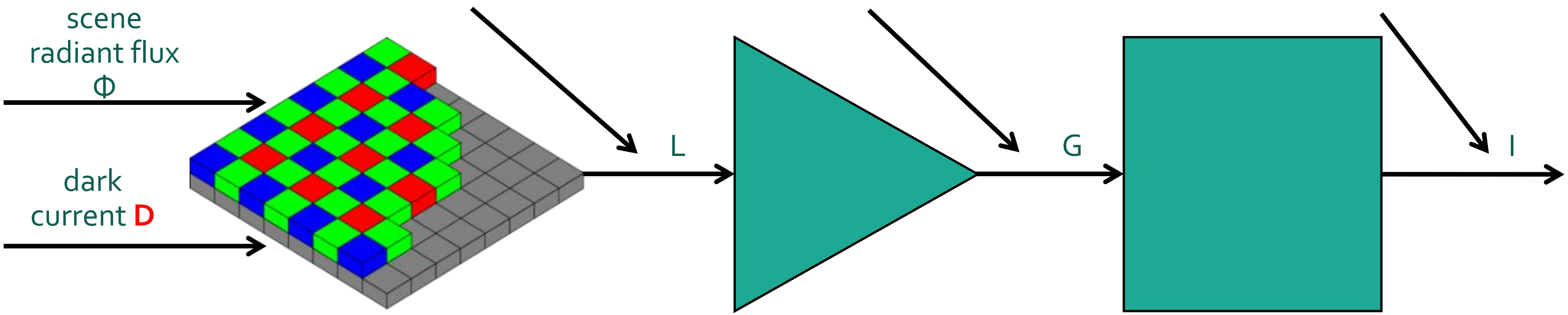
For the rest of these slides, we assume that we have calibrated D and removed it from captured images (by subtracting from them the dark frame).

Noise Model Before Dark frame Subtraction

analog voltage L,
$L \sim \text{Poisson}(t \cdot (a \cdot \Phi + D))$

analog voltage $G = L \cdot g + n_{\text{read}} \cdot g$
$n_{\text{read}} \sim \text{Normal}(0, \boldsymbol{\sigma}_{\textbf{read}})$

discrete signal $I = G + n_{\text{ADC}}$
$n_{\text{ADC}} \sim \text{Normal}(0, \boldsymbol{\sigma}_{\textbf{ADC}})$



sensor (exposure t,
quantum efficiency α)

analog amplifier
(gain g = **k** · ISO)

analog-to-digital
converter (ADC)

discrete image intensity (with saturation):

$$I = \min\left(L \cdot g + n_{\text{read}} \cdot g + n_{\text{ADC}}, I_{\max}\right)$$

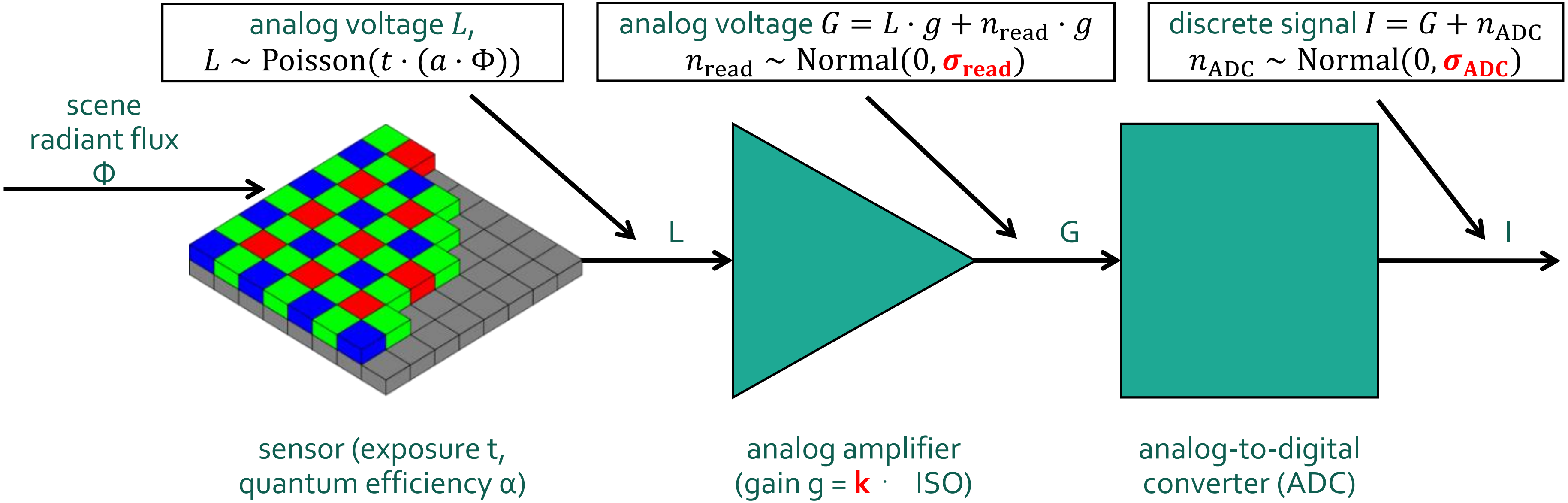
saturation level

intensity mean and variance (without saturation):

$$E(I) = t \cdot (a \cdot \Phi + D) \cdot g$$

$$\sigma(I)^2 = t \cdot (a \cdot \Phi + D) \cdot g^2 + \sigma_{\text{read}}^2 \cdot g^2 + \sigma_{\text{ADC}}^2$$

Noise Model After Dark frame Subtraction



discrete image intensity (with saturation):

$$I = \min\left(L \cdot g + n_{\text{read}} \cdot g + n_{\text{ADC}}, I_{\max}\right)$$

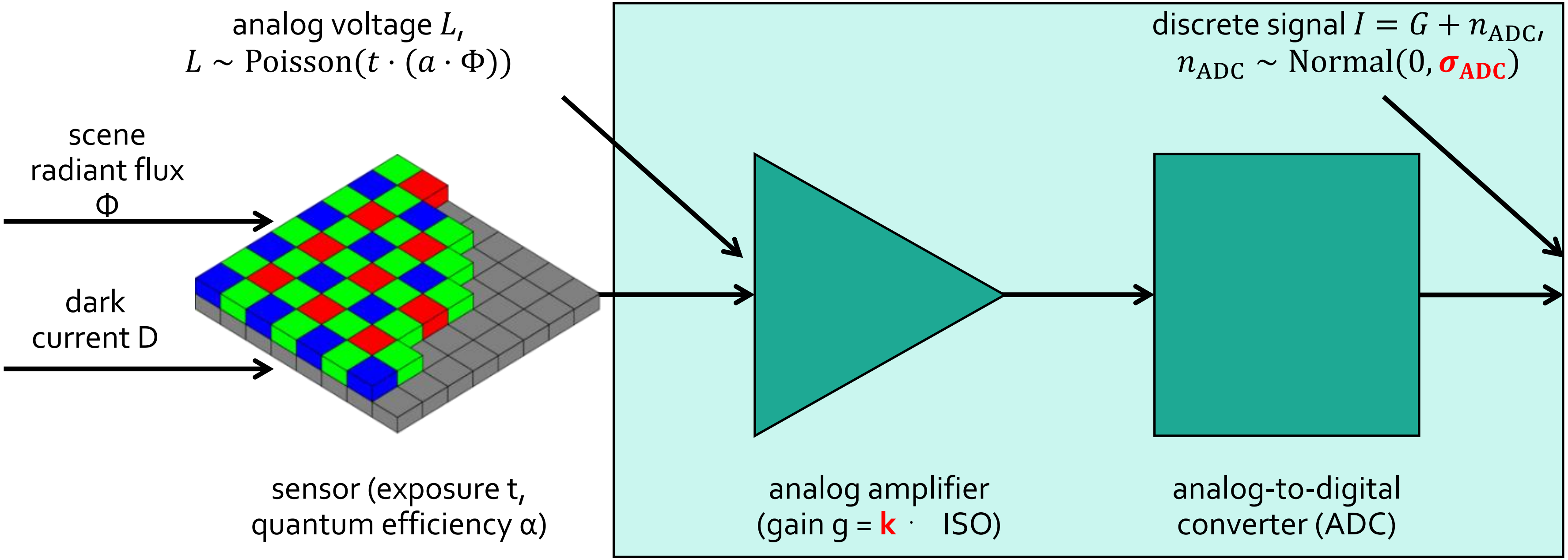
saturation level

intensity mean and variance (without saturation):

$$E(I) = t \cdot (a \cdot \Phi) \cdot g$$

$$\sigma(I)^2 = t \cdot (a \cdot \Phi) \cdot g^2 + \sigma_{\text{read}}^2 \cdot g^2 + \sigma_{\text{ADC}}^2$$

Affine Noise Model After Dark Frame Subtraction



discrete image intensity (with saturation):

$$I = \min\left(L \cdot g + n_{\text{read}} \cdot g + n_{\text{ADC}}, I_{\max}\right)$$

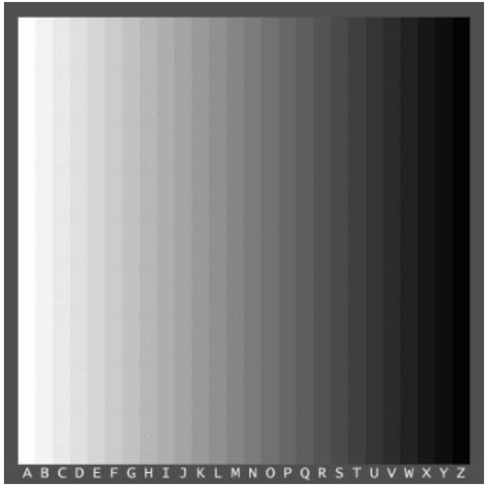
intensity mean and variance (without saturation):

$$E(I) = t \cdot (a \cdot \Phi) \cdot g$$

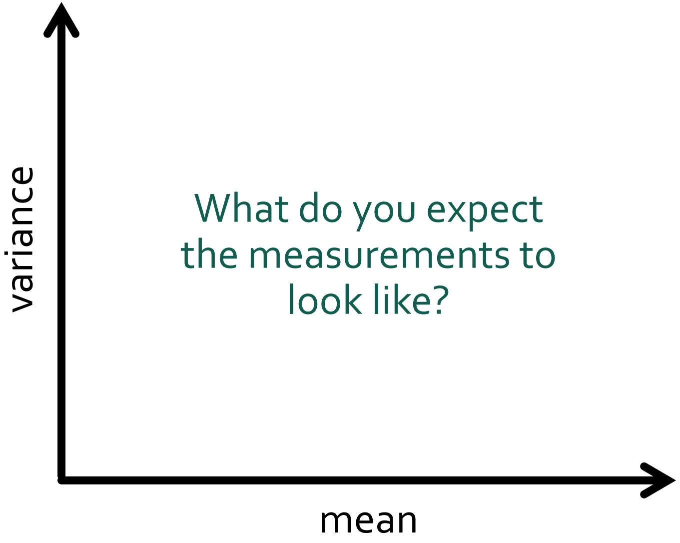
$$\sigma(I)^2 = t \cdot (a \cdot \Phi) \cdot g^2 + \sigma_{\text{read}}^2 \cdot g^2 + \sigma_{\text{ADC}}^2$$

Estimating the Gain and Additive Noise Variance

1. Capture a large number of images of a grayscale target.



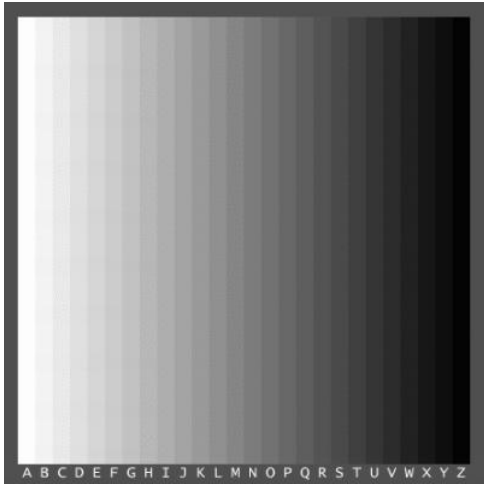
2. Compute the empirical mean and variance for each pixel, then form a mean-variance plot.



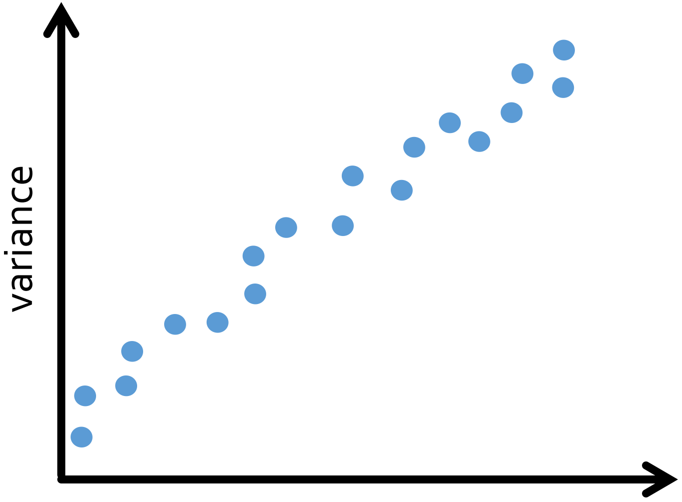
What do you expect the measurements to look like?

Estimating the Gain and Additive Noise Variance

1. Capture a large number of images of a grayscale target.



2. Compute the empirical mean and variance for each pixel, then form a mean-variance plot.



$$E(I) = t \cdot (a \cdot \Phi) \cdot g$$

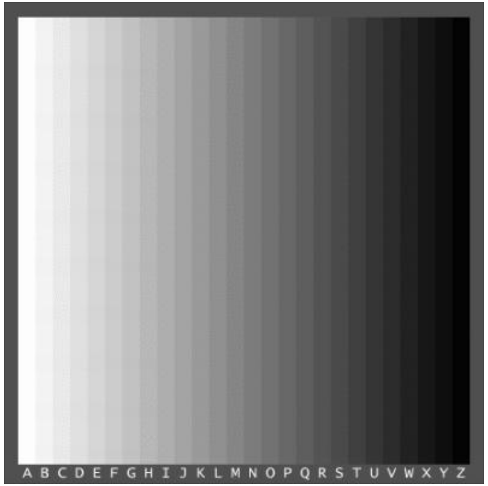
$$\sigma(I)^2$$
$$= t \cdot (a \cdot \Phi) \cdot g^2 + \sigma_{\text{add}}^2$$
$$\Rightarrow \sigma(I)^2 = E(I) \cdot g + \sigma_{\text{add}}^2$$

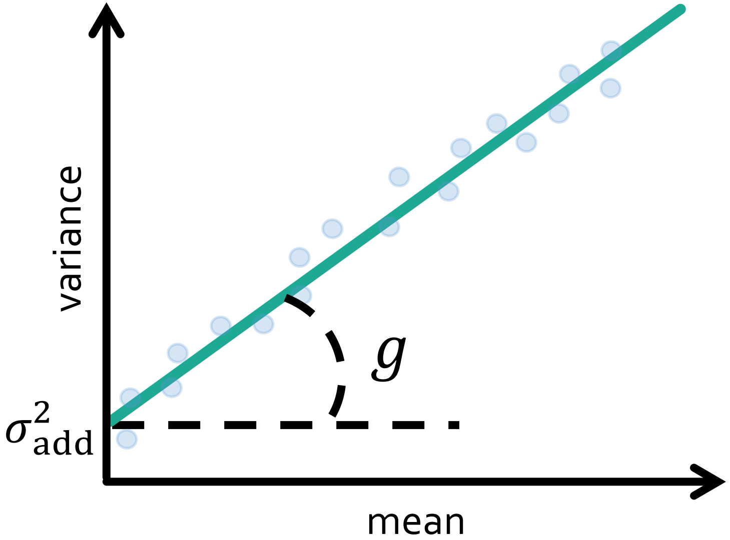
Estimating the Gain and Additive Noise Variance

1. Capture a large number of images of a grayscale target.

2. Compute the empirical mean and variance for each pixel, then form a mean-variance plot.

3. Fit a line and use slope and intercept to estimate the gain and variance.





equal to line slope

$$\sigma(I)^2 = E(I) \cdot g + \sigma^2_{\text{add}}$$

equal to line intercept

How would you modify this procedure to separately estimate read and ADC noise?

- Perform it for a few different ISO settings (i.e., gains g).

Notes

Perform Noise calibration with RAW images!

The above procedure assumes that all pixels have the same noise characteristics.

- If that is not the case, then you need to capture multiple images under multiple exposure times, and use those to form the mean-variance plot for each pixel.

Optimal Weights for HDR Merging

Merging Non-linear Exposure Stacks

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1. Calibrate response curve
2. Linearize images

For each pixel:

3. Find “valid” images ← (noise) $0.05 < \text{pixel} < 0.95$ (clipping)
4. Weight valid pixel values appropriately ← (pixel value) / t_i
5. Form a new pixel value as the weighted average of valid pixel values

→ Same steps as in the RAW case.

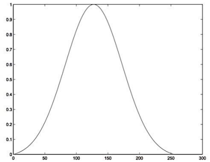
Note: many possible weighting schemes

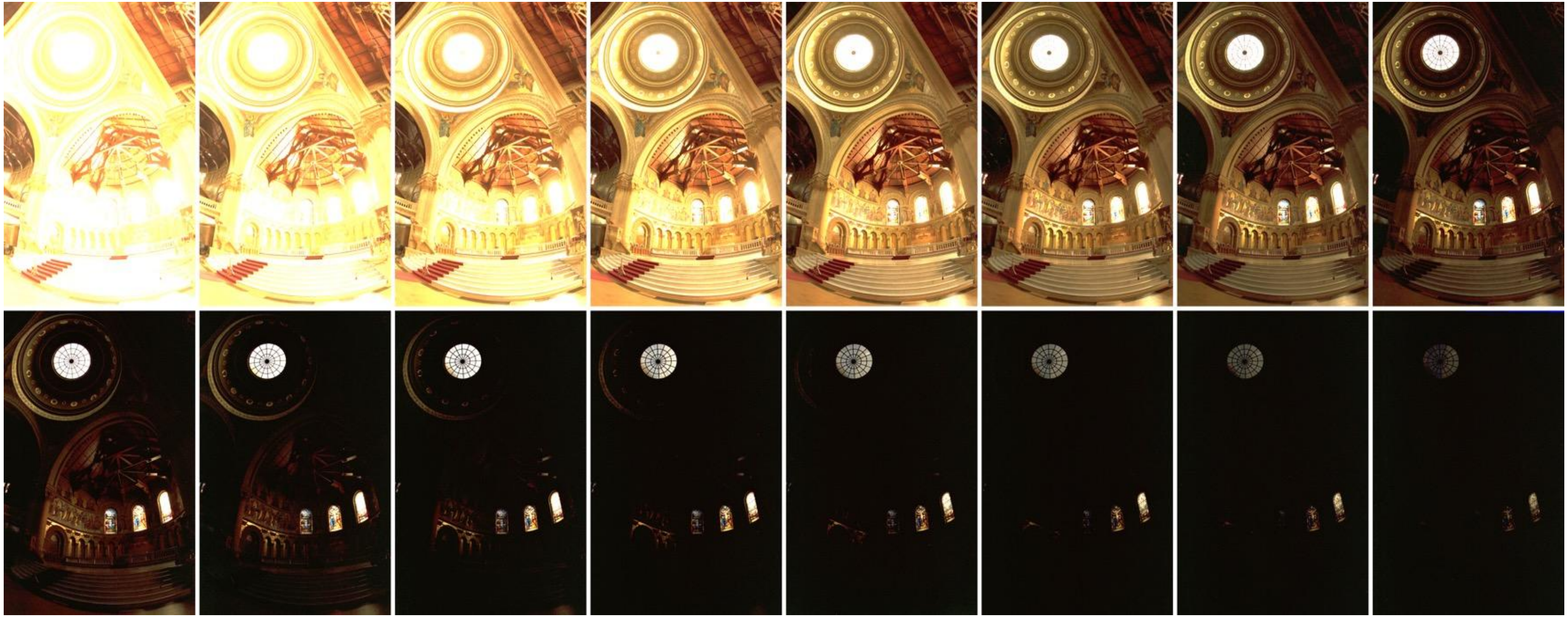
Many possible weighting schemes

"Confidence" that pixel is noisy/clipped

- What are the $\boxed{\text{optimal weights}}$ for merging an exposure stack?

$$w_{ij} = exp(-4\frac{(I_{lin_{ij}} - 0.5)^2}{0.5^2})$$





RAW (linear) Image Formation Model

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(Weighted) radiant flux for image pixel (x,y): $\alpha \cdot \Phi(x, y)$

Exposure time:

t_5 t_4 t_3 t_2 t_1

What weights should we use to merge these images, so that the resulting HDR image is an optimal estimator of the **weighted radiant flux**?

Different images in the exposure stack will have **different noise** characteristics

Simple estimation example

We have two *independent unbiased* estimators x and y of the same quantity I (e.g., pixel intensity) with variance $\sigma[x]^2$ and $\sigma[y]^2$.

- What does unbiased mean?

$$E[x] = E[y] = I$$

- Assume we form a new estimator from the *convex* combination of the other two:

$$z = a \cdot x + (1 - a) \cdot y$$

- Is the new estimator z unbiased? → Yes, convex combination preserves unbiasedness.

$$E[z] = E[a \cdot x + (1 - a) \cdot y] = a \cdot E[x] + (1 - a) \cdot E[y] = I$$

- How should we select a? → **Minimize variance** (= expected squared error *for unbiased estimators*).

$$E[(z - I)^2] = E[z^2] - 2 \cdot E[z] \cdot I + I^2 = E[z^2] - E[z]^2 = \sigma[z]^2$$

- What is the variance of z as a function of a?

$$\sigma[z]^2 = a^2 \cdot \sigma[x]^2 + (1 - a)^2 \cdot \sigma[y]^2$$

- What value of a minimizes $\sigma[z]^2$?

Simple estimation example

Simple optimization problem:

$$\frac{\partial \sigma[z]^2}{\partial a} = 0$$

$$\Rightarrow \quad \frac{\partial(a^2 \cdot \sigma[x]2 + (1 - a)^2 \cdot \sigma[y]^2)}{\partial a} = 0$$

$$\Rightarrow \quad 2 \cdot a \cdot \sigma[x]2 - 2 \cdot (1 - a) \cdot \sigma[y]^2 = 0$$

$$\Rightarrow \quad a = \frac{\sigma[y]^2}{\sigma[x]^2 + \sigma[y]^2}$$ and $$1 - a = \frac{\sigma[x]^2}{\sigma[x]^2 + \sigma[y]^2}$$

Simple Estimation Example

Putting it all together, the optimal linear combination of the two estimators is

$$z = \underbrace{\frac{\sigma[x]^2 \sigma[y]2}{\sigma[x]^2 + \sigma[y]2}}_{\text{normalization factor}} \cdot \underbrace{\left(\frac{1}{\sigma[x]2} x + \frac{1}{\sigma[y]^2} y \right)}_{\text{weights inversely proportional to variance}}$$

More generally, for more than two estimators,

$$z = \frac{1}{\sum_{i=1}^{N} \frac{1}{\sigma[x_i]^2}} \cdot \sum_{i=1}^{N} \frac{1}{\sigma[x_i]^2} x_i$$

This is weighting scheme is called Fisher weighting and is a BLUE estimator.

Back to HDR

Given *unclipped* and *dark-frame-corrected* intensity measurements $I_i[x, y]$ at pixel $[x, y]$ and exposures t_i, we can merge them optimally into a single HDR intensity $I[x, y]$ as

$$I[x,y] = \frac{1}{\sum_{i=1}^{N} w_i[x,y]} \cdot \sum_{i=1}^{N} w_i[x,y] \frac{1}{t_i} I_i[x,y] = \frac{1}{\sum_{i=1}^{N} \frac{1}{\sigma[\frac{1}{t_i} I_i[x,y]]^2}} \cdot \sum_{i=1}^{N} \frac{1}{\sigma[\frac{1}{t_i} I_i[x,y]]^2} \frac{1}{t_i} I_i[x,y]$$

The <u>per-pixel</u> weights $w_i[x,y]$ should be selected to be inversely proportional to the variance $\sigma[\frac{1}{t_i} I_i[x,y]]^2$ at each image in the exposure stack.

➢ How do we compute this variance? $\longrightarrow$ Use affine noise model.

$$\sigma[\frac{1}{t_i} I_i[x,y]]^2 = \frac{1}{t_i^2} \sigma[I_i[x,y]]^2$$

$$\Rightarrow \quad \sigma[\frac{1}{t_i} I_i[x,y]]^2 = \frac{1}{t_i^2} (t_i \cdot \alpha \cdot \Phi[x,y] \cdot g^2 + \sigma_{add}^2)$$

Computing the optimal weights requires:

1. calibrated noise characteristics.
2. knowing the radiant flux $\alpha \cdot \boxed{\Phi[x,y].}$

This is what we wanted to estimate!

Simplification: Only Photon Noise

If we assume that our measurements are dominated by photon noise, the variance becomes:

$$\sigma[\frac{1}{t_i} I_i[x,y]]^2 = \frac{1}{t_i^2}(t_i \cdot \alpha \cdot \Phi[x,y] \cdot g^2 + \sigma_{add}^2) \simeq \frac{1}{t_i} \alpha \cdot \Phi[x,y] \cdot g^2$$

By replacing in the merging formula and *assuming only valid pixels*, the HDR estimate becomes:

$$I[x,y] = \frac{1}{\sum_{i=1}^{N} \frac{1}{\frac{1}{t_i} \alpha \cdot \Phi[x,y] \cdot g^2}} \cdot \sum_{i=1}^{N} \frac{1}{\frac{1}{t_i} \alpha \cdot \Phi[x,y] \cdot g^2} \frac{1}{t_i} I_i[x,y] = \boxed{\frac{1}{\sum_{i=1}^{N} t_i} \cdot \sum_{i=1}^{N} I_i[x,y]}$$

Notice that we no longer weight each image in the exposure stack by its exposure time!

Some Comparisons

original weights

optimal weights assuming only photon noise

Simplification: Only Photon Noise

When is this a good assumption?

More General Case

If we cannot assume that our measurements are dominated by photon noise, we can approximate the variance as:

$$\sigma[\frac{1}{t_i} I_i[x,y]]^2 = \frac{1}{t_i^2}(t_i \cdot \alpha \cdot \Phi[x,y] \cdot g^2 + \sigma_{add}^2) \simeq \frac{1}{t_i^2}(I_i[x,y] \cdot g + \sigma_{add}^2)$$

Where does this approximation come from?

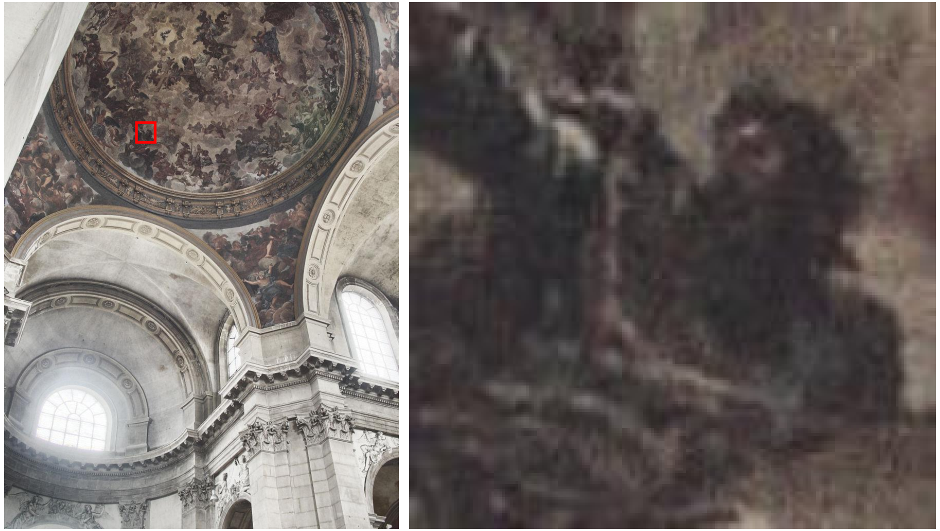
- We use the fact that each pixel intensity (after dark frame subtraction) is an unbiased estimate of the radiant flux, weighted by exposure and gain:

$$\mathrm{E}[I_i[x,y]] = t_i \cdot \alpha \cdot \Phi[x,y] \cdot \mathrm{g}$$

Some Comparisons

Tone-mapped Merged HDR

Standard Weights



Optimal weights

What about ISO?

Noise-Optimal Capture for High Dynamic Range Photography

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Abstract

Taking multiple exposures is a well-established approach both for capturing high dynamic range (HDR) scenes and for noise reduction. But what is the optimal *set of photos to capture? The typical approach to HDR capture uses a set of photos with geometrically-spaced exposure times, at a fixed ISO setting (typically ISO 100 or 200). By contrast, we show that the capture sequence with optimal worst-case performance, in general, uses much higher and variable ISO settings, and spends longer capturing the dark parts of the scene. Based on a detailed model of noise, we show that optimal capture can be formulated as a mixed integer programming problem. Compared to typical HDR capture, our method lets us achieve higher worst-case SNR in the same capture time (for some cameras, up to 19 dB improvement in the darkest regions), or much faster capture for the same minimum acceptable level of SNR. Our experiments demonstrate this advantage for both real and synthetic scenes.*

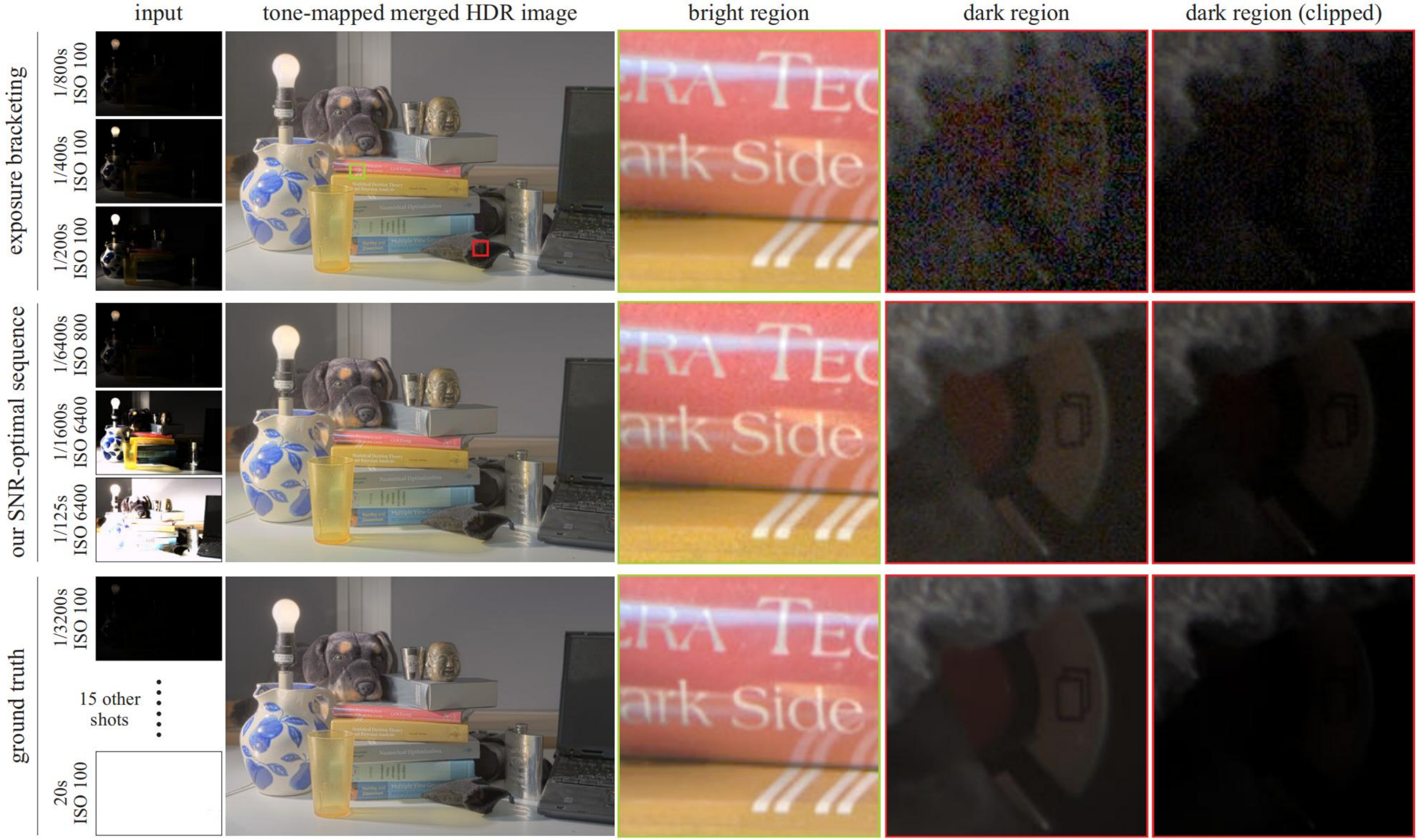
rameters of an exposure sequence, and we show that this reduces to solving a mixed integer programming problem. In particular, we show that, contrary to suggested practice (*e.g.*, [5]), using high ISO values is desirable and can enable significant gains in signal-to-noise ratio.

The most important feature of our noise model is its explicit decomposition of additive noise into pre- and post-amplifier sources (Fig. 1), which constitutes the basis for the high ISO advantage. The same model has been used in several unpublished studies characterizing the noise performance of digital SLR cameras [7, 20], supported by extensive empirical validation. Although all the components in our model are well-established, previous treatments of noise in the vision literature [13, 18] do not model the dependence of noise on ISO setting (*i.e.*, sensor gain).

To the best of our knowledge, varying the ISO setting has not previously been exploited to optimize SNR for high dynamic range capture. However, in the much simpler context of single-shot photography, the *expose to the right* tech-

- We need to separately account for read and ADC noise, as read noise is gain-dependent.
- We can optimize our exposure bracket by varying both shutter speed and ISO

Real Capture Results



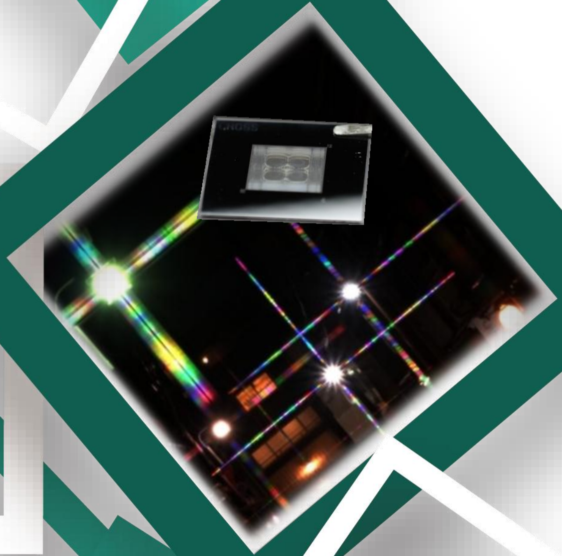
Today's Topic

- Sensor Noise Formation
- Signal-to-Noise Ratio (SNR)
- Noise Calibration
- Optimal Weights for HDR Merging

References

Basic reading:
- Szeliski textbook, Sections 10.1, 10.2.
- Hasinoff et al., "Noise-Optimal Capture for High Dynamic Range Photography," CVPR 2010.
  A paper on weighting different exposures based on a very detailed sensor noise model, additionally discussing combining shutter speed and ISO changes.
- Healey and Kondepudy, "Radiometric CCD camera calibration and noise estimation," PAMI 1994.
  A detailed paper on radiometric and noise calibration based on the noise model we discussed.
- Martinec, "Noise, Dynamic Range and Bit Depth in Digital SLRs," 2008, http://theory.uchicago.edu/~ejm/pix/20d/tests/noise/index.html
  A very detailed discussion of noise characteristics and other performance aspects of digital sensors.

Additional reading:
- Kirk and Andersen, "Noise characterization of weighting schemes for combination of multiple exposures," BMVC 2006.
  A great paper on the variance characteristics of most common HDR weighting schemes.
- Granados et al., "Optimal HDR Reconstruction with Linear Digital Cameras," CVPR 2010.
  This paper extends the analysis of optimal HDR weights to consider spatially-varying noise effects.
- Hasinoff, "Fundamentals of Computational Photography: Sensors and Noise," ICCP 2010 tutorial, https://people.csail.mit.edu/hasinoff/hdrnoise/hasinoff-sensornoise-tutorial-iccp10.pptx
  A detailed tutorial on sensors and noise.
- Hasinoff et al., "Time-constrained photography," ICCV 2009.
- Hasinoff and Kutulakos, "Light-efficient photography," PAMI 2011.
  These two papers examine noise-optimal acquisition and merging schemes for *focal* and *aperture* stacks, rather than exposure stacks.
- Ratner et al., "Optimal multiplexed sensing: bounds, conditions and a graph theory link," Optics Express 2007.
- Ratner and Schechner, "Illumination Multiplexing within Fundamental Limits," CVPR 2007.
  These two papers discuss the effect of different types of noise when fusing multiple images in the context of illumination multiplexing.
- Gupta et al., "Photon-Flooded Single-Photon 3D Cameras," CVPR 2019.
  A paper on the noise characteristics of single-photon-sensitive cameras.



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Thank You!

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