Imagery numérique

Lecture 3

Image acquisition and sensing

Content of course

Semester 1

Lecture 1: Introduction to image processing

Lecture 2: The HVS perception and color

$\boxed{\textbf{Lecture 3: Image acquisition and sensing}}$

Lecture 4: Histograms and point operations

Lecture 5: Geometric operations

Lecture 6: Spatial filters

Lecture 7: The 2D Discrete Fourier Transform

Lecture 8: Frequency domain filtering, sampling and aliasing

Lecture 9: Unitary Image Transforms

Lecture 10: Edge detection

Lecture 11: Edge linking and line detection

Lecture 12: Thresholding

Lecture 13: Morphological image processing

Lecture 14: Object and feature detection

Content of course

Semester 2

Lecture 15: Lossless image coding

Lecture 16: Lossy image compression

Lecture 17: Image restoration

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Lecture 19: Fan beam corrections

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Lecture 21: Digital watermarking

Lecture 22: Image blending (or digital forensics)

Lecture 23: Photomontage and inpaining

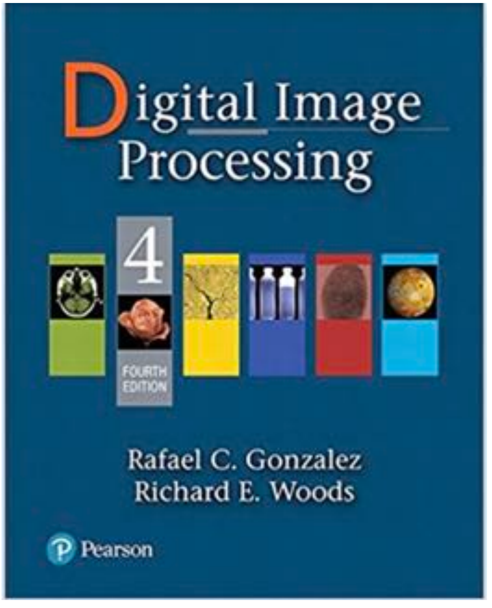
Lecture 24: Image retargeting

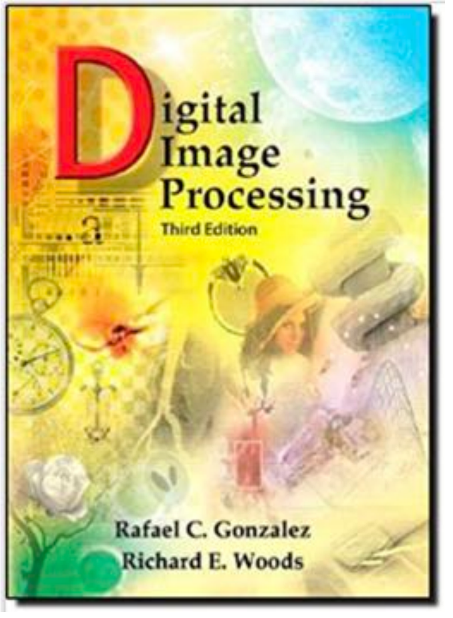
Lecture 25: Active shape models

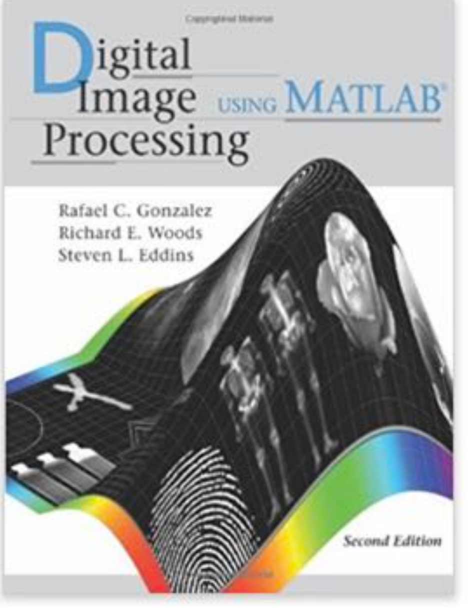
Lecture 26: Sparse modeling and compressive sensing

Lecture 27: Machine learning based applications

Recommended books







YouTube lectures

Intro to Digital Image Processing (ECSE-4540) Lectures, Spring 2015

by Prof. Rich Radke from Rensselaer Polytechnic Institute

Goal

- In lecture 1, we have seen many applications of modern image processing:
  - Different imaging principles
  - Different wavelength
- However, besides all this diversity of imaging tools and applications, all of them share a lot of common principles that can be generalized to a model

Continuous scene

$\mathbf{f}_{cont}$ → Imaging system

$$\mathbf{g} = \mathbf{P}\mathbf{H}\mathbf{f}_{cont} + \mathbf{z}$$

→ $\mathbf{g}$

Sampled scene

Quantization ↓ Compression ↓ Visualization

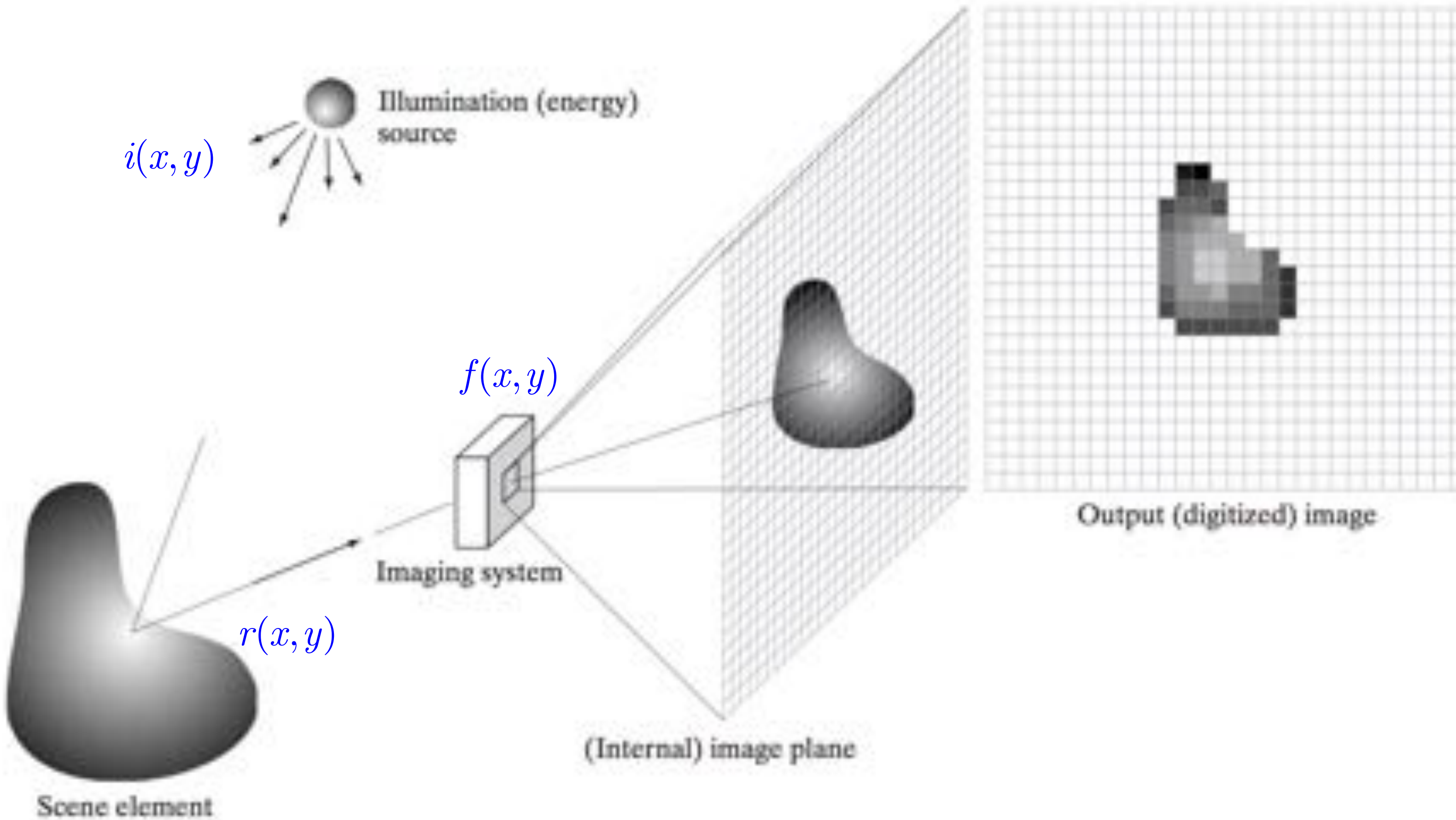
$$\mathbf{g} = Q\left(\mathbf{P}\mathbf{H}\mathbf{f}_{cont} + \mathbf{z}\right)$$

$\mathbf{H}$ - "imaging" operator
$\mathbf{P}$ - sampling
$\mathbf{z}$ - noise

Our goal:

To consider common principles in the design of imaging systems, to generalize them and to introduce a uniform approach to most of image processing applications

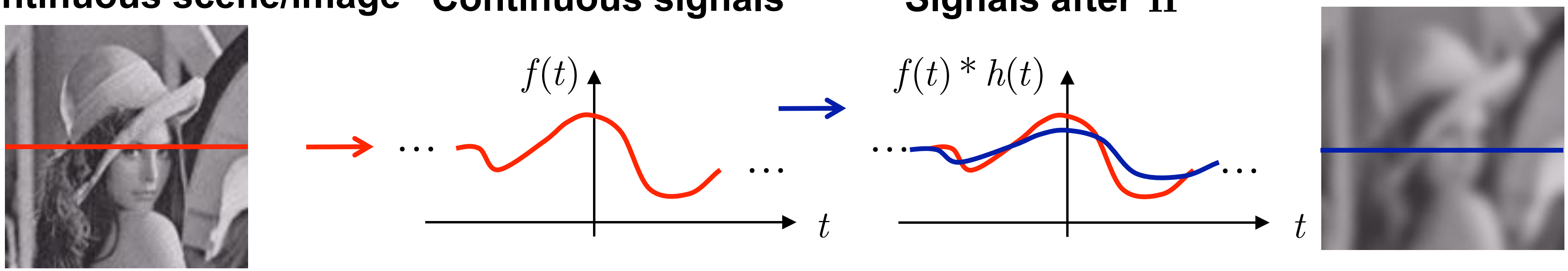
Digital image acquisition – general setup



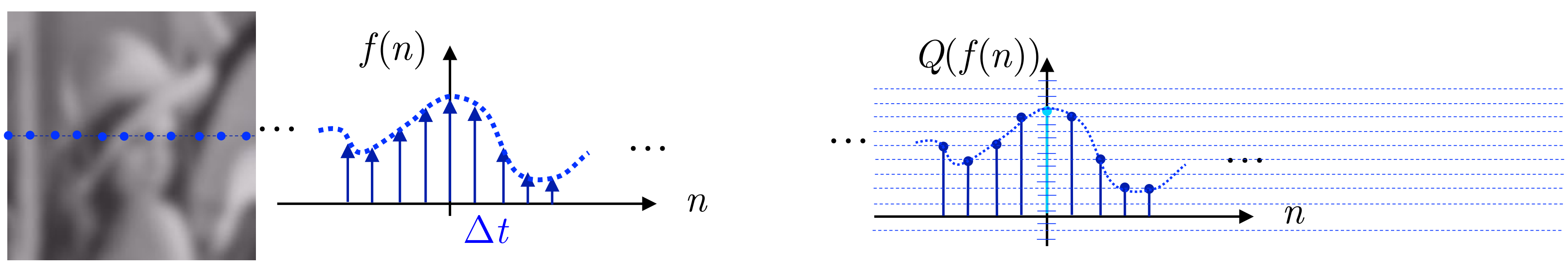
Gonzalez, p. 51

Imaging, Sampling and Quantization

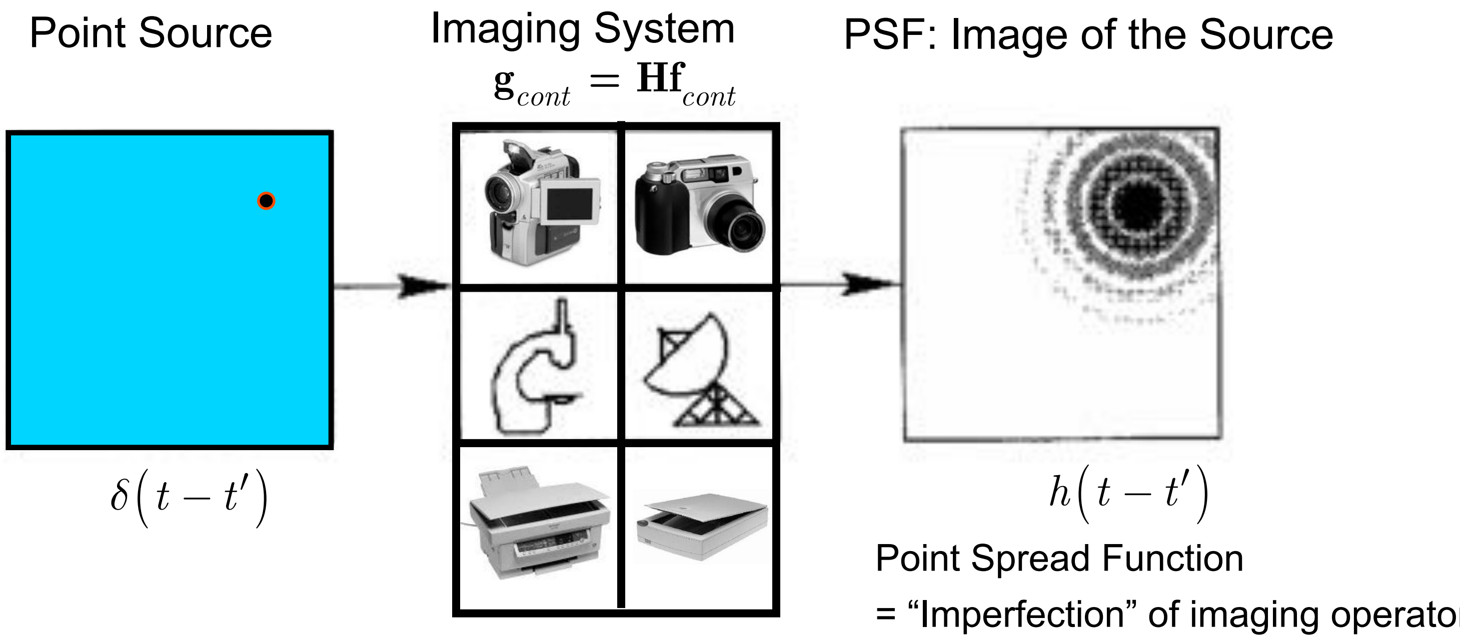
Continuous scene/image **Continuous signals** **Signals after $\mathbf{H}$**



Discrete signals - sampling $\mathbf{P}$ **Discrete quantized signals – Q(.)**

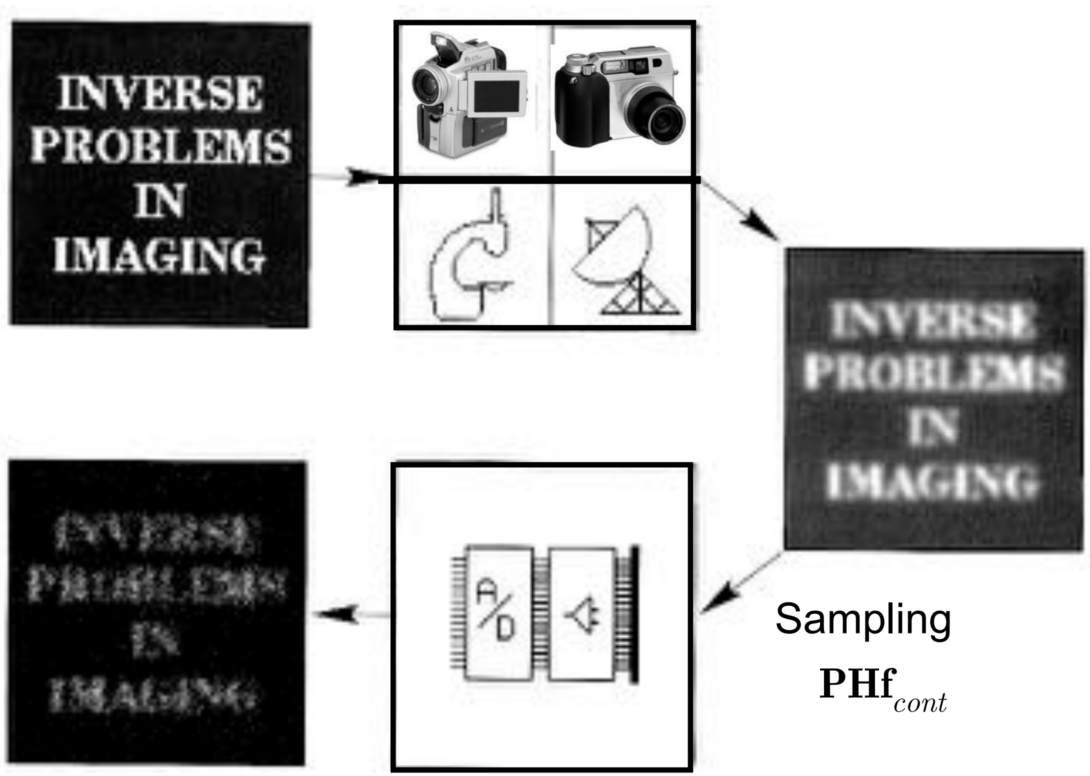


Typical imaging pipeline – “imaging” operator



Different systems designed for imaging in different part of electromagnetic spectrum have different PSFs (note that they might be called differently but the physics is the almost same)

Typical issues: blur, sampling, quantization



$$\mathbf{g}_{cont} = \mathbf{H}\mathbf{f}_{cont}$$

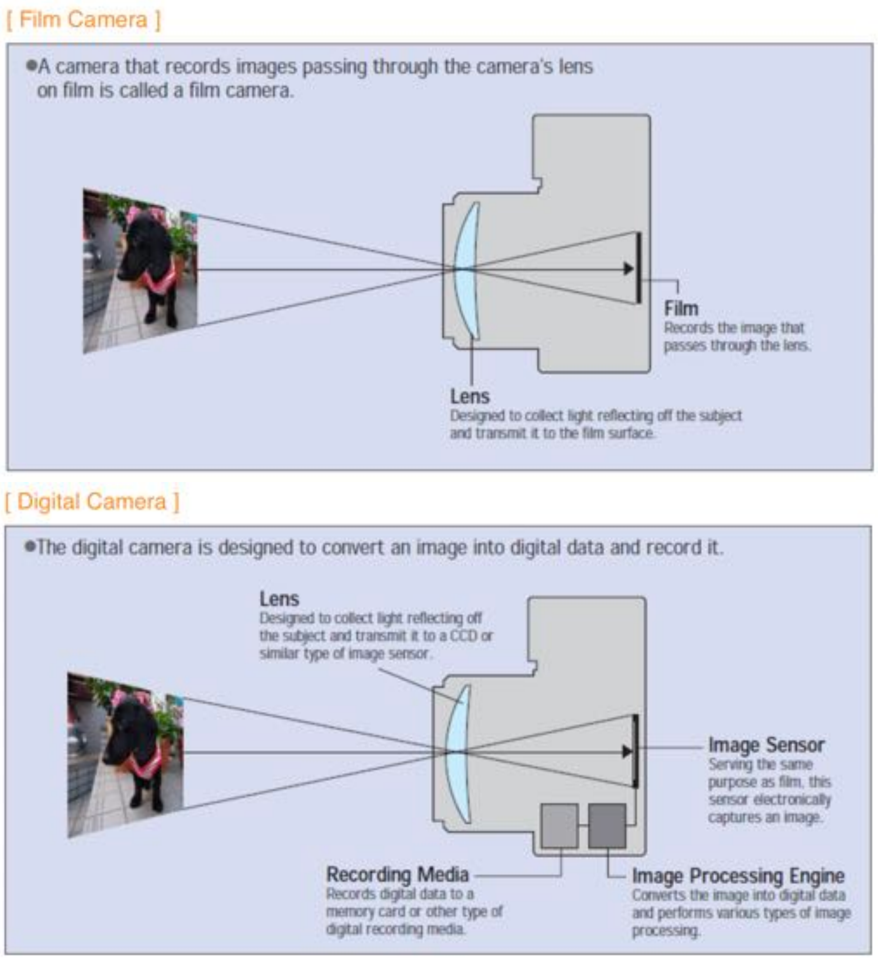
Sampling

$$\mathbf{PHf}_{cont}$$

$$\mathbf{g} = Q\left(\mathbf{PHf}_{cont}\right)$$

Quantization

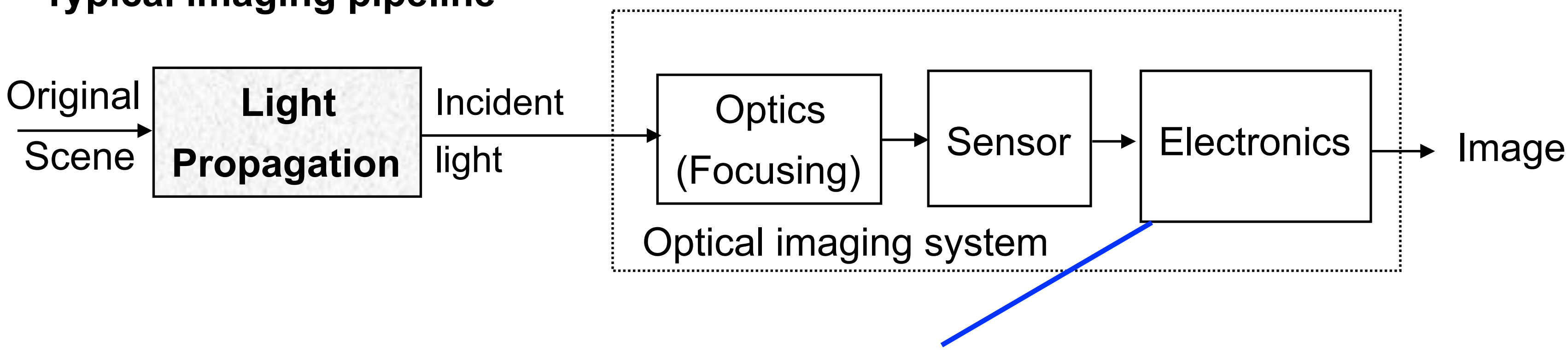
Typical issues: blur, sampling, quantization



http://av.jpn.support.panasonic.com/support/global/cs/dsc/knowhow/knowhow01.html

Typical issues: blur, sampling, quantization

Typical imaging pipeline



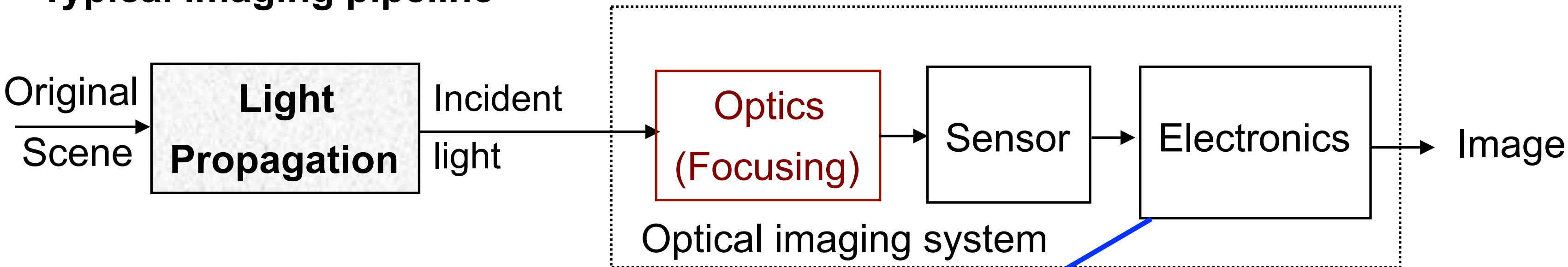
- **ADC** – analog-to-digital convertor
- **Processing** – demosiacing, gamma correction, white balancing, denoising, compression

Main issues:

- Every camera has its own optics, sensors and processing algorithms
- Many algorithms are not standardized
- The order of processing may vary
- The parameters of algorithms remain often unknown and proprietary

Typical issues: blur, sampling, quantization

Typical imaging pipeline

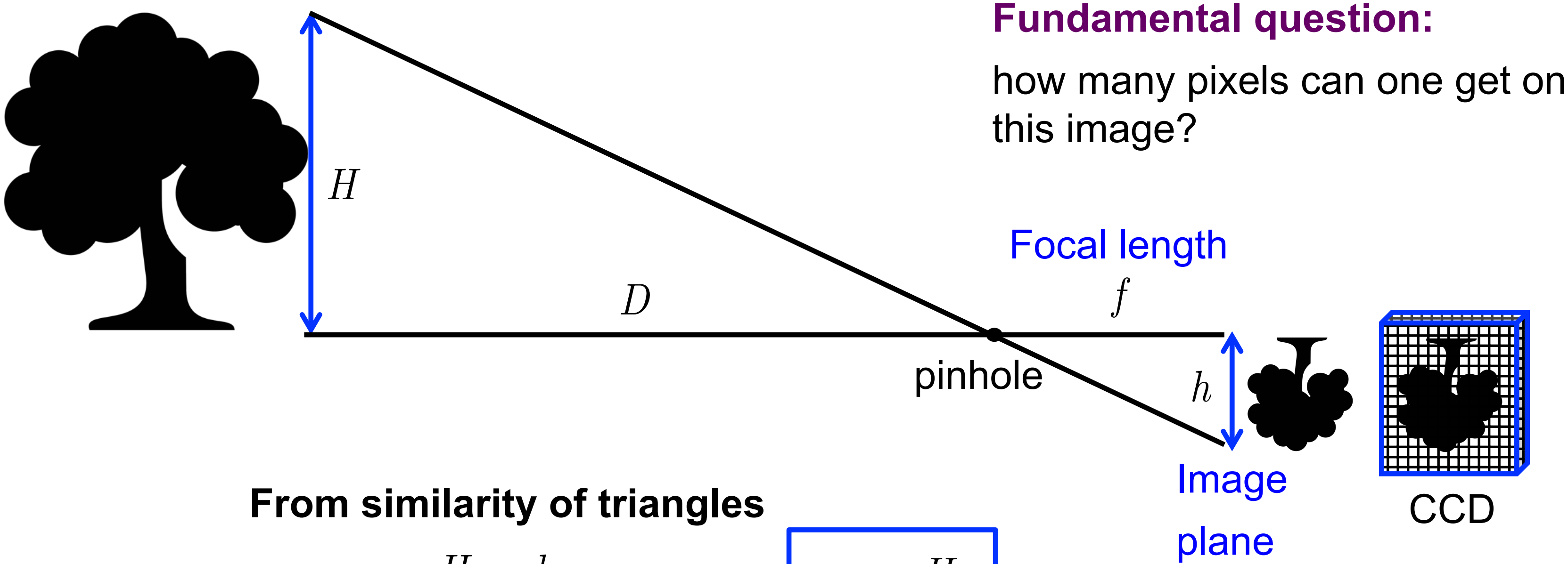


- **ADC** – analog-to-digital convertor
- **Processing** – demosiacing, gamma correction, white balancing, denoising, compression

Main elements:

- **Optics**
- Sensors
- Electronics - Processing

Imaging operator H: focal length and focusing



Fundamental question:

how many pixels can one get on this image?

From similarity of triangles

$$\frac{H}{D} = \frac{h}{f} \quad \Rightarrow \quad \boxed{h = f\frac{H}{D}}$$

The focal length is a distance between the pinhole and the image plane.

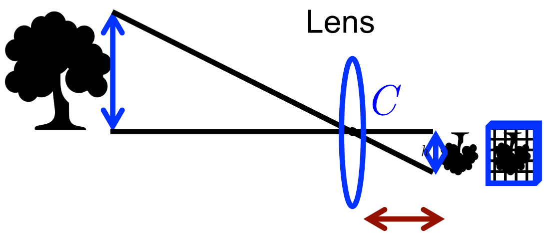
It is a very small number.

Imaging operator H: focal length and focusing

Reminder

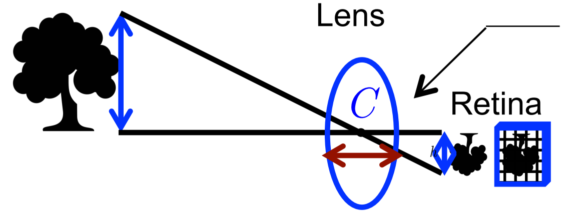
Important difference in focusing:

ordinary camera



To focus - change the distance between the lens and the image plane

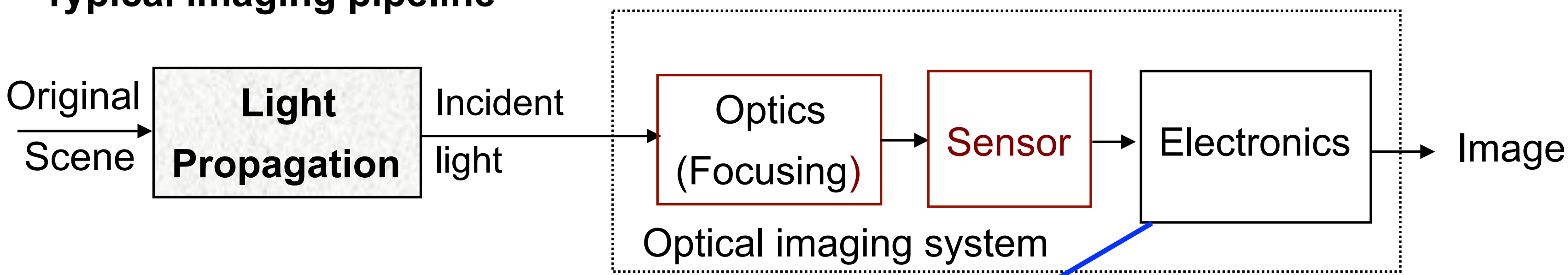
the human eye



To focus - change the focal distance by varying the lens

Typical issues: blur, sampling, quantization

Typical imaging pipeline



- **ADC** – analog-to-digital convertor
- **Processing** – demosiacing, gamma correction, white balancing, denoising, compression

Main elements:

- Optics
- **Sensors**
- Electronics – Processing (we will not consider it here; see later)

Image sensors - optical

Imaging sensors are responsible for:

① Sampling of scene projected onto the focal plane

② Conversion of light (photons) into the electric current (electrons)

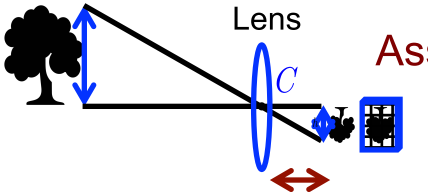
③ Conversion of current into the bits (analog-to-digital conversion) and corresponding low-level processing accompanying such a conversion (like gamma correction)

The role of image sensor in the overall process of image formation is very important and complex.

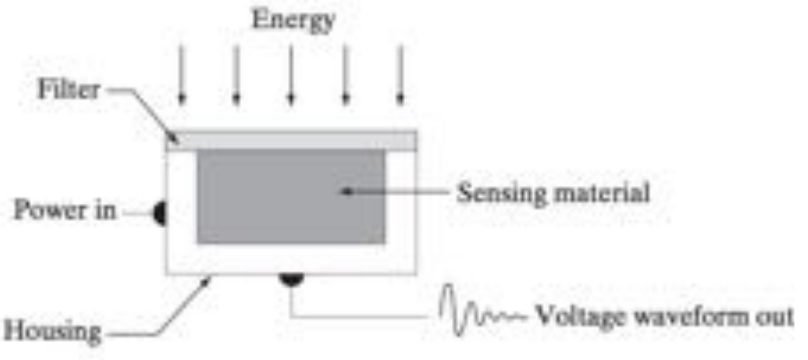
We will start with a simple optical sensors, extend them to more complex optical systems, show several applications requiring dedicated processing and show the links with the radio and microwave imaging systems.

Image sensors - optical

Single imaging sensor

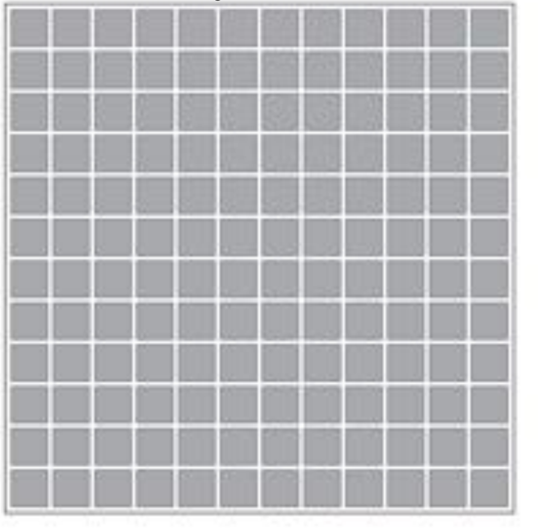


Assume after optics $\mathbf{Hf}_{cont}$



Line sensor

Array sensor



Photon counting

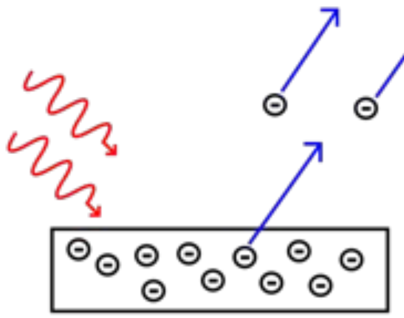
The larger size of sensor, the higher sensitivity (more photons can be collected)

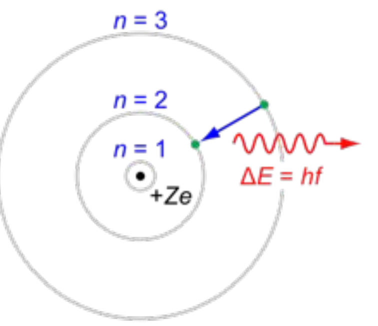
Gonzalez, p. 47

Note: the output of array represents $\mathbf{PHf}_{cont}$

Image sensors – optical: foundations

Photon-to-electron conversion





A schematization of the Bohr model of the hydrogen atom. The transition shown from the *n* = 3 level to the *n* = 2 level gives rise to visible light of wavelength 656 nm (red), as the model predicts.

- A photon of light might lead to the emission of an electron, when a photon hits metal. The emission depends in the photon energy, which is a function of its wavelength

$$E_{photon} = h\underbrace{\frac{c}{\lambda}}_{f} = hf \qquad h - \text{ Planck constant}$$

- Remark: there is no definition of brighter or darker photons. One only distinguishes more or fewer of photons achieving the sensor

https://en.wikipedia.org/wiki/Photoelectric_effect

Image sensors - optical

Quantum efficiency

- Not all photons produce an electron:
  - depends on quantum efficiency of device (sensor)

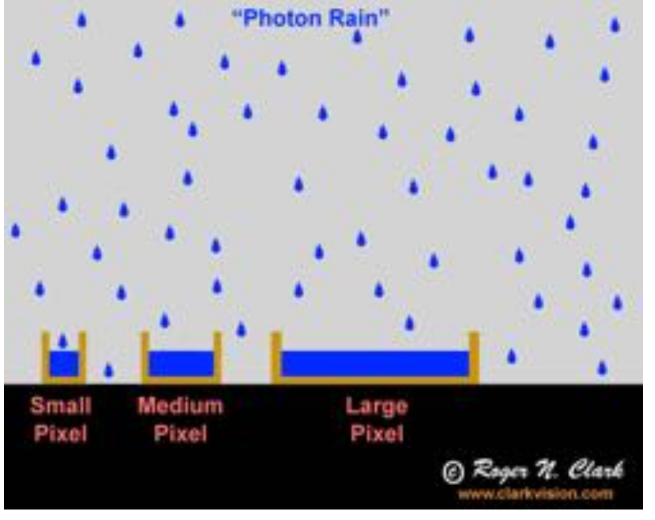
$$QE = \frac{No\ electrons}{No\ photons}$$

  - Human vision: about 15%
  - Typical digital camera: <50%
  - Best CCD: >90%

Image sensors – optical: photon counting

Pixel size (but be careful with what will follow!)

- Assume a system without a lens and any aperture
- Consider a "rain" of photons that hit pixels of different sizes



Intuition:

The larger pixel, the more photons can be "collected"

Typical sizes of pixels:

1.4um x 1.4um

2.5um x 2.5um

6.5um x 6.4um

- The current from a single electron is very small
- Therefore, one can "accumulate" multiple photons to produce more electrons by:
  - accumulating over space (larger pixel size or adding pixels) – loss of resolution
  - accumulating over time (larger exposure time) – not applicable for moving objects

http://www.clarkvision.com/articles/does.pixel.size.matter/#SameLens

Image sensors – optical: photon shot noise

Pixel size (but be careful with what will follow!)

- Why is it so important to collect more electrons per pixel?
  - the number of photons arriving during an exposure varies from exposure to exposure and from pixel to pixel, even if the scene is completely uniform
  - this number is governed by **the Poisson distribution**

Image sensors – optical: photon shot noise

Pixel size (but be careful with what will follow!)

- Why is it so important to collect more electrons per pixel?

Less photons

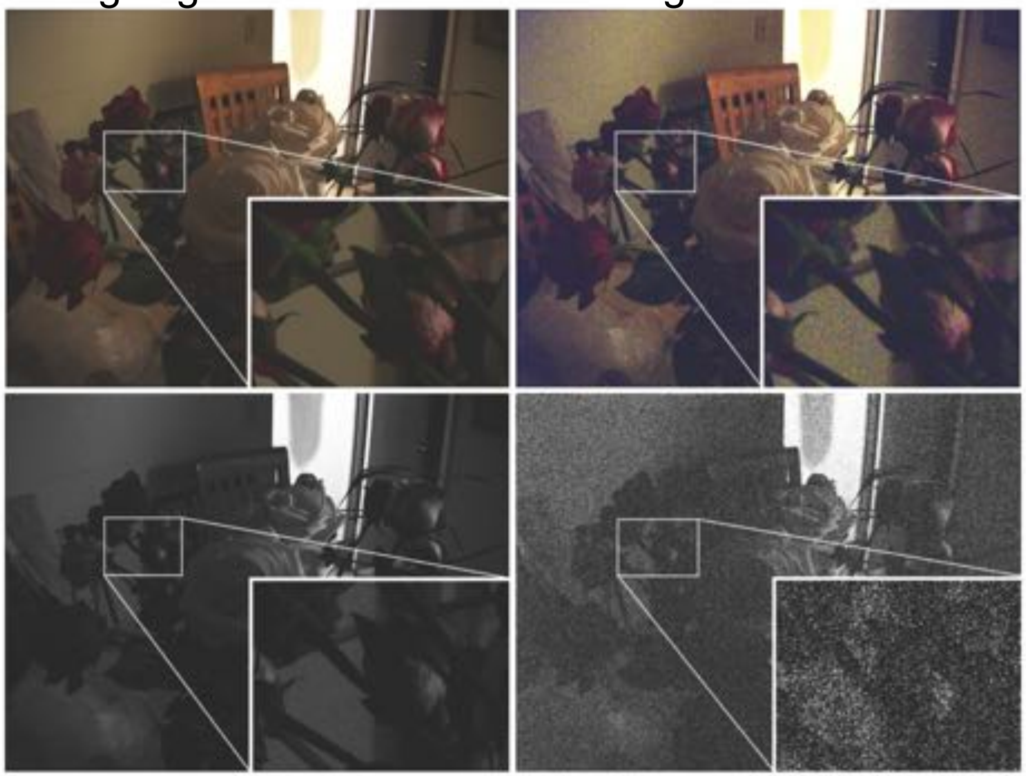
More photons

Number of photons per pixel increases from left to right and from upper row to bottom row.

https://en.wikipedia.org/wiki/Shot_noise

Noise in digital images: photon noise

High light environment   Low light environment



Canon PowerShot S90

Blue channel

RENOIR - A Dataset for Real Low-Light Image Noise Reduction

Josue Anaya[a], Adrian Barbu[a,*]

https://arxiv.org/pdf/1409.8230.pdf

Image sensors – optical: photon shot noise

Pixel size (but be careful with what will follow!)

Poisson distribution

- Governs the probability that a certain number of events will occur during an interval of time
- To apply the Posson pmf we should:
  - Define the average rate α
  - Assume the independence of events
- If on average α events occur on some defined interval of time, the probability p that k events occur instead is defined as:

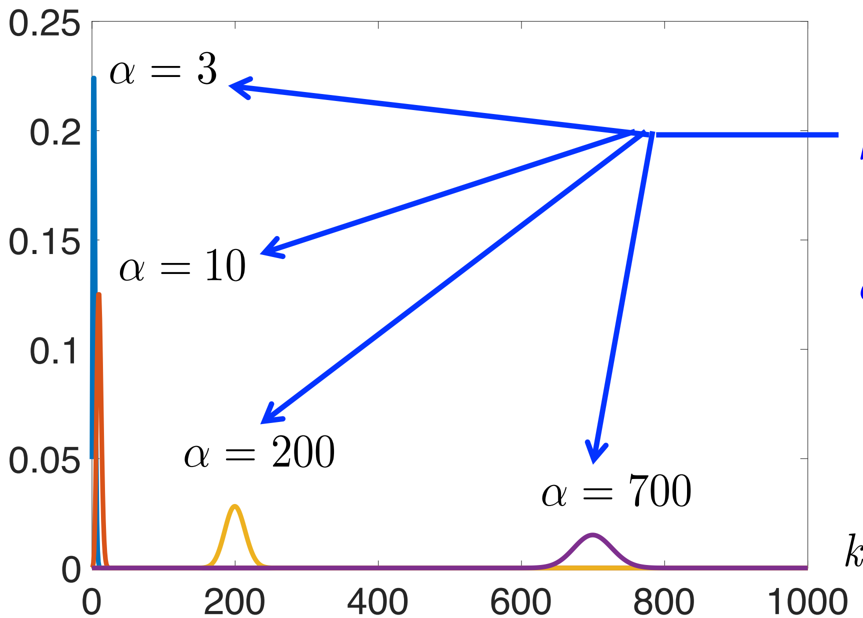
$$p(k;\alpha) = \frac{\alpha^k e^{-\alpha}}{k!} \qquad k = 0,1,2,....,\infty$$

Image sensors – optical: photon shot noise

Pixel size (but be careful with what will follow!)

Poisson distribution

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



$$\mu = E\left[K\right] = \sum_{k=0}^{\infty} k p(k) = \alpha$$

$$\sigma^2 = Var\left[K\right] = \sum_{k=0}^{\infty} (k - E\left[K\right])^2 p(k) = \alpha$$

$$\sigma = \sqrt{\alpha}$$

Std grows slower than the mean

Image sensors – optical: photon shot noise

Pixel size (but be careful with what will follow!)

Signal-to-noise ratio

$$SNR = \frac{\text{mean pixel value}}{\text{standard deviation of pixel value}} = \frac{\mu}{\sigma}$$

$$SNR[dB] = 20\log_{10}\left(\frac{\mu}{\sigma}\right)$$

In our case of Poisson pmf:

$$SNR[dB] = 20\log_{10}\left(\frac{\alpha}{\sqrt{\alpha}}\right) = 20\log_{10}\left(\sqrt{\alpha}\right) = 10\log_{10}\left(\alpha\right)$$

The SNR of Poisson noise (photon counting) increases with the average number of photons.

It means that we have less deviation from the mean value for more electrons.

As a result, we observe less noise.

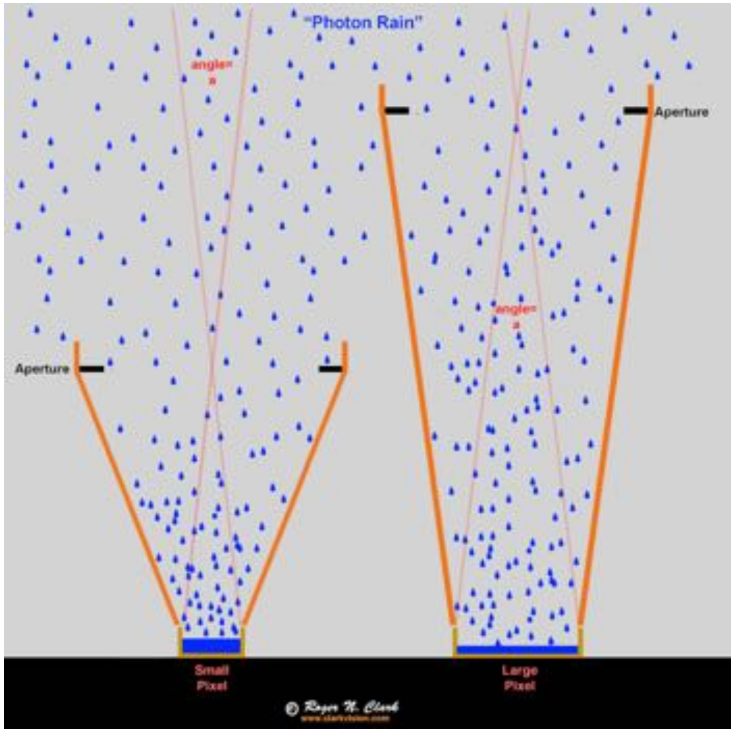
Conclusion: the larger pixel size, the more photons we collect….but ….

Image sensors – optical: photon counting

Pixel size and aperture

The number of photons that is collected is not only controlled by the pixel size.

Remember: we have assumed no lens and no aperture. We can control the process.



Note:

The aperture size is the same in both cases

But the focusing is different!

Conclusion: theoretically (neglecting diffraction for small pixels) we can collect the same amount of electrons for small and large pixels -> **aperture matters**

http://www.clarkvision.com/articles/does.pixel.size.matter/#SameLens

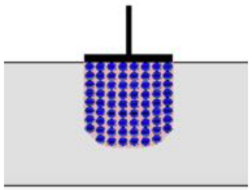
Image sensors – optical: photon counting

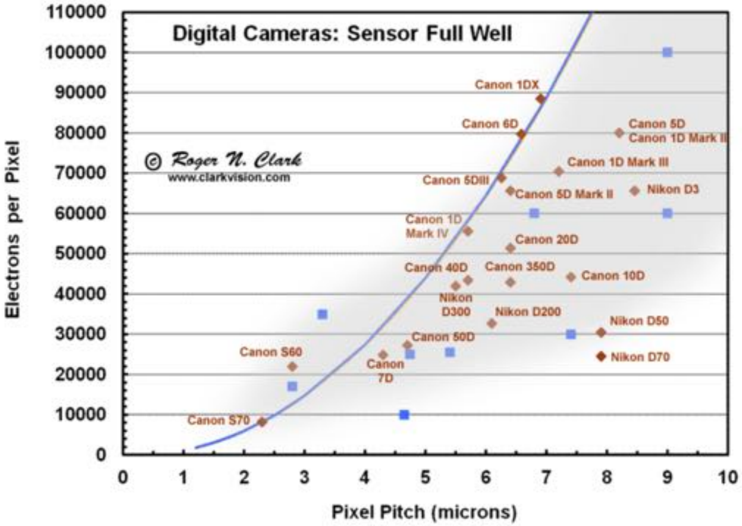
Pixel size and full well capacity

However, there is one more important issue related with the size of pixel.

The capacity to hold the electrons in each pixel that are generated from photons is called the **Full Well Capacity**.

Too many electrons (like an overflow for a small pixel size) might cause a **saturation** (white spot in images)





Because of the finite and fixed absorption lengths of photons in silicon, the full well capacities are basically a function of pixel area (and not volume).

Conclusion: larger pixel size has higher Full Well Capacity that prevents the saturation

http://www.clarkvision.com/articles/does.pixel.size.matter/#SameLens

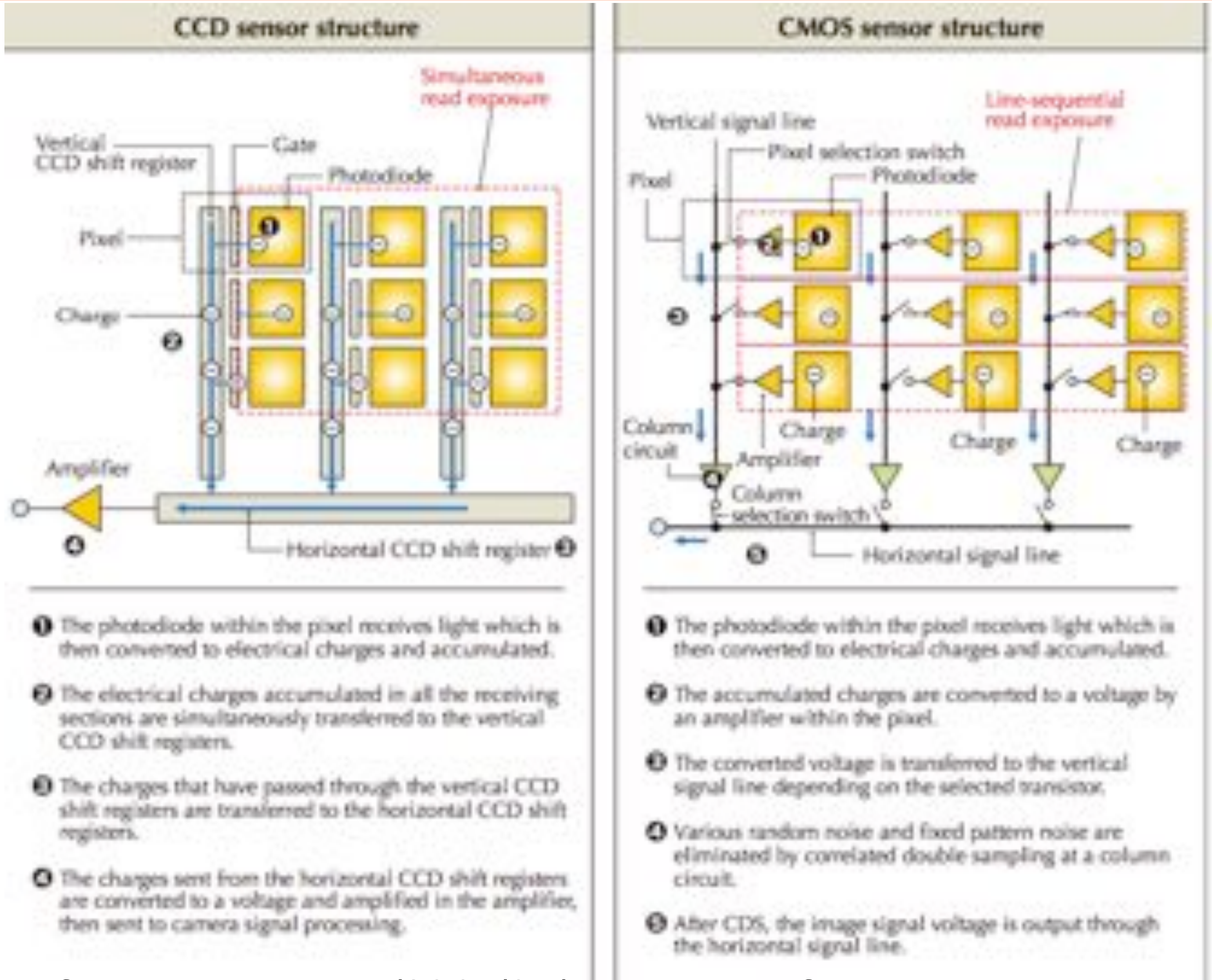
Image sensors – main types of optical sensors

- **CMOS** = complementary metal-oxide semiconductor
  - Each pixel has its own amplifier; each row has its own ADC
  - Output is digital
  - Low power, fast but generally noisy (recent models are better)

- **CCD** = charge-coupled device
  - Charge shifted along columns to an output amplifier and ADC (off chip)
  - Historically among the first solid-state image sensors
  - Highest image quality but more expensive then CMOS
  - Slow but low noise

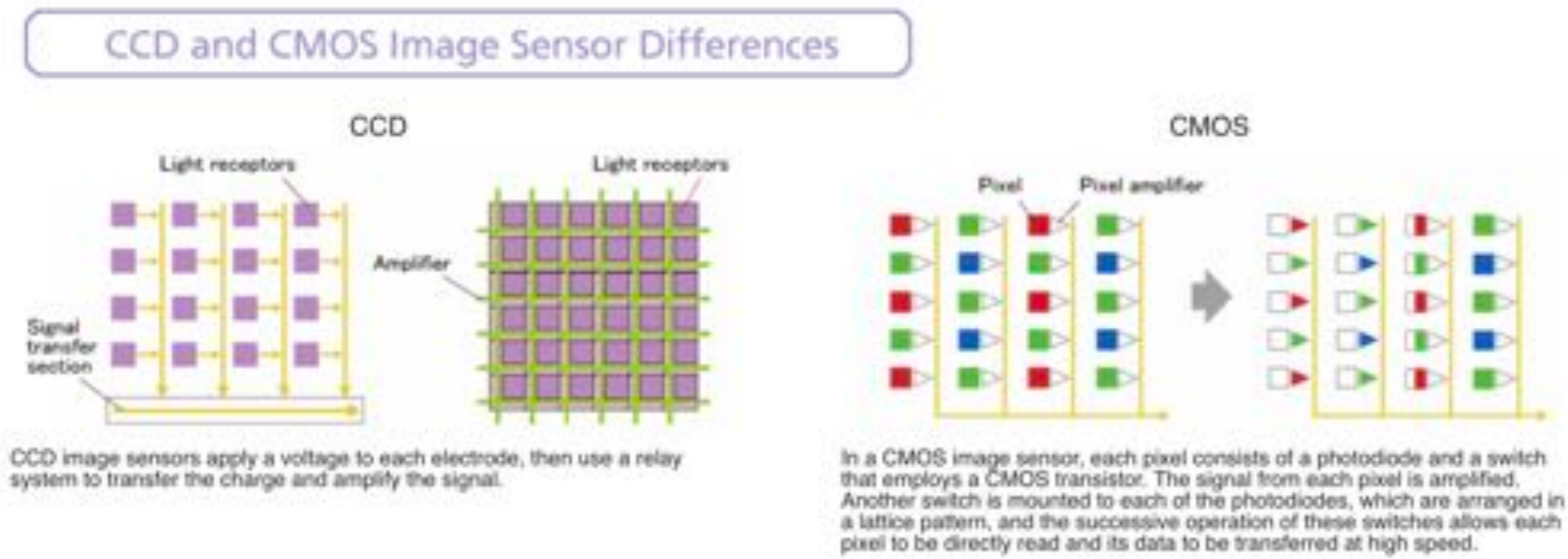
The main difference between **CCD** and **CMOS** is how they amplify and transfer the charge out of the pixel.

Image sensors – main types of optical sensors



http://market-sell-free.blogspot.com/2014/07/advantage-of-cmos-sensor.html

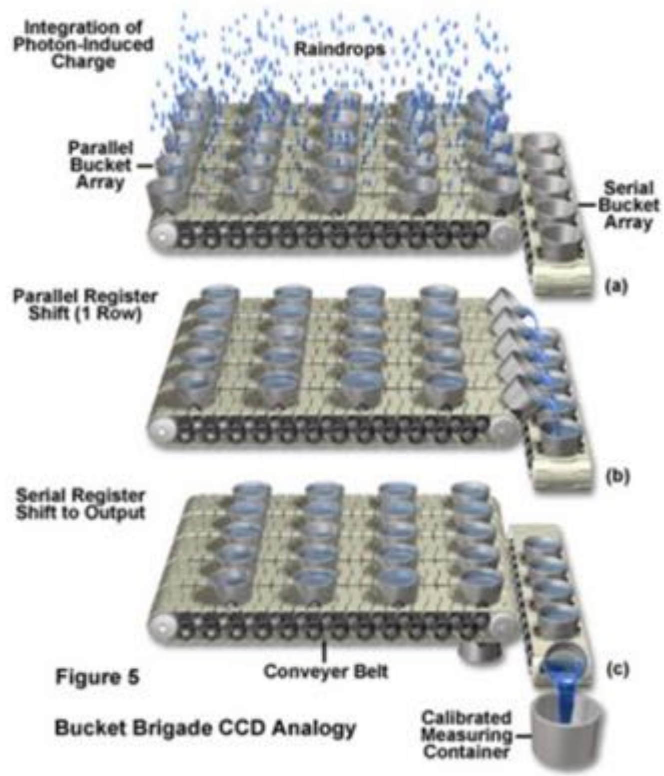
Image sensors - optical



http://av.jpn.support.panasonic.com/support/global/cs/dsc/knowhow/knowhow28.html

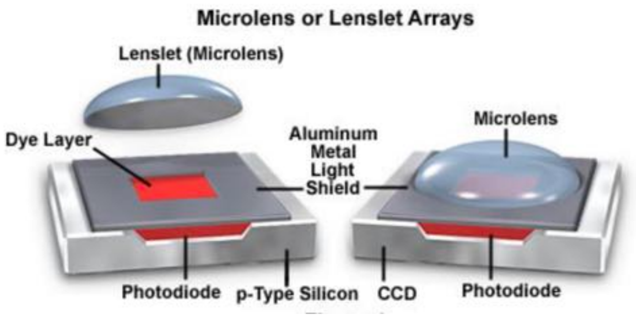
Image sensors – CCD read out

CCD “bucket-brigade” analogy

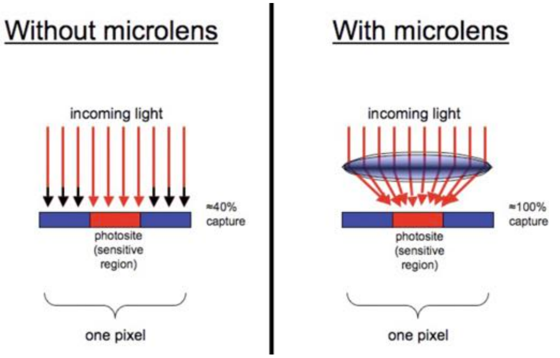


https://slideplayer.com/slide/10531209/

Image sensors – CCD microlens

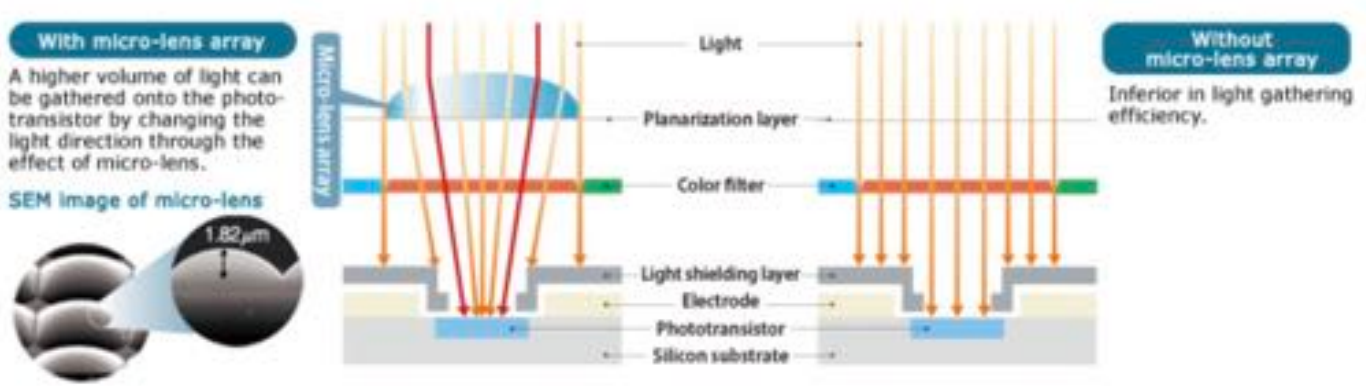


http://hamamatsu.magnet.fsu.edu/articles/microlensarray.html



http://www.digitalbirdphotography.com/2.3.html

Microlenses increase the number of photons. This also increases the quantum efficiency of pixel and focus the photons into the photosensitive area



https://www.toppan.co.jp/electronics/english/semicon/onchip/

Image sensors

Sensor Name	Medium Format	Full Frame	APS-H	APS-C	4/3	1"	1/1.63"	1/2.3"	1/3.2"
Sensor Size	53.7 x 40.2mm	36 x 23.9mm	27.9x18.6mm	23.6x15.8mm	17.3x13mm	13.2x8.8mm	8.38x5.59mm	6.16x4.62mm	4.54x3.42mm
Sensor Area	21.59 cm²	8.6 cm²	5.19 cm²	3.73 cm²	2.25 cm²	1.16 cm²	0.47 cm²	0.28 cm²	0.15 cm²
Crop Factor	0.64	1.0	1.29	1.52	2.0	2.7	4.3	5.62	7.61
Image									
Example									

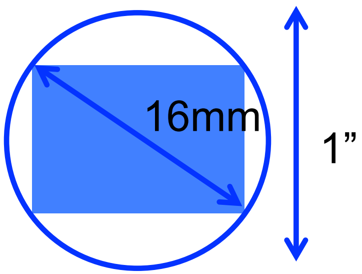
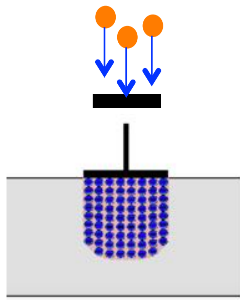
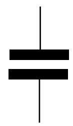


Image sensors - summary

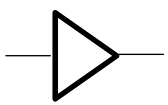


A number of **photons** hit a **pixel** during the **exposure time** for a given **aperture**

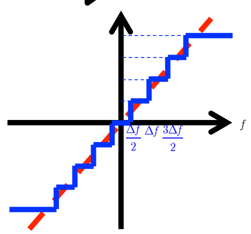
… create a number of **electrons** …



… forming a **charge** that is converted by a **capacitor** to a **voltage** …



… and then **amplified** …



… and then **digitized (ADC)** …

127 … resulting in a **digital gray level value.**

CCD: high image quality, lower speed

CMOS: high spped, lower quality, lower energy consumption

Image sensors – quality and origin of noise

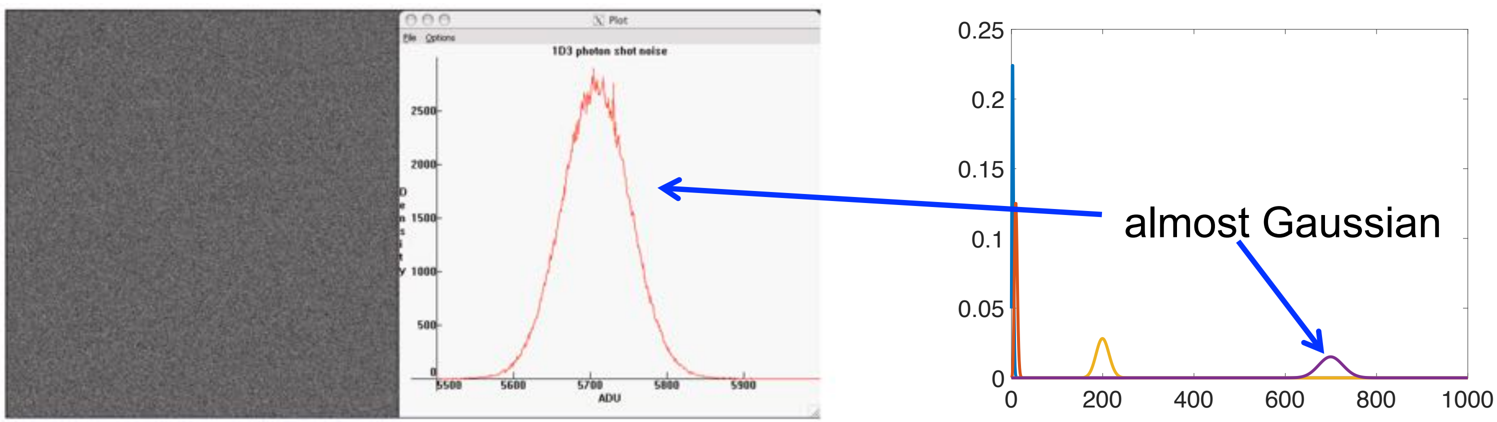
- **Pixel size** and **number**
- **Aperture** and **exposure time**
- **Quantum efficiency**: the fraction of photons hitting the CCD that are converted to electrons
- **Full well depth**: total number of electrons that can be recorded per pixel

- **Noise origin**:
  - **Shot noise / Photon noise**:
    - Photon counting
  - **Dark current or thermal noise**:
    - The rate at which electrons are produced due to thermal effects (potential cooling of sensors)
  - **Pattern noise**
  - **Quantization noise**:
    - Errors caused by ADC process

Noise in digital images: photon noise

Origin of noise

- Discrete nature of photon counting (see slide 24)
- The more intense the light, the higher the number of photons per second that illuminate the scene (the better SNR)



Photon shot noise in an image of the sky from a Canon 1D3 (in the green channel).

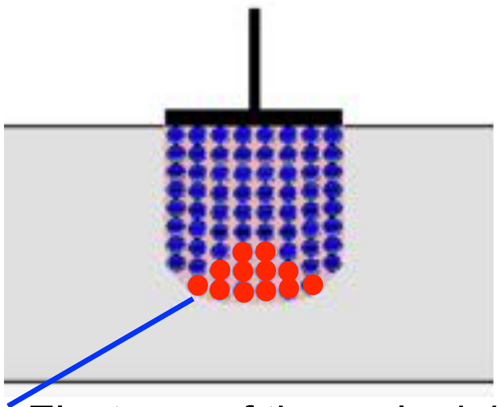
The photon noise was estimated by taking the difference of two successive images; the raw values for any one pixel then differ only by the fluctuations in the photon count due to Poisson statistics

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

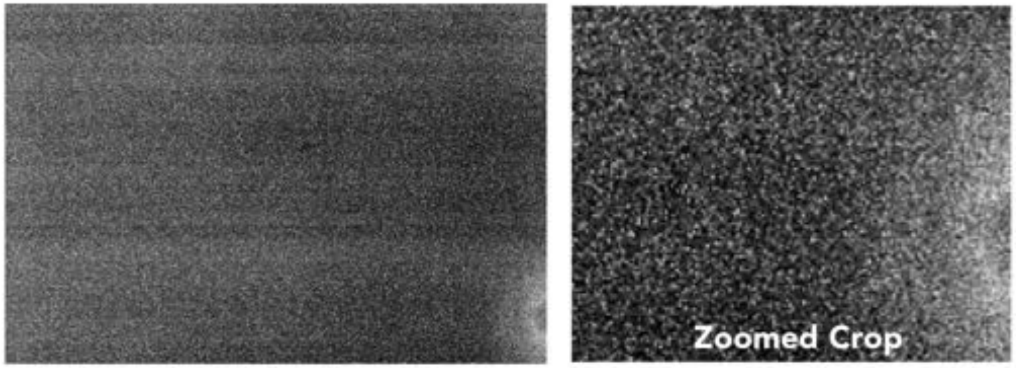
Noise in digital images: dark current or thermal noise

Origin of noise

- Thermal agitation of electrons in a sensel can liberate a few electrons
- These electrons are independent of sensor incident light
- Increases linearly with exposure time and exponentially with temperature



Electrons of thermal origin
(independent to input)



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

Noise in digital images: pattern noise

Origin of noise

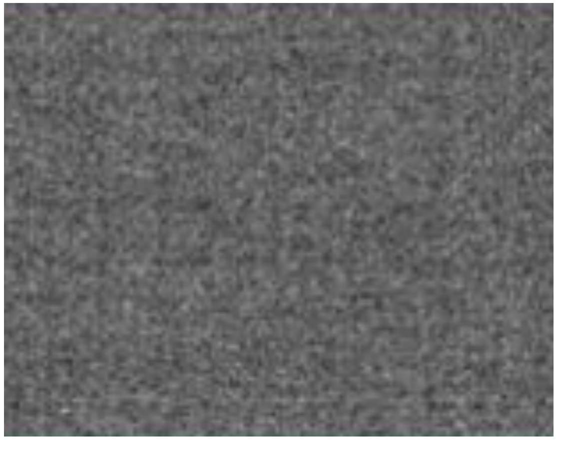
- Not all pixels in a sensor have exactly the same efficiency in capturing and counting photons
- This might cause a so-called **pattern noise**:
  - **Fixed pattern noise (FPN)**: pixel to pixel differences when not exposed to light (additive in nature)
  - **Photo response non-uniformity (PRNU)**: depends on illumination (multiplicative in nature)
- **Both types of noise are systematic for a given sensor**

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

Noise in digital images: pattern noise

FPN:

- Crystal defects in the silicon lattice introduced during growth
- Impurities
- The size of detector/potential well
- Contamination during fabrication
- Non-uniform oxide/gate thickness
- In CMOS: additional variability for each transistor
- Does not change over time; FPN can be estimated and removed from each image



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

Noise in digital images: pattern noise

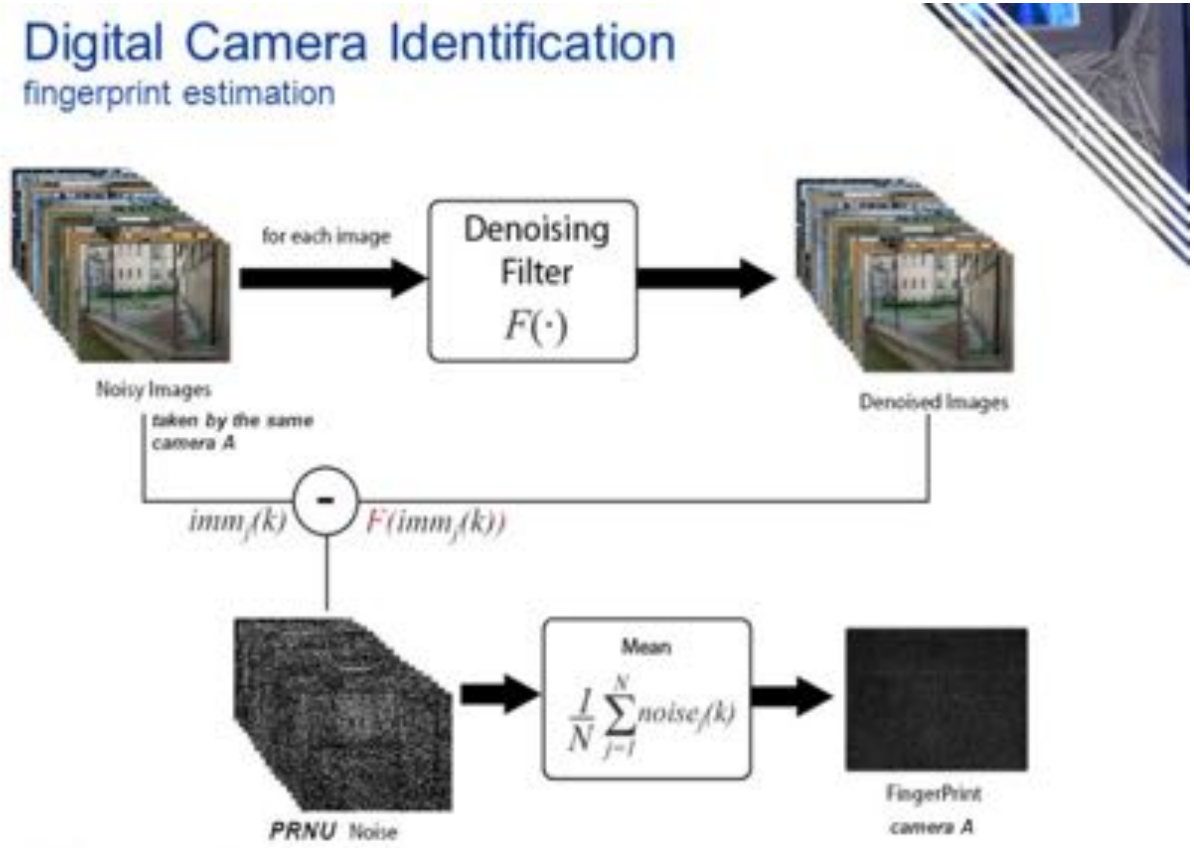
PRNU:

- The depth of the detector/potential well
- Larger active areas – more incident photons
- Non-uniform oxide layer: results in non-uniform potential wells
- Deeper potential well: more photons absorbed (wavelength dependent)
- PRNU can be estimated and removed from each image

PRNU is a "fingerprint" of sensor

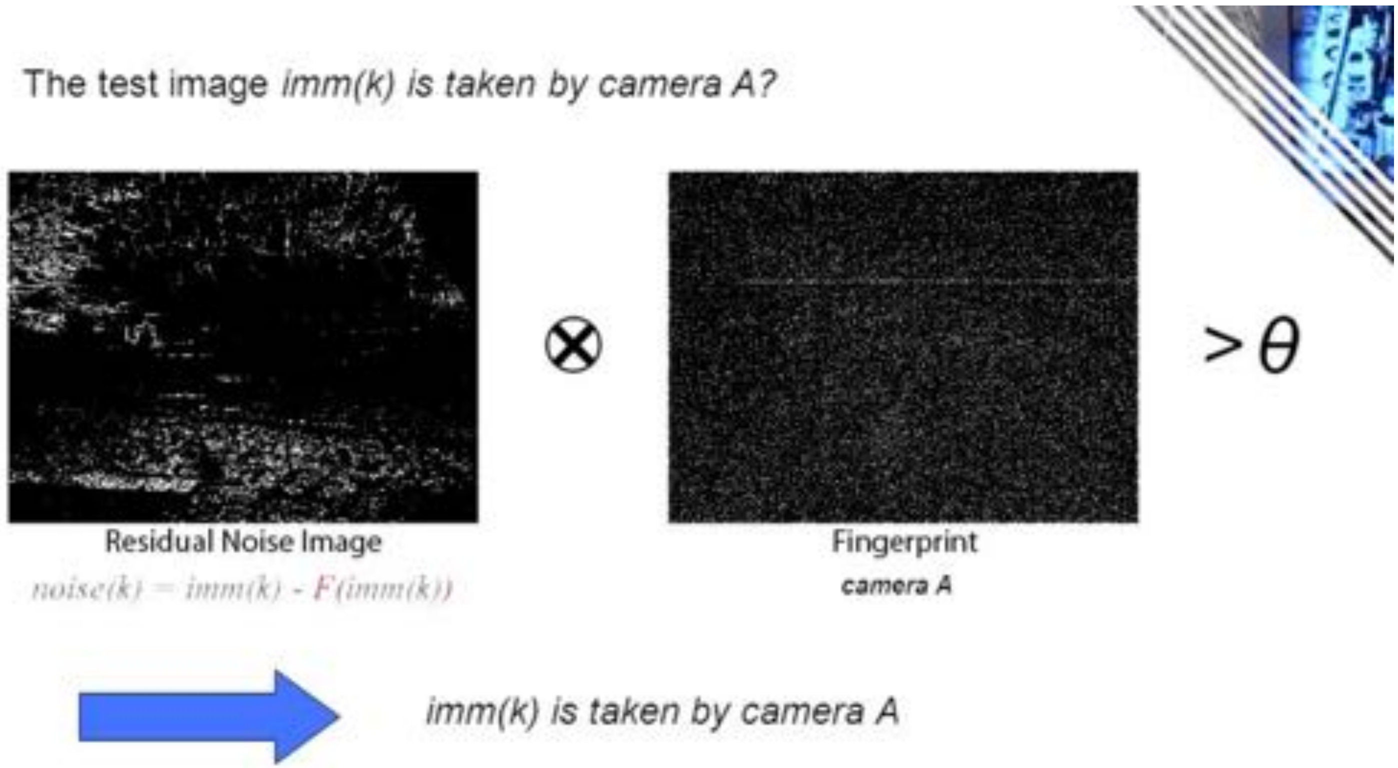
http://theory.uchicago.edu/~ejm/pix/20d/tests/noise/#patternnoise

Noise in digital images – pixel response non-uniformity (PRNU)



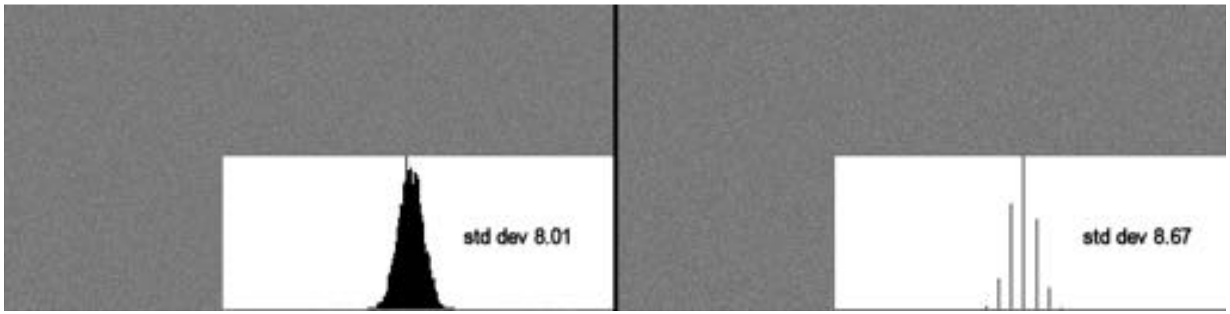
https://slideplayer.com/slide/10390280/

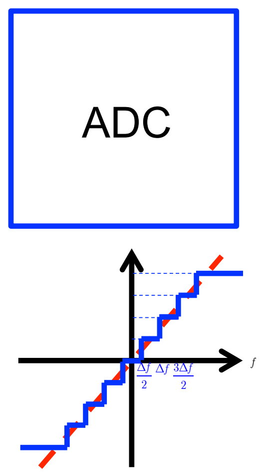
Noise in digital images – pixel response non-uniformity (PRNU)



https://slideplayer.com/slide/10390280/

Noise in digital images– quantization noise





Noise in digital images – summary

Photon shot noise:

- Unavoidable randomness in number of photons arriving
- Grows as the square root of the number of photons, so brighter lighting and longer exposures will be less noisy

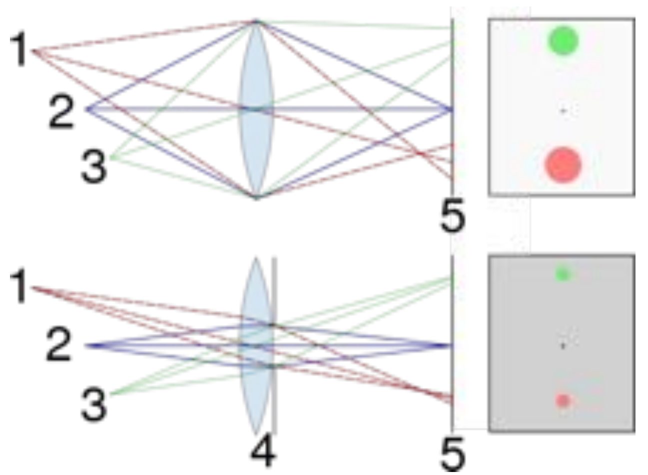
Dark current noise:

- Grows with exposure time and sensor temperature
- Minimal for most exposure times used in photography
- Corrected for average dark current

Quantization noise:

- Determined by the ADC: quantization step, properties of quantizer

Factors impacting the noise in images

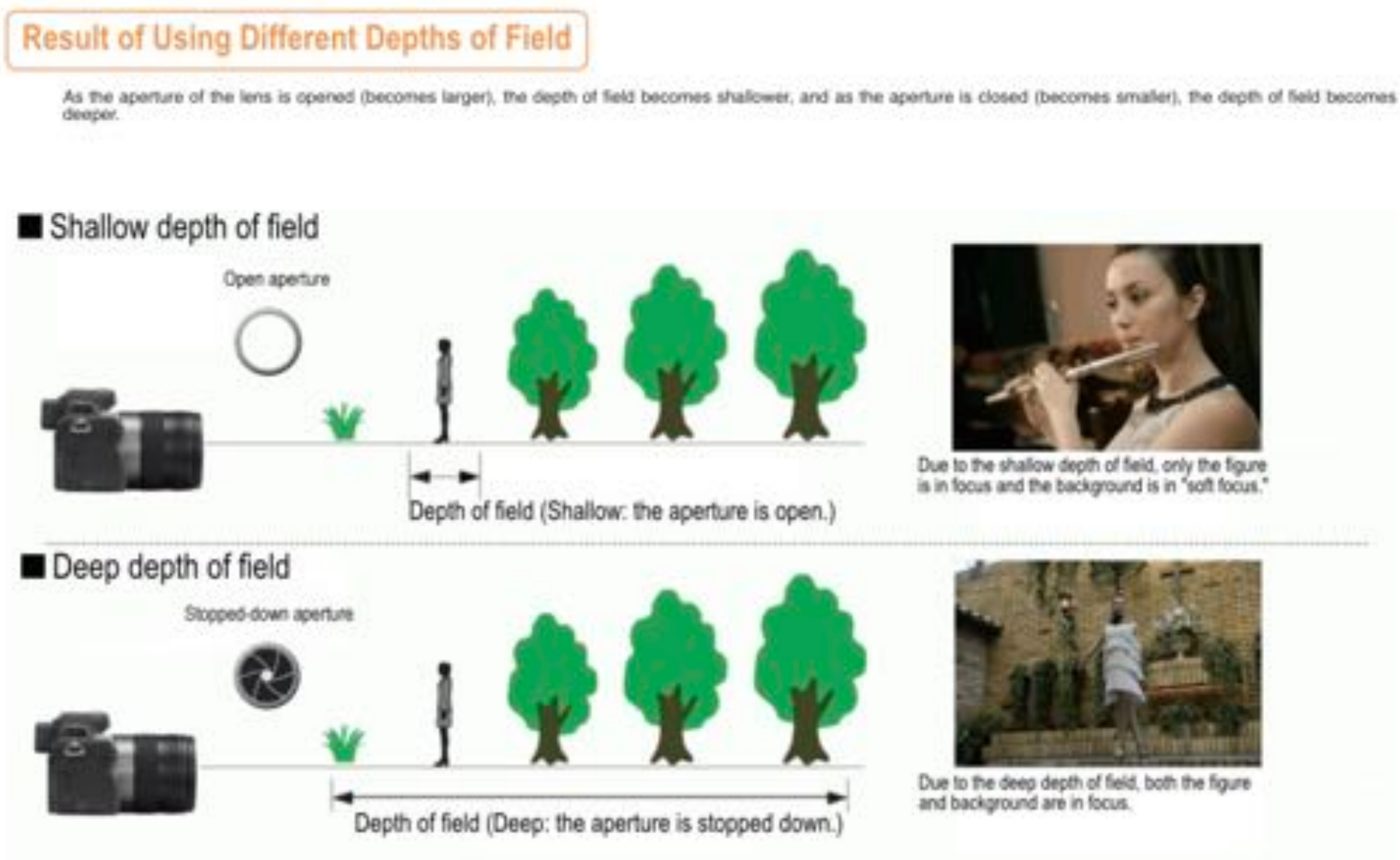


Positive impact of aperture on **depth of field (DoF)**

Effect of aperture on blur and DOF. The points in focus (**2**) project points onto the image plane (**5**), but points at different distances (**1** and **3**) project blurred images, or circles of confusion. Decreasing the aperture size (**4**) reduces the size of the blur spots for points not in the focused plane, so that the blurring is imperceptible, and all points are within the DoF.

https://en.wikipedia.org/wiki/Depth_of_field

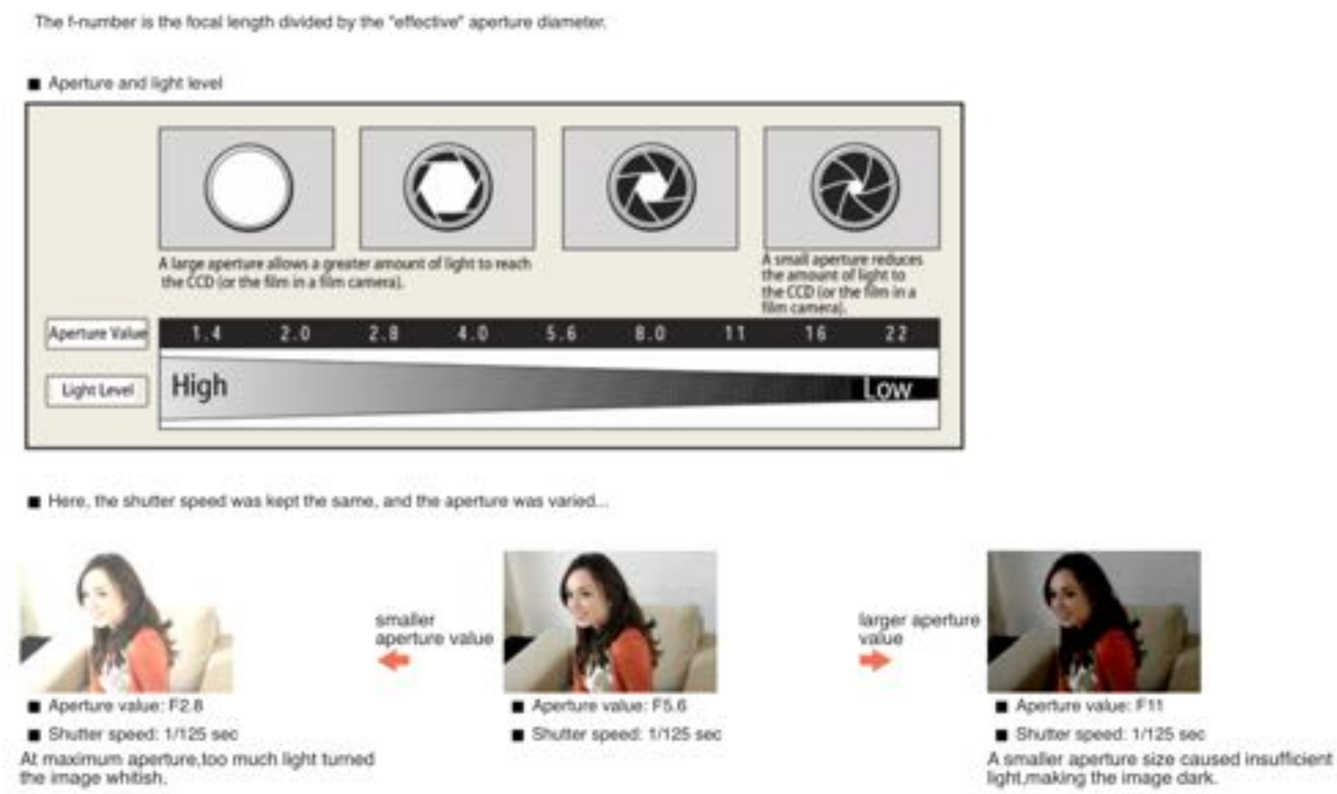
Factors impacting the noise in images



http://av.jpn.support.panasonic.com/support/global/cs/dsc/knowhow/knowhow05.html

Factors impacting the noise in images

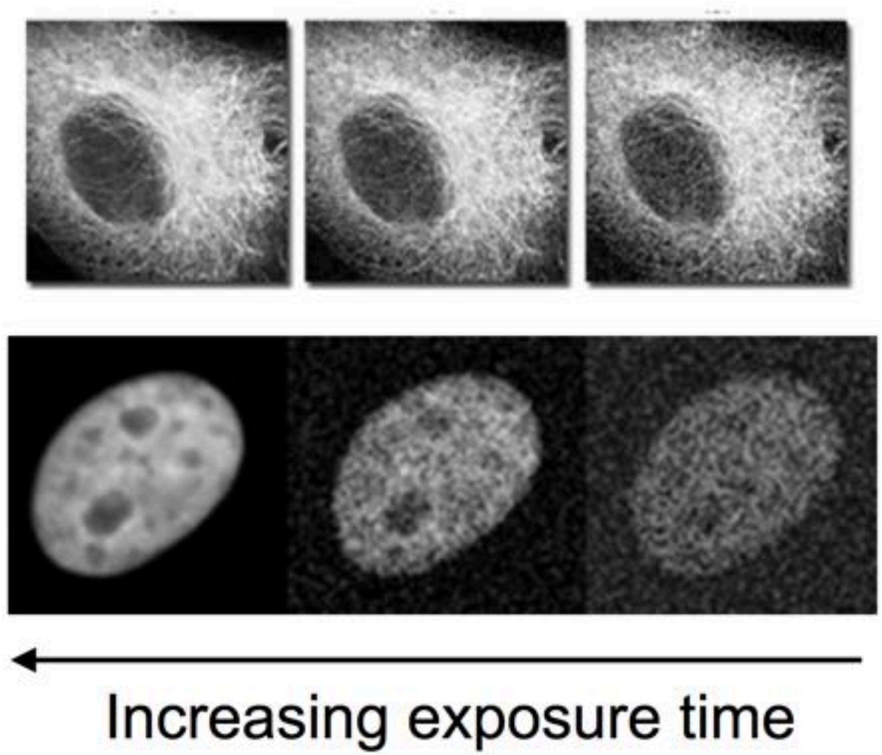
However, the aperture restricts the amount of light (number of photons) and thus impacts the level of noise



http://av.jpn.support.panasonic.com/support/global/cs/dsc/knowhow/knowhow06.html

Factors impacting the noise in images

It can be compensated by **longer exposure time** – more photons are collected



https://slideplayer.com/slide/10531209/

Factors impacting the noise in images - ISO

ISO in Traditional/Film Photography

In traditional (film) photography ISO (or ASA) was the indication of how sensitive a film was to light. It was measured in numbers (100, 200, 400, 800 etc). The lower the number the lower the sensitivity of the film and the finer the grain in the shots.

ISO in Digital Photography

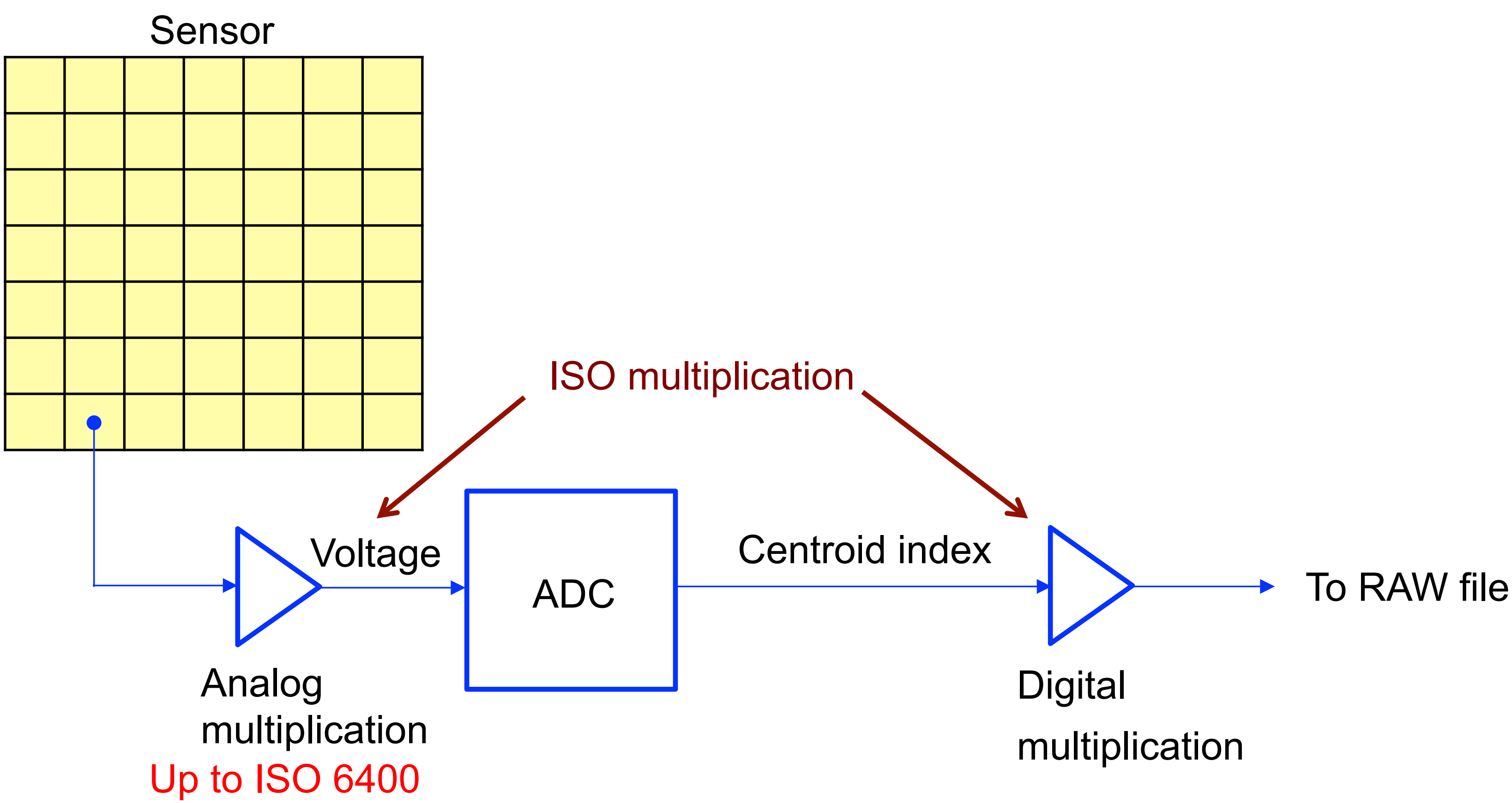
In Digital Photography ISO measures the sensitivity of the image sensor.

The same principles apply as in film photography – the lower the number the less sensitive your camera is to light and the finer the grain.

Higher numbers mean your sensor becomes more sensitive to light which allows you to use your camera in darker situations. The cost of doing so is more grain.

Factors impacting the noise in images - ISO

ISO implementation

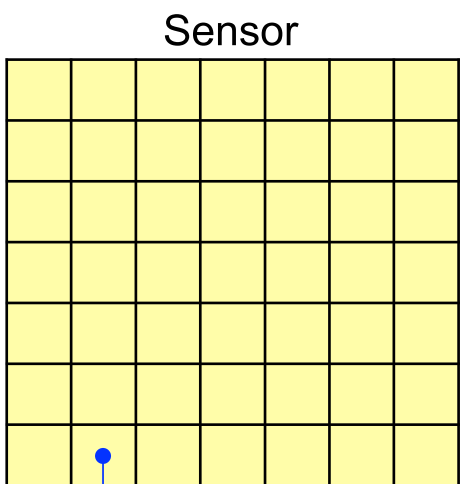


Factors impacting the noise in images - ISO

100 ISO 3200 ISO

https://digital-photography-school.com/iso-settings/

Signal amplification pipeline



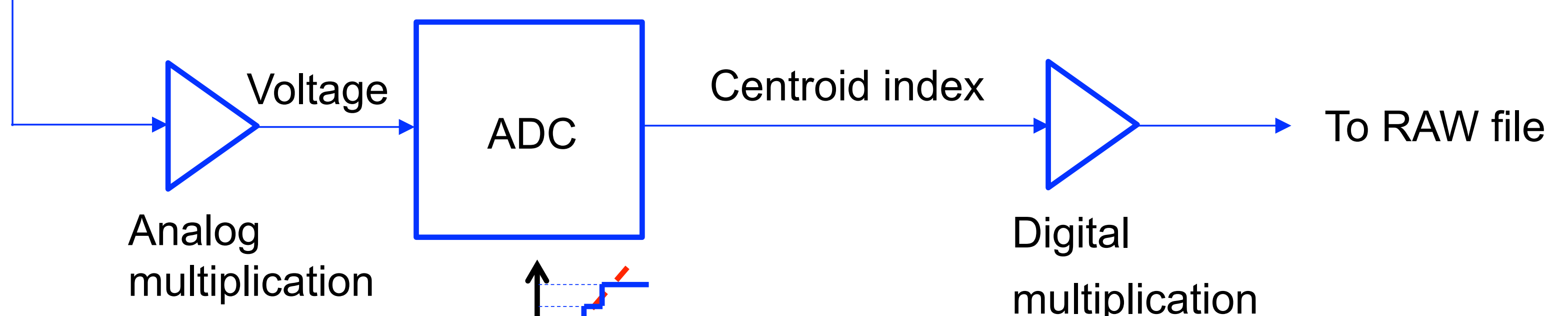
However, think about the math of multiplication

$$Var\left[\alpha X\right] = \alpha^2 Var\left[X\right]$$

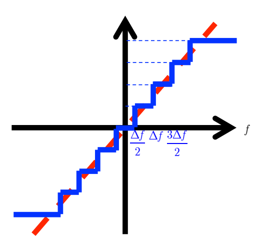
Assume a flat region with value c and noise Z

$$Var\left[\alpha(c+Z)\right] = \alpha^2 Var\left[Z\right] = \alpha^2 \sigma_Z^2$$

This leads to a strong magnification of noise.

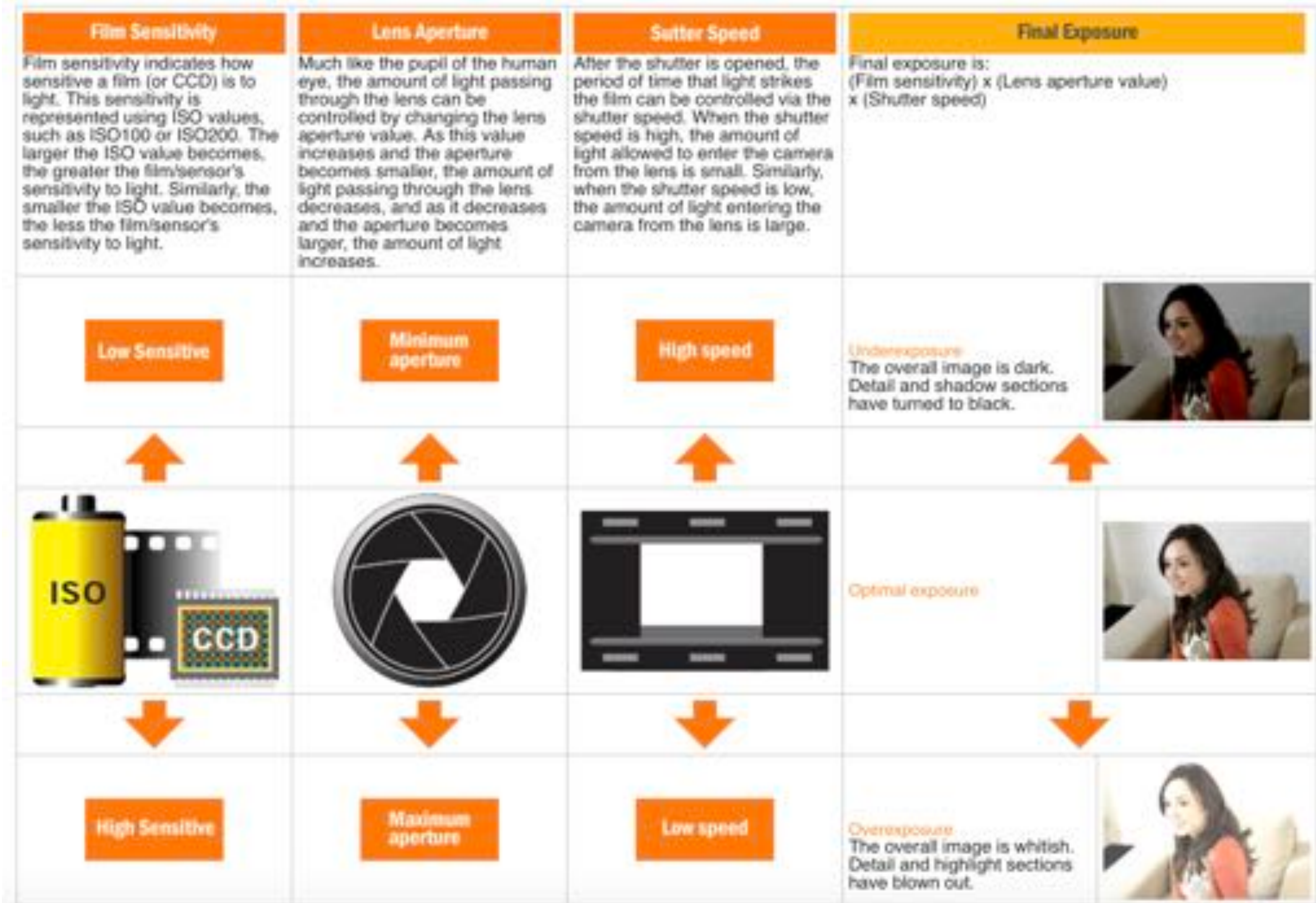


ISO multiplication



Some cameras also produce digital multiplication for high ISO (but it is just rescaling)

Three factors determining the exposure



http://av.jpn.support.panasonic.com/support/global/cs/dsc/knowhow/knowhow03.html

Image processing methods to reduce the noise

General approaches to fight with noise in imaging systems (assuming we proceed with the reduction of pixel size):

1. Use simple downsampling by NN averaging (single frame): when displayed on lower resolution displays, the loss of number of pixels is almost unperceived but image quality is superior; – loose resolution but gain in SNR (less noise)
2. Use frame averaging (assuming scene is static and noise is different in each frame)
3. Use denoising methods (single frame) – image processing (like BM3D, more recently CNN based)
4. Use trained mappers (DNN) to map low photon aquired images to high qualtiy images (problem: like a black box)

Image processing methods to reduce the noise

Motivation for downsampling based noise removal:

Remarks:

- A lot of improvements to increase the quality of sensosrs leading to the overal increase of SNR
- At the same time the number of pixels (still magepixels, soon gigapixels) increases. This leads to the deacrese of pixel size and so to the inrease of level of noise
- The evolution of displays is not not so fast
- Practically, we reduce the resolution of image to fit it to those of a dispay
- The simplest operation of reducing the resolution is an averaging

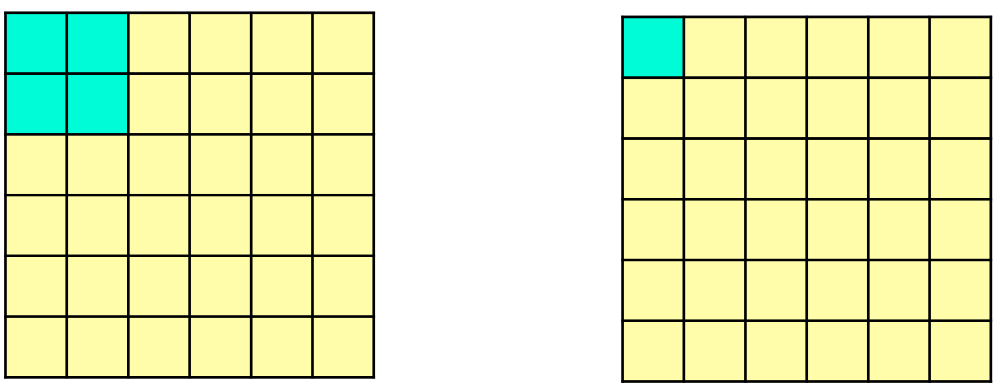
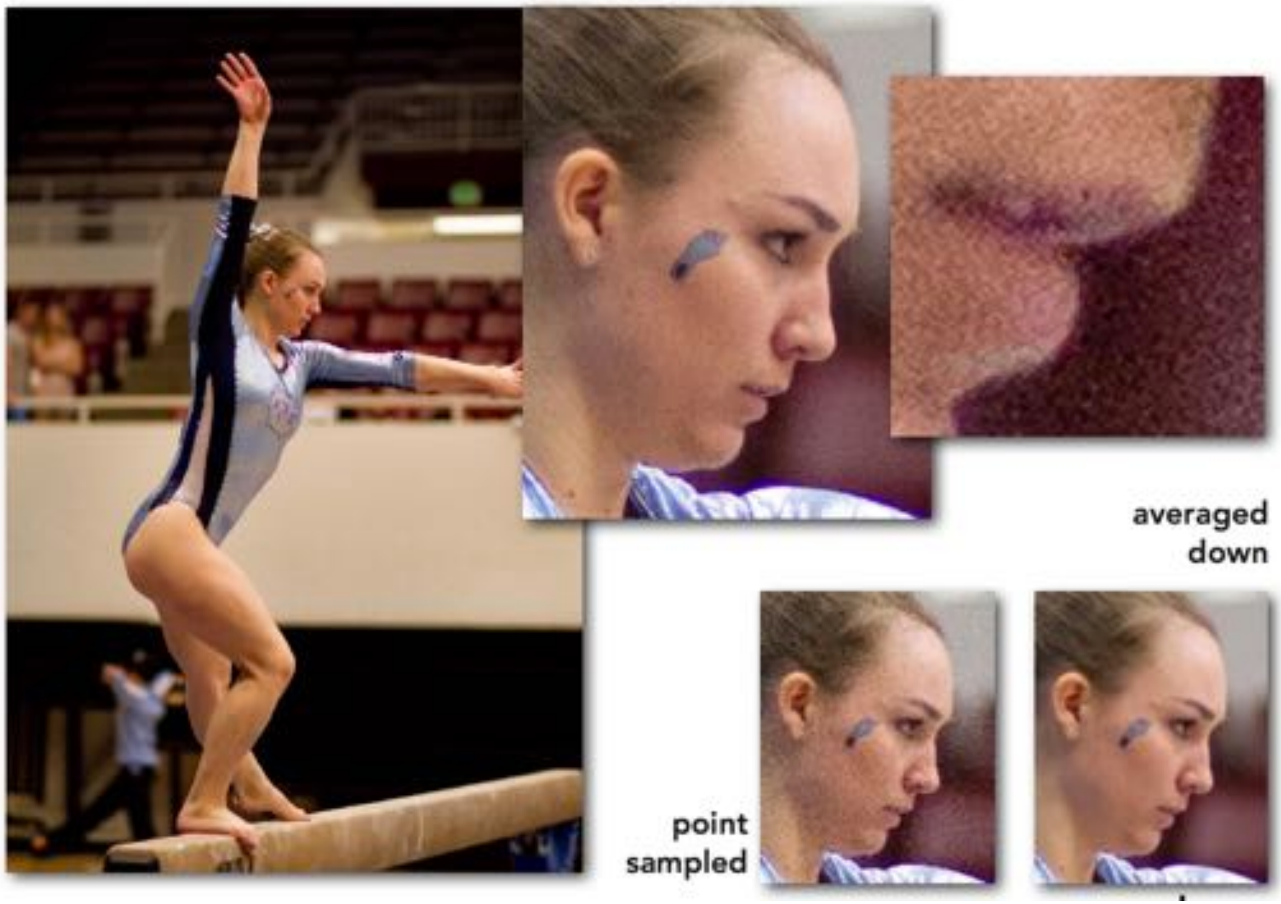


Image processing methods to reduce the noise

Effect of downsizing on image noise



Levoy

Image processing methods to reduce the noise

Noise reduction by multi-frame image averaging (assume static images)

Single frame in dark room using iPhone 4

Levoy

Image processing methods to reduce the noise

Noise reduction by multi-frame image averaging (assume static images)

Average of
~30 frames using
SynthCam app by Marc
Levoy

Levoy

Image processing methods to reduce the noise

Learning to See in the Dark

Chen Chen
UIUC

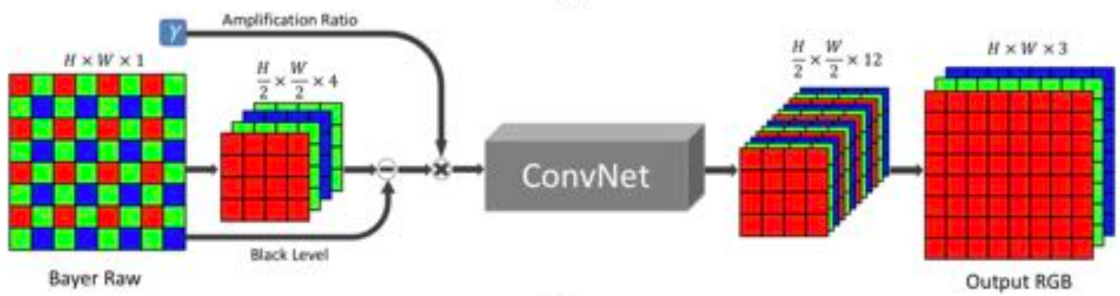
Qifeng Chen
Intel Labs

Jia Xu
Intel Labs

Vladlen Koltun
Intel Labs

(a) Camera output with ISO 8,000 (b) Camera output with ISO 409,600 (c) Our result from the raw data of (a)

Figure 1. Extreme low-light imaging with a convolutional network. Dark indoor environment. The illuminance at the camera is < 0.1 lux. The Sony α7S II sensor is exposed for 1/30 second. (a) Image produced by the camera with ISO 8,000. (b) Image produced by the camera with ISO 409,600. The image suffers from noise and color bias. (c) Image produced by our convolutional network applied to the raw sensor data from (a).



http://cchen156.web.engr.illinois.edu/SID.html

Image processing methods to reduce the noise

(a) JPEG image produced by camera (b) Raw data via traditional pipeline (c) Our result

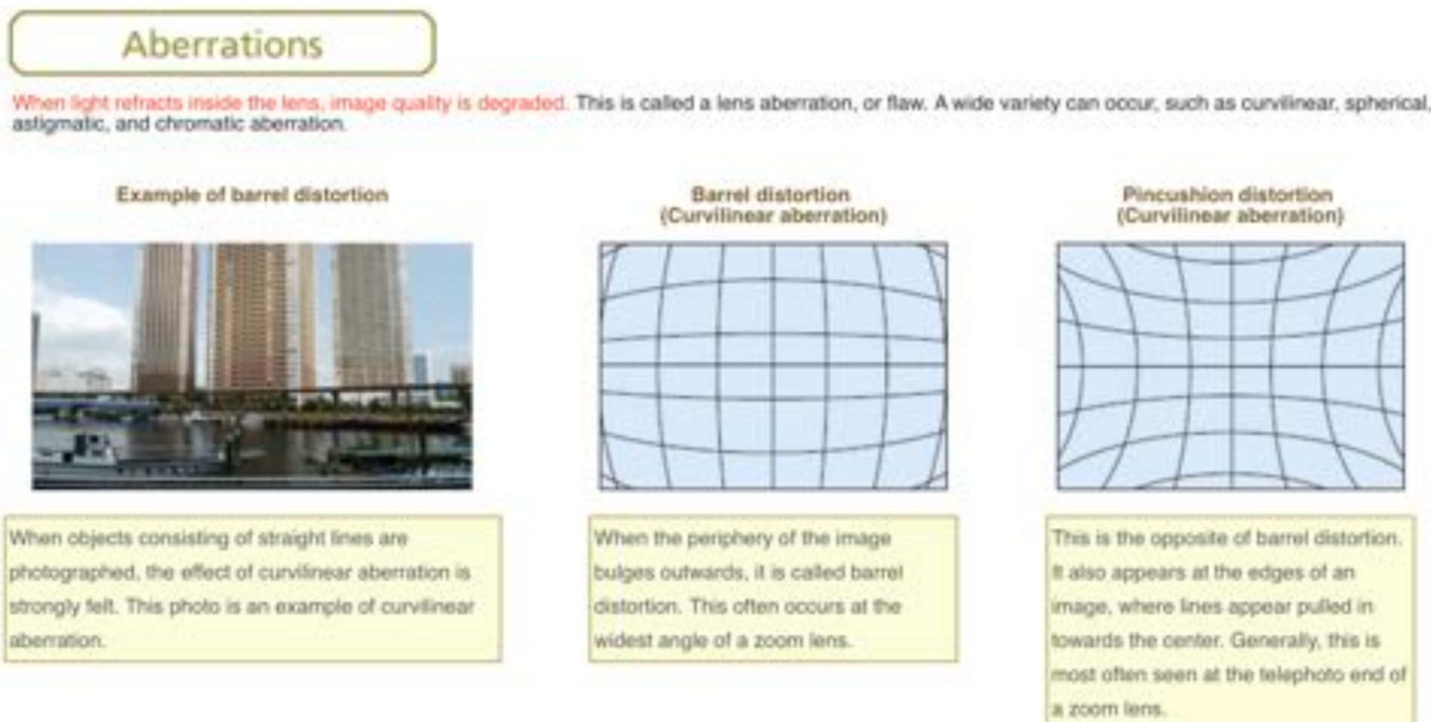
Figure 5. (a) An image captured at night by the Fujifilm X-T2 camera with ISO 800, aperture f/7.1, and exposure of 1/30 second. The illuminance at the camera is approximately 1 lux. (b) Processing the raw data by a traditional pipeline does not effectively handle the noise and color bias in the data. (c) Our result obtained from the same raw data.

(a) Traditional pipeline (b) ... followed by BM3D denoising (c) Our result

Figure 7. An image from the Sony x300 set. (a) Low-light input processed by the traditional image processing pipeline and linear scaling. (b) Same, followed by BM3D denoising. (c) Our result.

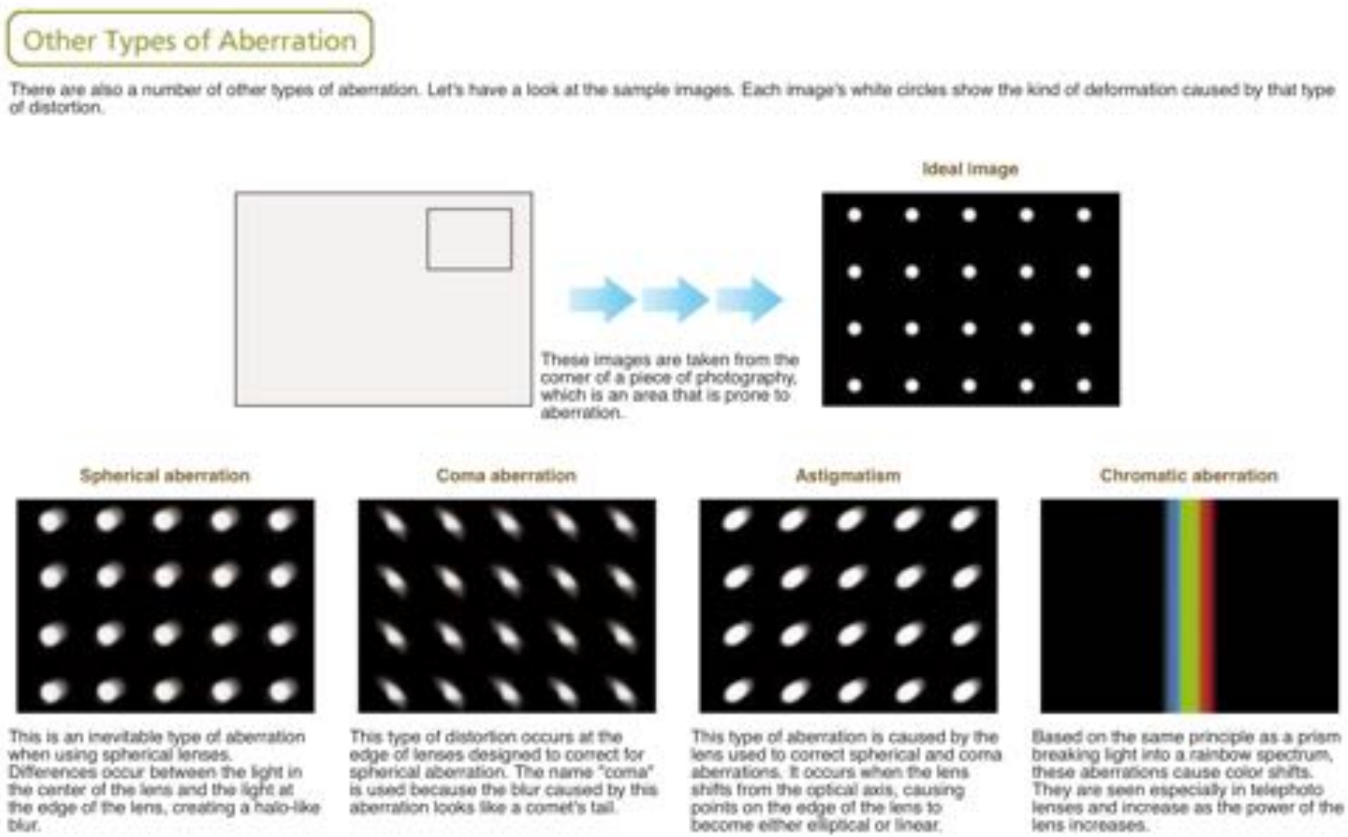
http://cchen156.web.engr.illinois.edu/SID.html

Lens distortions



http://av.jpn.support.panasonic.com/support/global/cs/dsc/knowhow/knowhow15.html

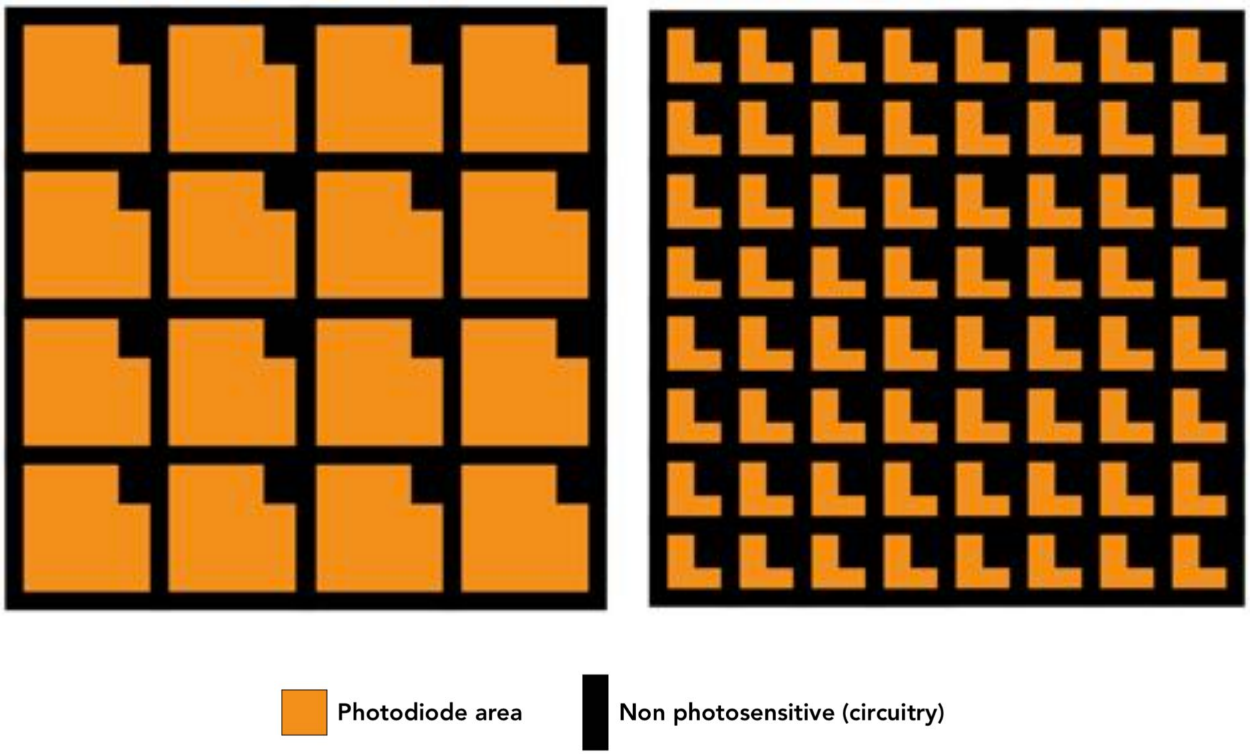
Lens distortions



http://av.jpn.support.panasonic.com/support/global/cs/dsc/knowhow/knowhow15.html

Pixel fill factor

Fraction of pixel area that integrates incoming light



https://cs184.eecs.berkeley.edu/uploads/lectures/30_sensors-2/30_sensors-2_slides.pdf Ren Ng

Pixel sampling and aliasing

https://cs184.eecs.berkeley.edu/uploads/lectures/30_sensors-2/30_sensors-2_slides.pdf

Image sensors – color imaging (history)

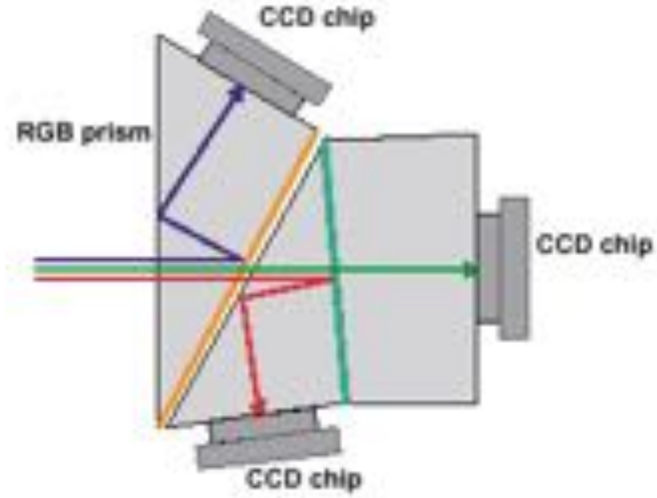
The Emir of Bukhara, Alim Khan, in a 1911 color photograph by Sergey Prokudin-Gorsky. At right is the triple color-filtered black-and-white glass plate negative, shown here as a positive.

- Images have been shot sequentially trough R, G and B filters

https://en.wikipedia.org/wiki/Color_photography

Image sensors – color imaging

3-CCD architecture

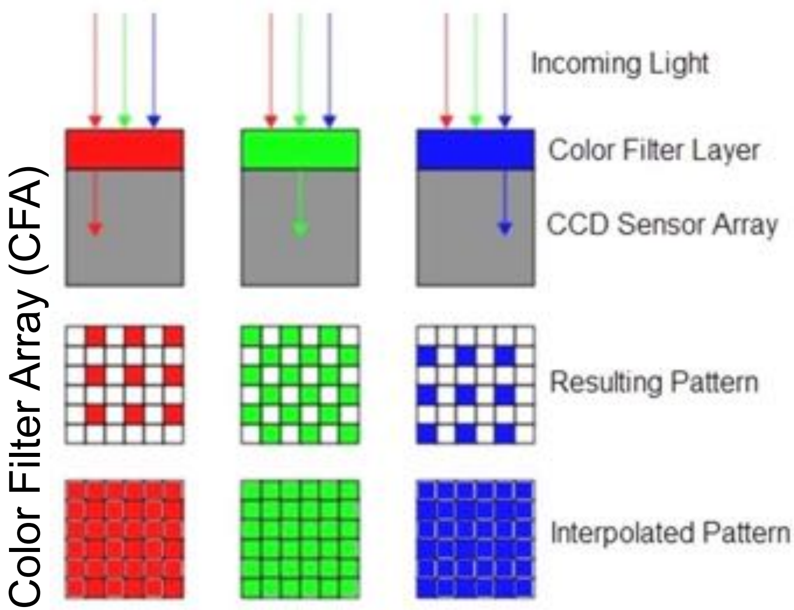


- High quality cameras
- Prism and mirrors split the image into 3 colors directed to separate sensors (CCD)
- No light loss (in comparison to filters which absorb light, see below)
- Expensive and quite complicated lens design

http://spectracore.com/cameras/digital/c7780.html

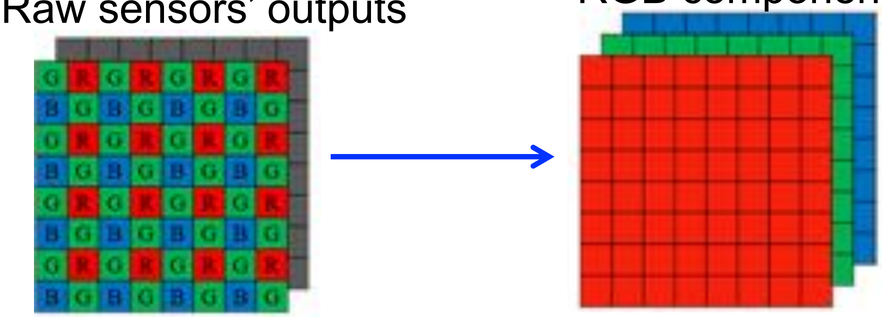
Image sensors - color imaging

Single CCD Color Camera



Raw sensors' outputs

RGB components

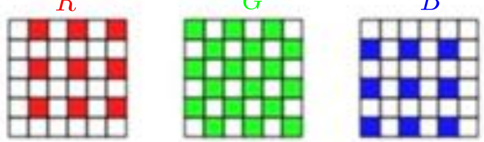


Special type of interpolation

(aka demosaicing)

One can consider as 3 types of sampling

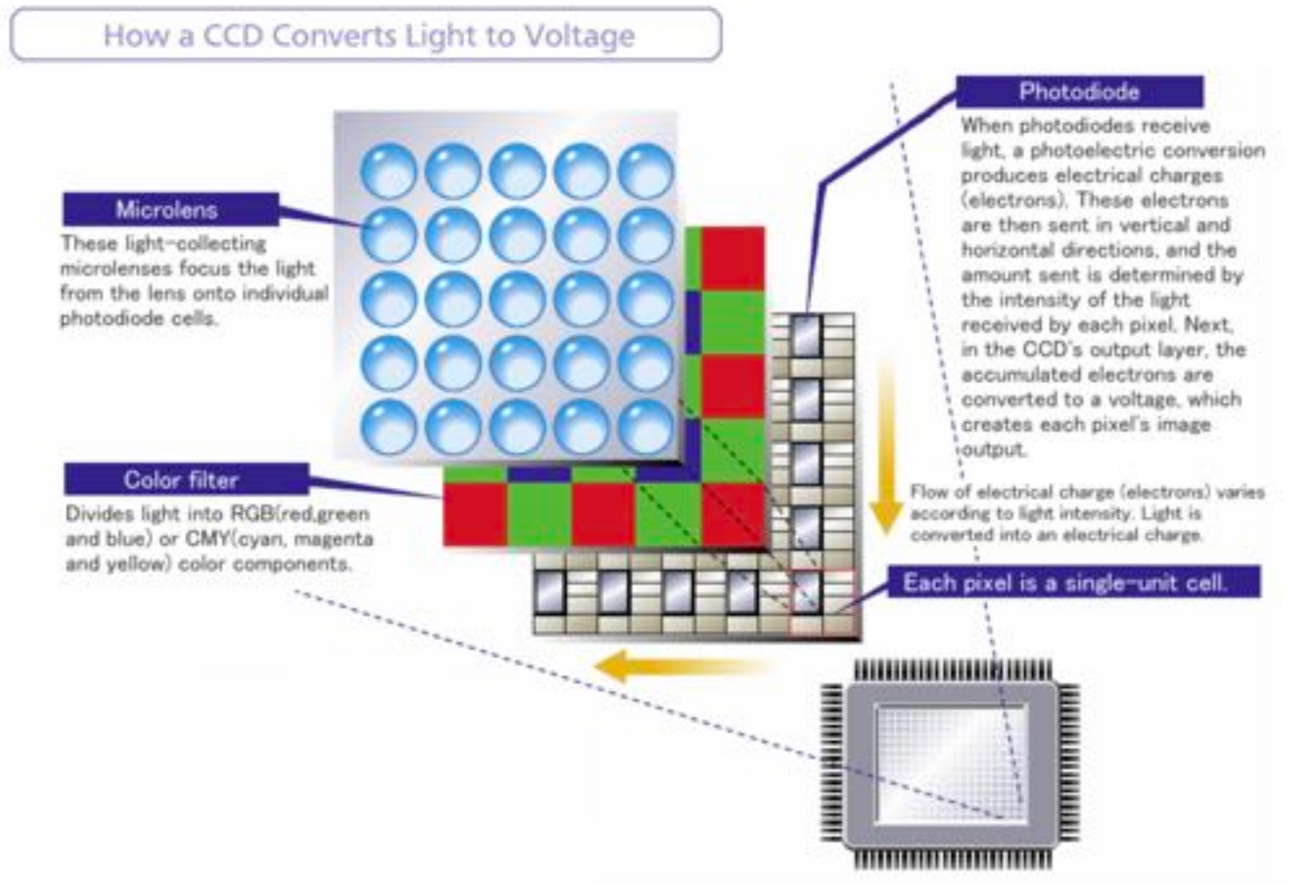
$\mathbf{P}_R$ $\mathbf{P}_G$ $\mathbf{P}_B$



$$\mathbf{g}_R = Q_R\left(\mathbf{P}_R\mathbf{H}\mathbf{f}_{cont}\right)$$
$$\mathbf{g}_G = Q_G\left(\mathbf{P}_G\mathbf{H}\mathbf{f}_{cont}\right)$$
$$\mathbf{g}_B = Q_B\left(\mathbf{P}_B\mathbf{H}\mathbf{f}_{cont}\right)$$

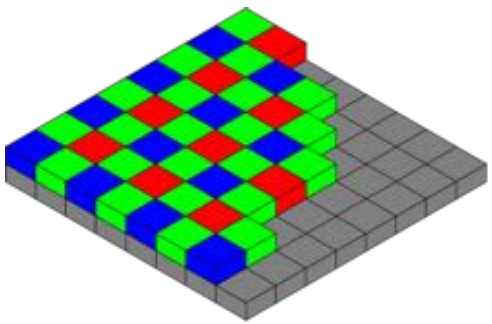
Image sensors - color imaging

Single CCD Color Camera



http://av.jpn.support.panasonic.com/support/global/cs/dsc/knowhow/knowhow27.html

Image sensors – color filters



The Bayer color filter mosaic. Each two-by-two submosaic contains 2 green, 1 blue, and 1 red filter, each filter covering one pixel sensor

Various proprietary designs

Image	Name	Description	Pattern size (pixels)
	Bayer filter	Very common RGB filter. With one blue, one red, and two green.	2×2
	RGBE filter	Bayer-like with one of the green filters modified to "emerald"; used in a few Sony cameras.	2×2
	CYYM filter	One cyan, two yellow, and one magenta; used in a few cameras of Kodak.	2×2
	CYGM filter	One cyan, one yellow, one green, and one magenta; used in a few cameras.	2×2
	RGBW Bayer	Traditional RGBW similar to Bayer and RGBE patterns.	2×2
	RGBW #1	Three example RGBW filters from Kodak, with 50% white. (*See Bayer filter#Modifications*)	4×4
	RGBW #2		
	RGBW #3		2×4
	X-Trans	Fujifilm-specific RGB matrix filter, with a large pattern, studied for diminishing Moiré effect.	6×6

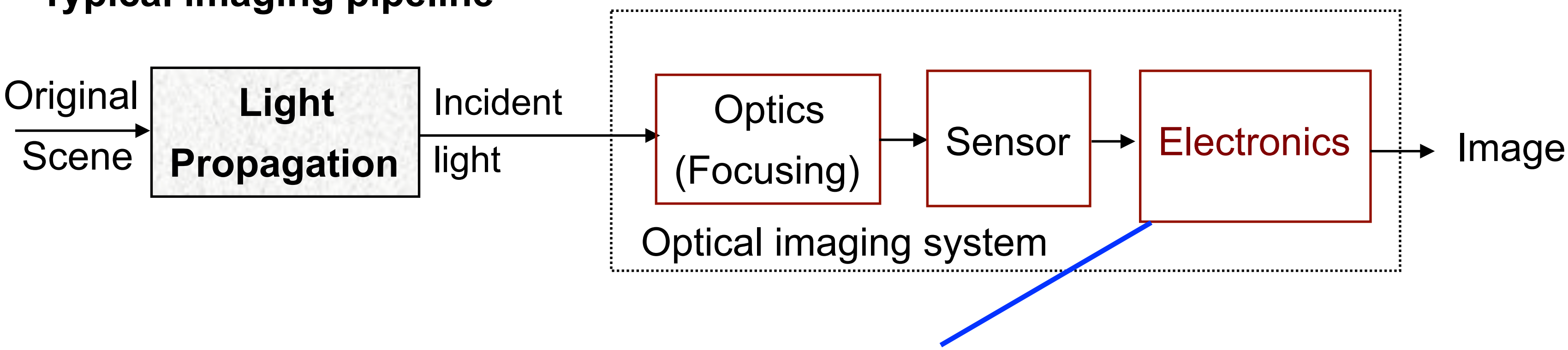
Why more green pixels than red and blue?

Humans are more sensitive to the “green” range of spectrum (see lecture 2)

https://en.wikipedia.org/wiki/Color_filter_array

Typical issues: blur, sampling, quantization

Typical imaging pipeline



- **ADC** – analog-to-digital convertor
- **Processing** – demosiacing, gamma correction, white balancing, denoising, compression

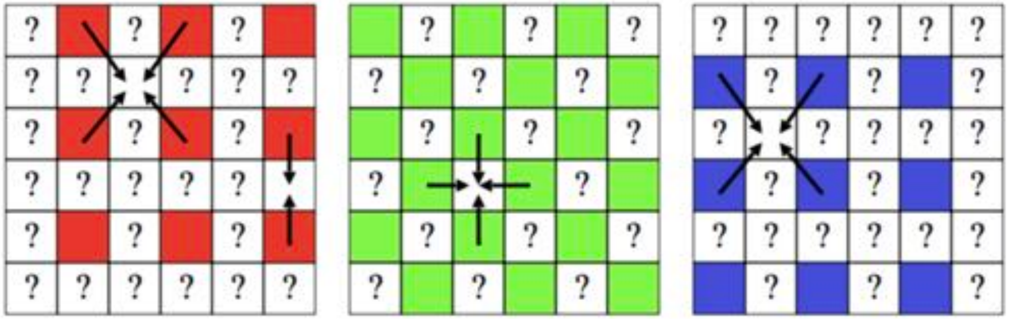
Main elements:

- Optics
- Sensors
- **Electronics - Processing**
  - **Demosaicing**
  - **Quantization**

CCD arrays – demosaicing

Linear interpolation (naïve way)

- for each pixel, fill in the two missing channels by averaging either the four or the two neighboring known channel values:



Modern cameras use special demosaicing:

- Special filtering along edges (mostly proprietary)
- Combination with denoising and sharpening

New directions:

- Usage of machine learning for demosaicing based on training

CCD arrays – demosaicing

Matlab implementation

Syntax

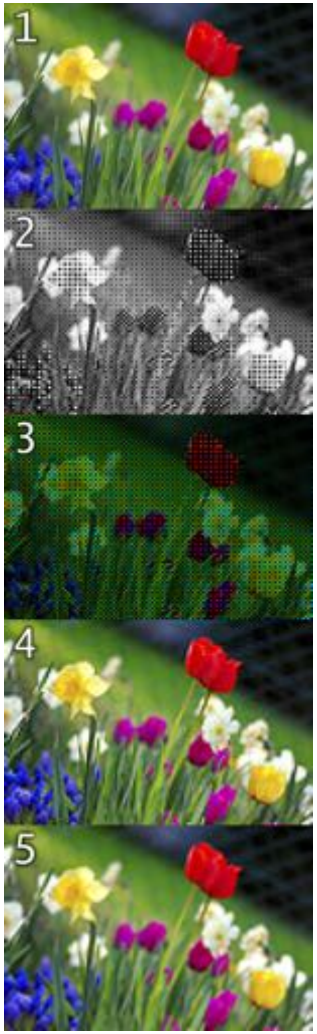
```
RGB = demosaic(I,sensorAlignment)
```

`sensorAlignment` — Bayer pattern
`'gbrg'` | `'grbg'` | `'bggr'` | `'rggb'`

Pattern	2-by-2 Sensor Alignment	
'gbrg'	Green	Blue
	Red	Green
'grbg'	Green	Red
	Blue	Green
'bggr'	Blue	Green
	Green	Red
'rggb'	Red	Green
	Green	Blue

CCD arrays – demosaicing

https://en.wikipedia.org/wiki/Bayer_filter



1 Original scene

2 Output of a 120×80-pixel sensor with a Bayer filter

3 Output color-coded with Bayer filter colors

4 Reconstructed image after interpolating missing color information

5 Full RGB version at 120×80-pixels for comparison (e.g. as a film scan might appear)

3-CDD vs Bayer CCD

5 Megapixel Bayer image after demosaicing

2 Megapixel AT-200 image (no demosaicing)

https://www.1stvision.com/machine-vision-solutions/2016/11/jai-3ccd-camera-color-machine-vision.html

Demosaicing – practical advise

For many useful practical hints see:

Processing RAW Images in MATLAB

Rob Sumner

Department of Electrical Engineering, UC Santa Cruz

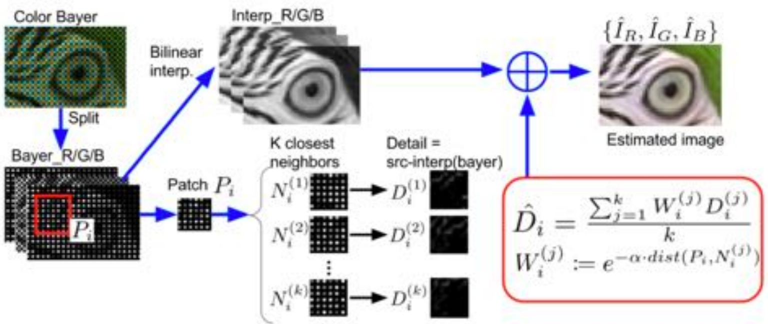
May 19, 2014

https://rcsumner.net/raw_guide/RAWguide.pdf

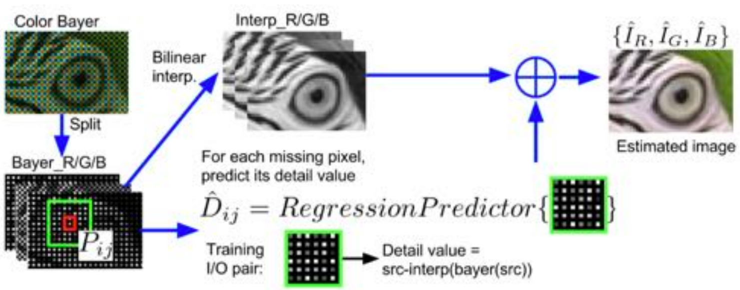
Demosaicing – machine learning landscape

Machine learning algorithms

K-NN based regressor

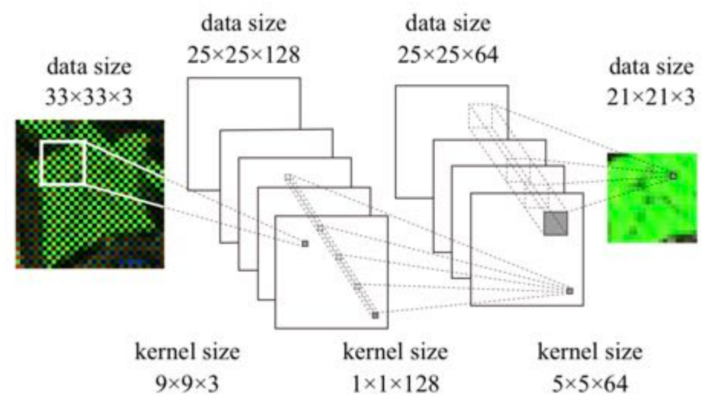


Specially trained regressor



http://stanford.edu/class/ee367/Winter2017/Chen_Sanchez_ee367_win17_report.pdf

CNN trained regressors



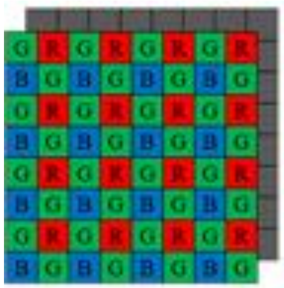
https://arxiv.org/pdf/1802.03769.pdf

$$L(\Theta) = \frac{1}{n}\sum_{i=1}^{n} \|F(\mathbf{Y}_i;\Theta) - \mathbf{X}_i\|^2,$$

Image sensors – summary

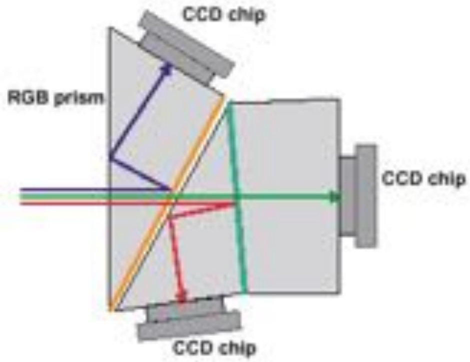
Single chip vs 3-CCD architecture

Single CCD Color Camera



- Each pixel has one color filter
- Color interpolation needed (demosaicing)
- Not true color
- Spectral response depends on the design of the color filter

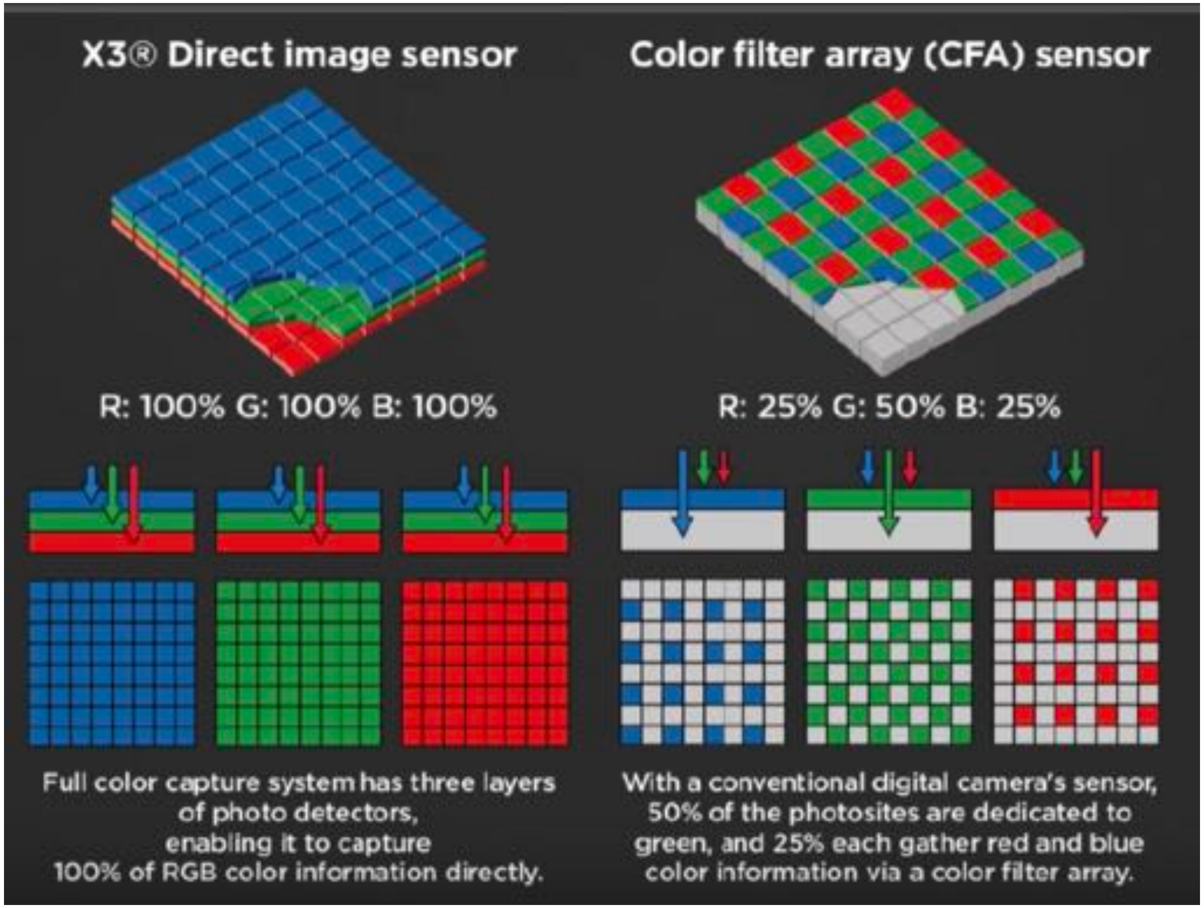
3-CCD Color Camera



- Each pixel has its own CCD
- No need in interpolation
- True RGB data for each pixel
- Spectral response can be flexible
- Superior quality of image for the same CCD resolution (see previous slide)

CCD arrays – beyond CFA – Foveon X3 sensor

More advanced systems (Foveon sensor) – every pixel might have its own color

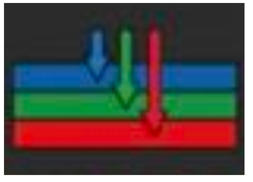


http://www.foveon.com/article.php?a=67

CCD arrays – beyond CFA

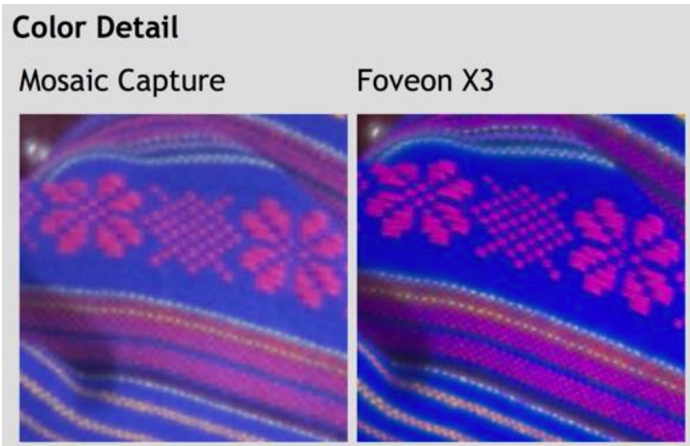
Foveon sensors – every pixel might have its own color

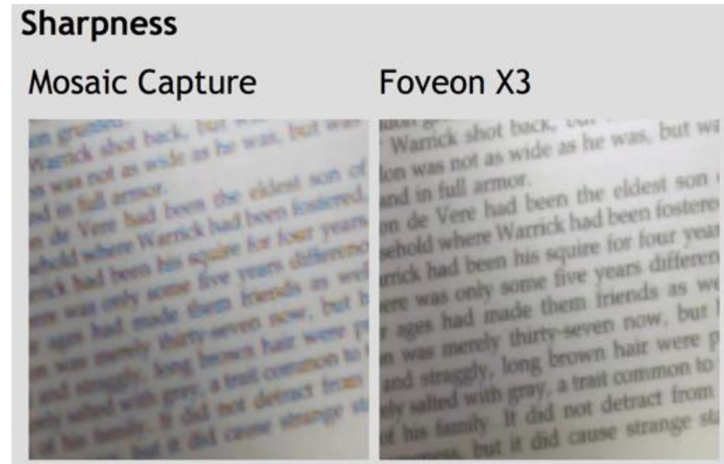
- Longer wavelengths penetrate deeper into silicon
- A set of vertical detectors is arrange as:

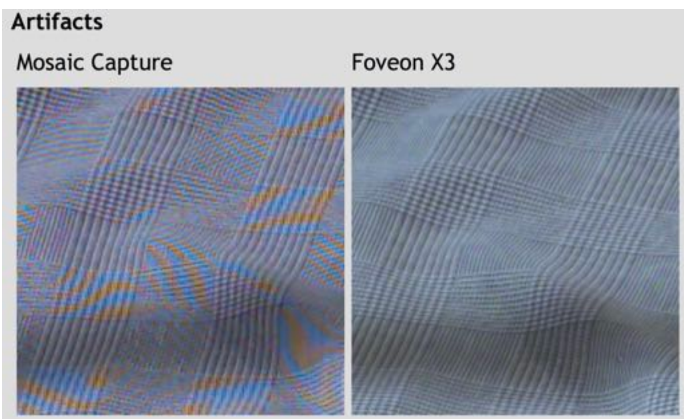


- However, there is no control on spectral responses. Processing is needed
- No need in demosaicing

CCD arrays – beyond CFA







http://www.foveon.com/article.php?a=67

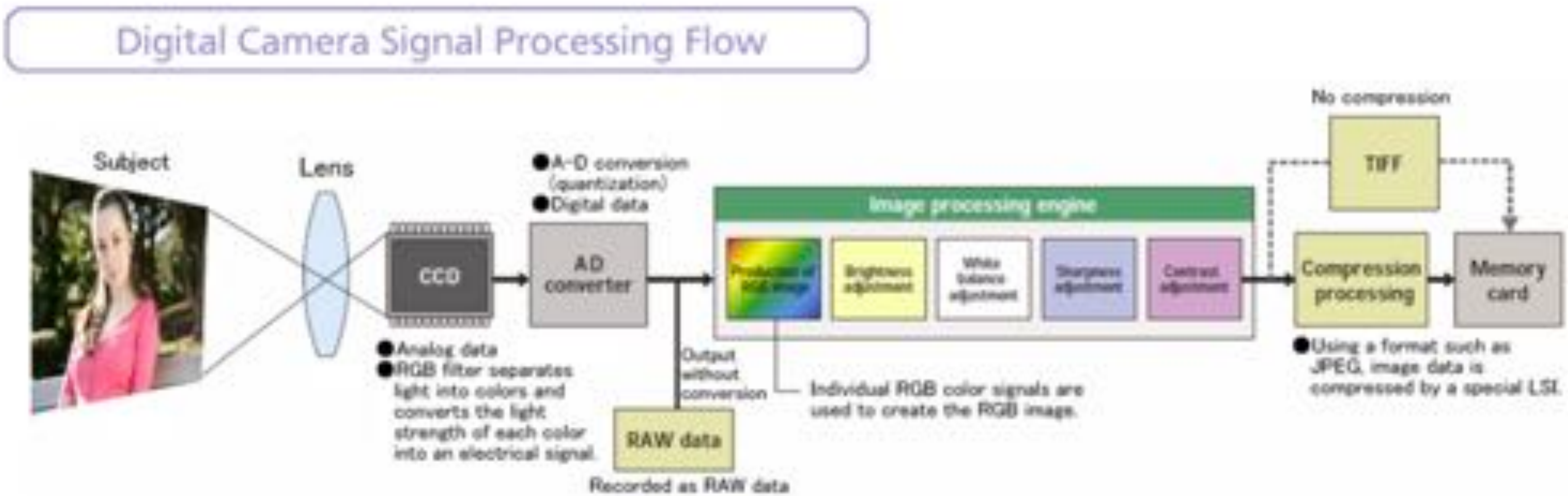
CCD arrays – beyond Foveon X3

The authors claim to take advantage of a physical phenomenon by virtue of which each photon penetrates at a different depth depending on its wavelength, i.e., its color.

In this way, by collecting these photons at different depths on the silice surface of the sensor, the different channels of color can be separated without the necessity of filters.

https://www.mirrorlessrumors.com/new-tfd-foveon-alike-sensor-has-36-layers/

Image sensors: summary on optical cameras



http://av.jpn.support.panasonic.com/support/global/cs/dsc/knowhow/knowhow30.html

Image sensors – beyond “classical” sensors

Traditional sensors

- Increase of amount of pixels (better resolution)
- However it has also side effects:
  - Larger storage memory and communication burden
  - New compression algorithms are needed
  - More pixels = smaller size of pixel = less photons = a lot of noise especially for the dark environment:
    - Image quality
    - More noise = higher entropy = more bits are used for nothing

Image sensors – beyond multipixel sensors

Compressive sensing

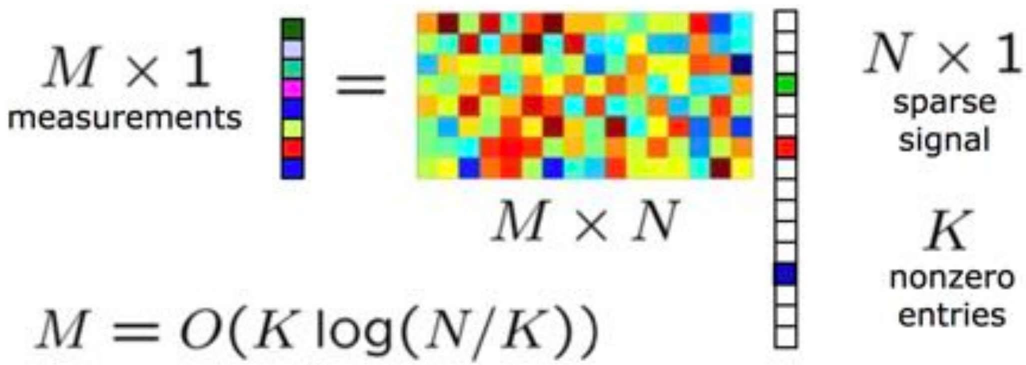
- An alternative to classical imaging
- Based on computational methods
- In a limit, a single pixel (!) is needed to create Mega pixel size image
- Price:
  - More time of observation is needed
  - It might not be suitable for highly dynamic scene imaging
  - Computing to reconstruct the image

Image sensors – beyond multipixel sensors

Main idea behind Compressive sensing

Sensing – as a projection (matrix-by-vector multiplication)

$\mathbf{g}$ Φ-sampling operator $\mathbf{f}$



$\mathbf{g} = \Phi \mathbf{f}$

can be random or structured $\Phi = \mathbf{PH}$

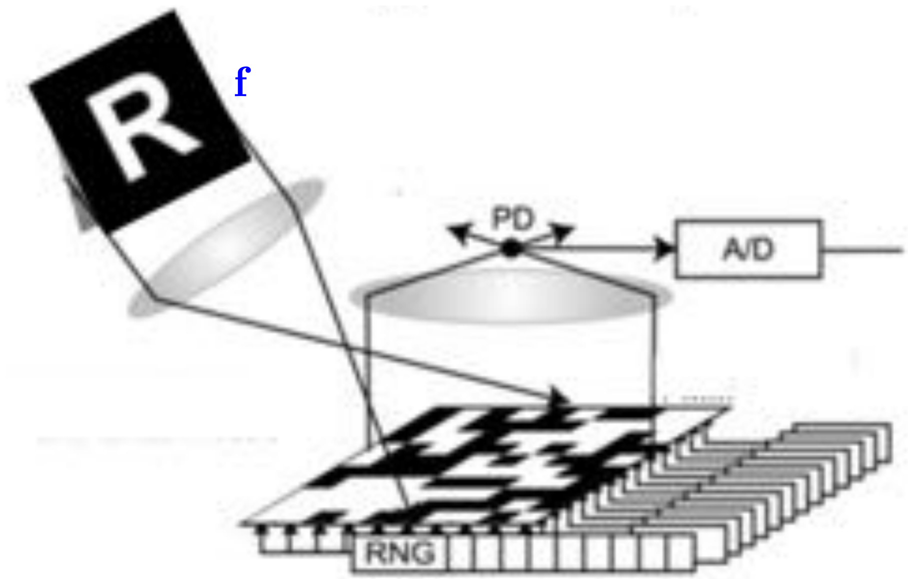
Recovery – as inverse (ill-posed) problem solution

$$\hat{\mathbf{f}} = \arg\min \left\| \mathbf{g} - \Phi \mathbf{f} \right\|_2^2 + \lambda \Omega_{\mathbf{f}} \left(\mathbf{f} \right)$$

Prior to compensate the loss of information

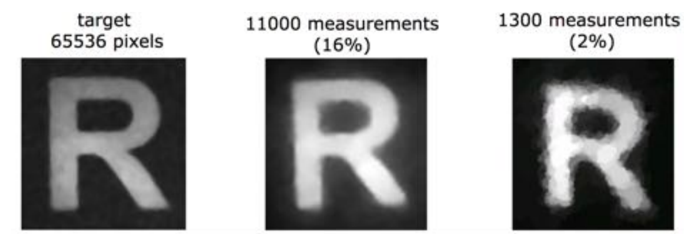
Image sensors – beyond multipixel sensors

"Single pixel" CS camera



g

$$\arg\min \left\| \mathbf{g} - \Phi \mathbf{f} \right\|_2^2 + \lambda \Omega_{\mathbf{f}} \left(\mathbf{f} \right) \rightarrow \hat{\mathbf{f}}$$



M random patterns

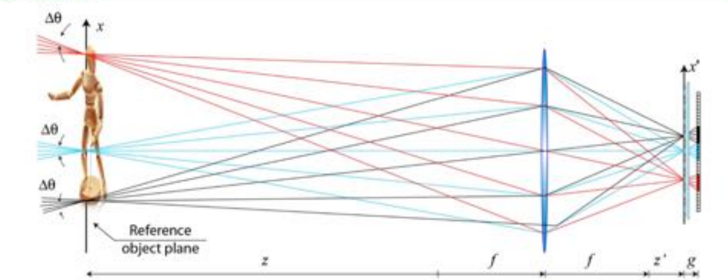
$\Phi =$ [] $\rightarrow$ g

R. Baranuk, Rice University

Image sensors – beyond optical band

Plenoptic cameras

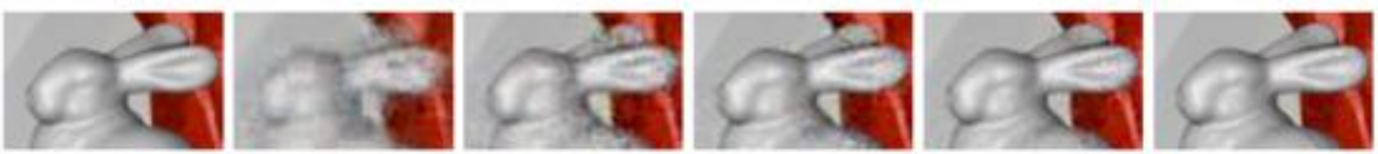
Figure 21



Single scheme of a plenoptic camera.

$$
\underbrace{\begin{bmatrix} \mathbf{y}^{R,1} \\ \mathbf{y}^{G,1} \\ \mathbf{y}^{B,1} \\ \mathbf{y}^{R,2} \\ \mathbf{y}^{G,2} \\ \mathbf{y}^{B,2} \\ \vdots \\ \mathbf{y}^{R,s} \\ \mathbf{y}^{G,s} \\ \mathbf{y}^{B,s} \end{bmatrix}}_{\triangleq \mathbf{y} \in \mathbb{R}^{w\lambda s}} = \underbrace{\begin{bmatrix} \Phi^{1,R,1} & \dots & \Phi^{\nu,R,1} & 0 & \dots & 0 & 0 & \dots & 0 \\ 0 & \dots & 0 & \Phi^{1,G,1} & \dots & \Phi^{\nu,G,1} & 0 & \dots & 0 \\ 0 & \dots & 0 & 0 & \dots & 0 & \Phi^{1,B,1} & \dots & \Phi^{\nu,B,1} \\ \Phi^{1,R,2} & \dots & \Phi^{\nu,R,2} & 0 & \dots & 0 & 0 & \dots & 0 \\ 0 & \dots & 0 & \Phi^{1,G,2} & \dots & \Phi^{\nu,G,2} & 0 & \dots & 0 \\ 0 & \dots & 0 & 0 & \dots & 0 & \Phi^{1,B,2} & \dots & \Phi^{\nu,B,2} \\ \vdots & \vdots & \ddots & \vdots & & & & & \\ \Phi^{1,R,s} & \dots & \Phi^{\nu,R,s} & 0 & \dots & 0 & 0 & \dots & 0 \\ 0 & \dots & 0 & \Phi^{1,G,s} & \dots & \Phi^{\nu,G,s} & 0 & \dots & 0 \\ 0 & \dots & 0 & 0 & \dots & 0 & \Phi^{1,B,s} & \dots & \Phi^{\nu,B,s} \end{bmatrix}}_{\triangleq \Phi \in \mathbb{R}^{w\lambda s \times w\nu\lambda}} \underbrace{\begin{bmatrix} \mathbf{x}^{1,R} \\ \vdots \\ \mathbf{x}^{\nu,R} \\ \mathbf{x}^{1,G} \\ \vdots \\ \mathbf{x}^{\nu,G} \\ \mathbf{x}^{1,B} \\ \vdots \\ \mathbf{x}^{\nu,B} \end{bmatrix}}_{\triangleq \mathbf{x} \in \mathbb{R}^{w\nu\lambda}},
$$

$$\mathbf{y} = \mathbf{P}\Phi\mathbf{x},$$



(a) *reference* (b) *1 shot* (c) *3 shots* (d) *5 shots* (e) *9 shots* (f) *15 shots*

Fig. 3: Visual quality comparison for the number of shots (s). See Fig. 4 for the corresponding PSNR values.

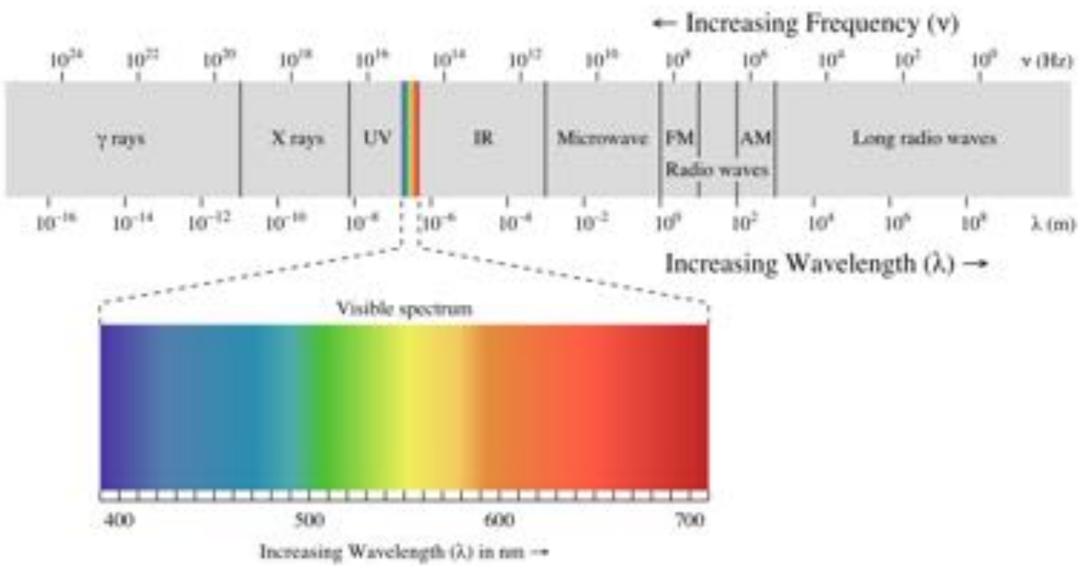
Multi-Shot Single Sensor Light Field Camera
Using a Color Coded Mask

Ehsan Miandji
dept. of Science and Technology
Linköping University, Sweden

Jonas Unger
dept. of Science and Technology
Linköping University, Sweden

Christine Guillemot
INRIA, Campus de Beaulieu
Rennes, France

Image sensors – beyond optical band



Imaging in infrared band

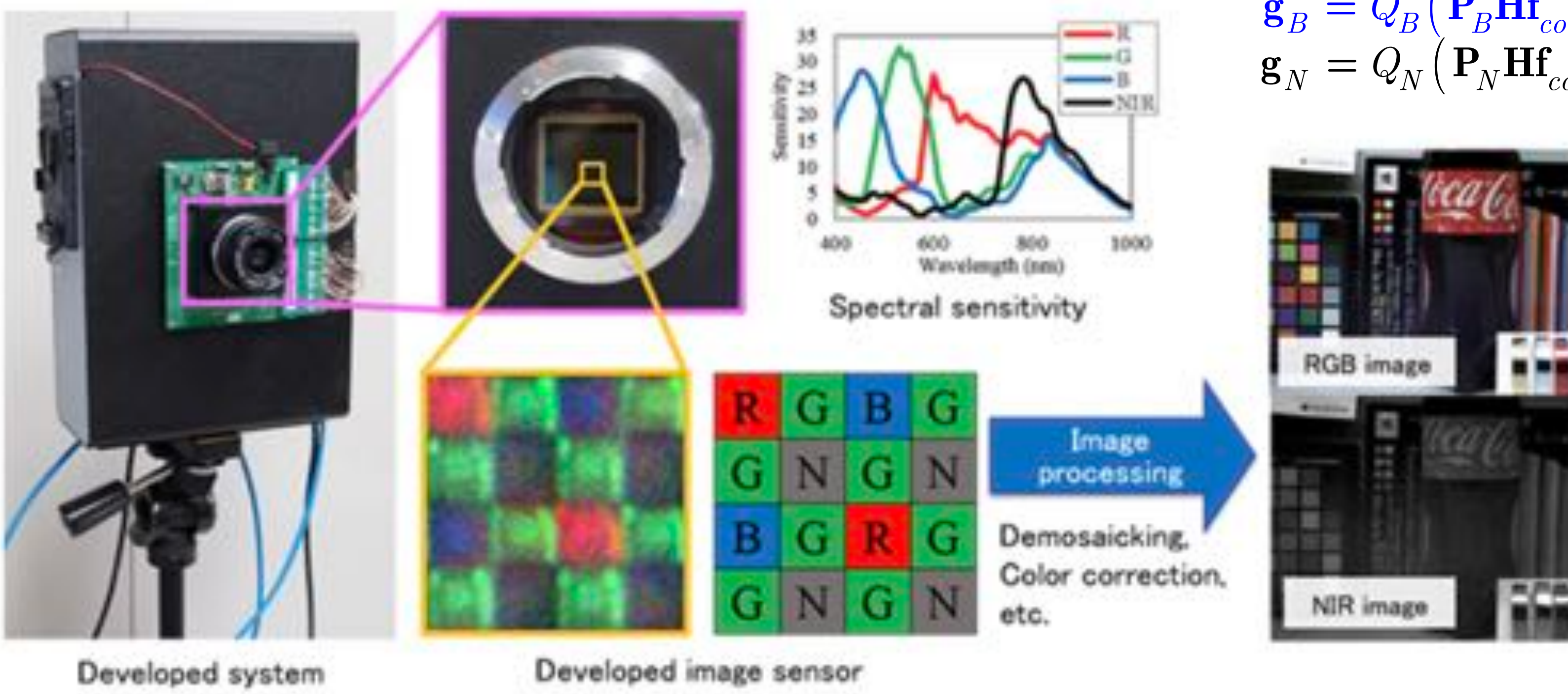
Imaging in microwave-radio frequency bands

Image sensors – beyond optical band

Olympus shows a new “hybrid” RGB-IR sensor

Near IR (NIR)

$$\mathbf{g}_R = Q_R\left(\mathbf{P}_R\mathbf{H}\mathbf{f}_{cont}\right)$$
$$\mathbf{g}_G = Q_G\left(\mathbf{P}_G\mathbf{H}\mathbf{f}_{cont}\right)$$
$$\mathbf{g}_B = Q_B\left(\mathbf{P}_B\mathbf{H}\mathbf{f}_{cont}\right)$$
$$\mathbf{g}_N = Q_N\left(\mathbf{P}_N\mathbf{H}\mathbf{f}_{cont}\right)$$



https://www.43rumors.com/olympus-presents-new-olympus-rgb-ir-sensor/

Image sensors – beyond optical band (NIR)

FLIR

Separate sensors RGB and FLIR

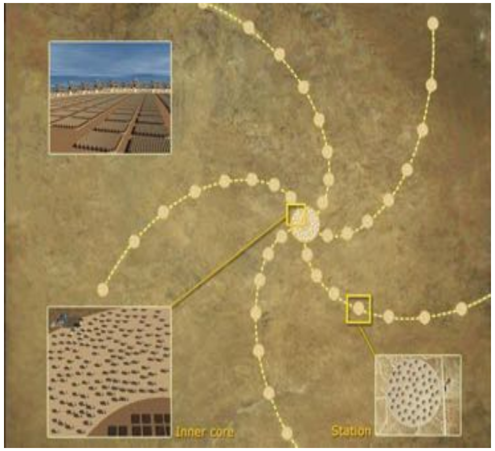
$$\mathbf{g}_R = Q_R\left(\mathbf{P}_R\mathbf{H}\mathbf{f}_{cont}\right)$$
$$\mathbf{g}_G = Q_G\left(\mathbf{P}_G\mathbf{H}\mathbf{f}_{cont}\right)$$
$$\mathbf{g}_B = Q_B\left(\mathbf{P}_B\mathbf{H}\mathbf{f}_{cont}\right)$$
$$\mathbf{g}_N = Q_N\left(\mathbf{P}_N\mathbf{H}\mathbf{f}_{cont}\right)$$

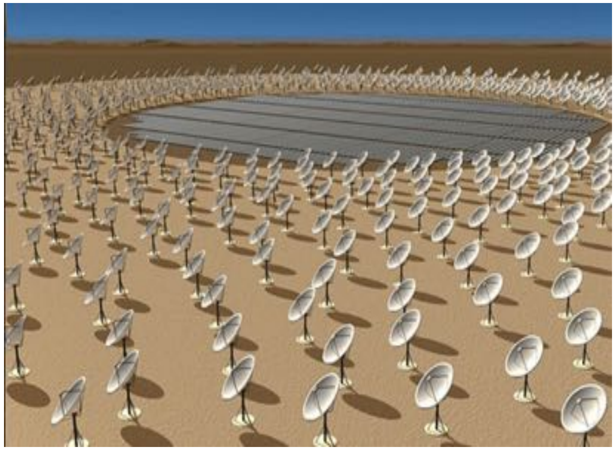
https://www.flir.com

Imaging in the microwave band

Radio imaging – not CCD but antenna that register electromagnetic radiation in microwave and radio bands

SKA geometry for radioastronomy

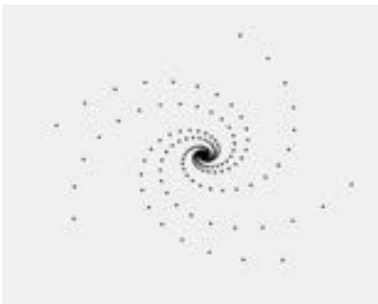


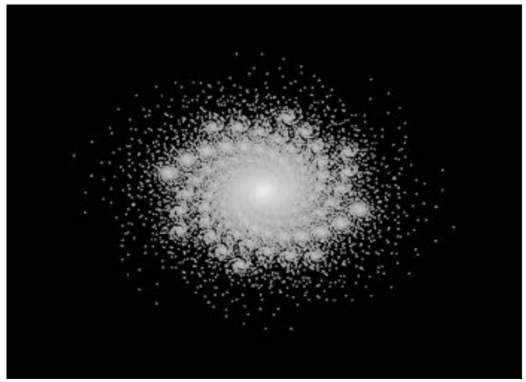


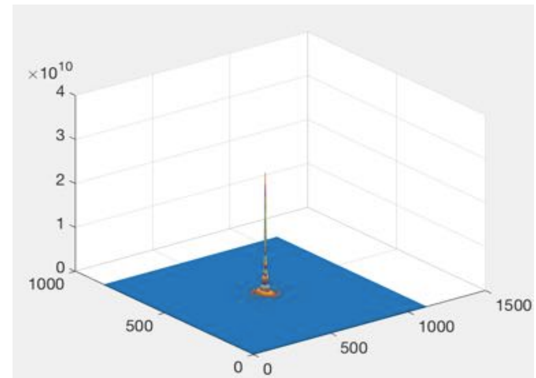
Credits: SKA

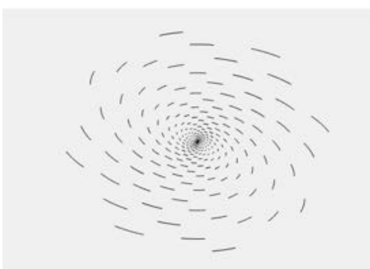
Imaging in the microwave band

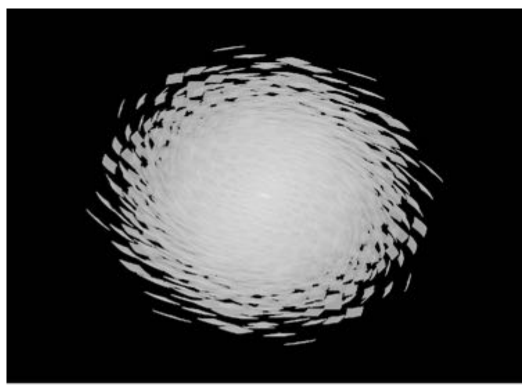
Geometry of antenna | Spatial spectrum (uv-plane) | PSF (directional antenna pattern)

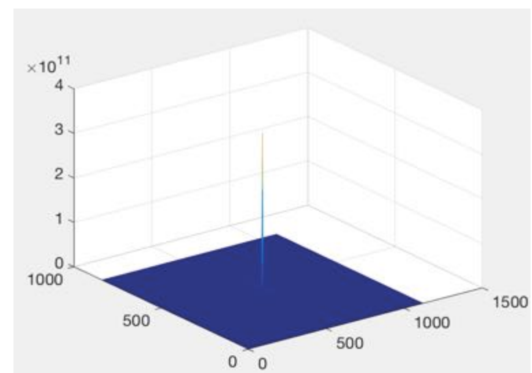












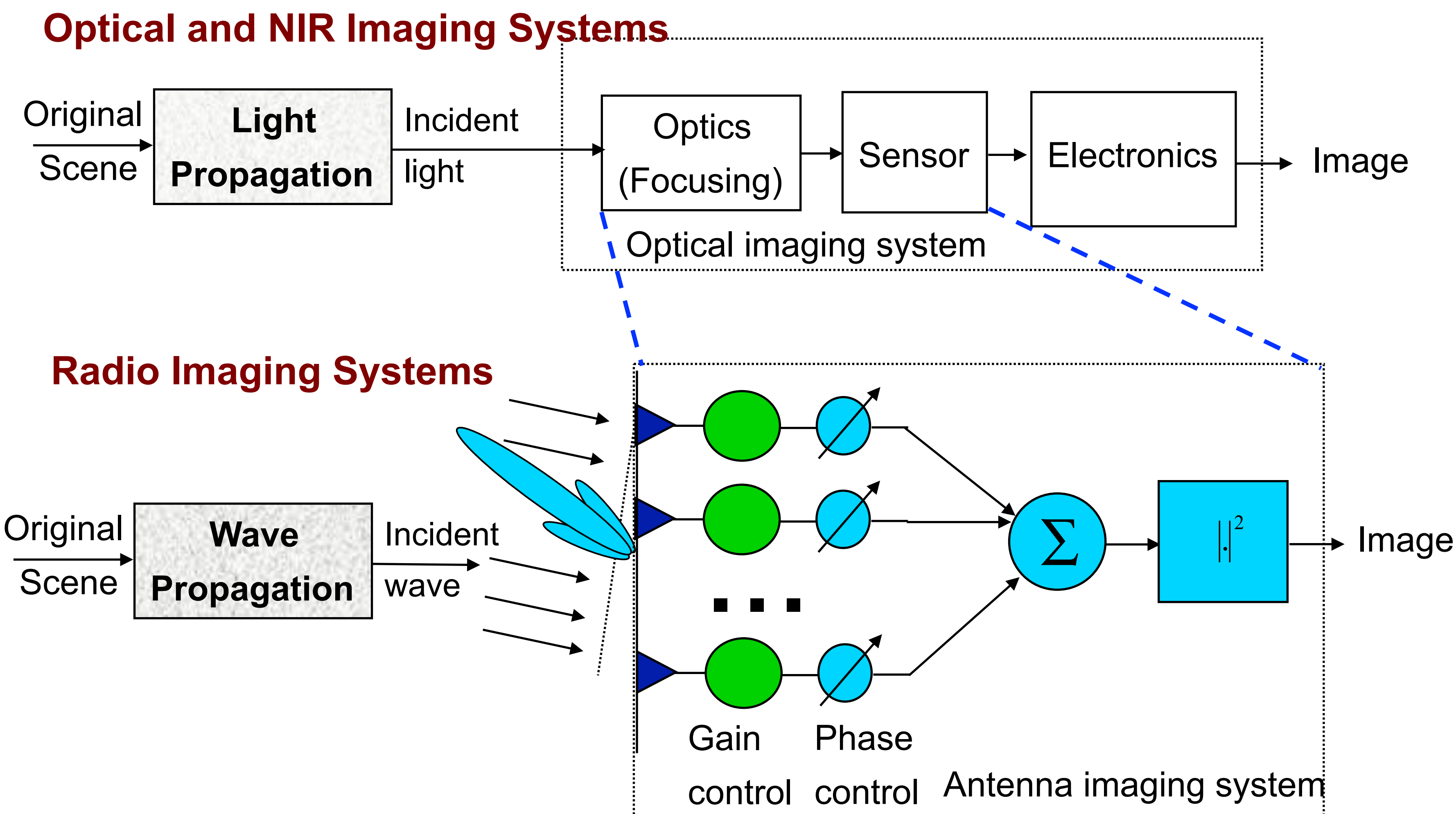
$\mathbf{P}\Psi$

Ψ - unitary transform (like Fourier)

Equivalent $\mathbf{H}$

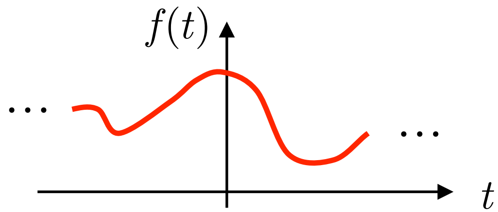
Credits: SKA

Image sensors – generalized diagram

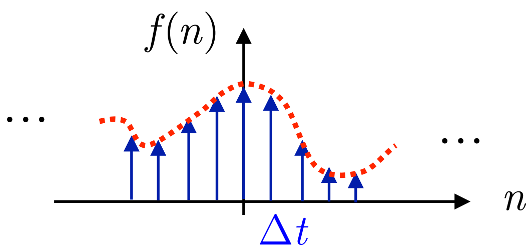


Sampling and quantization

Continuous signals



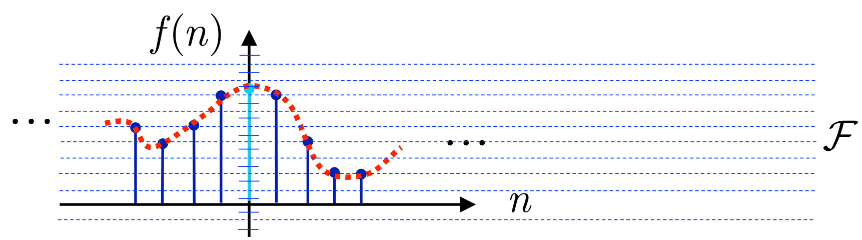
Discrete signals



The discrete signals are defined only a discrete grid $n = 0, \pm 1, \pm 2, \cdots$

Information between the samples is lost!

Discrete quantized signals=digital signals



Additionally, the signal can be quantized, i.e., each sample might take a value from some alphabet $f(n) \in \mathcal{F}$

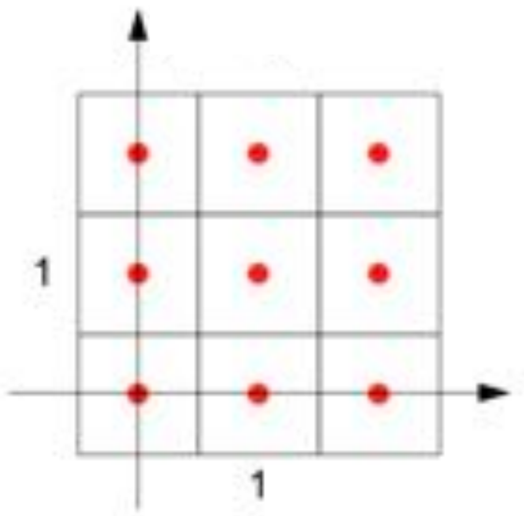
Information between the quantization levels is lost!

Sampling in 2D

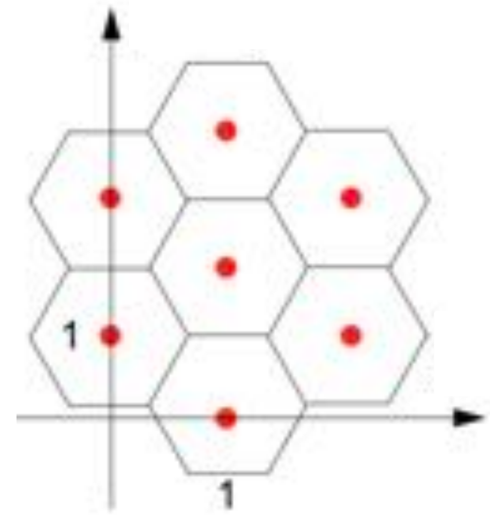
In time domain (1D signals), the sampling grid is equally spaced train of delta functions.

The sampling grid in 2D is more flexible

Rectangular grid

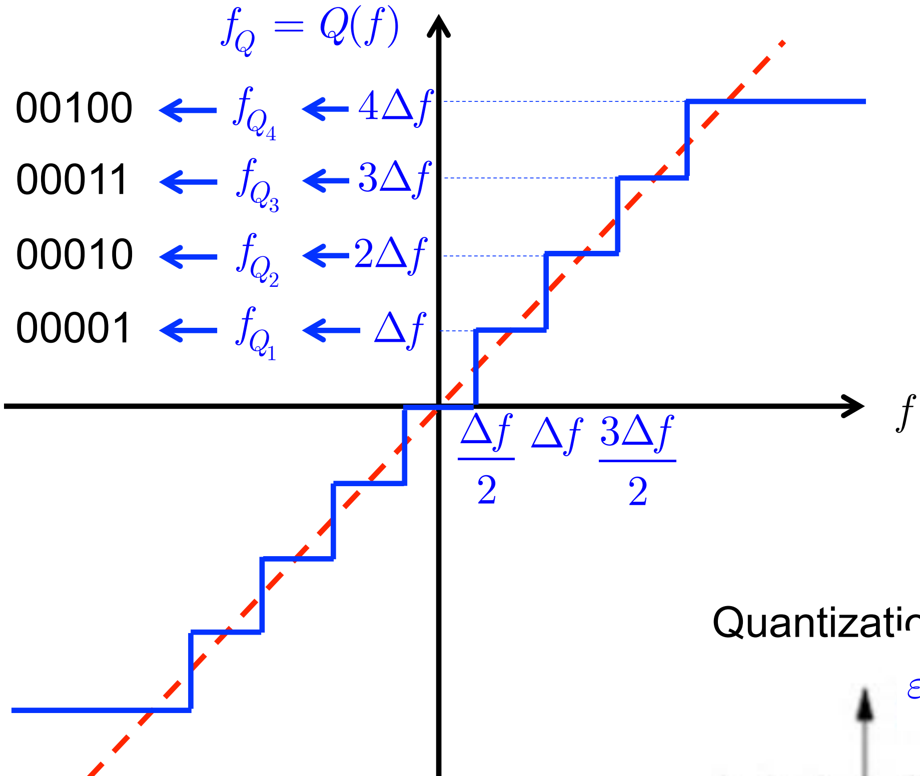


Hexagonal grid



Scalar and vector quantization

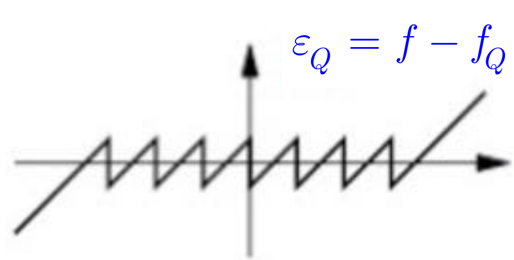
Linear scalar quantization



Vector quantization

We will see it later

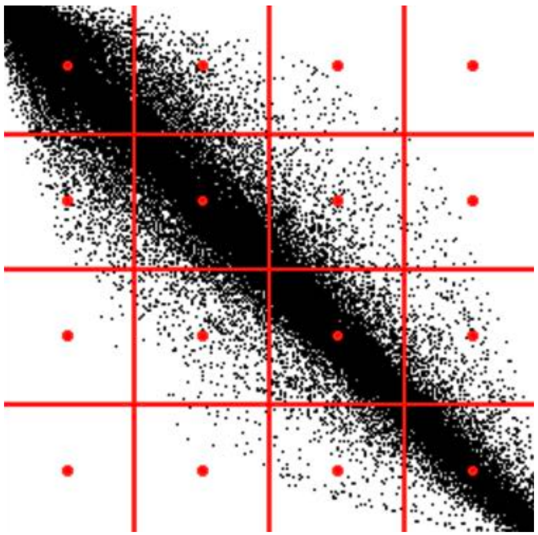
Quantization error

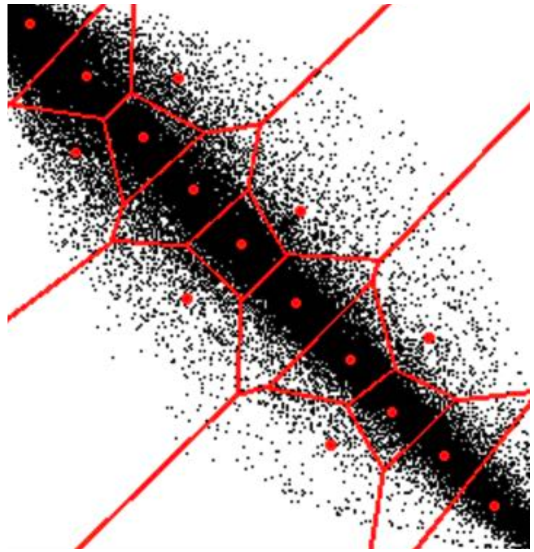


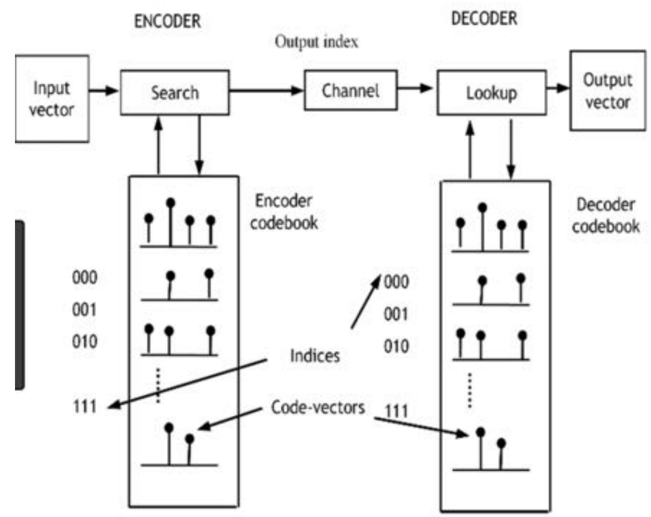
Uniform distribution

Scalar and vector quantization

Vector quantization







Pixel representation

Values of pixels:

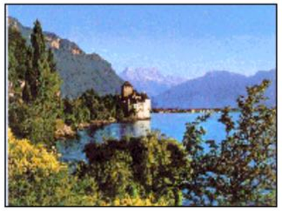
- Binary images: $f(x,y) \in \{0,1\}$
- Grayscale images: $f(x,y) \in \{0,1,\cdots,256\}$
  assuming 8 bits/pixel

Black pixel: 0

White pixel: 255

Gray pixel: 127

- Color images: in RGB space with each component 8 bits/pixel. In total 24 bits/pixel



$\Rightarrow$

R

G

B

$f_R(x,y) \in \{0,1,\cdots,256\}$ $f_G(x,y) \in \{0,1,\cdots,256\}$ $f_B(x,y) \in \{0,1,\cdots,256\}$

Impact of the number of gray levels

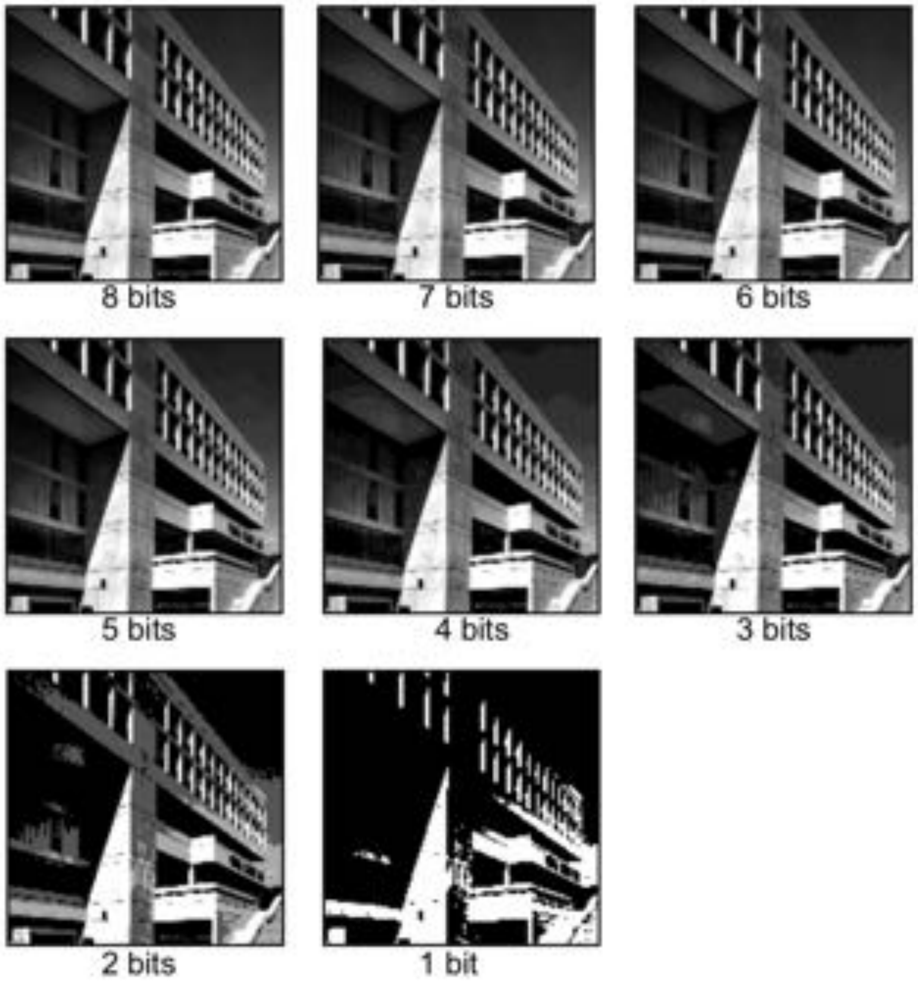


Image T. Pun

Impage representation by bit planes

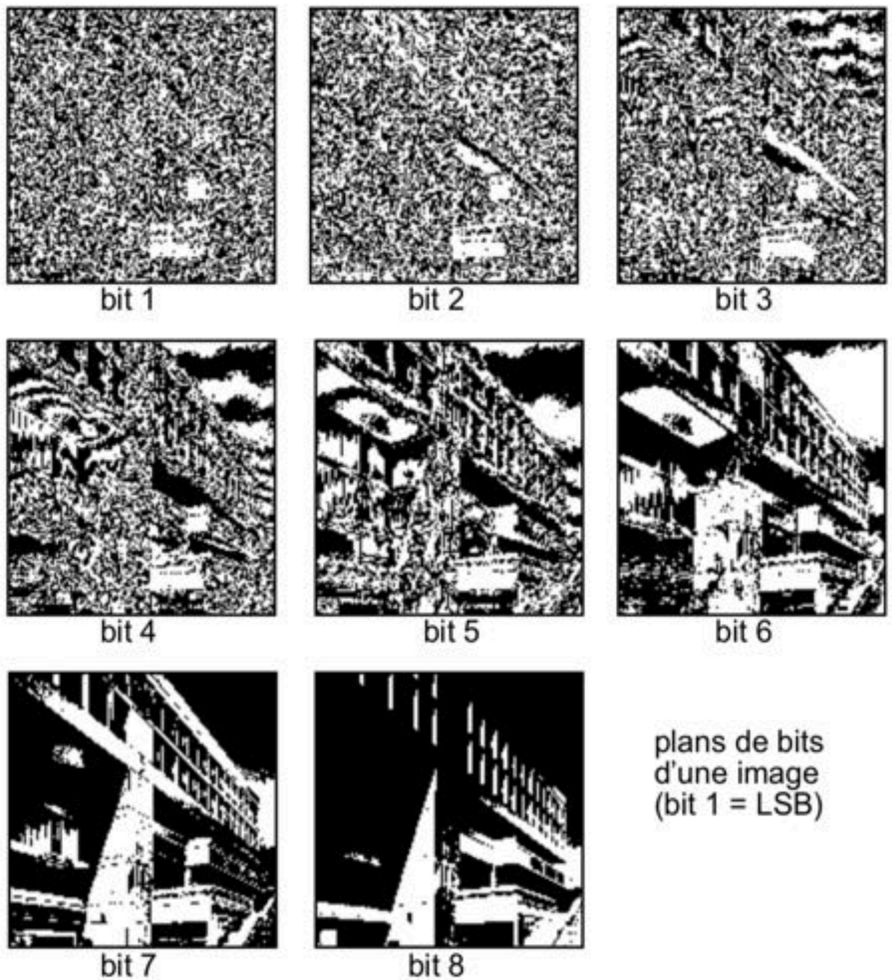


Image T. Pun