Emmetra

Shaping the future of Imaging

"Exploring Camera Systems: From Fundamentals to Advanced Electronic Imaging"

By

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CTO & Co-founder

Emmetra Technology

www.emmetra.com

October 24th-26th 2024

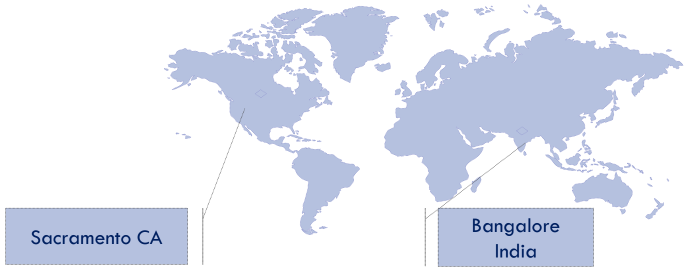
Boot Camp - Agenda

Exploring Camera Systems: From Fundamentals to Advanced Electronic Imaging

Day	Session	Content	Appr. Time (Hours)
Day 1 Oct 24th 2024 (2PM-5PM)	Session 1: Overview of Camera Systems	Introduction to digital cameras and components – Lens, sensor, ISP Review of color models and color spaces	1.5
	Session 2: Image Sensors and Capture Process	Image sensors, pixels, resolution, camera terminologies	1.5
Day 2 Oct 26th 2024 (9AM – 1PM)	Session 1: Introduction to ISP Advanced ISP Techniques	✓ Overview of Image signal processors, ✓ Need for ISP and sub blocks – Demosaicing, Color correction, denoising, tone mapping etc. ✓ High Dynamic Range (HDR), Low light imaging	1
	Session 2: Image Quality Basics Quantifying Image quality	✓ Understand image quality factors – Sharpness, Noise, Color accuracy. ✓ Camera components affecting IQ ✓ Imaging lab, Objective and subjective image quality assessment	1
	Session 3: Camera ISP/IQ tuning & Embedded Camera Software	✓ Need for Camera ISP tuning and techniques ✓ Calibration and Tuning, Challenges ✓ Objective and subjective tuning, Human vision and machine vision ✓ Introduction to embedded camera system ✓ Interfacing embedded camera software with Hardware ✓ Real time image processing on embedded systems	1
	Session 4: Technology Trends in camera – Role of AI in imaging	✓ New technology innovations especially AI based camera technology ✓ AI based image enhancements – noise reduction, super resolution etc. ✓ AI based camera tuning – proxy ISP etc.	0.5
	Session 5: Demo using Raspberry Pi	Demonstration of camera applications, ISP tuning on Raspberry Pi + camera	0.5
	Q&A and General Discussion, **Internship Assignment details**		0.5

EMMETRA - Company Overview

- Emmetra is a deeptech startup based out of California and with a development center in Bangalore.
- Our mission is to disrupt the lengthy and costly development process of camera SW stacks and boards with an AI-driven automated tool.
- Emmetra's innovative solution reduces the development cycle from several months to just a few days per design, offering a substantial cost saving of upto 70% to OEMs, ODMs, and design houses



Sensor, Optics + ISP Calibration

Precise calibration, tuning, and benchmarking of sensors, optics, and Image Signal Processors (ISP) to achieve ***superior image quality***.

Camera Software + Optimization

Specialized services for ***enhancing camera software*** through development and ***optimization*** processes.

Image Sensor Driver + Integration

Efficient development and ***integration*** of image sensor drivers into System on Chip (SoC) and Image Signal Processor (ISP) systems.

Camera Imaging Algorithm

Expert research and development services focusing on ***camera imaging algorithm advancement.***

Technical Publications	Team Size 10+	Strategic Partnerships	Advanced Imaging Lab

Leadership Profile

Co-Founders

Ajay Basarur
CEO

Radhesh Bhat
CTO

Chethan KR
COO

Geo Sales

Radha Manohar V
CBO

My Profile

Radhesh Bhat - CTO & Co-founder, Emmetra

Experience Highlights:

- **20+ Years Expertise:**
  - **Digital Camera Systems | Image Processing | Computer Vision | Deep Learning | Digital Video Codecs | Camera Tuning | Image Quality Optimization | Embedded Multimedia Software**
  - **Director of Technology, PathPartner Technology (KPIT), Bangalore June '07 – July '24**
  - **DSP Architect , Aricent Communications (Emuzed), Bangalore July '04 – June '07**
- **Key Contributions:**
  - **Founded Imaging & Vision Division, propelling PathPartner into top 3 global imaging players**
  - **Led development of cutting-edge camera products for**
    - **Amazon, Meta, Motorola, GoPro, Mercedes-Benz, VW, Audi, Samsung, Nokia and many more**

- **Key Achievements:**
  - **Early pioneers in establishing camera development, ISP and IQ tuning competency and state of the art Imaging lab in India and became one of the top 3 in global imaging industry**
  - **Successfully delivered 100+ camera projects to clients across globe with enablement for production programs across consumer, IOT and automotive**
  - **Built IP portfolio in imaging and successfully licensed to many key camera customers**
  - **Established R&D division in imaging and computer vision , state-of-the-art Imaging Lab**
  - **Holder of multiple imaging technology patents**
  - **Published research in international journals/conferences on camera/imaging and computer vision**

Internship at Emmetra – Opportunities and Benefits

Why Emmetra?

- ✓ **Impactful work** – Real camera products and solutions
- ✓ **Startup culture** – Experience the dynamic and innovation environment of a tech start up
- ✓ **Growth opportunities** – High performing interns may be offered full time positions post-graduation
- ✓ **Networking** – Build connections with industry professionals
- ✓ **Stipend & Perks** – Competitive stipend and access to company resources and facilities
- ✓ **Flexible Work Hours** - Ideal for students balancing academics with practical experience

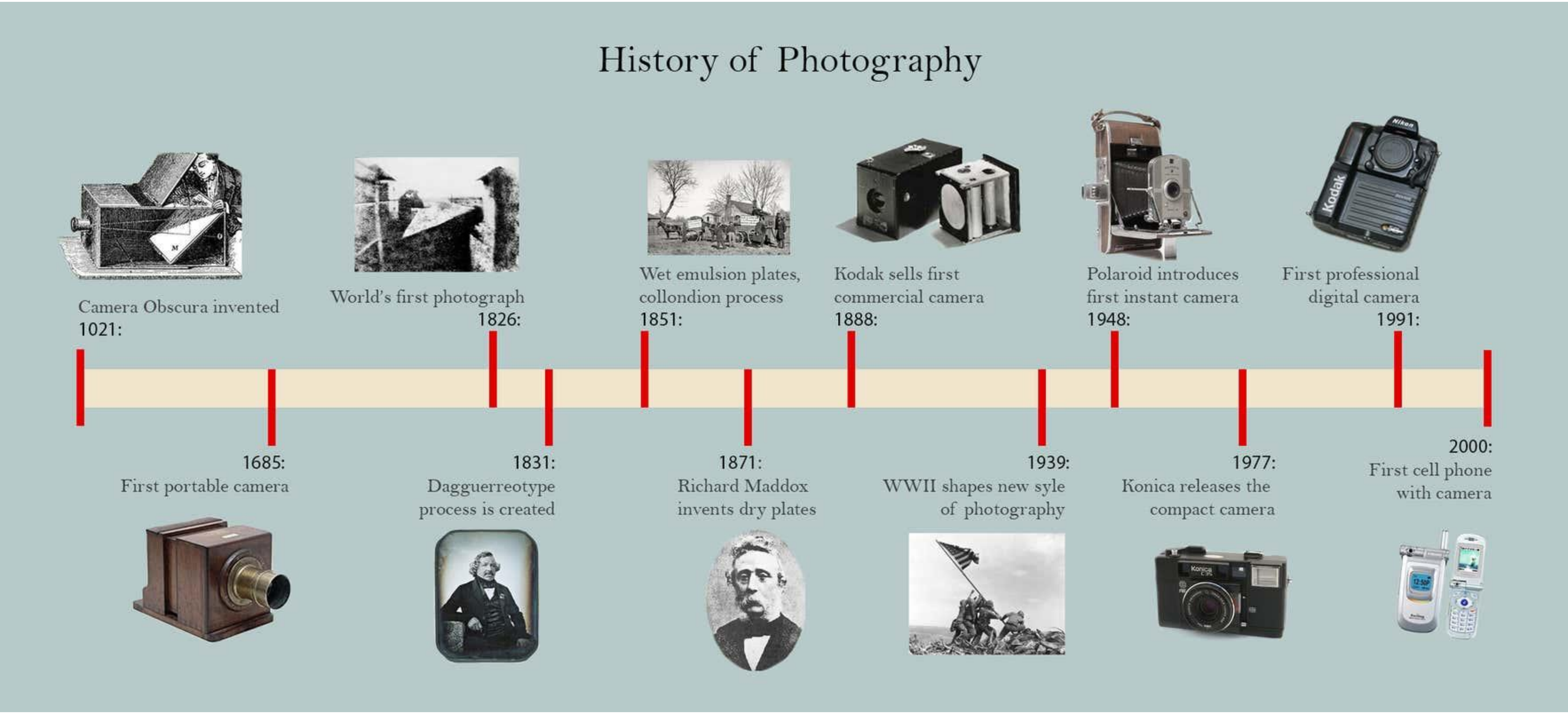
Learning and Development

- ✓ **Hands on experience** – Image processing, Computer Vision, AI, Optics, Color Science, Embedded Systems, Camera embedded software
- ✓ **Mentorship** – Learn from industry experts who will guide through the complexities of tech development
- ✓ **Research projects** – Real world imaging challenges and opportunities to innovate
- ✓ **Publications** – Opportunities in leading journals and conferences
- ✓ **State of the art imaging lab** – Equipped with latest technology and tools for practical learning on camera calibration, tuning and testing

Camera technology is integral to smartphones, automotive, security, and more. The need for innovation is high, and we're at the forefront of this change. **As an intern at Emmetra, you'll be directly involved in projects that shape the future of imaging technology.**

Apply Now and Be a Part of the Future of Imaging!

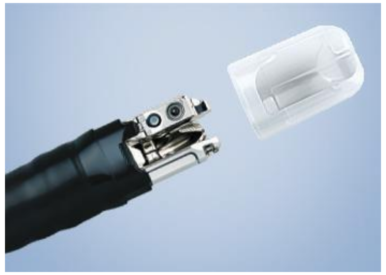
History of Photography



New cameras - new applications

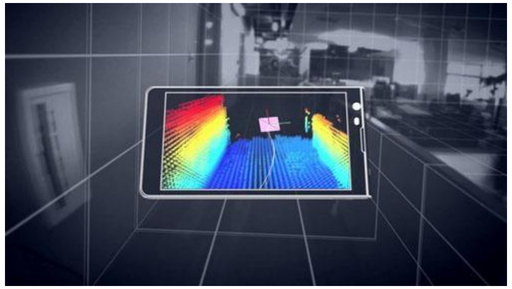
Cameras include:

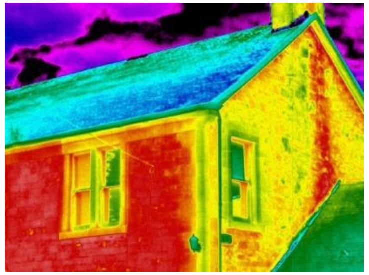
- Phones
- DSLR
- Sports cameras
- Endoscopes
- Wearable
- Stereo (dual) cameras
- Light field cameras
- Time of flight
- IR camera
- Multispectral-hyperspectral



Application include:

- Photo
- Video
- Security
- Medical imaging
- Self-driving cars
- Robots, drones
- 3D stereo
- Computational imaging
- Depth/volumes
- Thermal imaging
- Forensics





AI Enhanced Vision Based Applications

AI Enhanced Vision Based Applications - Success

- AI models accuracy relies on its input quality

- Efficiency in data capture and processing in edge AI applications

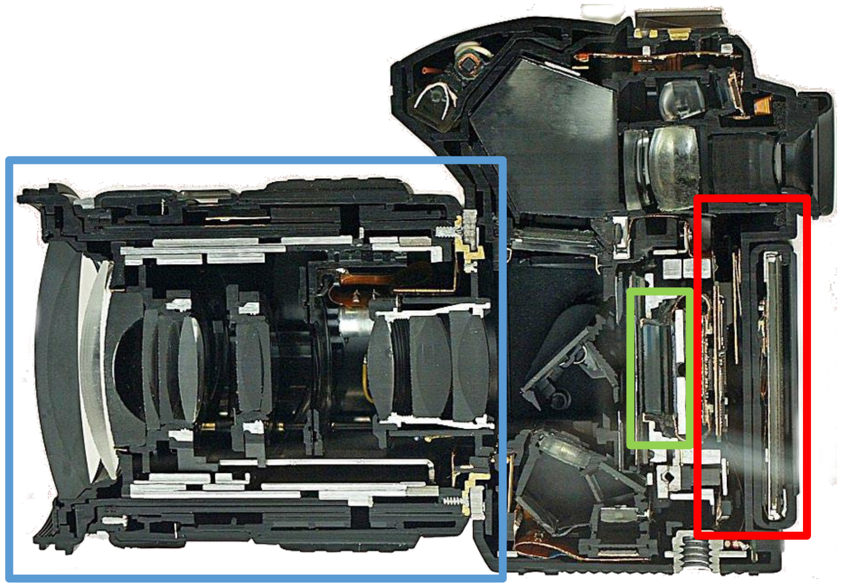
- Successful employment of AI-enhanced applications with high-quality sensors paired with the right optics , interfaces and signal processing which provides precise, detailed and efficient visual data

Camera engineers' challenges

- **Camera engineers need:**
  - To select the best "bang for the bucks" components for their application
  - To understand what are the shortcomings and defects affecting their cameras; what is the "weak link"
  - To test components and sub system in production
  - To design and test camera algorithms, calibration and tuning parameters
  - How to ensure camera is producing best quality for the target applications – human vs machine need?
  - How to leverage AI ?
- **Motivation**
  - Cameras are the primary tool used to capture digital images.
  - Digital images are the primary inputs to CV/DL algorithms.
  - CV/DL researchers/engineers should have a basic understanding of how cameras work to inform their algorithms.

The modern photography pipeline

post-capture processing

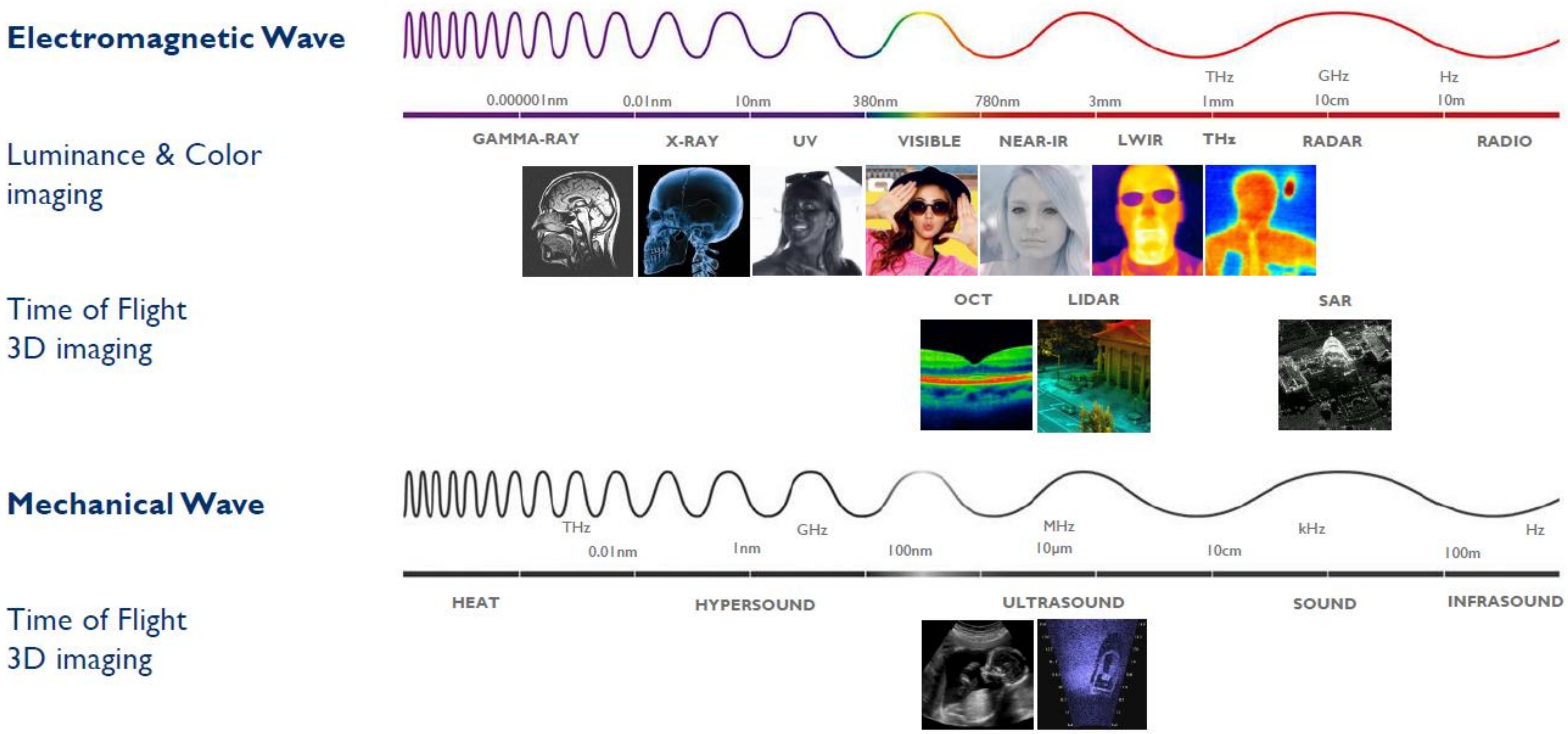


optics and optical controls → sensor, analog front-end, and color filter array → in-camera image processing pipeline

Basics of Digital Camera and its Components

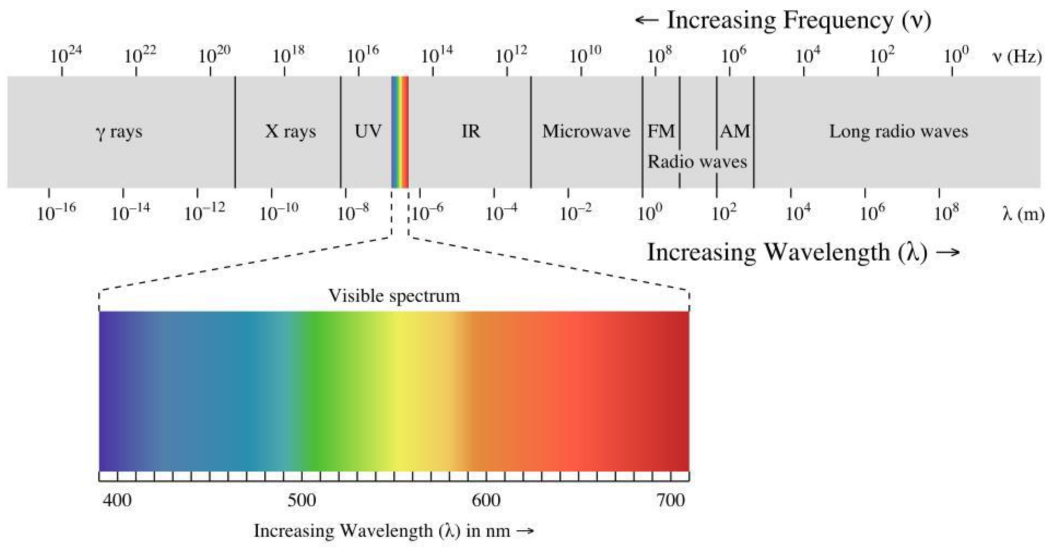
What is Imaging?

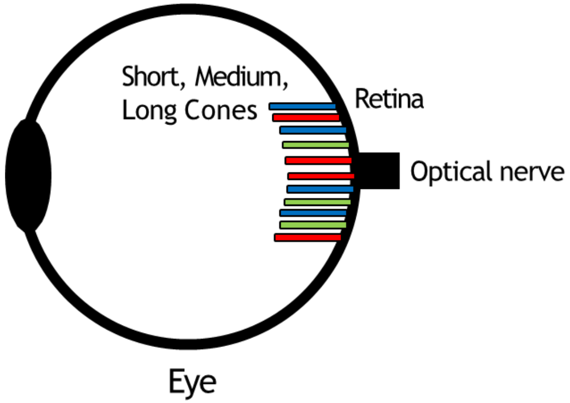
- Ability to “perceive” the environment at a distance using propagating waves

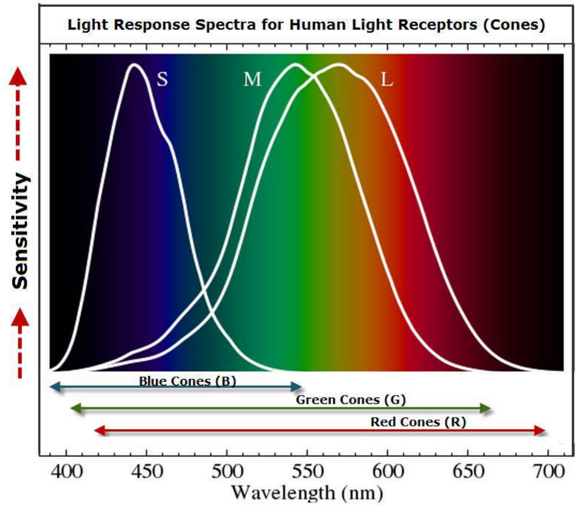


Sensations?

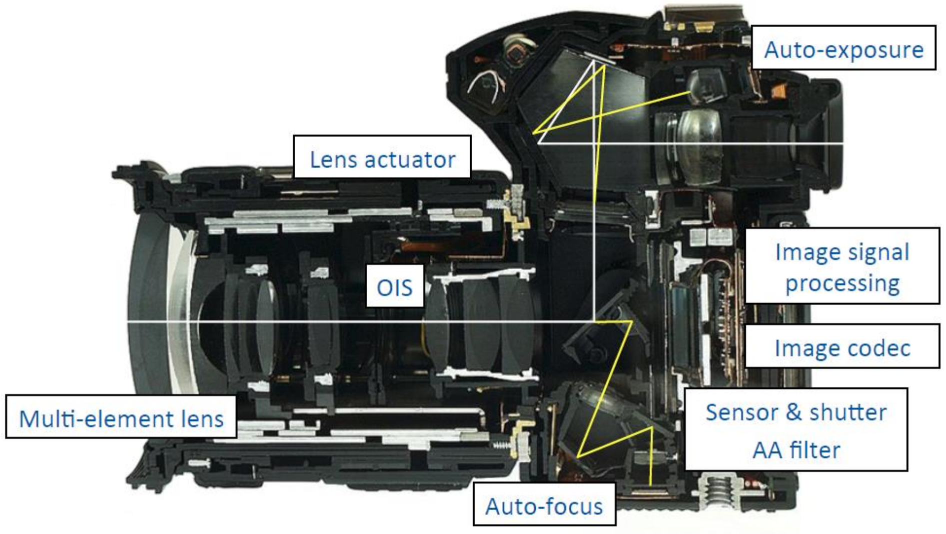
- Our eye has three receptors (cone cells) that respond to visible light and give the sensation of color
- “Color” is not an objective physical property of light (electromagnetic radiation).
- Instead, light is characterized by its wavelength.
- Cones and rods
  - We have additional light sensitive cells called rods that are not responsible for color but at night
  - Cones are most concentrated on the fovea and responsible for color sensation







Digital Camera



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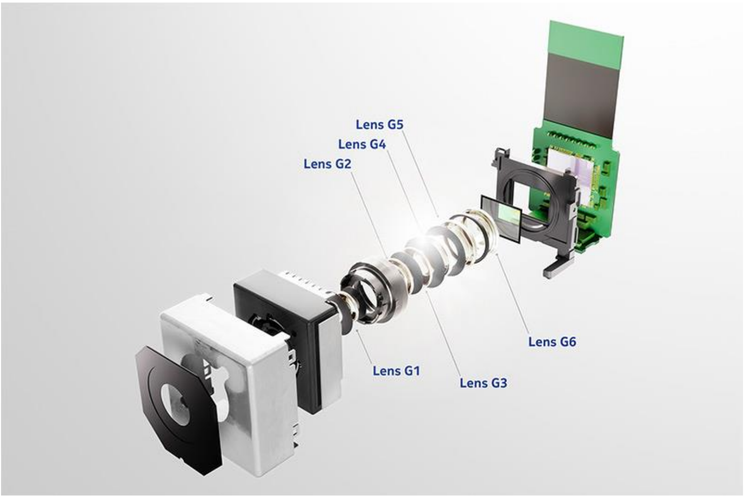
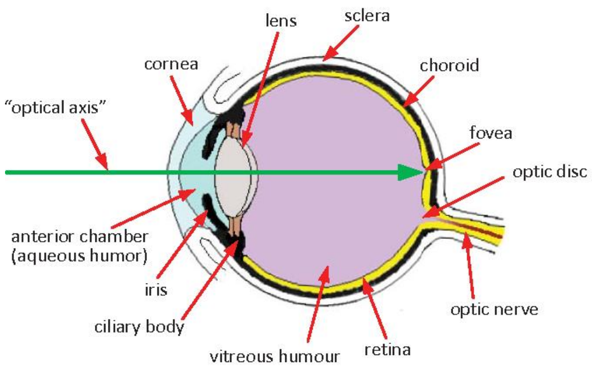
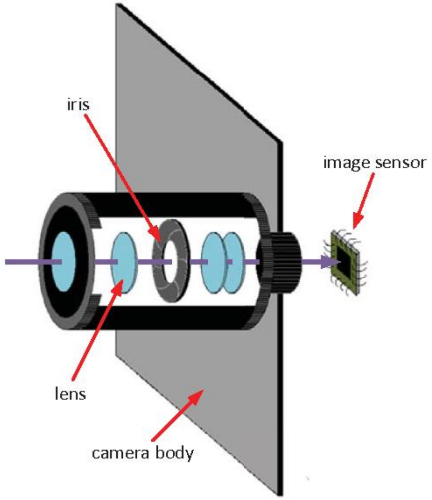


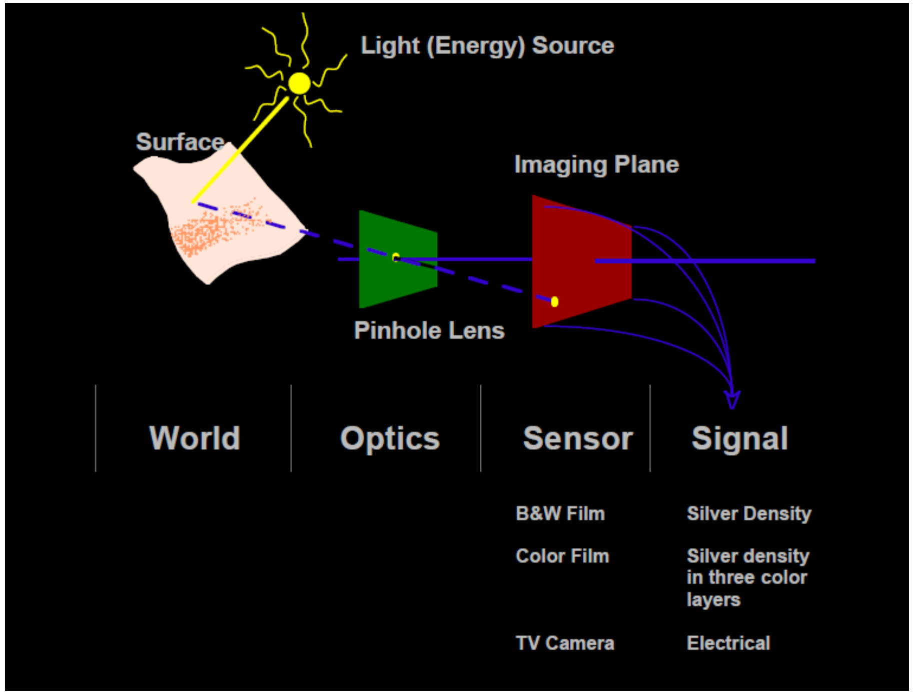
(b)



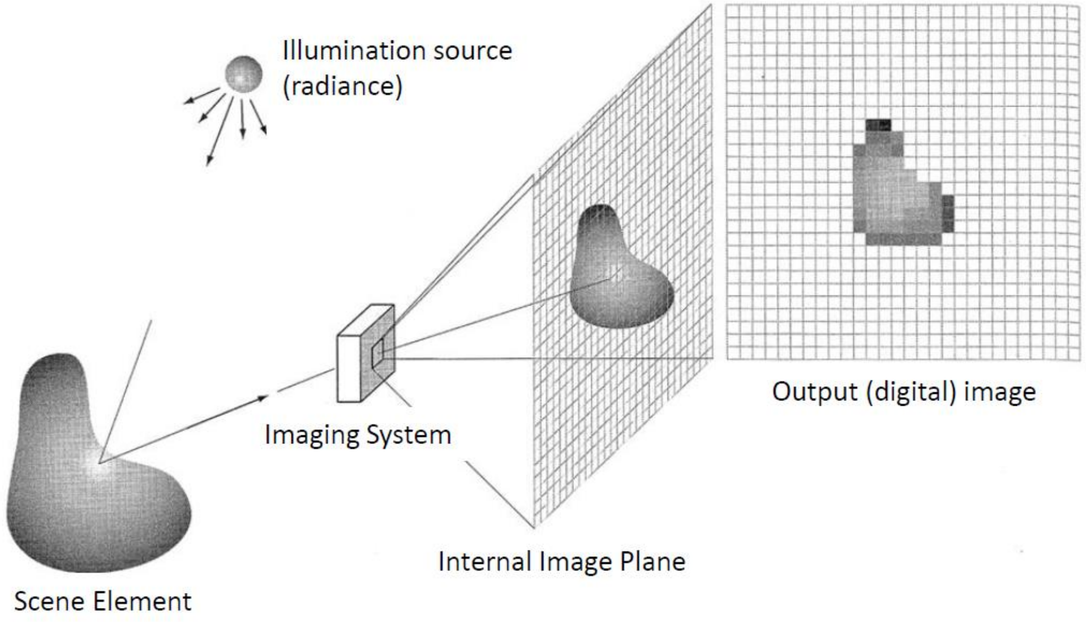


Factors in Image Formation

- Geometry
  - concerned with the relationship between points in the three-dimensional world and their images
- Radiometry
  - concerned with the relationship between the amount of light radiating from a surface and the amount incident at its image
- Photometry
  - concerned with ways of measuring the intensity of light
- Digitization
  - concerned with ways of converting continuous signals (in both space and time) to digital approximations



Digital Image Formation



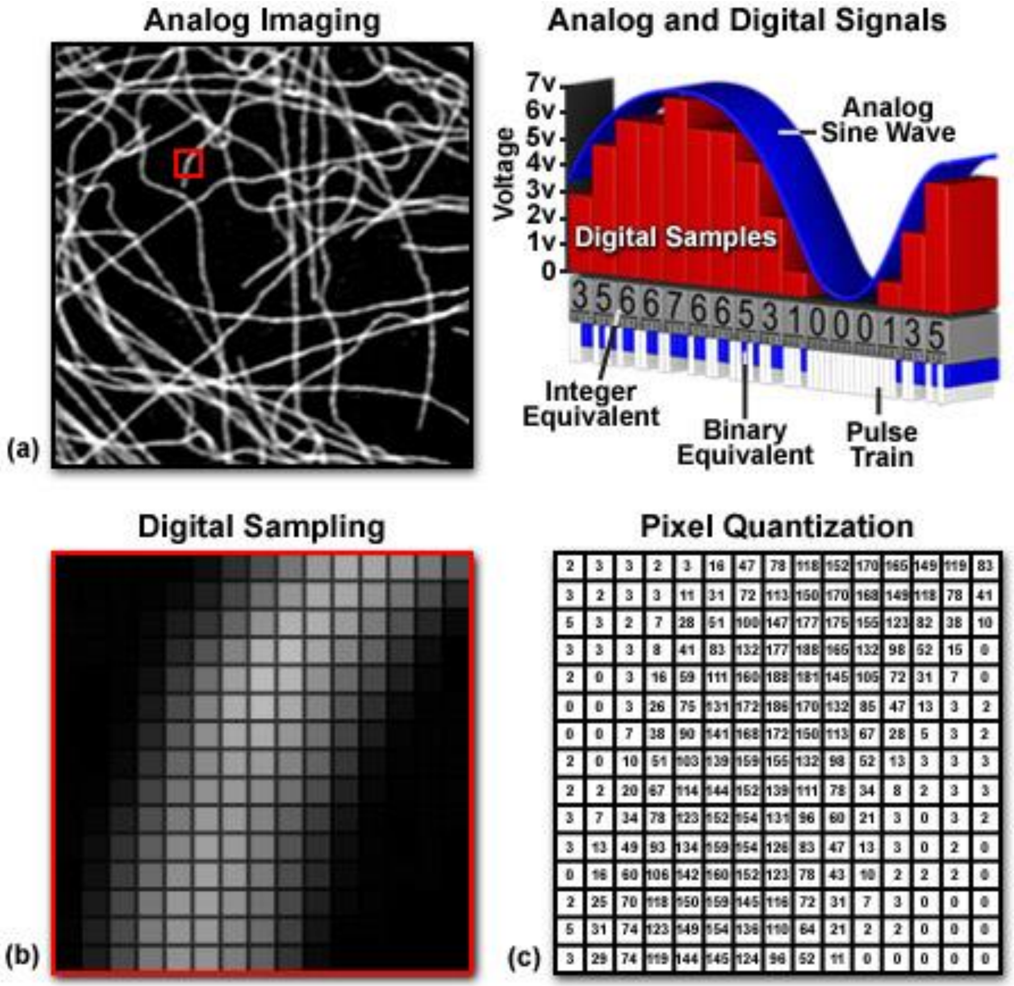
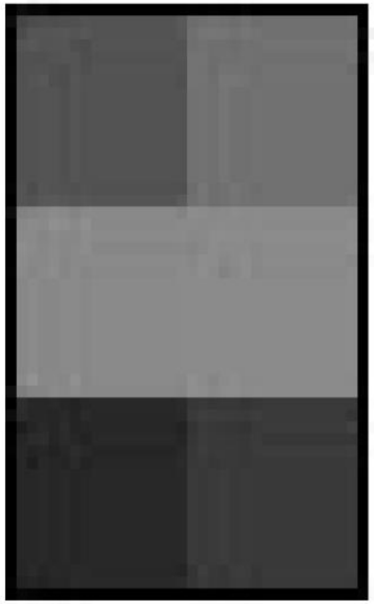


Figure 1

Pixels – Basic Unit of Digital Images



2 x 3 pixels
(takes much less than 1K of memory)

20 x 30 pixels
(takes 2K of memory)

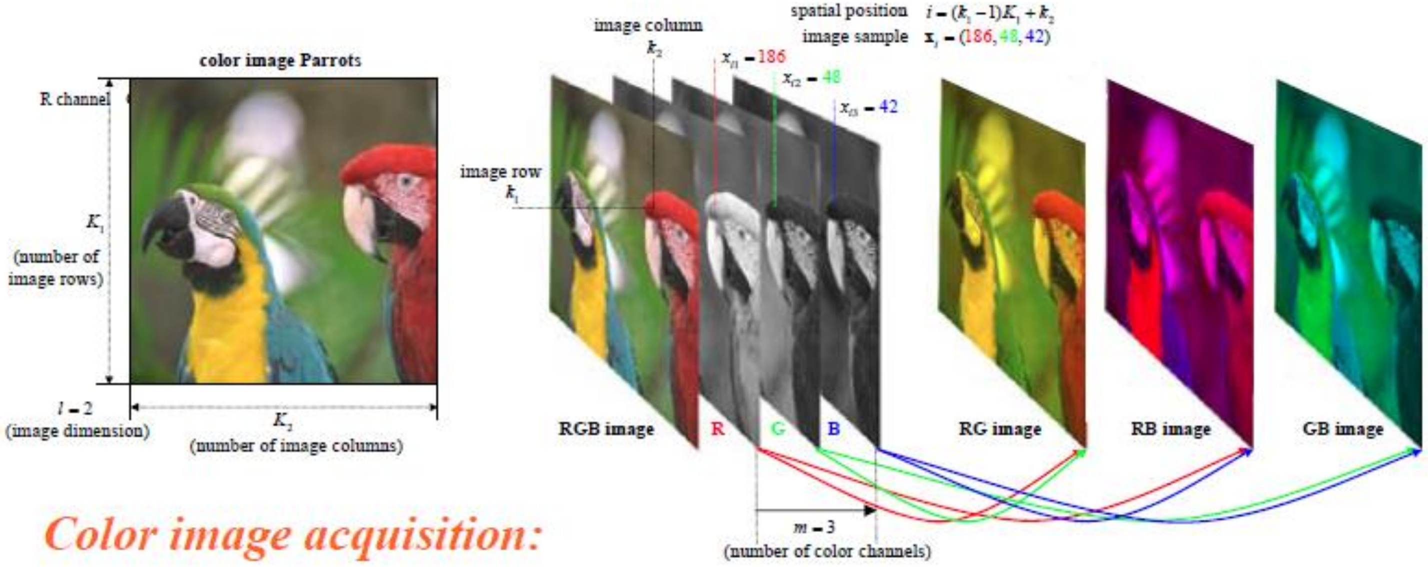
40 x 60 pixels,
(takes 8K of memory)

200 x 300 pixels
(takes 170K of memory)

- The digital value of a pixel is based on several factors.
  - Exposure (which is a function of both shutter speed and exposure)
  - Gain (ISO setting on the camera)
  - Camera hardware that digitizes the signal

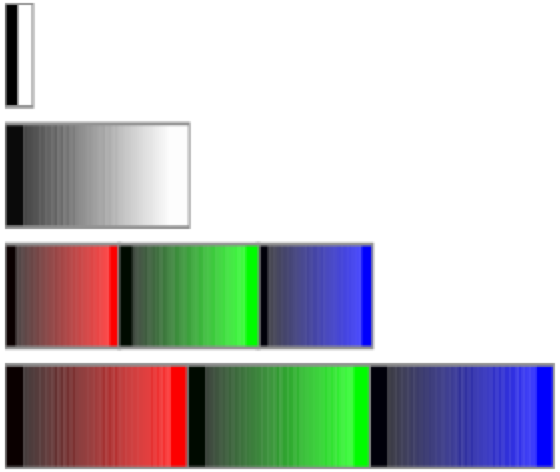
Digital Images

- Can be encoded as 2D arrays of RGB triplets
- Formally:
  - The domain is the 2D plane
  - The range is the RGB space
- Values are often encoded as 8 or 16 byte integers



Color image acquisition:

Digital Image Bit Depth

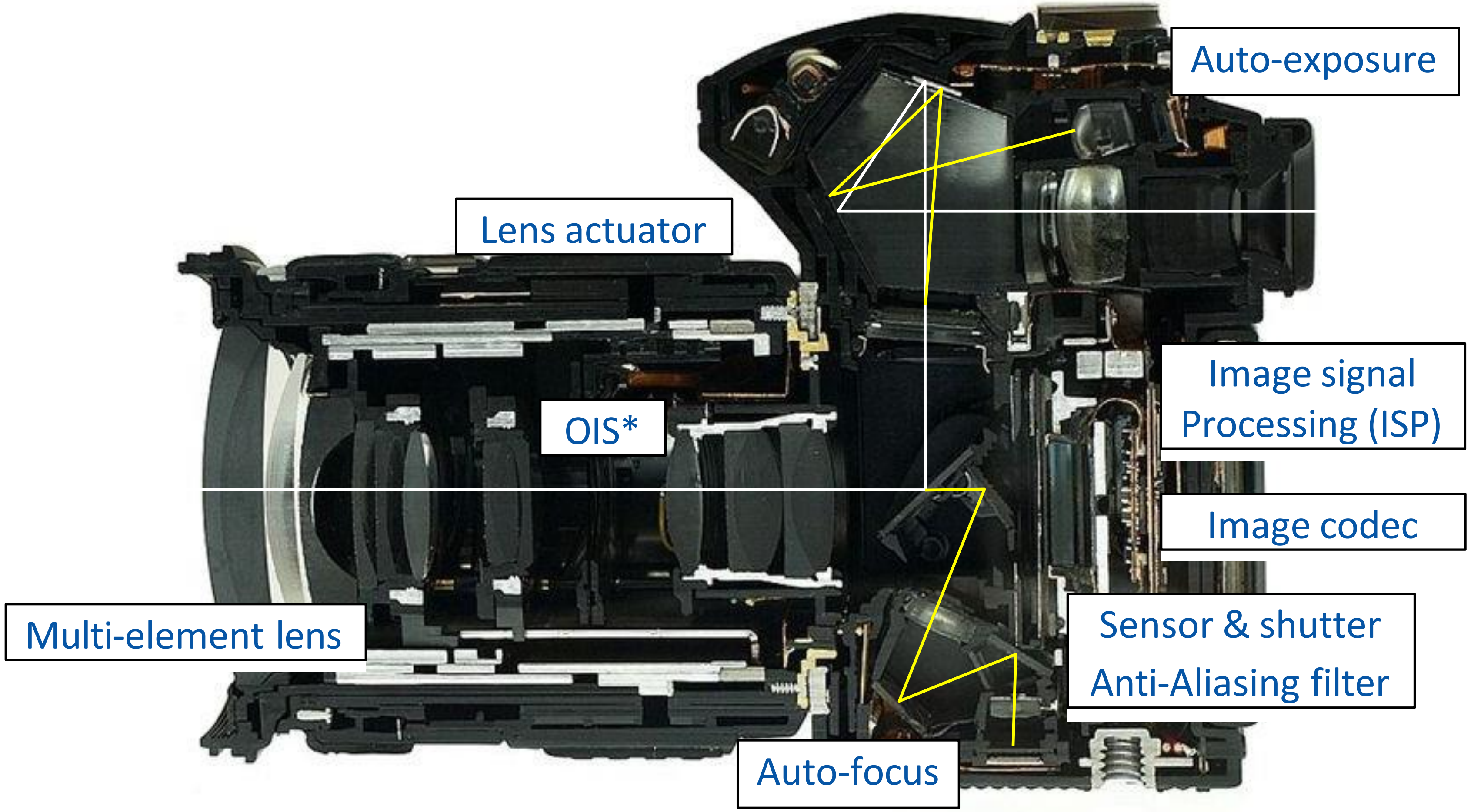


1 Bit -> black and white
8 Bit -> greyscale
16 Bit -> 64.000 colours (High Colour)
24 Bit -> 16 Mil. colours (True Colour)

File size for True Colour

640 x 480 x 3 = 0,87 MB
800 x 600 x 3 = 1,37 MB
1024 x 768 x 3 = 2,25 MB
1280 x 1024 x 3 = 3,75 MB

Camera models



* Optical Image Stabilization

Camera models - Mobile Camera Module

Auto-exposure

Multi-element lens

EIS*

Image signal Processing (ISP)

Image codec

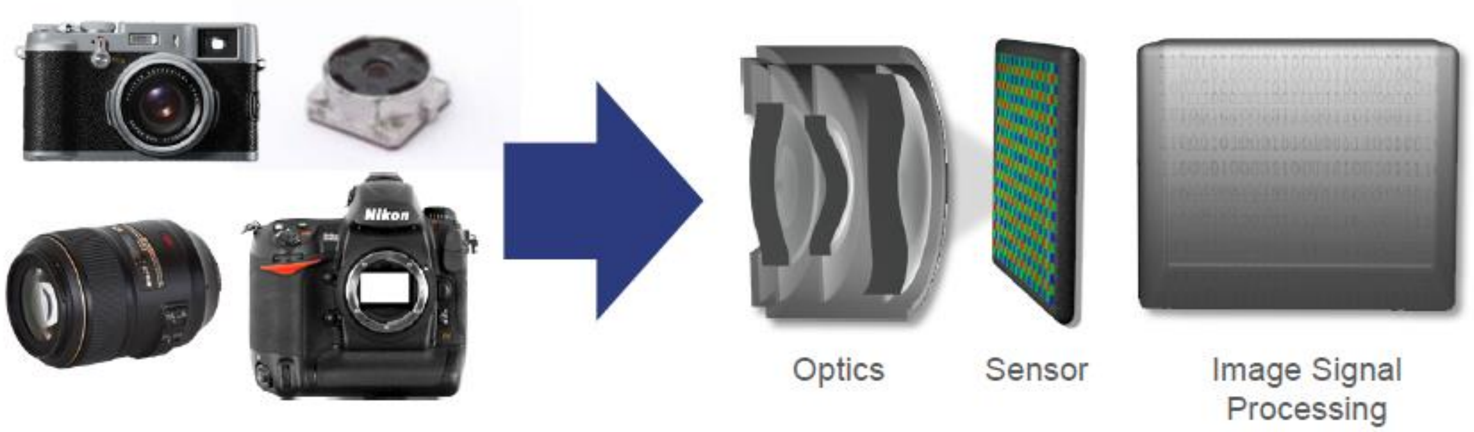
Autofocus

Sensor, Anti-Aliasing filter, Electronic Rolling shutter

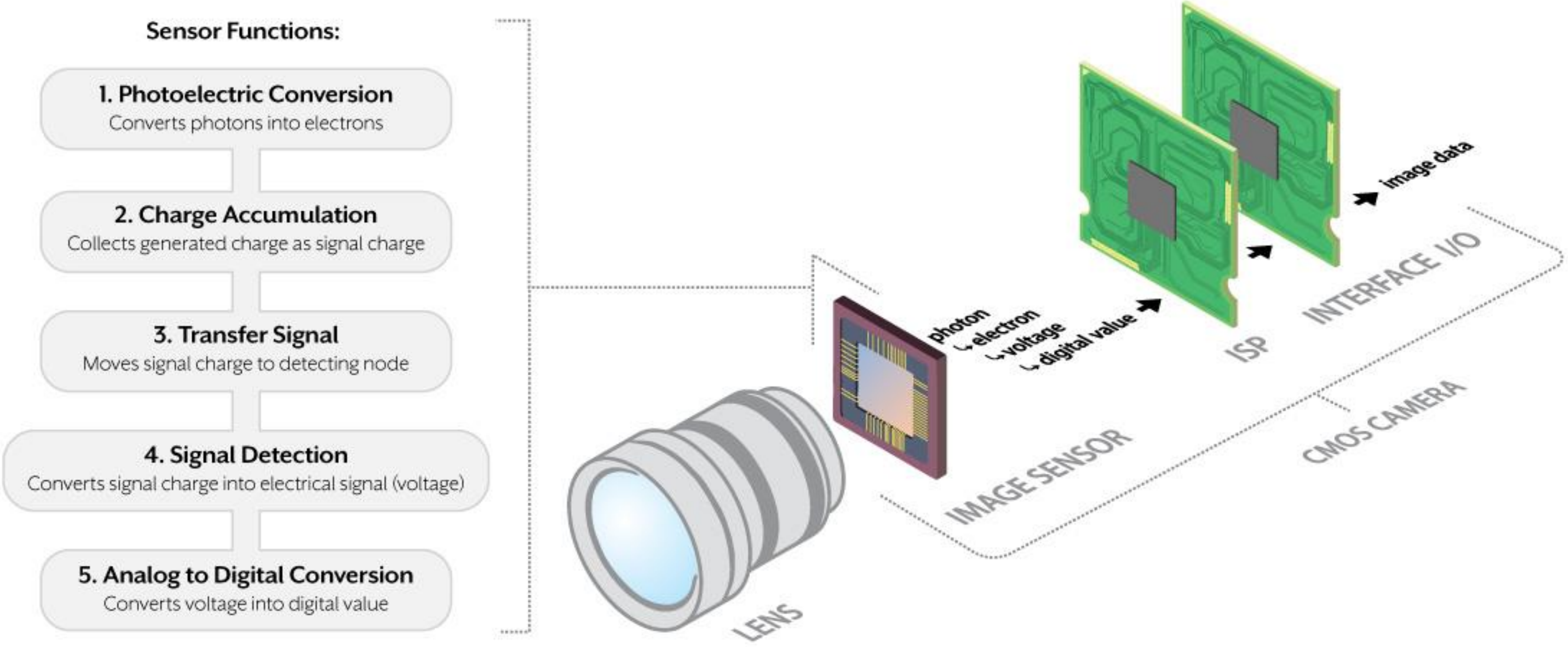
* Electronic Image Stabilization

Camera Model

- Optics – Project and focus the light on the photo sensitive surface
- Shutter – Let light being acquired during a determined period of time
- Sensor – convert the luminuous signal into electrical then digital signal
- ISP – makes the signal of the sensor a visible and good looking image



Typical CMOS Camera Layout



Let’s say we have a sensor…

digital sensor
(CCD or CMOS)

… and an object we like to photograph

real-world
object

digital sensor
(CCD or CMOS)

What would an image taken like this look like?

Bare-sensor imaging

real-world
object

digital sensor
(CCD or CMOS)

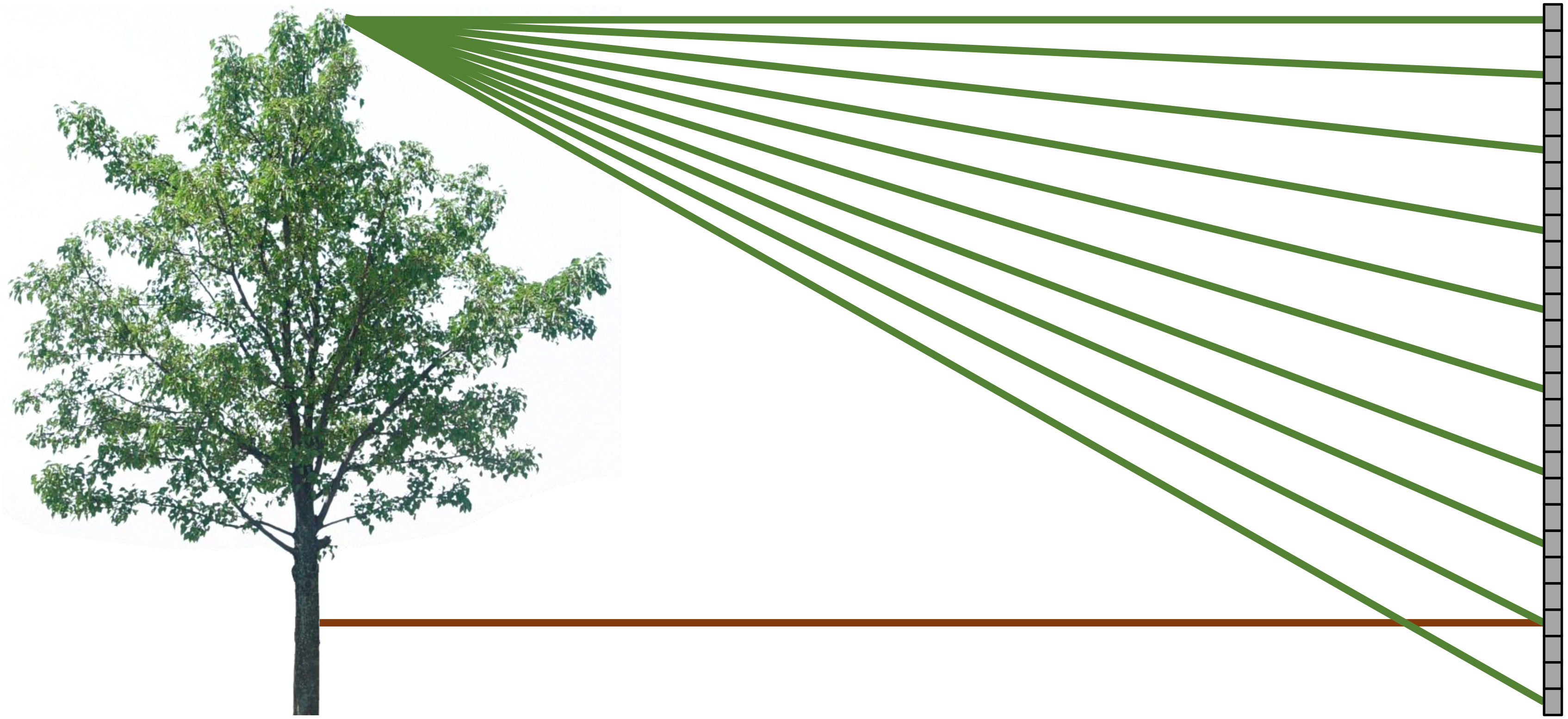
Bare-sensor imaging

real-world
object

digital sensor
(CCD or CMOS)

Bare-sensor imaging

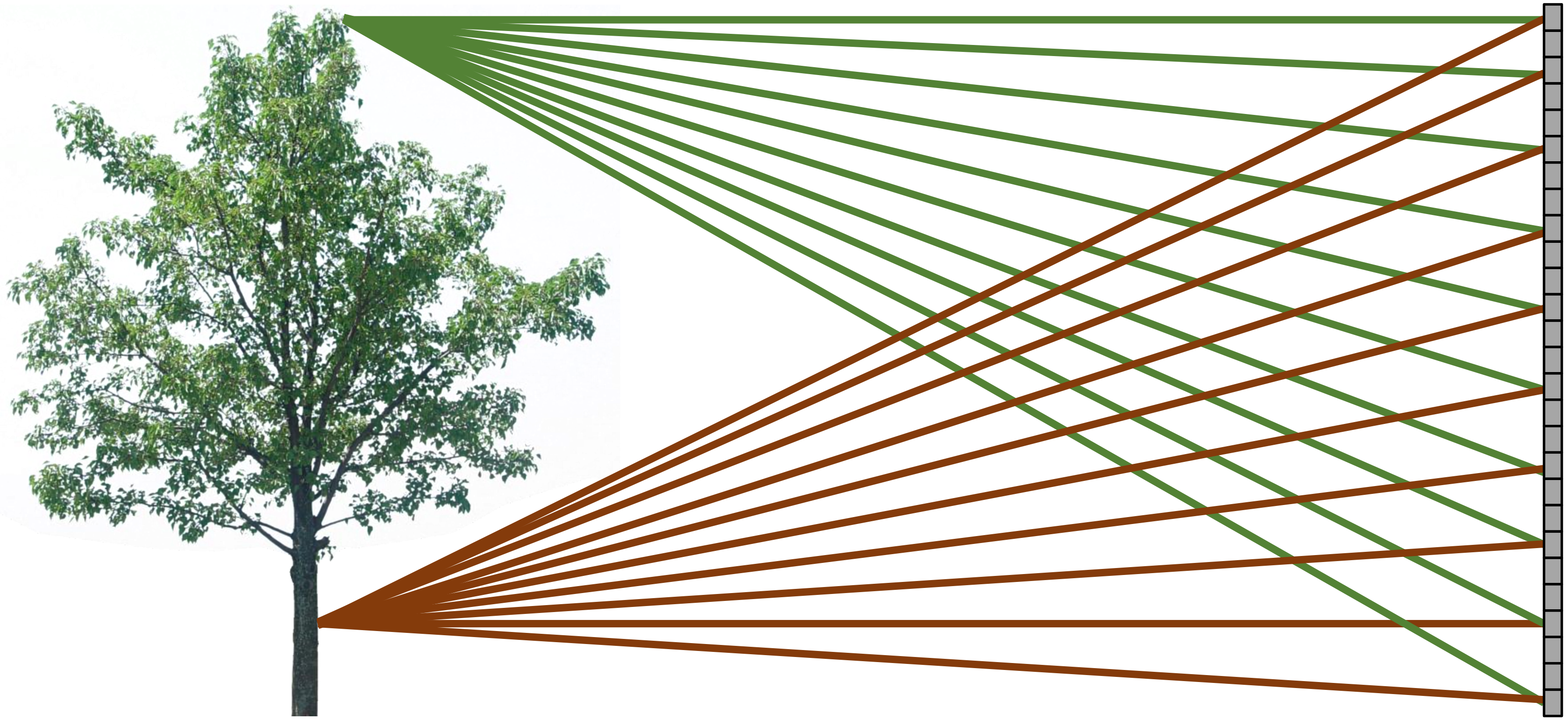
real-world object



digital sensor (CCD or CMOS)

Bare-sensor imaging

real-world
object



All scene points contribute to all sensor pixels

What does the
image on the
sensor look like?

Bare-sensor imaging

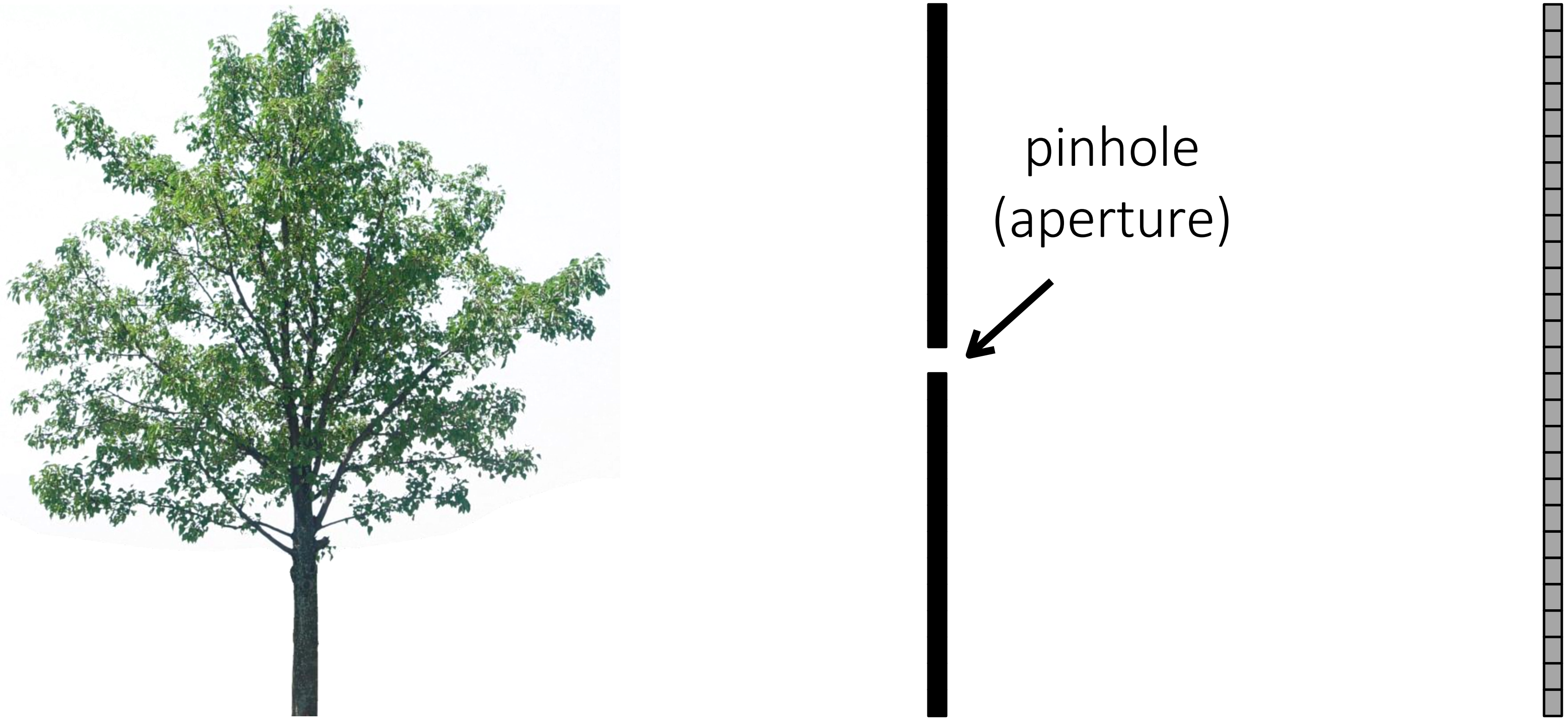
All scene points contribute to all sensor pixels

What can we do to make our image look better?

real-world
object

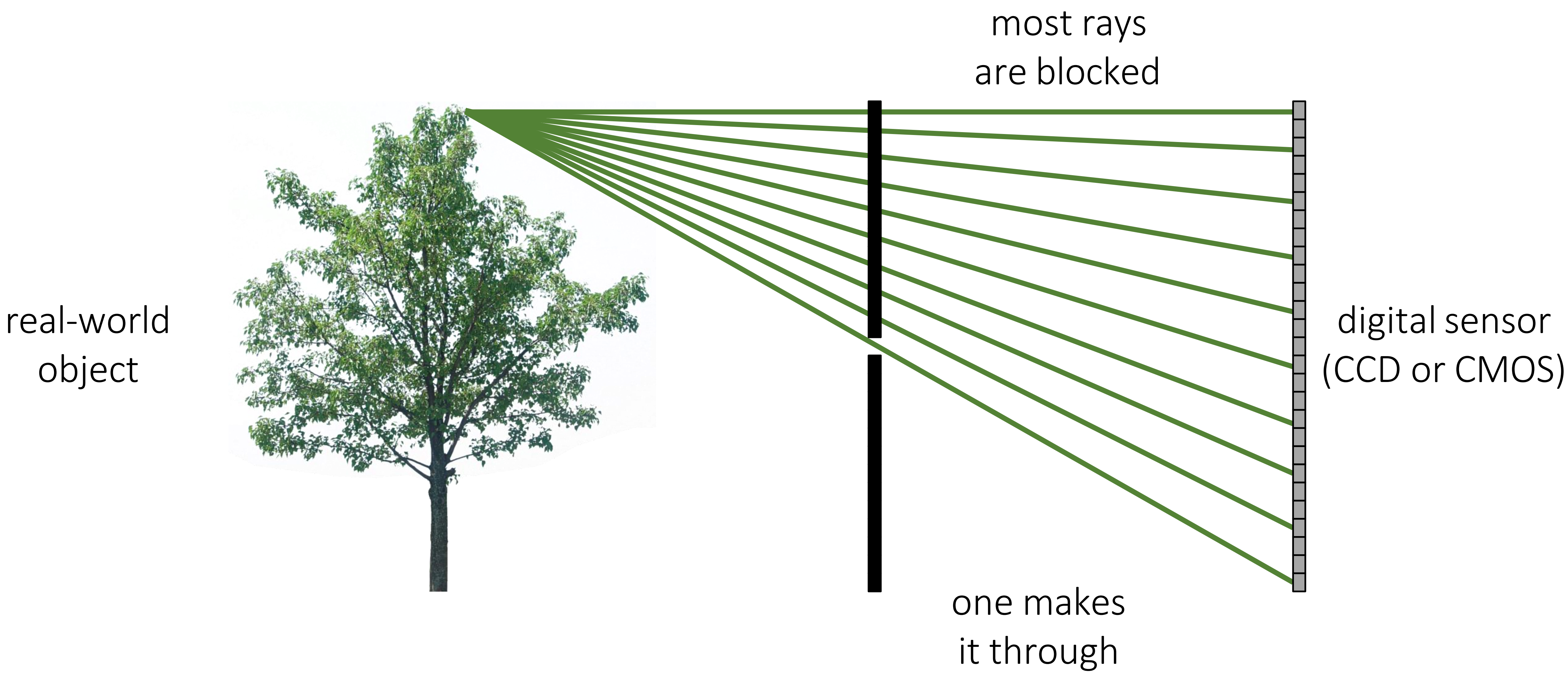
digital sensor
(CCD or CMOS)

Let’s add something to this scene

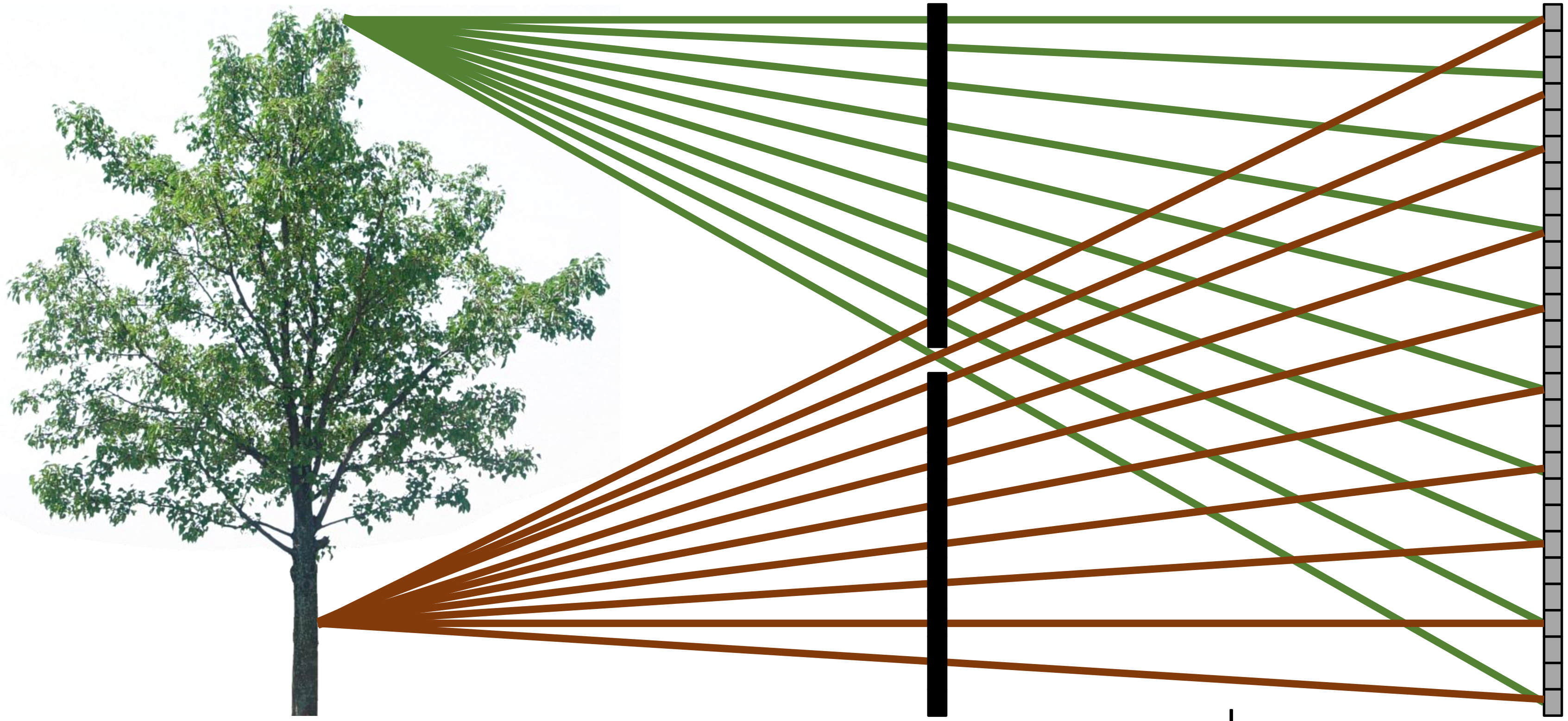


What would an image taken like this look like?

Pinhole imaging

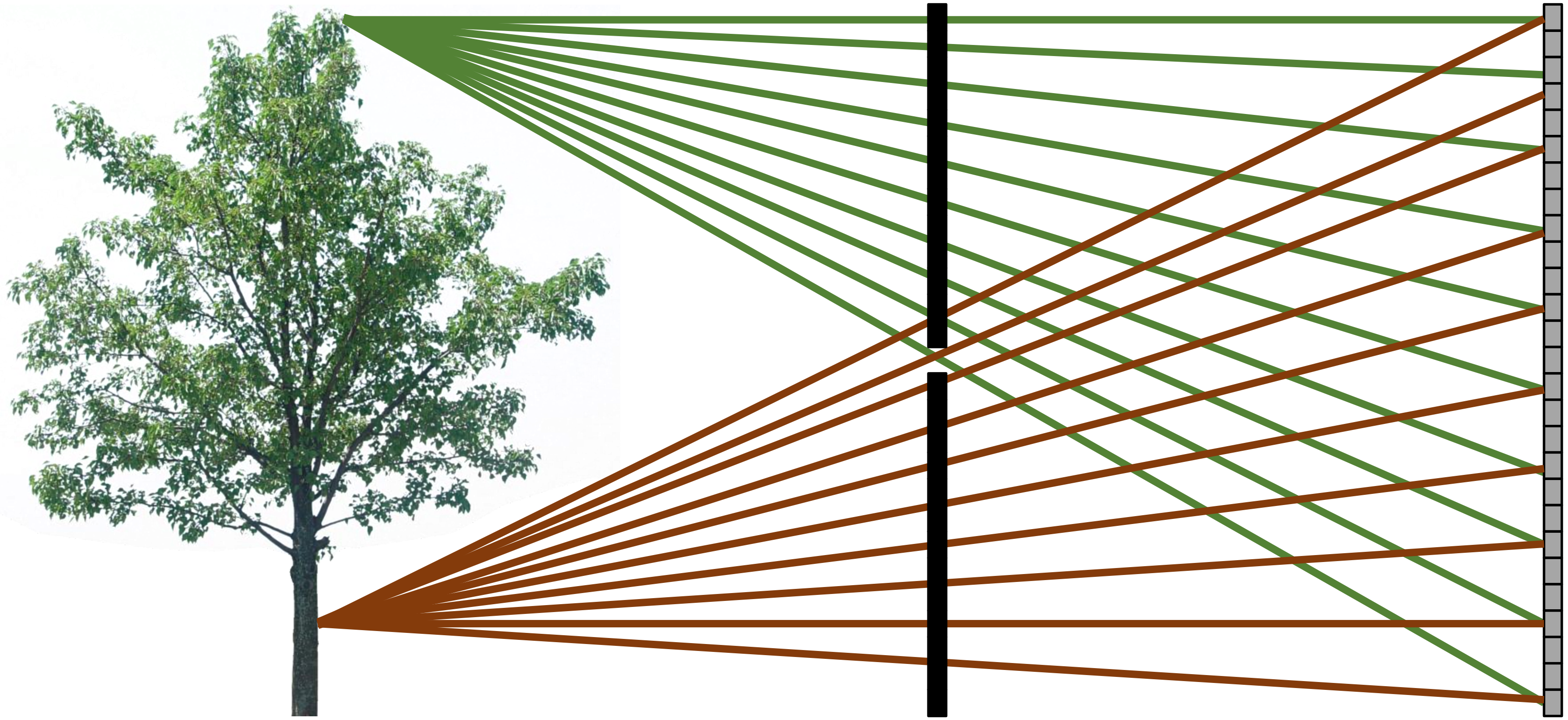


Pinhole imaging



Pinhole imaging

real-world object

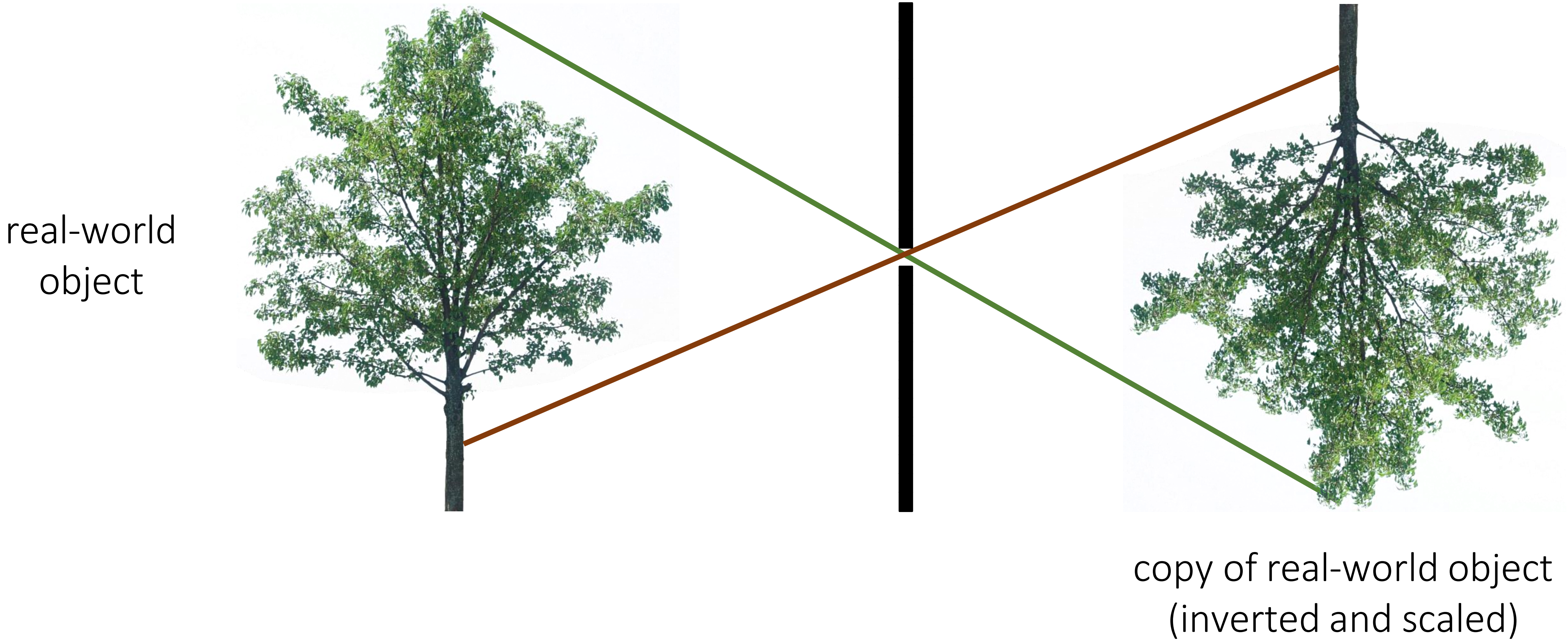


digital sensor (CCD or CMOS)

Each scene point contributes to only one sensor pixel

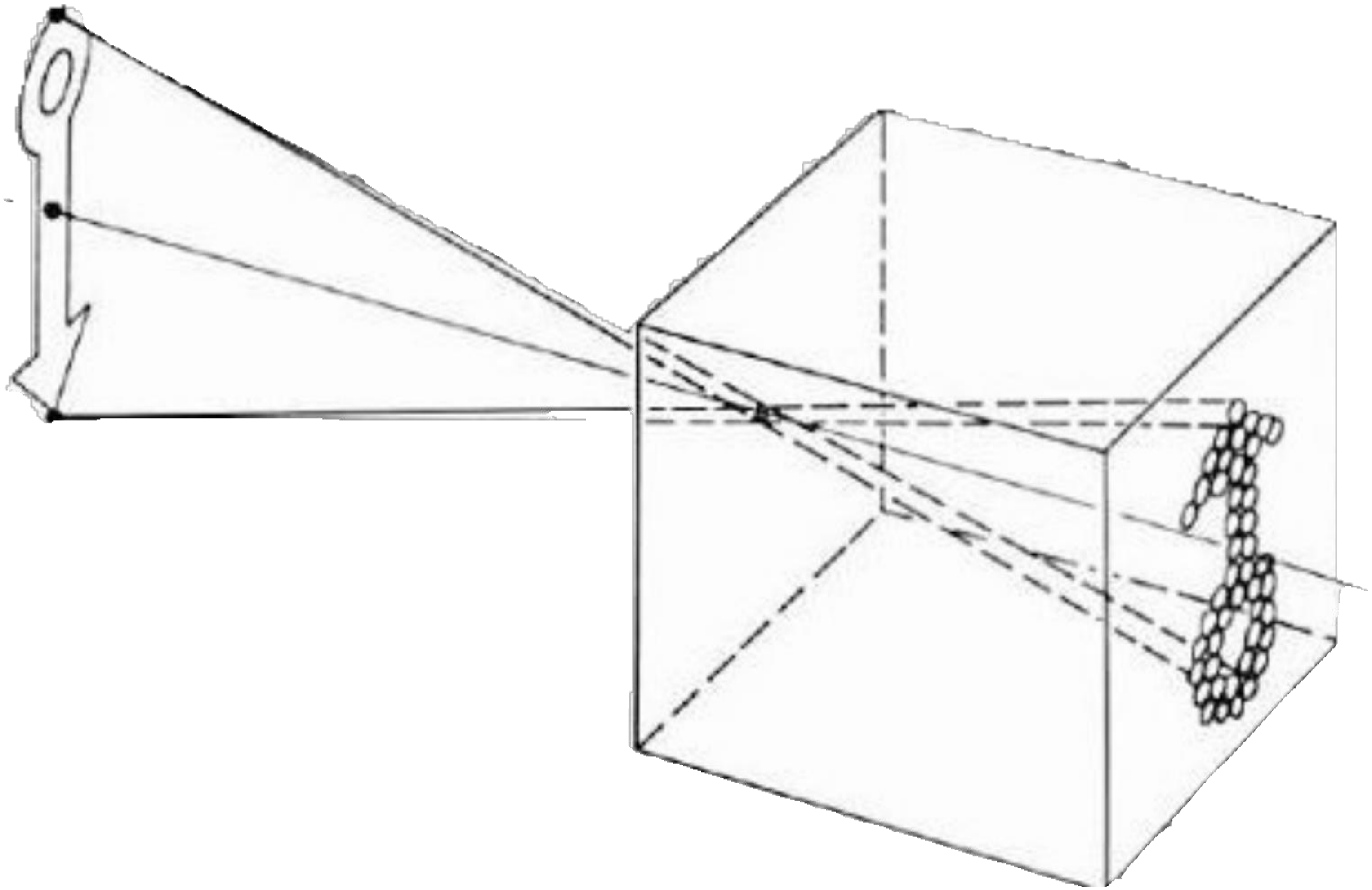
What does the image on the sensor look like?

Pinhole imaging

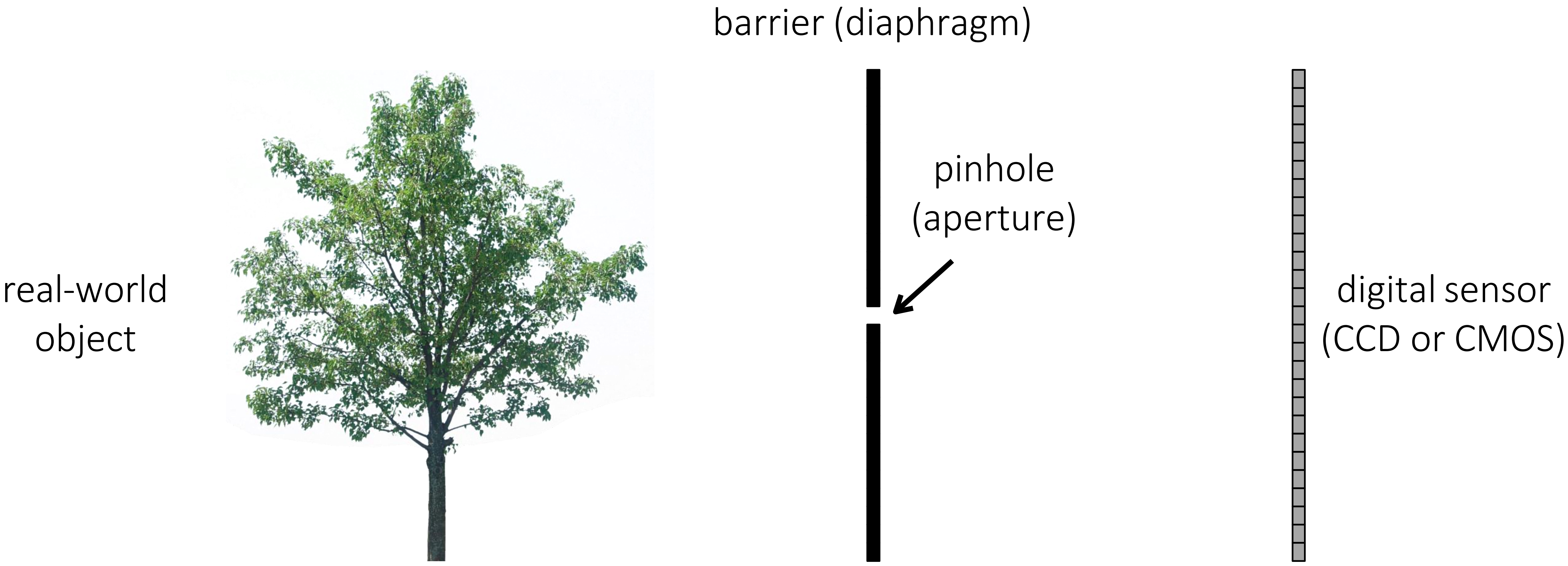


Pinhole camera

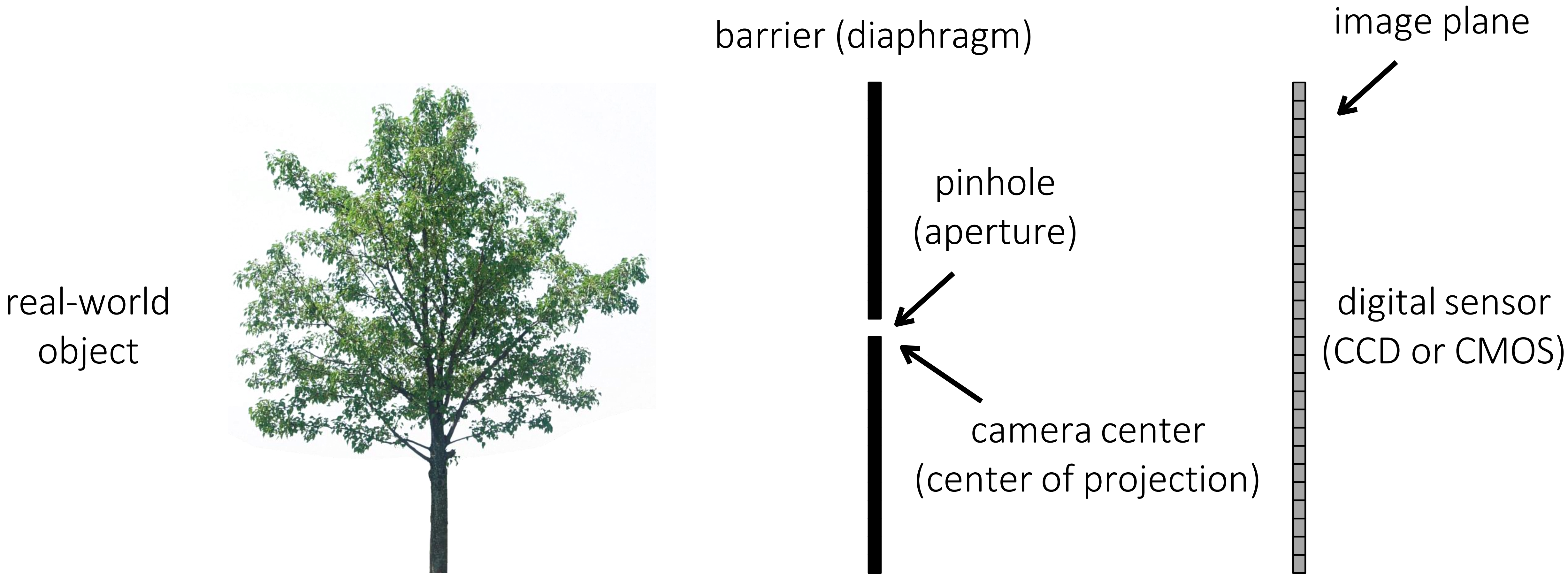
Pinhole camera a.k.a. camera obscura



Pinhole camera terms

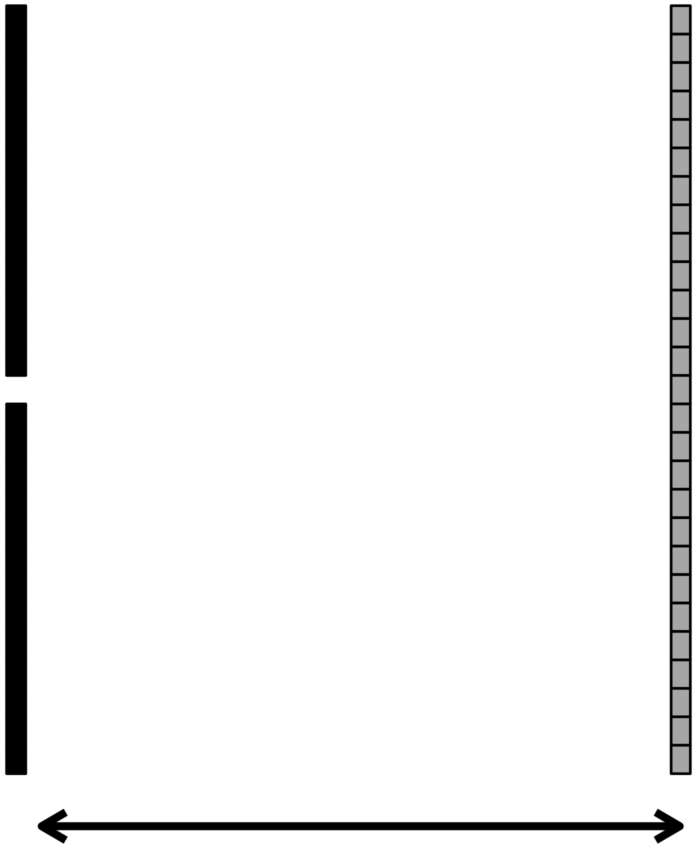


Pinhole camera terms



Focal length

real-world
object



focal length f

Focal length

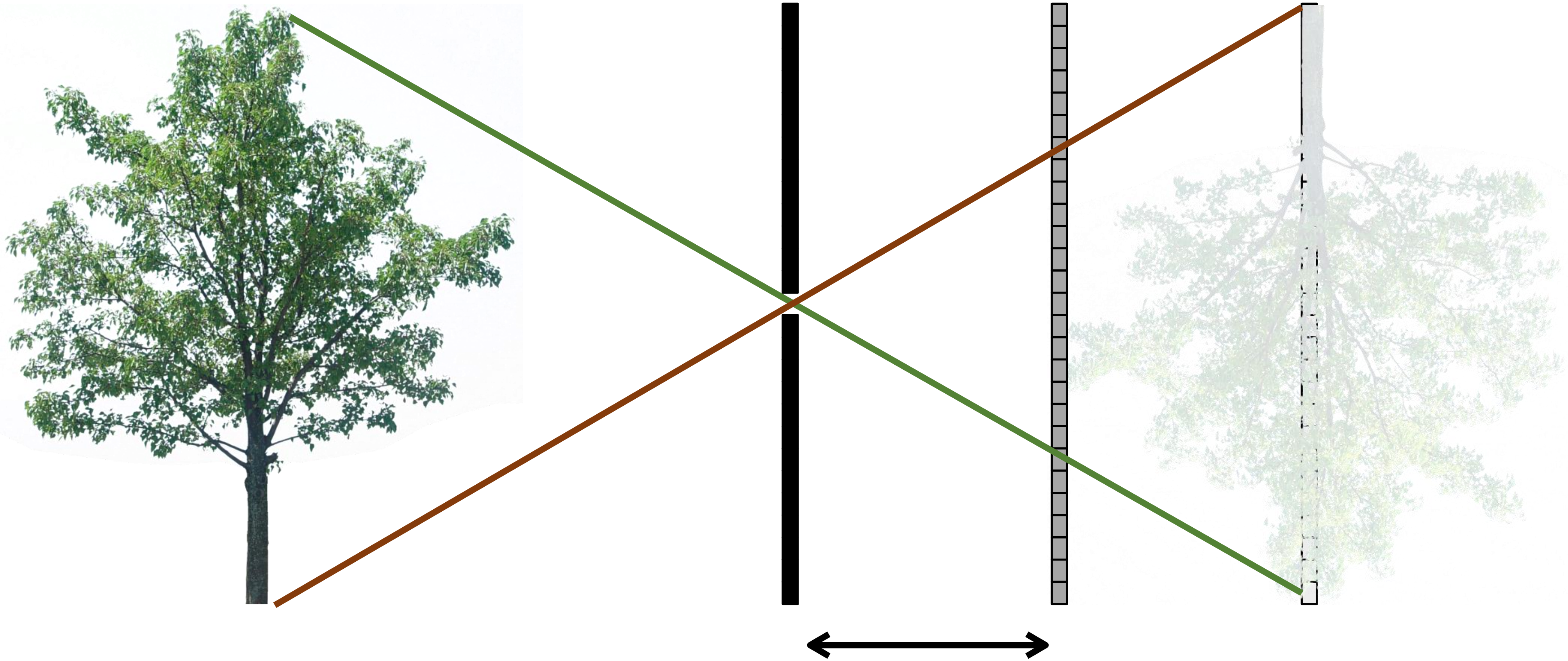
What happens as we change the focal length?

real-world
object

Focal length

What happens as we change the focal length?

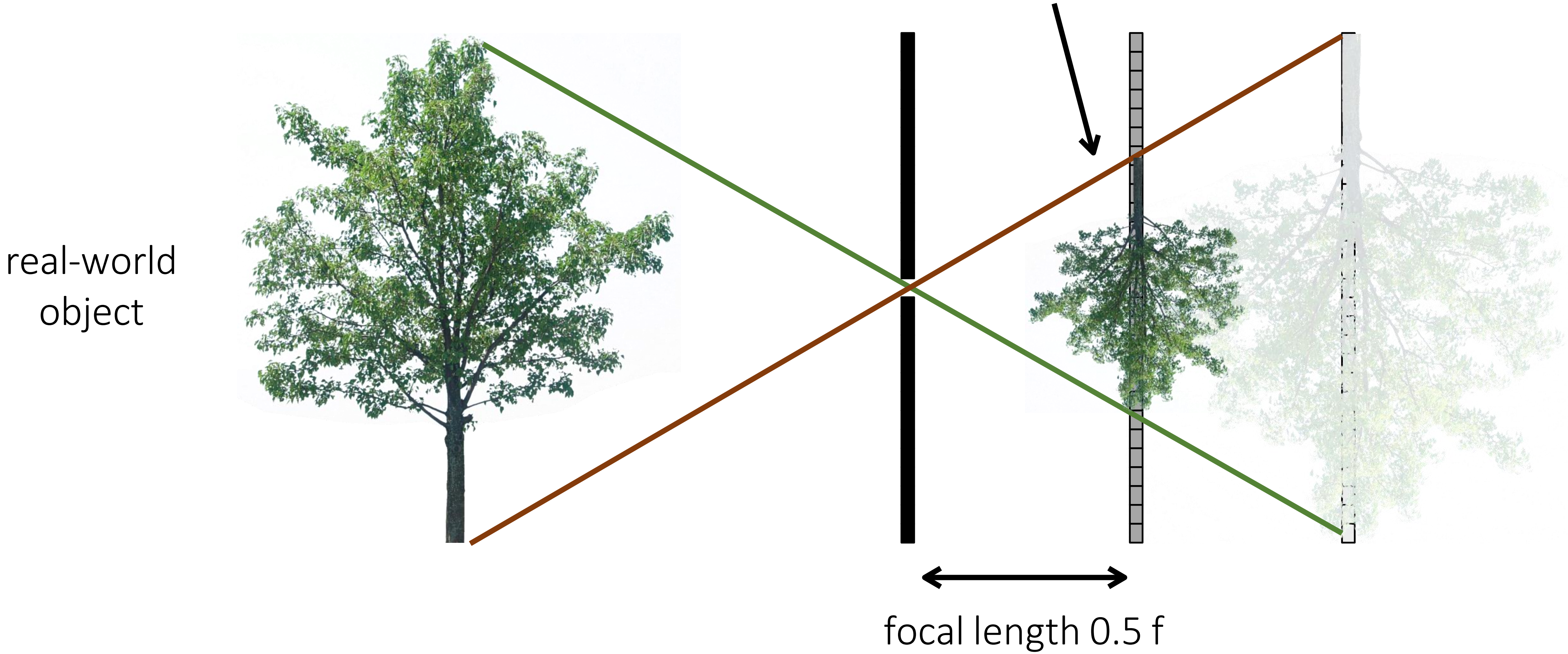
real-world
object



focal length 0.5 f

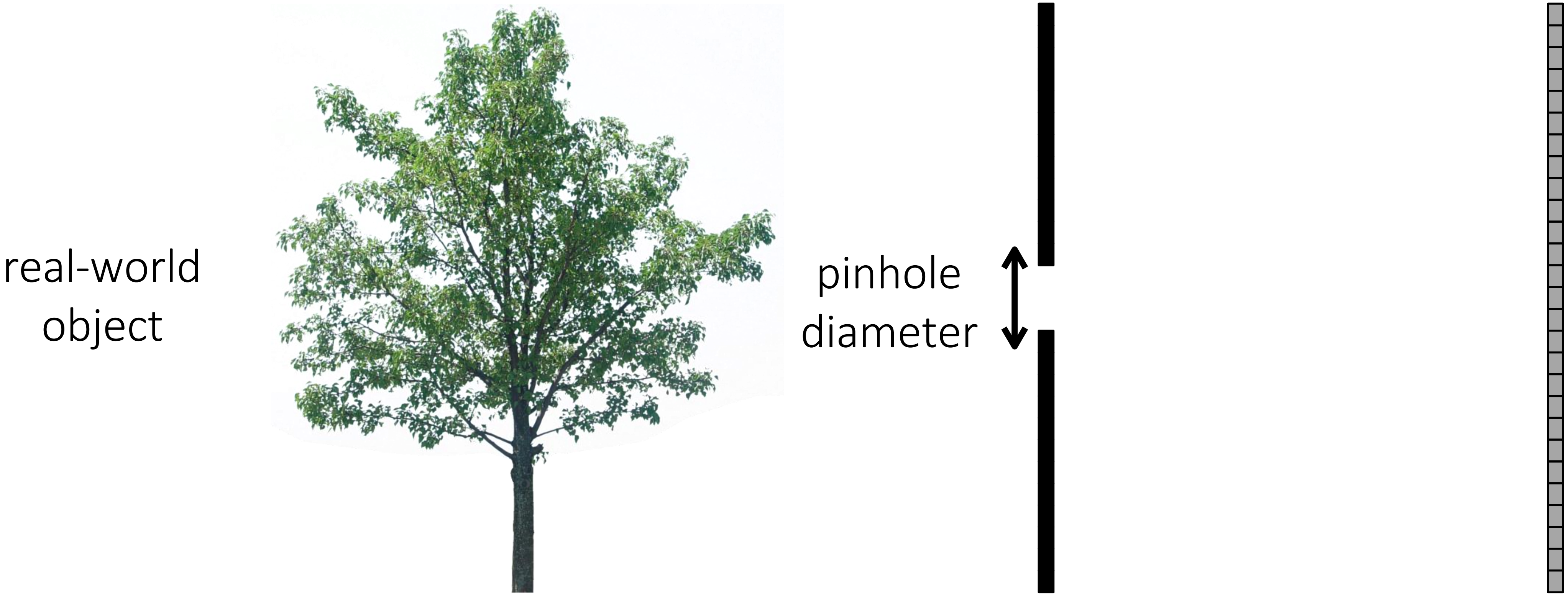
Focal length

What happens as we change the focal length?



Pinhole size

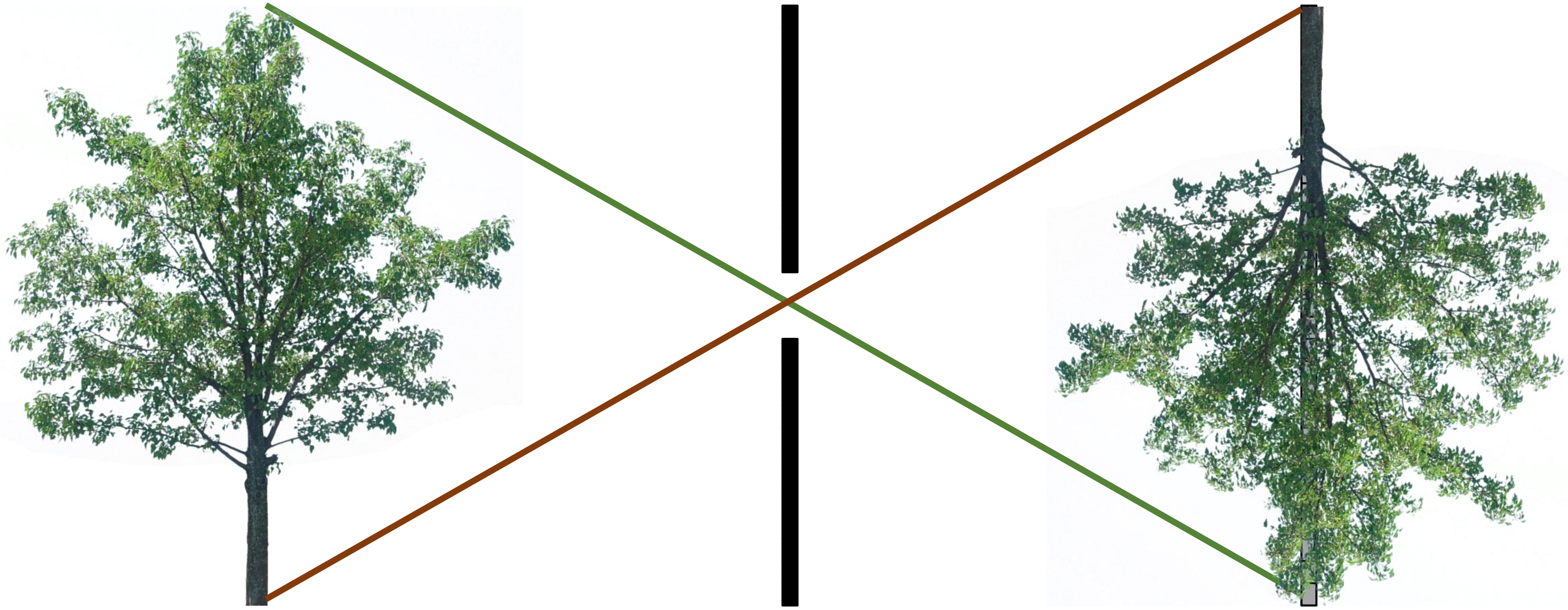
What happens as we change the pinhole diameter?



Pinhole size

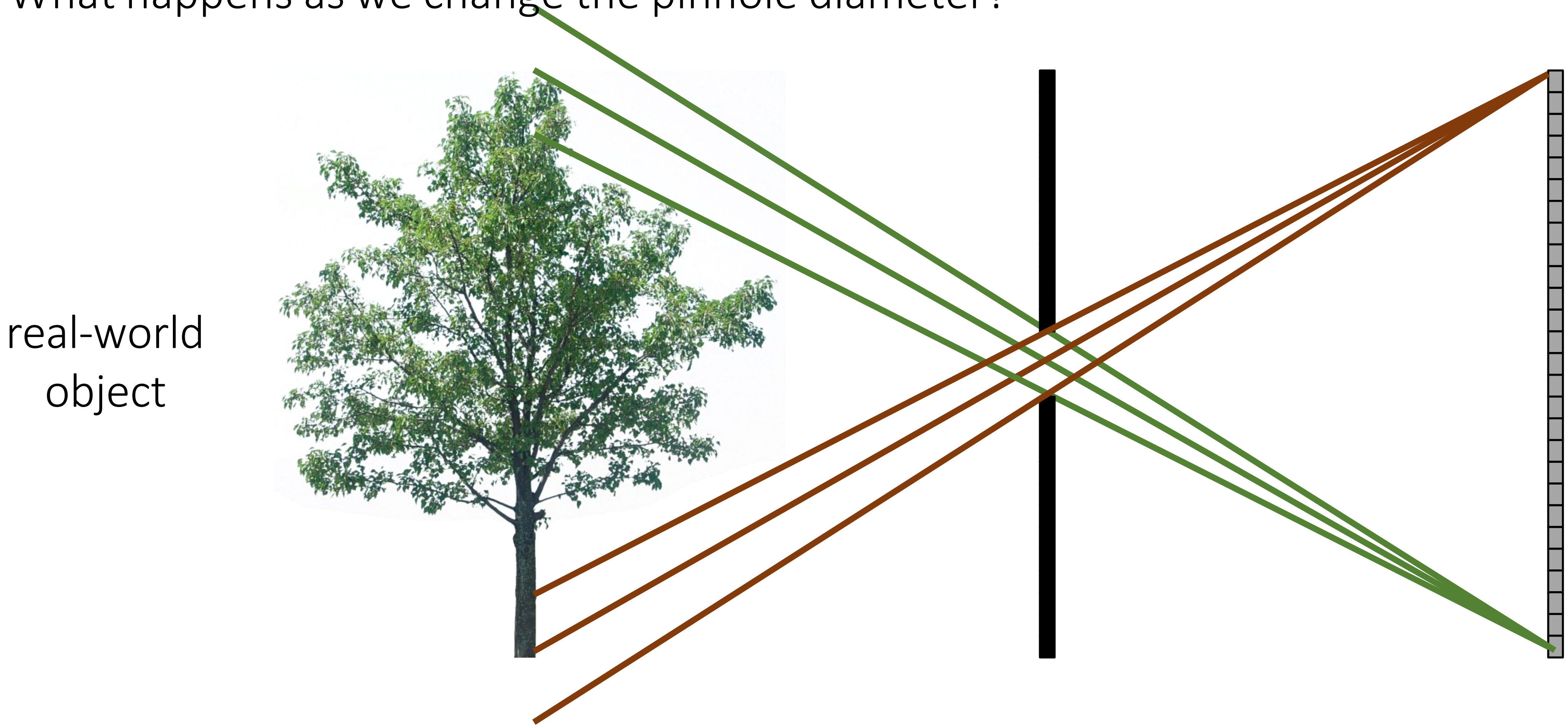
What happens as we change the pinhole diameter?

real-world
object



Pinhole size

What happens as we change the pinhole diameter?

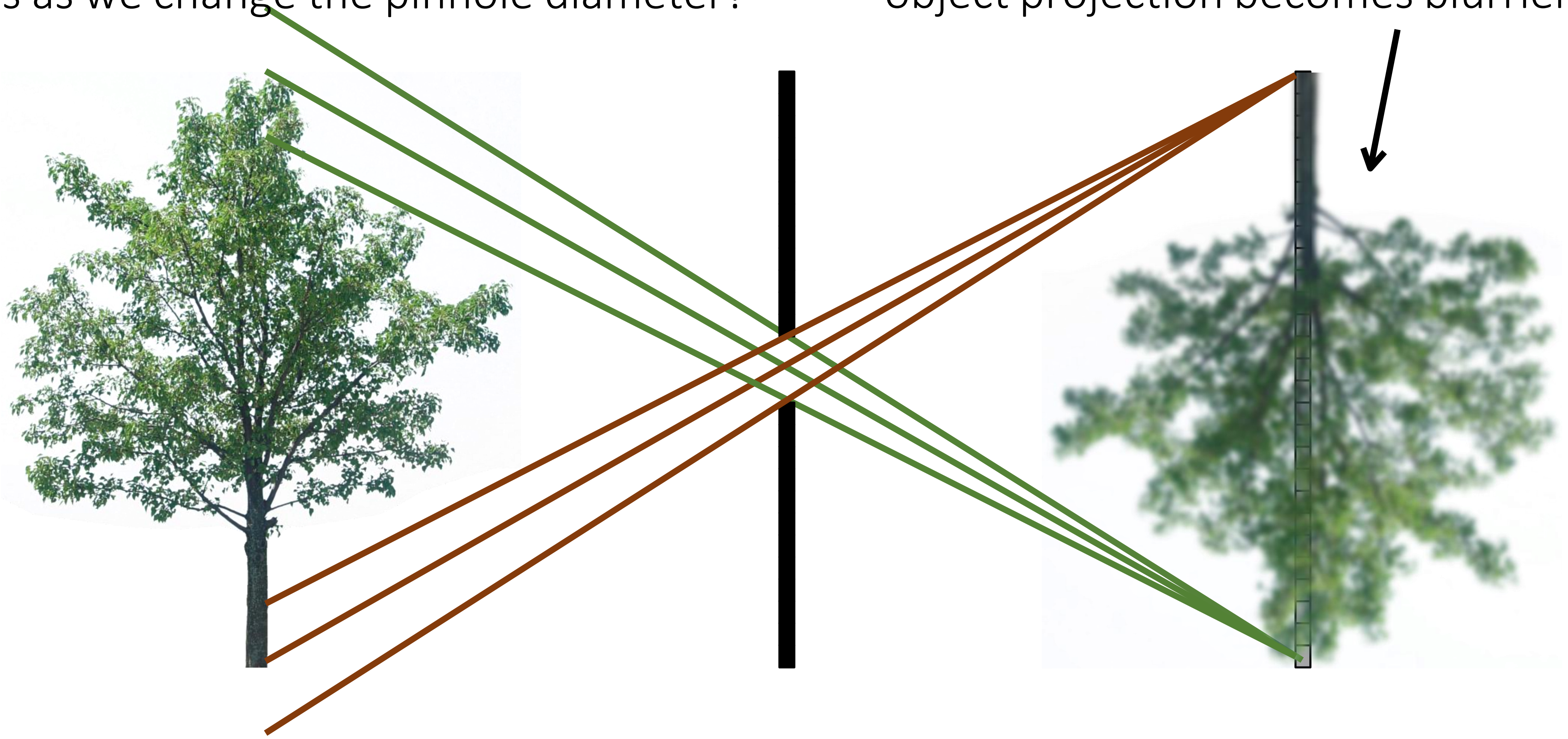


Pinhole size

What happens as we change the pinhole diameter?

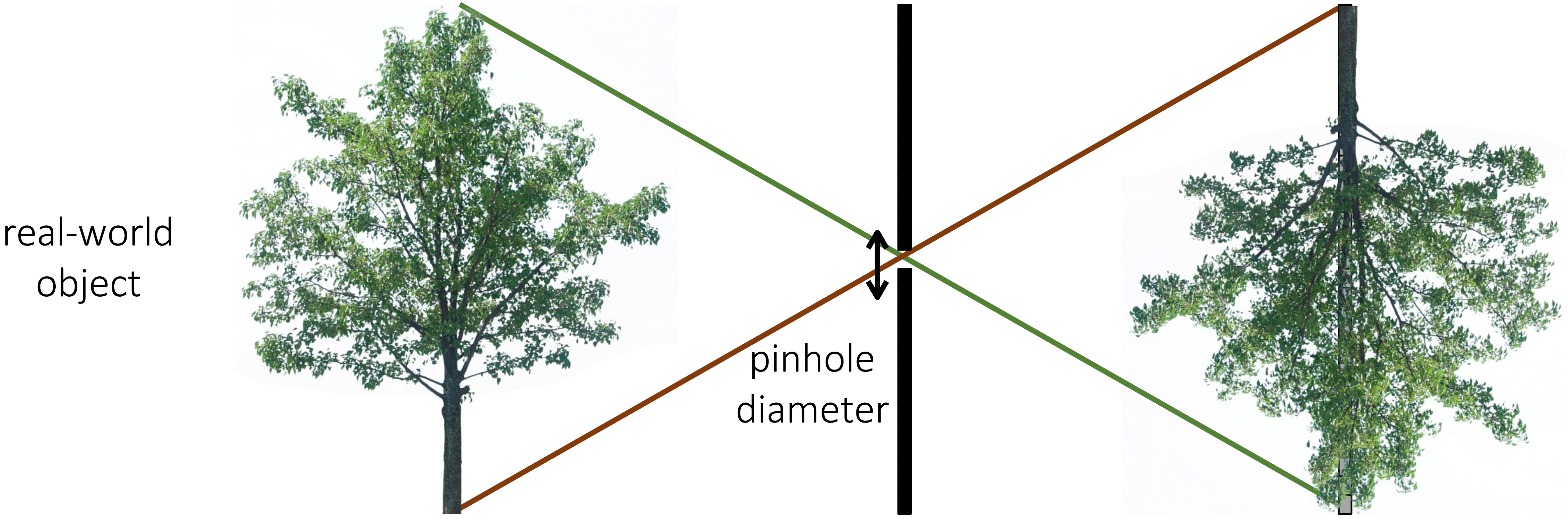
object projection becomes blurrier

real-world object



Pinhole size

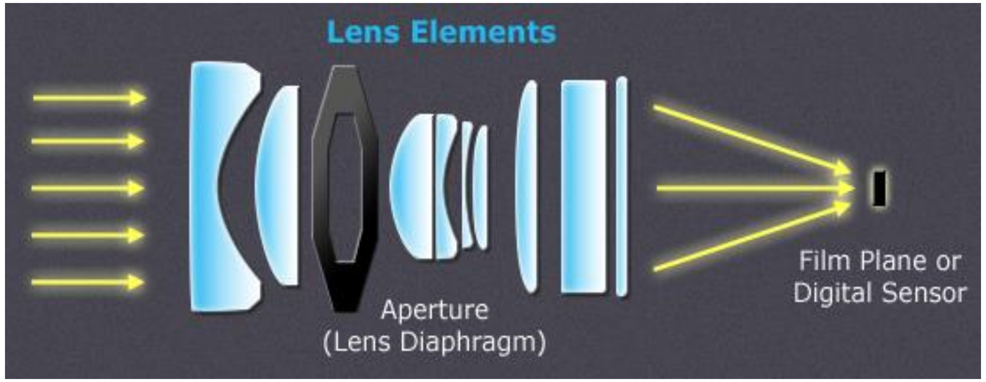
What happens as we change the pinhole diameter?

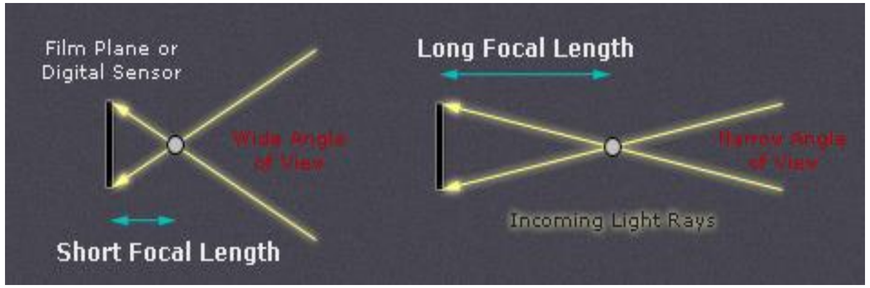


Will the image keep getting sharper the smaller we make the pinhole?

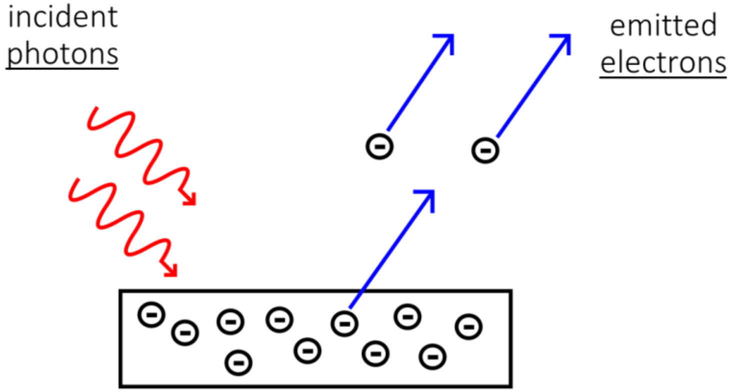
Lens/Optics

- Gathers light from subject
- Focuses it on light sensitive surface (film, sensor)
- Optional - Variable opening to control amount of light – Aperture – Manual / Automatic
- Optional - Variable focal length to control field of view - Zoom – Manual / Motorized





Imaging Sensor

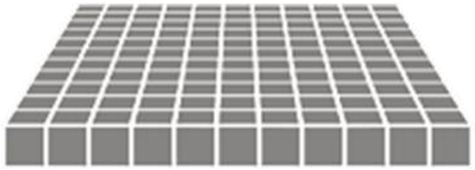


Camera shutter opens

↓

Exposure begins

↓

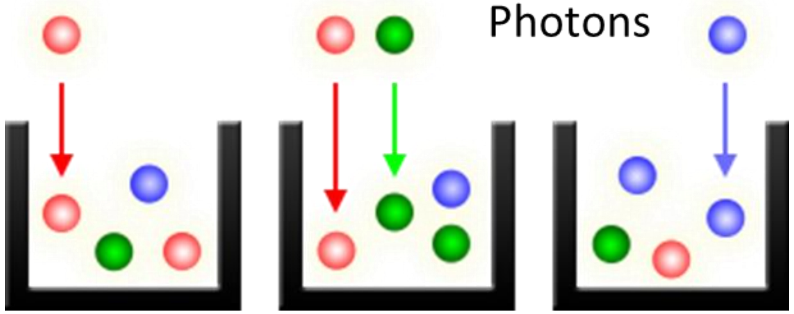


Array of photon buckets

Photon buckets begin to store photons

↓

Camera shutter closes and "stored photons" are converted to intensity values

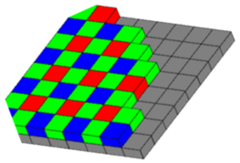


Close-up view of photon buckets

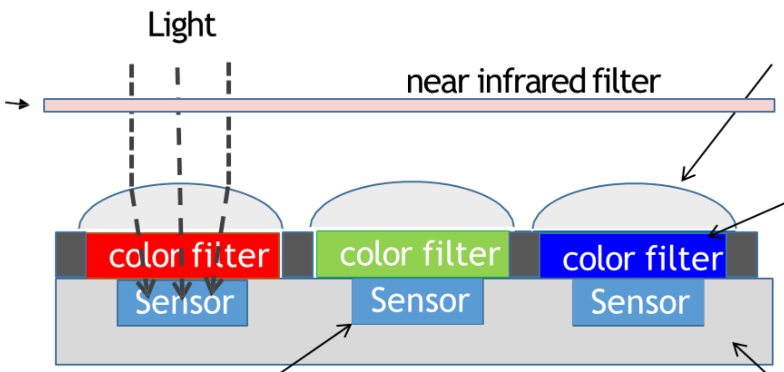
$$QE = \frac{\#\text{electrons}}{\#\text{photons}}$$

Imaging Sensor

A Near Infrared (NIR) filter is often placed before the sensor. (This is sometimes called a "hot mirror"). This is because red filters often respond to NIR light.



Color filter array or "Bayer" pattern.



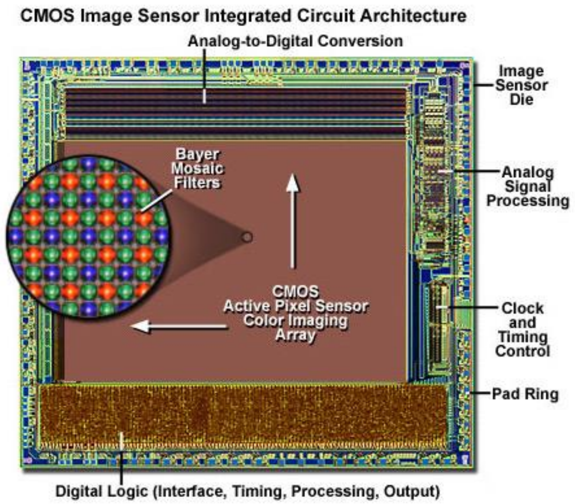
Micro-lenses are placed over the diode to help increase light collection on the sensor

Color filters place over the sensor. This forms a Color Filter Array (CFA) also called a "Bayer Pattern" after inventor Bryce Bayer.

Photodiode
Photons hit the diode and force out electrons. This design is similar to a solar cell!

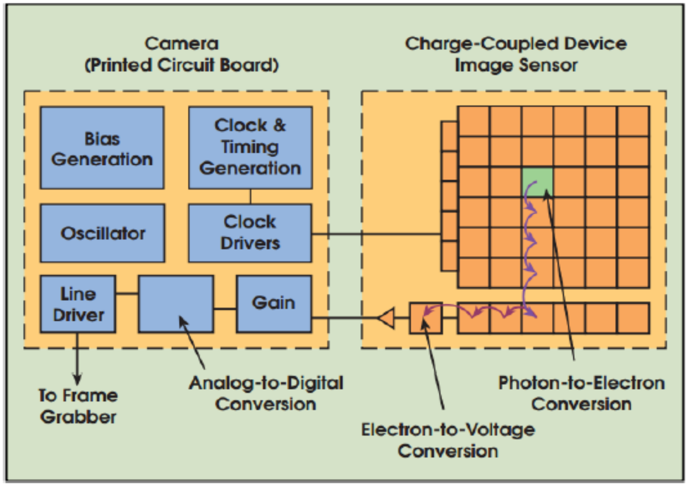
Silicon/Circuitry

CMOS sensor

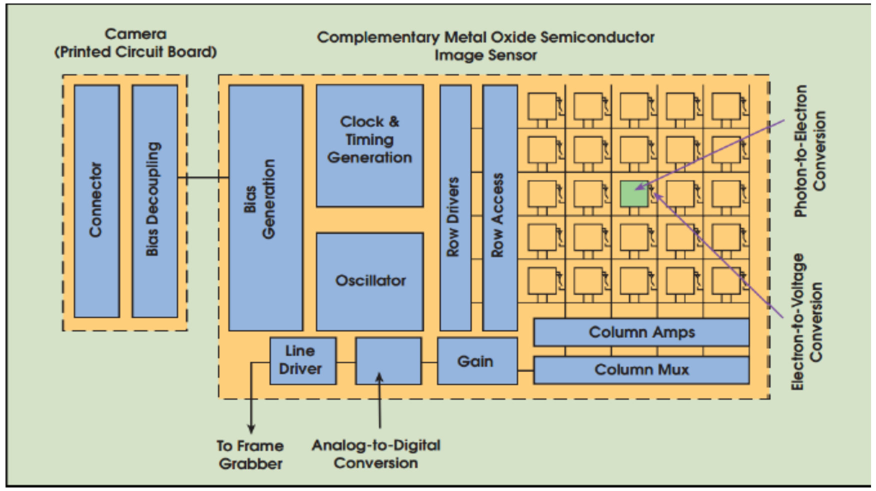


Imaging Sensor

CCD & CMOS



CCD



CMOS

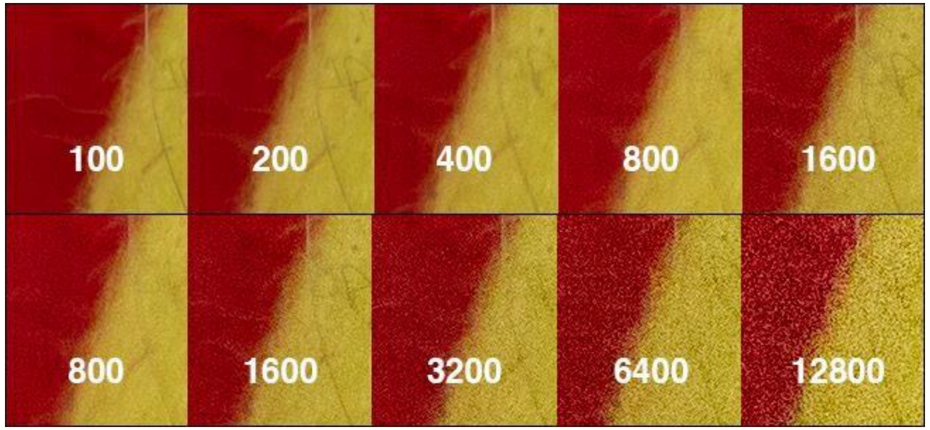
CCD (**c**harge **c**oupled **d**evice) has a different readout technology to convert charge to voltage and buffer it for output. The plus side is there is more space on the pixel for the photo sensor.

CMOS (**c**omplementary **m**etal **o**xide **s**emiconductor) converts charge to voltage at the pixel site. This allows faster readouts, but less space for the photo sensor per pixel.

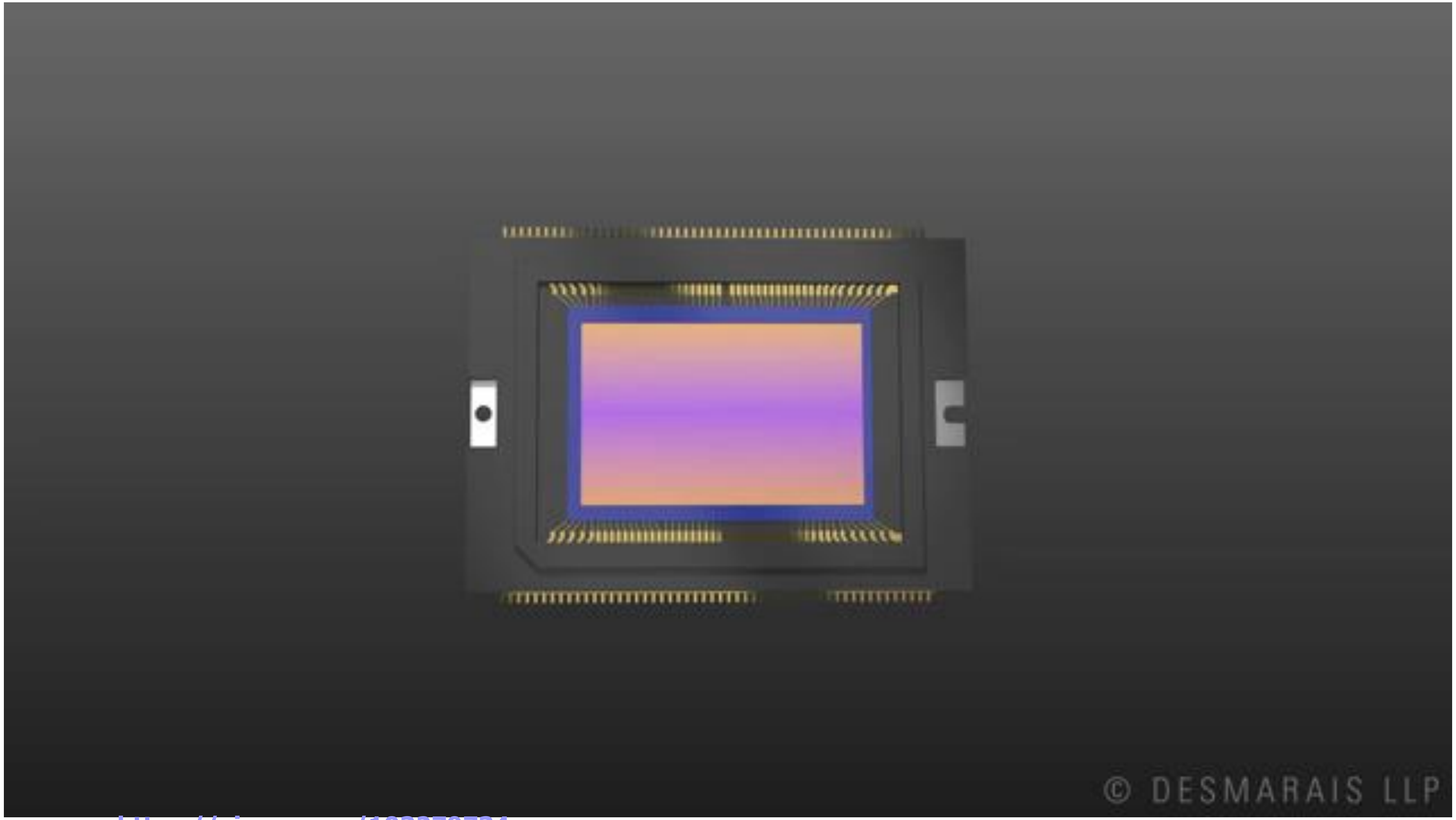
Imaging Sensor

- Imaging sensor signal is amplified and digitized.
- Amplification to assist A/D conversion.
  - Need to get the voltage to the range required for the desired digital output.
- This gain is used to accommodate camera ISO settings.
  - Gain to signal applied on the sensor.
  - Note – gaining the signal also gains image noise.

Different ISO settings (note: the exposure will be shorter for higher ISO)



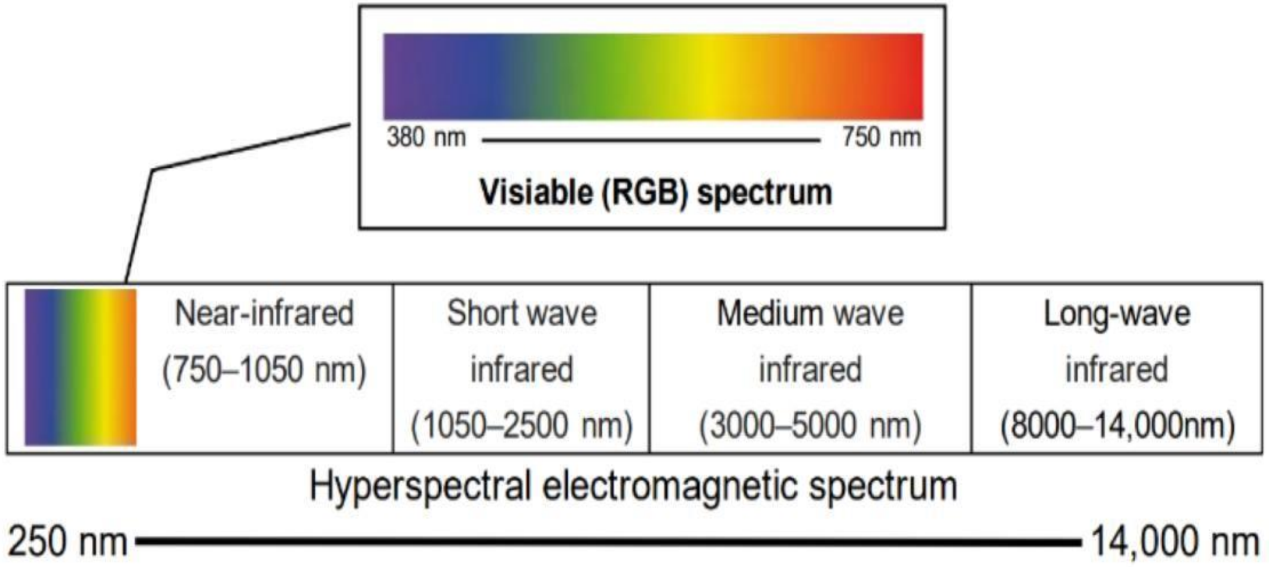
How CCD/CMOS Works



https://vimeo.com/103279734

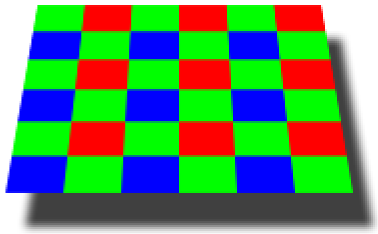
Specialized Sensors—Beyond the Visible Spectrum

- Depth Sensors (ToF, LiDAR): Measure distance to objects, enabling 3D imaging like object recognition and navigation
- Hyperspectral Sensors: Capture detailed spectral info beyond the visible spectrum, enabling material identification and environmental monitoring
- Astronomy, Automotive, Machine vision, Agriculture etc.

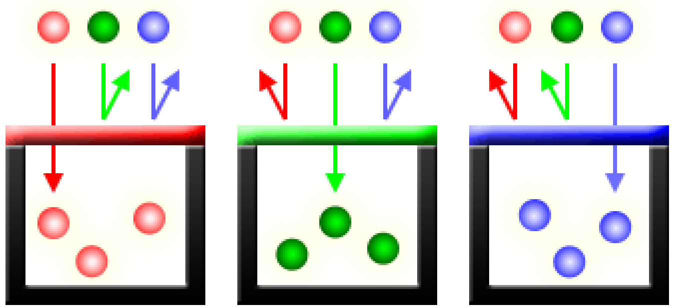


Color Filter Array

- A color filter array (CFA), or color filter mosaic (CFM), is a mosaic of tiny color filters placed over the pixel sensors of an image sensor to capture color information

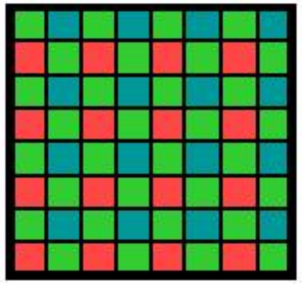


Color Filter Array

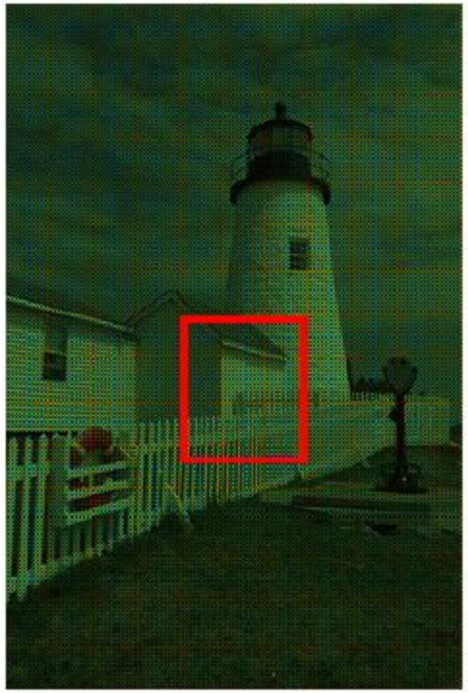


Photosites with CFA

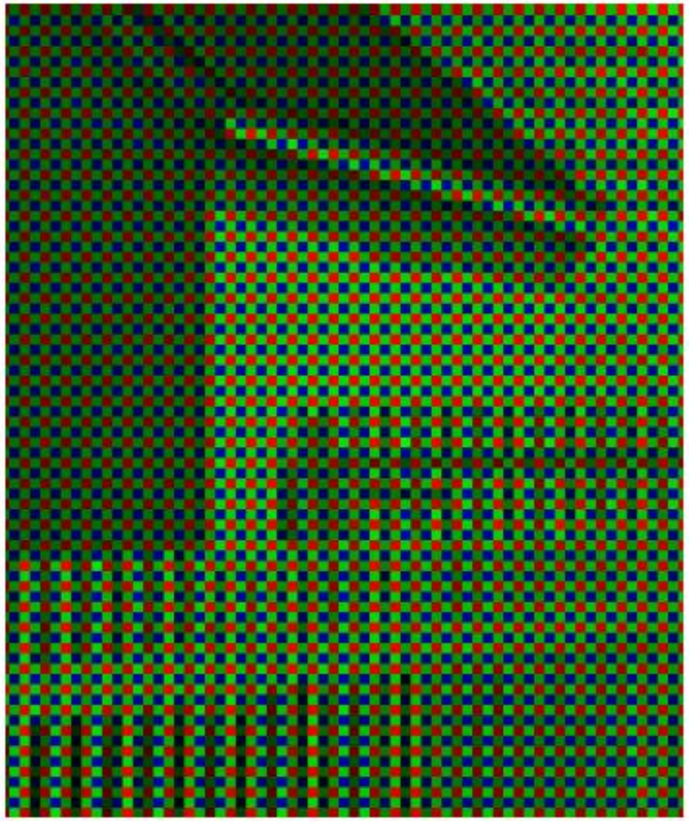
Color Filter Array



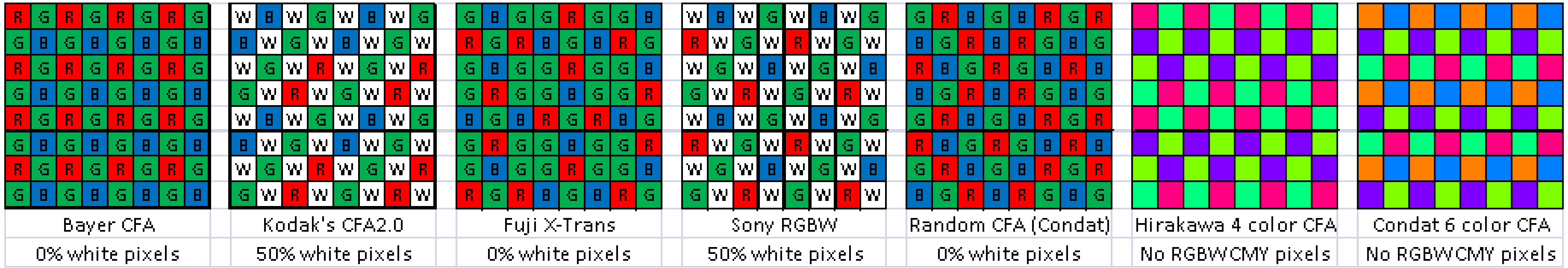
Bayer CFA



CFA image



Different CFA



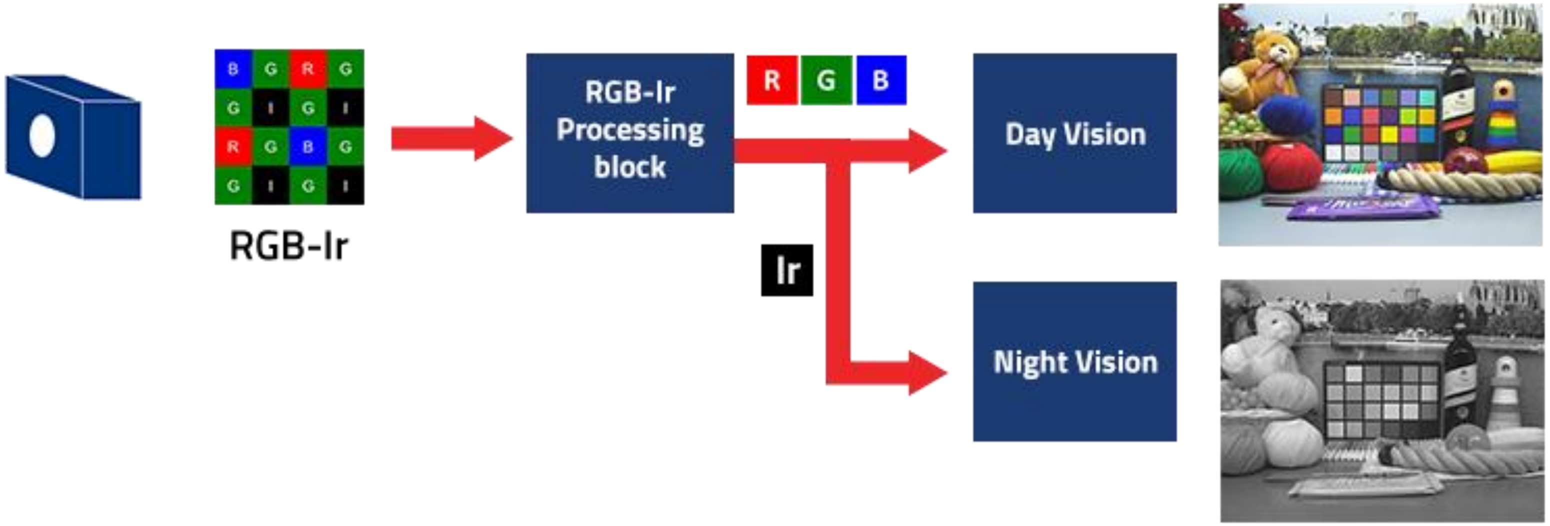
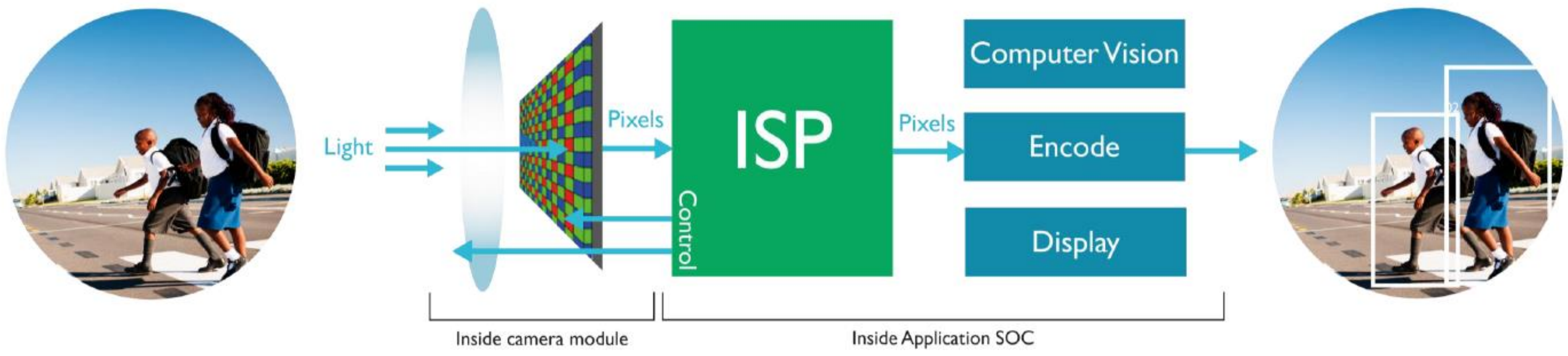


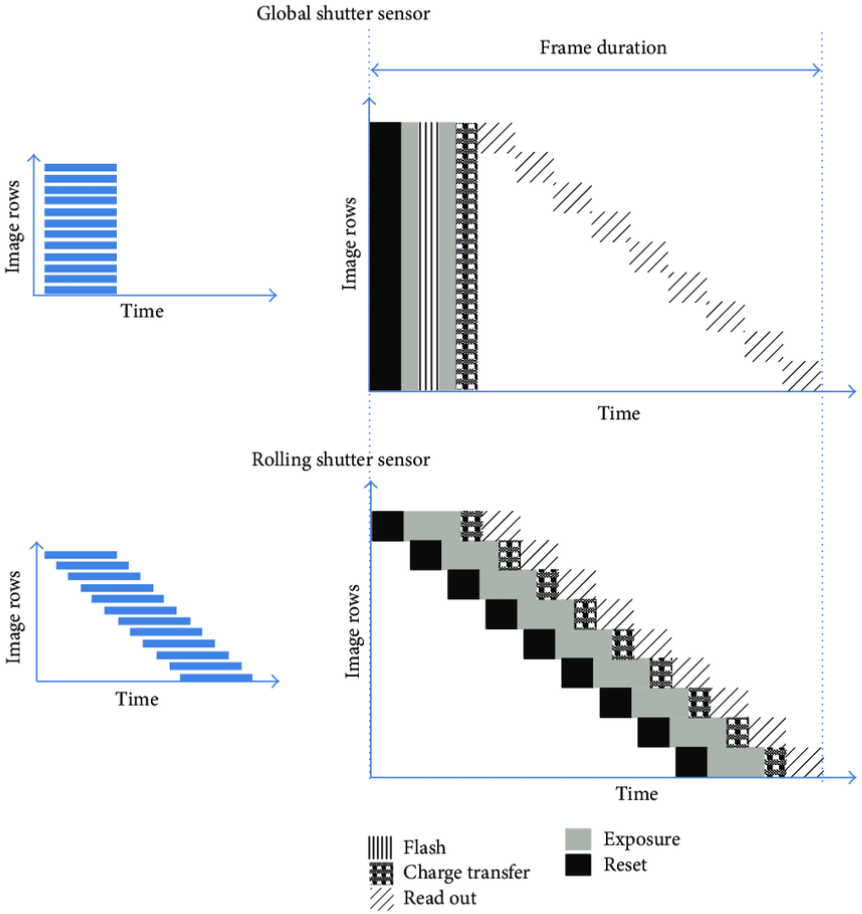
Image Signal Processor (ISP)

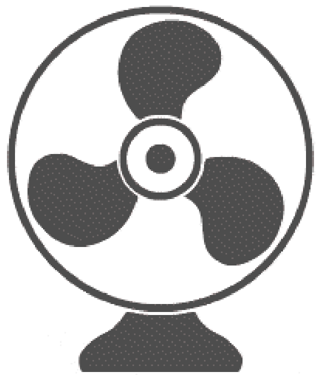
- Processes Image captured by sensor to a typical form and format recognizable by other systems / processes.
- Typically done by specialized hardware blocks in SoC or on image sensor itself or sometimes discrete chips
- ISP Roles
  - Demosaicing
  - 3A – Auto Focus, Auto Exposure, Auto White Balance
  - Correct for lens imperfections
  - Noise reduction, filtering, HDR etc

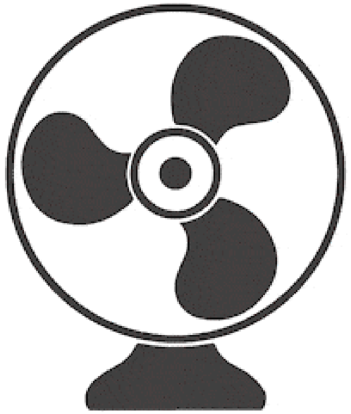


Important Digital Camera Terminology

Rolling vs Global Shutter







https://www.teledynedalsa.com/en/learn/knowledge-center/global-shutter-imaging/

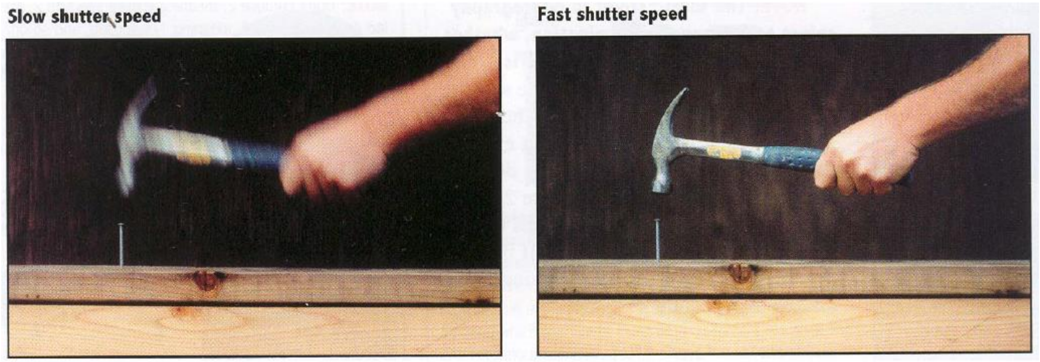
https://www.researchgate.net/figure/Global-shutter-and-rolling-shutter-operation-17-18_fig6_303816203

Rolling Shutter Effect

https://www.youtube.com/watch?v=CmjeCchGRQo

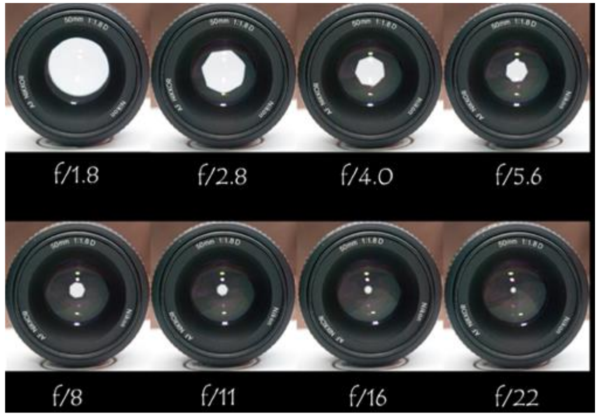
Shutter Speed

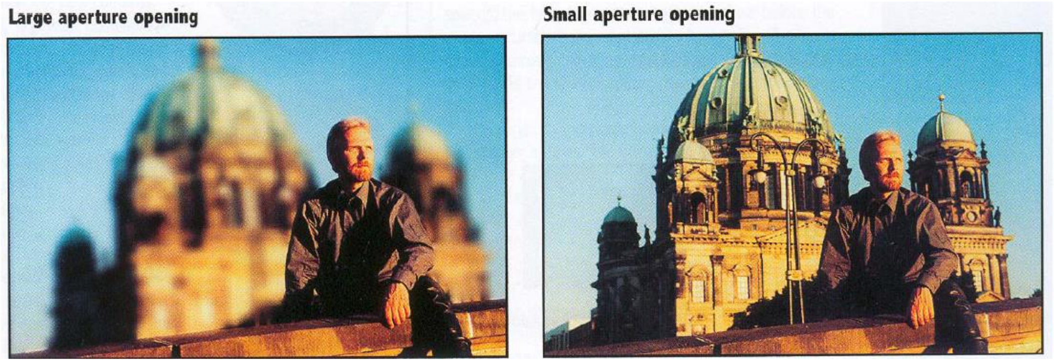
- Controls how long the film/sensor is exposed
- Pretty much linear effect on exposure
- Usually in fraction of a second:
  - 1/30, 1/60, 1/125, 1/250, 1/500
- On a normal lens, normal humans can hand-hold down to 1/60
- Main effect – Motion Blur

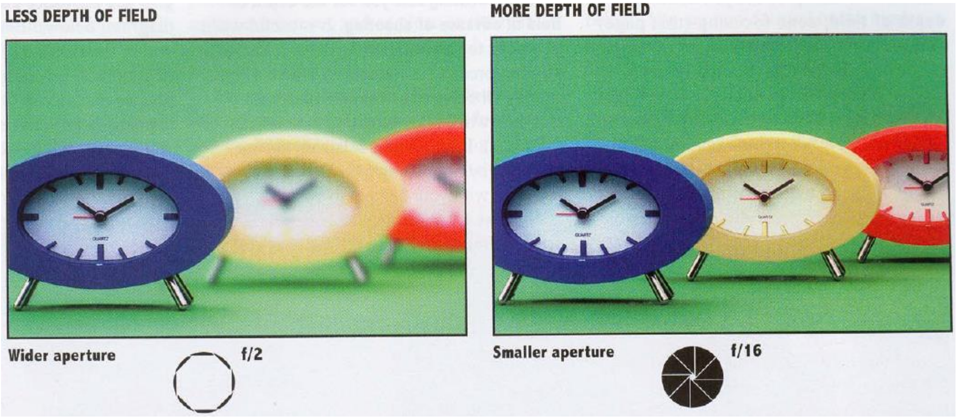


Aperture

- Diameter of the lens opening (controlled by diaphragm)
- Expressed as a fraction of focal length, in f-number
  - f/2.0 on a 50mm means that the aperture is 25mm
  - f/2.0 on a 100mm means that the aperture is 50mm
- Main effect of aperture – Depth of Field

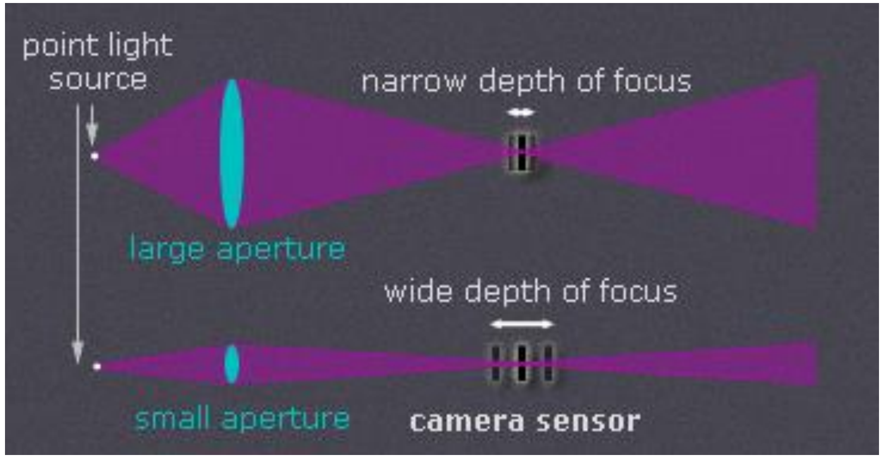






Depth of Field

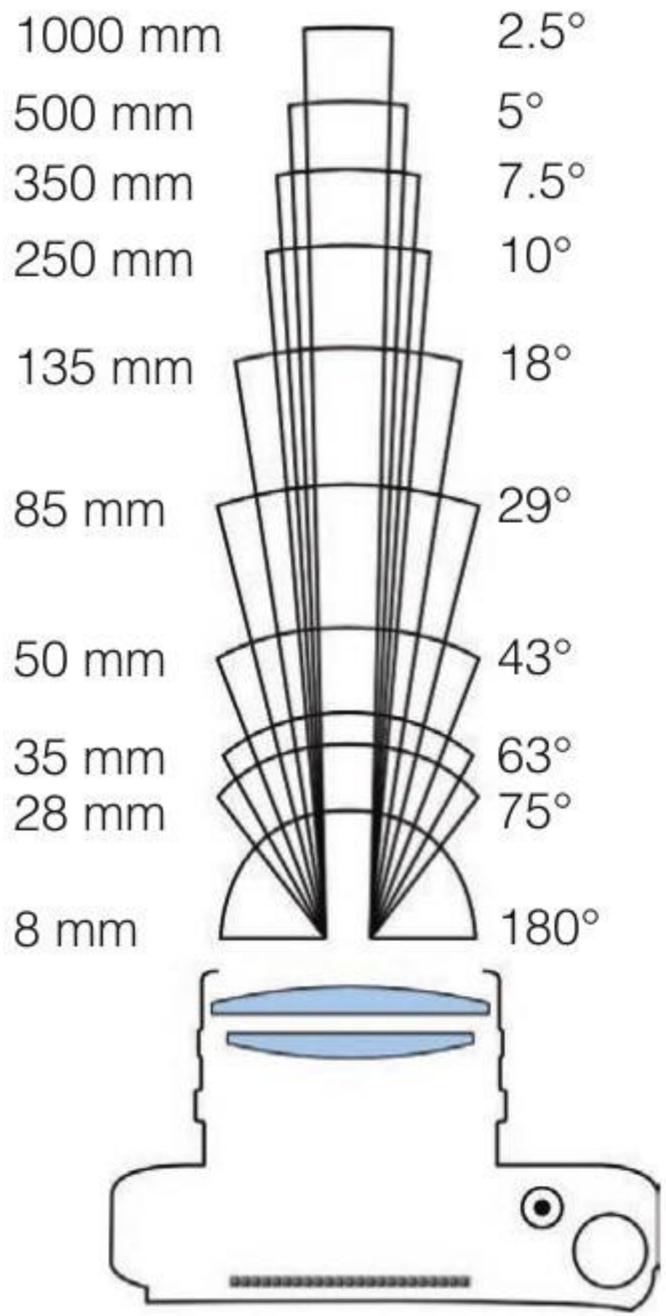
- Range of distance that appears acceptably sharp
- Does not abruptly change from sharp to unsharp, but as gradual transition

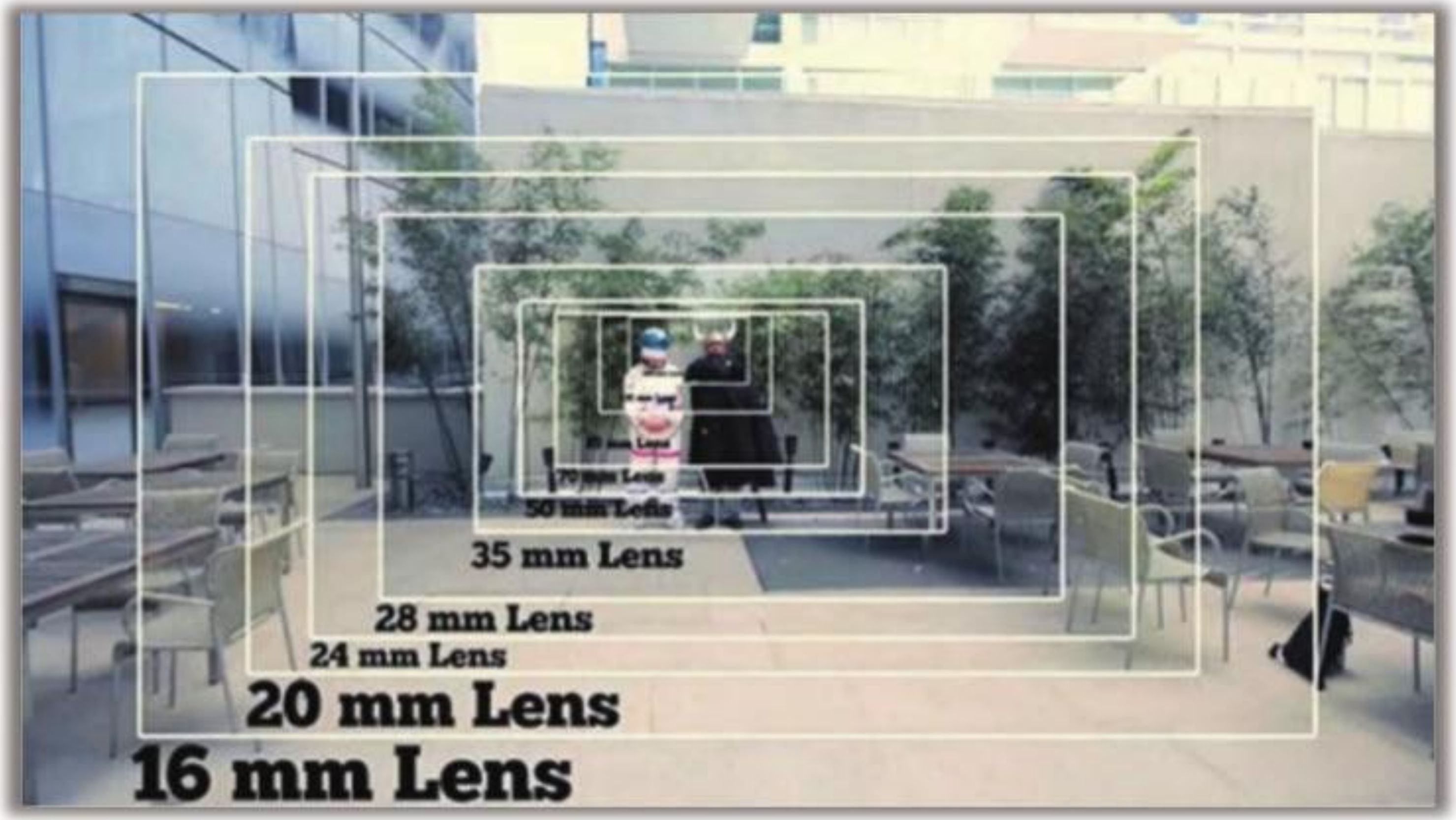


Bokeh

Sharp depth of field ("bokeh") is often desirable.

Field of view

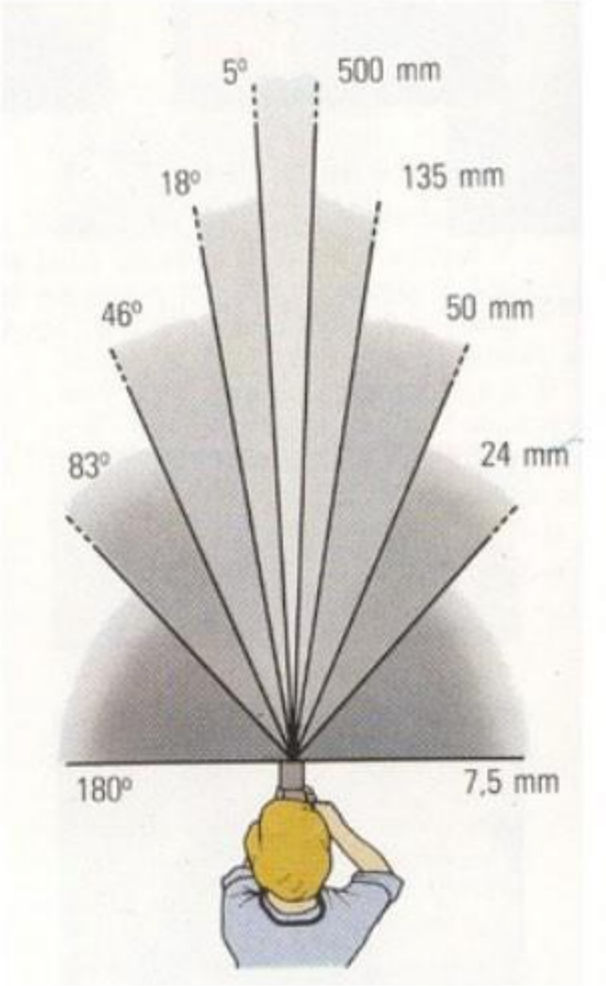




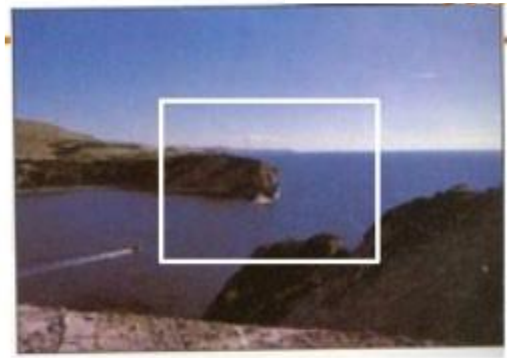
Andrew McWilliams

Field of view

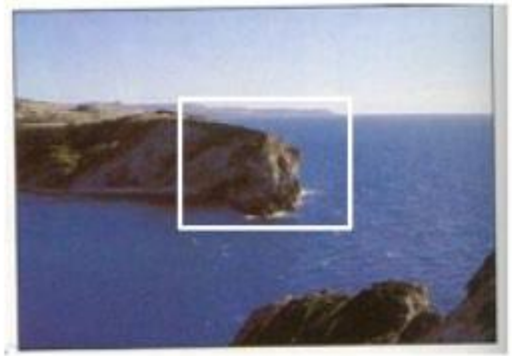
Increasing the lens focal length is similar to cropping



f = 25 mm



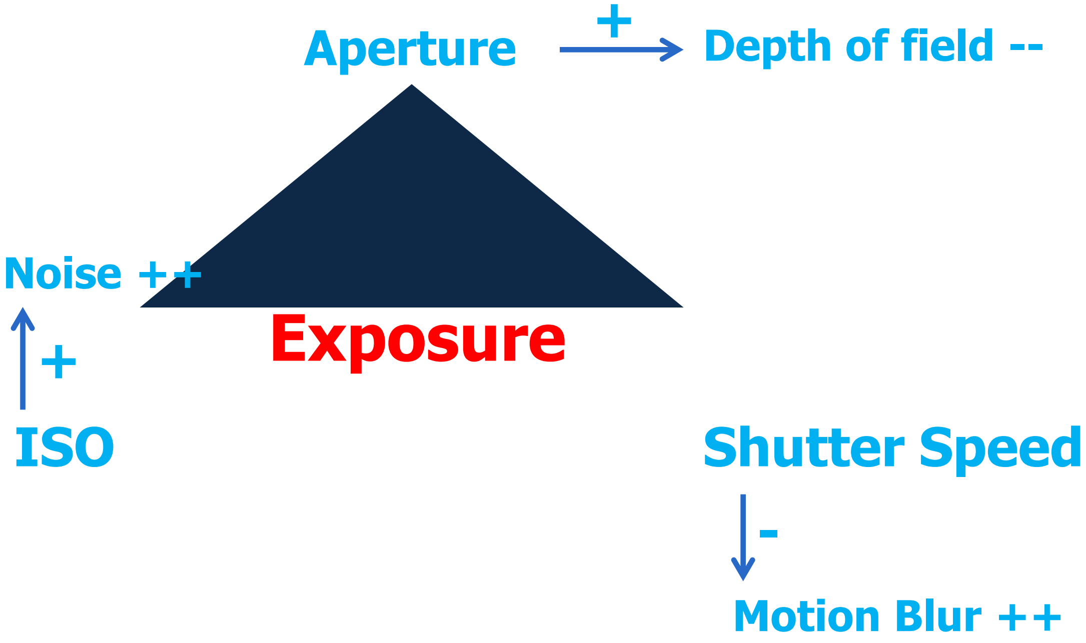
f = 50 mm



f = 135 mm

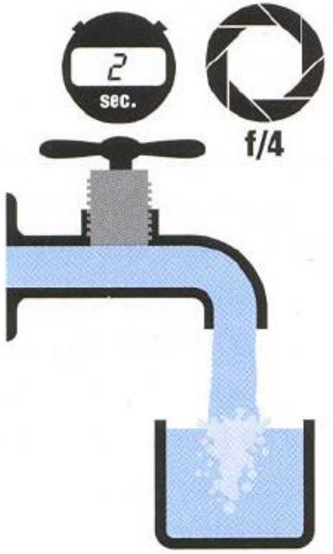
Exposure

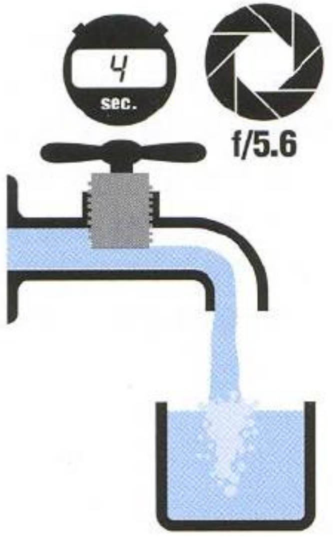
- Determines how light or dark final image appears
- "well exposed" image is proper, "underexposed" is too dark and "overexposed" is too bright
- Controlled by
  - Aperture = amount of light
  - Shutter Speed = the time sensor is exposed to light
  - Gain = sensitivity of sensor (ISO)



Exposure

- The same exposure is obtained with an exposure twice as long and an aperture area half as big
- What will guide our choice of a shutter speed?
  - Freeze motion vs. motion blur, camera shake
- What will guide our choice of an aperture?
  - Depth of field, diffraction limit





Exposure Triangle

- If one parameter of the triangle changes, the other two have to compensate.

F22, ISO6400, T = 1/15sec

Large amount of noise due to high gain.

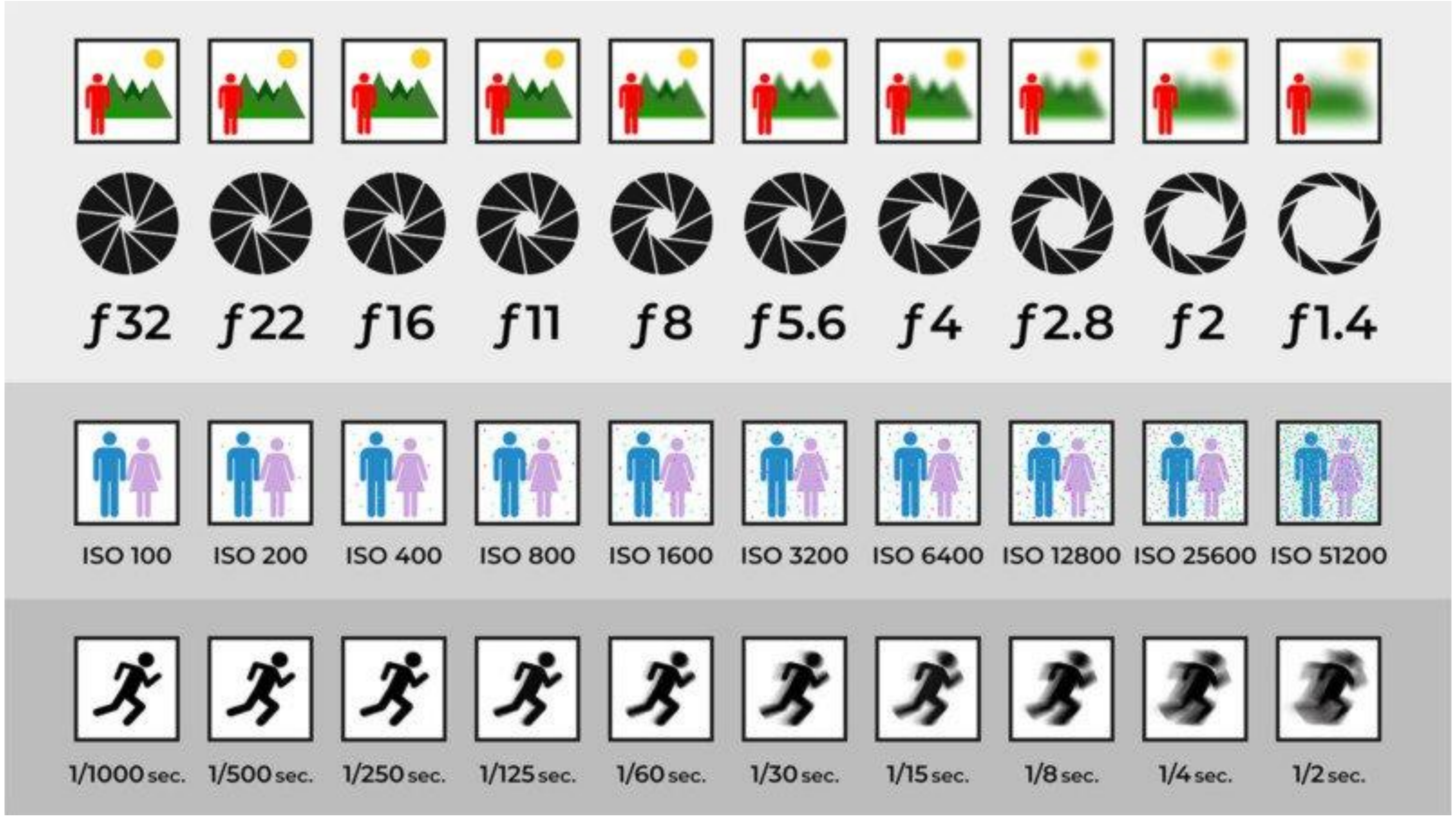
F1.8, ISO100, T = 1/30sec

Depth of Field is narrow – slight distance from focus obj results in blur

F22, ISO100, T = 5sec

Motion blur due to long exposure – second hand is not rendered well

Exposure Triangle



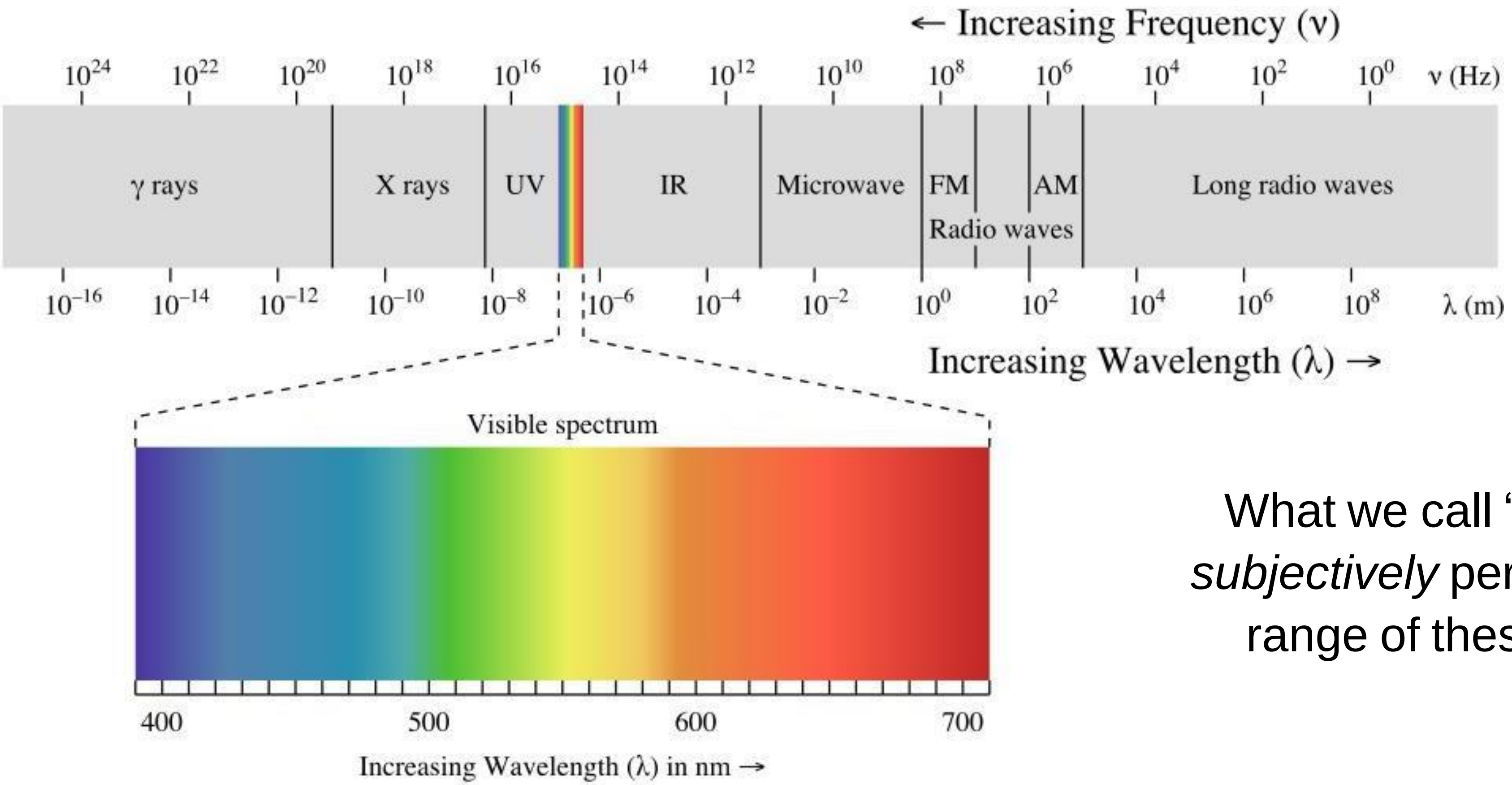
https://canon.ca/CanonOutsideOfAuto/play

Camera Exposure Modes

Exposure Mode	How It Works
Auto (□)	Camera automatically selects all exposure settings.
Program (P)	Camera automatically selects aperture & shutter speed; you can choose a corresponding ISO speed & exposure compensation. With some cameras, P can also act as a hybrid of the Av & Tv modes.
Aperture Priority (Av or A)	You specify the aperture & ISO; the camera's metering determines the corresponding shutter speed.
Shutter Priority (Tv or S)	You specify the shutter speed & ISO; the camera's metering determines the corresponding aperture.
Manual (M)	You specify the aperture, ISO and shutter speed — regardless of whether these values lead to a correct exposure.
Bulb (B)	Useful for exposures longer than 30 seconds. You specify the aperture and ISO; the shutter speed is determined by a remote release switch, or by the duration until you press the shutter button a second time.

Color

- “Color” is not an *objective* physical property of light (electromagnetic radiation).
- Instead, light is characterized by its wavelength.



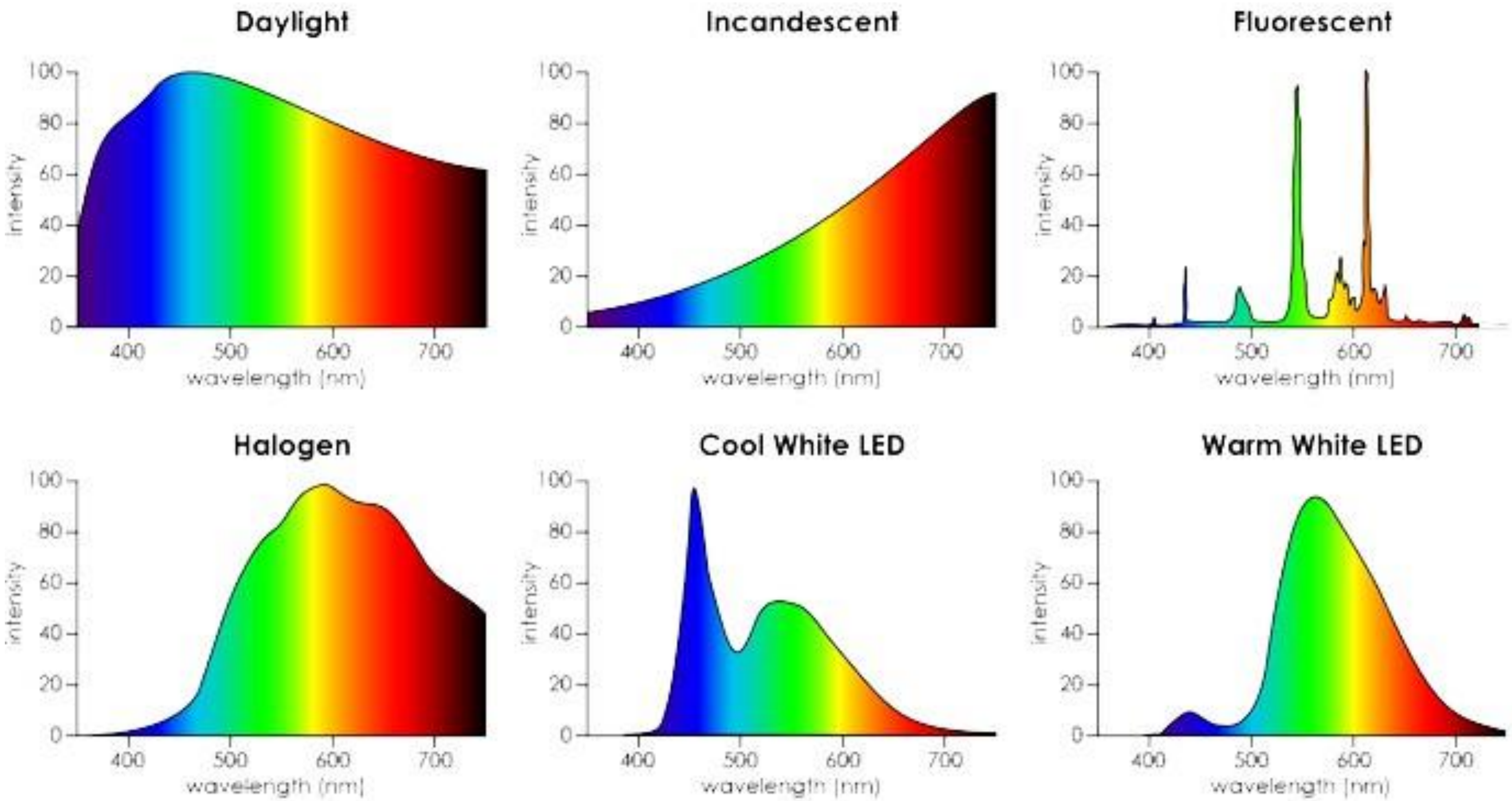
electromagnetic spectrum

What we call “color” is how we *subjectively* perceive a very small range of these wavelengths.

Spectral Power Distribution (SPD)

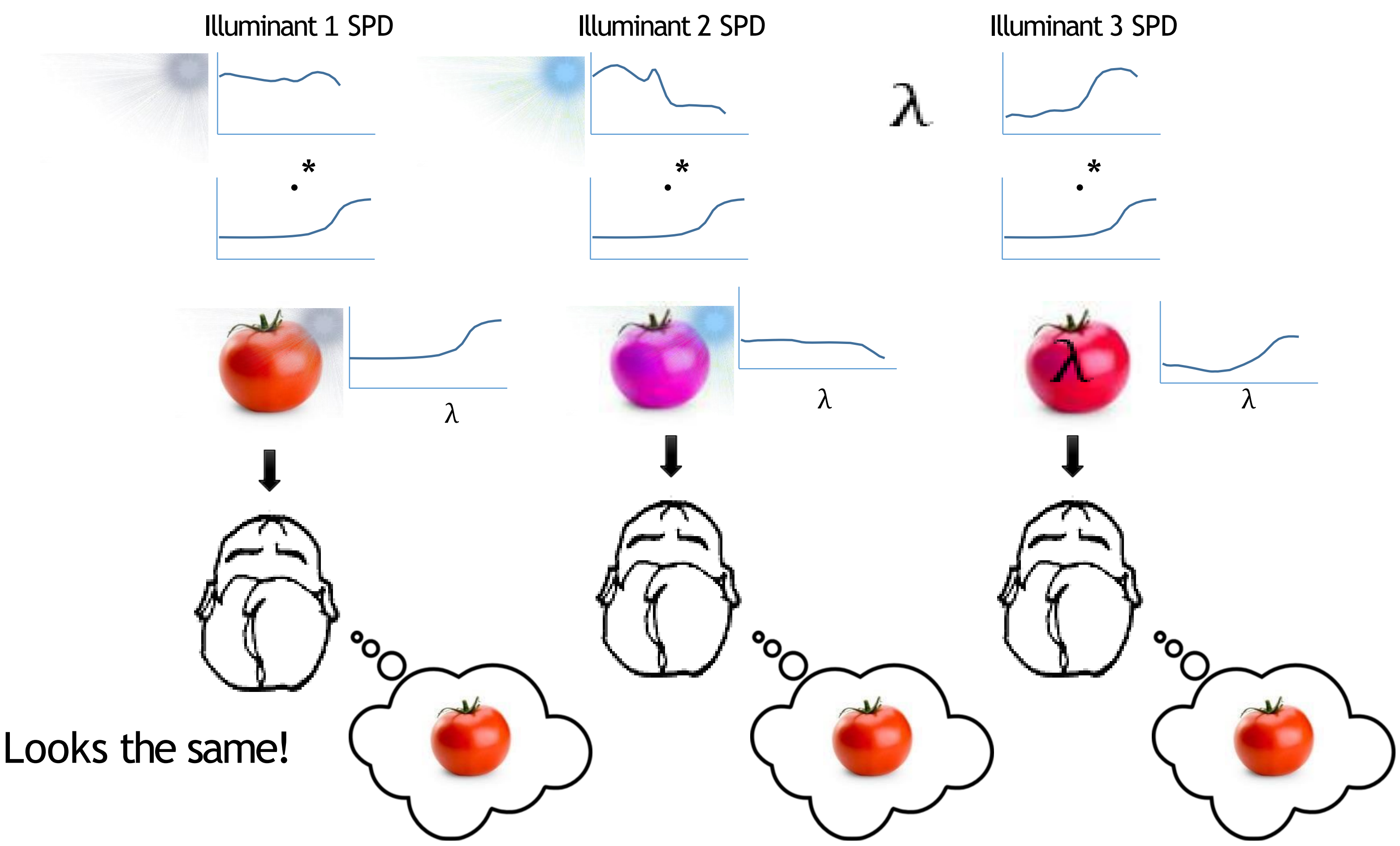
- Most types of light “contain” more than one wavelengths.
- We can describe light based on the distribution of power over different wavelengths.

We call our sensation of all of these distributions “white”.



Color constancy

Our visual system has an amazing ability to compensate for environmental illumination such that objects are perceived as the same color.

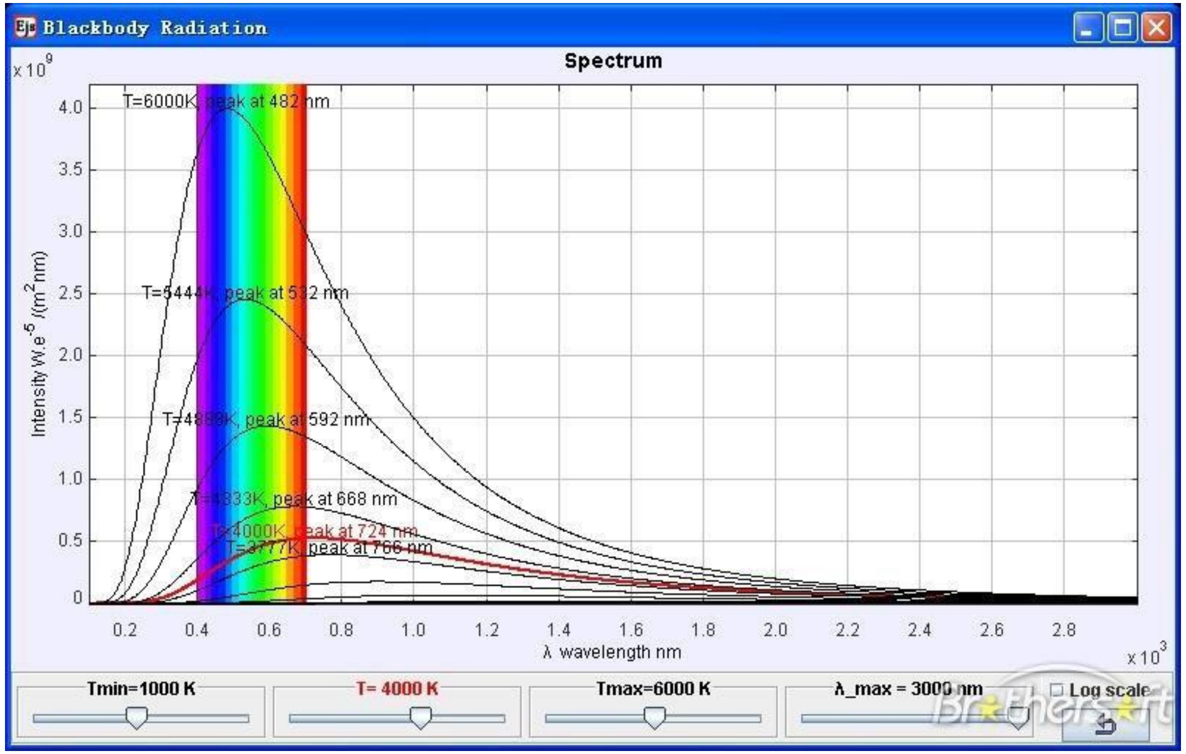


Color constancy/chromatic adaptation

- Color constancy (*chromatic adaptation*) is the ability of the human visual system to adapt to scene illumination.
- This ability is not perfect, but it works fairly well.
- **Image sensors do not have this ability! We will discuss this in ISP ..this is related to the camera's white-balance module.**

Color temperature

- Illuminants are often described by their "color temperature."
- This mapping is based on theoretical *blackbody radiators* that produce SPDs for a given temperature expressed in Kelvin (K).
- We map light sources (both real and synthetic) to their closest color temperature.



$$B_\lambda(\lambda, T) = \frac{2hc^2}{\lambda^5} \frac{1}{e^{\frac{hc}{\lambda k_B T}} - 1}$$

Plank's law
Spectral density of electromagnetic radiation emitted by a blackbody radiator at a given temperature T.

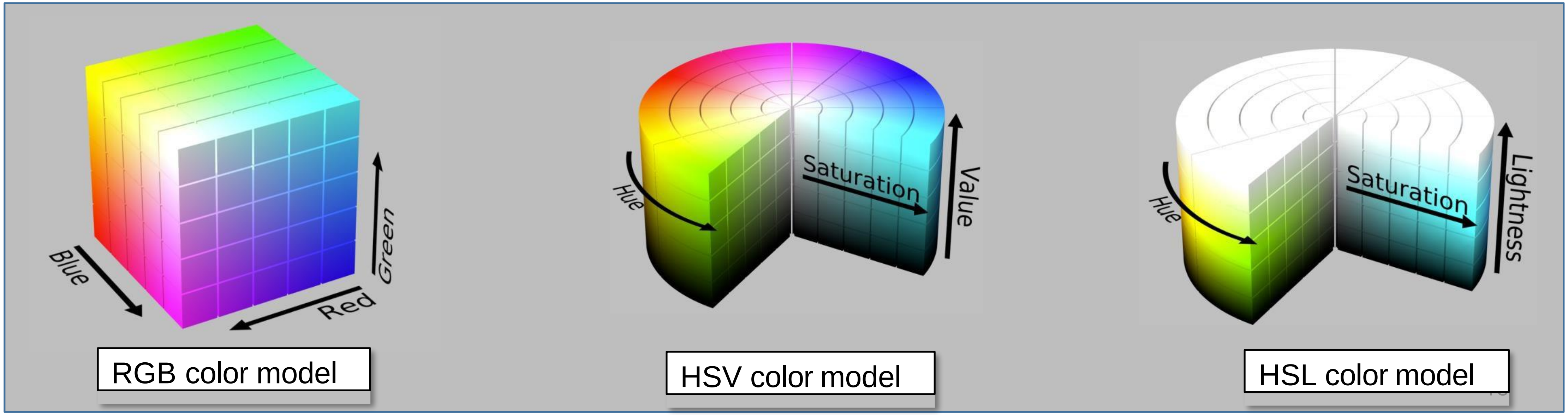
Lighting industry uses color temperature

Usage of correlated color temperature in these ads relate to the perceived color of the bulb's light.The heat output of a typical LED bulb is between 60C-100C (~333-373K).

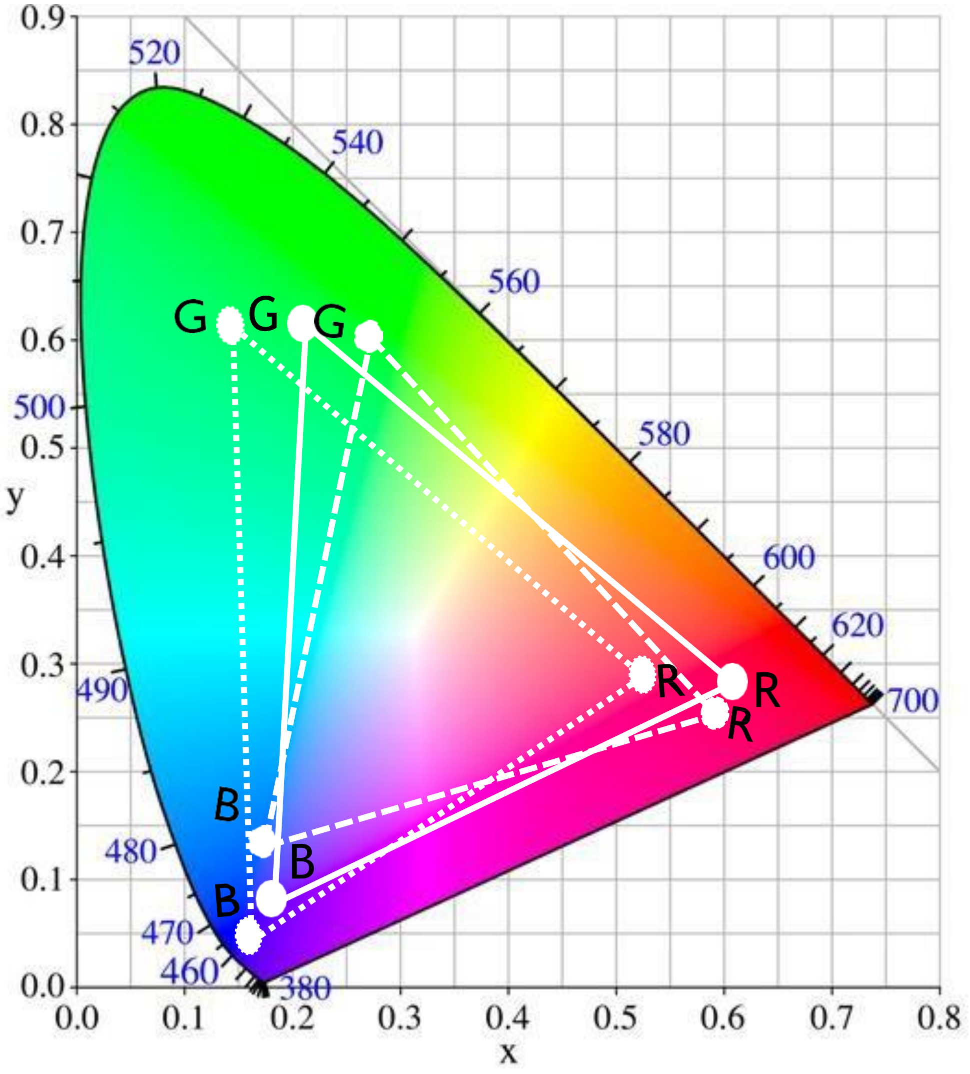
Color model versus color space

- **A color model** is a mathematical system for describing a color as a tuple of numbers (RGB, HSV, HSL, more…)
- **A color space** is a specific range of colors *within a color model*. The range of color (gamut) can be expressed in CIE XYZ. Color spaces typically also define the viewing environment and, therefore, the “white point” of the space.

Color models (not color spaces)



Problem with just a color model. .

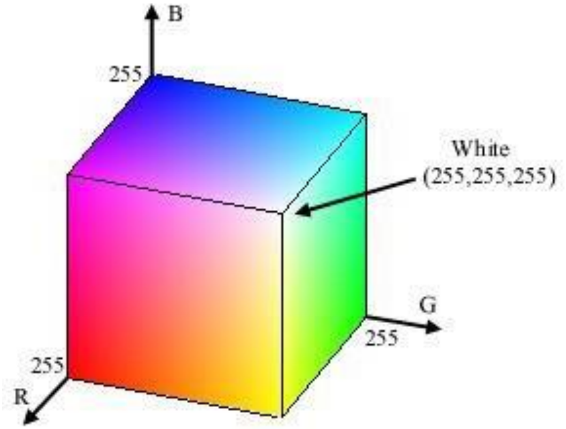


RGB 1 ——

RGB 2 ·············

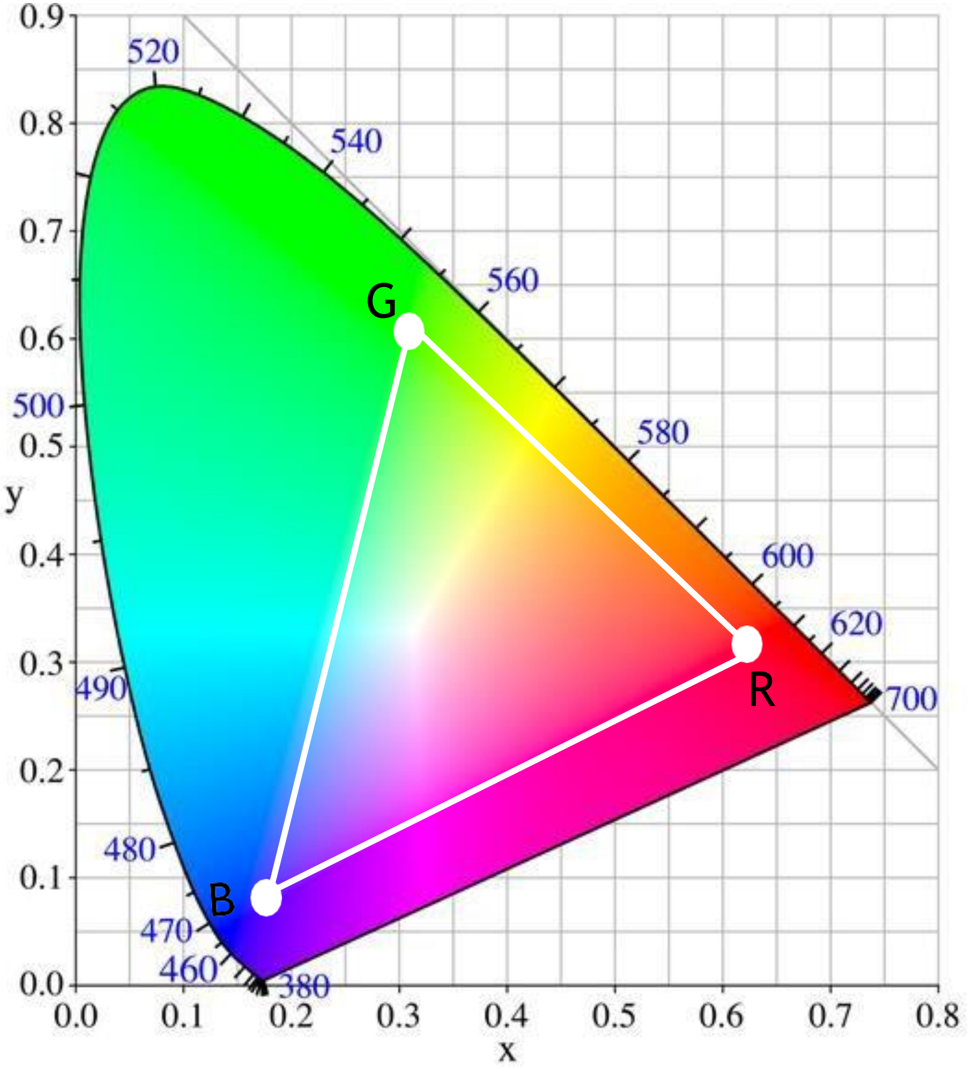
RGB 3 -------

Which RGB primaries are the right ones?



RGB values must be specified.
If not, this is a **huge** problem for color reproduction from one device to the next.

Standard RGB (sRGB) – Rec. 709



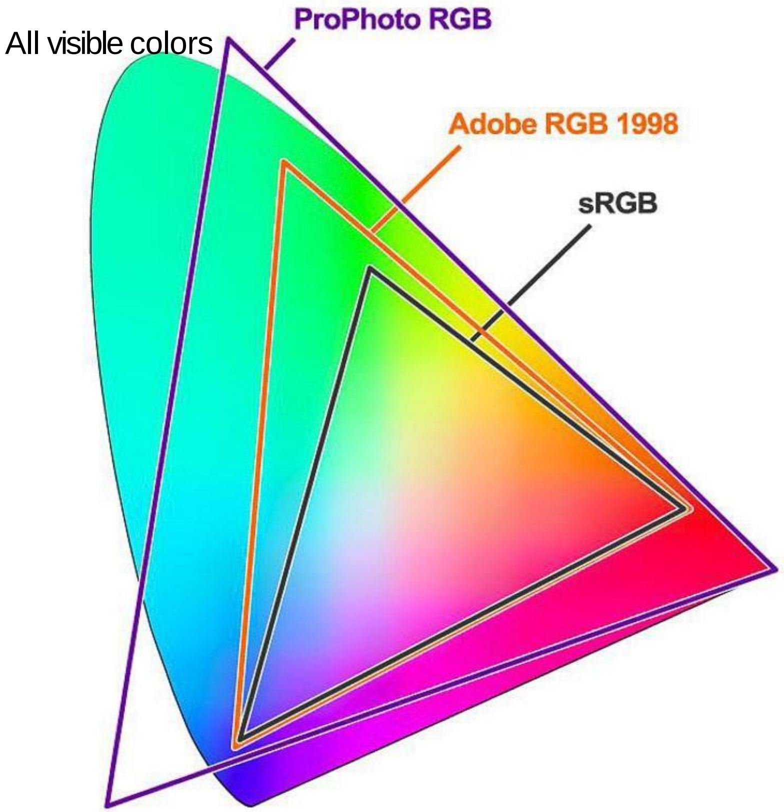
In 1996, Microsoft and HP defined a set of "standard" RGB primaries.

```
R=CIE xyY (0.64, 0.33, 0.2126)
G=CIE xyY (0.30, 0.60, 0.7153)
B=CIE xyY (0.15, 0.06, 0.0721)
```

This was considered an RGB space achievable by most devices at the time.

The white point was set to the D65 illuminant. **This is an important to note.** It means sRGB has built in the assumed viewing condition (6500K daylight).

Color space's gamut



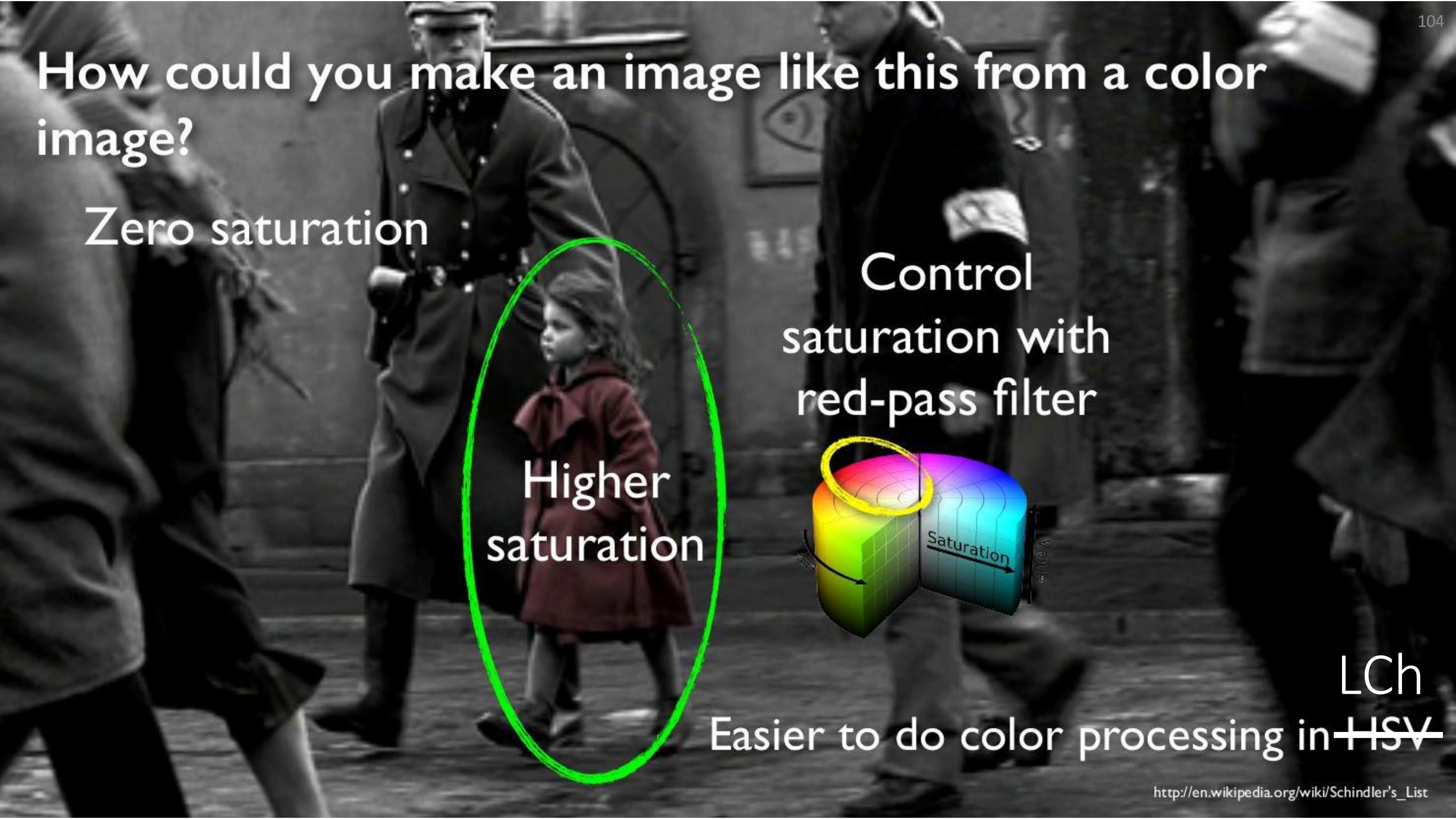
CIE Yxy chromaticity

A color space's gamut is the span of colors that can be represented. The 3D gamuts are plotted in CIE L*ab.

How could you make an image like this from a color image?

http://en.wikipedia.org/wiki/Schindler's_List

How could you make an image like this from a color image?



Zero saturation

Higher saturation

Control saturation with red-pass filter

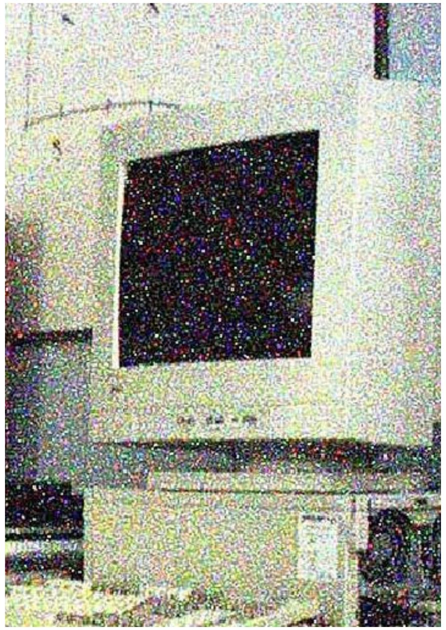
LCh

Easier to do color processing in ~~HSV~~

http://en.wikipedia.org/wiki/Schindler's_List

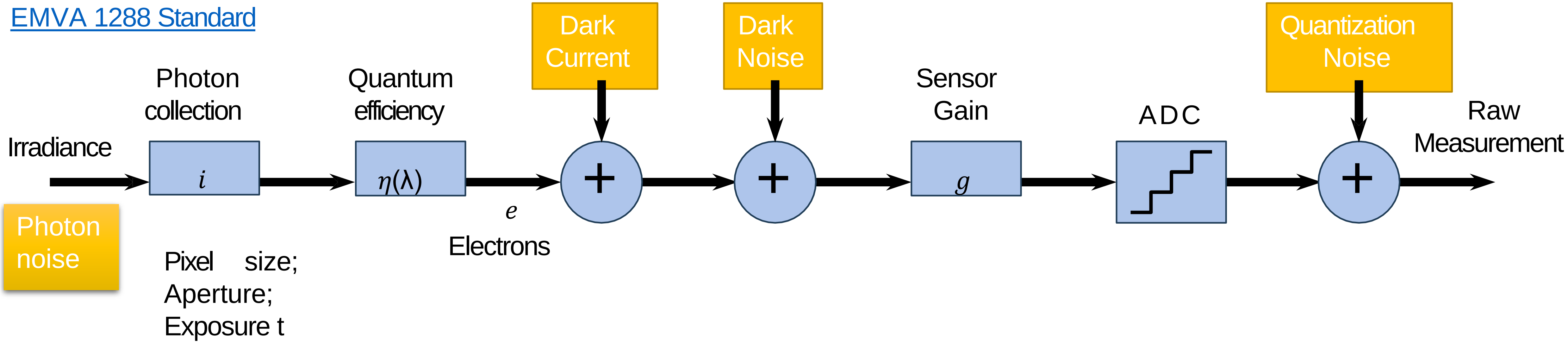
Noise

- Among the many factors contributing to image quality degradation, noise is one of the most recurrent and difficult elements to deal with
- Noise in a digital raw image can be classified into two main categories:
  - Fixed Pattern Noise (FPN);
  - Temporal (Random) Noise:
    - Photon Shot Noise
    - Dark Current (Thermal Noise)
    - Readout noise (Bias Noise)
    - Quantization noise



Sensor Noise Model

[EMVA 1288 Standard]



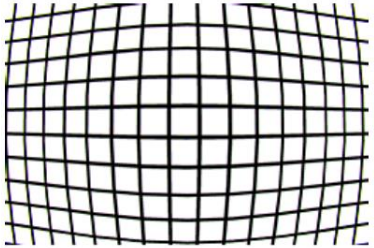
- Two main **sources** of image noise:
  1. The quantum nature of light (photon noise/shot noise); unrelated to the imaging sensor. Follows a Poisson distribution.
  2. Electronic sources associated with the imaging sensor circuitry (dark current and dark noise). Often follows a Normal distribution.
- Gain factor g amplifies noise.

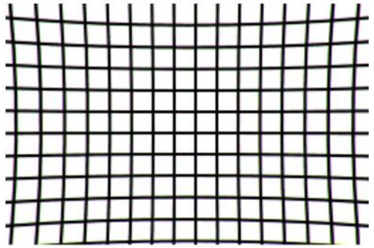
Dynamic Range

- Dynamic range is the ratio between largest and smallest brightness that can be “ accurately” captured
  - Highlights: limited by sensor saturation (hard limit) ~ Full Well
  - Shadows: limited by noise (soft limit) ~ Read noise
- When a scene dynamic range exceeds the camera DR, the camera cannot accurately capture highlights and shadows at the same time

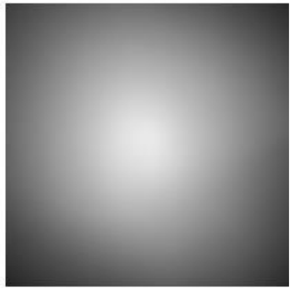
Lens Distortion

- Geometric deformation
  - Straight lines may not remain straight



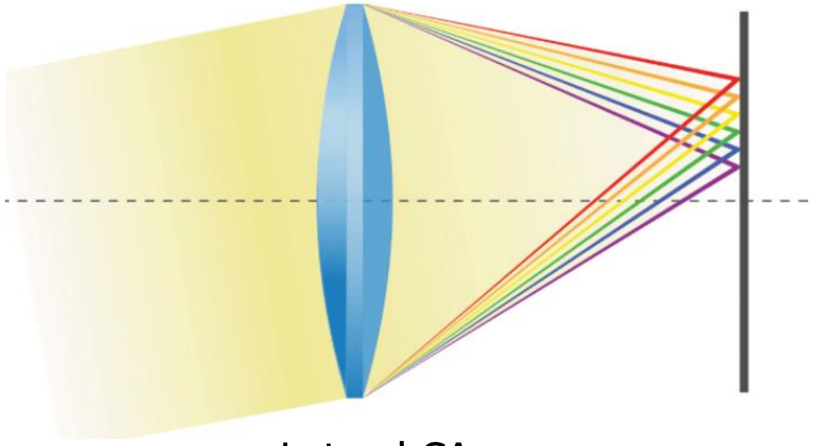


- Vignetting (Lens Shading)

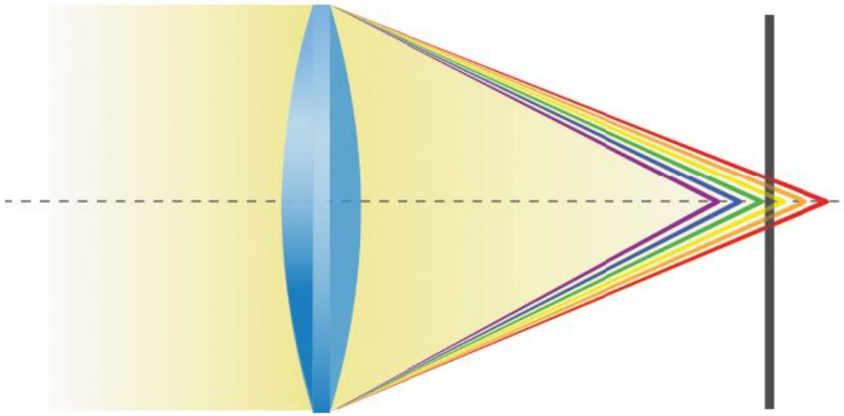


Uniform light falling on the sensor may not appear uniform in the raw-RGB image. This can be caused by the lens, sensor position in the camera housing, etc.

Lens Distortion – Chromatic Aberration



Lateral CA



Longitudinal CA

Camera Pipeline - ISP

Image Signal Processing (ISP) Pipeline

- An ISP is dedicated hardware that renders the sensor image to produce the final output.
- Companies such as Qualcomm, HiSilicon, Intel (and more) sell ISP chips (often as part of a System on a Chip – SoC).
  - Companies can customize the ISP.
- Many ISPs now have neural processing units (NPUs).

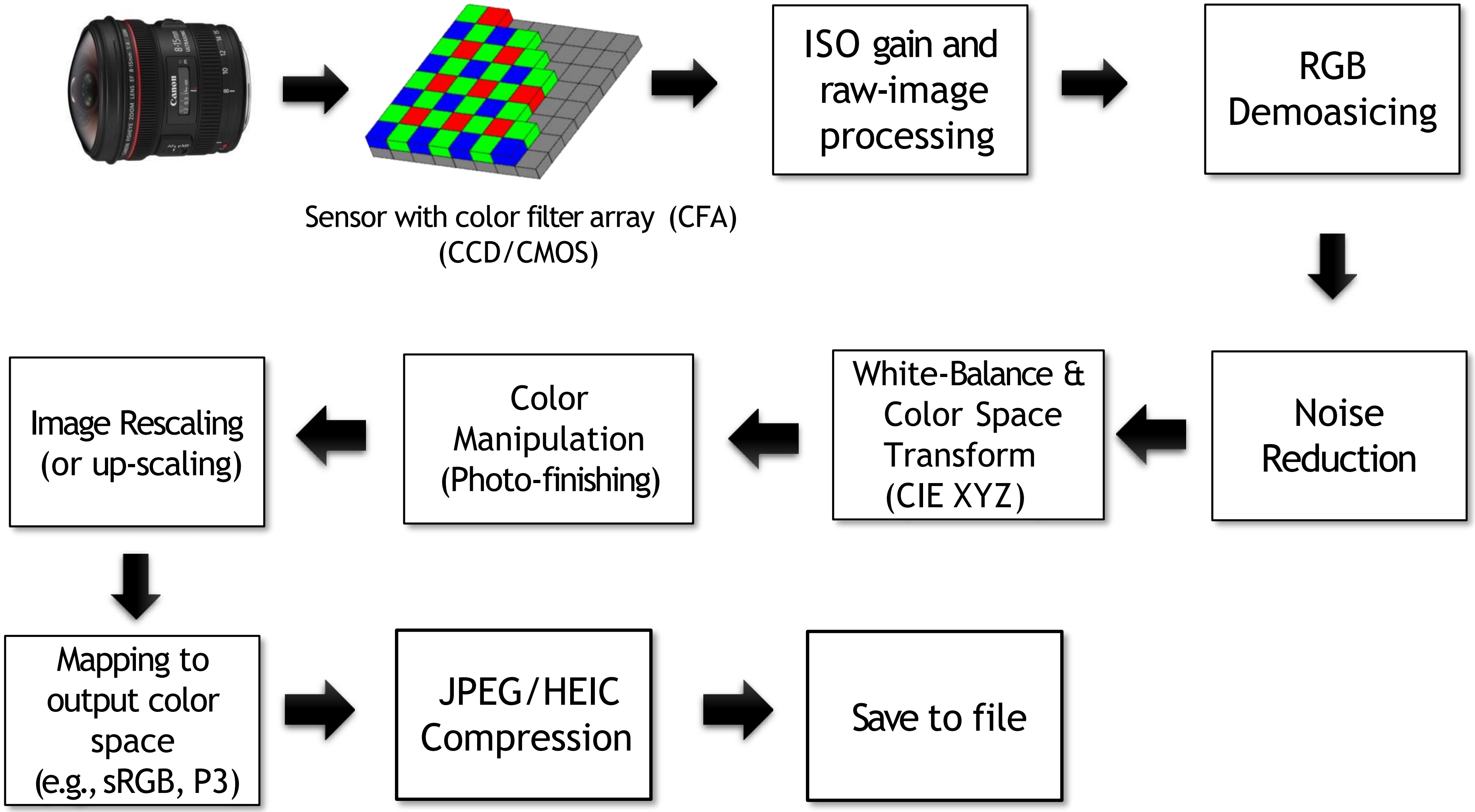
Samsung

Huawei

Apple

Samsung/Pixel/OnePlus/Xiaomi/....

A typical color imaging pipeline



NOTE: This diagram represents the steps applied on a typical consumer camera pipeline. ISPs may apply these steps in a different order or combine them in various ways. A modern camera ISP will undoubtedly be more complex but will almost certainly implement these steps in some manner.

Image Signal Processing (ISP) Pipeline

- Why?
  - Overcome limitations of sensors whether imposed by design, cost or physics
  - Overcome distinct characteristics of sensor models and present near identical image to viewer every time
  - Intelligently modify sensor parameters based on image quality, scene content, etc
  - Provide hardware resources and feedback paths to implement algorithms like AE / AWB
  - Tweak final image according to customer preferences

Sensor

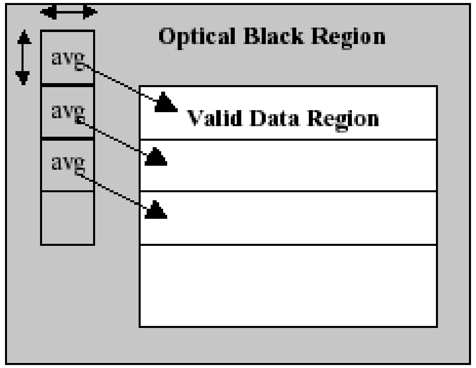
Noise (low SNR)
Defect pixels
Electrical cross-talk
Nonlinear response (low DR)
Green imbalance

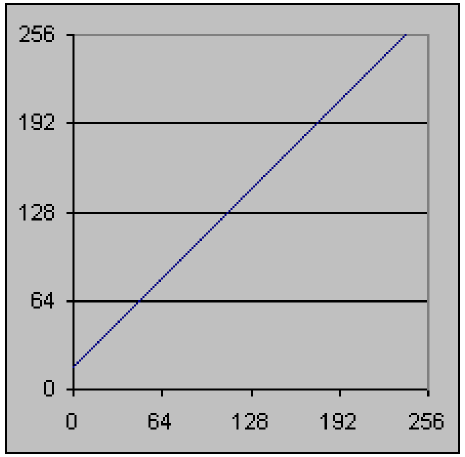
Optics

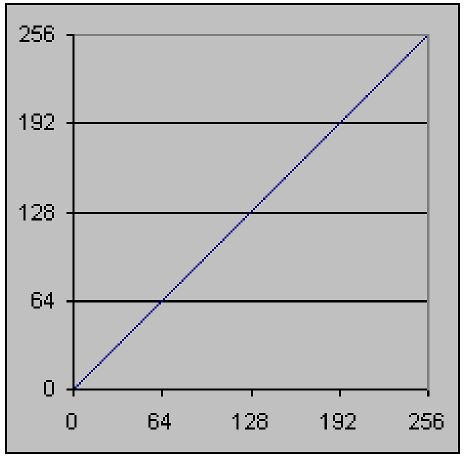
Lens shading
Optical cross-talk
Color shading
Chromatic aberration
Geometric (barrel) distortion

Optical Black Clamping

- Compensate image sensors' dark signal
- Subtract OB (Optical Black) from pixel signal
- OB value
  - Computed by DSP from image sensor's OB area
  - Manually set by firmware

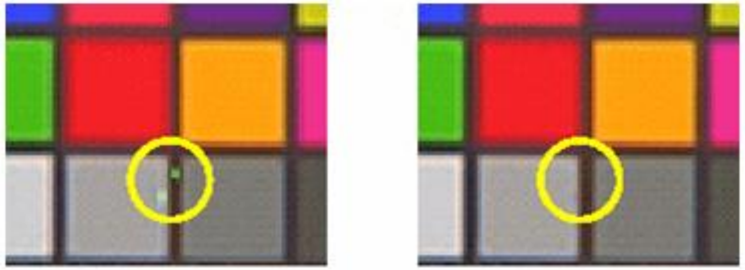






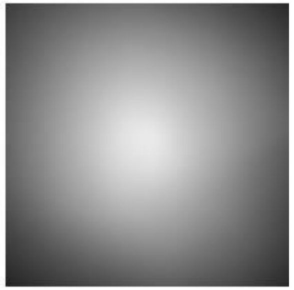
Defect (Bad) Pixel Correction

- Non-perfect image sensors
- Must be done in raw data space to prevent bad pixels from polluting neighborhood
- Consider edge and gradient information



Error Pixel (Uncorrected)   Corrected

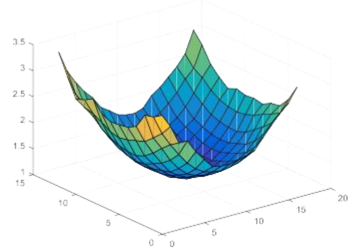
Flat-field correction



Uniform light falling on the sensor may not appear uniform in the raw-RGB image. This can be caused by the lens, sensor position in the camera housing, etc.

We want to correct this problem such that we get a "flat" (or uniform) output.

Before correction



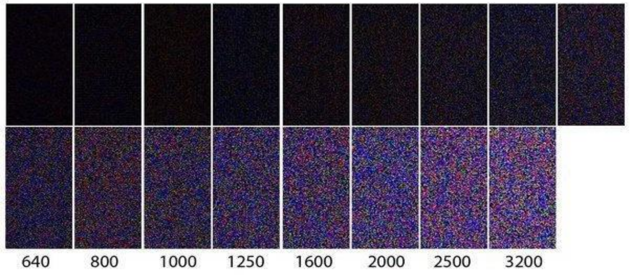
Apply a correction gain over the sensor values.

After correction

Noise Reduction

- What is noise?
  - Unnatural artifacts: power, readout, flicker...
  - Too many possible noise sources
  - Focus on removing noise sources first
- For high-end cameras, it is likely that cameras apply different strategies depending on the ISO settings, e.g. high ISO will result in more noise, so a more aggressive NR could be used
- Smartphone cameras, because the sensor is small, apply aggressive noise reduction

Camera ISO setting and noise



Noise Reduction

$$\frac{1}{9} \times \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

Blur filter

$$\frac{1}{17} \times \begin{bmatrix} 1 & 1 & 1 \\ 1 & 9 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

Soften filter

$$\frac{1}{273} \begin{bmatrix} 1 & 4 & 7 & 4 & 1 \\ 4 & 16 & 26 & 16 & 4 \\ 7 & 26 & 41 & 26 & 7 \\ 4 & 16 & 26 & 16 & 4 \\ 1 & 4 & 7 & 4 & 1 \end{bmatrix}$$

Gaussian filter

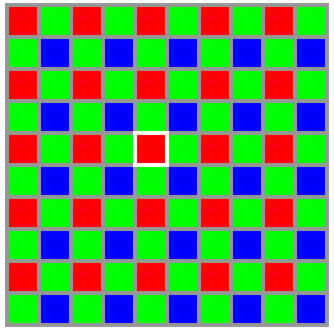
Original image

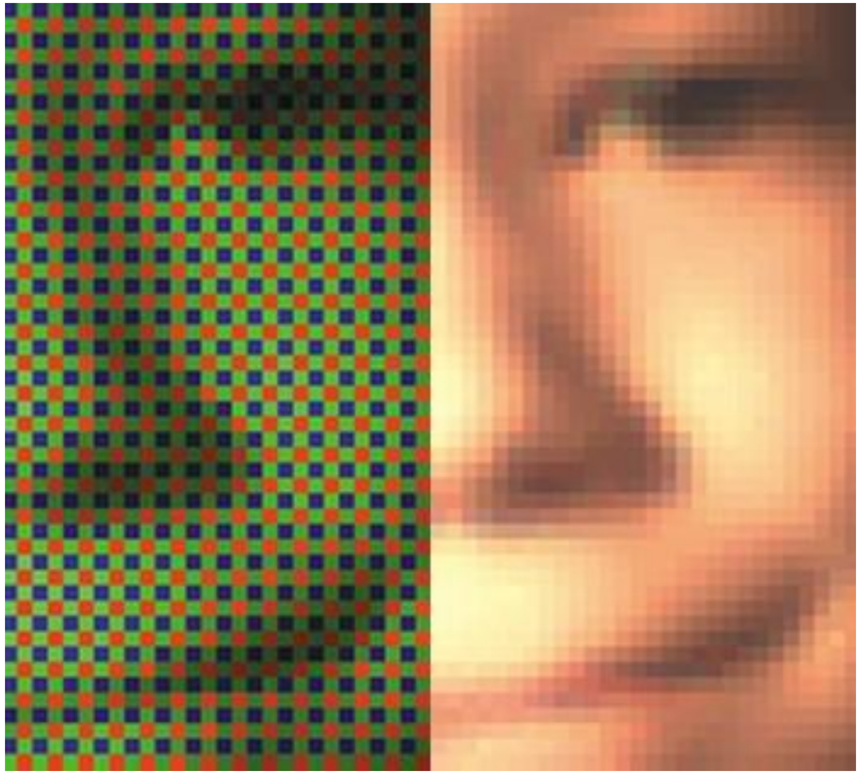
Gaussian Filter

SUSAN Filter

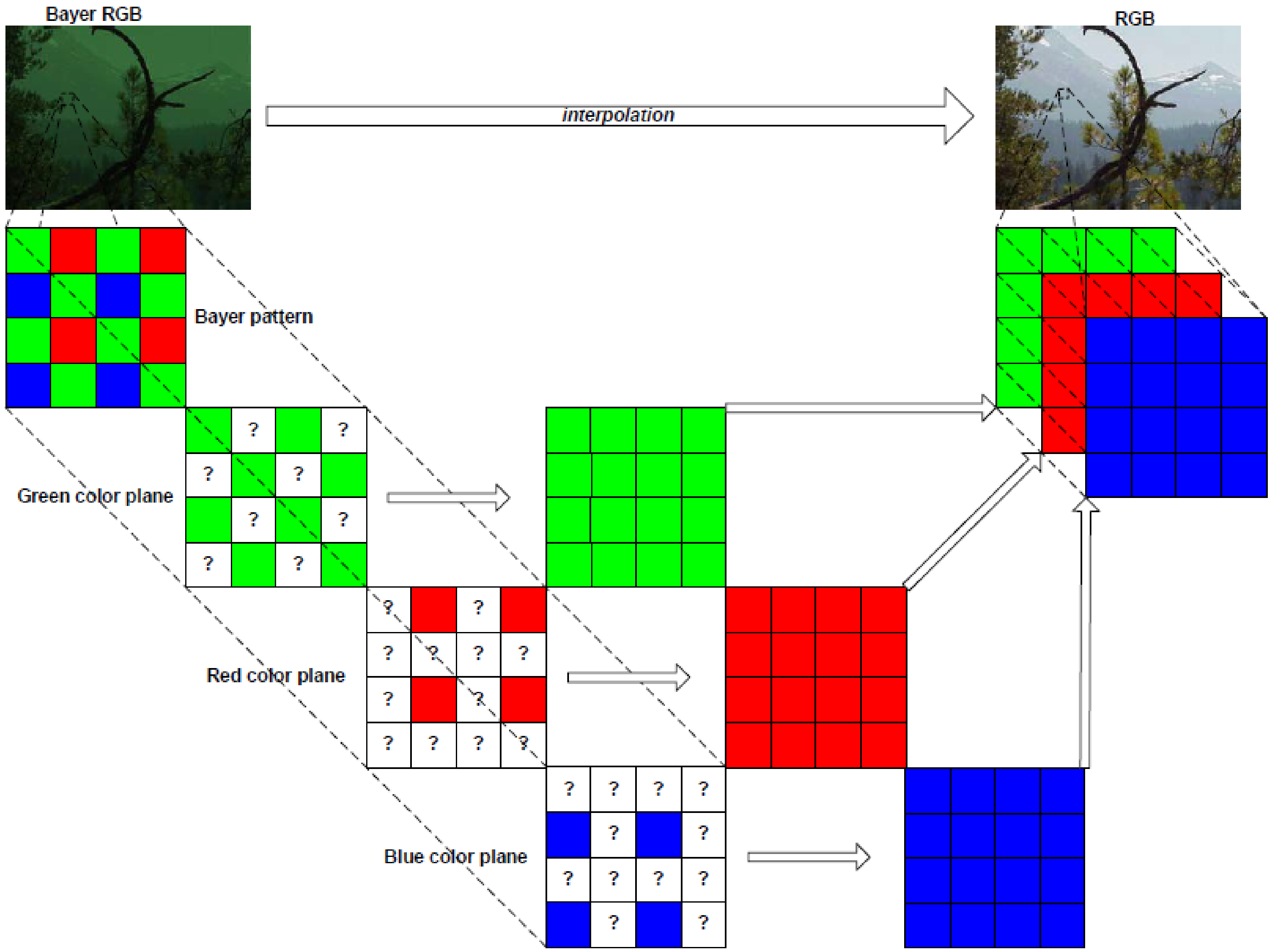
Color Interpolation - Demosaicking

- Also called de-mosaic / raw2rgb...
- Guess missing channels for each pixel by the following:
  - Neighbor pixels
  - Edge
  - Gradient
  - ...
- Avoid zigzag and false color artifacts



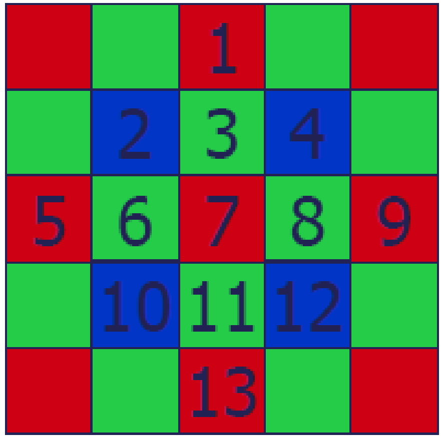


CFA Interpolation Process



CFA Interpolation Process - Demosaicking

- Conventional - Bilinear



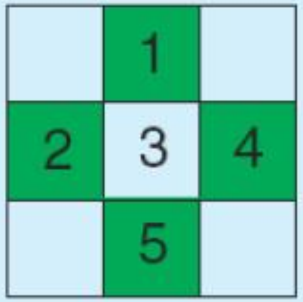
$$G7=(G3+G6+G8+G11)/4$$

$$B3=(B2+B4)/2$$

$$B7=(B2+B4+B10+B12)/4$$

CFA Interpolation Process - Demosaicking

- Edge aware



1. Calculate horizontal gradient $\Delta H = |G2 - G4|$
2. Calculate vertical gradient $\Delta V = |G1 - G5|$
3. If $\Delta H > \Delta V$,

   $G3 = (G1 + G5)/2$

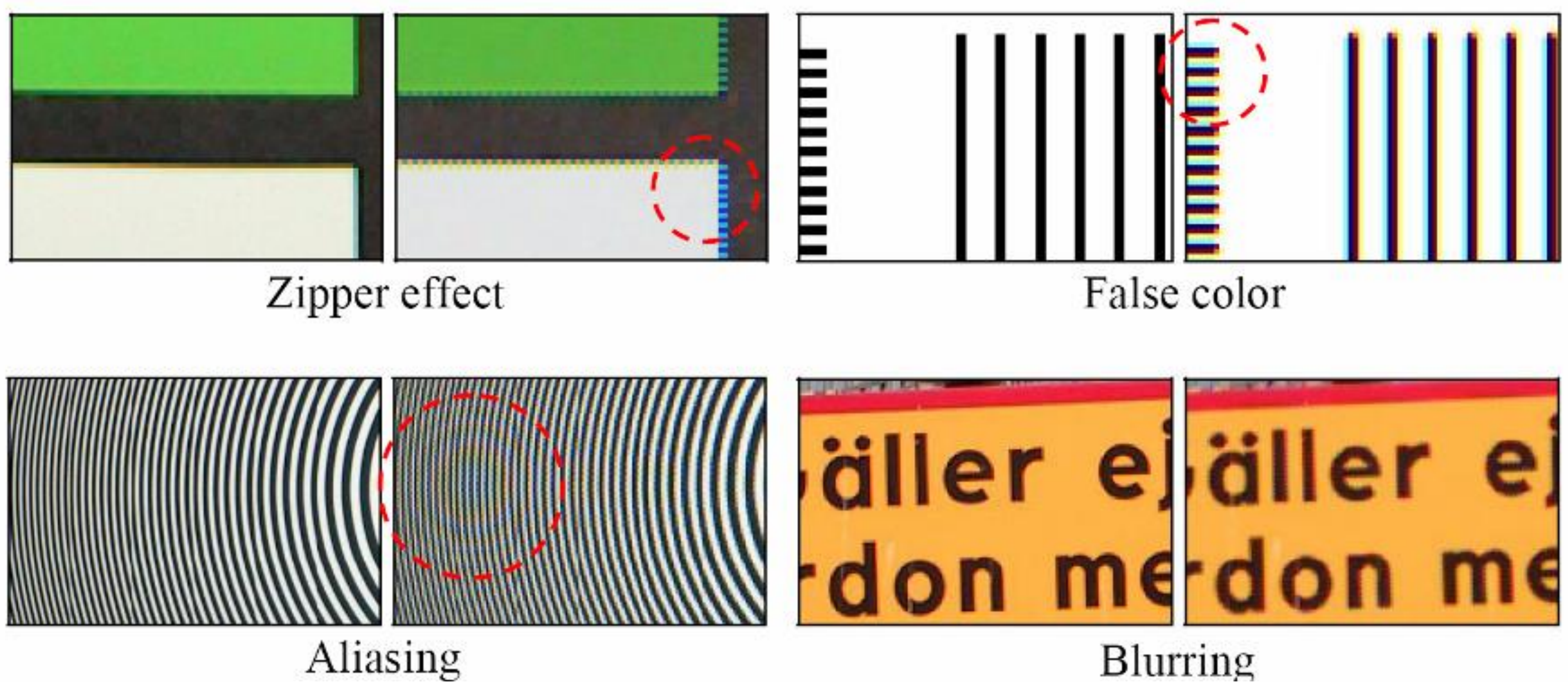
   Else if $\Delta H < \Delta V$,

   $G3 = (G2 + G4)/2$

   Else

   $G3 = (G1 + G5 + G2 + G4)/4$

Color Artifacts

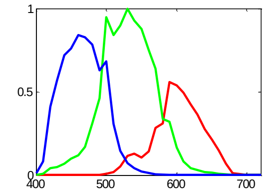


Color mapping/colorimetric stage Balance

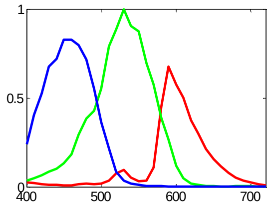
- This step in the ISP converts the sensor raw-RGB values to a device independent color space

Camera sensors have their own spectral response.

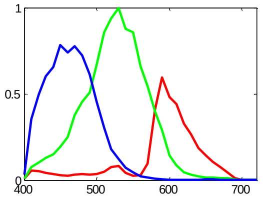
We need to map it into a standard response (CIE XYZ).



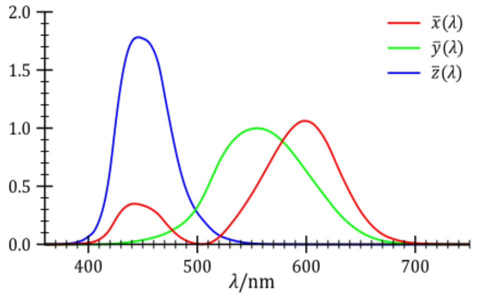
Canon 1D



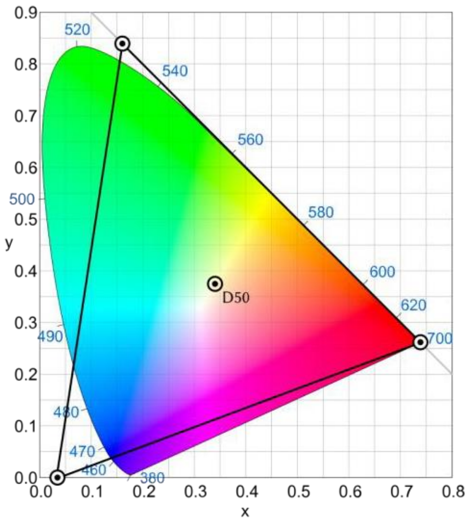
Nikon D40



Sony $\alpha 57$



CIE XYZ



ProPhoto RGB

Two step procedure

(1) apply a white-balance correction to the raw-RGB values

(2) map the white-balanced raw-RGB values to CIE XYZ

White balance

$$\begin{bmatrix} \# & & \\ & \# & \\ & & \# \end{bmatrix}$$

3x3 diagonal matrix

Color space transform (CST)

$$\begin{bmatrix} \# & \# & \# \\ \# & \# & \# \\ \# & \# & \# \end{bmatrix}$$

3x3 full matrix (or polynomial function)

White Balance – Part 1

- Human visual system has *chromatic adaptation*:
- We can perceive white (and other colors) correctly under different light sources.
- Cameras cannot do that (there is no “camera perception”).
- White balancing: The process of removing color casts so that colors that we would
- *perceive* as white are *rendered* as white in final image.

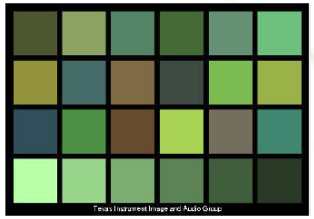
different whites

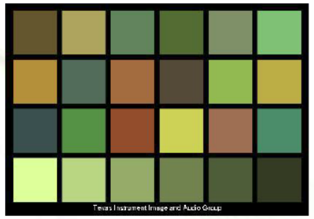
image captured under fluorescent

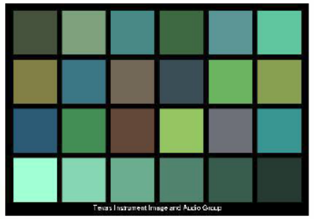
image white-balanced to daylight

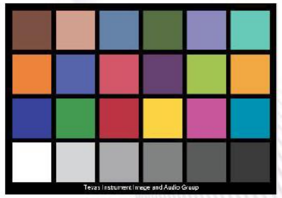
White Balance

- Remove unrealistic colour casts so that white object appears white
- Remove influence of colour temp. of light source on subject
- Presets are provided for various common light conditions (Sunny, Incandescent, Fluorescent, etc)
- In automatic mode, camera tries to estimate colour cast and compensate various algorithms present
- Cameras nowadays come with a large number of presets: You can select which light you are taking images under, and the appropriate white balancing is applied.


Incandescent Light


Fluorescent Light


Daylight

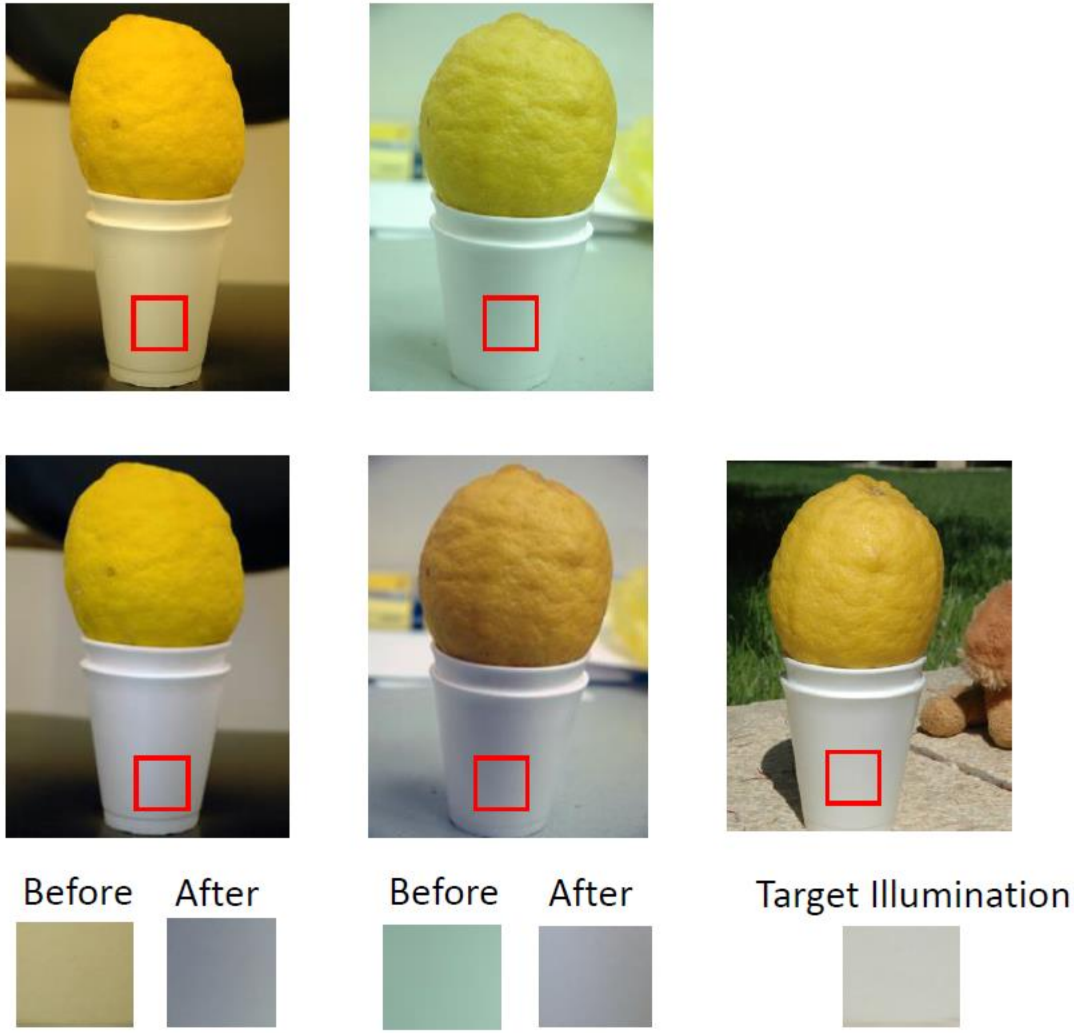

Human Perception

WB SETTINGS	COLOR TEMPERATURE	LIGHT SOURCES
	10000 - 15000 K	Clear Blue Sky
	6500 - 8000 K	Cloudy Sky / Shade
	6000 - 7000 K	Noon Sunlight
	5500 - 6500 K	Average Daylight
	5000 - 5500 K	Electronic Flash
	4000 - 5000 K	Fluorescent Light
	3000 - 4000 K	Early AM / Late PM
	2500 - 3000 K	Domestic Lightning
	1000 - 2000 K	Candle Flame

Example

Input

Adapted to
“target”
illuminant

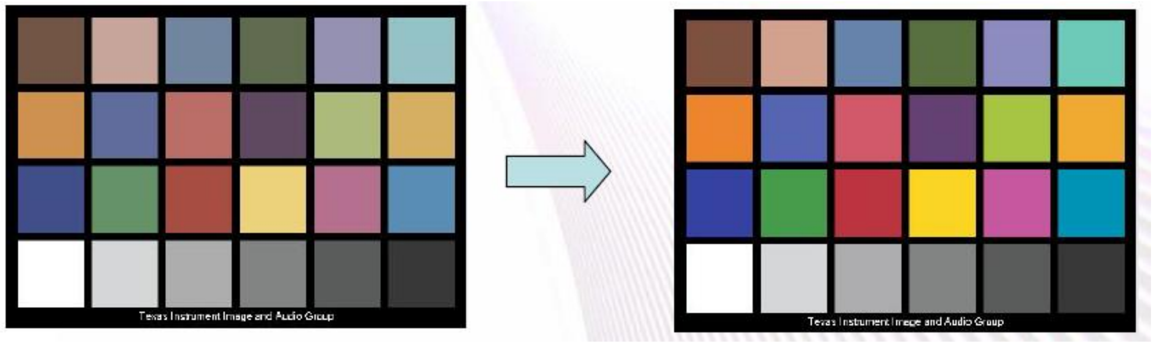


Auto white balance (AWB)

- If manual white balance is not used, then an AWB algorithm is performed.
- AWB must determine the sensor's raw-RGB response to the scene illumination from an arbitrary image.
- AWB is not easy and this remains an open research problem.

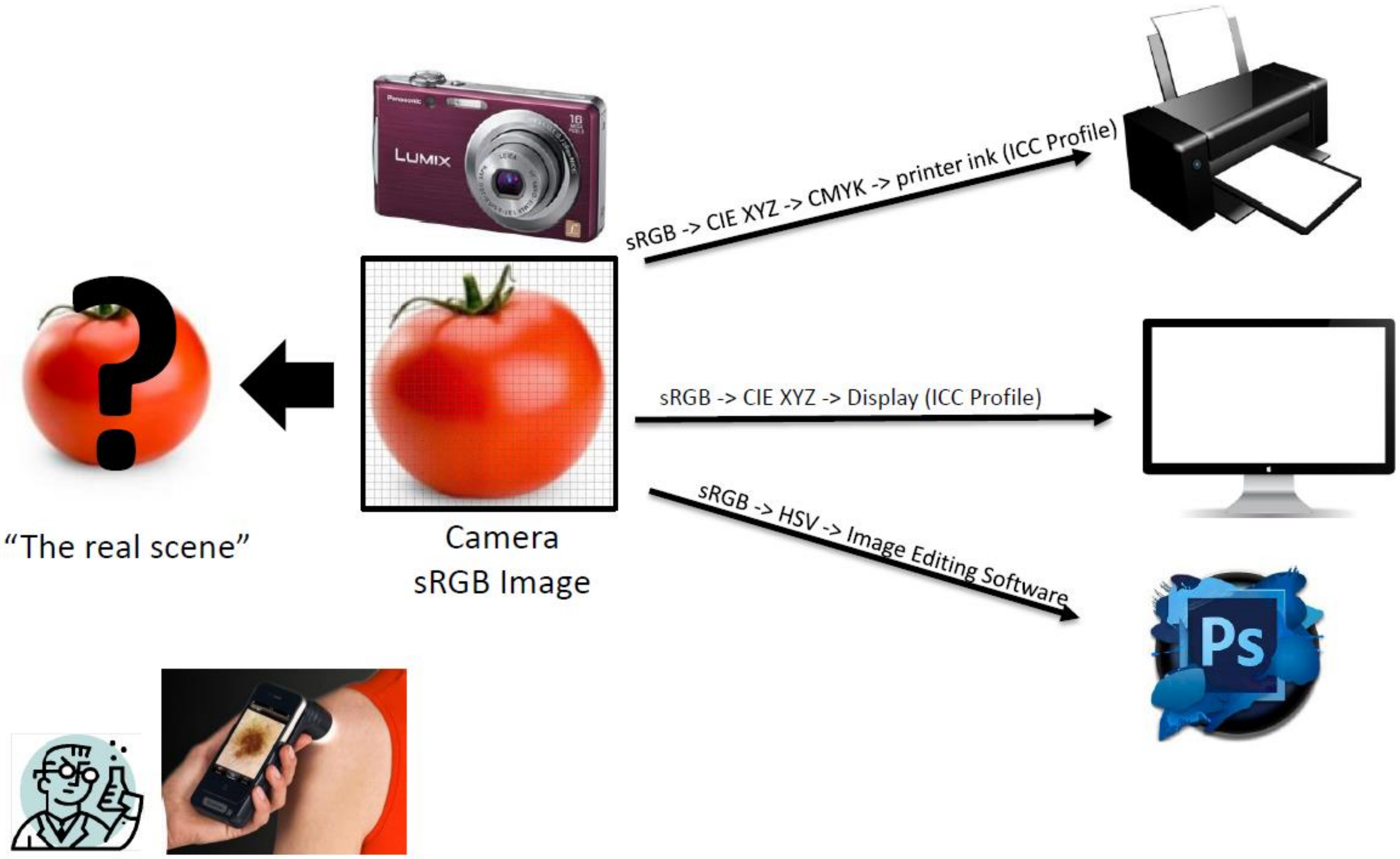
Color Correction – Part 2

- Image sensor’s color sensitivity is different from human eyes.
- A 3x3 matrix multiplication and a nonlinear gamma mapping are used to correct color to match TRUE color.
- Color target is used to replace TRUE color.
- Correction means solving best matrix and gamma.
- sRGB, AdobeRGB etc.

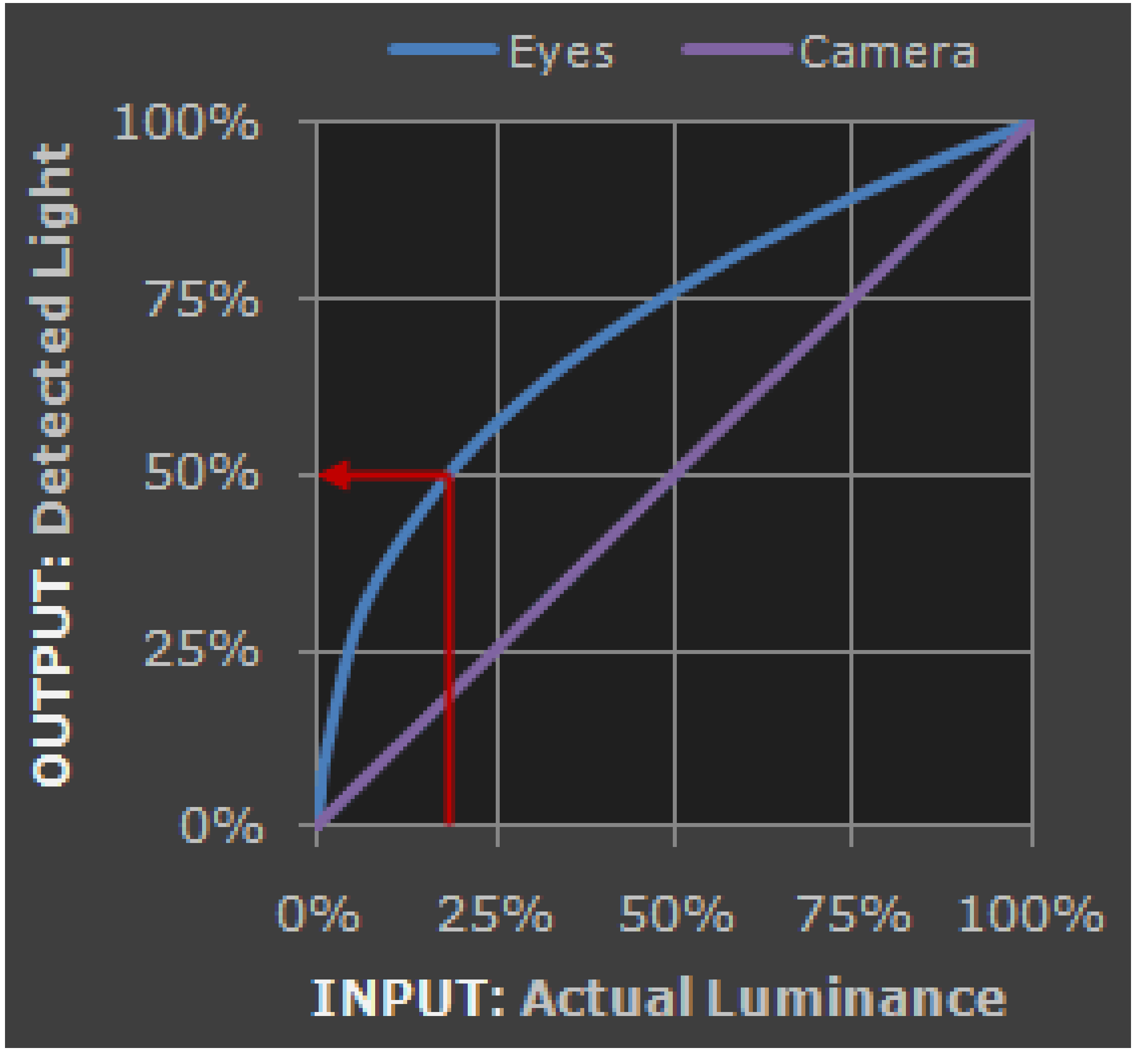


$$\begin{bmatrix} R' \\ G' \\ B' \end{bmatrix} = \begin{bmatrix} M_{11} & M_{12} & M_{13} \\ M_{21} & M_{22} & M_{23} \\ M_{31} & M_{32} & M_{33} \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

Standard color spaces are great



Perceived vs measured brightness by human eye



Sensor response is linear.

Human-eye *response* (measured brightness) is also linear.

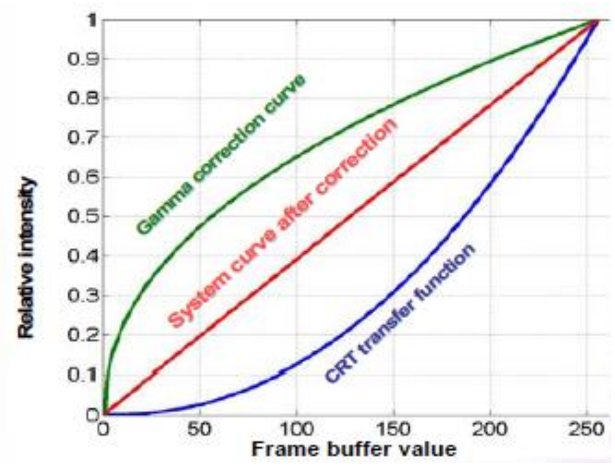
However, human-eye *perception* (perceived brightness) is *non-linear*:

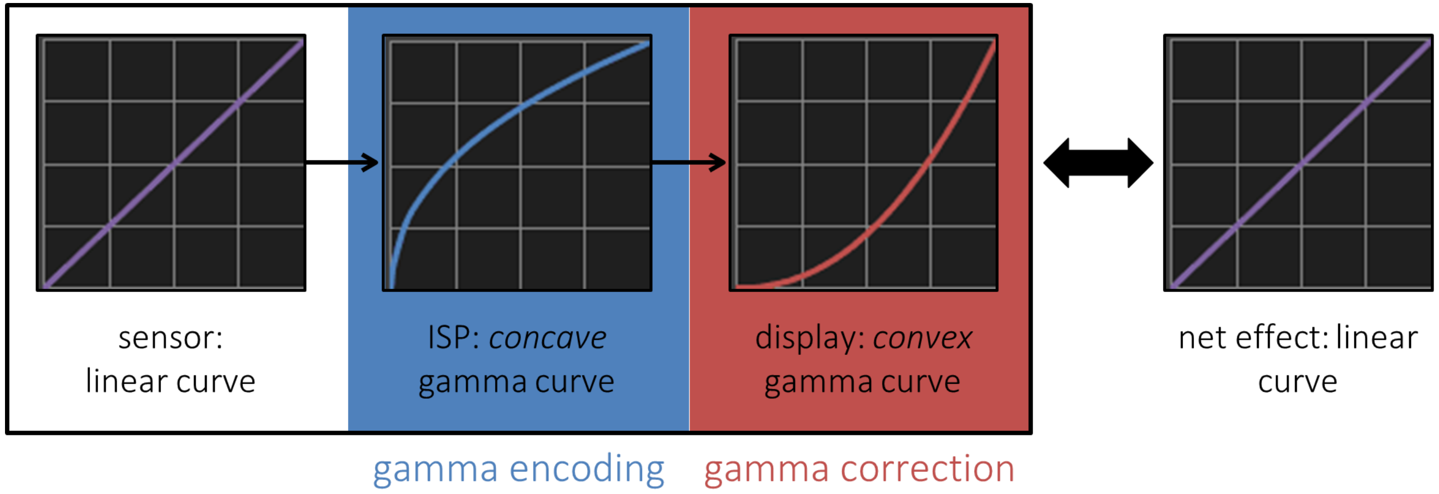
- More sensitive to dark tones.
- Approximately equal to square root function (concave “gamma curve” L^γ with $\gamma = 1/2.2$).

Gamma encoding & Correction

- Goal: Compensate the nonlinearity of the output device
- Model :

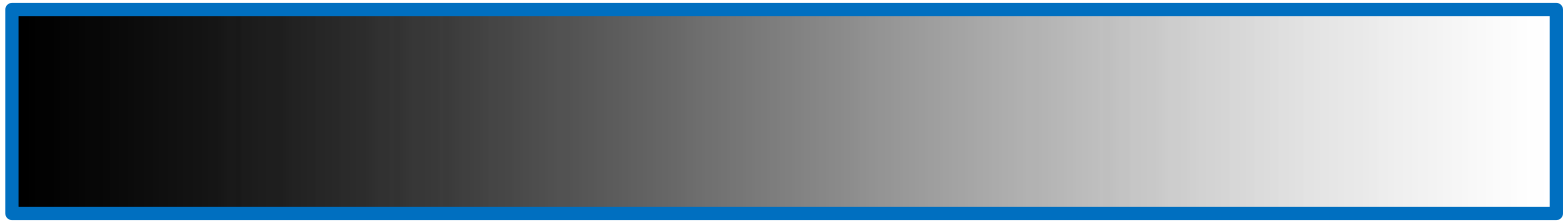
$$R' = R^{1/\gamma} \quad G' = G^{1/\gamma} \quad B' = B^{1/\gamma}$$





Demonstration

original (8-bits, 256 tones)



Can you predict what will happen if we linearly encode this tone range with only 5 bits?

Can you predict what will happen if we gamma encode this tone range with only 5 bits?

Demonstration

original (8-bits, 256 tones)

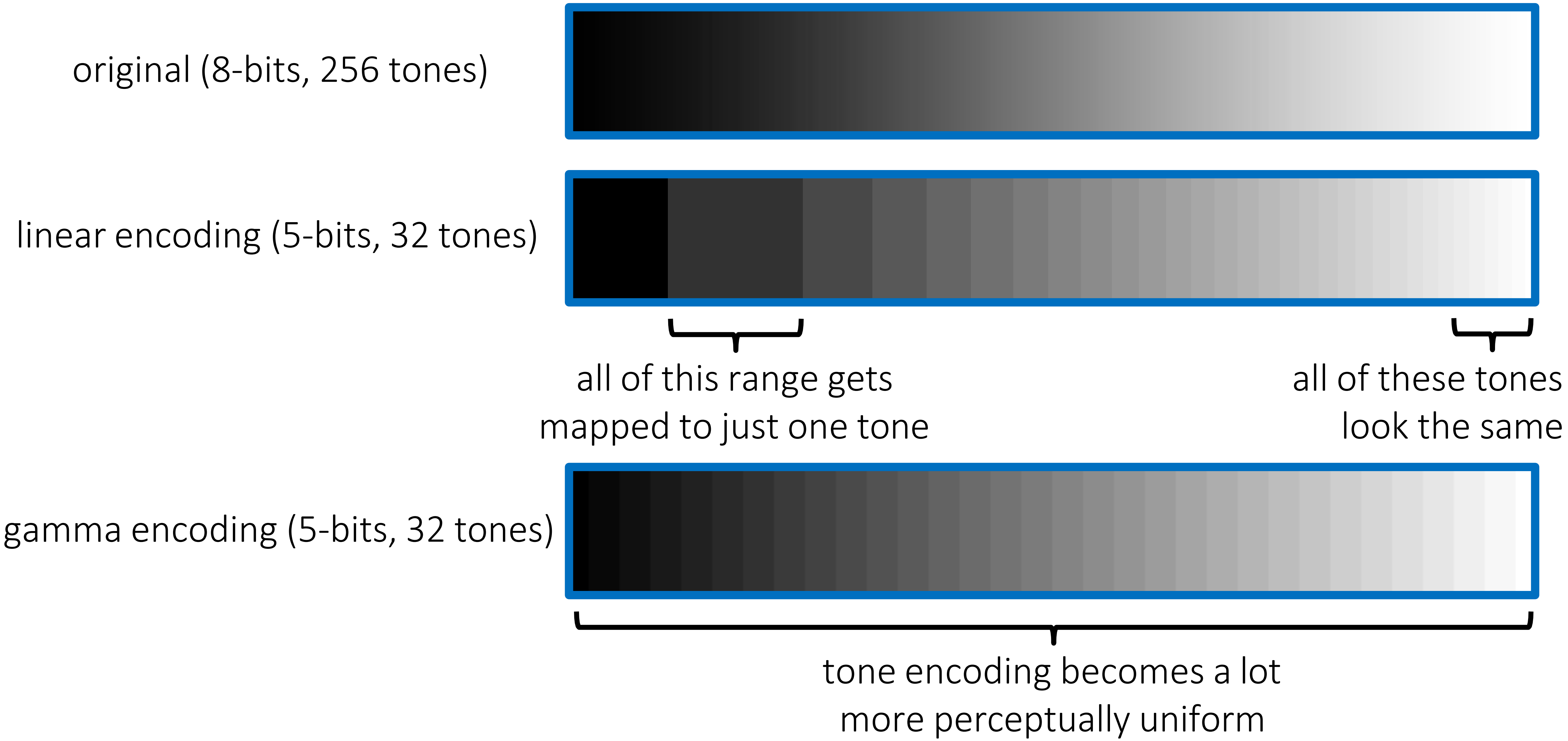
linear encoding (5-bits, 32 tones)

all of this range gets mapped to just one tone

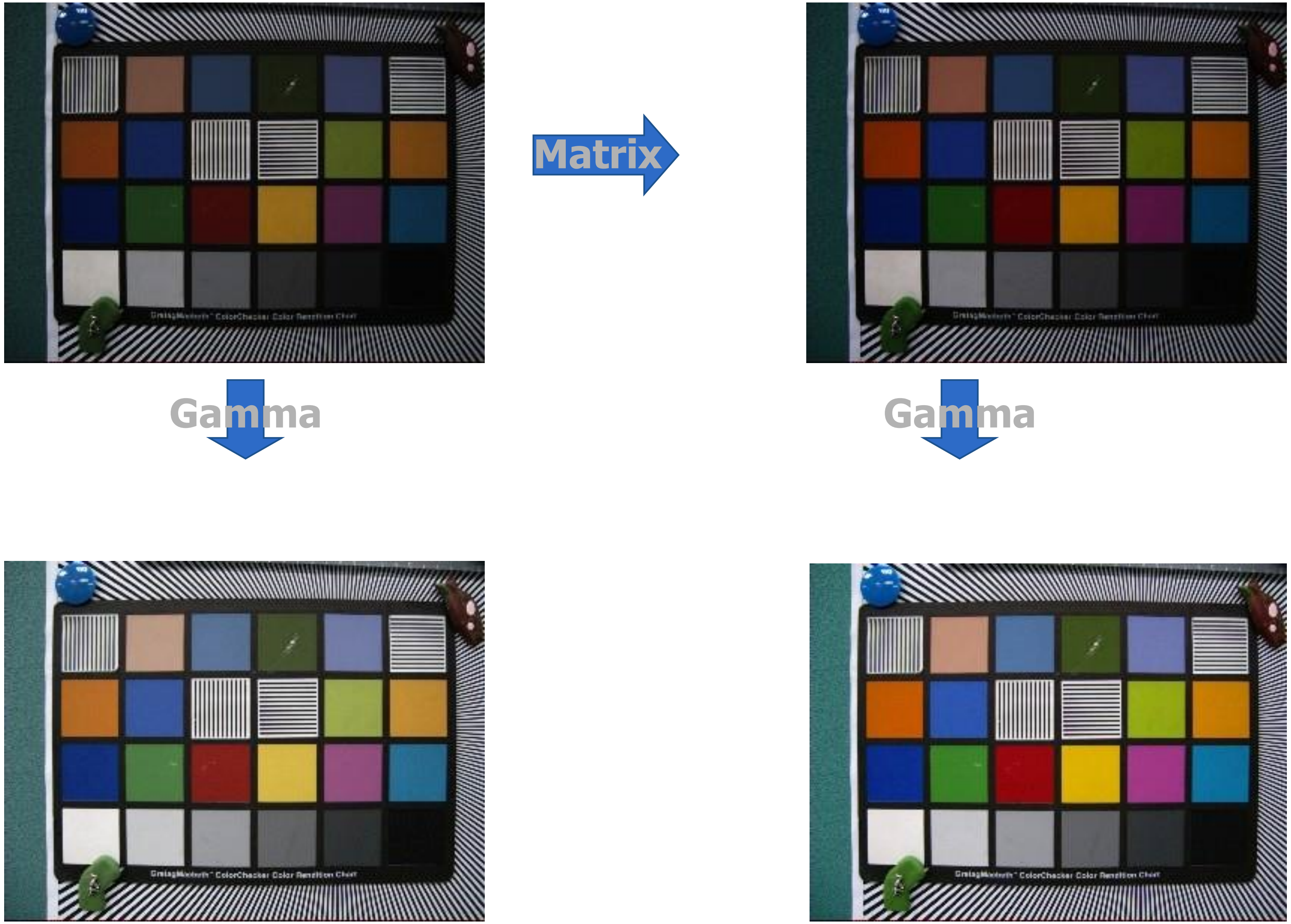
all of these tones look the same

Can you predict what will happen if we gamma encode this tone range with only 5 bits?

Demonstration



Influence of Color and Gamma



Tone mapping

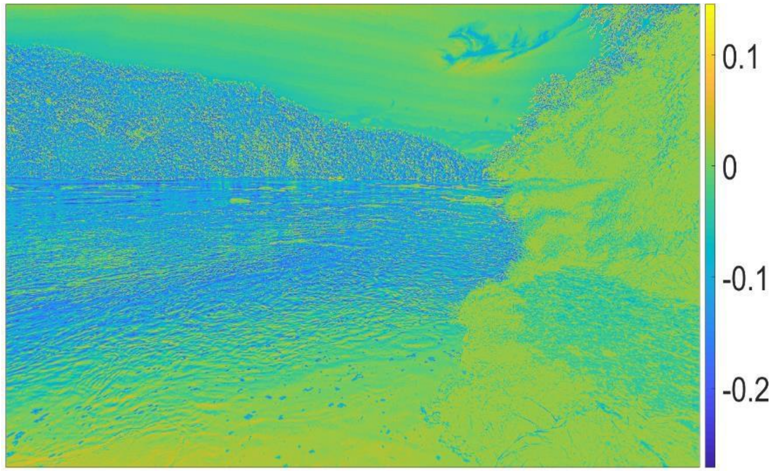
- Non-linear mapping of RGB tones
- Applied to achieve some preferred tone-reproduction
  - This is not sRGB gamma
  - This is to make the images look nice
- To some degree this mimics the nonlinearity in film (known as the Hurter-Driffield Curves)
- Each camera has its own unique tone-mapping (possibly multiple ones)

Local tone mapping (LTM)

Global tone-mapping
Camera mode - Manual

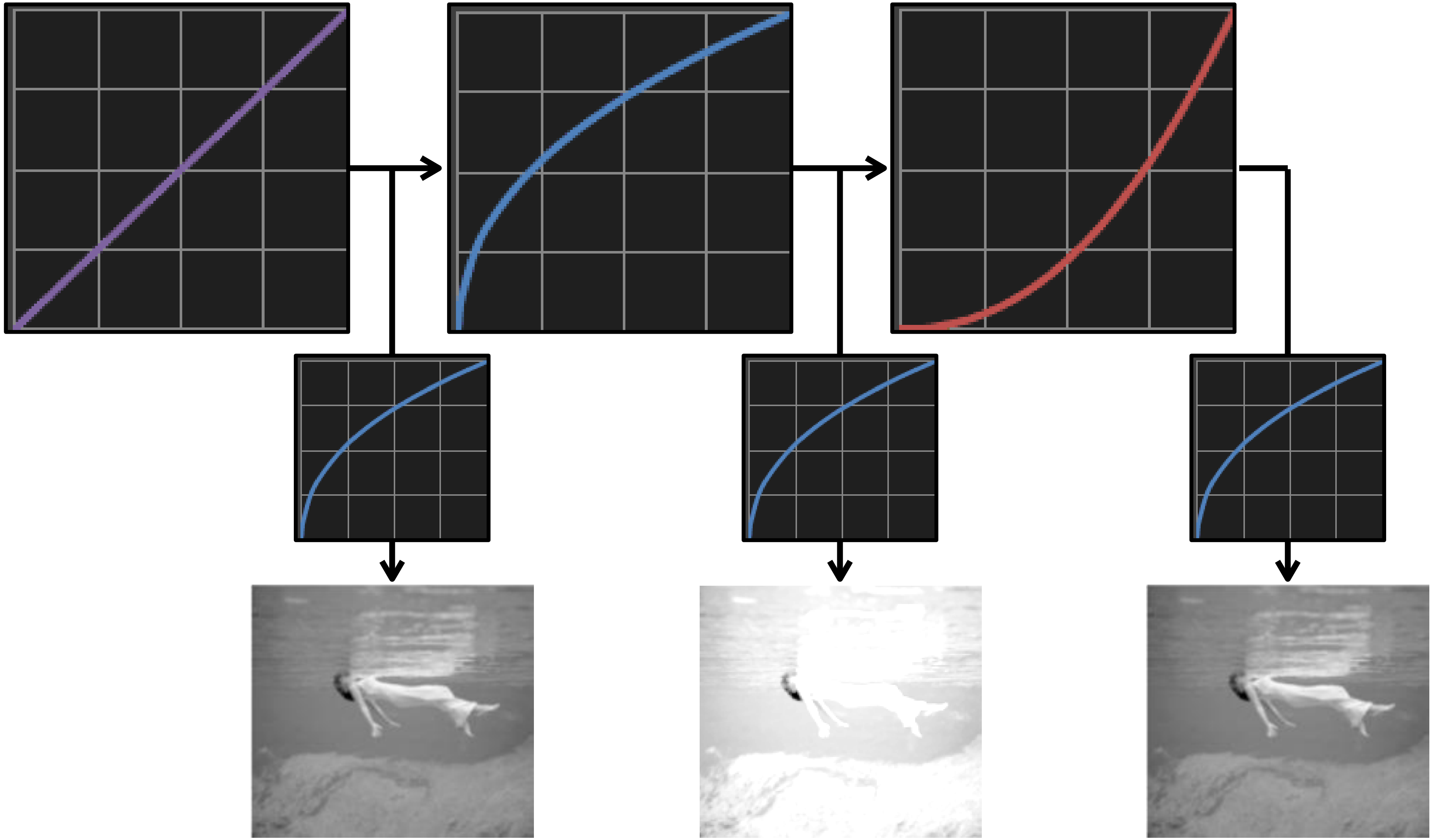
Local tone-mapping
Camera mode - Auto

NOTE: On many cameras, esp smartphones, a local tone map is applied as part of the photo-finishing.
This helps bring out highlights in the image.



Difference map between image before and after LTM

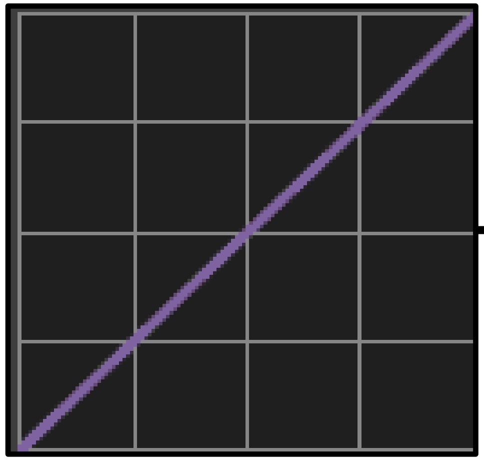
Tone reproduction pipeline



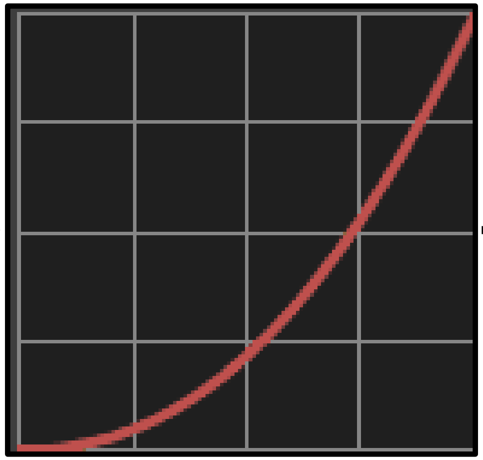
human visual system: *concave* gamma curve

image a human would see at different stages of the pipeline

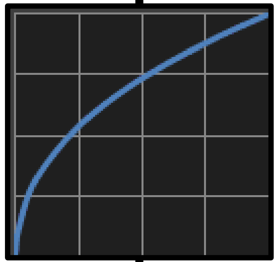
RAW pipeline

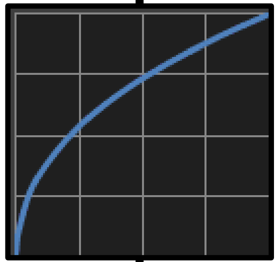


gamma encoding is skipped!



display still applies gamma correction!





human visual system: *concave* gamma curve

RAW image appears very dark! (Unless you are using a RAW viewer)

image a human would see at different stages of the pipeline

Color Space Conversion

- RGB <-> YUV
- Human eyes are more sensitive to luminance than color information
- We need to separate luminance component (Y) from color components (Cb, Cr) for different processing using different precisions
- Prepare for brightness/contrast/hue/saturation adjustment and JPEG (Joint Photographic Experts Group) compression
- Typically done by 3x3 matrix multiplication

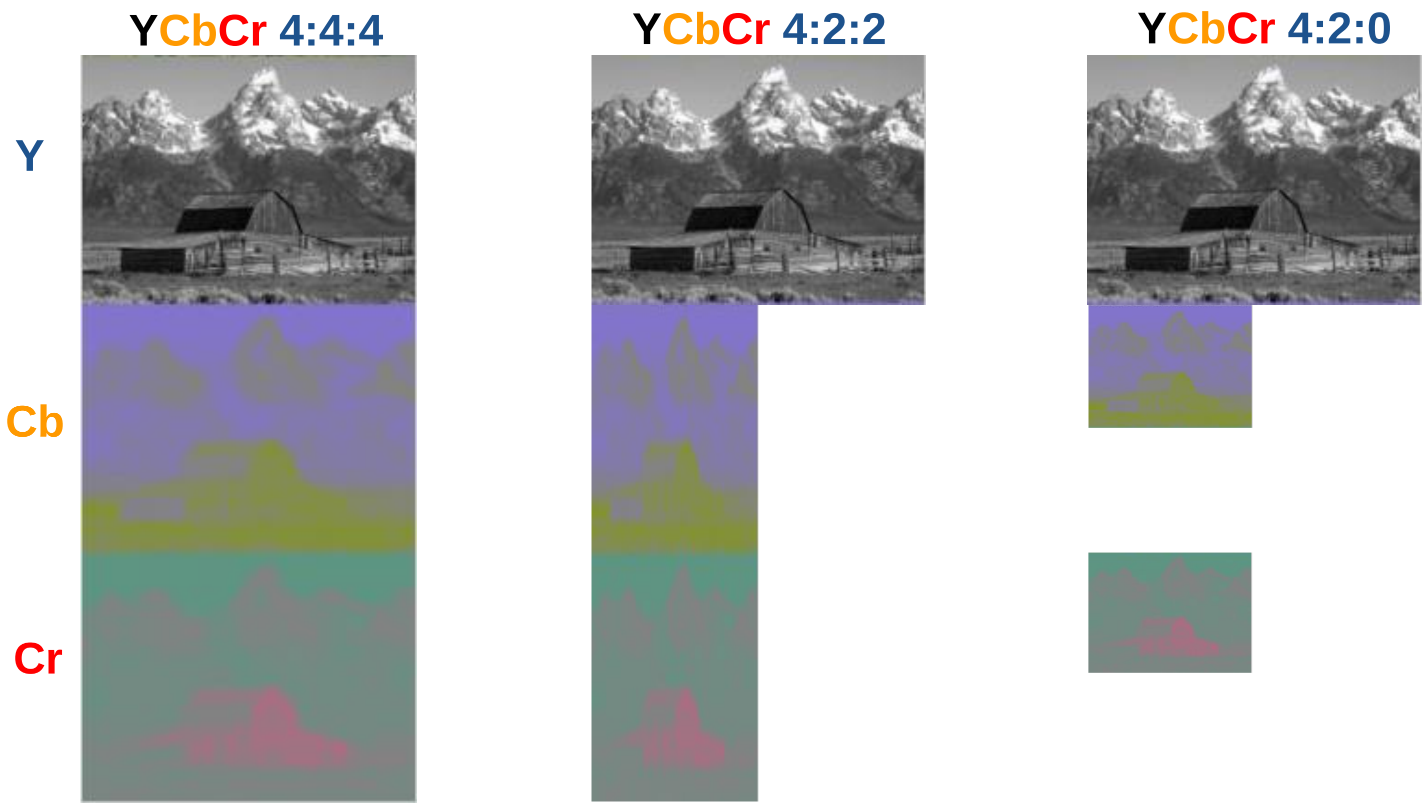
RGB888 to YUV444

$$Y = ((\ 66 * R + 129 * G + \ 25 * B + 128) >> 8) + \ 16$$
$$U = ((-38 * R - \ 74 * G + 112 * B + 128) >> 8) + 128$$
$$V = ((112 * R - \ 94 * G - \ 18 * B + 128) >> 8) + 128$$

With C = Y – 16; D = U – 128; E = V - 128

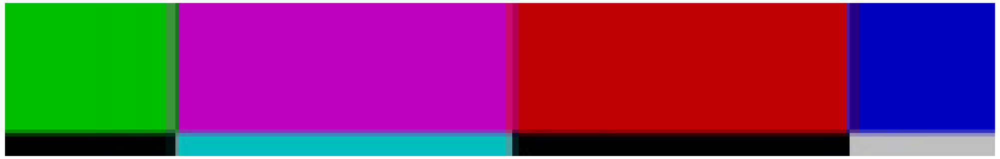
$$R = clip((298 * C \qquad\qquad + 409 * E + 128) >> 8)$$
$$G = clip((298 * C - 100 * D - 208 * E + 128) >> 8)$$
$$B = clip((298 * C + 516 * D \qquad\qquad + 128) >> 8)$$

YCbCr Pixel Ratios

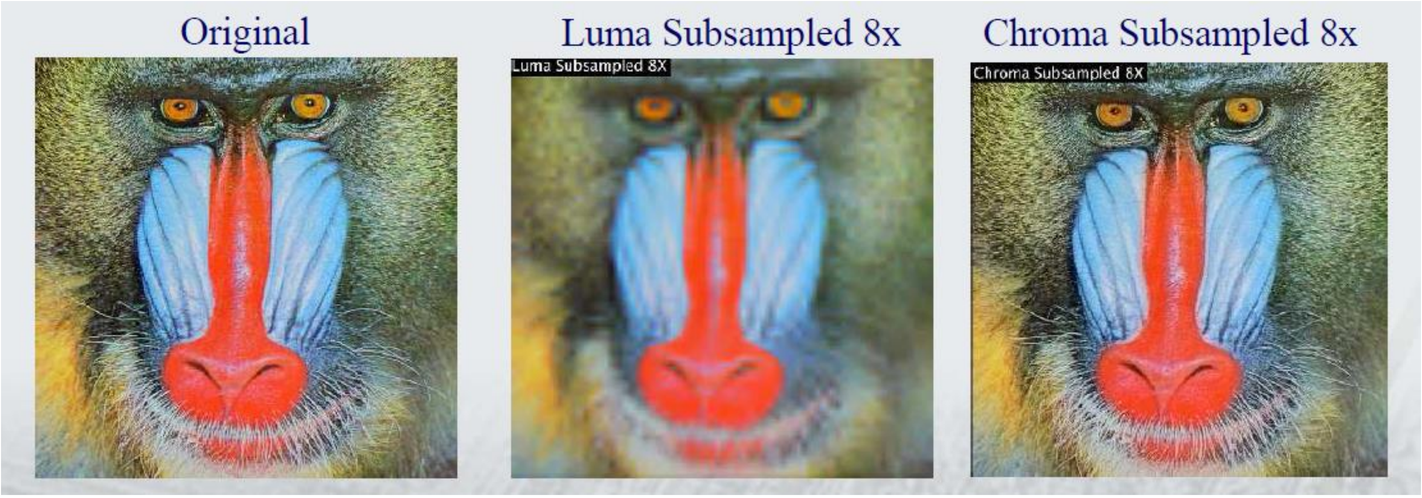


Effects of chroma sub-sampling

- Original color test strip



- Y’CbCr with sub sampling done – effects seen at highly saturated colors

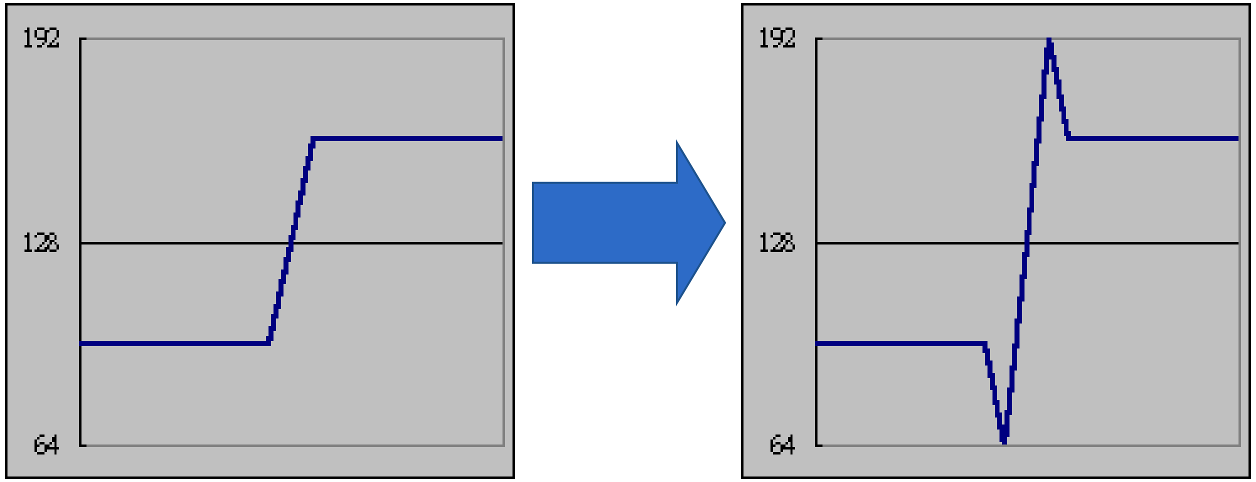


Contrast Enhancement

- Contrast: Increasing or decreasing the range
- Brightness: Increasing or decreasing the level

Edge Enhancement

- A must - all cameras add edges
- General approaches
  - Edge filter: NxN, 1xN+Nx1
  - Edge gain control
  - Edge detection module
- Noise should not be enhanced



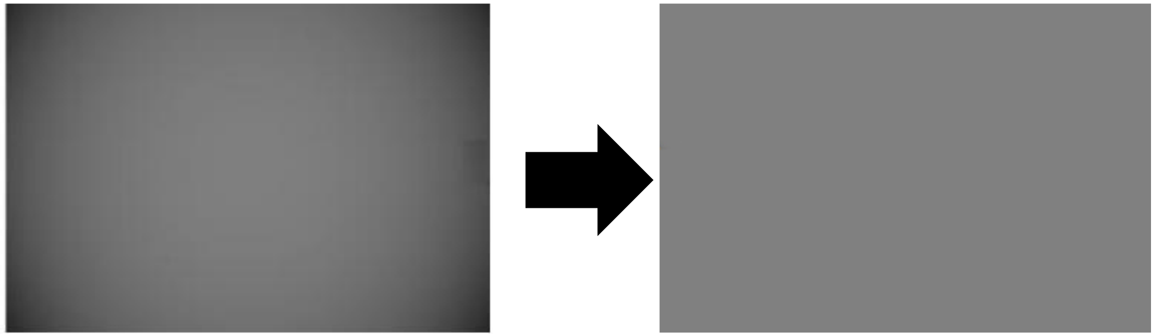
Edge Enhancement

- Normal and strong edge enhancement

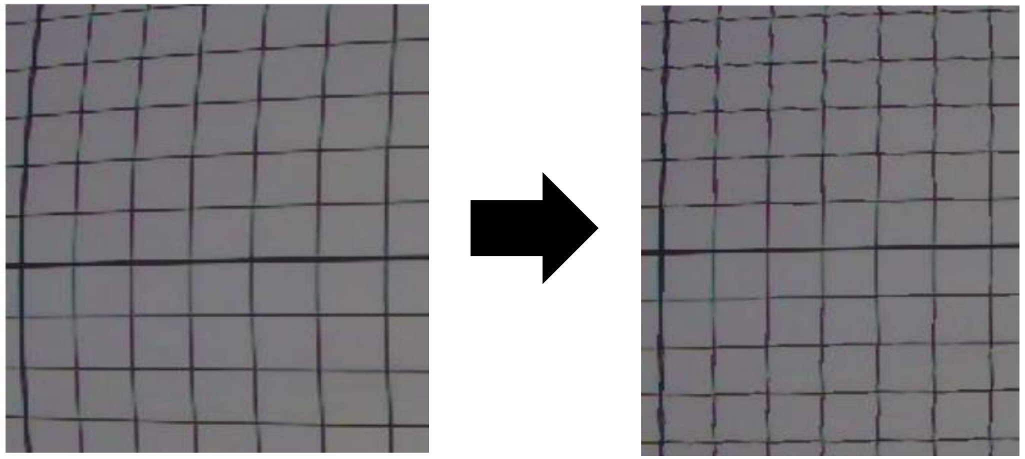
 

Optical Distortion Correction Module

- LSC
  - To compensate for lens which cause vignetting at outer fringe
  - Gain Offset look-up table for corresponding lens is used

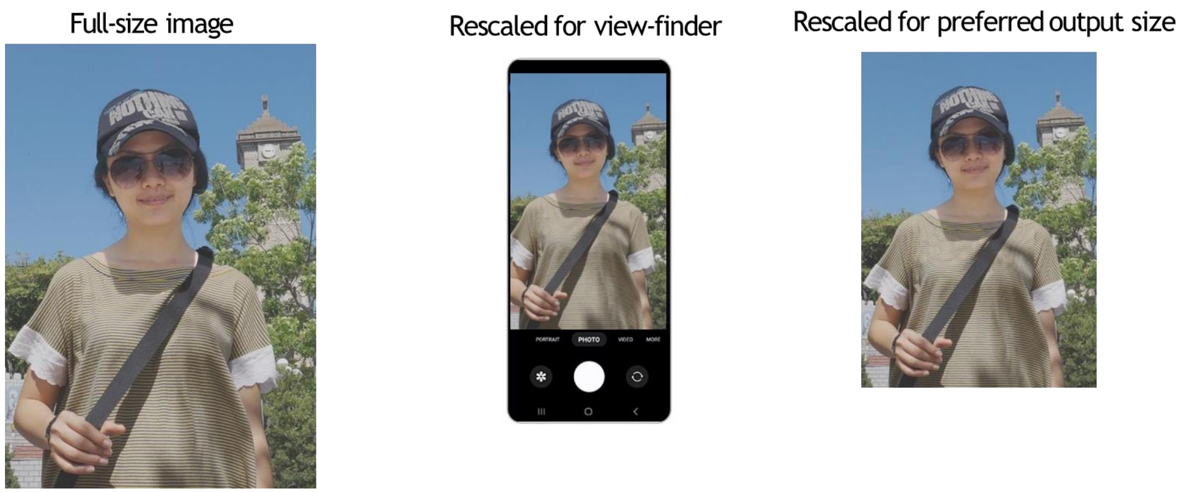


- LDC
  - Compensation for distortion caused by lens where parallel lines are rendered curved – barrel or pincushion



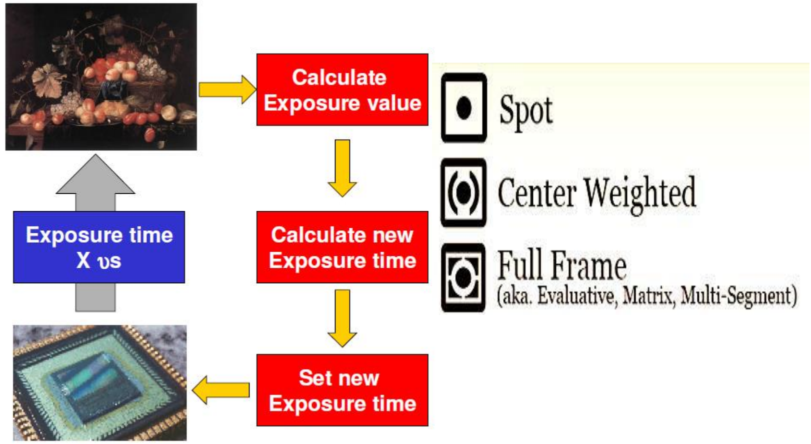
Resizing and Cropping

- Preview display
  - Sensor lines number doesn't match with LCD.
- Video capture
  - Sensor lines number doesn't match with output.
- Digital zoom
  - Crop smaller area centered at original center
- Raw data space or YUV space
- Performance vs. quality
  - Dropping or duplication, bilinear interpolation, bicubic interpolation



3A (Auto Exposure, WB, Focus)

- Auto Exposure
  - Measures average brightness of captured frame
  - Is hooked to sensor for exp time and gain, lens for aperture and IPIPE for digital gain
  - Depending on application and/or mode, different parameter will be prioritized
- Auto White Balance
  - Measures average colour content of captured frame
  - Is hooked to WB module to manipulate gain and offset of each colour channel
- Auto Focus
  - Measures sharpness of captured frame
  - Is hooked to lens stepper motor for adjusting focus



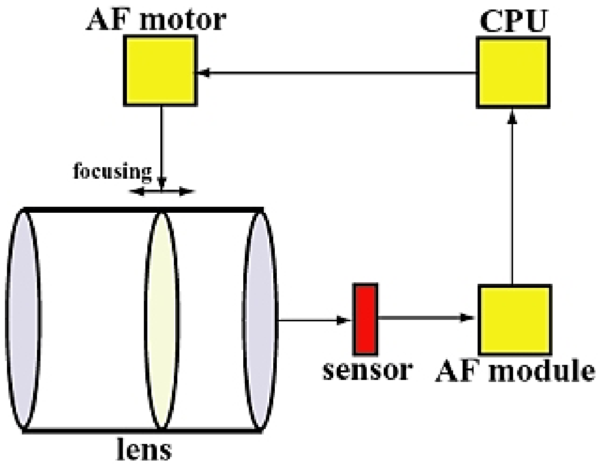


Image Processing in Camera

Raw image from sensor

Image Processing in Camera

Raw image from sensor

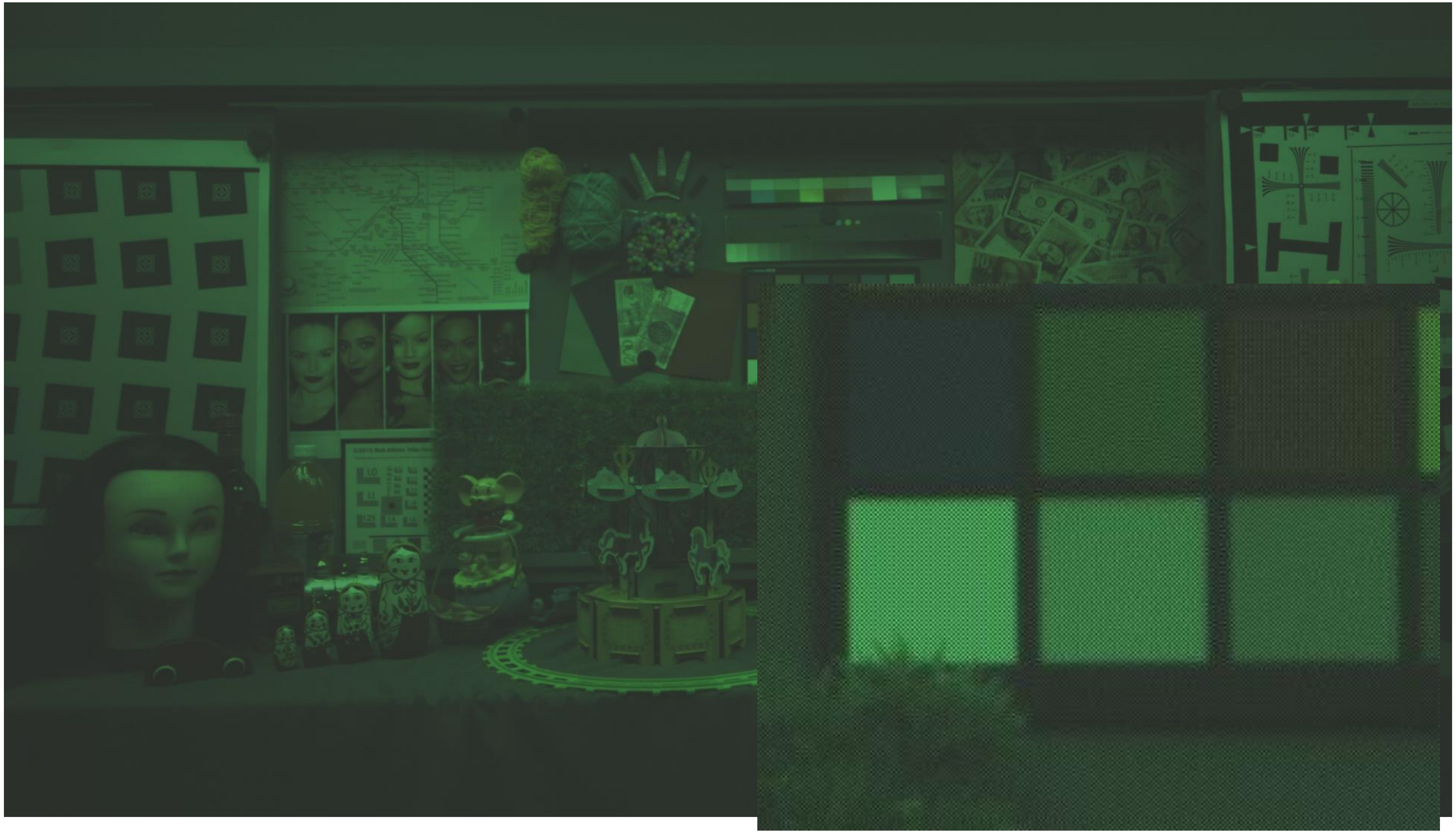


Image Processing in Camera

After optical black and shading correction

Image Processing in Camera

After demosaicing

Image Processing in Camera

After white balance

Image Processing in Camera

After color correction

Image Processing in Camera

After exposure adaption (Gamma/tone mapping)

Image Processing in Camera

After denoising

Image Processing in Camera

After denoising

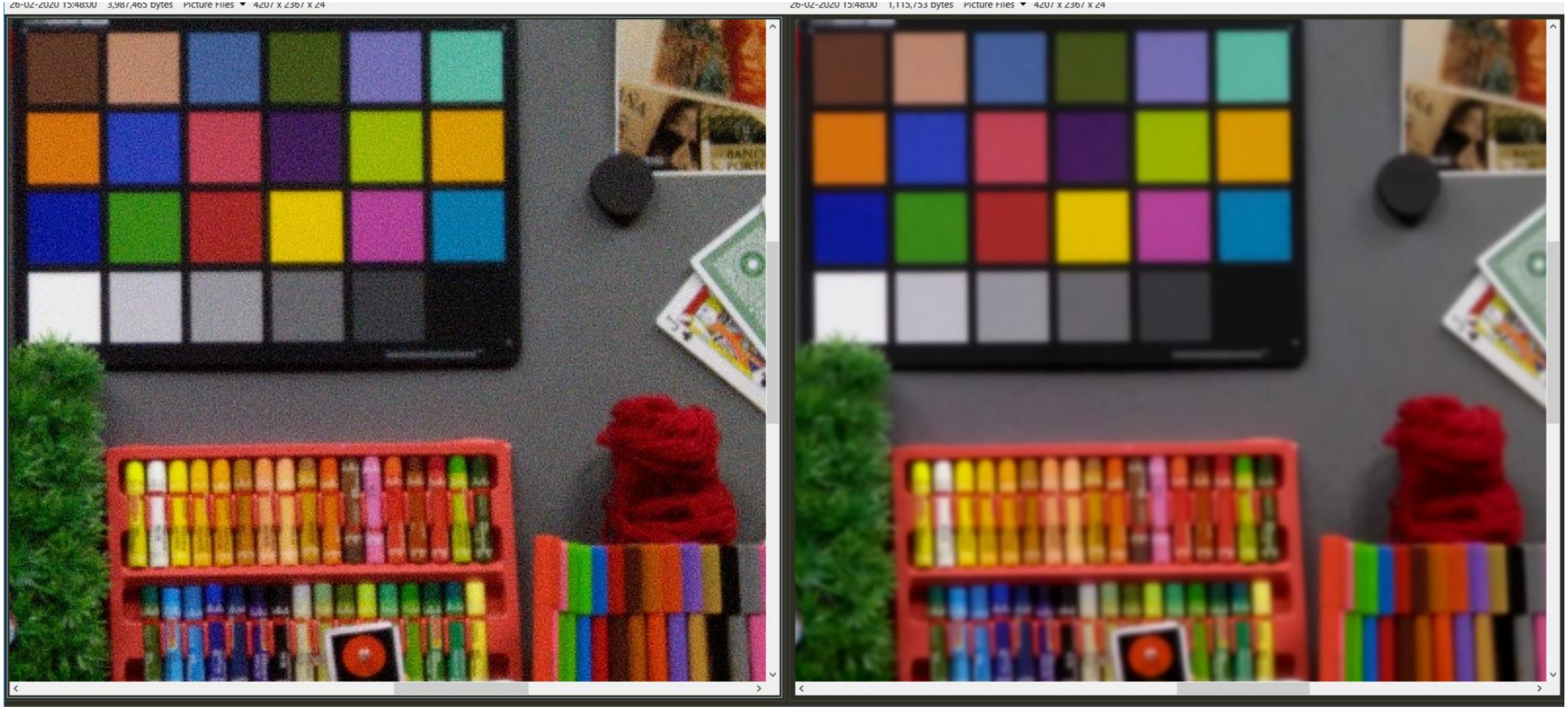
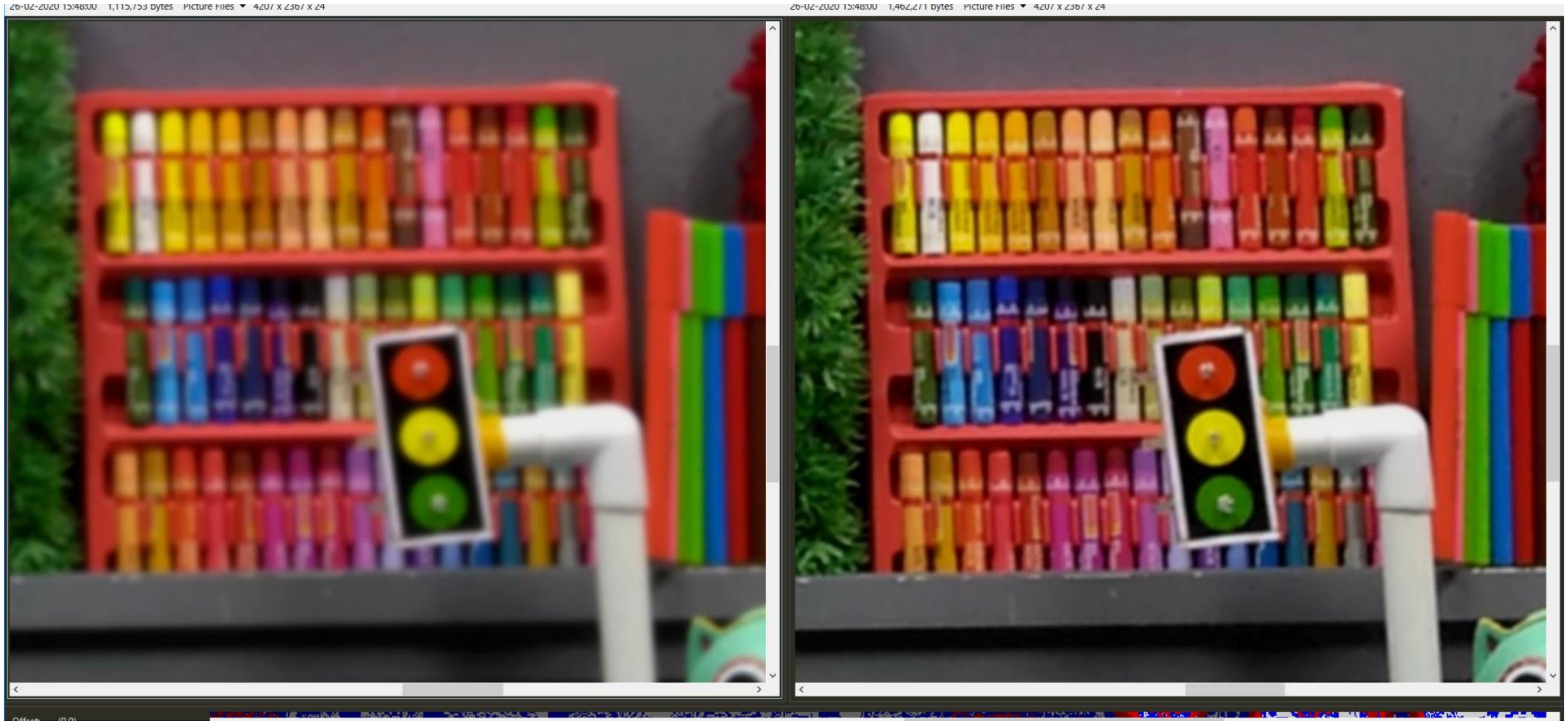


Image Processing in Camera

After sharpening

Image Processing in Camera

After sharpening



ISP - Comments

- Again, it is important to stress that the exact steps mentioned in these notes only serve as a guide to what takes place in a camera
- Smartphone camera pipelines are more complex.
- Note: for the different camera makes/models, the operations could be performed in a different order and in different ways (e.g., combining sharpening with demosaicing).
- Large set of parameters that influences final image or video quality

Advanced ISP Techniques

High dynamic range imaging

The world has a high dynamic range

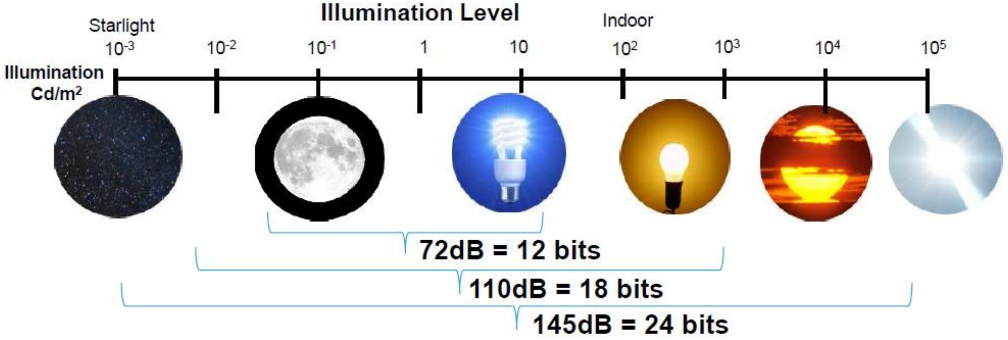
1

1500

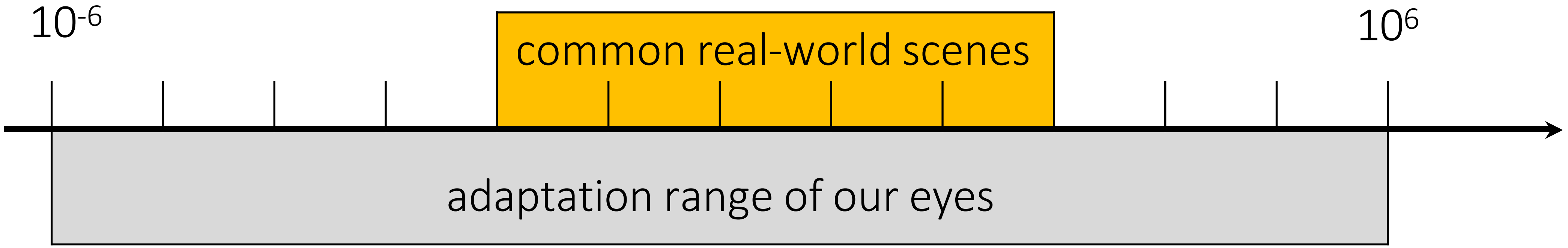
25,000

400,000

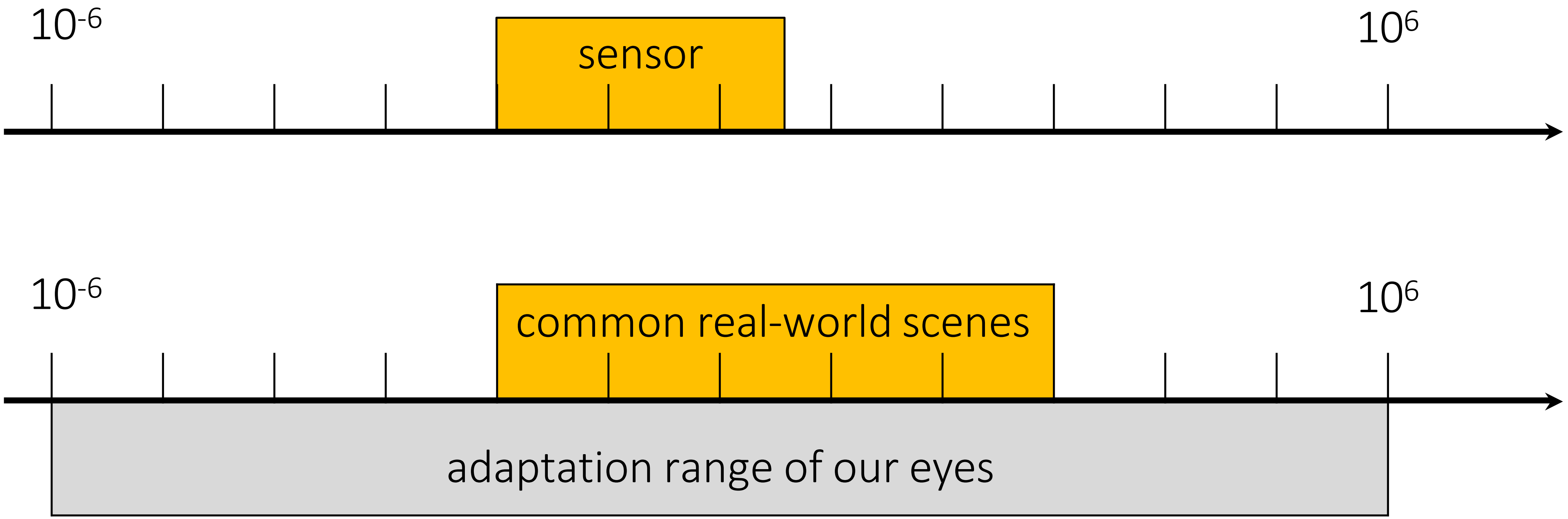
2,000,000,000



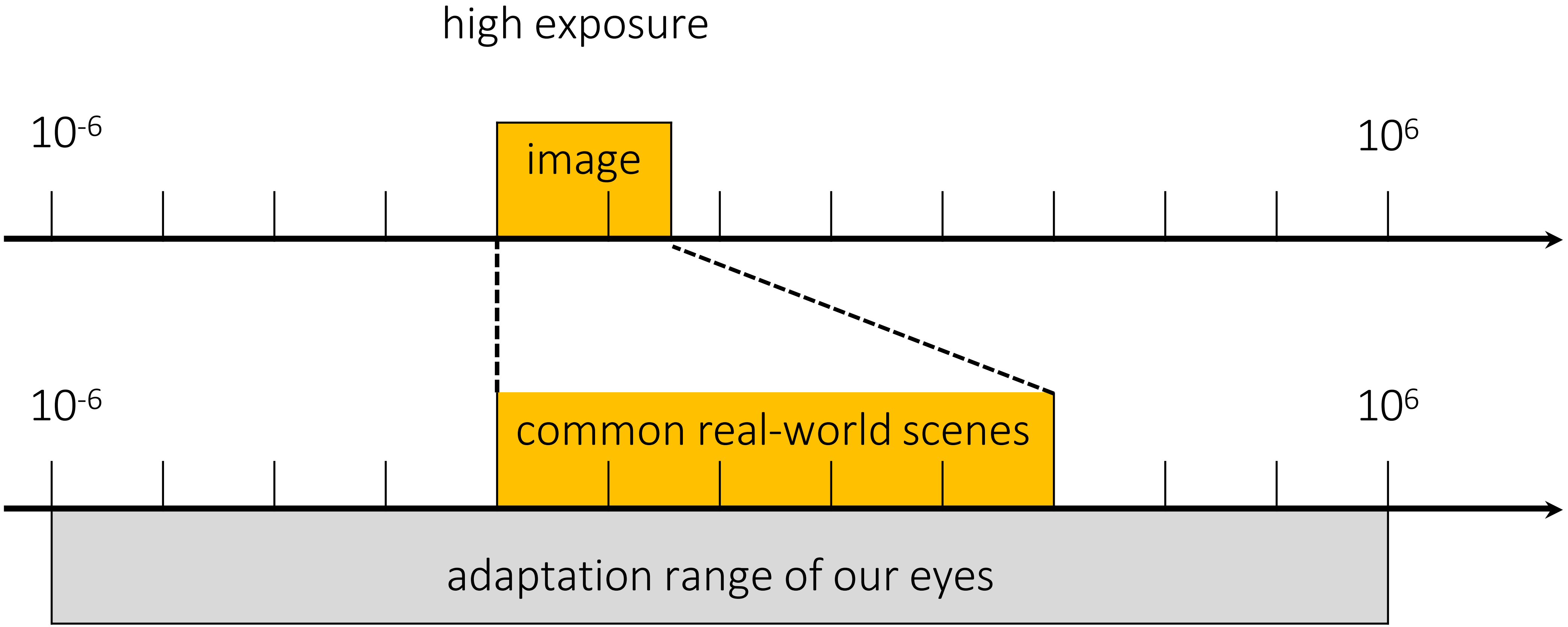
The world has a high dynamic range



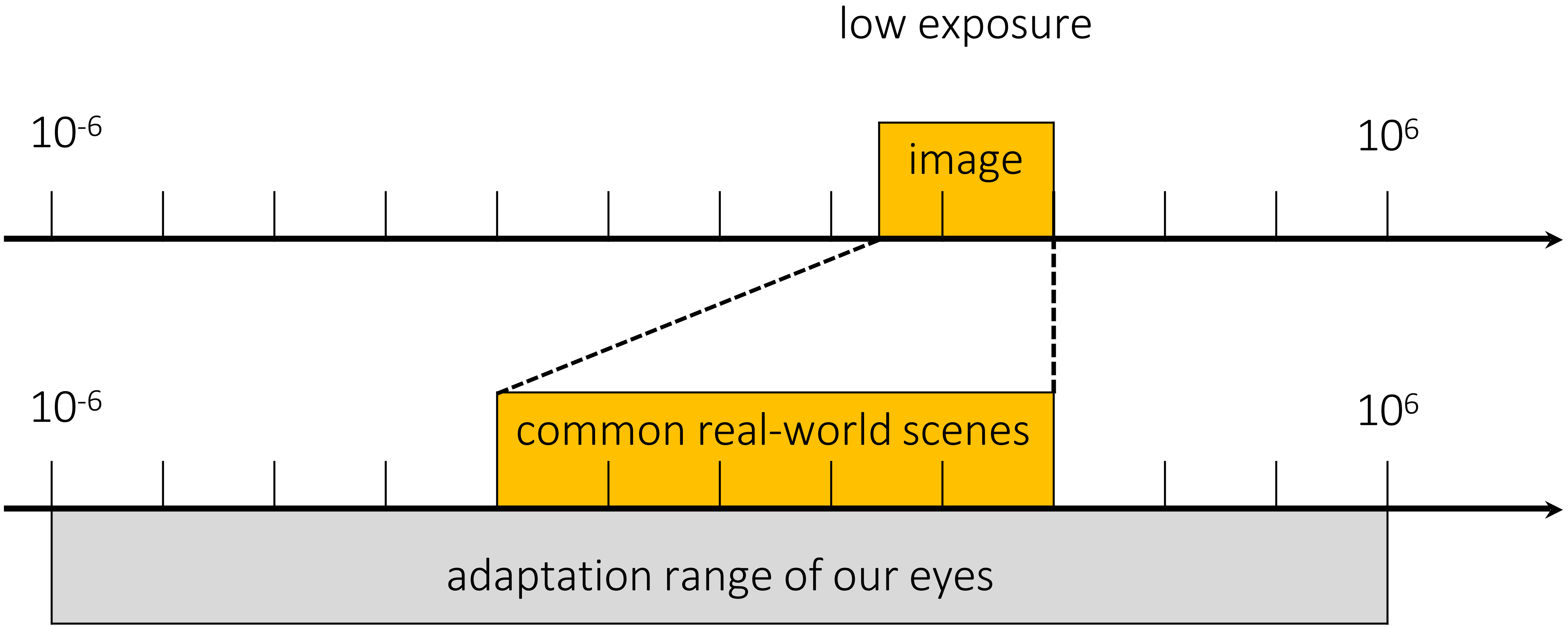
(Digital) sensors also have a low dynamic range



(Digital) images have an even lower dynamic range



(Digital) images have an even lower dynamic range



Our devices do not match the real world

- 10:1 photographic print (higher for glossy paper)
- 20:1 artist's paints
- 200:1 slide film
- 500:1 negative film
- 1000:1 LCD display
- 2000:1 digital SLR (at 12 bits)
- 100000:1 real world

HDR imaging and tonemapping are distinct techniques with different goals

Two challenges:

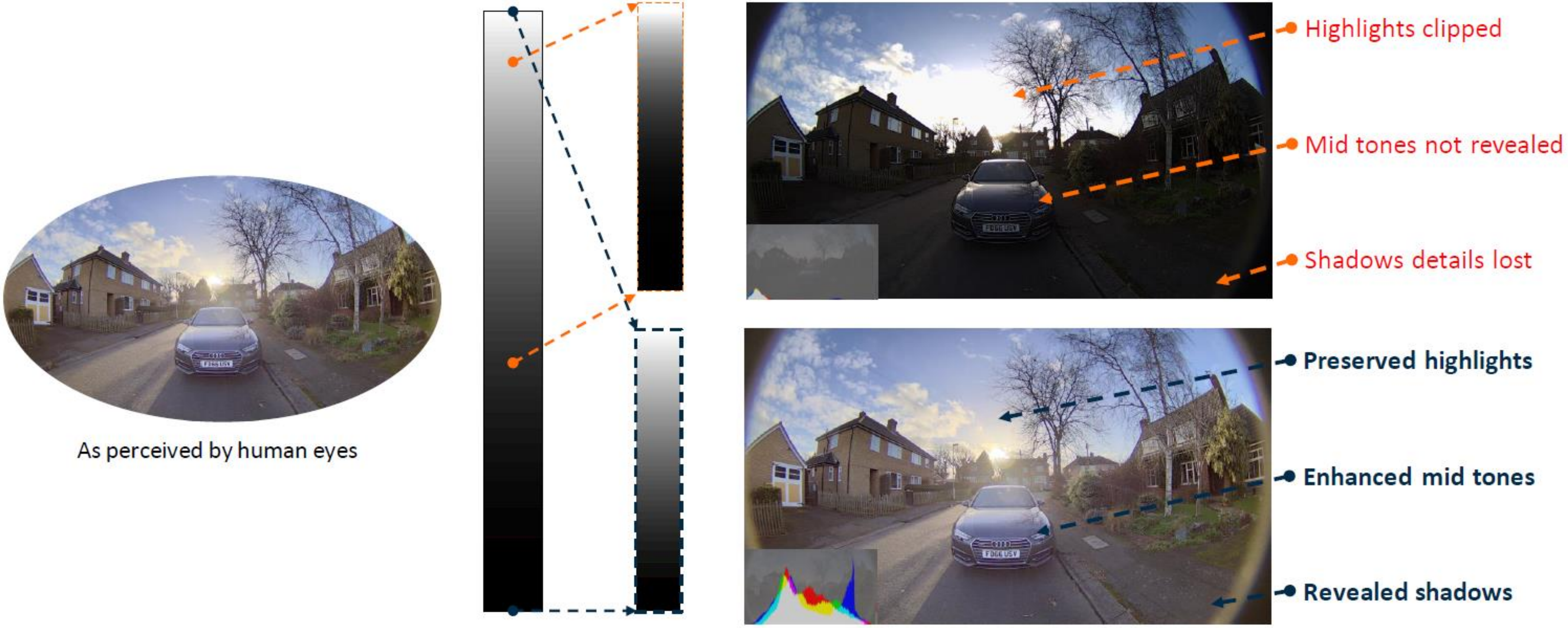
HDR imaging compensates for *sensor* limitations

1. HDR imaging – which parts of the world do we measure in the 8-14 bits available to our sensor?
2. Tonemapping – which parts of the world do we show in the 4-10 bits available to our display?

Tonemapping compensates for *display* limitations

HDR Imaging

$$ISO\,Dynamic\,Range = \frac{L_{sat}}{L_{\min}}$$



As perceived by human eyes


HYATT


HYATT


HYATT


HYATT


HYATT
THE INTERNATIONAL FUR EXCHANGE

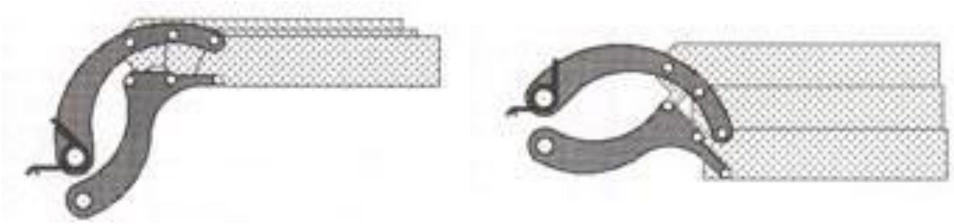
Key idea

1. Exposure bracketing: Capture multiple LDR images at different exposures

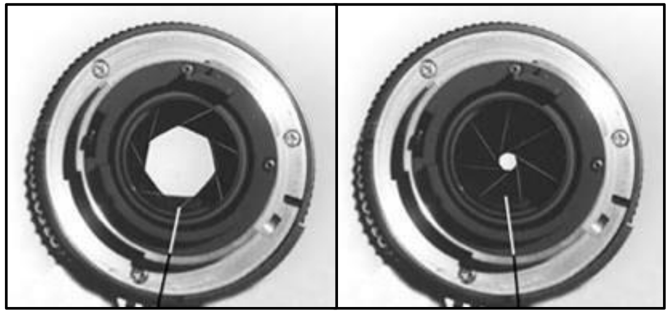
2. Merging: Combine them into a single HDR image

Ways to vary exposure

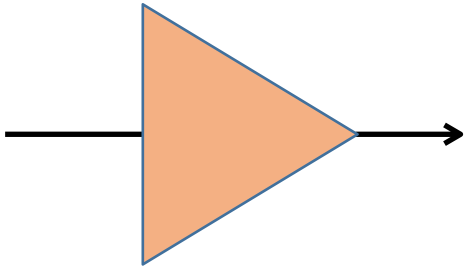
1. Shutter speed



2. F-stop (aperture, iris)



3. ISO

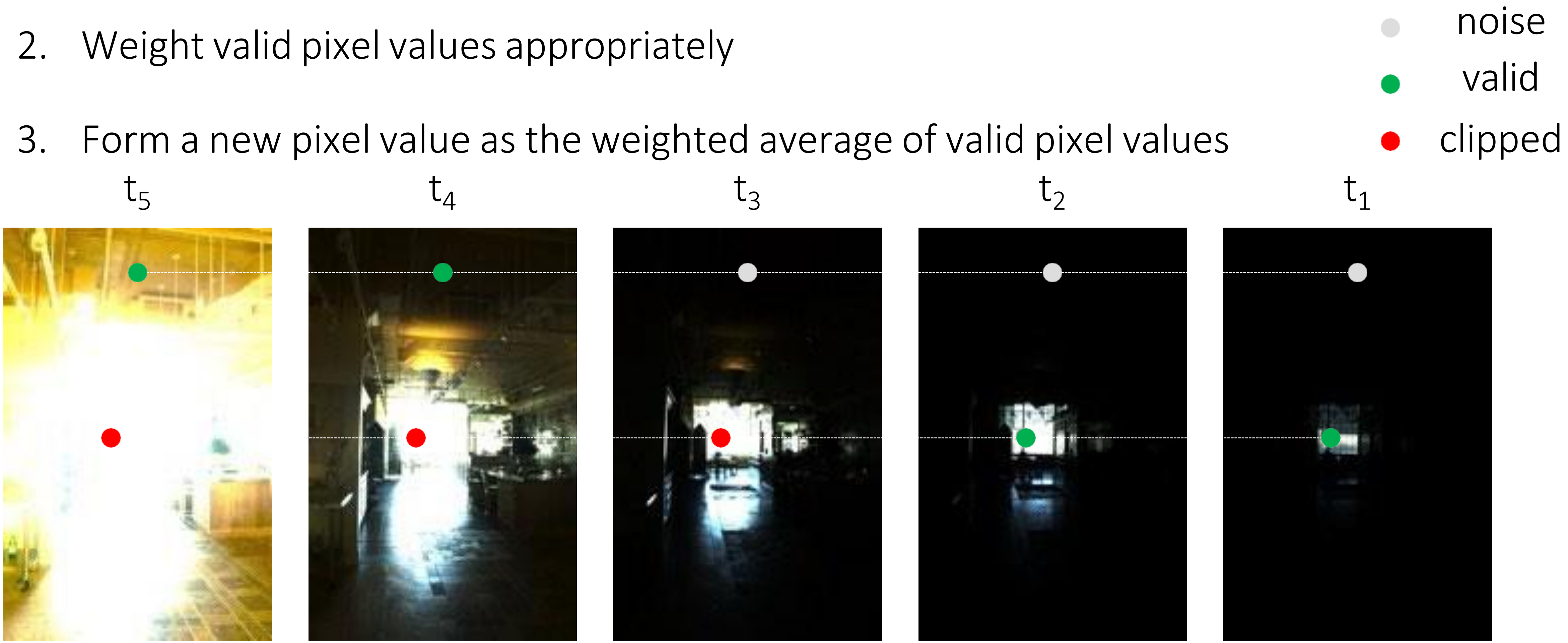


4. Neutral density (ND) filters

Merging RAW (linear) exposure stacks

For each pixel:

1. Find “valid” images ← (noise) 0.05 < pixel < 0.95 (clipping)
2. Weight valid pixel values appropriately
3. Form a new pixel value as the weighted average of valid pixel values



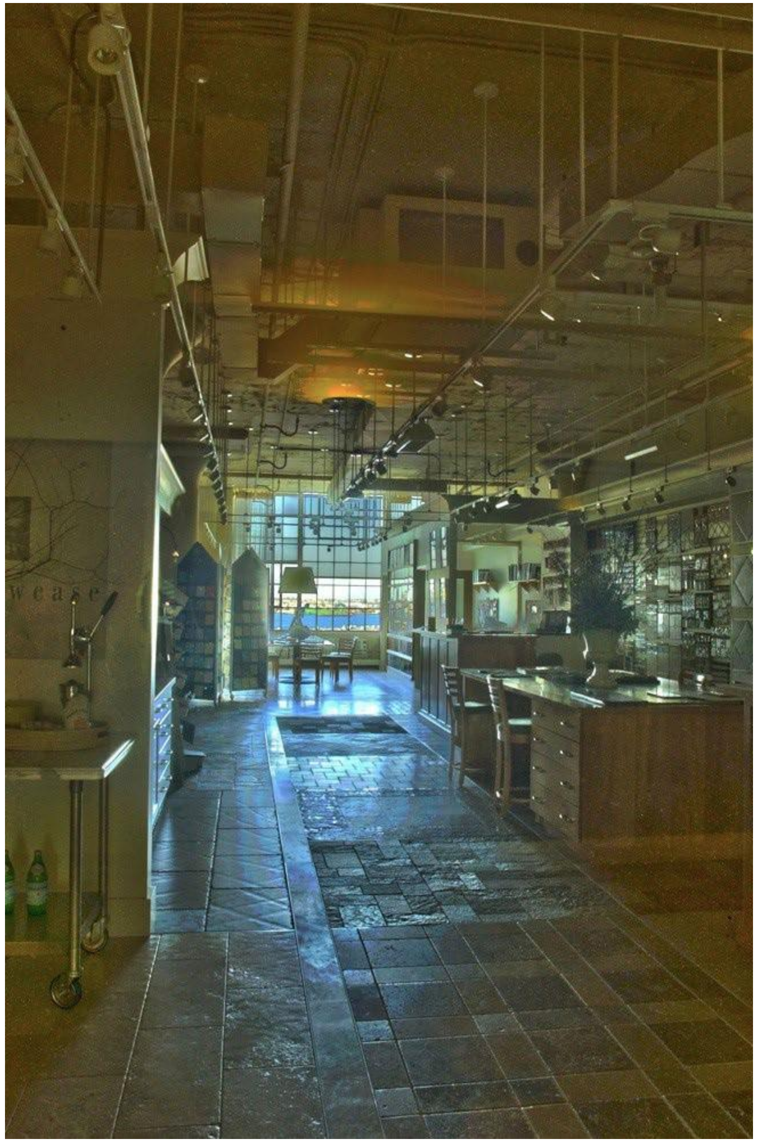
Merging RAW (linear) exposure stacks

For each pixel:

1. Find "valid" images ⟵ (noise) 0.05 < pixel < 0.95 (clipping)
2. Weight valid pixel values appropriately ⟵ (pixel value) / t_i
3. Form a new pixel value as the weighted average of valid pixel values

t_5 t_4 t_3 t_2 t_1

Merging result (after tonemapping)



How do we store HDR images?

- Most standard image formats store integer 8-bit images
- Some image formats store integer 12-bit or 16-bit images
- HDR images are floating point 32-bit or 64-bit images

How do we store HDR images?

Use specialized image formats for HDR images

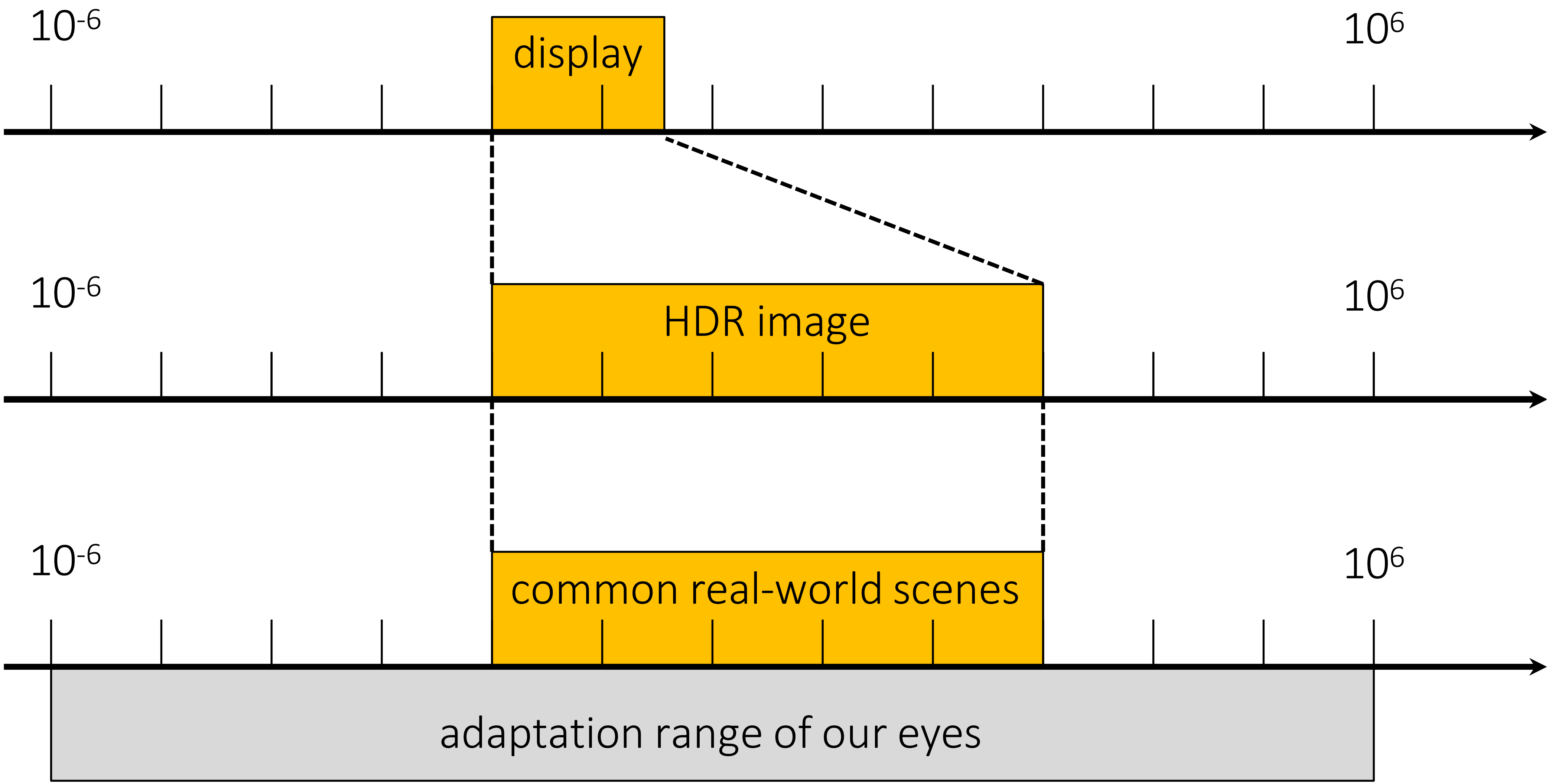
portable float map (.pfm)
- very simple to implement

Radiance format (.hdr)
- supported by Matlab

OpenEXR format (.exr)
- multiple extra features

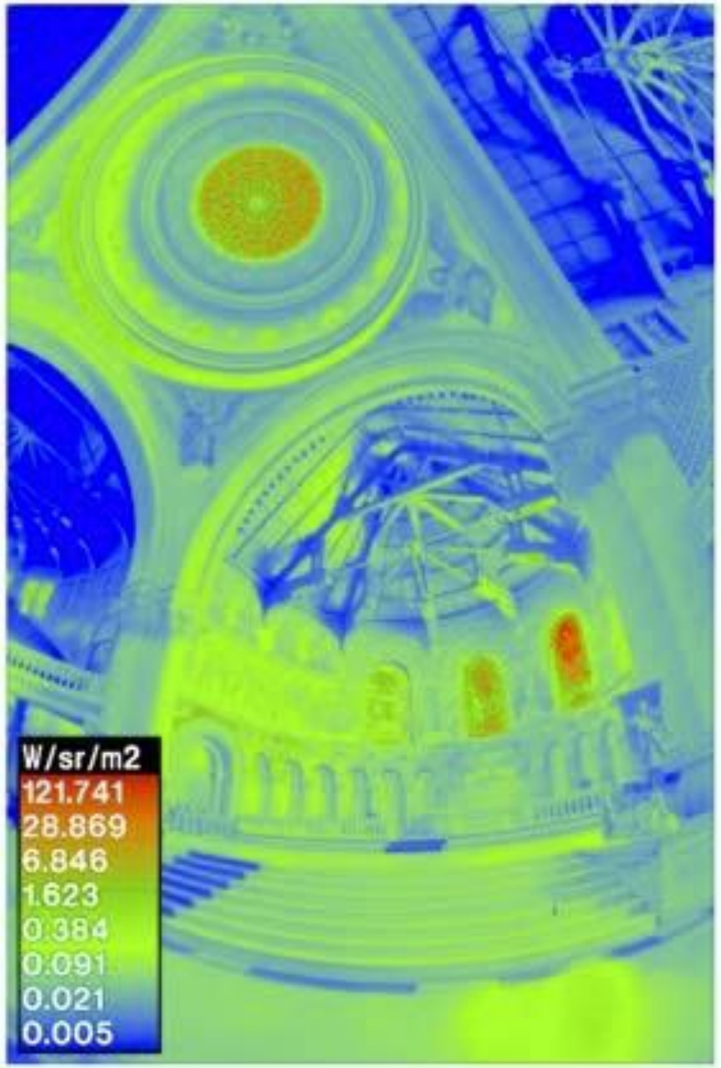
Tonemapping

How do we display our HDR images?



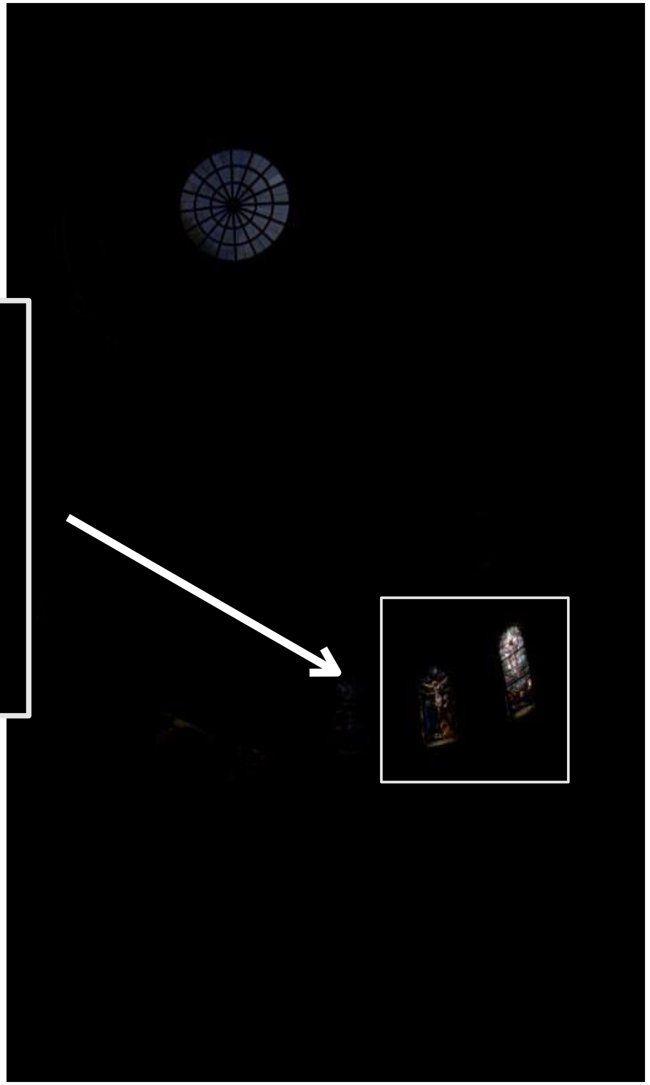
Linear scaling

Scale image so that maximum value equals 1.



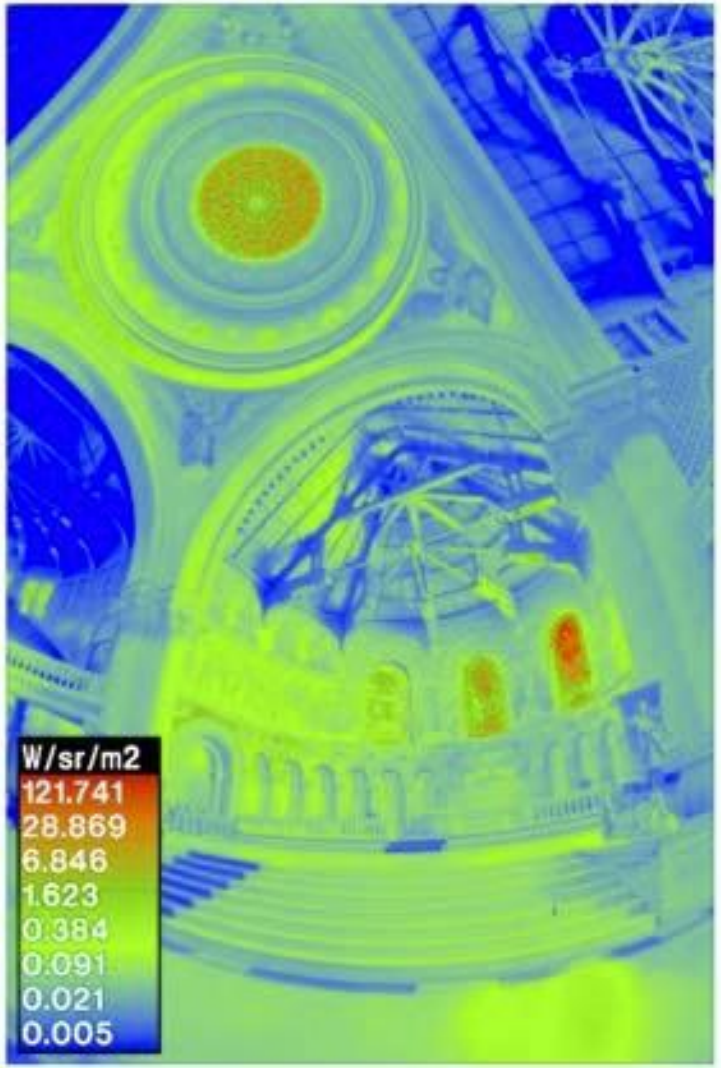
→

HDR image *looks* underexposed because of the display's limited dynamic range, but is *not* actually underexposed.

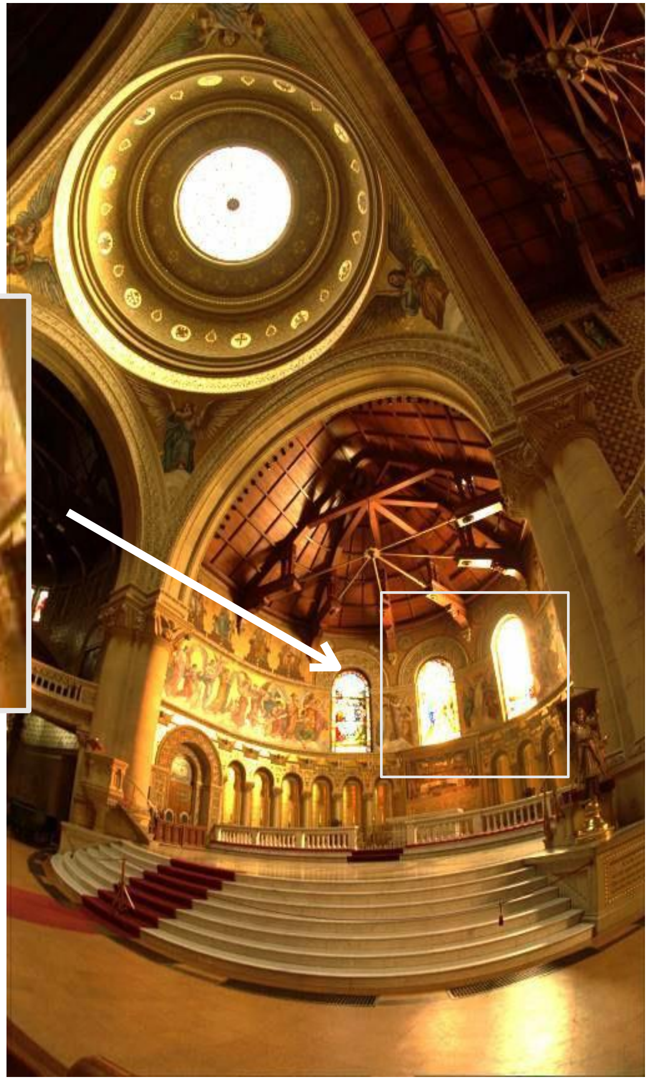


Linear scaling

Scale image so that 10% value equals 1.



HDR image *looks* saturated because of the display's limited dynamic range, but is *not* actually saturdated.

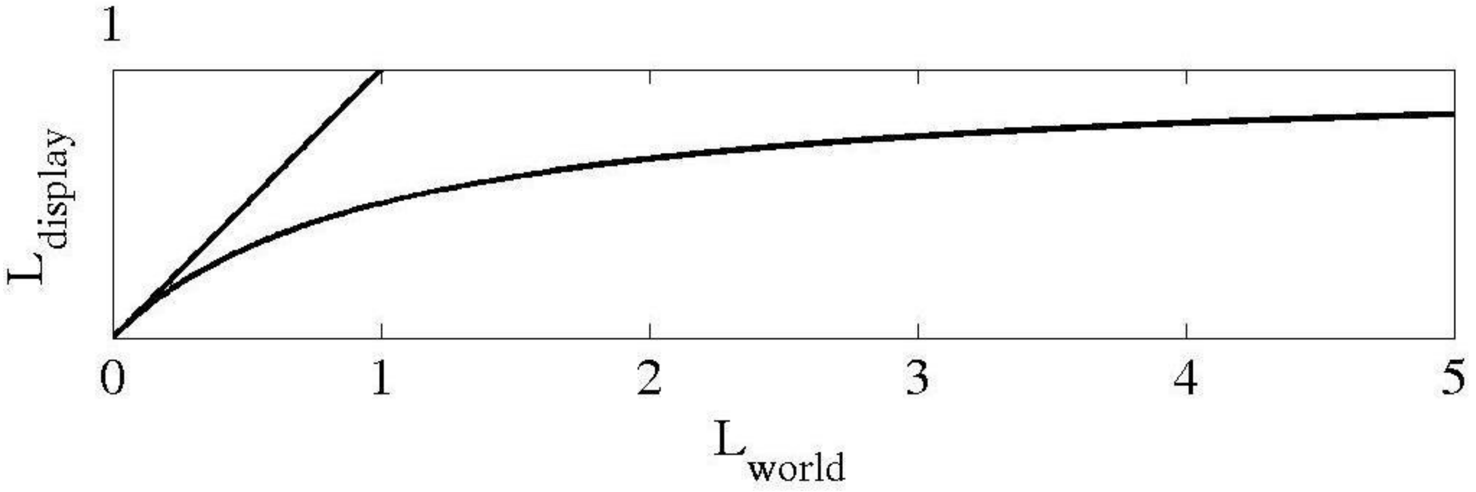


Can you think of something better?

Photographic tonemapping

Apply the same non-linear scaling to all pixels in the image so that:

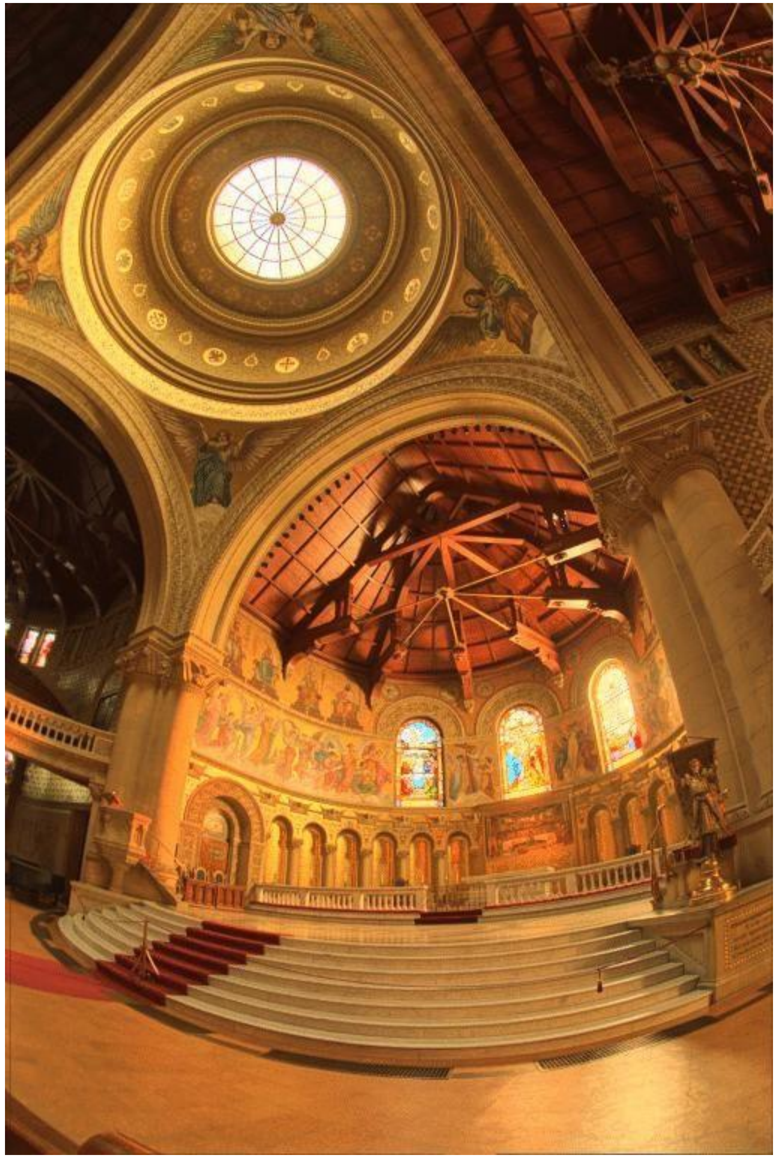
- Bring everything within range → asymptote to 1
- Leave dark areas alone → slope = 1 near 0



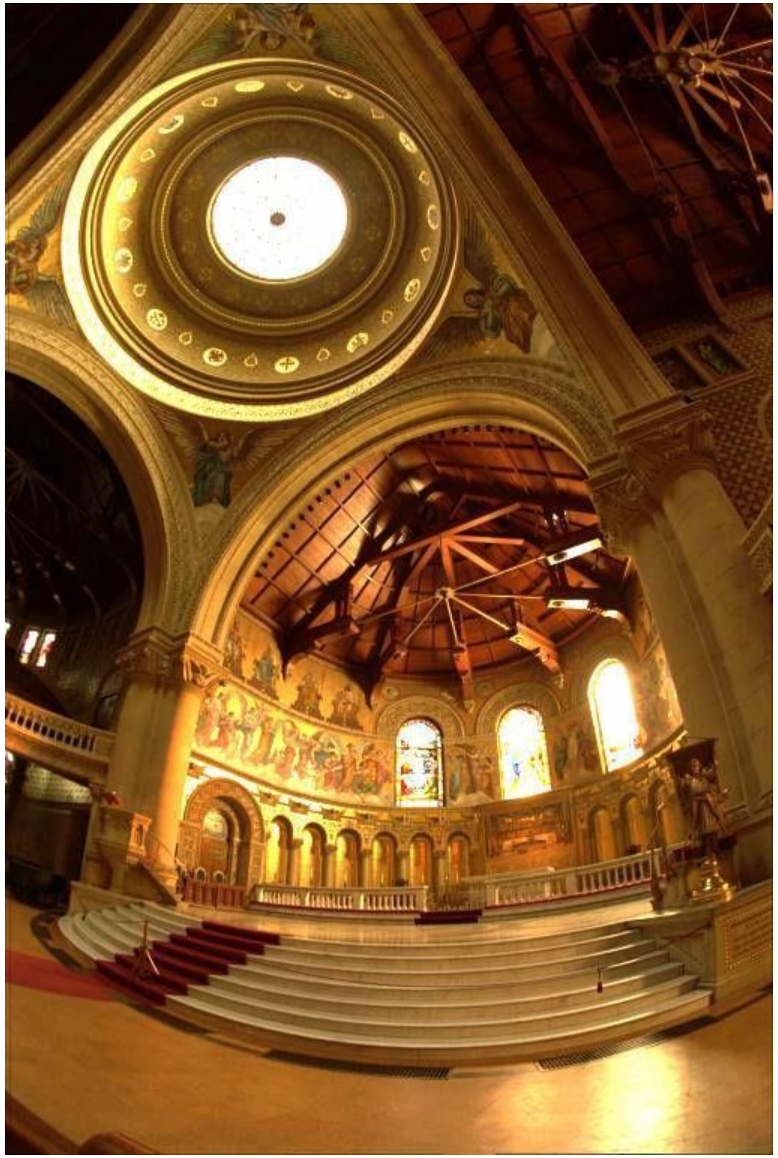
$$I_{display} = \frac{I_{HDR}}{1 + I_{HDR}}$$

- Photographic because designed to approximate film zone system.
- Perceptually motivated, as it approximates our eye's response curve.

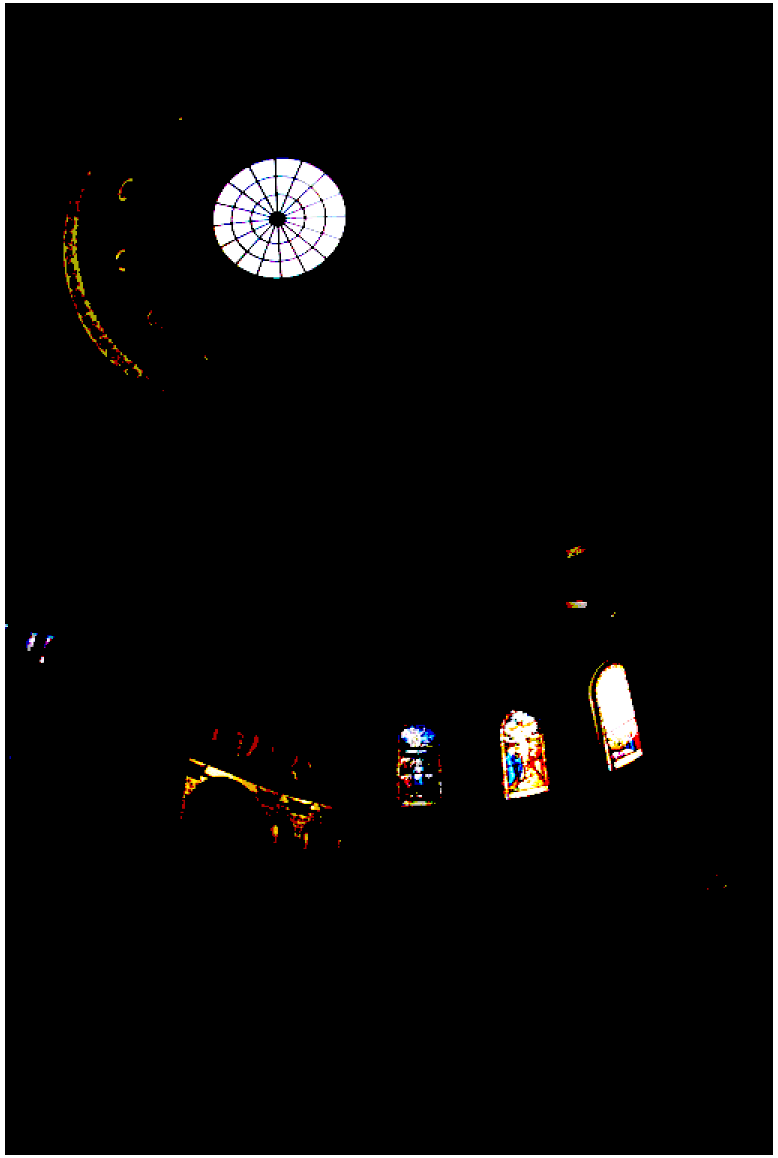
Examples



photographic tonemapping

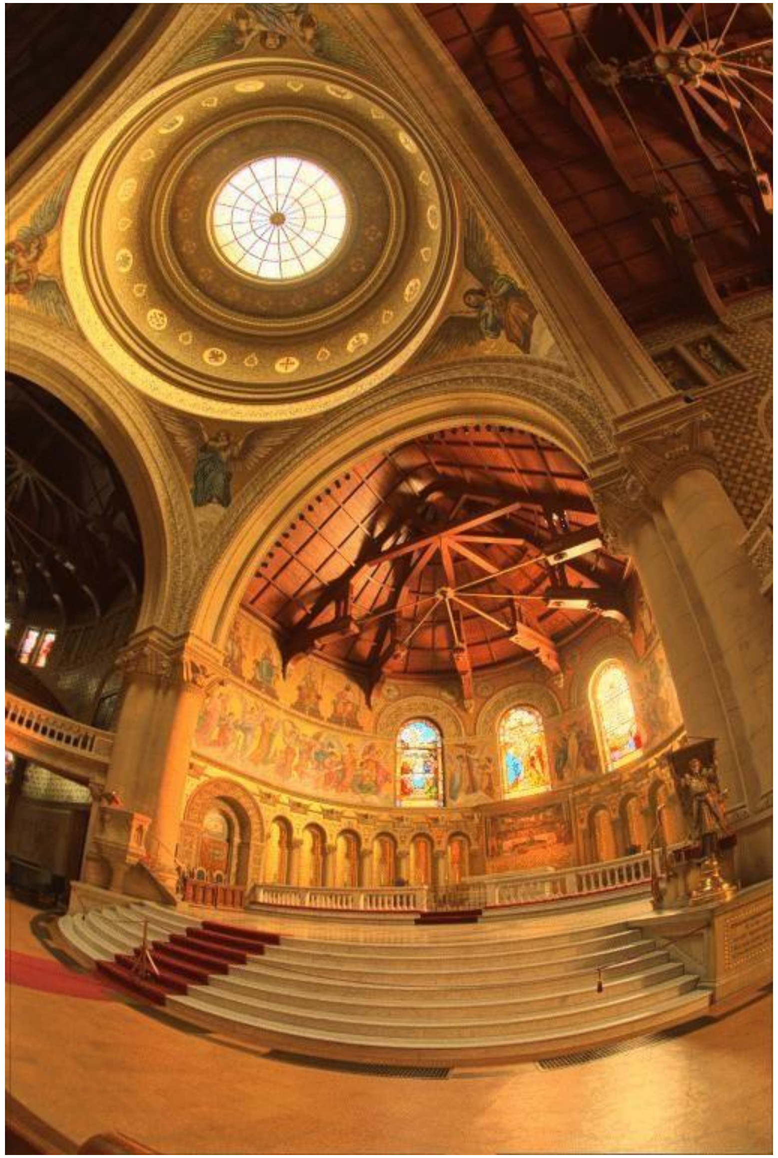


linear scaling (map 10% to 1)

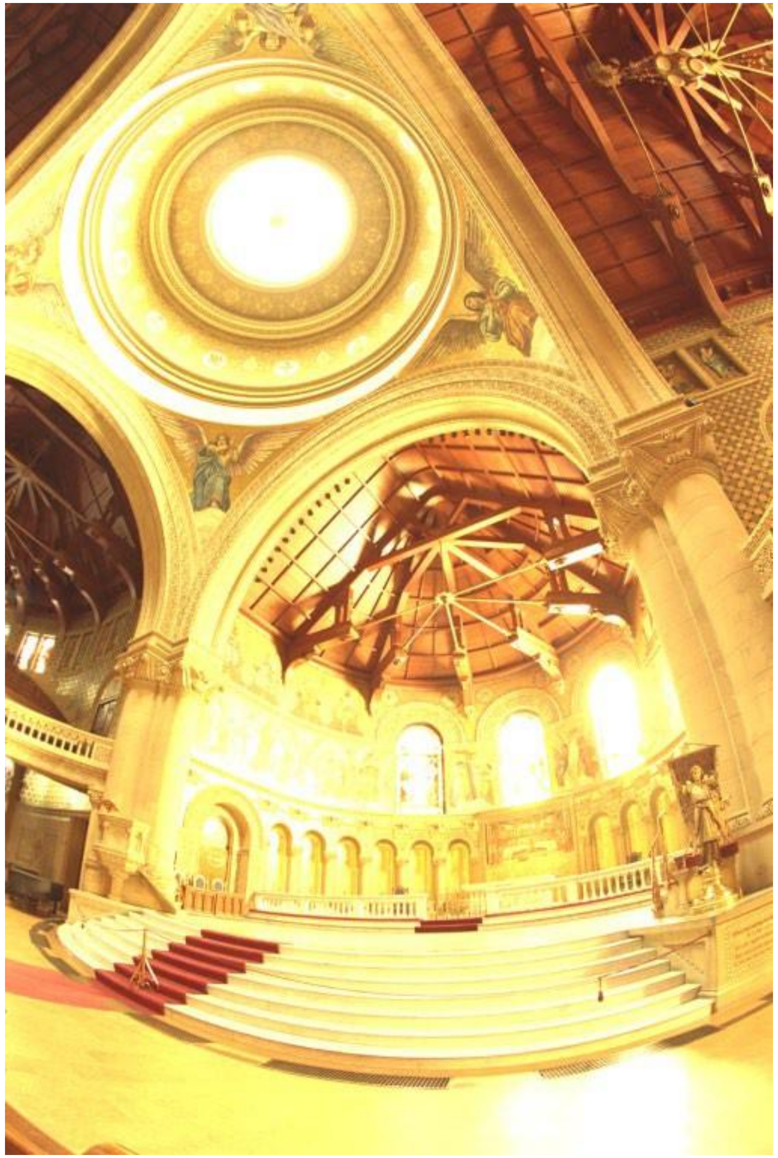


linear scaling (map 100% to 1)

Compare with LDR images



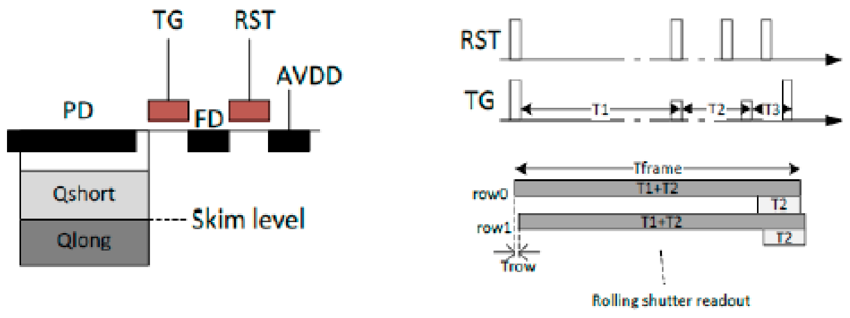
photographic tonemapping



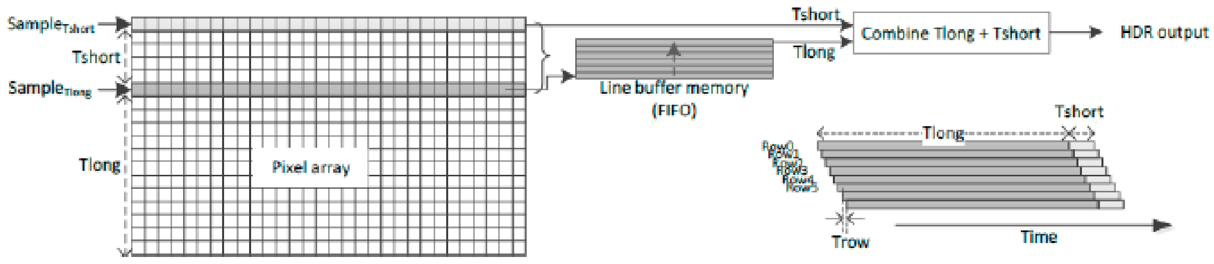
high exposure

low exposure

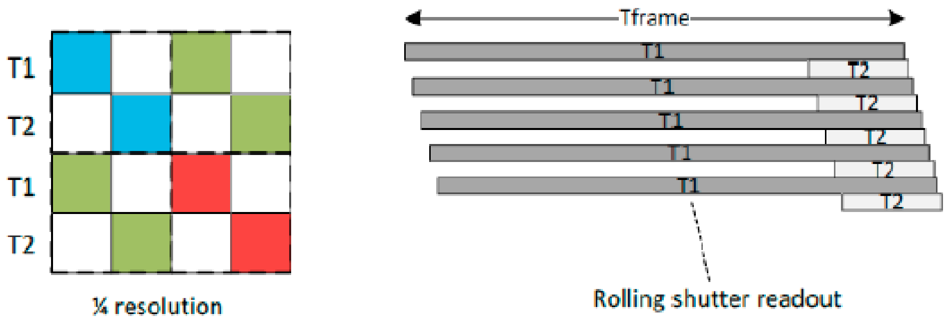
HDR Imaging – different sensor architectures



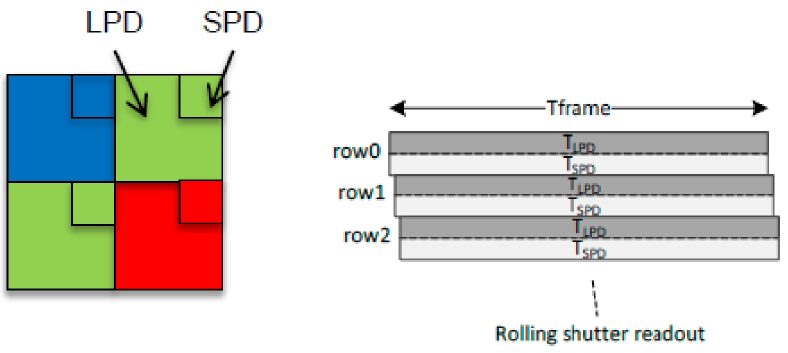
Skimming (later overflow) HDR



Staggered HDR



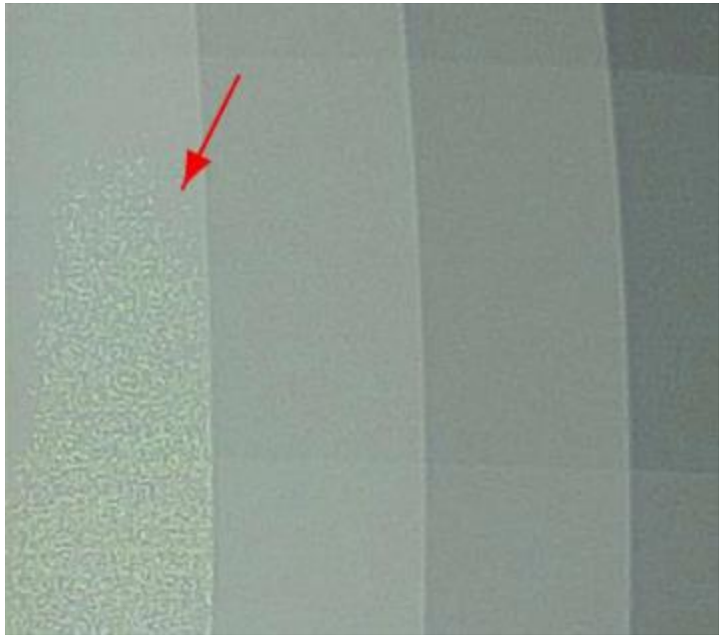
Down-sampling HDR



Split Pixel HDR

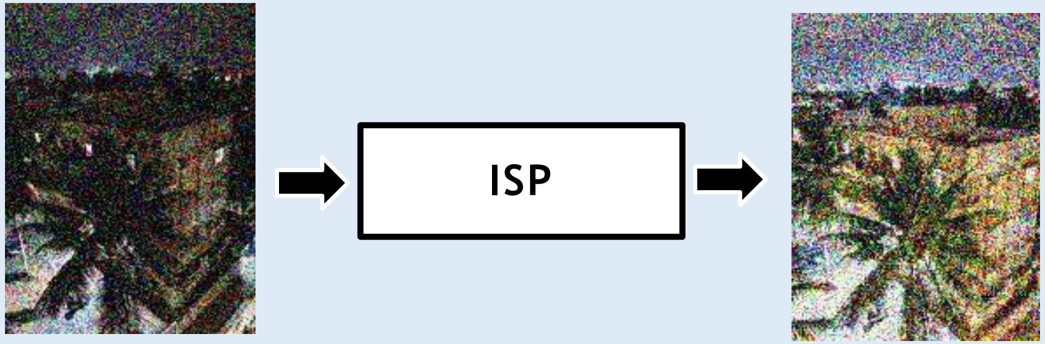
HDR Imaging – Common Issues

Ghosting

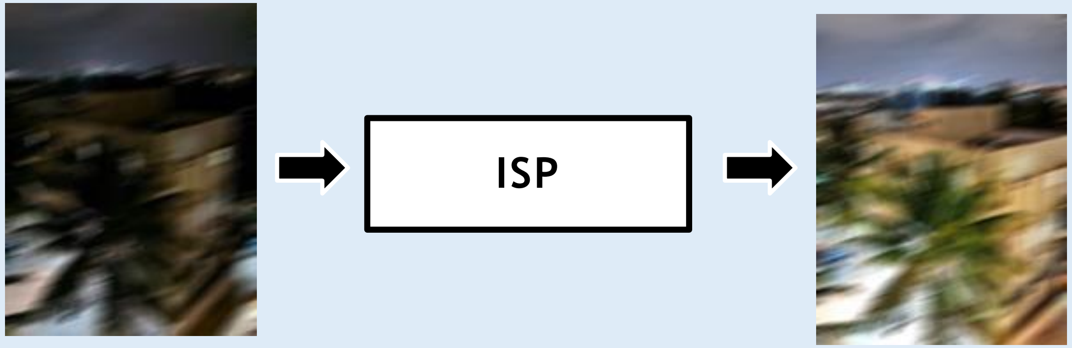


SNR Discontinuity

Low-light imaging

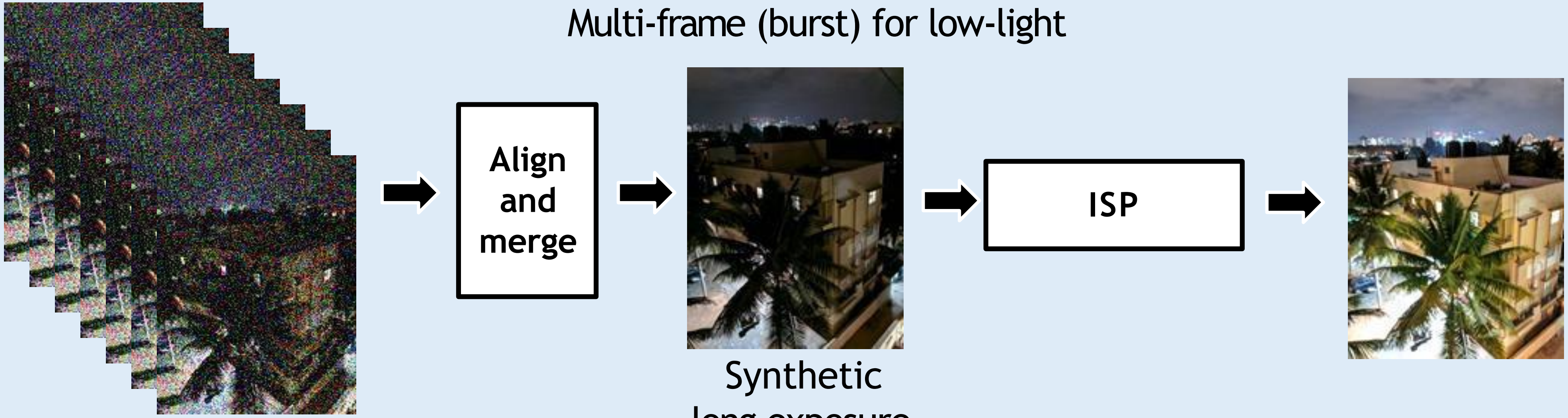


Single short exposure (noise corruption)



Long exposure (motion blur)

Multi-frame (burst) for low-light

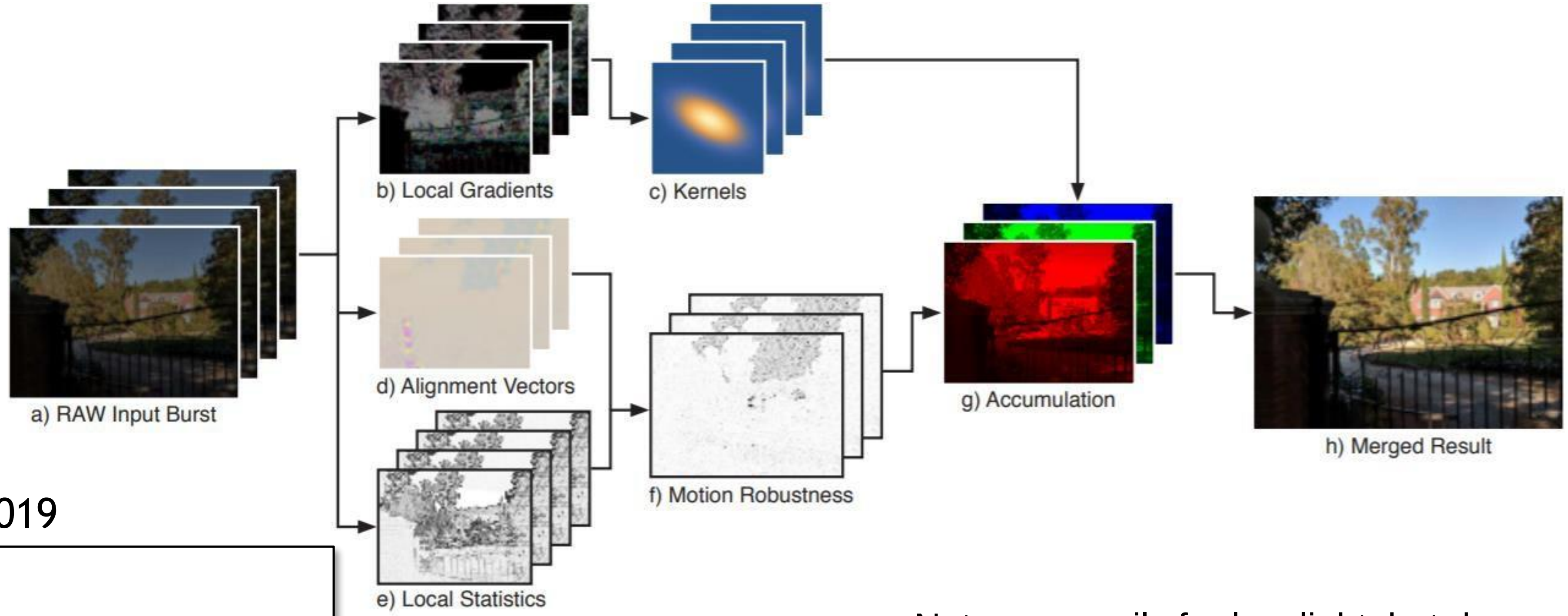


Single short exposure (burst)

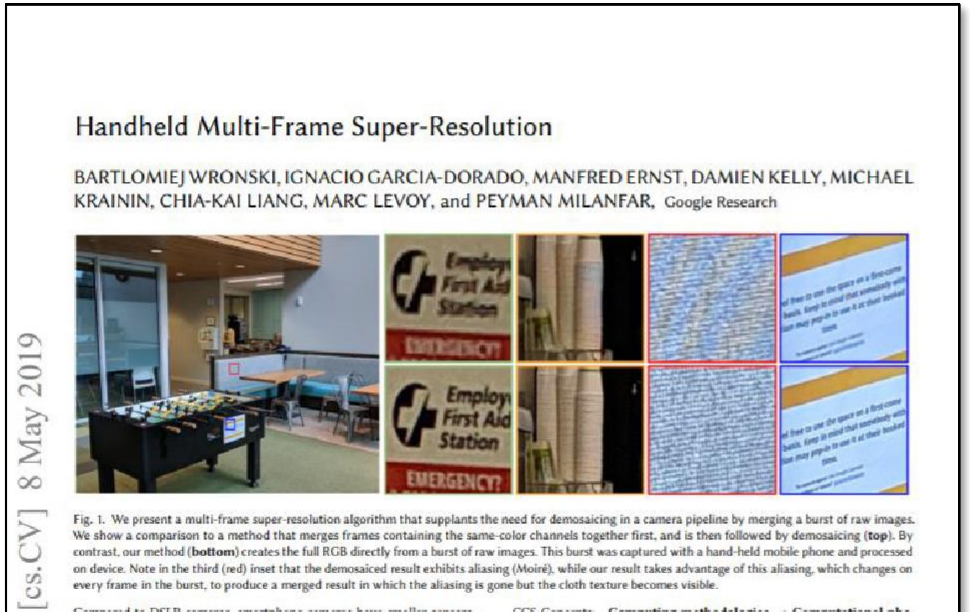
Synthetic
long exposure

Low-light imaging is essentially a noise-reduction problem.

Google pixel phones multi-frame



Wronski et al SIGGRAPH 2019

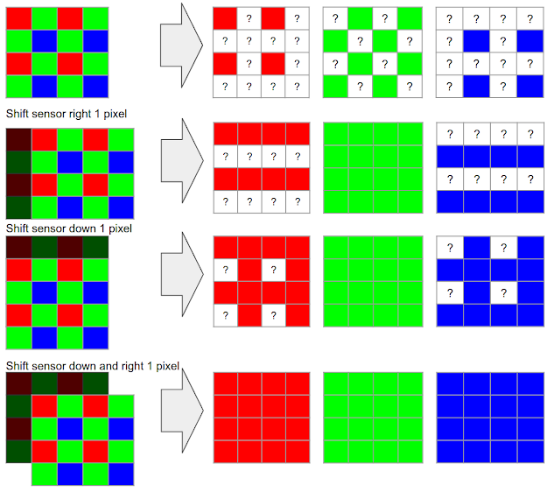


Handheld Multi-Frame Super-Resolution

BARTLOMIEJ WRONSKI, IGNACIO GARCIA-DORADO, MANFRED ERNST, DAMIEN KELLY, MICHAEL KRAININ, CHIA-KAI LIANG, MARC LEVOY, and PEYMAN MILANFAR, Google Research

[cs.CV] 8 May 2019

Fig. 1. We present a multi-frame super-resolution algorithm that supplants the need for demosaicing in a camera pipeline by merging a burst of raw images. We show a comparison to a method that merges frames containing the same-color channels together first, and is then followed by demosaicing (**top**). By contrast, our method (**bottom**) creates the full RGB directly from a burst of raw images. This burst was captured with a hand-held mobile phone and processed on device. Note in the third (red) inset that the demosaiced result exhibits aliasing (Moiré), while our result takes advantage of this aliasing, which changes on every frame in the burst, to produce a merged result in which the aliasing is gone but the cloth texture becomes visible.



Not necessarily for low-light, but does target RAW.

This paper uses multiple frames and very small camera motion (from hand tremors) to perform demosaicing and super-resolution. By exploiting motion, they can fill in missing Bayer data too.

Image Quality

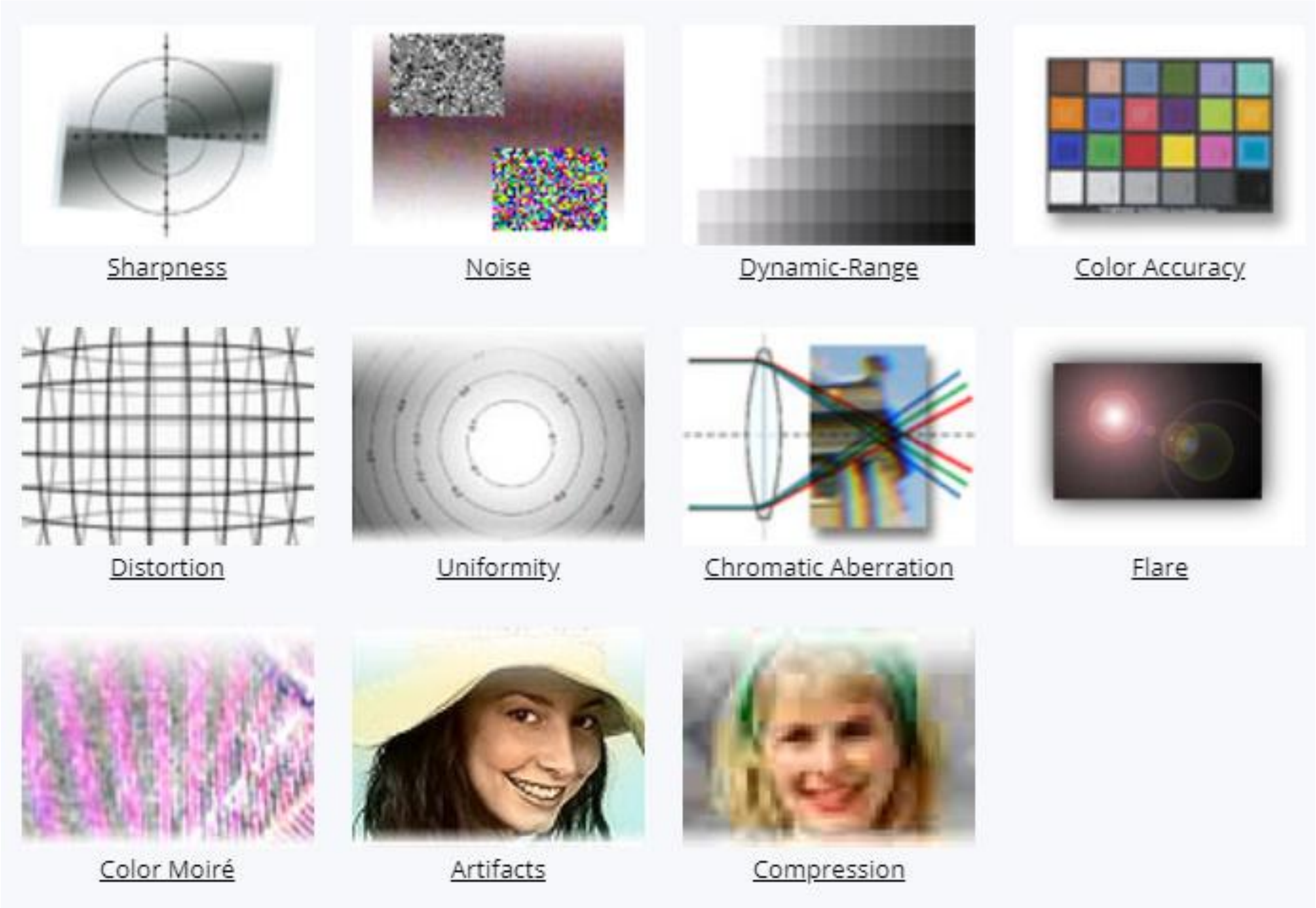
Introduction – Image Quality (IQ)

- What is Image Quality (IQ) ?
  - Perception of how picture “looks good”
  - In essence a subject matter
- What influences “IQ”?
  - Camera performance, which depends on shooting conditions: illumination, illuminant, optical parameters, sensor sensitivity, processing parameters…
  - Content has a strong influence on image quality perception
  - IQ perception is different between imaging expert, professional photographers and consumers

Image Quality Evaluation

- Subjective evaluation
  - “Subjective” means real people giving an opinion like: “big, small, heavy, light, cold, hot,…”'
  - People can judge the quality of photographs
  - Methodology is key to get non biased results
- Objective evaluation
  - Objective means a measurement that is neutral, operator independent : “2cm, 15ms, 150Kg etc.”
  - A device must provide figures (metrics) that are related to image quality
  - Normalizations may be necessary to have comparable metrics (cameras with different resolutions)

IQ factors


Sharpness
Noise
Dynamic-Range
Color Accuracy
Distortion
Uniformity
Chromatic Aberration
Flare
Color Moiré
Artifacts
Compression

Quantifying Camera Image Quality

Still Objective Measurements

Global Attributes

(independent of viewing distance)

- Exposure and tone
- Dynamic range
- Color
- Shading
- Geometric distortion
- Stray light

Local Attributes

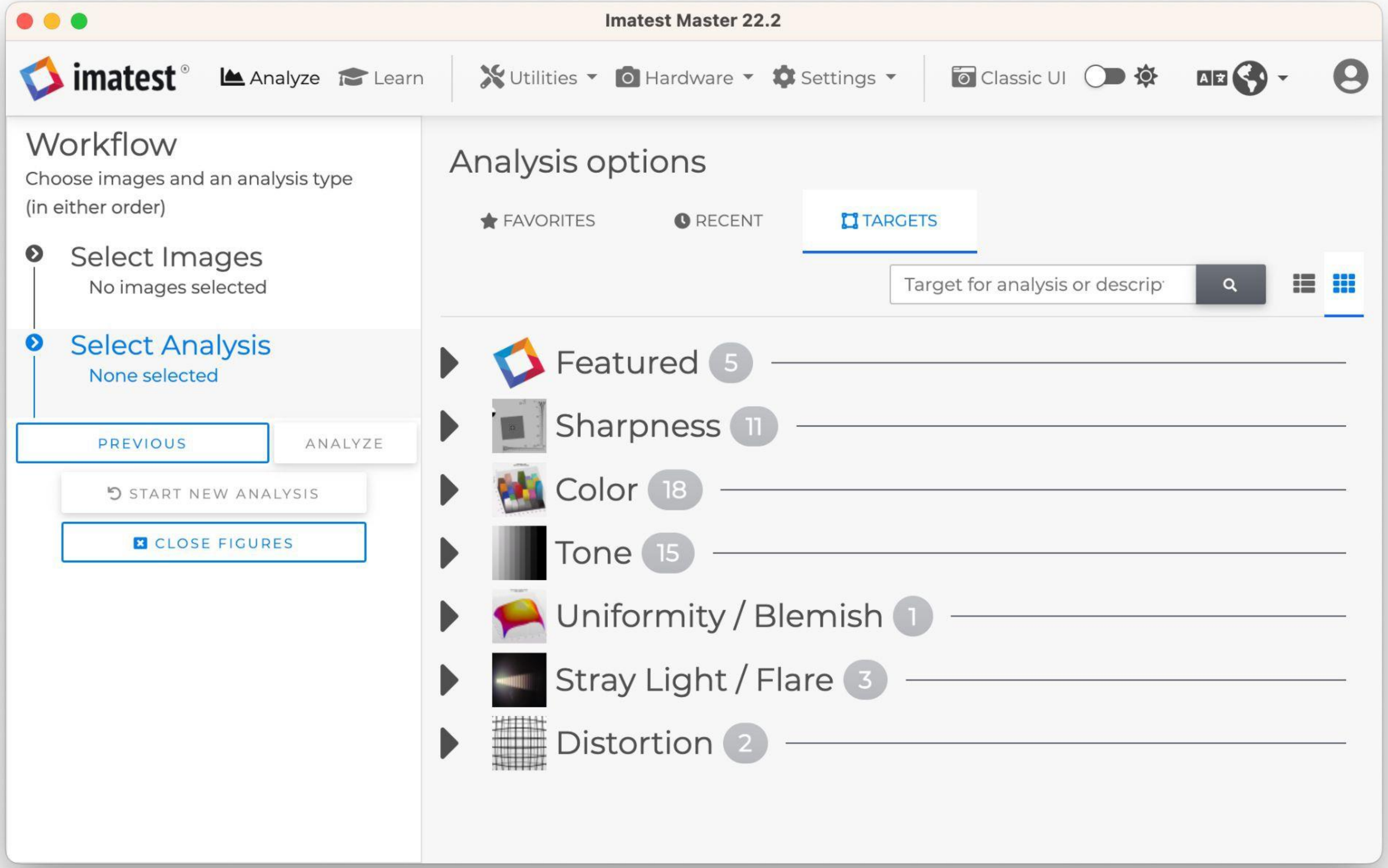
(impacted by viewing distance)

- Sharpness and resolution
- Texture blur
- Noise
- Color fringing
- Image defects

Video Objective Measurements

- Frame rate and frame rate consistency
- Frame exposure time and consistency
- Auto white balance consistency
- Autofocusing time and stability
- Video stabilization performance
- Audio-visual synchronization
- Temporal noise
- Fixed pattern noise

Imatest's Comprehensive Analysis



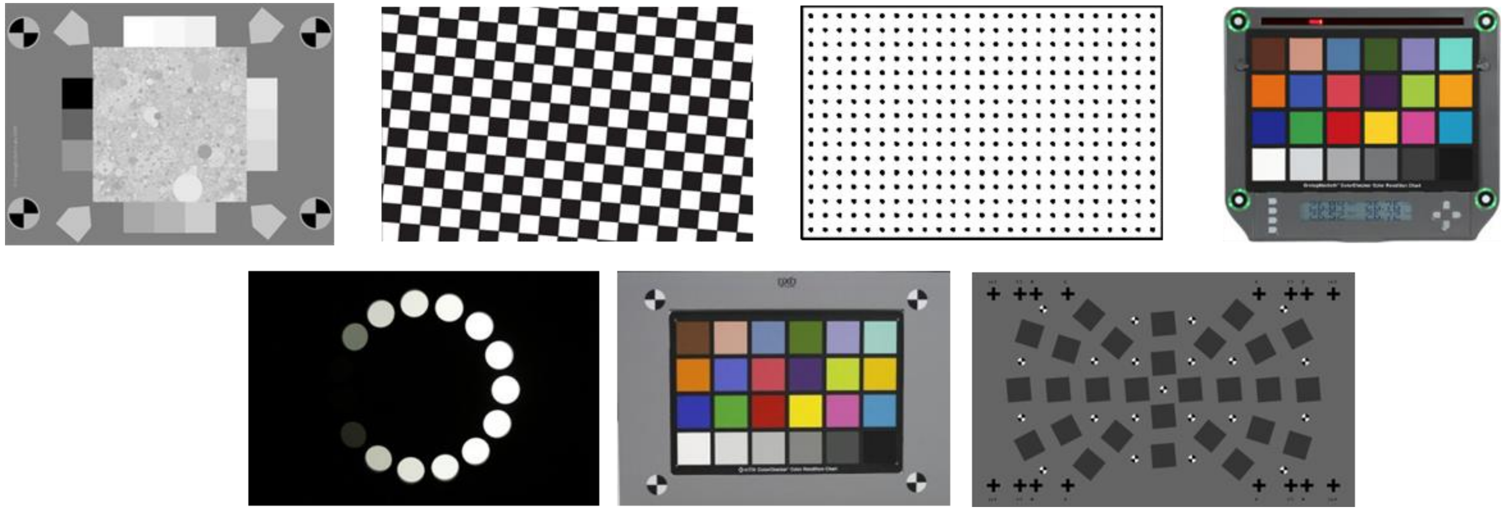
Objective Measurement – Infrastructure?

Objective Measurements – Environment and Factors

- Objective measurements
  - Scene content has known statistics (chart)
  - Extract metrics from images captured by the camera
  - Implies that the camera is part of the objective measurement process: the camera must be repeatable and to some extend follow a “reasonable” model.
- Influencing factors must be controlled
  - Lighting: illuminant, illumination, uniformity
  - Camera parameters: aperture, focal length, focusing, ISO sensitivity (sensor gain), camera parameters,…
  - Camera positioning must be repeatable (alignment protocol)
  - If a factor is not repeatable enough, like auto-focus (or other auto controls), its repeatability can be evaluated from a series of images

Objective Measurements – Environment and Factors

- Charts provide a “ground truth” with known statistics (perfect black to white edge, features aligned on a grid, uniform area, controlled color,…)
- Examples: Color, MTF, optics, noise, texture, Timing…

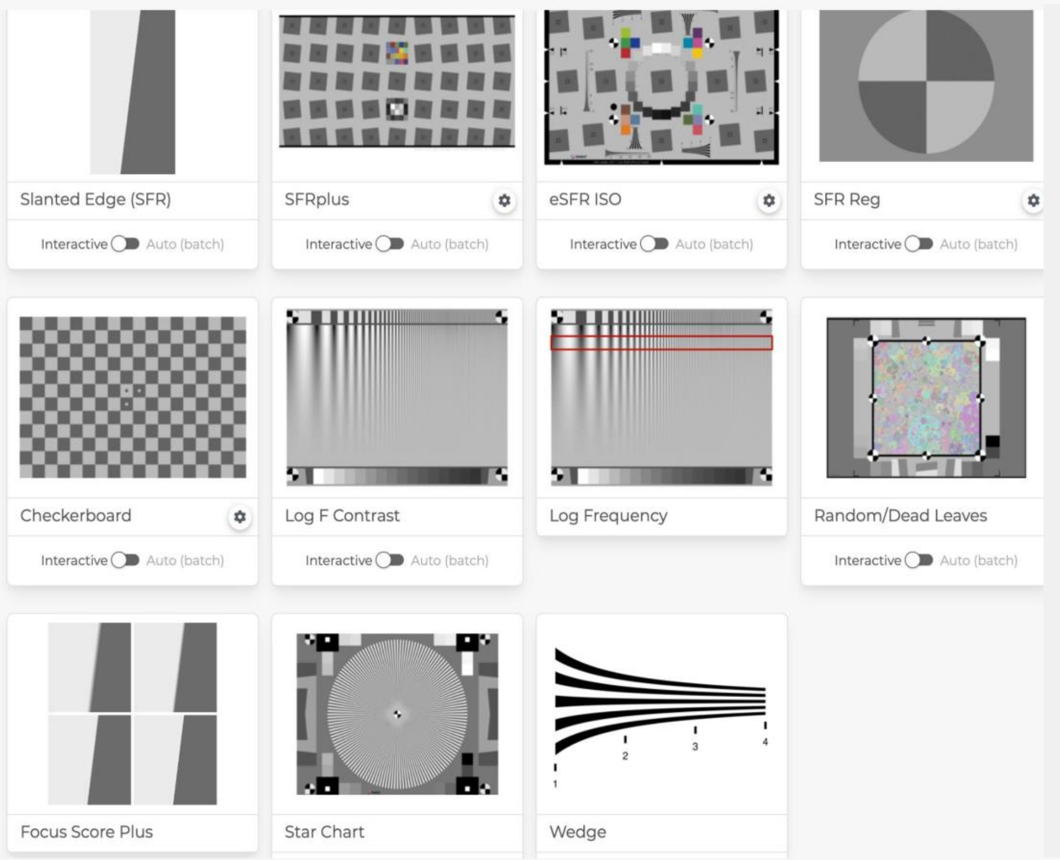


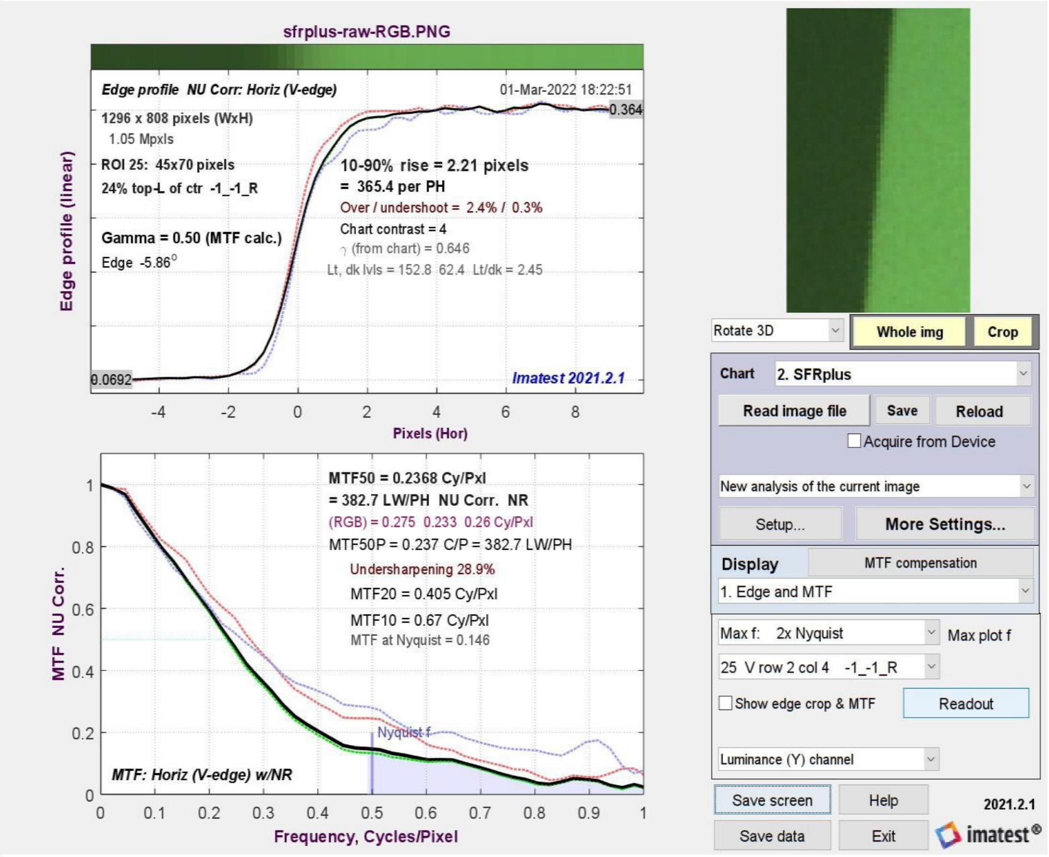
- Scene Type and Test Plan
- Lab!!!!

Imaging Lab

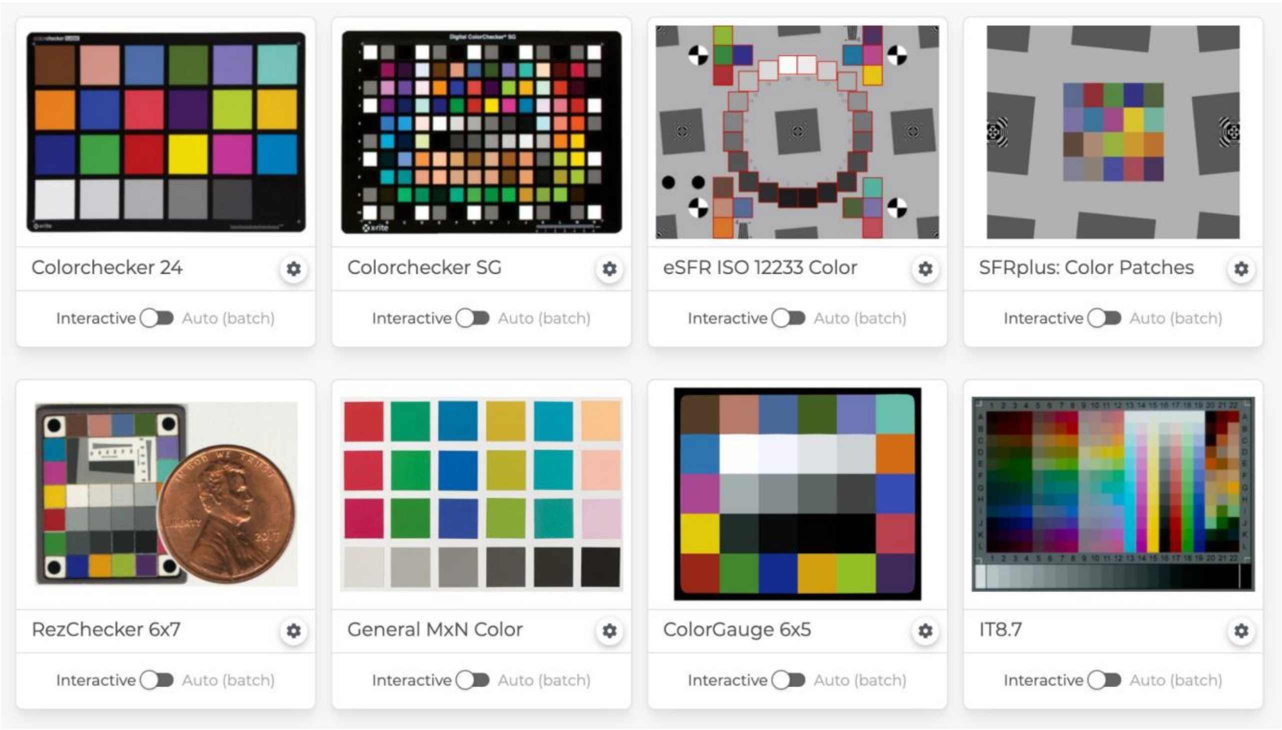
- Room with no windows
- Dark or neutral painted walls
- Controlled Lightings
- Charts
- Tripods, Accessories
- Measurement devices:
  - Luxmeter
  - Chroma/Spectral Meters

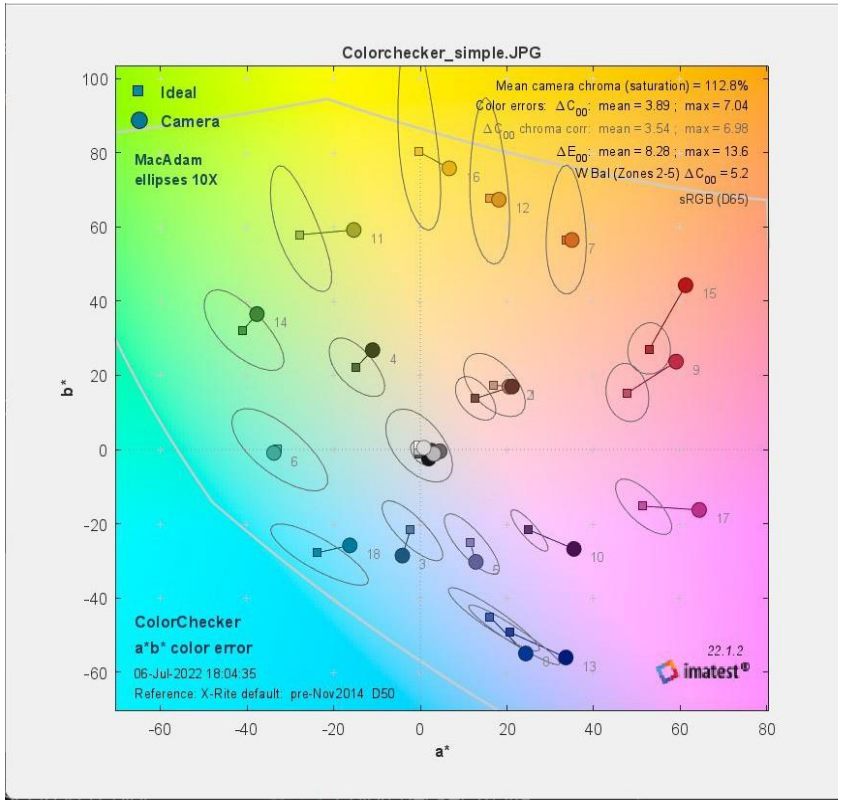
Key Attributes – Sharpness / Texture



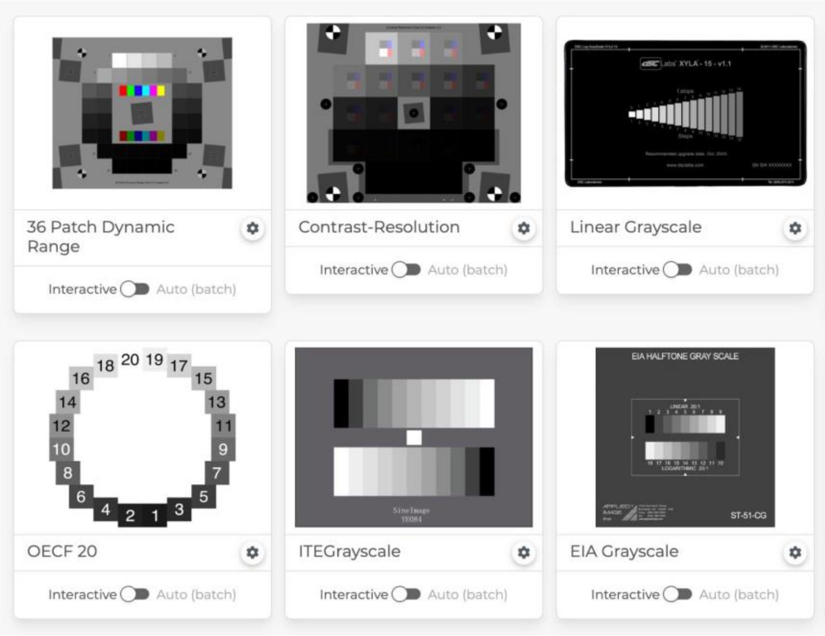


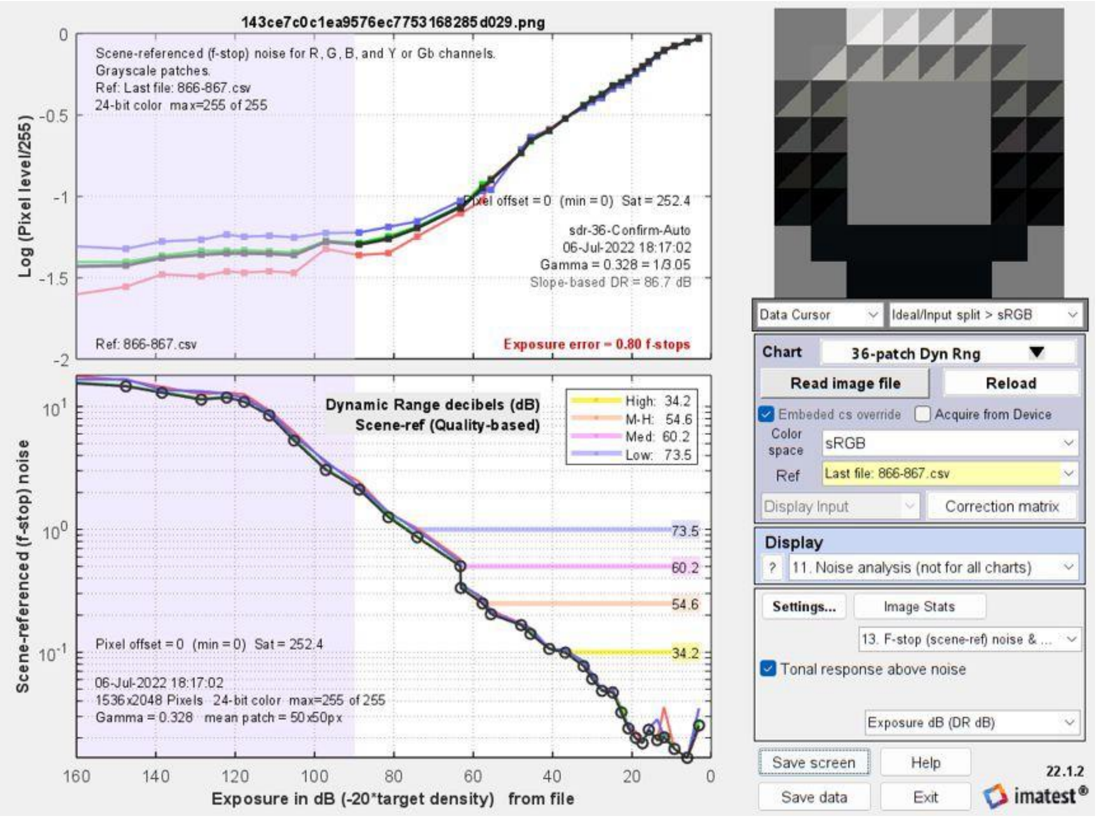
Key Attributes – Color



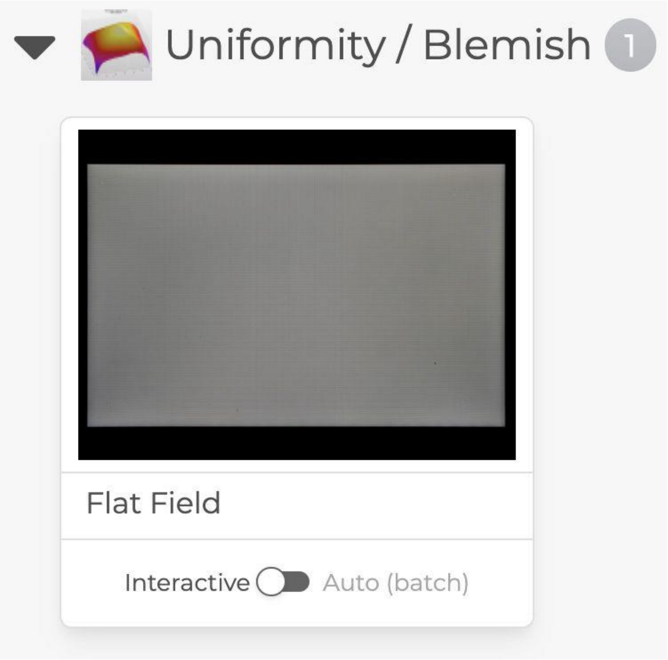


Key Attributes – Tone

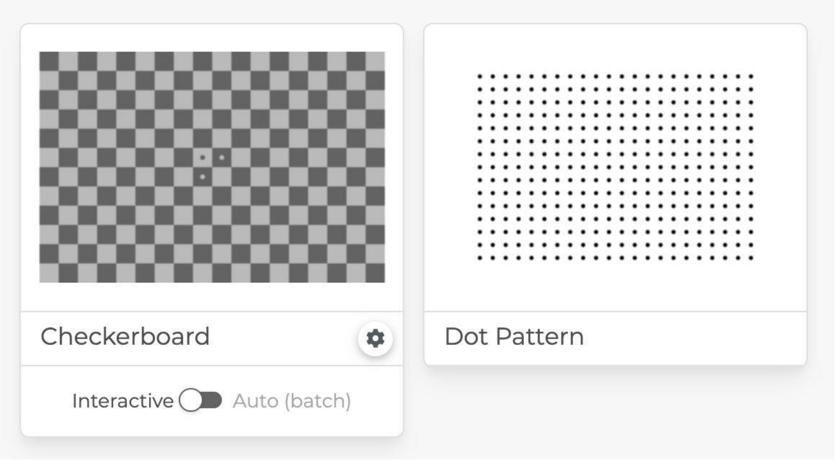


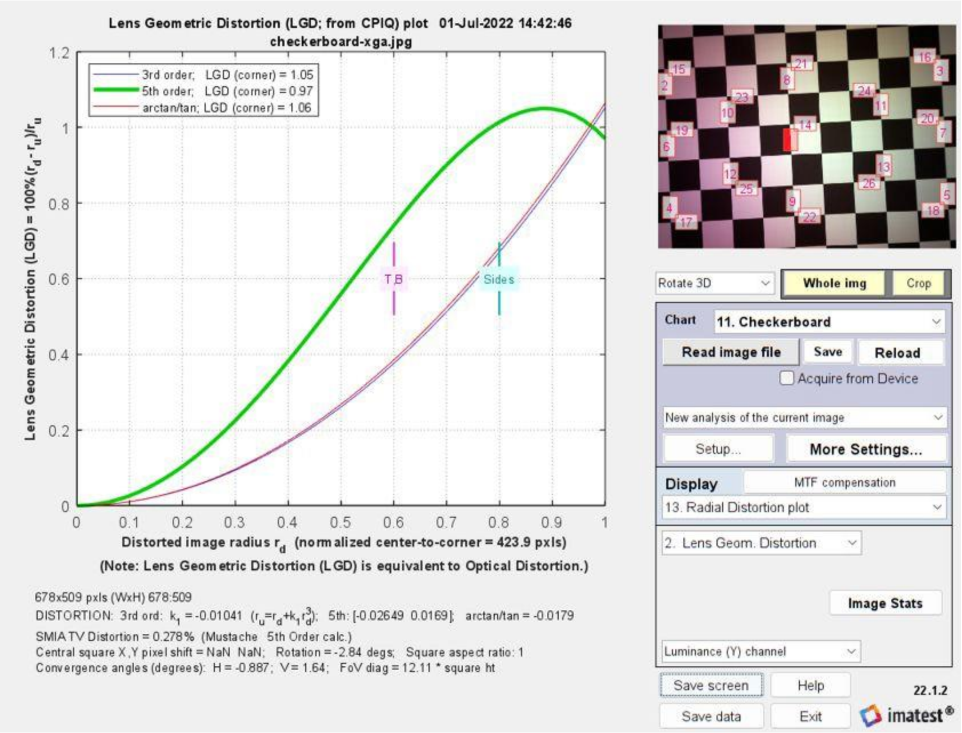


Key Attributes – Uniformity



Key Attributes – Distortion

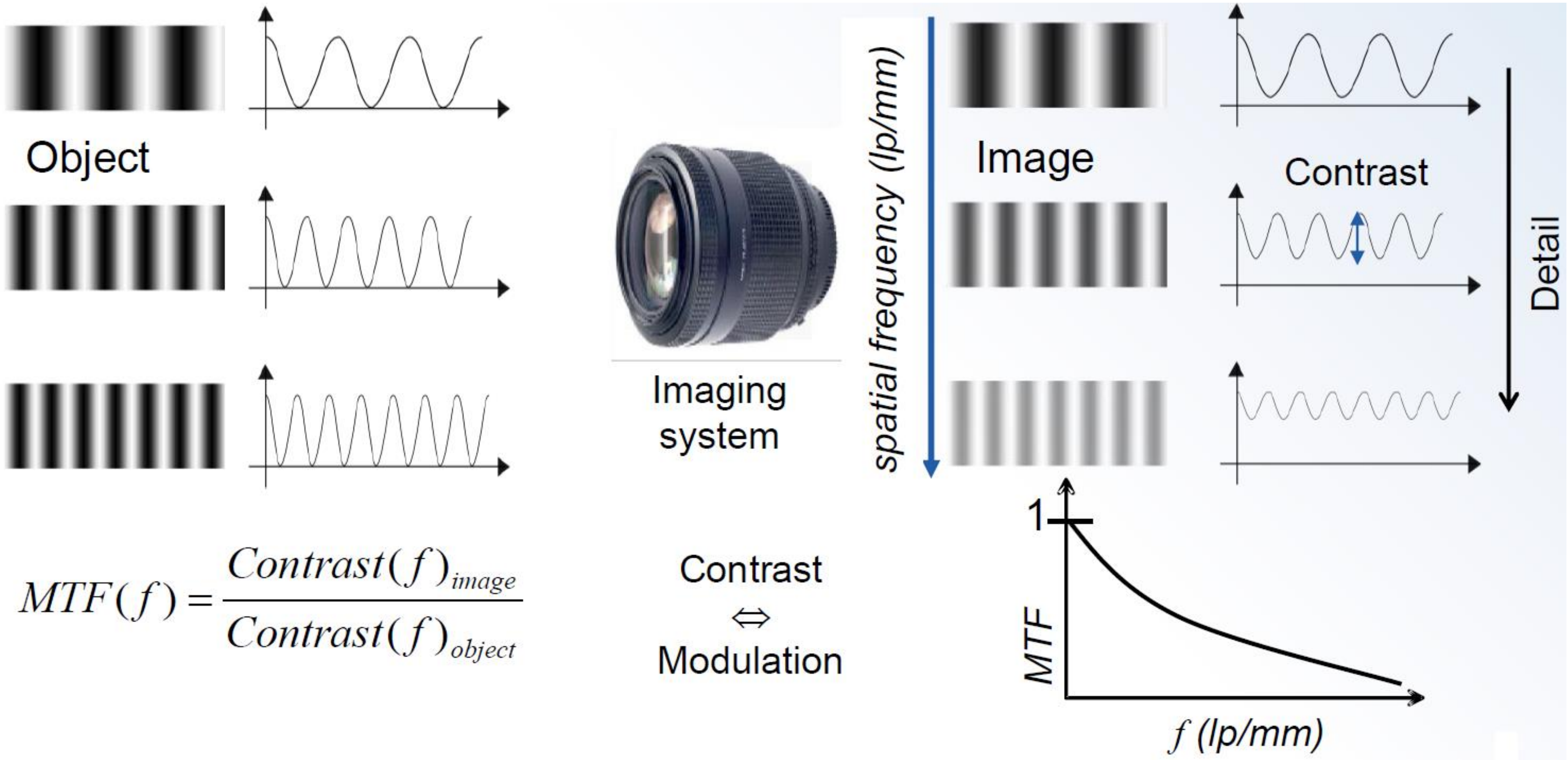




One example - Sharpness

- Spatial image quality is a measure for the degradation of the “signal” strength in the image and is therefore influencing the signal to noise directly
- Sharpness is about spatial information content in an image
- Various terms are used to describe different aspects of sharpness
  - Resolution – small spots/details
  - Contrast – strong “white to black” or “bright to dark” ratio
  - Sharpness/acutance – steep intensity change at edges

Measuring sharpness



Influence of ISP on IQ attributes

	ISP components							
Attribute	**Auto exposure**	**Auto white balance**	**Auto focus**	**Color rendering**	**Demosaicing**	**Denoising**	**Sharpening**	**Other**
Exposure	X							X
Color		X		X				X
Field uniformity				X				X
Geometry								X
Sharpness			X		X	X	X	X
Graininess				X		X	X	X
Chromatic aberrations				X				X
Other artifacts					X	X	X	X

Influence of Camera on IQ attributes

	Optics			Sensor			ISP	Light	
	Aperture	Focal length	Focusing	Sensor gain	Frame rate	Exposure time		Illuminant	Illumination
Exposure	X			X		X	X		X
Color							X	X	
Field uniformity	X	X					X	X	
Geometry		X	X		X		X		
Sharpness	X	X	X				X		
Graininess				X			X		X
Chromatic aberrations	X	X					X		
Other artifacts							X		

Camera Benchmarking

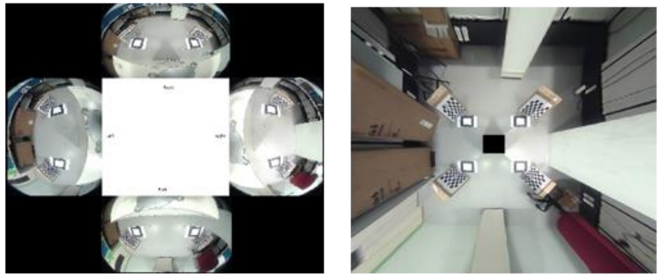
https://www.yugatech.com/feature/dxomark-camera-rankings-explained/

IQ – Human vs Machine

Two sequential video frames while entering a tunnel that demonstrate contrast reduction by veiling glare, caused by sunlight illuminated dust particles

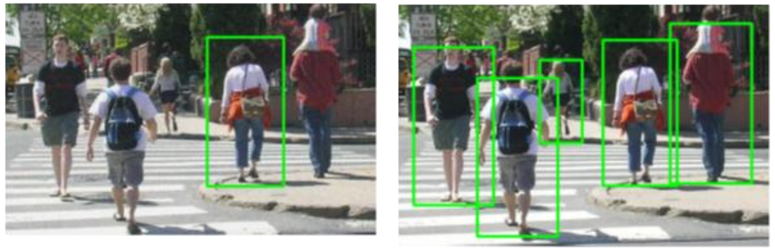
IQ impact on Computer Vision

Distortion and exposure



Improper distortion & photometric correction

Noise

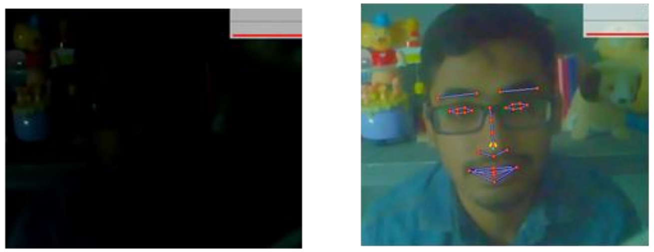


With noise

With reduction in noise

Dynamic Range

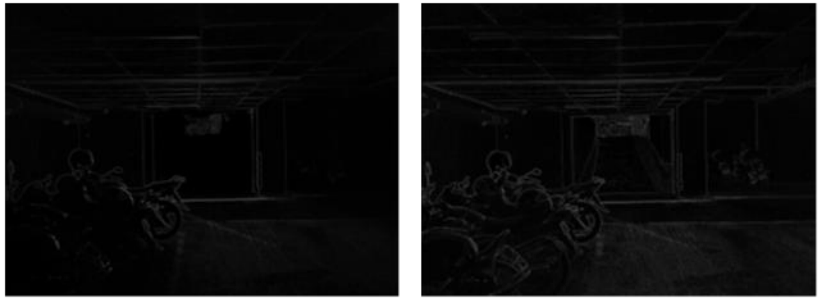
Low Light



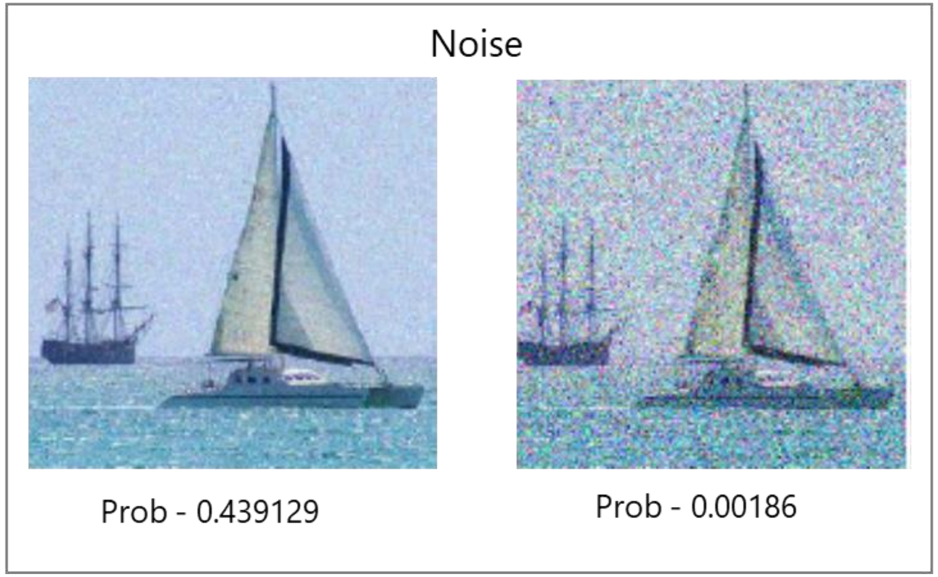
Face analysis with improved low light performance

Better edge features

Edge features



IQ impact on Computer Vision



Key Image Quality Standards

P2020

Automotive Image Quality

Established 2016

P1858

Camera Phone Image Quality (CPIQ)

Conformity Assessment Program (ICAP)

Established 2006

TC/42 – Digital Photography

ISO 12233 Resolution

ISO 14524 Tonal Response
ISO 15739 Noise
ISO 18844 Flare
ISO 19567 Texture

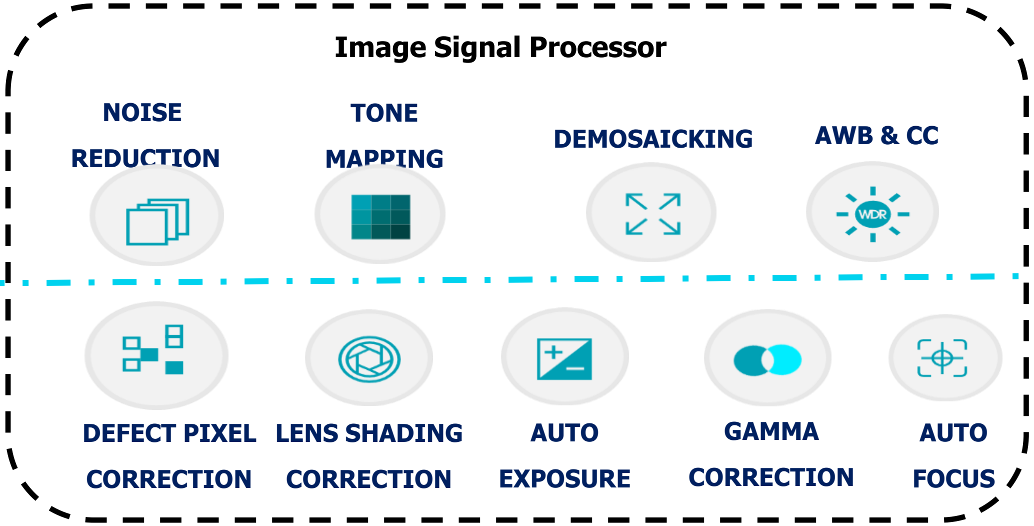
...and many more

Camera ISP/IQ Tuning

Camera IQ Tuning

- IQ tuning, or Image Quality tuning, is the process of adjusting various settings and parameters in a camera or image processing system to optimize the quality of the final image
- Why? To ensure that the final image is representative of the scene that was captured, with accurate colors and a good balance between light and dark areas
- Complex and Iterative !!!!

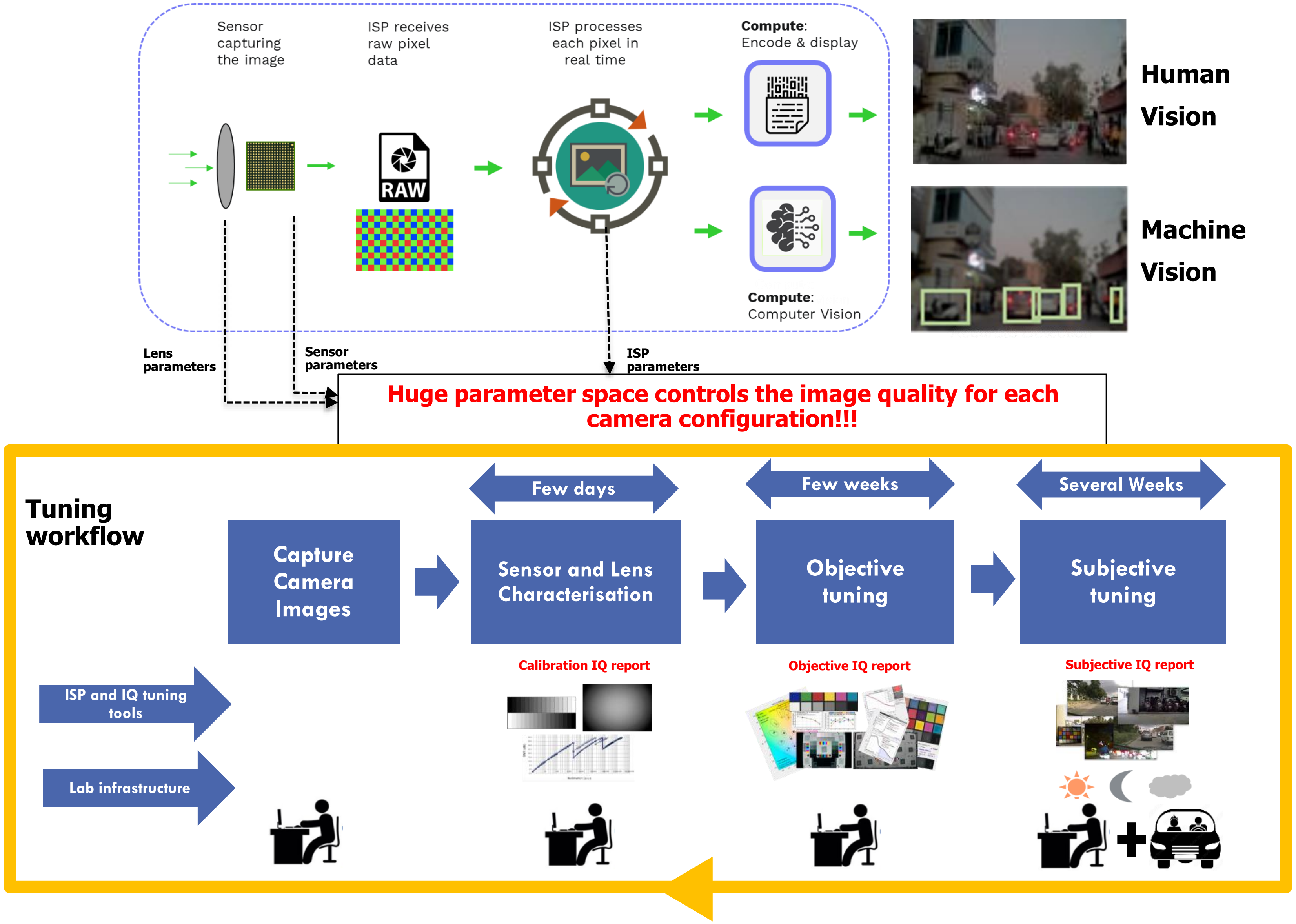
Sensor Raw Image



Output Image After Tuning

3A Algorithms | Sensor characterization & calibration | HDR | Low light | Use case specific tuning (HV & CV) |

Camera IQ Tuning



Camera IQ Tuning

Camera Maker A

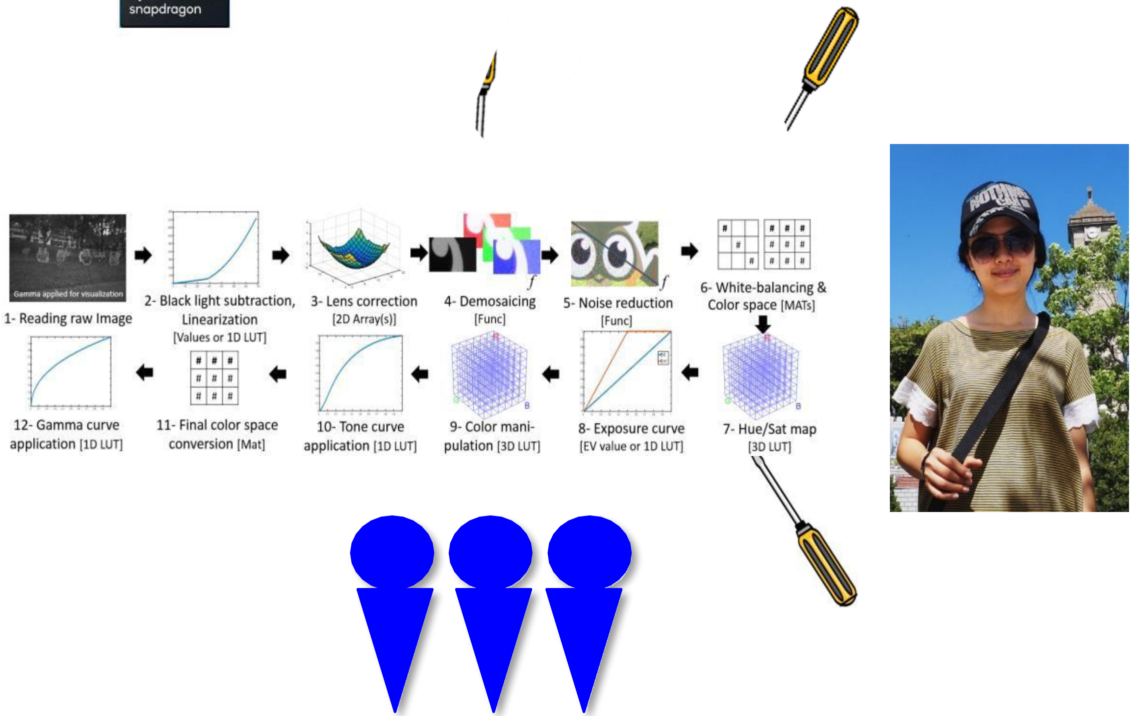


Image Quality Engineers

Camera Maker B

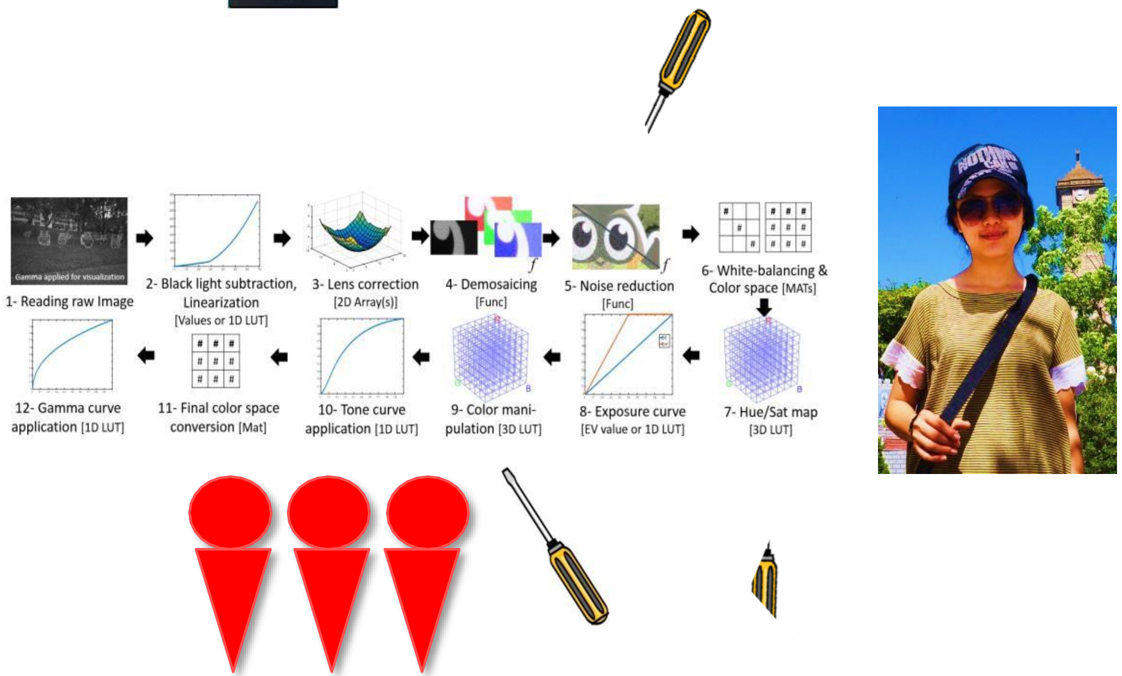


Image Quality Engineers

The algorithms on an ISP are often predefined. Camera engineers can “tune” the algorithm parameters to produce the output they want. The "tuning" of the ISP is a labor-intensive procedure.

The role of AI in Imaging

Key AI Trends in Camera Imaging

Phones Earbuds Tablets Watches & Trackers Smart Home Accessories Subscriptions Offers

← All stories

How an AI-powered camera can make everyone's photos better.

Google AI elevates your photography game
with Best Take,[1] Audio Magic Eraser,[2] and more.

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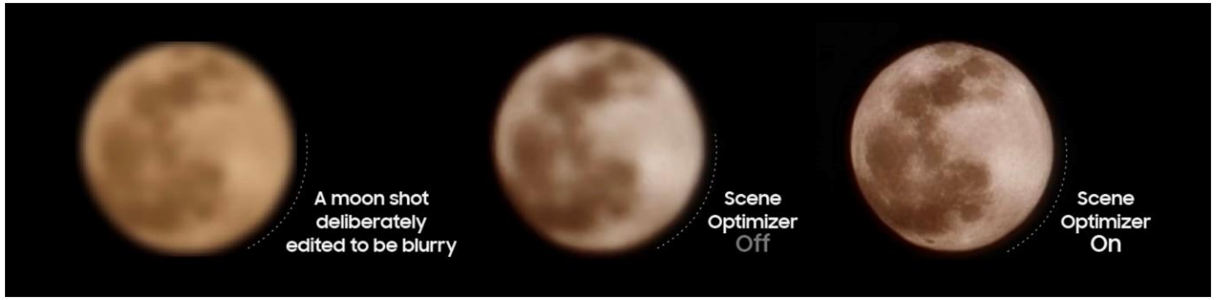
How Samsung Galaxy Cameras Combine Super Resolution Technologies With AI Technology to Produce High-Quality Images of the Moon

March 15, 2023

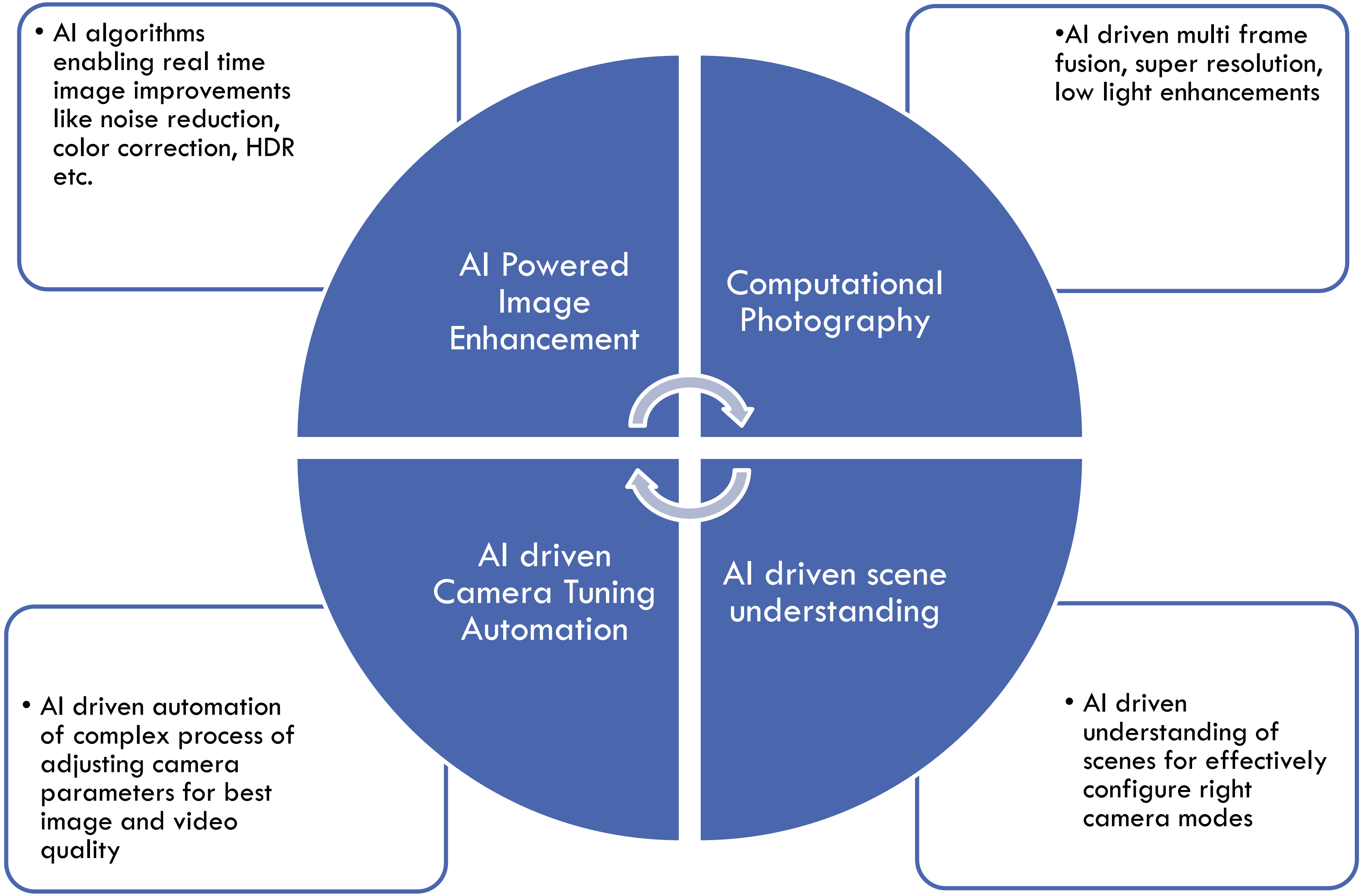
Samsung is committed to delivering best-in-class camera experiences in all conditions. Since the introduction of the Galaxy S10, the Samsung Galaxy series has harnessed artificial intelligence (AI) technologies in its cameras to help users capture every epic moment anytime, anywhere.

As part of this, Samsung developed the Scene Optimizer feature, a camera functionality which uses advanced AI to recognize objects and thus deliver the best results to users. Since the introduction of the Galaxy S21 series, Scene Optimizer has been able to recognize the moon as a specific object during the photo-taking process, and applies the feature's detail enhancement engine to the shot.

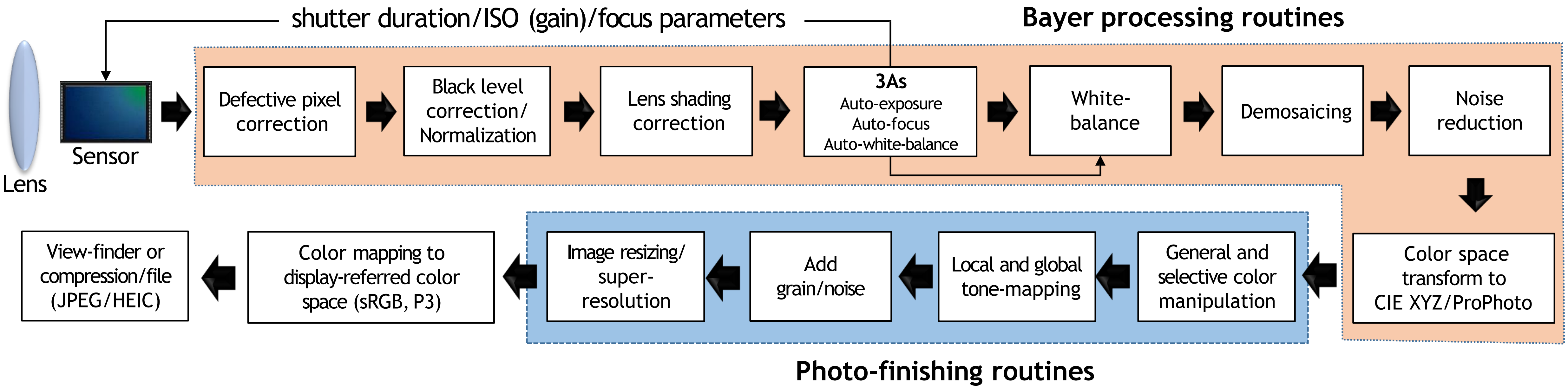
When you're taking a photo of the moon, your Galaxy device's[1] camera system will harness this deep learning-based AI technology, as well as multi-frame processing in order to further enhance details. Read on to learn more about the multiple steps, processes and technologies that go in to delivering high-quality



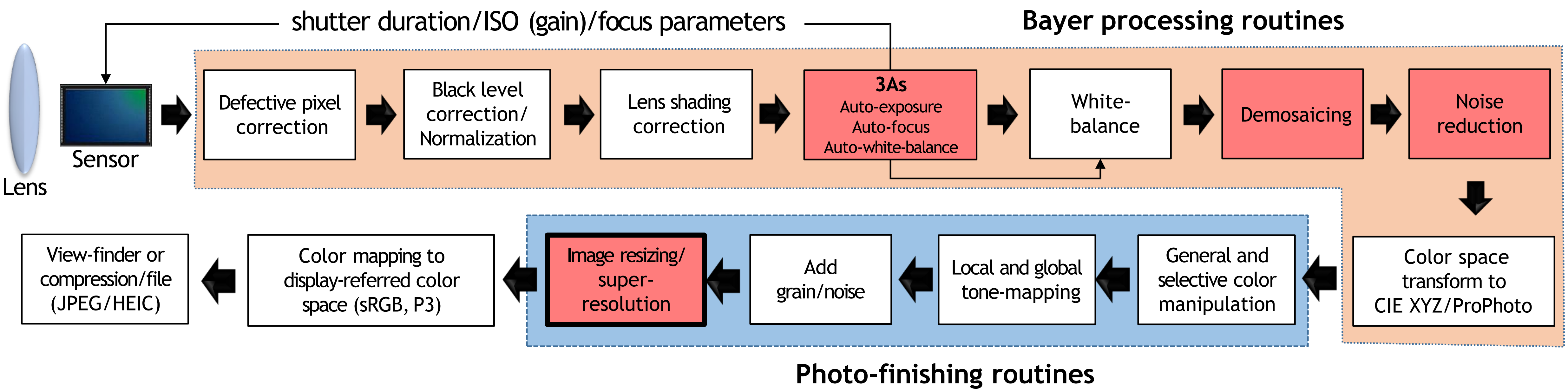
Key AI Trends in Camera Imaging



A bit more complex ISP



Use deep learning for hard problems



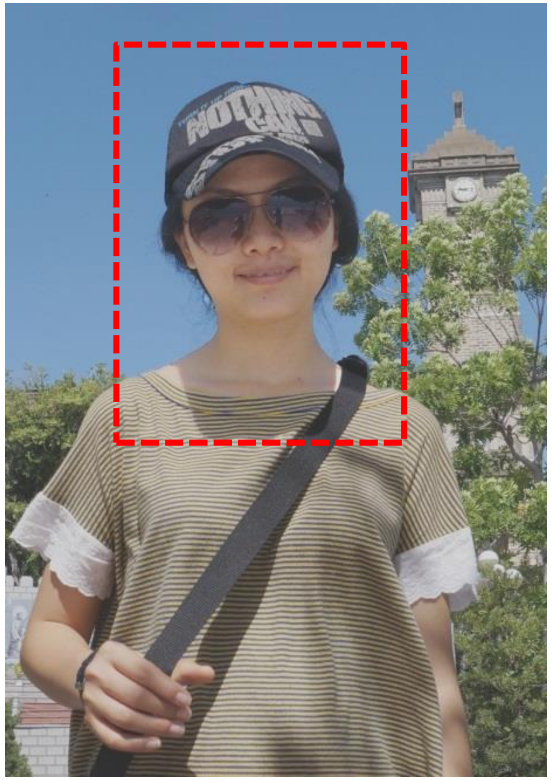
The highlighted components are camera pipeline steps that are challenging and areas AI can make notable gains:

AWB (illumination estimation)
Demosaicing
Noise reduction
Super-resolution
HDR

Digital zoom

A distinguishing feature in the smartphone camera market is zoom quality.

Full frame



Digital zoom
(super res)

Machine learning (ML) for super-resolution

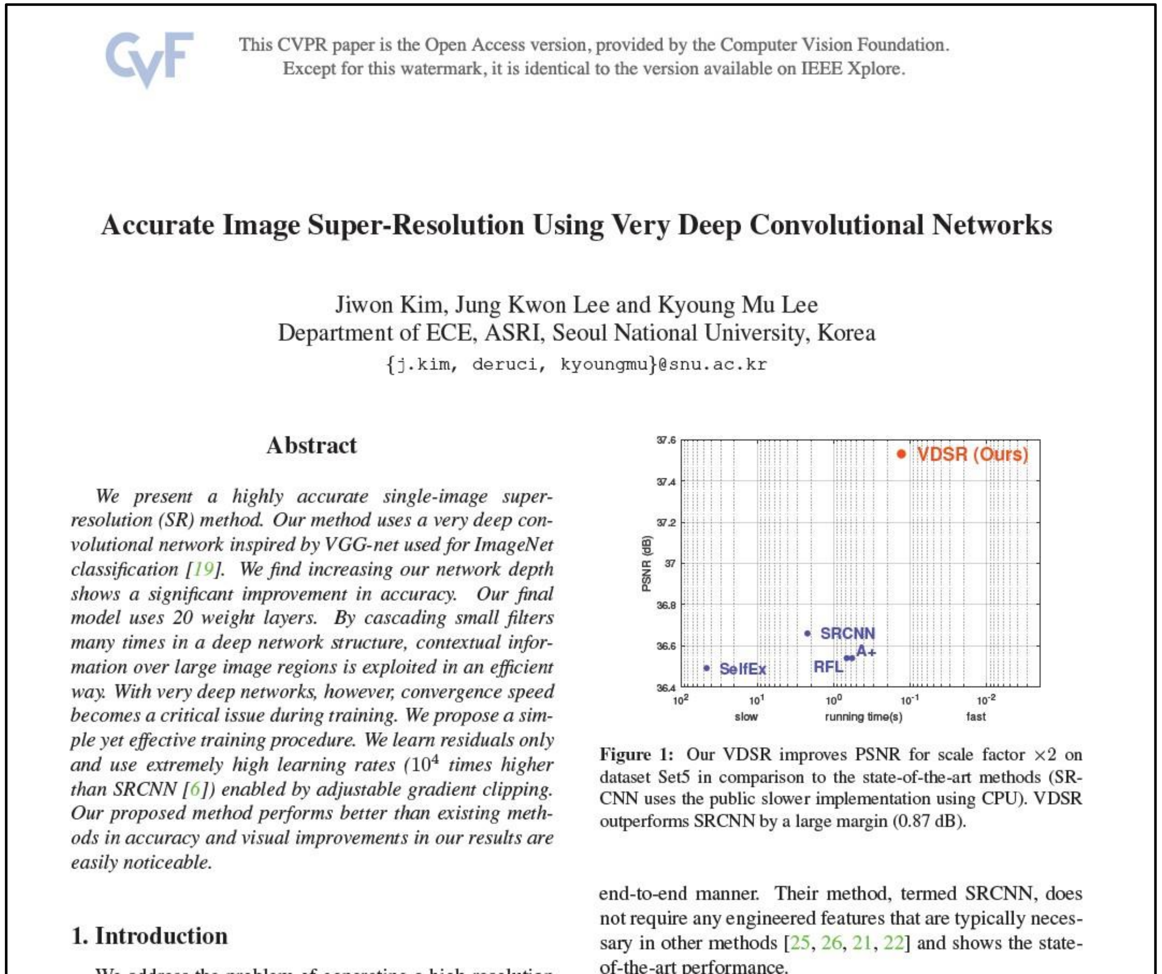
- SR has been addressed by machine learning methods for a long time.

- Required "training data"
  - Quality of results are directly correlated to training data suitability.

- Before deep learning, used "non-learnable" machine learning.
  - Hand-crafted features
  - Conditional random fields
  - K-Nearest Neighbor
  - Support vector machines

Super-resolution with very deep networks

Kim, Lee, Lee CVPR'16



This CVPR paper is the Open Access version, provided by the Computer Vision Foundation.
Except for this watermark, it is identical to the version available on IEEE Xplore.

Accurate Image Super-Resolution Using Very Deep Convolutional Networks

Jiwon Kim, Jung Kwon Lee and Kyoung Mu Lee
Department of ECE, ASRI, Seoul National University, Korea
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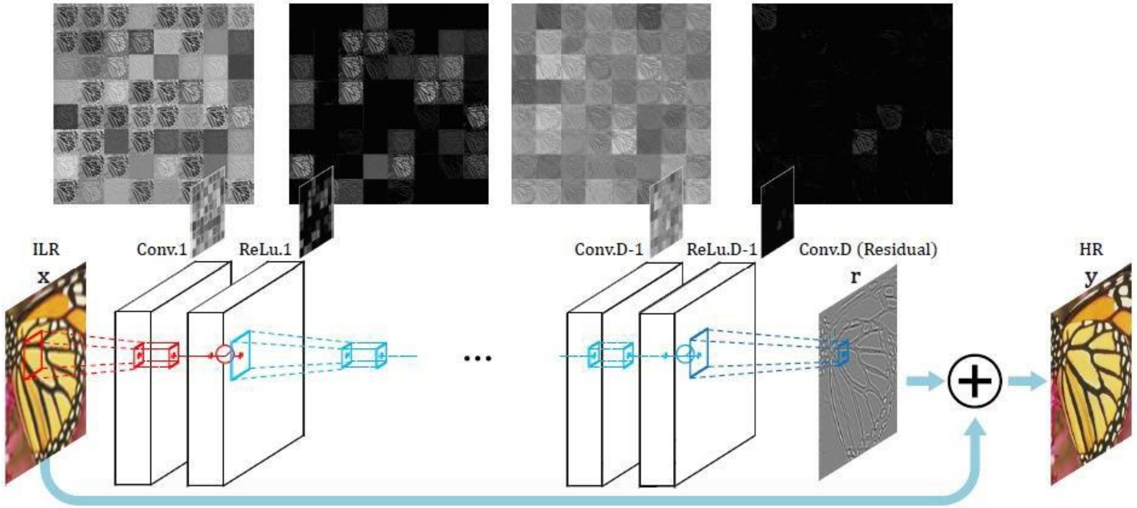
Abstract

We present a highly accurate single-image super-resolution (SR) method. Our method uses a very deep convolutional network inspired by VGG-net used for ImageNet classification [19]. We find increasing our network depth shows a significant improvement in accuracy. Our final model uses 20 weight layers. By cascading small filters many times in a deep network structure, contextual information over large image regions is exploited in an efficient way. With very deep networks, however, convergence speed becomes a critical issue during training. We propose a simple yet effective training procedure. We learn residuals only and use extremely high learning rates (10^4 times higher than SRCNN [6]) enabled by adjustable gradient clipping. Our proposed method performs better than existing methods in accuracy and visual improvements in our results are easily noticeable.

Figure 1: Our VDSR improves PSNR for scale factor ×2 on dataset Set5 in comparison to the state-of-the-art methods (SRCNN uses the public slower implementation using CPU). VDSR outperforms SRCNN by a large margin (0.87 dB).

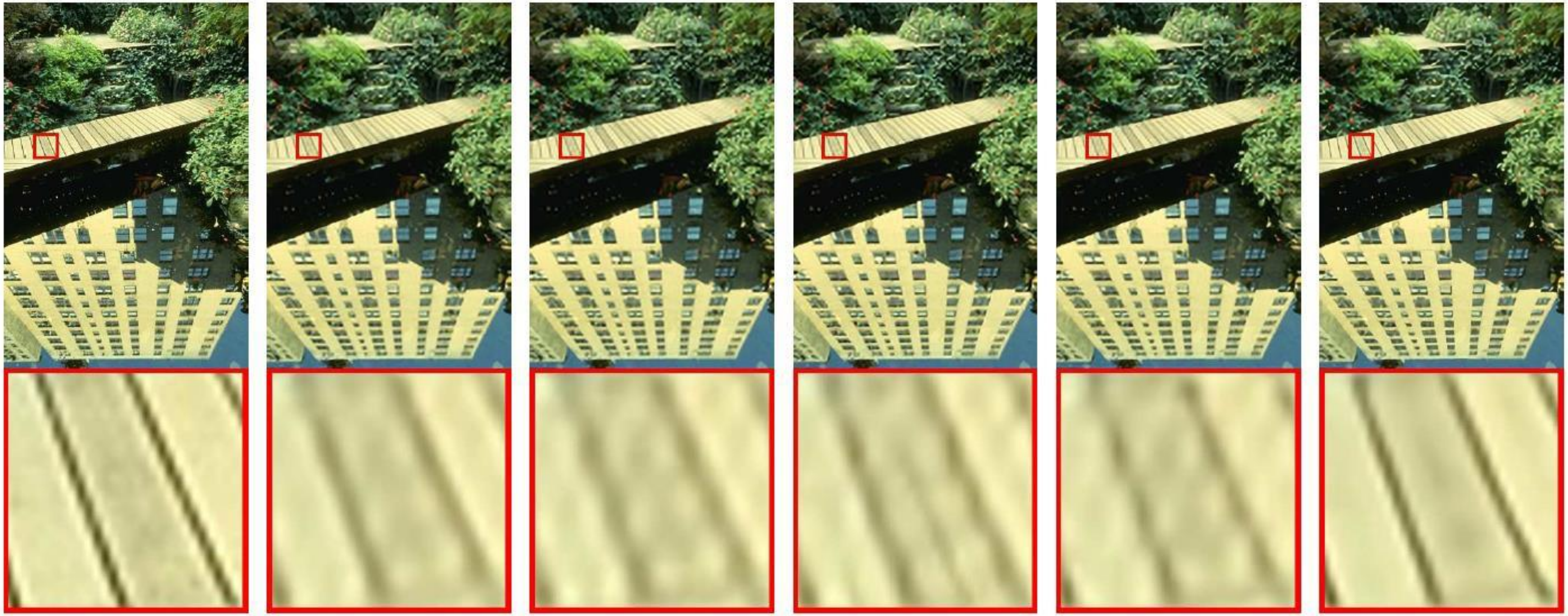
1. Introduction

end-to-end manner. Their method, termed SRCNN, does not require any engineered features that are typically necessary in other methods [25, 26, 21, 22] and shows the state-of-the-art performance.



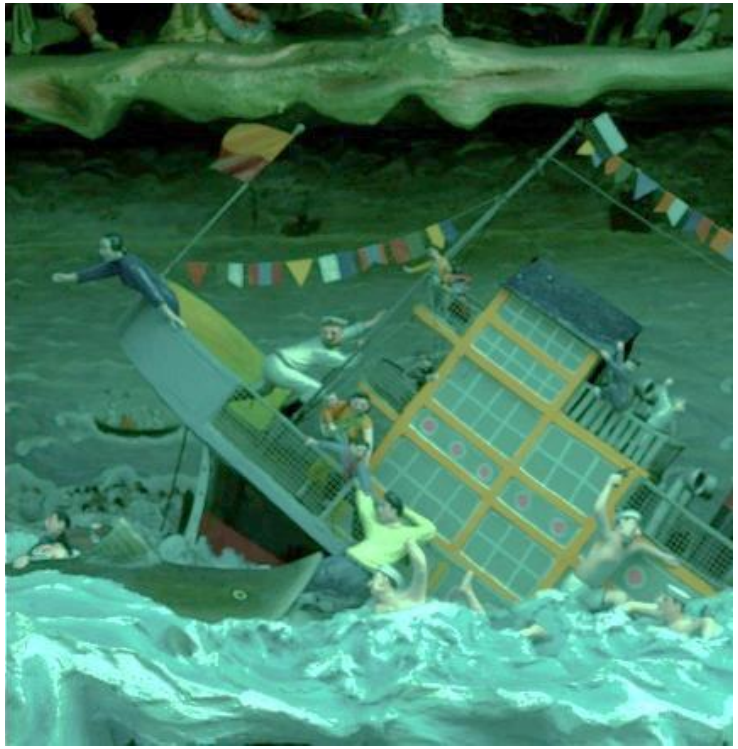
- Pairs of convolution layers + nonlinear activations
- Prediction is added to upsampled low-res input
- Special care for gradient clipping

Took "SR" to the next level visually



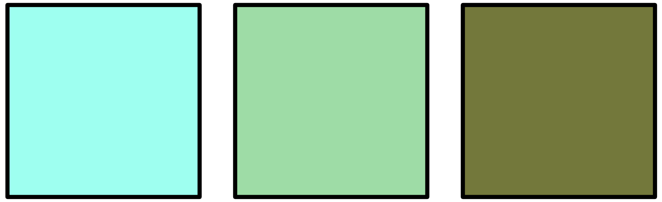
Ground Truth	A+ [22]	RFL [18]	SelfEx [11]	SRCNN [5]	VDSR (Ours)
(PSNR, SSIM)	(22.92, 0.7379)	(22.90, 0.7332)	(23.00, 0.7439)	(23.15, 0.7487)	(23.50, 0.7777)

Recall why illumination estimation is hard



RAW sensor image

What is the sensor's response to illumination?

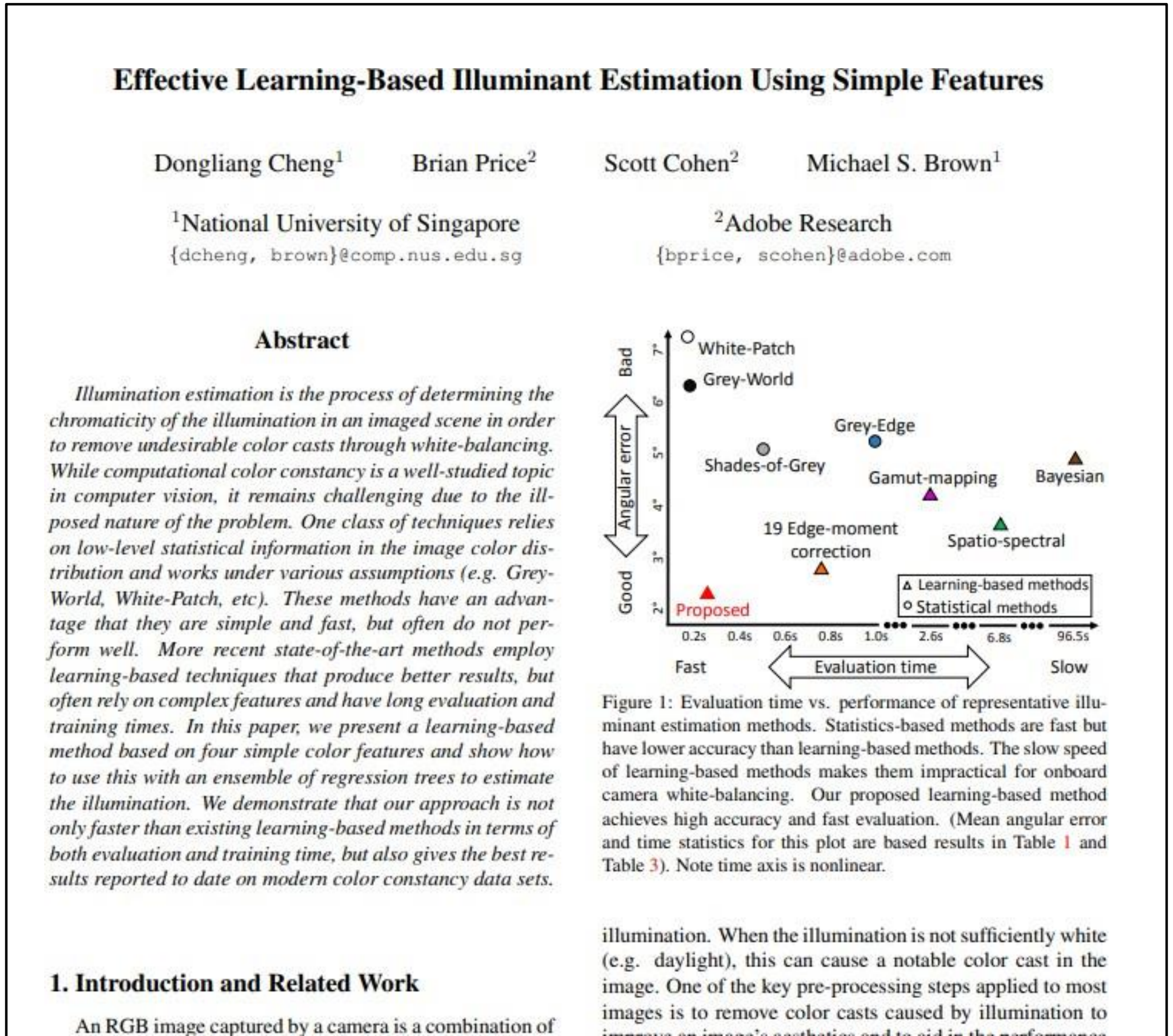


Given an arbitrary input image, predict the scene illumination.

Getting this *incorrect* has significant impact on image quality/color reproduction.

Many ML approaches before deep learning

Cheng et al CVPR'15



Effective Learning-Based Illuminant Estimation Using Simple Features

Dongliang Cheng[1] Brian Price[2] Scott Cohen[2] Michael S. Brown[1]

[1]National University of Singapore
{dcheng, brown}@comp.nus.edu.sg

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{bprice, scohen}@adobe.com

Abstract

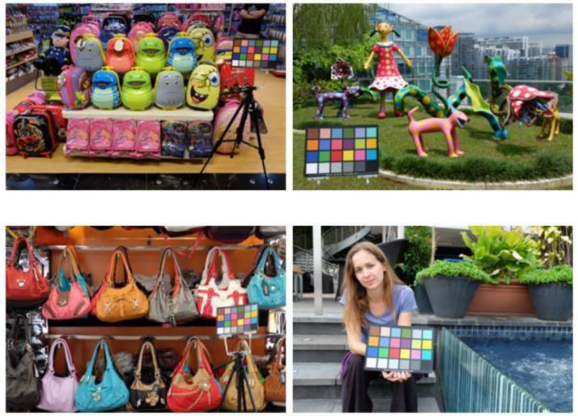
Illumination estimation is the process of determining the chromaticity of the illumination in an imaged scene in order to remove undesirable color casts through white-balancing. While computational color constancy is a well-studied topic in computer vision, it remains challenging due to the ill-posed nature of the problem. One class of techniques relies on low-level statistical information in the image color distribution and works under various assumptions (e.g. Grey-World, White-Patch, etc). These methods have an advantage that they are simple and fast, but often do not perform well. More recent state-of-the-art methods employ learning-based techniques that produce better results, but often rely on complex features and have long evaluation and training times. In this paper, we present a learning-based method based on four simple color features and show how to use this with an ensemble of regression trees to estimate the illumination. We demonstrate that our approach is not only faster than existing learning-based methods in terms of both evaluation and training time, but also gives the best results reported to date on modern color constancy data sets.

Figure 1: Evaluation time vs. performance of representative illuminant estimation methods. Statistics-based methods are fast but have lower accuracy than learning-based methods. The slow speed of learning-based methods makes them impractical for onboard camera white-balancing. Our proposed learning-based method achieves high accuracy and fast evaluation. (Mean angular error and time statistics for this plot are based results in Table 1 and Table 3). Note time axis is nonlinear.

1. Introduction and Related Work

An RGB image captured by a camera is a combination of

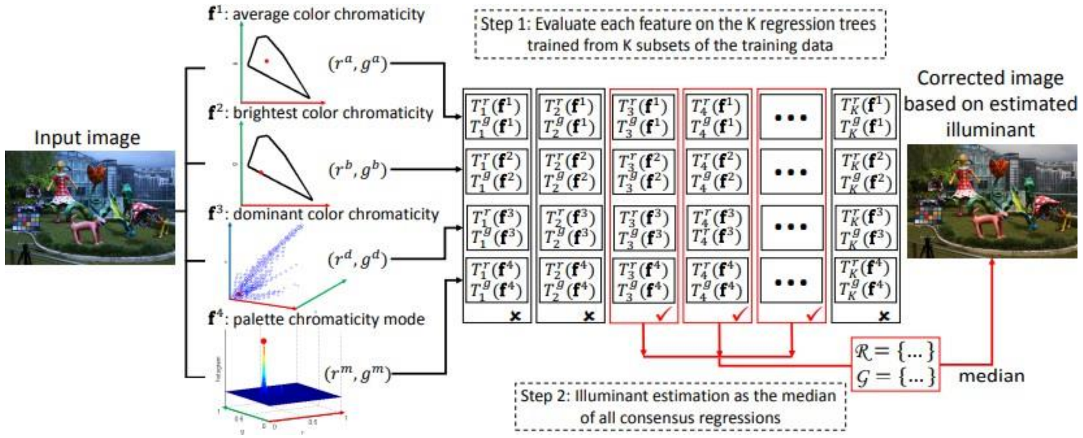
illumination. When the illumination is not sufficiently white (e.g. daylight), this can cause a notable color cast in the image. One of the key pre-processing steps applied to most images is to remove color casts caused by illumination to



Training images
(sensor specific)

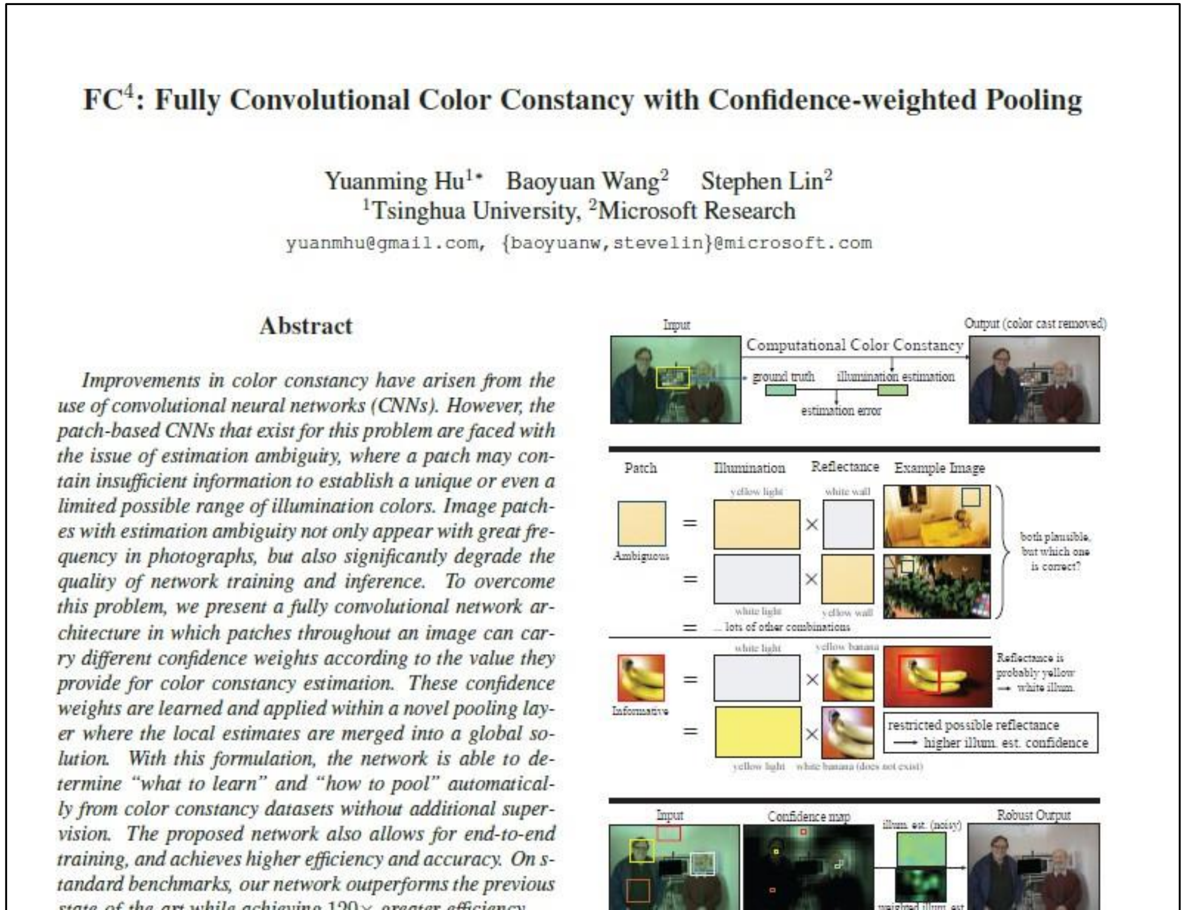
Derive some features
(usually histogram
statistics)

Apply ML method
to predict illumination of
scene.



Improving AWB with CNN

Hu et al. CVPR'17

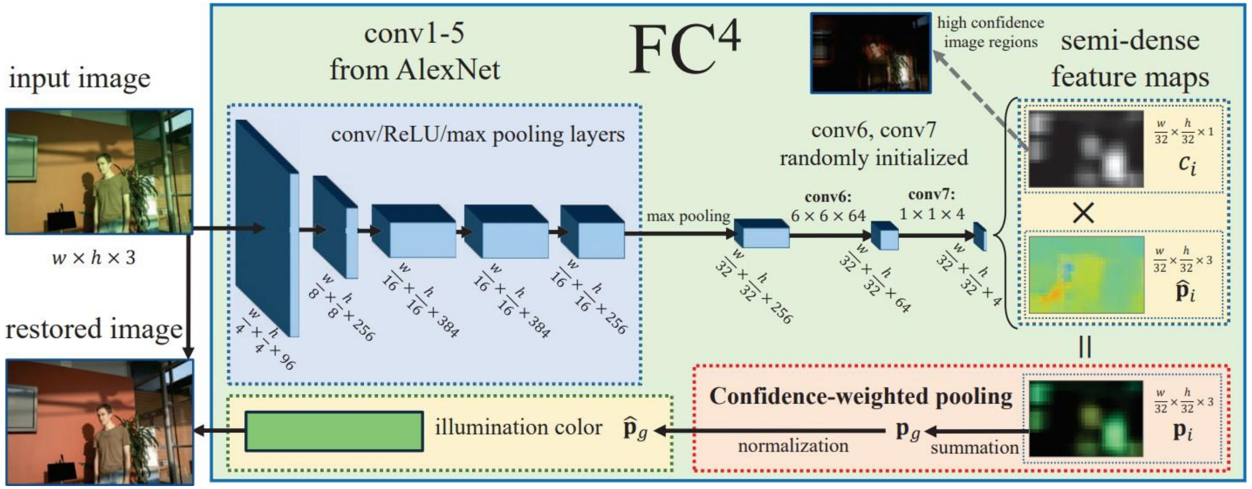


FC⁴: Fully Convolutional Color Constancy with Confidence-weighted Pooling

Yuanming Hu[1*] Baoyuan Wang[2] Stephen Lin[2]
[1]Tsinghua University, [2]Microsoft Research
yuanmhu@gmail.com, {baoyuanw,stevelin}@microsoft.com

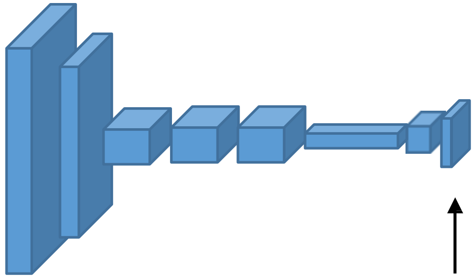
Abstract

Improvements in color constancy have arisen from the use of convolutional neural networks (CNNs). However, the patch-based CNNs that exist for this problem are faced with the issue of estimation ambiguity, where a patch may contain insufficient information to establish a unique or even a limited possible range of illumination colors. Image patches with estimation ambiguity not only appear with great frequency in photographs, but also significantly degrade the quality of network training and inference. To overcome this problem, we present a fully convolutional network architecture in which patches throughout an image can carry different confidence weights according to the value they provide for color constancy estimation. These confidence weights are learned and applied within a novel pooling layer where the local estimates are merged into a global solution. With this formulation, the network is able to determine "what to learn" and "how to pool" automatically from color constancy datasets without additional supervision. The proposed network also allows for end-to-end training, and achieves higher efficiency and accuracy. On standard benchmarks, our network outperforms the previous state of the art while achieving 120× greater efficiency.

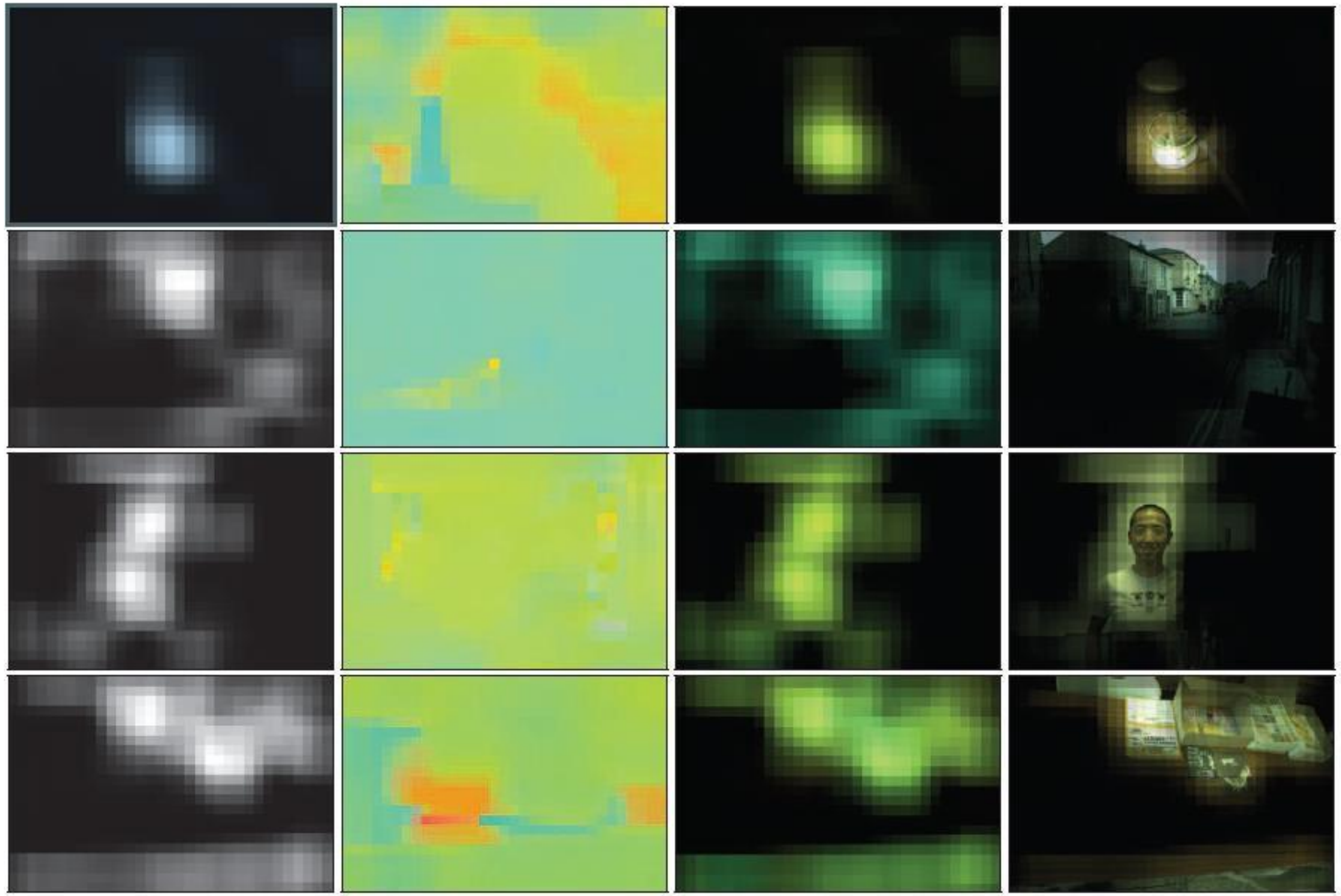


Predicts local estimates over the image and their confidence.
Pools confident weighted estimates for final result.

What did it learn?



Predicts low-res
4 channel ouput
(estimation r,g,b
+ confidence map)

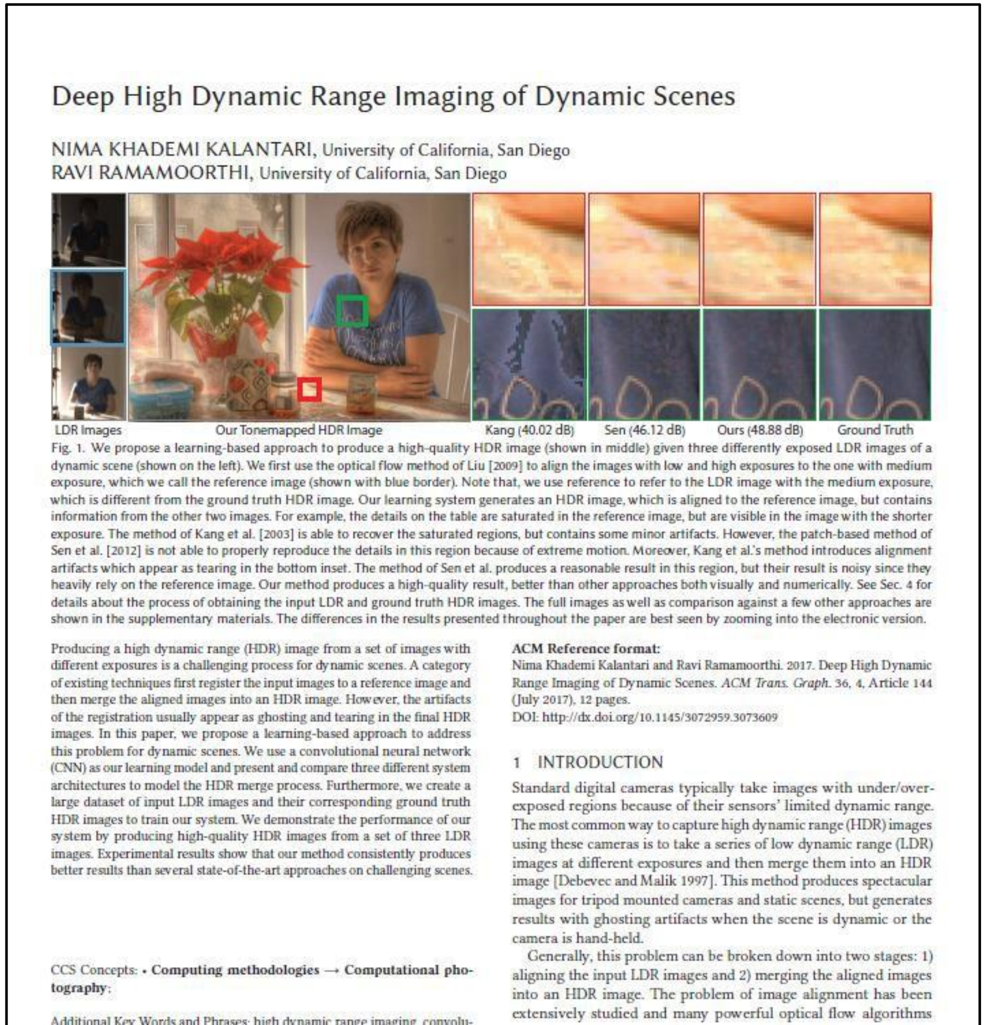


confidence map | estimation map | weighted estimation | image × confidence

The method appears to learns to identify pixels that are most likely "neutral/achromatic" scene patches.

DNN-based multi-frame HDR

Kalantari and Ramanoorthi SIGGRAPH'17



Deep High Dynamic Range Imaging of Dynamic Scenes

NIMA KHADEMI KALANTARI, University of California, San Diego
RAVI RAMAMOORTHI, University of California, San Diego

LDR Images | Our Tonemapped HDR Image | Kang (40.02 dB) | Sen (46.12 dB) | Ours (48.88 dB) | Ground Truth

Fig. 1. We propose a learning-based approach to produce a high-quality HDR image (shown in middle) given three differently exposed LDR images of a dynamic scene (shown on the left). We first use the optical flow method of Liu [2009] to align the images with low and high exposures to the one with medium exposure, which we call the reference image (shown with blue border). Note that, we use reference to refer to the LDR image with the medium exposure, which is different from the ground truth HDR image. Our learning system generates an HDR image, which is aligned to the reference image, but contains information from the other two images. For example, the details on the table are saturated in the reference image, but are visible in the image with the shorter exposure. The method of Kang et al. [2003] is able to recover the saturated regions, but contains some minor artifacts. However, the patch-based method of Sen et al. [2012] is not able to properly reproduce the details in this region because of extreme motion. Moreover, Kang et al.'s method introduces alignment artifacts which appear as tearing in the bottom inset. The method of Sen et al. produces a reasonable result in this region, but their result is noisy since they heavily rely on the reference image. Our method produces a high-quality result, better than other approaches both visually and numerically. See Sec. 4 for details about the process of obtaining the input LDR and ground truth HDR images. The full images as well as comparison against a few other approaches are shown in the supplementary materials. The differences in the results presented throughout the paper are best seen by zooming into the electronic version.

Producing a high dynamic range (HDR) image from a set of images with different exposures is a challenging process for dynamic scenes. A category of existing techniques first register the input images to a reference image and then merge the aligned images into an HDR image. However, the artifacts of the registration usually appear as ghosting and tearing in the final HDR images. In this paper, we propose a learning-based approach to address this problem for dynamic scenes. We use a convolutional neural network (CNN) as our learning model and present and compare three different system architectures to model the HDR merge process. Furthermore, we create a large dataset of input LDR images and their corresponding ground truth HDR images to train our system. We demonstrate the performance of our system by producing high-quality HDR images from a set of three LDR images. Experimental results show that our method consistently produces better results than several state-of-the-art approaches on challenging scenes.

CCS Concepts: • **Computing methodologies → Computational photography**;

Additional Key Words and Phrases: high dynamic range imaging, convolu-

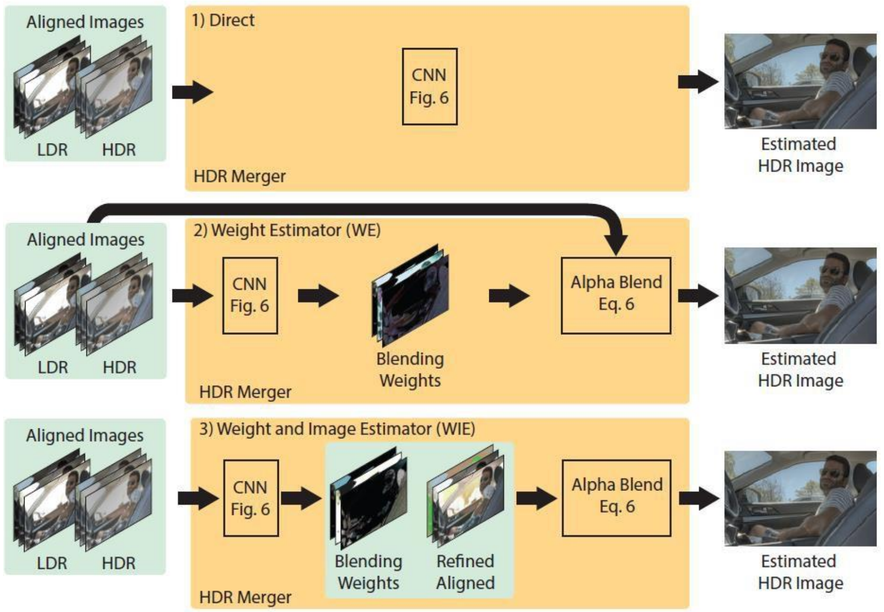
ACM Reference format:
Nima Khademi Kalantari and Ravi Ramamoorthi. 2017. Deep High Dynamic Range Imaging of Dynamic Scenes. *ACM Trans. Graph.* 36, 4, Article 144 (July 2017), 12 pages.
DOI: http://dx.doi.org/10.1145/3072959.3073609

1 INTRODUCTION

Standard digital cameras typically take images with under/over-exposed regions because of their sensors' limited dynamic range. The most common way to capture high dynamic range (HDR) images using these cameras is to take a series of low dynamic range (LDR) images at different exposures and then merge them into an HDR image [Debevec and Malik 1997]. This method produces spectacular images for tripod mounted cameras and static scenes, but generates results with ghosting artifacts when the scene is dynamic or the camera is hand-held.

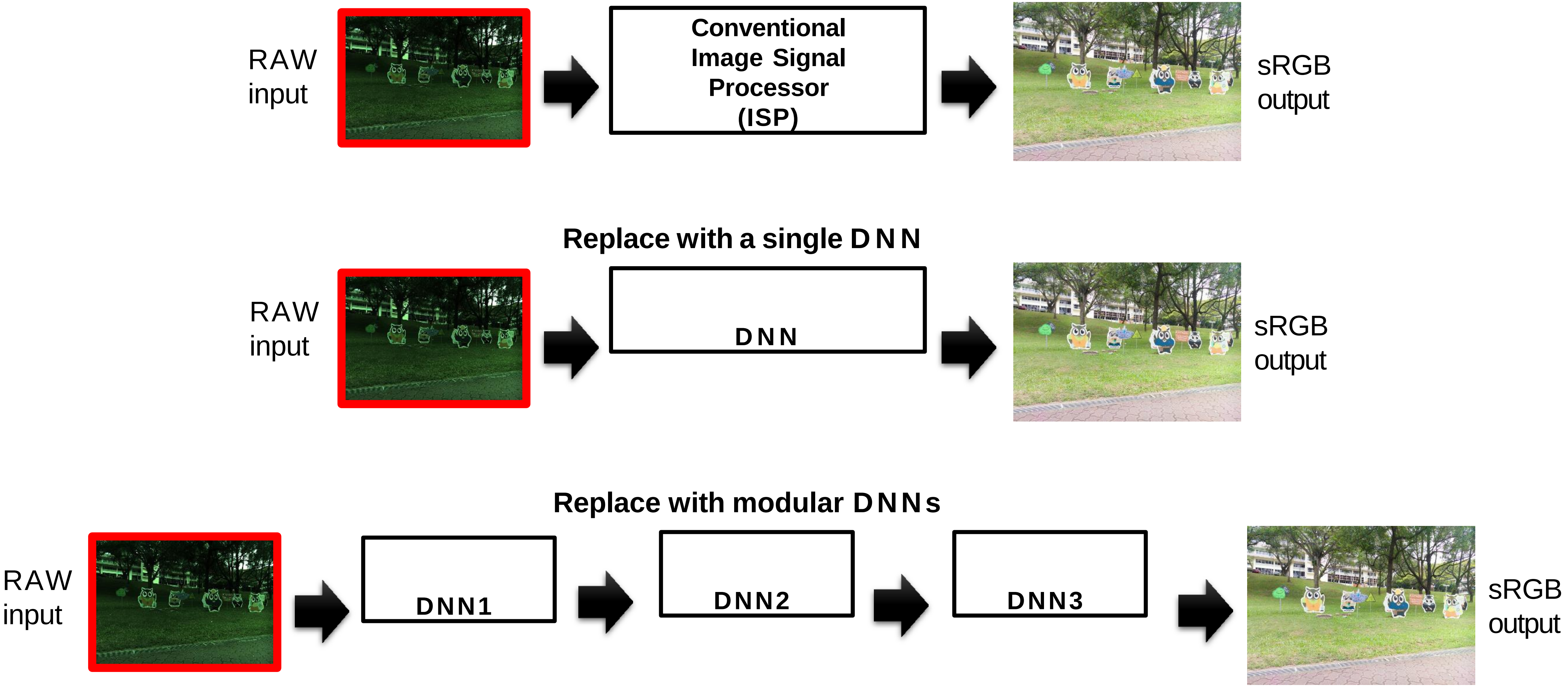
Generally, this problem can be broken down into two stages: 1) aligning the input LDR images and 2) merging the aligned images into an HDR image. The problem of image alignment has been extensively studied and many powerful optical flow algorithms

Paper examined three strategies.
(1) Multi-frame and CNN to predict final HDR.
(2) Multi-frame and CNN to predict blending weights, then HDR.
(3) Multi-frame and CNN to predict blending weights and align misaligned regions
Found that (#2) is the best; (3) works for small motions.

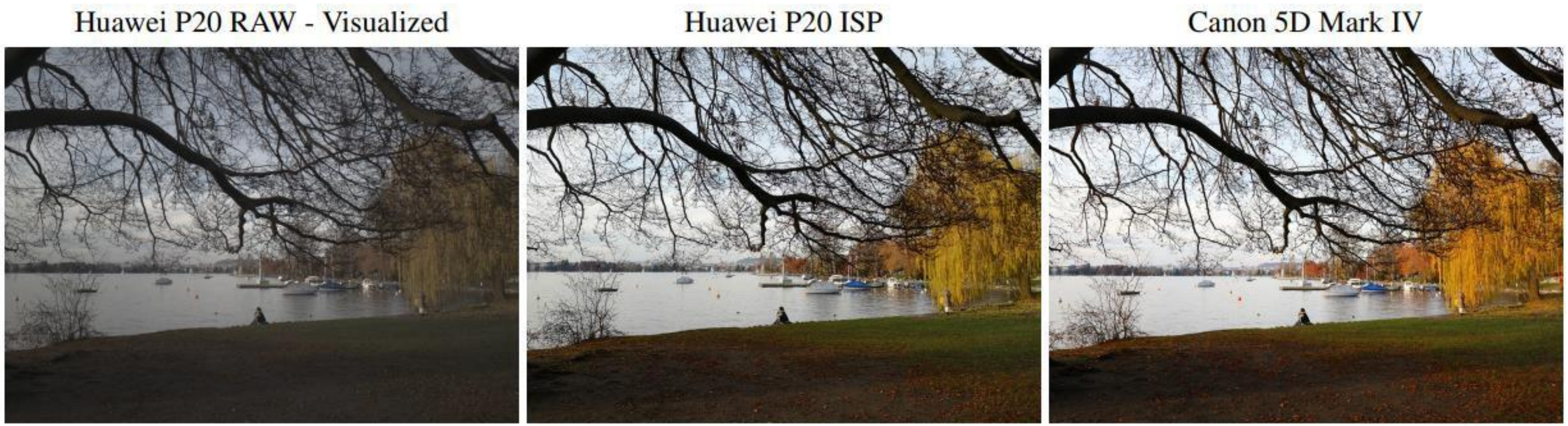


AI-based ISPs

Replacing the conventional ISP



ISP replacement to mimic better camera



Training images RAW from smartphone sRGB from DSLR Images are misaligned!

Images are globally aligned, and then patch wise aligned.

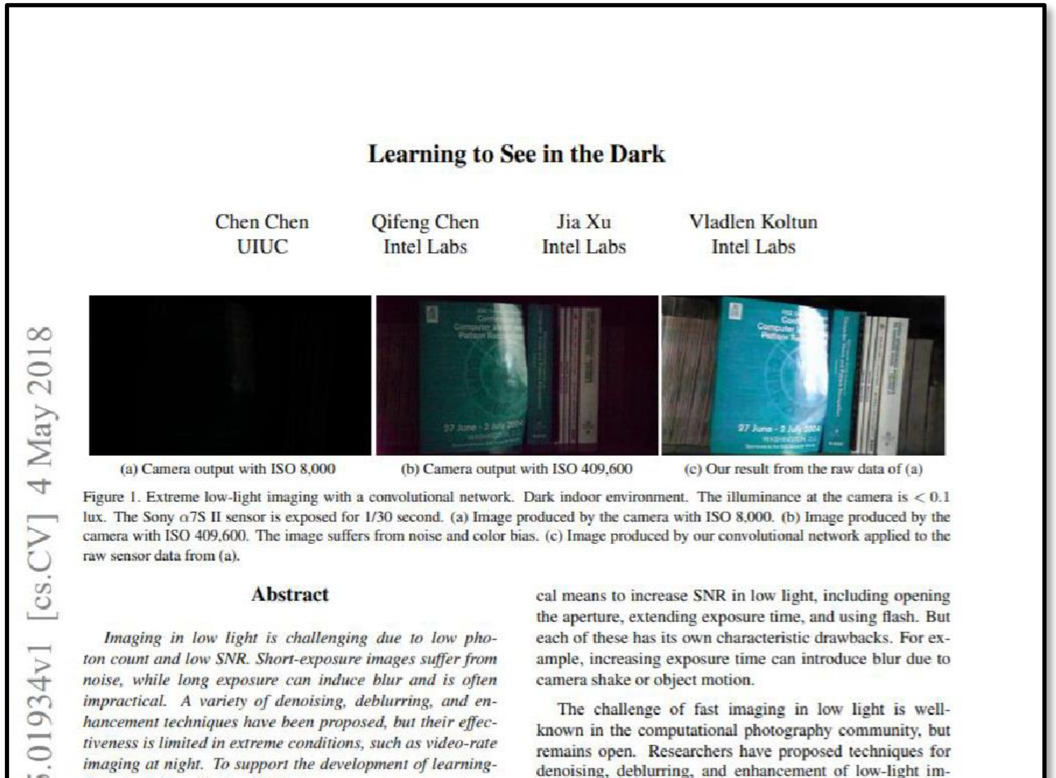
Additional perceptual loss (VGG) is included in training at different U- net scales.

ISP replacement to mimic better camera

"Learning to see in the dark"

This paper is essentially a learned ISP. However, it learns to process noisy RAW to clean sRGB.

Chen et al CVPR 2018



Learning to See in the Dark

Chen Chen
UIUC

Qifeng Chen
Intel Labs

Jia Xu
Intel Labs

Vladlen Koltun
Intel Labs

5.01934v1 [cs.CV] 4 May 2018

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

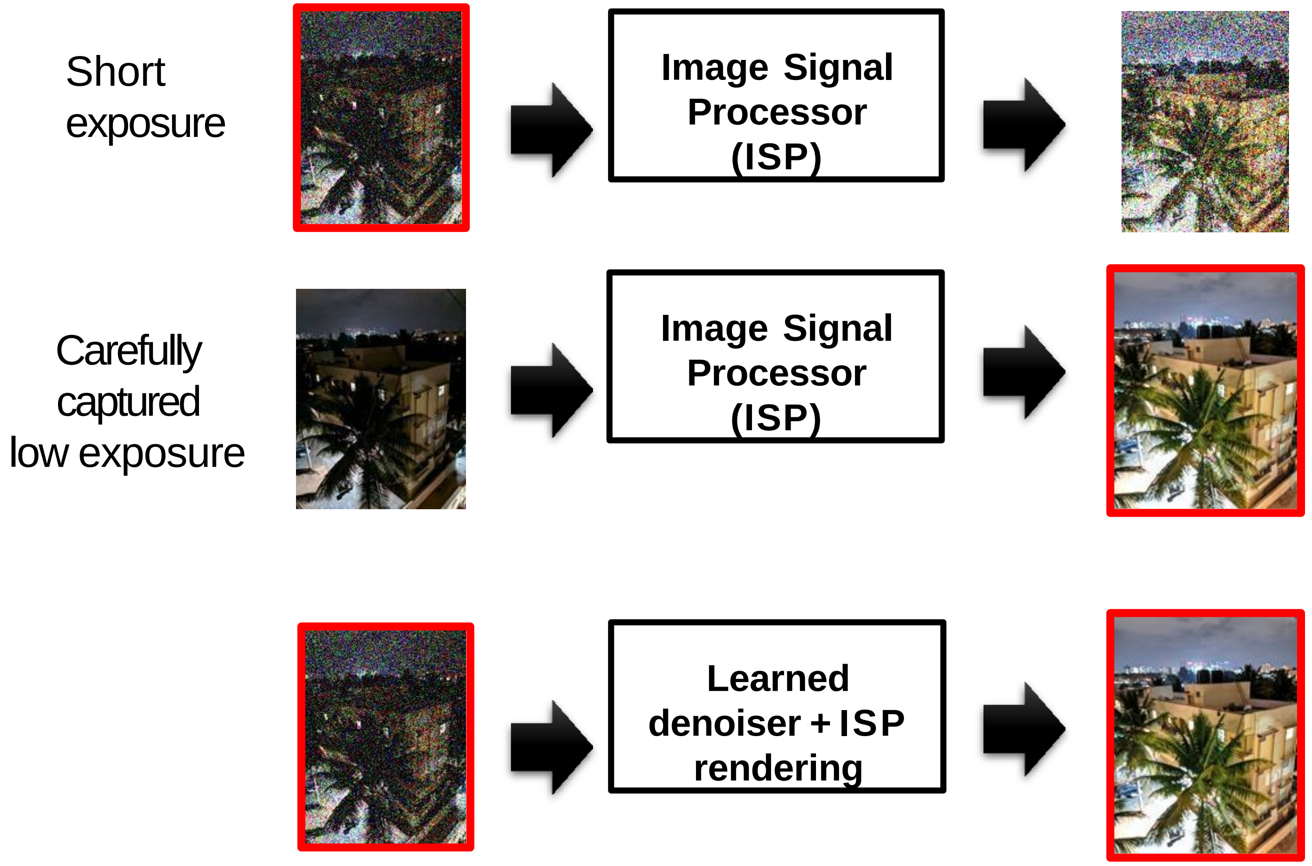
Figure 1. Extreme low-light imaging with a convolutional network. Dark indoor environment. The illuminance at the camera is < 0.1 lux. The Sony α7S II sensor is exposed for 1/30 second. (a) Image produced by the camera with ISO 8,000. (b) Image produced by the camera with ISO 409,600. The image suffers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

Abstract

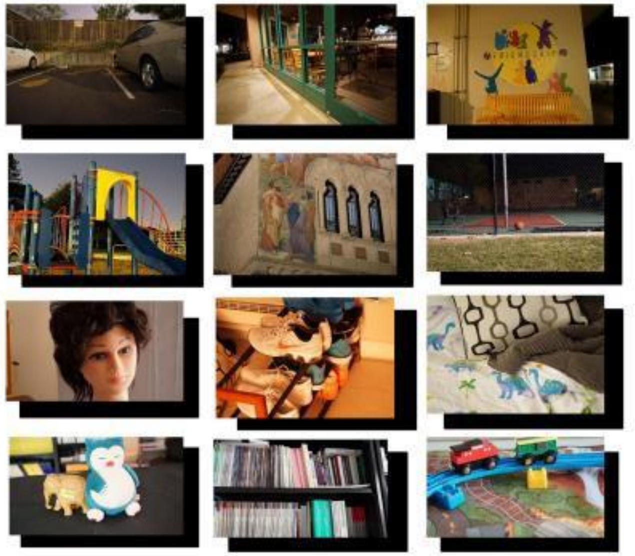
Imaging in low light is challenging due to low photon count and low SNR. Short-exposure images suffer from noise, while long exposure can induce blur and is often impractical. A variety of denoising, deblurring, and enhancement techniques have been proposed, but their effectiveness is limited in extreme conditions, such as video-rate imaging at night. To support the development of learning-

cal means to increase SNR in low light, including opening the aperture, extending exposure time, and using flash. But each of these has its own characteristic drawbacks. For example, increasing exposure time can introduce blur due to camera shake or object motion.

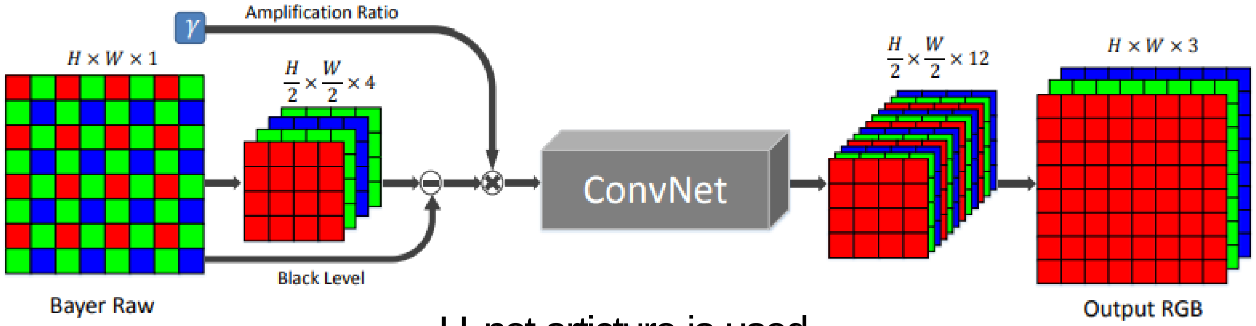
The challenge of fast imaging in low light is well-known in the computational photography community, but remains open. Researchers have proposed techniques for denoising, deblurring, and enhancement of low-light im-



"Learning to see in the dark"

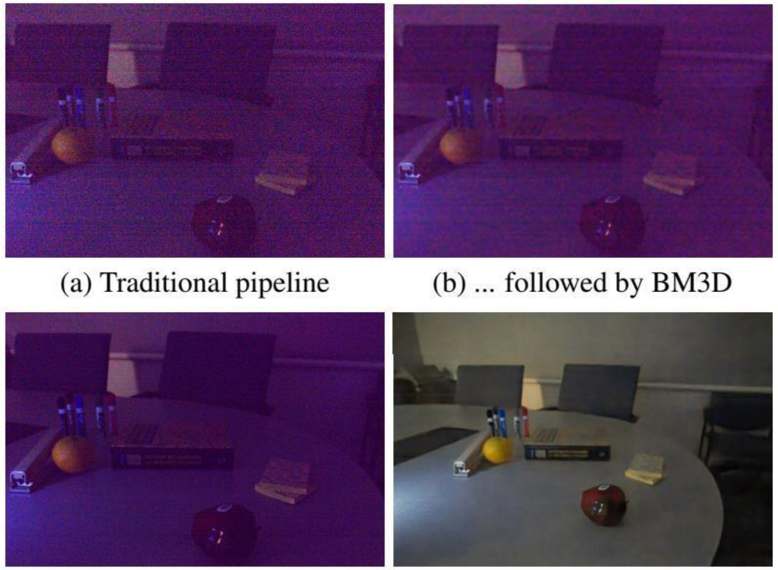


Key to this paper is the careful alignment of data.



U-net articture is used.

Results show for very low-light cases so significant performance.



(a) Traditional pipeline

(b) ... followed by BM3D

(c) Burst denoising

(d) Our result

Winner of the night photography challenge (2022)

NTIRE 2022 Challenge on Night Photography Rendering

Egor Ershov, Alex Savchik, Denis Shepelev, Nikola Banić, Michael S. Brown,
Radu Timofte, Karlo Koščević, Michael Freeman, Vasily Tesalin, Dmitry Bocharov,
Illya Semenkov, Marko Subašić, Sven Lončarić, Arseniy Terekhin, Shuai Liu,
Chaoyu Feng, Hao Wang, Ran Zhu, Yongqiang Li, Lei Lei, Zhihao Li, Si Yi,
Ling-Hao Han, Ruiqi Wu, Xin Jin, Chunle Guo, Furkan Kınlı, Sami Menteş,
Barış Özcan, Furkan Kıraç, Simone Zini, Claudio Rota, Marco Buzzelli,
Simone Bianco, Raimondo Schettini, Wei Li, Yipeng Ma, Tao Wang, Ruikang Xu,
Fenglong Song, Wei-Ting Chen, Hao-Hsiang Yang, Zhi-Kai Huang, Hua-En Chang,
Sy-Yen Kuo, Zhexin Liang, Shangchen Zhou, Ruicheng Feng, Chongyi Li,
Xiangyu Chen, Binbin Song, Shile Zhang, Lin Liu, Zhendong Wang,
Dohoon Ryu, Hyokyoung Bae, Taesung Kwon, Chaitra Desai, Nikhil Akalwadi,
Amogh Joshi, Chinmayee Mandi, Sampada Malagi, Akash Uppin,
Sai Sudheer Reddy, Ramesh Ashok Tabib, Ujwala Patil, Uma Mudenagudi

Abstract

This paper reviews the NTIRE 2022 challenge on night photography rendering. The challenge solicited solutions that processed RAW camera images captured in night scenes to produce a photo-finished output image encoded in the standard RGB (sRGB) space. Given the subjective nature of this task, the proposed solutions were evaluated based on the mean opinions of viewers asked to judge the visual appearance of the results. Michael Freeman, a world-renowned photographer, further ranked the solutions with the highest mean opinion scores. A total of 13 teams competed in the final phase of the challenge. The proposed methods provided by the participating teams represent state-of-the-art performance in nighttime photography. Results from the various teams can be found here: https://nightimaging.org/

lighting environment present in night photography makes it unclear which of the illuminants should be taken into account during the correction of scene colors, see Figure 1. In addition, tone curves and similar photo-finishing strategies used to process daytime images may not be appropriate for night photography. Moreover, common image metrics (e.g., SSIM [53] and LPIPS [59]) may not be suitable for night images. Finally, there is significantly less published research focused on image processing for night photography [38]. As a result, there are fewer "best practices" regarding night photography than daytime photography. Because of that, the main motivation of this challenge was to encourage the research targeting night photography. The following sections describe the NTIRE challenge and solutions for the various teams.

This challenge is one of the NTIRE 2022 associated challenges: spectral recovery [6], spectral demosaicing [5], perceptual image quality assessment [26], inpainting [46], efficient super-resolution [35], learning the super-resolution

Welcome to the "Night Photography" challenge part of the NTIRE workshop at CVPR 2022.

NEWS AND UPDATES

- Teams were asked to process night RAW images to sRGB

- Toloka was used to evaluate results.

- Professional photographer Michael Freeman also evaluated.

- Winning team was from Xiaomi (net slide)

FlexISP

Liu et al NTIRE'22/CVPRW'22 (Xiaomi)

Deep-FlexISP: A Three-Stage Framework for Night Photography Rendering

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Abstract

Night photography rendering is challenging due to images' high noise level, less vivid color, and low dynamic range. In this work, we propose a three-stage cascade framework named Deep-FlexISP, which decomposes the ISP into three weakly correlated sub-tasks: raw image denoising, white balance, and Bayer to sRGB mapping, for the following considerations. First, task decomposition can enhance the learning ability of the framework and make it easier to converge. Second, weak correlation sub-tasks do not influence each other too much, so the framework has a high degree of freedom. Finally, noise, color, and brightness are essential for night photographs. Our framework can flexibly adjust different styles according to personal preferences with the vital learning ability and the degree of freedom. Compared with the other Deep-ISP methods, our proposed Deep-FlexISP shows state-of-the-art performance and achieves first place in people's choice and photographer's choice in NTIRE 2022 Night Photography Render Challenge.

(a) Baseline

1. Introduction

Night photography is a challenging task due to several reasons. First, the low light condition will cause high-level noise in the raw image. Second, it is hard to estimate the

-Winner for Night Photography challenge

- Results were far better than competitors

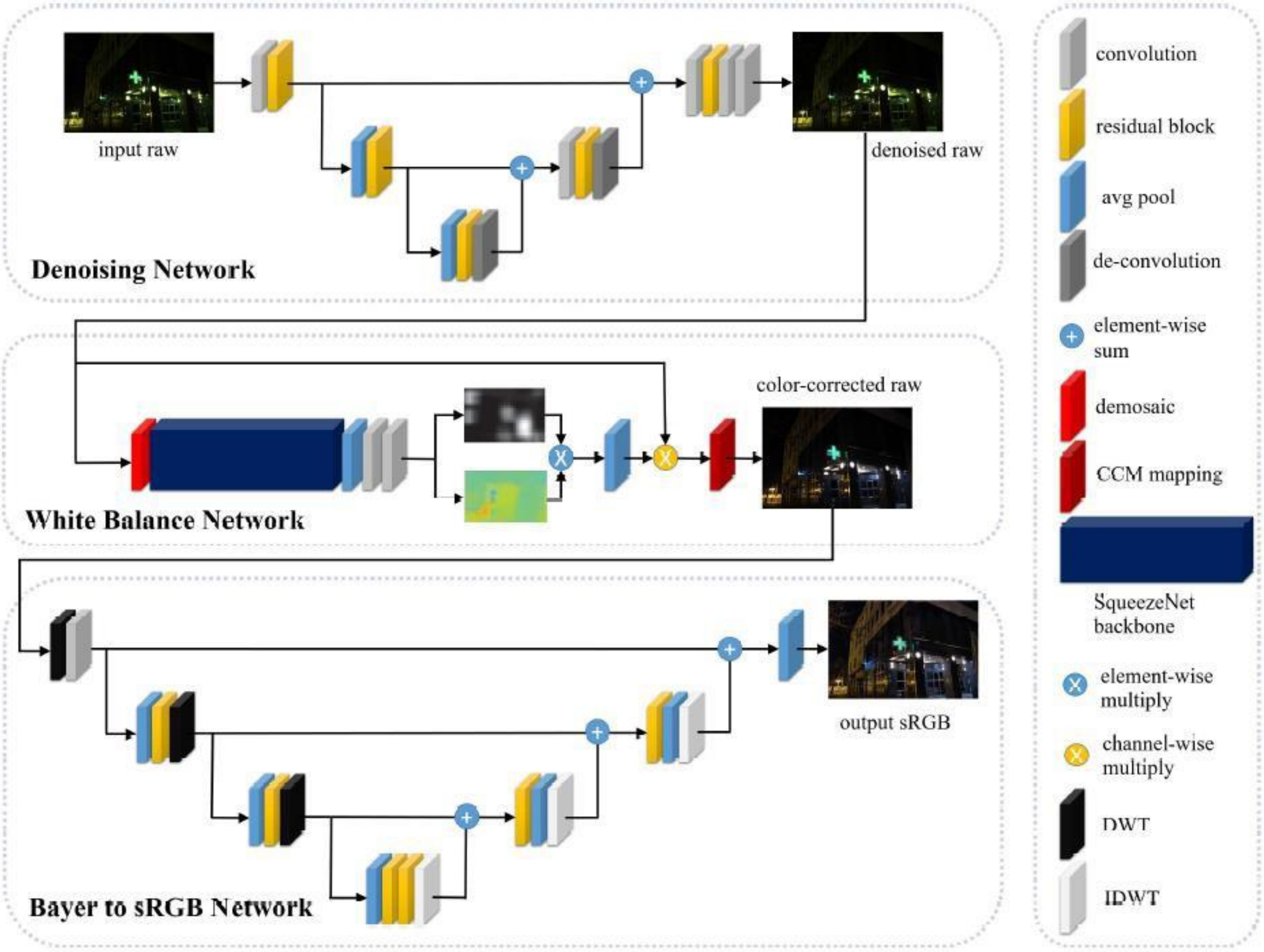
- Introduced a 3-stage ISP

FlexISP

Custom denoiser.Training data unclear (possibly in-house Xiaomi denoiser used to generate ground truth). Network was conditioned in noise level. Allowing adjustment.

F4C was used for white-balance. Two networks were used,each predicting biased results towards warm/cold ground truth. User can "slide" between results.

Images were manually adjusted (lightroom?) at different levels. Users could "slide" between results.



Baseline was a simple software ISP given to participants.

(a) Baseline

PyNet is single DNN method.

(b) PyNet

HERN (Enhancement network)

(c) HERN

FlexISP.

(d) Ours Deep-FlexISP

SAMSUNG / TECH / CAMERAS AND PHOTOGRAPHY

Samsung caught faking zoom photos of the Moon

A Samsung smartphone identified a blurry photo of the Moon and added detail to create the above image. Image: u/ibreakphotos

/ A viral Reddit post has revealed just how much processing the company's cameras apply to photos of the Moon, further blurring the line between real and fake imagery in the age of AI.

By James Vincent and Jon Porter
Mar 13, 2023, 7:46 PM GMT+5:30

145 Comments (145 New)

For years, Samsung "Space Zoom"-capable phones have been known for their ability to take incredibly detailed photos of the Moon. But a

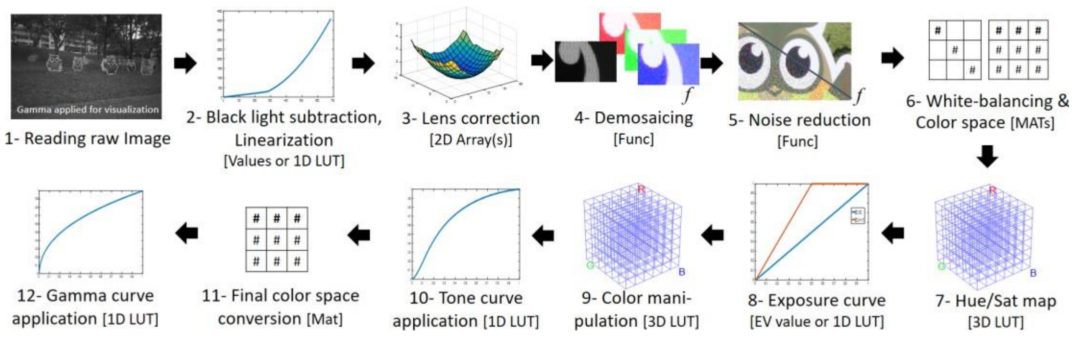
DNN-based ISP considerations and challenges

Training data

- It is important to remember that RAW images are sensor-specific
  - This means we often need to train ISPs (and ISP modules) per sensor
  - Modern smartphones can have 3-4 different sensors
  - Capturing training data can be overwhelming for camera engineers
- Care is required when capturing training data
  - Many of the low-light/HDR papers, the real contribution is the carefully captured training data
  - Again, this needs to be captured "per" sensors
- Single stage ISPs have limited "tune-ability"
  - Conventional ISP are designed to be tunable
  - DNNs are often tuned by changing the training data

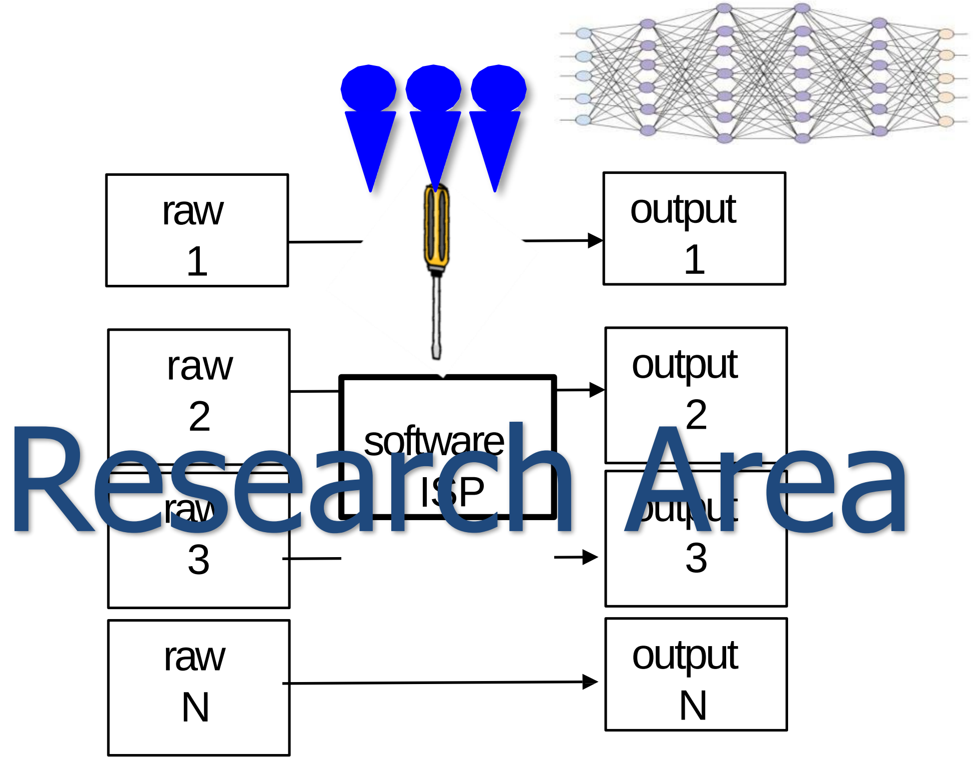
Consideration for DNN-based ISP

- **A conventional ISP is still required to produce training data**
- **Can we beat conventional ISPs?**



Current ISP workflow

Team of Image Quality Engineers tune ISP parameters to produce desired images.



Neural-ISP workflow

Team of Image Quality Engineers process thousand of RAW images with a "software ISP" to produce training data?

Summary

- Digital Camera Fundamentals
  - Components
  - Capture Process
  - Terminologies
- Overview of basic blocks on camera pipeline
- ISP Basics, need for ISP
- Image Quality, need for measurement
- Camera IQ tuning & challenges
- Discussion of some recent AI-based methods and trends
- Next step - Assignment and Internship !!!

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- http://www.imatest.com/docs/
- And many more!!

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Shaping the future of Imaging

Thank you all for your attention

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