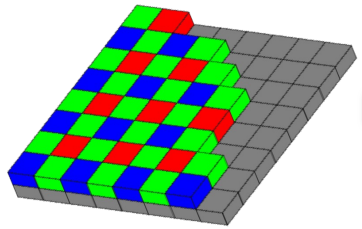
Lecture 4: Camera Imaging Pipeline

COMP 590/776: Computer Vision

Instructor: Soumyadip (Roni) Sengupta

TA: Mykhailo (Misha) Shvets

A typical color imaging pipeline



Sensor with color filter array (CFA)
(CCD/CMOS)

ISO gain and raw-image processing

RGB Demoasicing

Noise Reduction

White-Balance & Color Space Transform (CIE XYZ)

Color Manipulation (Photo-finishing)

Mapping to sRGB output

JPEG Compression

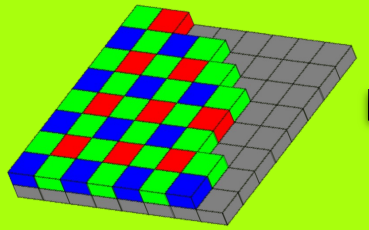
Save to file

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.

Integrated signal processor (ISP)

- You will hear the term "ISP" associated with camera pipelines
- An ISP is dedicated hardware used to process the sensor image to produce the final output (JPEG image) that is saved on your device
- The ISP is usually integrated as part of a system on a chip (SoC) that has other modules
- Companies such as Qualcomm, HiSilicon, Intel (and more) sell ISP chips
  - An ISP can be customized by the customer (Samsung, Huawei, LG, Apple, etc)
- Note that it is also possible to perform operations common on an ISP on your device's CPU and GPU

A typical color imaging pipeline



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Camera sensor

CMOS sensor

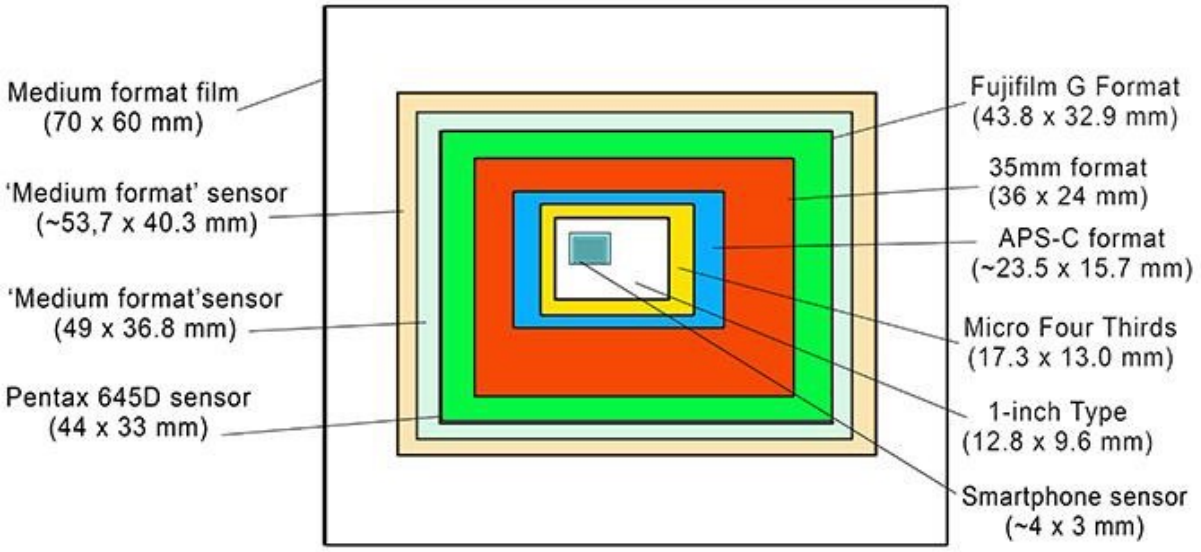
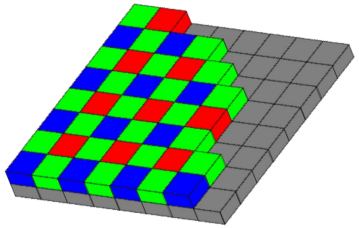


Figure from Photo Review website.

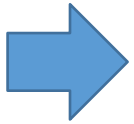
Almost all consumer camera sensors are based on complementary metal-oxide semiconductor (CMOS) technology.

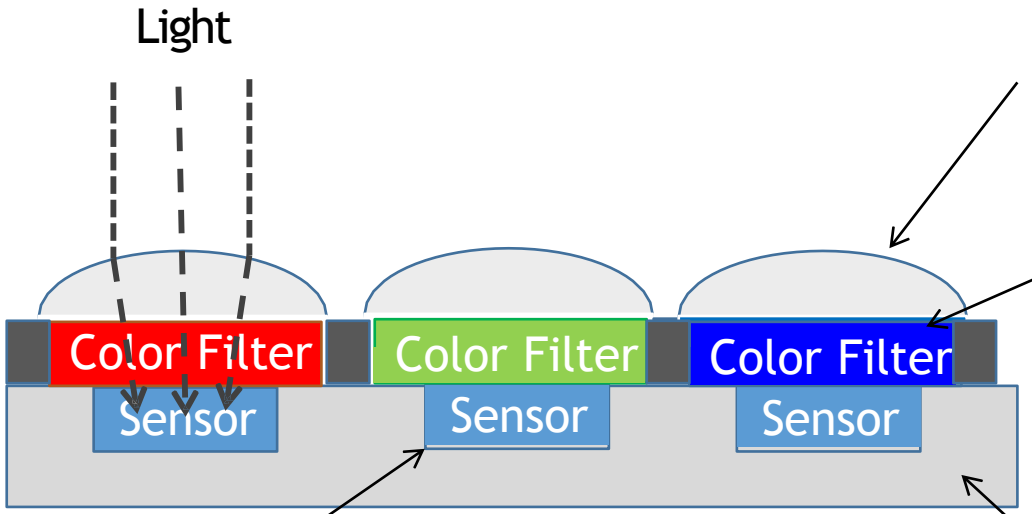
- We generally describe sensors in terms of number of pixels and size.
- The larger the sensor, the better the noise performance as more light can fall on each pixel.
- Smart phones have small sensors!

Camera sensor RGB values



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.

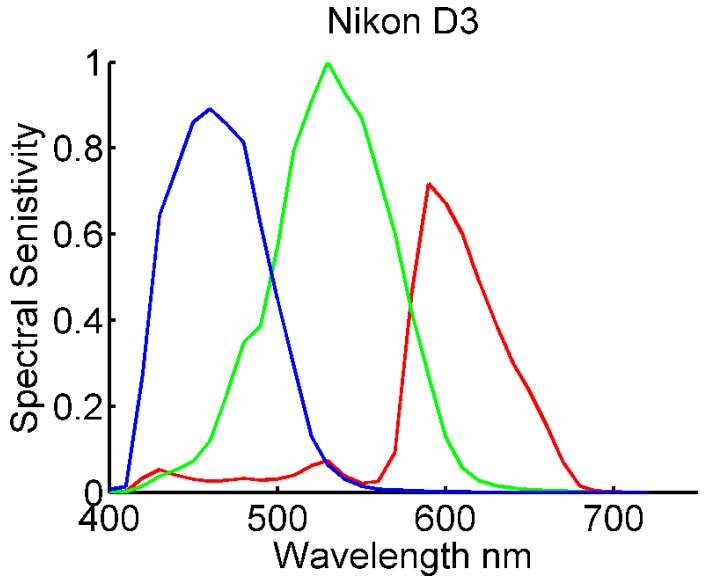
Photodiode
Photons hit the diode and force out electrons.
This design is similar to a solar cell!

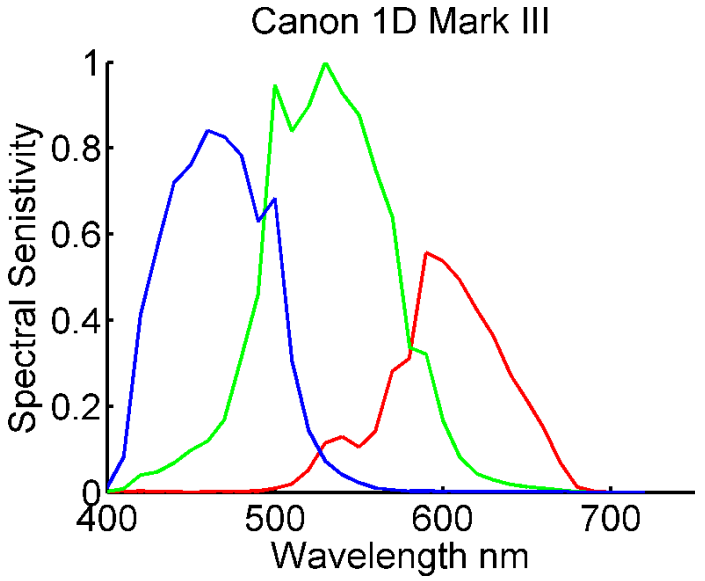
Silicon/Circuitry

Bryce Bayer

Camera RGB sensitivity

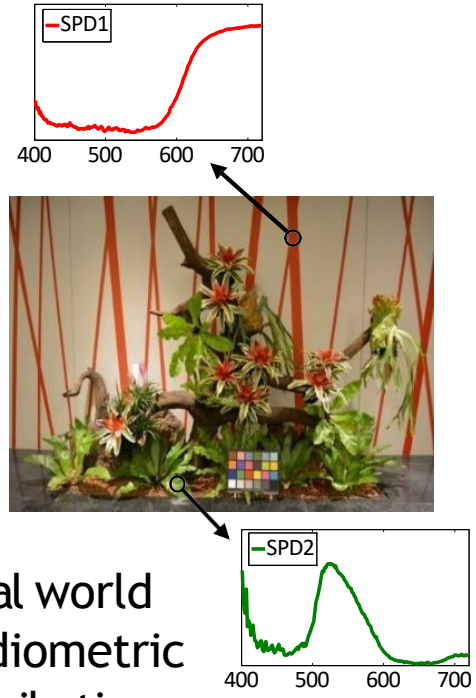
- The color filter array (CFA) on the camera filters the light into three *sensor-specific* RGB primaries



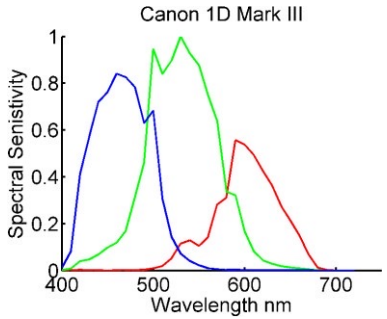


Plotted from camera sensitivity database by Dr. Jinwei Gu from Rochester Institute of Technology (RIT). Dr. Gu is now at SenseTime (USA). http://www.cis.rit.edu/jwgu/research/camspec/

Sensor raw-RGB image



Remember: physical world is measured by radiometric spectral power distributions.



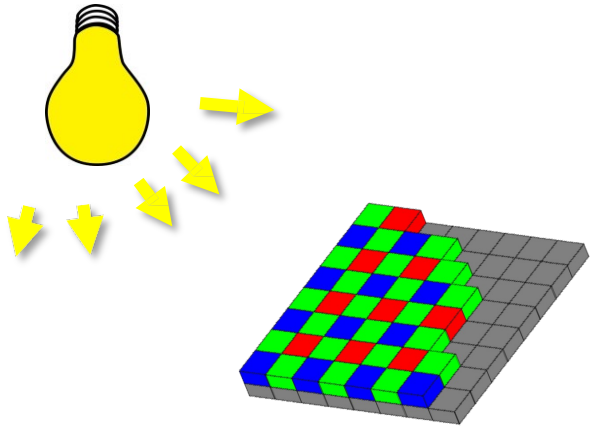
Color Matching Functions CIE XYZ

Your camera sensor RGB filter is sensitive to different regions of the incoming SPD.

raw-RGB represents the physical world's SPD "projected" onto the sensor's spectral filters.

Sensors are linear to irradiance

- Camera sensors are decent light measuring devices
- If you double the amount of light hitting a sensor's pixel, the digital value output of that pixel will double

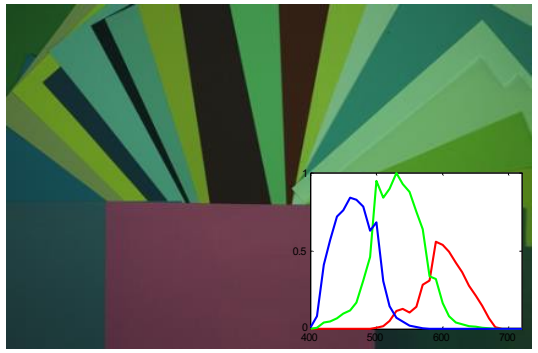


Sensor output is linear with respect to irradiance falling over the sensor over a certain amount of time.

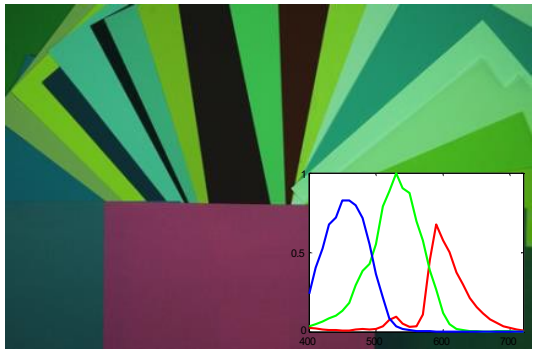
$$I = i * t$$

Digital value I is a linear function of irradiate i and exposure t.

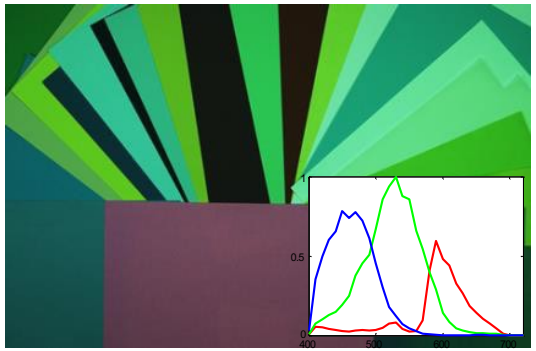
IMPORTANT: raw-RGB sensor images are not in a standard color space



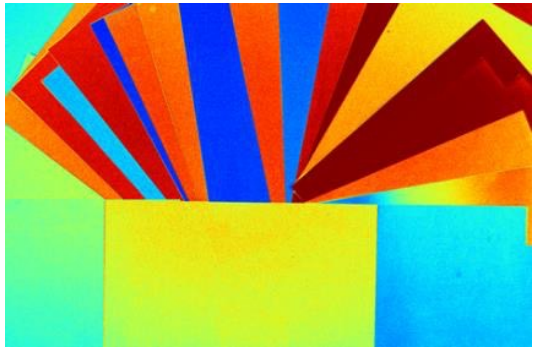
Canon 1D



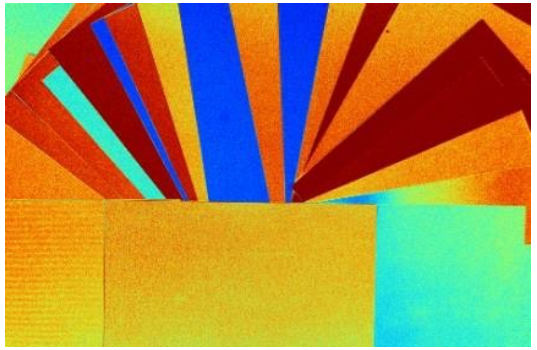
Nikon D40



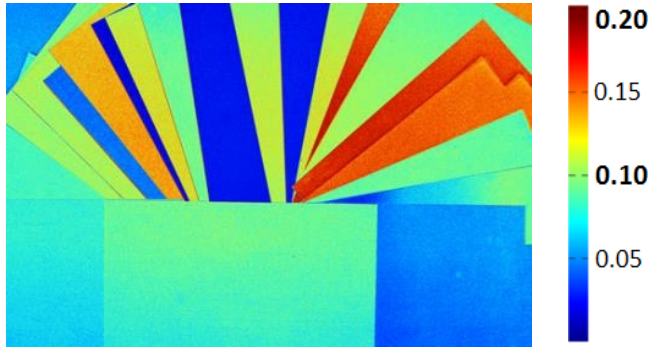
Sony α57



$||$Canon 1D – Nikon D40$||_2$



$||$Canon 1D - Sony α57$||_2$



$||$Nikon D40 - Sony α57$||_2$

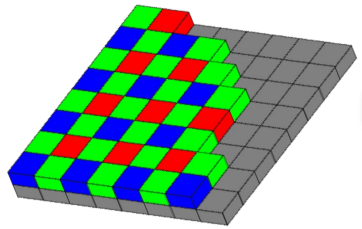
Color plots show L2 distance between the raw-RGB values with different cameras.

Displaying raw-RGB images

- Inserting a raw-RGB image in your slides, research paper, etc will result in strange colors.
- Why? Our devices (computers, printers, etc) expect the image to be in a standard color space like sRGB.

This is a raw-RGB image. Why does it look bad?
Because the RGB values are not sRGB values.
Knowing your color space is important!

A typical color imaging pipeline



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ISO signal amplification (gain)

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

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

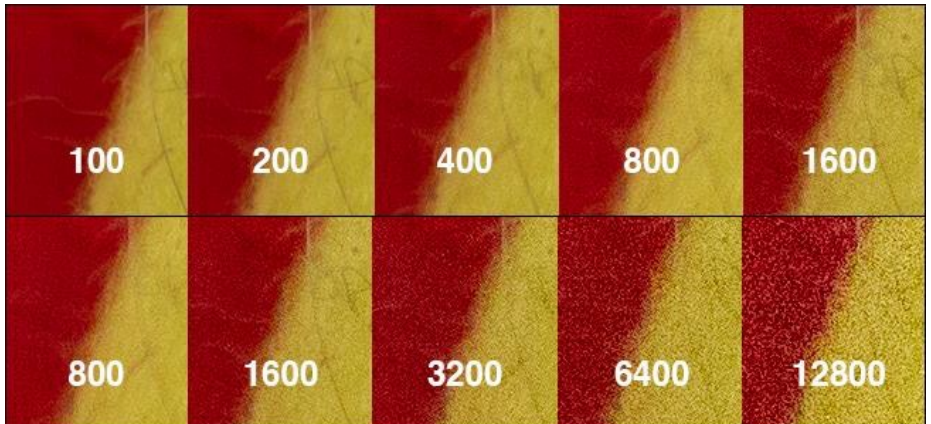


Image: Harry Guinness

ISO gain and raw-image processing

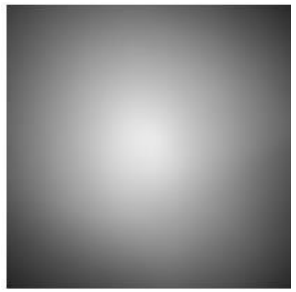
Pixel "intensity"

- We often talk about a pixel's intensity, however, a pixel's numerical value has no *unit*

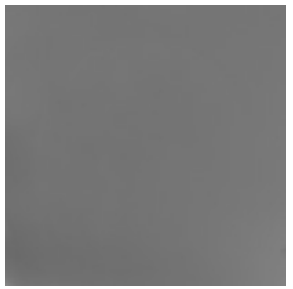
- The digital value of a pixel is based on several factors
  - Exposure (which is a function of both shutter speed and exposure)
  - Gain (ISO setting on the camera)
  - Camera hardware that digitizes the signal

- We typically rely on the ***relative*** digital values in the image and not the absolute digital values

Flat-field correction

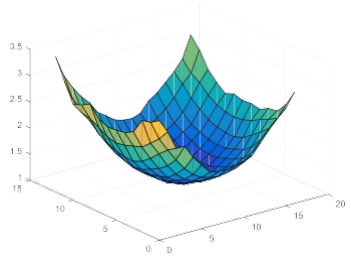


Uniform light falling on the sensor may not appear uniform in the raw-RGB image. This can be caused by the lens, sensor position in the camera housing, etc.

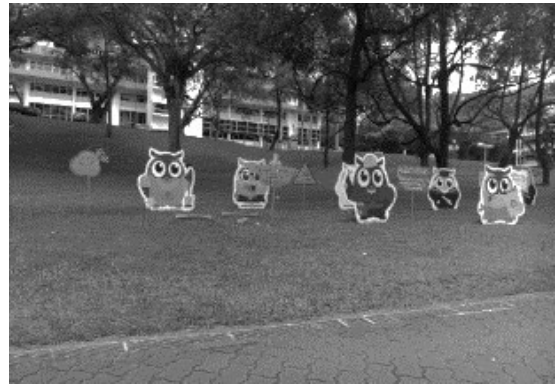


We want to correct this problem such that we get a "flat" output.

Before correction



Apply a correction gain over the sensor values.

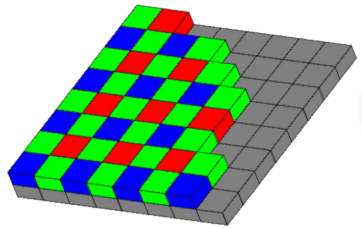


After correction

ISO gain and raw-image processing

This operation can also be called "lens shading" correction.

A typical color imaging pipeline



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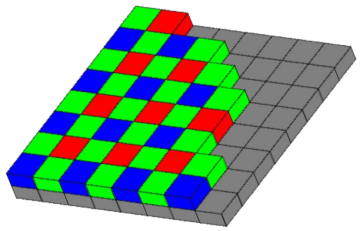
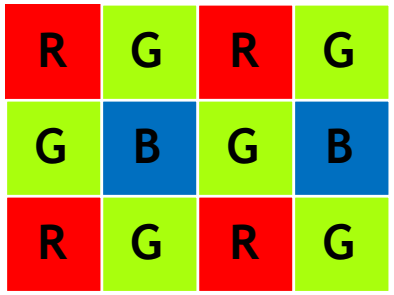
CFA/Bayer pattern demosaicing

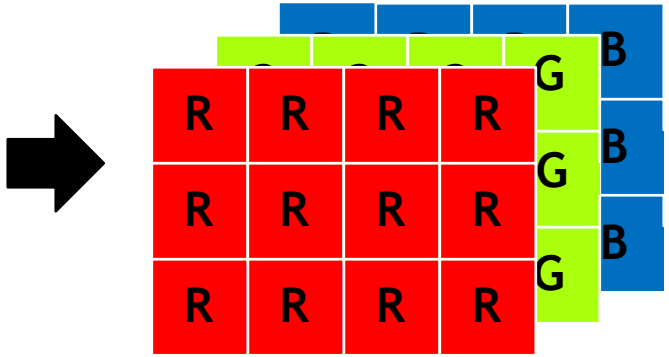
- Color filter array/Bayer pattern placed over pixel sensors
- We want an RGB value at each pixel, so we need to perform interpolation



Sensor with color filter array (CMOS)



Sensor RGB layout

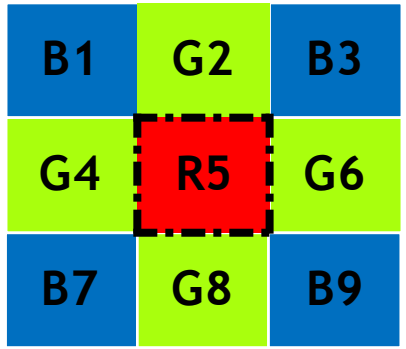


Desired output with RGB per pixel.

RGB Demoasicing

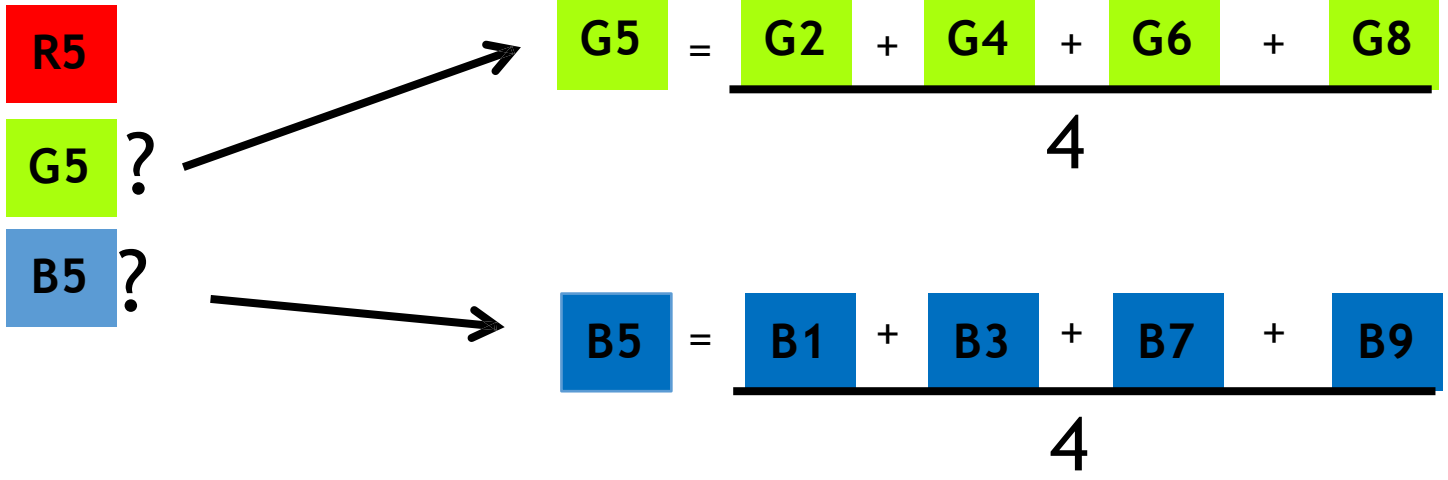
Simple interpolation

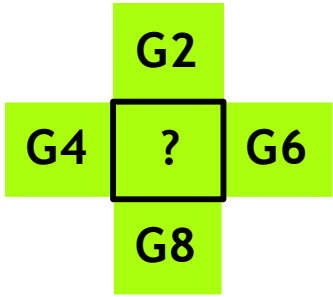
This is a zoomed up version of the Bayer pattern.

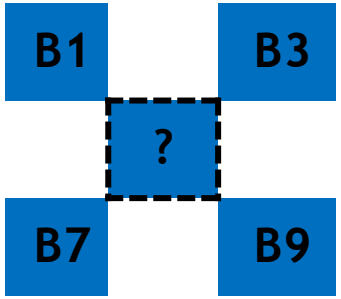


At location R5, we have a red pixel value, but no Green or Blue pixel.

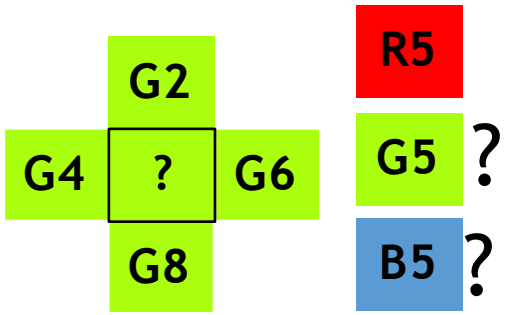
We need to estimate the G5 & B5 values at location R5.







Simple "edge aware" interpolation



If (|(G2–G8) && |(G4-G8)| both < Thres):

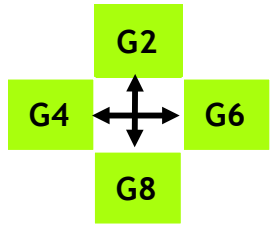
$$G5 = \frac{G2 + G4 + G6 + G8}{4}$$

elseif (|G2-G8| > Thres):

$$G5 = \frac{G4 + G6}{2}$$

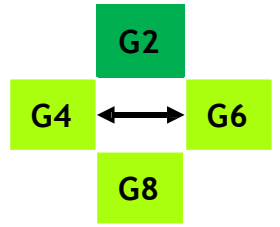
else:

$$G5 = \frac{G2 + G8}{2}$$



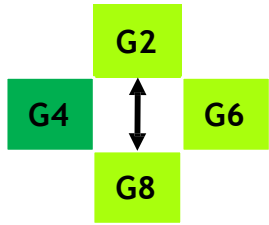
Case 1

All about the same.



Case 2

G2 and G8 differ - ignore them in the interpolation



Case 3

G4 and G6 differ - ignore them in the interpolation

Do this procedure also for the blue pixel, B5.

Demosaicing in practice

- The prior examples are illustrative algorithms only
- Camera IPSs use more complex and proprietary algorithms.
- Demosaicing can be combined with additional processing
  - Highlight clipping
  - Sharpening
  - Noise reduction

D N N for demosaicing (and denoising)

Gharbi et al SIGGRAPH Asia, 2016

Deep Joint Demosaicking and Denoising

Michaël Gharbi MIT CSAIL
Gaurav Chaurasia MIT CSAIL
Sylvain Paris Adobe
Frédo Durand MIT CSAIL

Figure 1: *We propose a data-driven approach for jointly solving denoising and demosaicking. By carefully designing a dataset made of rare but challenging image features, we train a neural network that outperforms both the state-of-the-art and commercial solutions on demosaicking alone (group of images on the left, insets show error maps), and on joint denoising–demosaicking (on the right, insets show close-ups). The benefit of our method is most noticeable on difficult image structures that lead to* moiré *or* zippering *of the edges.*

Abstract

Demosaicking and denoising are the key first stages of the digital imaging pipeline but they are also a severely ill-posed problem that infers three color values per pixel from a single noisy measurement.

1 Introduction

Demosaicking and denoising are simultaneously the crucial first steps of most digital camera pipelines. They are quintessentially ill-posed reconstruction problems: at least two-thirds of the data is

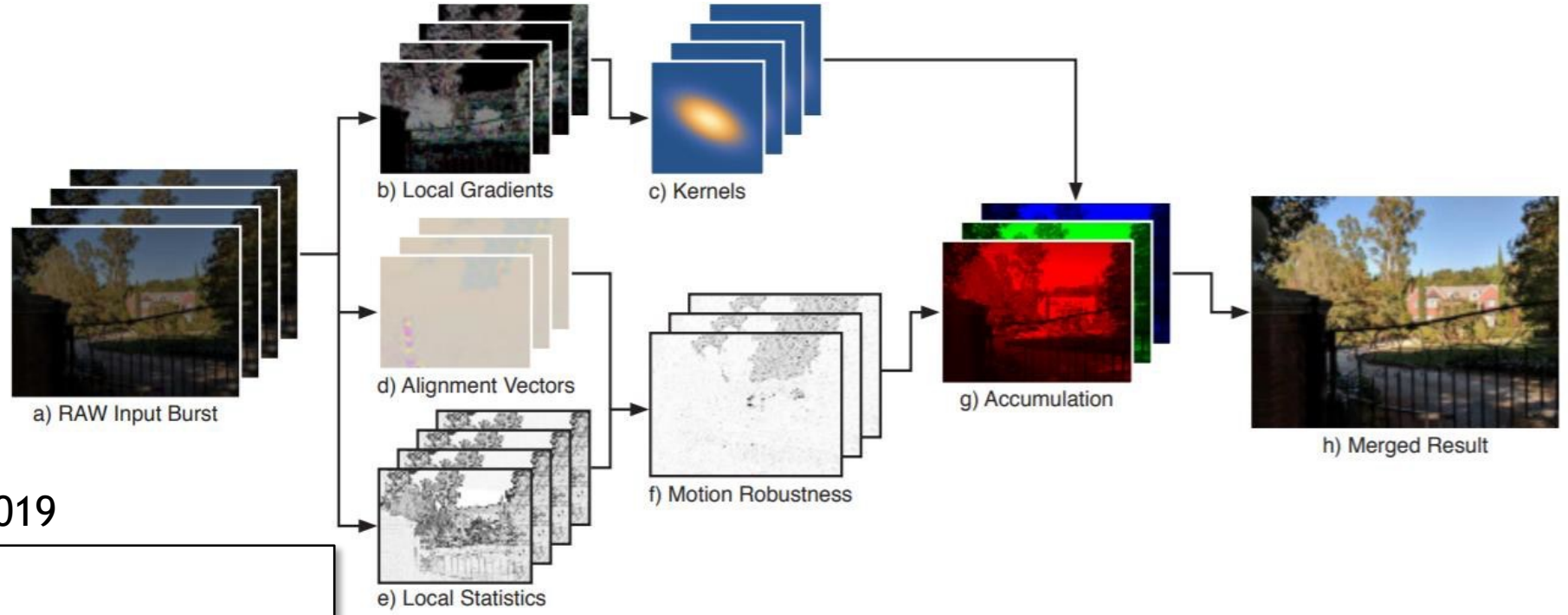
This is a very interesting paper that examines using a D N N to perform demoasicing.

Interestingly, the act of demosaicing to a clean ground truth image implicitly performs denoising.

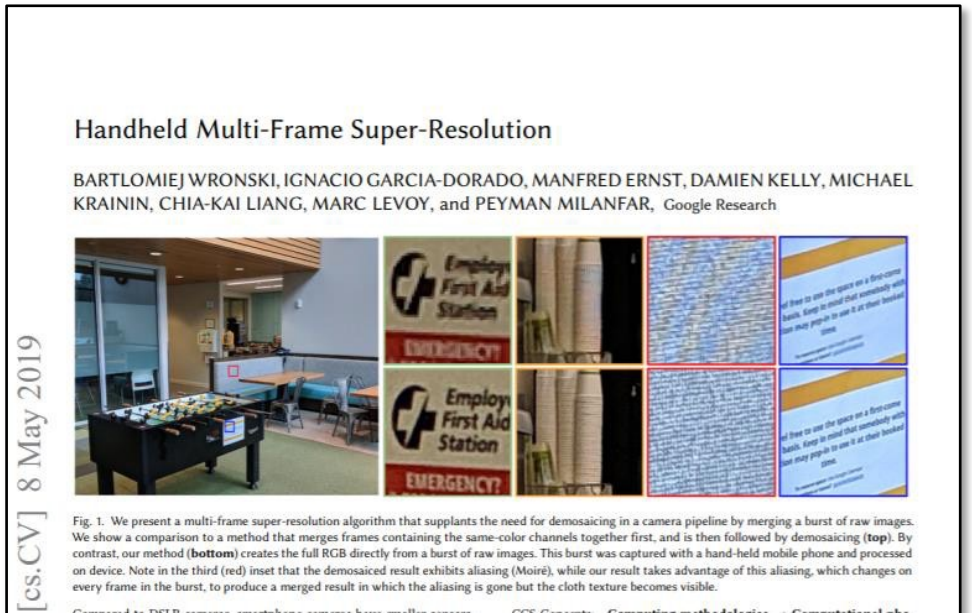
The only drawback of this paper is that training/testing demosiaced images were synthetically generated by sampling sRGB images and adding noise.

A lack of a raw-RGB dataset is a problem and would be a nice addition in this area.

Non-learning improvement for demosaicing



Wronski et al SIGGRAPH 2019

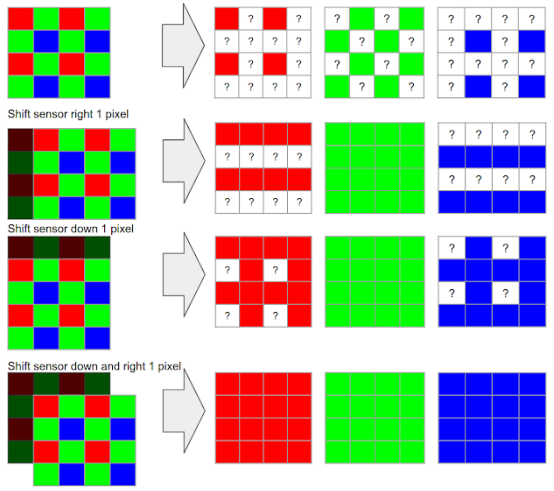


Handheld Multi-Frame Super-Resolution

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

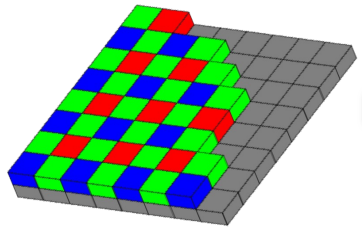
[cs.CV] 8 May 2019

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.



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.

A typical color imaging pipeline



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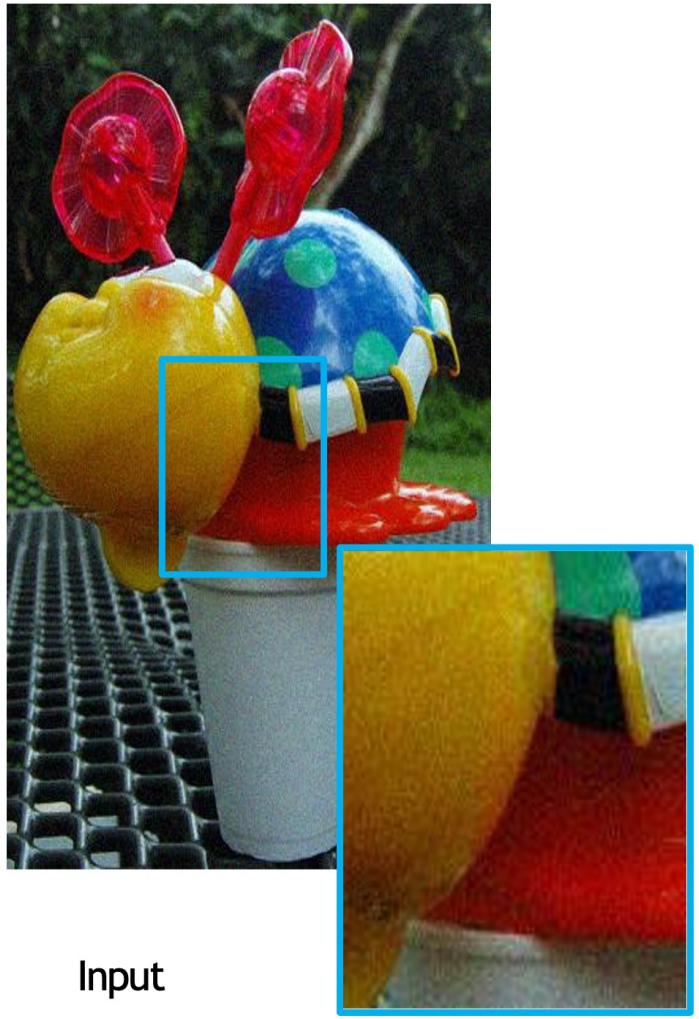
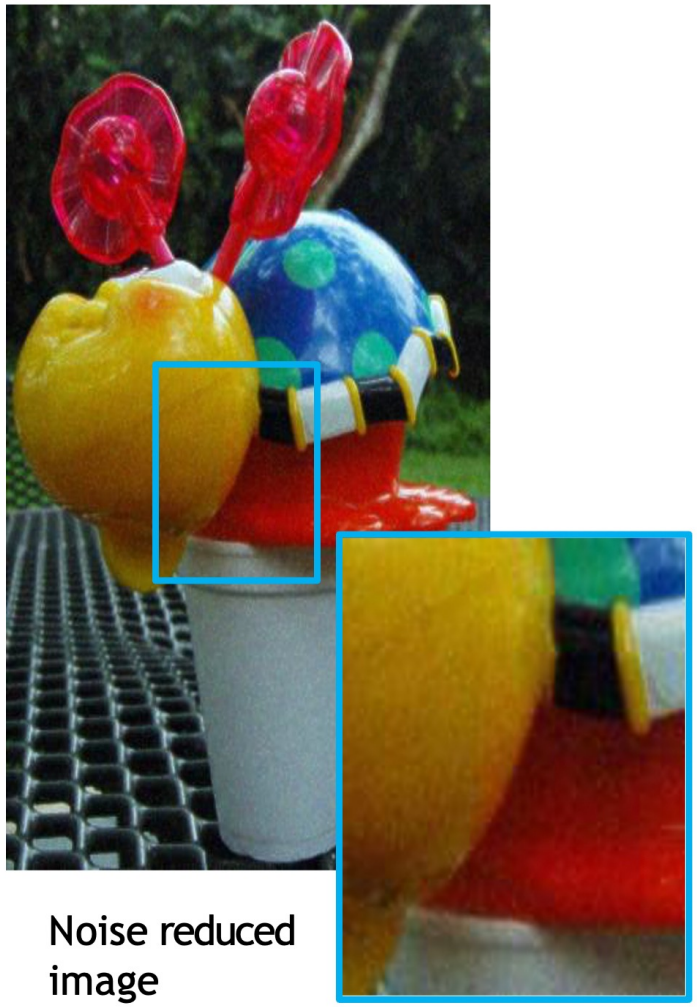
* Note that steps can be optional (e.g. noise reduction) or applied in slightly different order.

Noise reduction (NR)

- All sensors inherently have noise
- Most cameras apply additional NR after A/D conversion
- A simple method is described in the next slide
- 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.



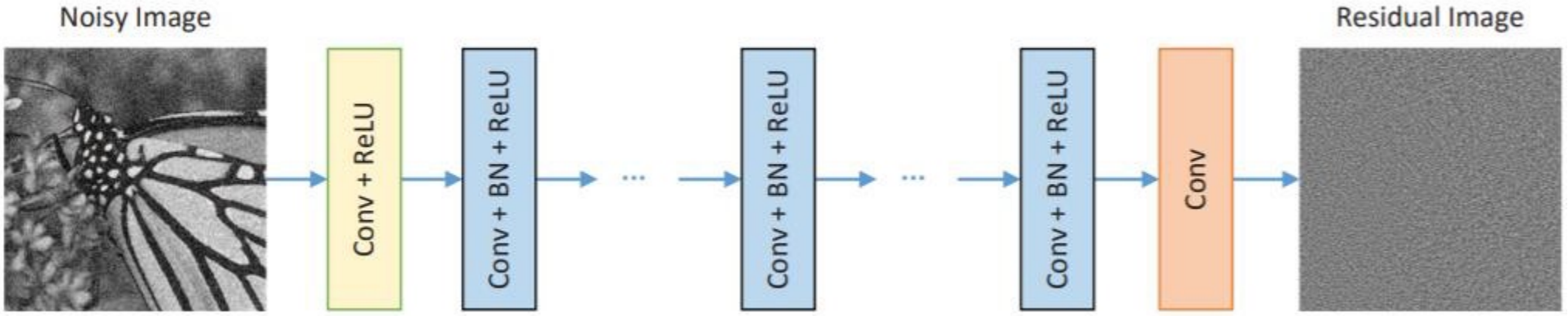
Input



Noise reduced image

DNNs for denoising

- Zhang et al "Beyond a Gaussian Denoiser: Residual Learning of Deep CNN for Image Denoising", TIP 2017
- The following is a website with many denoising papers with code available:
  https://paperswithcode.com/task/image-denoising?page=2



Many methods predict the noise image instead of the denoised image (DnNN from TIP 2017)

Denoising contest at CVPR'19

NTIRE denoising contest at CVPR'19

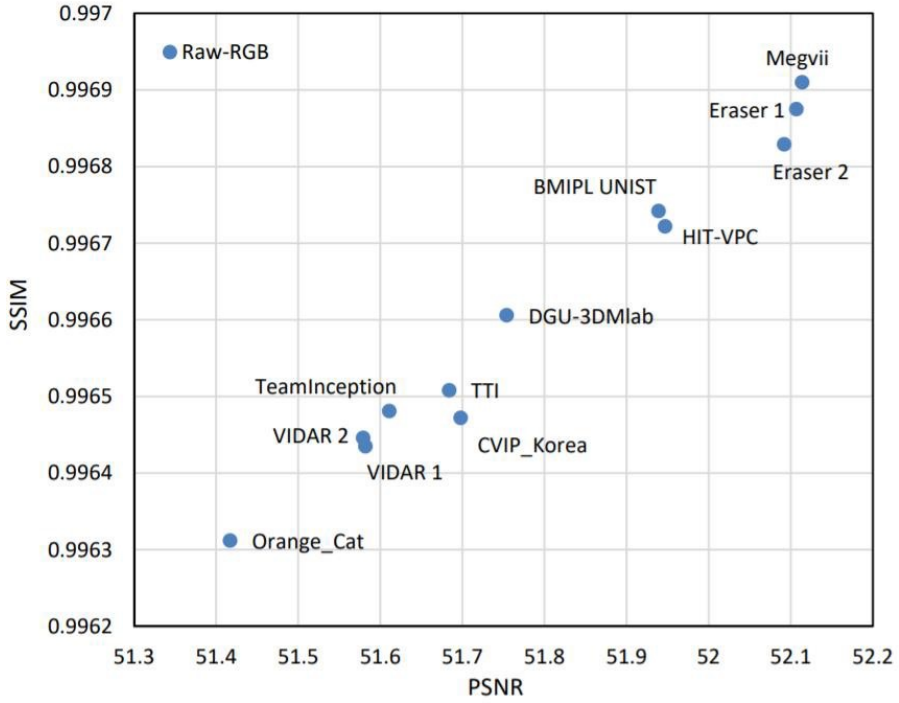
NTIRE 2019 Challenge on Real Image Denoising: Methods and Results

Abdelrahman Abdelhamed Radu Timofte Michael S. Brown Songhyun Yu
Bumjun Park Jechang Jeong Seung-Won Jung Dong-Wook Kim Jae-Ryun Chung
Jiaming Liu Yuzhi Wang Chi-Hao Wu Qin Xu Yuqian Zhou Chuan Wang
Shaofan Cai Yifan Ding Haoqiang Fan Jue Wang Kai Zhang Wangmeng Zuo
Magauiya Zhussip Dong Won Park Shakarim Soltanayev Se Young Chun
Zhiwei Xiong Chang Chen Muhammad Haris Kazutoshi Akita Tomoki Yoshida
Greg Shakhnarovich Norimichi Ukita Syed Waqas Zamir Aditya Arora
Salman Khan Fahad Shahbaz Khan Ling Shao Sung-Jea Ko Dong-Pan Lim
Seung-Wook Kim Seo-Won Ji Sang-Won Lee Wenyi Tang Yuchen Fan
Yuqian Zhou Ding Liu Thomas S. Huang Deyu Meng Lei Zhang
Hongwei Yong Yiyun Zhao Pengliang Tang Yue Lu Raimondo Schettini
Simone Bianco Simone Zini Chi Li Yang Wang Zhiguo Cao

Abstract

This paper reviews the NTIRE 2019 challenge on real image denoising with focus on the proposed methods and their results. The challenge has two tracks for quantitatively evaluating image denoising performance in (1) the Bayer-pattern raw-RGB and (2) the standard RGB (sRGB) color spaces. The tracks had 216 and 220 registered participants, respectively. A total of 15 teams, proposing 17 methods,

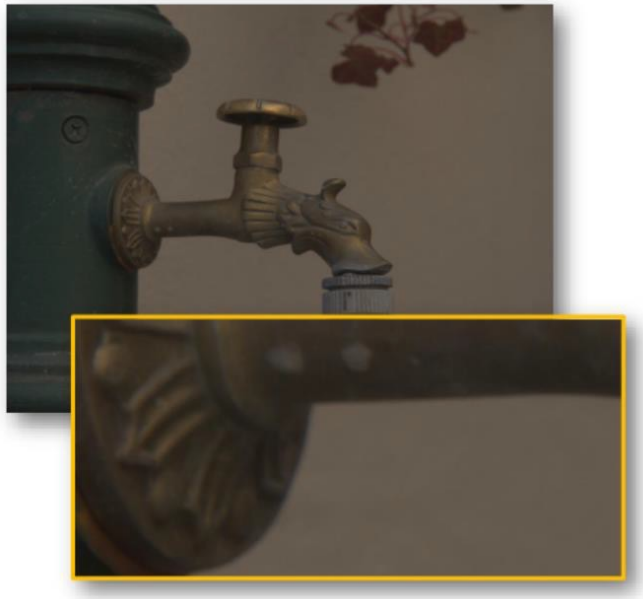
ing image denoisers, especially the additive white Gaussian noise (AWGN)—for example, [6, 9, 38]. Recently, more focus has been given to evaluating image denoisers on real noisy images [1, 25]. It was shown that the performance of learning-based image denoisers on real noisy images can be limited if trained using only synthetic noise. Also, hand-engineered and statistics-based methods have been shown to perform better on real noisy images. To this end, we have proposed this challenge as a means to evaluate and bench-



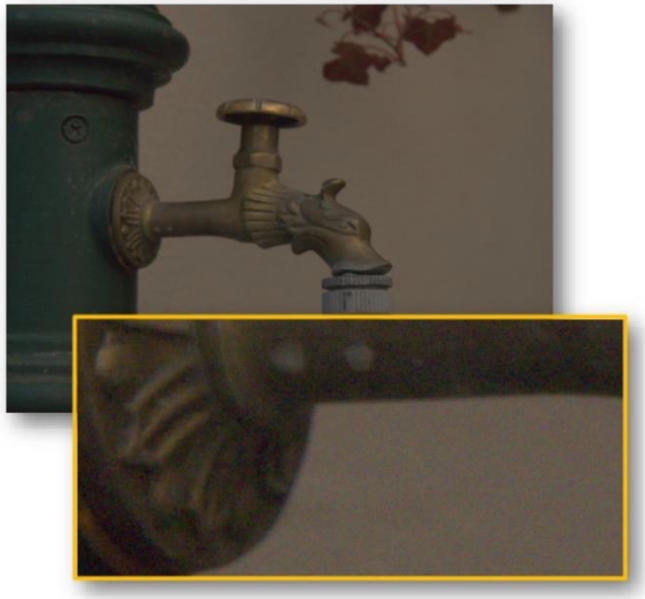
More than 10 DNN-based submissions

Training data for noise reduction (denoising)

Training/validation/testing images
Real images captured under low-ISO and high-ISO.
Or, synthetic images with noise added.



Label/ground truth image
Low ISO setting



Noisy image
High ISO setting

Example from Darmstadt Noise Dataset

Most DNNs operate on small patches (32x32). So, a single image provides many training samples.

Denoising dataset

SIDD: Smartphone Image Denoising Dataset

Abdelhamed et al CVPR 2018

A High-Quality Denoising Dataset for Smartphone Cameras

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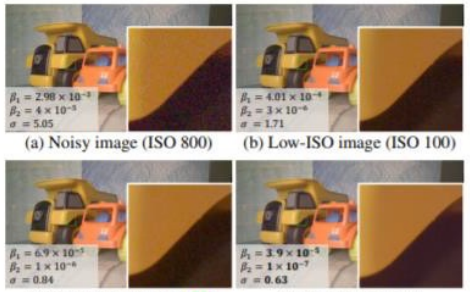
Abstract

The last decade has seen an astronomical shift from imaging with DSLR and point-and-shoot cameras to imaging with smartphone cameras. Due to the small aperture and sensor size, smartphone images have notably more noise than their DSLR counterparts. While denoising for smartphone images is an active research area, the research community currently lacks a denoising image dataset representative of real noisy images from smartphone cameras with high-quality ground truth. We address this issue in this paper with the following contributions. We propose a systematic procedure for estimating ground truth for noisy images that can be used to benchmark denoising performance for smartphone cameras. Using this procedure, we have captured a dataset – the Smartphone Image Denoising Dataset (SIDD) *– of ~30,000 noisy images from 10 scenes under different lighting conditions using five representative smartphone cameras and generated their ground truth images. We used this dataset to benchmark a number of denoising algorithms. We show that CNN-based methods perform better when trained on our high-quality dataset than when trained using alternative strategies, such as low-ISO images used as a proxy for ground truth data.*



(a) Noisy image (ISO 800) (b) Low-ISO image (ISO 100)

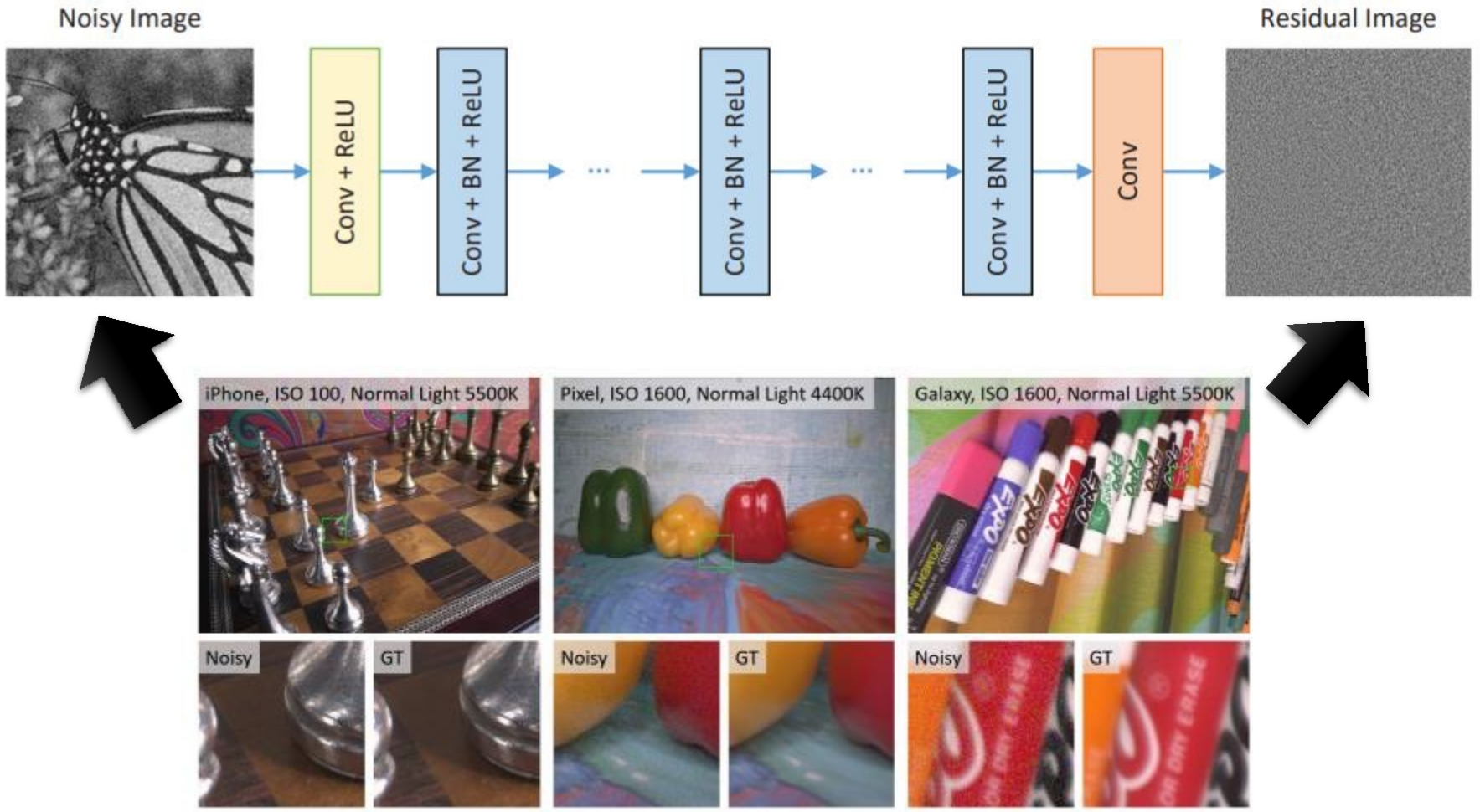
(c) Ground truth using [25] (d) Our ground truth

Figure 1: An example scene imaged with an LG *G4* smartphone camera: (a) a high-ISO noisy image; (b) same scene captured with low ISO – this type of image is often used as ground truth for (a); (c) ground truth estimated by [25]; (d) our ground truth. Noise estimates (β_1 and β_2 for noise level function and σ for Gaussian noise – see Section 3.2) indicate that our ground truth has significantly less noise than both (b) and (c). Images shown are processed in raw-RGB, while sRGB images are shown here to aid visualization.

dataset is essential both to focus attention on denoising of

- -30,000 images
- -5 cameras
- -160 scene instances
- -15 ISO settings
- -Direct current lighting
- -Three illuminations

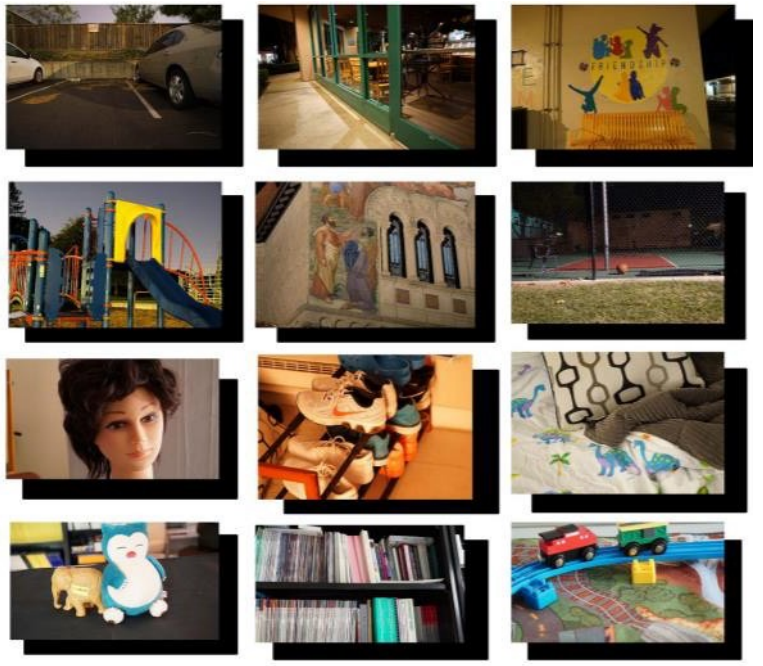
Instant denoising improvements with better training data



Learning-based DNNs get better performance when trained on real noisy images.

"Learning to see in the dark"

Sony α7S II	Filter array	Exposure time (s)	# images
x300	Bayer	1/10, 1/30	1190
x250	Bayer	1/25	699
x100	Bayer	1/10	808
Fujifilm X-T2	**Filter array**	**Exposure time (s)**	**# images**
x300	X-Trans	1/30	630
x250	X-Trans	1/25	650
x100	X-Trans	1/10	1117



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

(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-

SID dark data generated 5000+ pairs of raw-RGB images captured with very short and very long exposures.

Given a short exposure image, the DNN predicts the long exposure image.

While note a denoising paper, this extended ISO feature is quite similar.

“Burst photography for high dynamic range and low-light imaging on mobile cameras”, by Google Research.

Part of Google Pixel’s Night mode camera

Burst photography for high dynamic range and low-light imaging on mobile cameras

SIGGRAPH 2016

Samuel W. Hasinoff, Dillon Sharlet, Ryan Geiss, Andrew Adams
Jonathan T. Barron, Florian Kainz, Jiawen Chen, Marc Levoy
Google Research

Conventional Camera

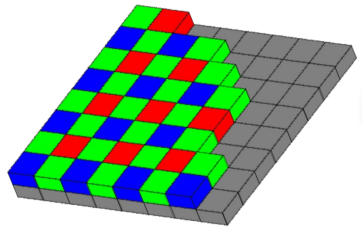
Burst Photography

Key Idea: Capture multiple images of fixed exposure. Merge and combine them in frequency domain for denoising.

See also: Bracketed Exposure (conventional way of denoising low-light imagery)

This is why you have to hold your pose for few seconds while imaging in low-light, else you get blurred images!

A typical color imaging pipeline



Sensor with color filter array (CFA)
(CCD/CMOS)

ISO gain and raw-image processing

RGB Demoasicing

Noise Reduction

White-Balance & Color Space Transform (CIE XYZ)

Color Manipulation (Photo-finishing)

Mapping to sRGB output

JPEG Compression

Save to file

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

#		
	#	
		#

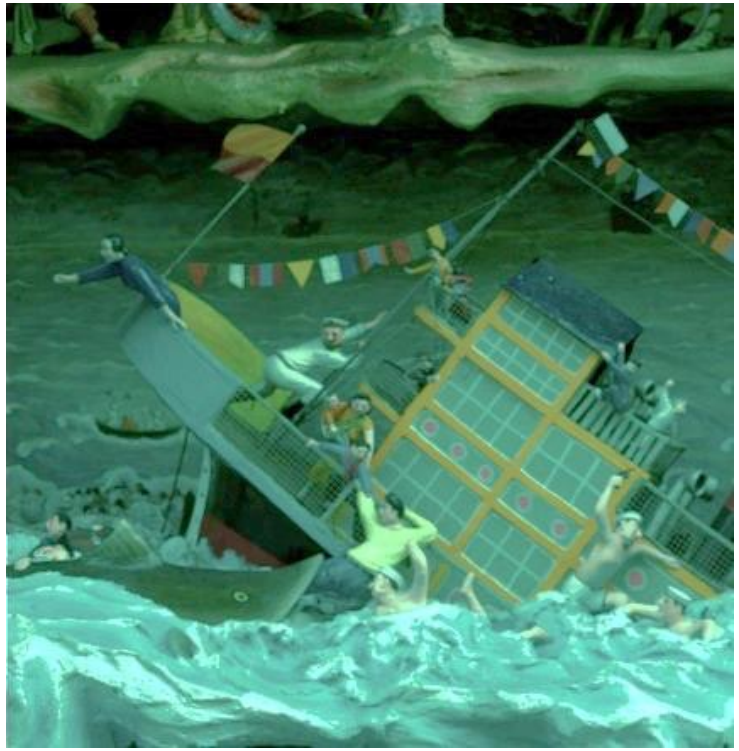
3x3 diagonal matrix

Color space transform (CST)

#	#	#
#	#	#
#	#	#

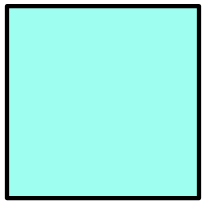
3x3 full matrix (or polynomial function)

How does white balance (WB) work?



raw-RGB sensor image
(pre-white-balance correction)

Sensor's response to illumination (ℓ)



$$\begin{bmatrix} \ell_r \\ \ell_g \\ \ell_b \end{bmatrix} = \begin{bmatrix} 0.2 \\ 0.8 \\ 0.8 \end{bmatrix}$$

Color of 'true' white patch under this illumination.

"White-balanced" raw-RGB image

White-balance diagonal matrix

$$\begin{bmatrix} r_{wb} \\ g_{wb} \\ b_{wb} \end{bmatrix} = \begin{bmatrix} 1/\ell_r & 0 & 0 \\ 0 & 1/\ell_g & 0 \\ 0 & 0 & 1/\ell_b \end{bmatrix} \begin{bmatrix} r \\ g \\ b \end{bmatrix}$$

White-Balance & Color Space Transform (CIE XYZ)

White balance (computational color constancy)

- **The challenging part for white-balance is determining the proper white-balance setting!**
- Users can manually set the white balance
  - Camera specific white-balance matrices for common illuminations
  - These can be manually selected by the user
- Otherwise auto white balance (AWB) is performed
  - In computer vision, we often refer to AWB as "illumination estimation"
  - Since the hard part is trying to determine what the illumination in the scene is.

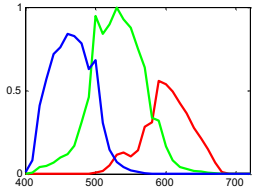
AWB is active research area

Color mapping/colorimetric stage

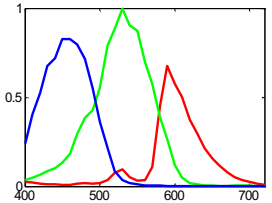
- This step in the IPS converts the sensor raw-RGB values to a device independent color space

Camera sensors have their own spectral response.

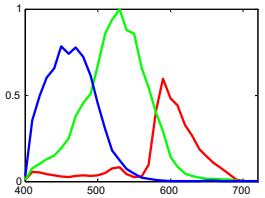
We need to map it into a standard response (CIE XYZ).



Canon 1D

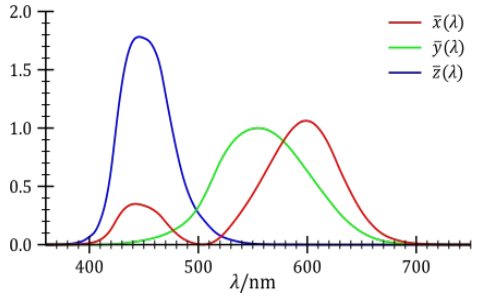


Nikon D40

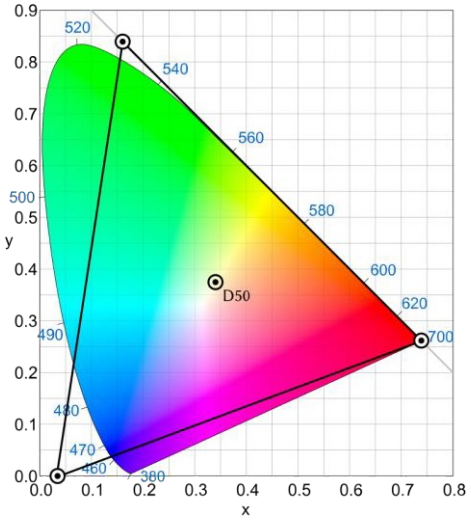


Sony α57

raw-RGB



CIE XYZ



ProPhoto RGB

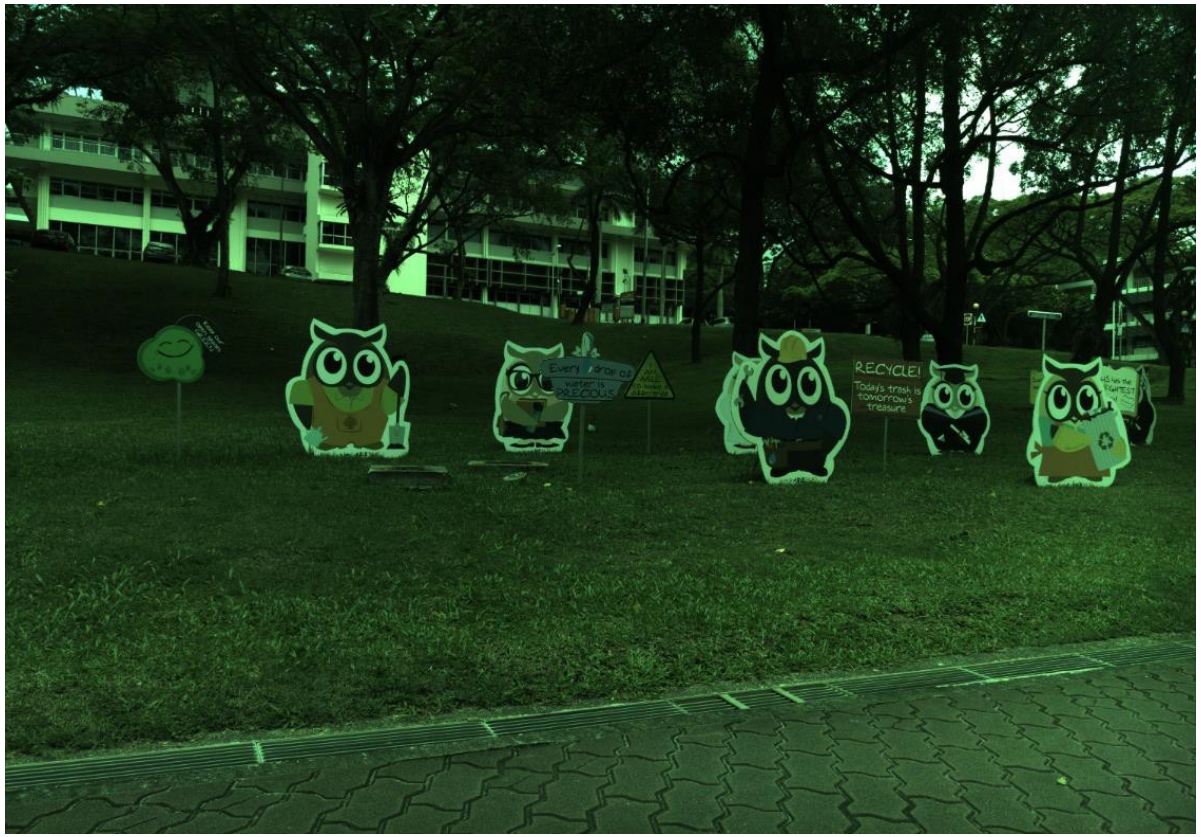
We will use CIE XYZ in this lecture, but most cameras use a related space called ProPhoto.

White-Balance & Color Space Transform (CIE XYZ)

Auto white balance (AWB)

- If manual white balance is not used, then an AWB algorithm is performed.
- AWB needs to determine the sensor's raw-RGB response to the scene illumination from an arbitrary image
- This is surprisingly hard and AWB still fails from time to time

AWB is not easy



raw-RGB input image before white-balance

Given an arbitrary raw-RGB image, determine what is the camera's response to the illumination.

The idea is that something that is *white** is a natural reflector of the scene's illuminations SPD.

So, if we can identify what is "white" in the raw-RGB image, we are observing the sensor's RGB response to the illumination.

* It doesn't have to be "white", but grey – sometimes we call these scene points "achromatic" or "neutral" regions.

AWB example

2 commonly used classical AWB algorithms

Input

Gray World

Assumes avg. reflectance of a scene is achromatic (i.e. gray), image average should have R=G=B.

White Patch

Assumes the brightest spot in the image are from white objects, so max R,G,B values are estimate of white point.

White-Balance & Color Space Transform (CIE XYZ)

Improving AWB with Deep Learning

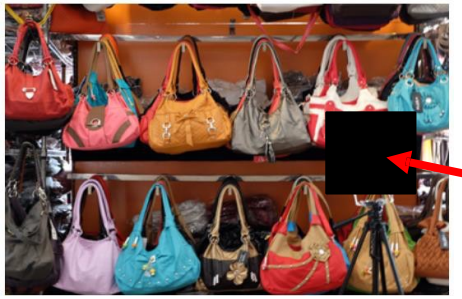
- Lou et al "Color Constancy by Deep Learning", BMVC 2015
- Hu et al "FC4: Fully Convolutional Color Constancy with Confidence- weighted Pooling", CVPR 2017
- Barron "Convolutional Color Constancy", ICCV 2015
- Oh et al "Approaching the computational color constancy as a classification problem through deep learning", Pattern Recognition, 2017
- Afifi et al “Auto White-Balance Correction for Mixed-Illuminant Scenes”, WACV 2022.
- **Many many more ...**

Training data for AWB

Training images
raw-RGB with a neutral or achromatic object inserted.
The label/ground-truth for the training data is the raw-RGB value in the region of the neutral object.

Neutral object in the scene. The raw-RGB values at this pixel location is considered to be the entire scenes illumination.
In the case of the color chart, only the white-patches are used.

Testing/validation
The neutral object is masked out.



Testing image

Neutral object masked out.

Original image

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

#		
	#	
		#

3x3 diagonal matrix

Color space transform (CST)

#	#	#
#	#	#
#	#	#

3x3 full matrix (or polynomial function)

Color space transform

Factory pre-calibration

Illumination 1 (CCT 2500K)

Illumination 2 (CCT 6500K)

white-balance matrix

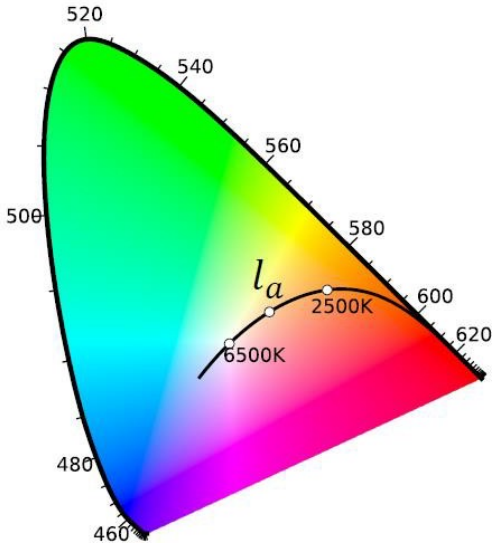
CST matrix

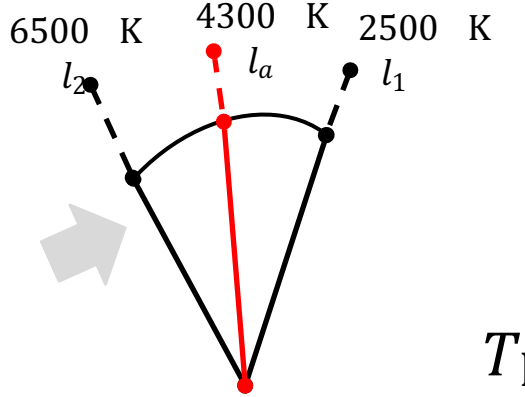
White-Balance & Color Space Transform (CIE XYZ)

CST matrices (T_{l_1} and T_{l_2}) are calibrated for two different illuminations (l1 and l2). Depending on the temperature of the white-balance, we use the corresponding CST.

Color space transform

Interpolation process





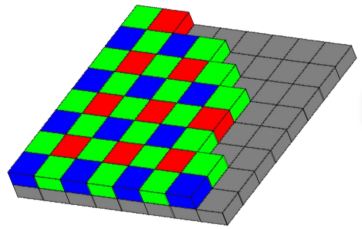
$$g = \frac{\mathrm{CCT}_{\mathbf{l_a}}^{-1} - \mathrm{CCT}_{\mathbf{l_2}}^{-1}}{\mathrm{CCT}_{\mathbf{l_1}}^{-1} - \mathrm{CCT}_{\mathbf{l_2}}^{-1}}$$

$$T_{\mathbf{l_a}} = gT_{\mathbf{l_1}} + (1-g)T_{\mathbf{l_2}}$$

New input (4300°K) $\boldsymbol{\Phi}_{\mathbf{cam}}^{\mathbf{l}_a}$ $W_D^{\mathbf{l_a}}$ $T_{\mathbf{l_a}}$

Given a new illumination (la) and its estimated correlated color temperature (CCT), we construct a CST matrix by blending the two factory pre-calibrated matrices.

Typical color imaging pipeline



Sensor with color filter array (CFA)
(CCD/CMOS)

ISO gain and raw-image processing

RGB Demoasicing

Noise Reduction

White-Balance & Color Space Transform (CIE XYZ)

Color Manipulation (Photo-finishing)

Mapping to sRGB output

JPEG Compression

Save to file

Color manipulation

- This is the stage were a camera applies its "secret sauce" to make the images look good
- This procedure can be called by many names:
  - Color manipulation
  - Photo-finishing
  - Color rendering or selective color rendering
  - Yuv processing engine
- DSLR will often allow the user to select various photo-finishing styles
- Smartphones often compute this per-image
- Photo-finishing may also tied to geographical regions!

DSLR "picture" styles

Standard

Glowing prints with crisp finishes.
It is the basic color of EOS DIGITAL.

Portrait

For transparent, healthy skin for women and children

Landscape

Crisp and impressive reproduction of blue skies and green trees in deep, vivid color

Neutral

Subjects are recorded in rich detail, giving the greatest latitude for image processing

Faithful

Accurate recording of the subject's color, close to the actual image seen with the naked eye

Monochrome

Filter work and sepia tone with the freedom of digital monochrome

From Canon's user manual

Picture styles

Example of four different picture styles from Nikon
This image is the **same** raw-RGB image processed in four different ways.

Photorealistic Stylization

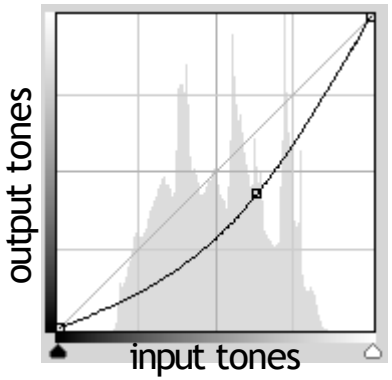
(a) Inputs

(d) Ours (WCT²)

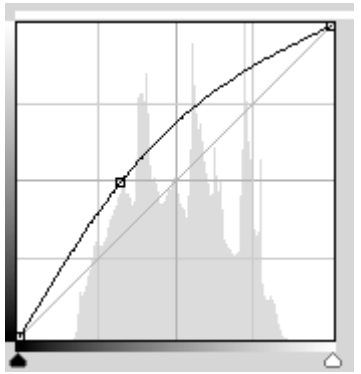
"Photorealistic Style Transfer via Wavelet Transforms", ICCV 2019.

Global tone map example (1D LUT)

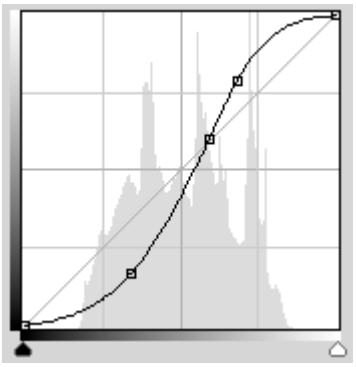
Input



Darkening the image



Brightening the image



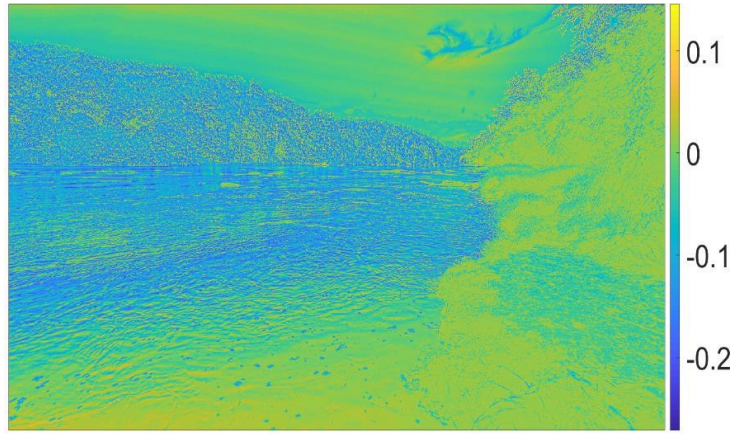
Enhancing contrast (called an S-curve)

Local tone mapping (LTM)

Global tone-mapping
Camera mode - Manual

Local tone-mapping
Camera mode - Auto

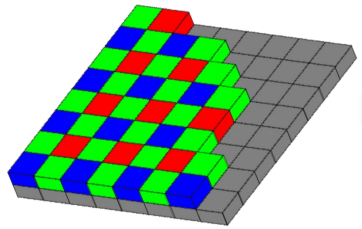
NOTE: On many cameras, esp smartphones, a local tone map is applied as part of the photo-finishing. This helps bring out highlights in the image.



Difference map between image before and after LTM

Color Manipulation (Photo-finishing)

Typical color imaging pipeline



Sensor with color filter array (CFA)
(CCD/CMOS)

ISO gain and raw-image processing

RGB Demoasicing

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White-Balance & Color Space Transform (CIE XYZ)

Color Manipulation (Photo-finishing)

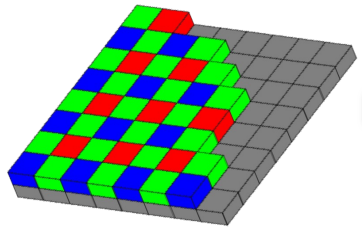
Mapping to sRGB output

JPEG Compression

Save to file

We will learn about this in Image Processing lectures next week.

Save to storage and we are done!



Sensor with color filter array (CFA)
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ISO gain and raw-image processing

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Color Manipulation (Photo-finishing)

Mapping to sRGB output

JPEG Compression

Save to file

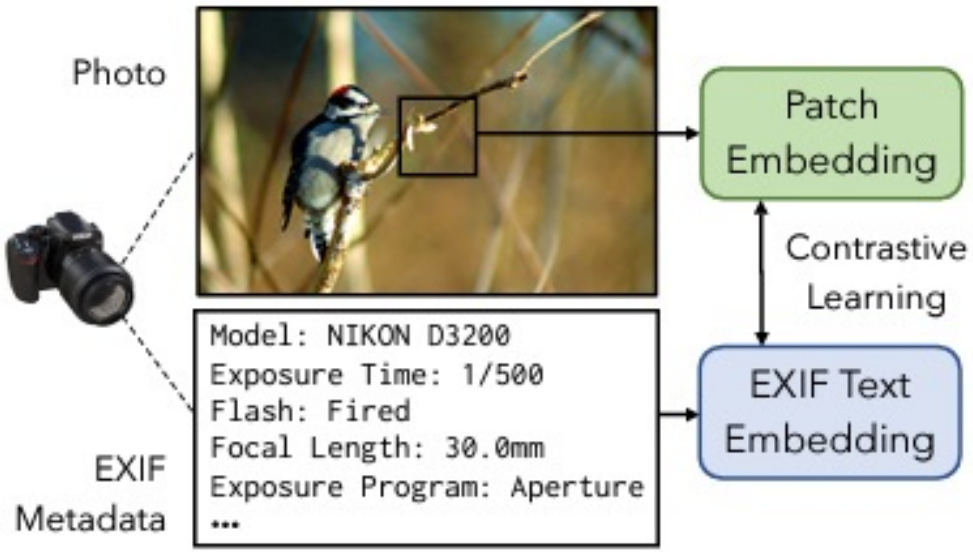
Exif metadata

- Exchangeable image file format (Exif)
- Associates meta data with images
  - Date/time
  - Camera settings (basic)
    - Image size, aperture, shutter speed, focal length, ISO speed, metering mode (how exposure was estimated)
  - Additional info (from in some Exif files)
    - White-balance settings, even matrix coefficients of white-balnace
    - Picture style (e.g. landscape, vivid, standard, portrait)
    - Output color space (e.g. sRGB, Adobe RGB, RAW)
    - GPS info
    - More ...

EXIF as Language: Learning Cross-Modal Associations Between Images and Camera Metadata

Chenhao Zheng Ayush Shrivastava Andrew Owens
University of Michigan

https://hellomuffin.github.io/exif-as-language

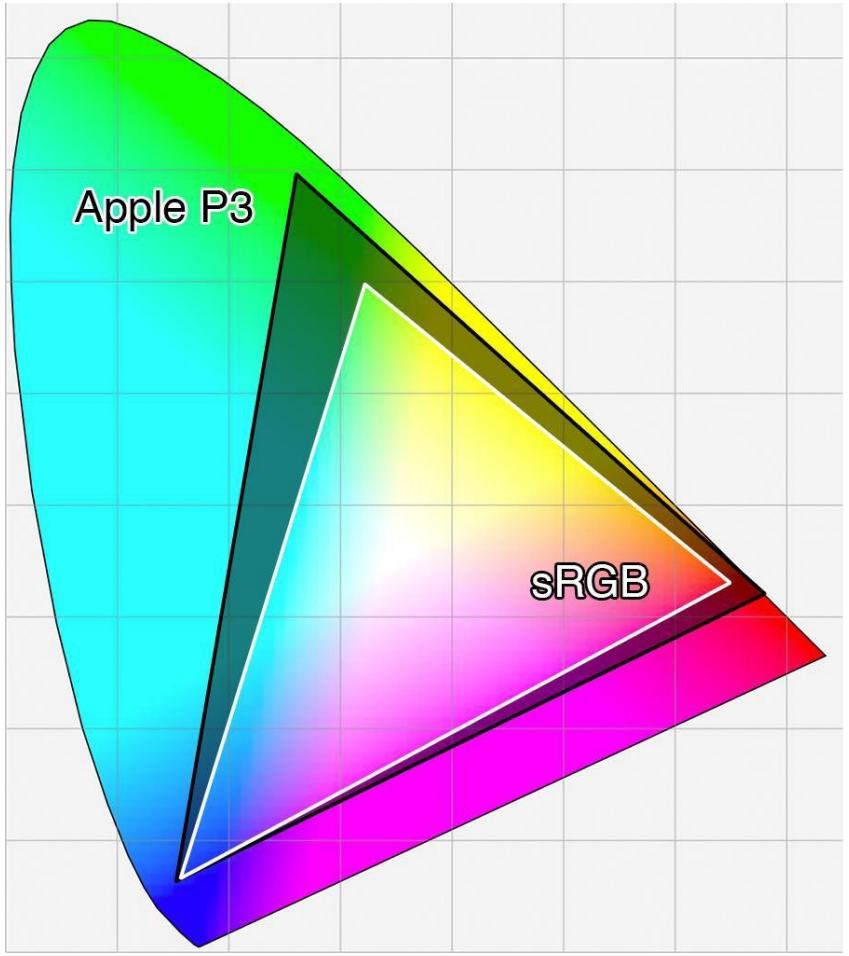


(a) Multimodal image-metadata embeddings

(b) Detecting spliced images by spotting inconsistent patch embeddings

Note: sRGB/JPEG is slowly being replaced

- sRGB was developed for monitors in the 1990s – it is an old standard.
- High Efficient Image Encoding (HEIC)
  - Better compression than JPEG
- Apple iPhone has started to use HEIC to *replace JPEG*
- HEIC supports multiple color spaces. Apple uses Display P3 – a variation on a Digitial Cinema Initiative P3 space.
- The P3 gamut is 25% wider than sRGB
- Pixel 4 and other Android devices are will support this color space soon.

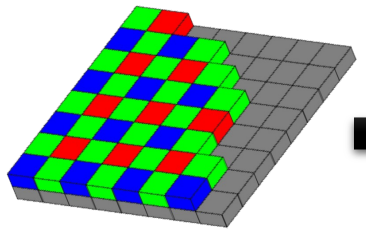


Pipeline comments

- Again, important to stress that the exact steps mentioned in these notes only serve as a guide of what takes place in a camera
- Modern pipelines are more complex, however, you will find steps similar to what was described
- Note: for different camera makes/models, the operations could be performed in different order (e.g. white-balance after demosaicing) and in different ways (e.g. combining sharpening with demosaicing)

What about machine vision cameras?

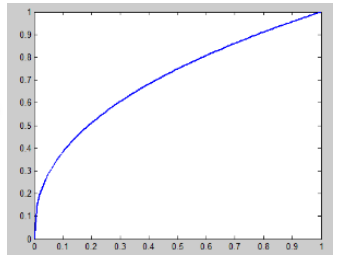
- Some industrial/machine vision cameras provide minimal ISP processing
- For example, some will only perform white-balance and apply a gamma to the raw-RGB values.
- This means the output is in a camera-specific color space



ISO gain and raw-image processing

RGB Demoasicing

White-Balance (per-channel gain)



per-channel gamma

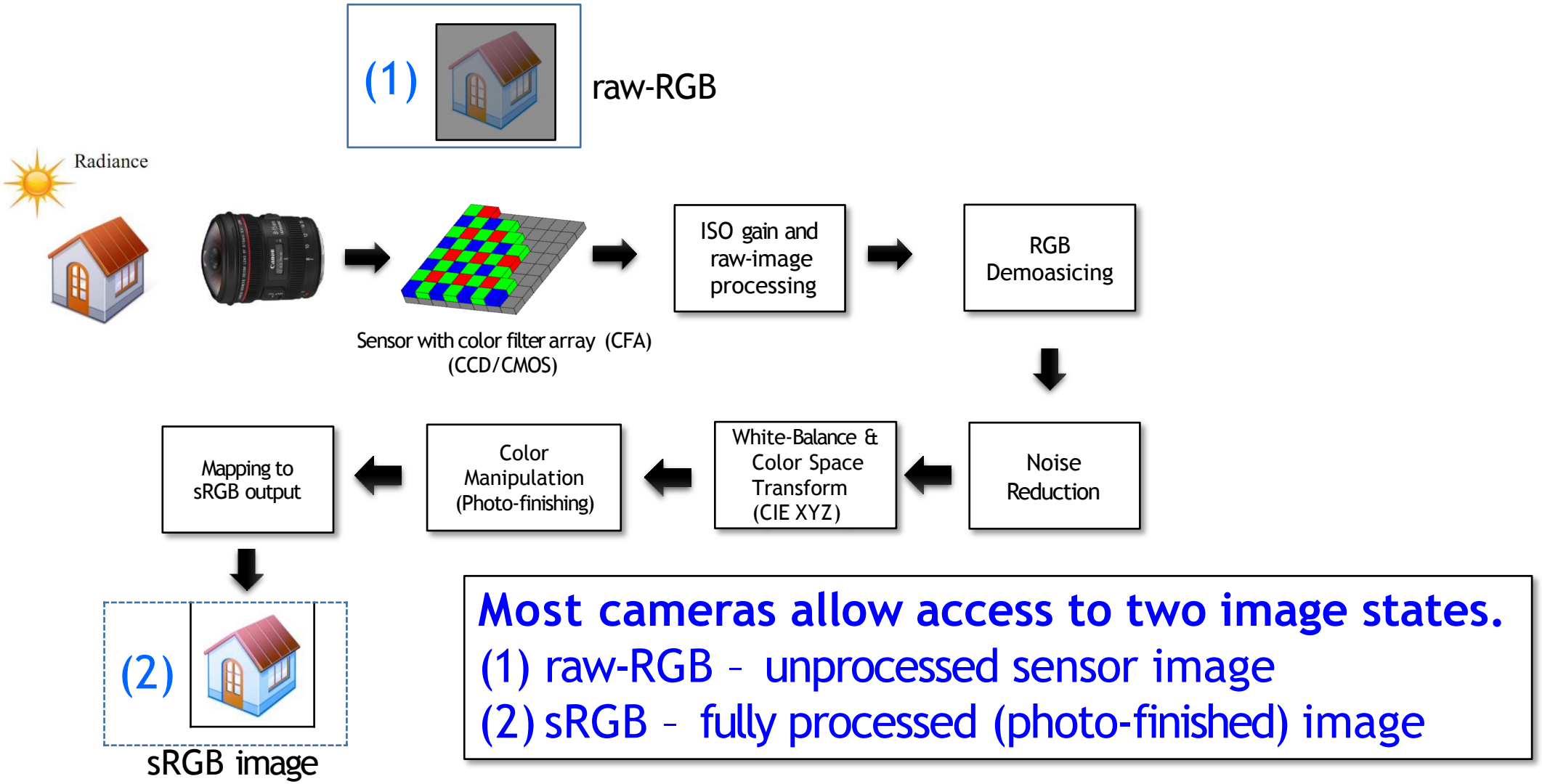
Typical machine vision pipeline

Point grey grasshopper camera.

Mistake: Working in the wrong color space

- This problem stems from a lack of understanding of color spaces
- You can't just say "RGB", you need to specify **which** RGB (e.g. , raw-RGB, sRGB, NTSC, P3, etc). If you got the image off the web, it is highly likely to be sRGB.
- Certain color spaces are more suitable than others depending on the application.

Current access to different image states



Most cameras allow access to two image states.

(1) raw-RGB – unprocessed sensor image

(2) sRGB – fully processed (photo-finished) image

Advantage of raw-RGB

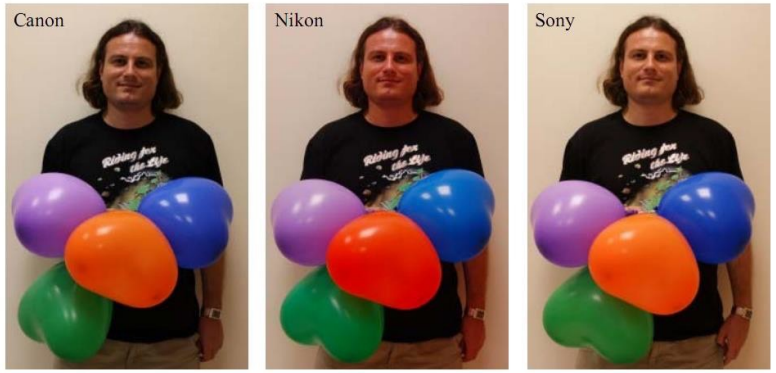
- It is linear with respect to the scene's physical light. This means the pixel values are ‘sort-of’ related to the scene.

- Certain Computer Vision problems make this assumption
  - Shape from shading (photometric stereo)
  - Intrinsic image decomposition
  - Image deblurring
  - However, many times these problems are attempted in the sRGB space!

sRGB images

- When you are working with an sRGB image, it represents the photo-finished image
- The colors represent the colors of the "photograph", not the colors of the "scene"
- These colors will be different for different cameras or even same camera with different picture styles!

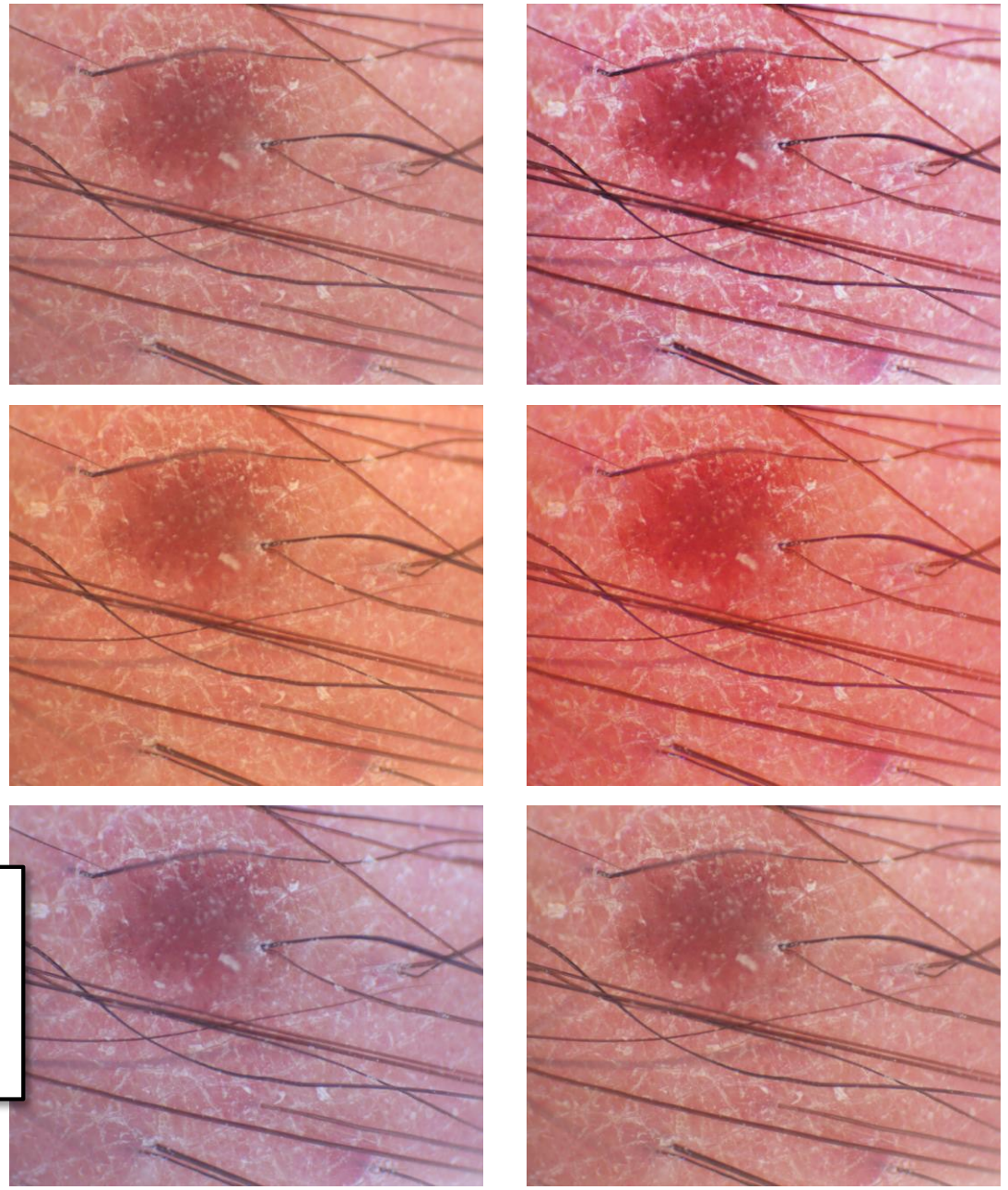
sRGB output on different cameras.



sRGB output on the same camera, w/ different color manipulation.

This assumption can led to serious mistakes in a computer vision application.

This type of processing is not suitable for scientific applications!

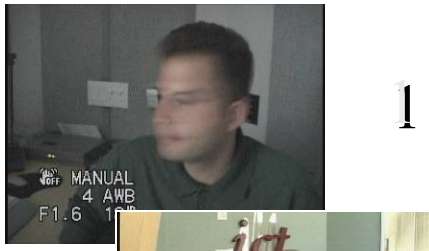


Which one is correct?

HDR Imaging

Why HDR?

Problem: Dynamic Range



1

1500

25,000

400,000

2,000,000,000

The real world is high dynamic range.

High dynamic range imaging


HYATT


HYATT

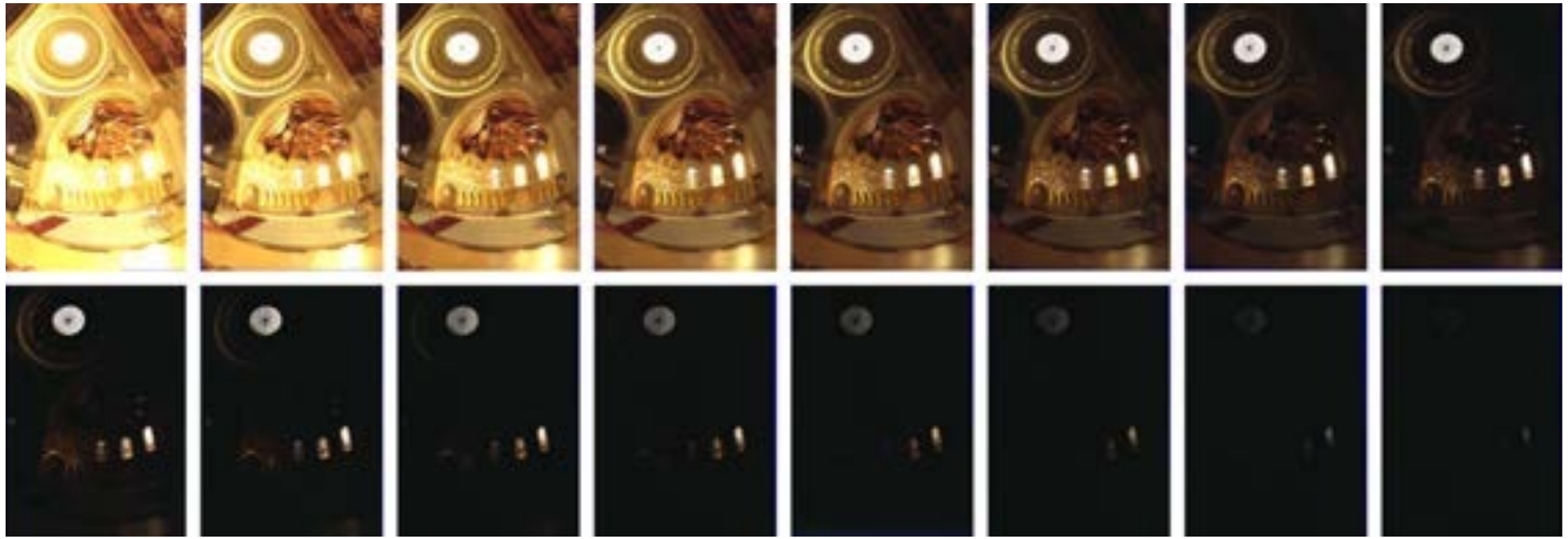

HYATT


HYATT


HYATT

Key idea

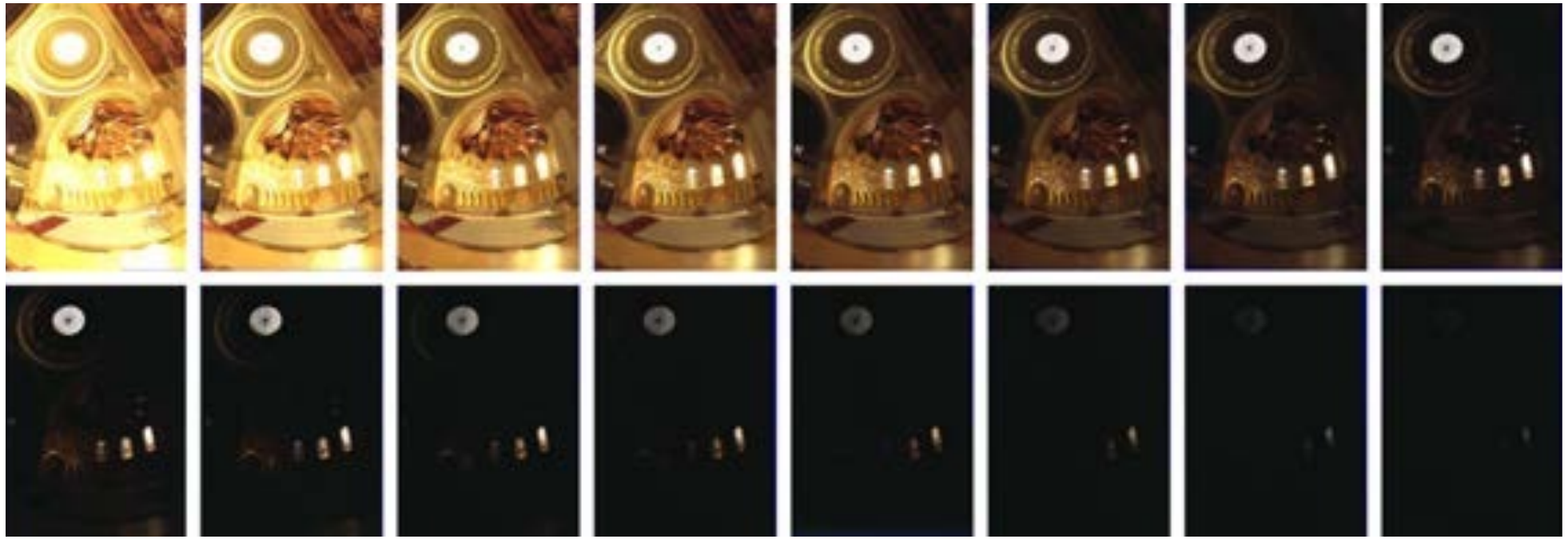
1. Exposure bracketing: Capture multiple LDR images at different exposures



2. Merging: Combine them into a single HDR image

Key idea

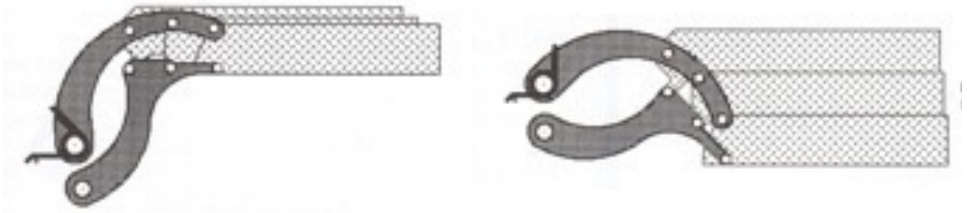
1. Exposure bracketing: Capture multiple LDR images at different exposures



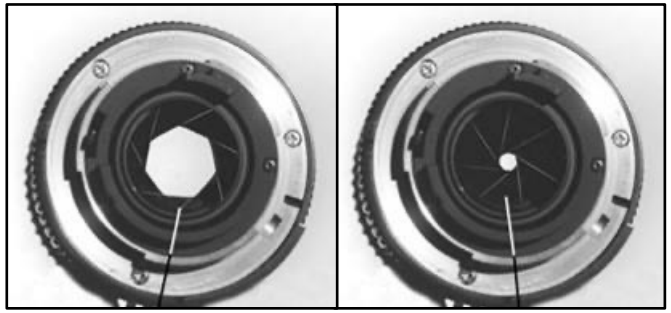
2. Merging: Combine them into a single HDR image

Ways to vary exposure

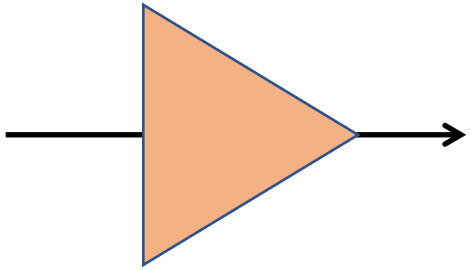
1. Shutter speed



2. F-stop (aperture, iris)



3. ISO

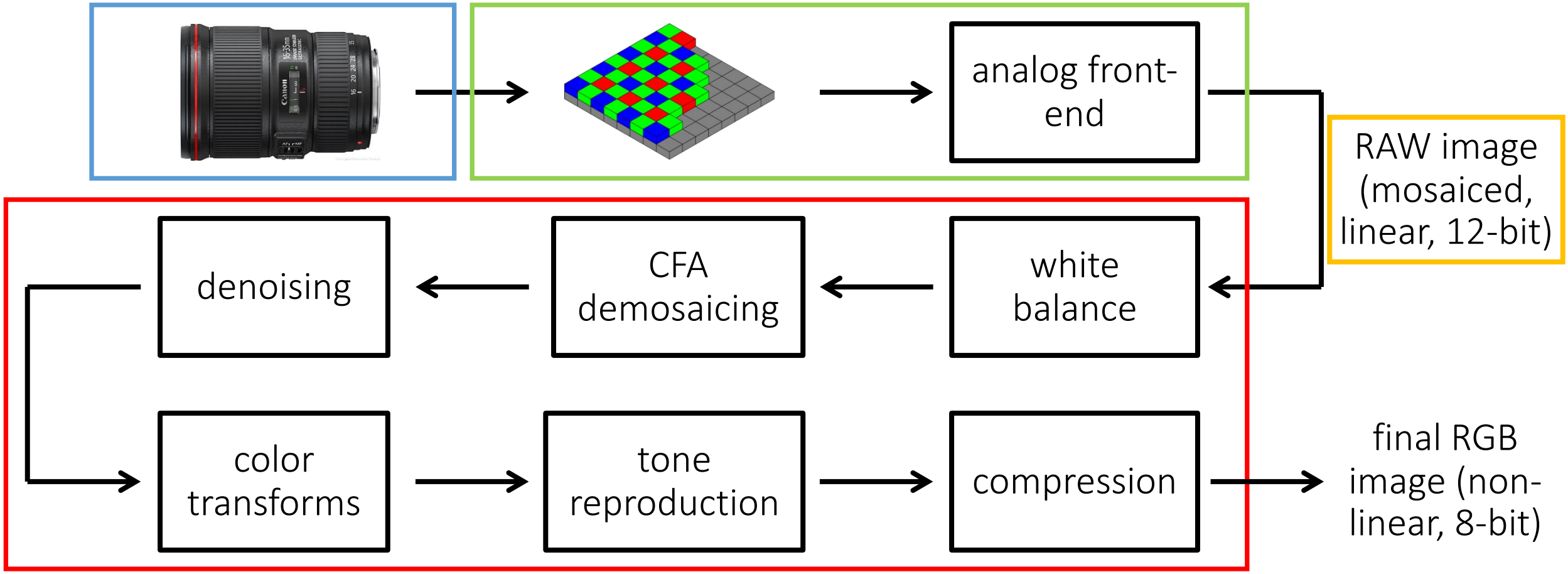


4. Neutral density (ND) filters

Pros and cons of each for HDR?

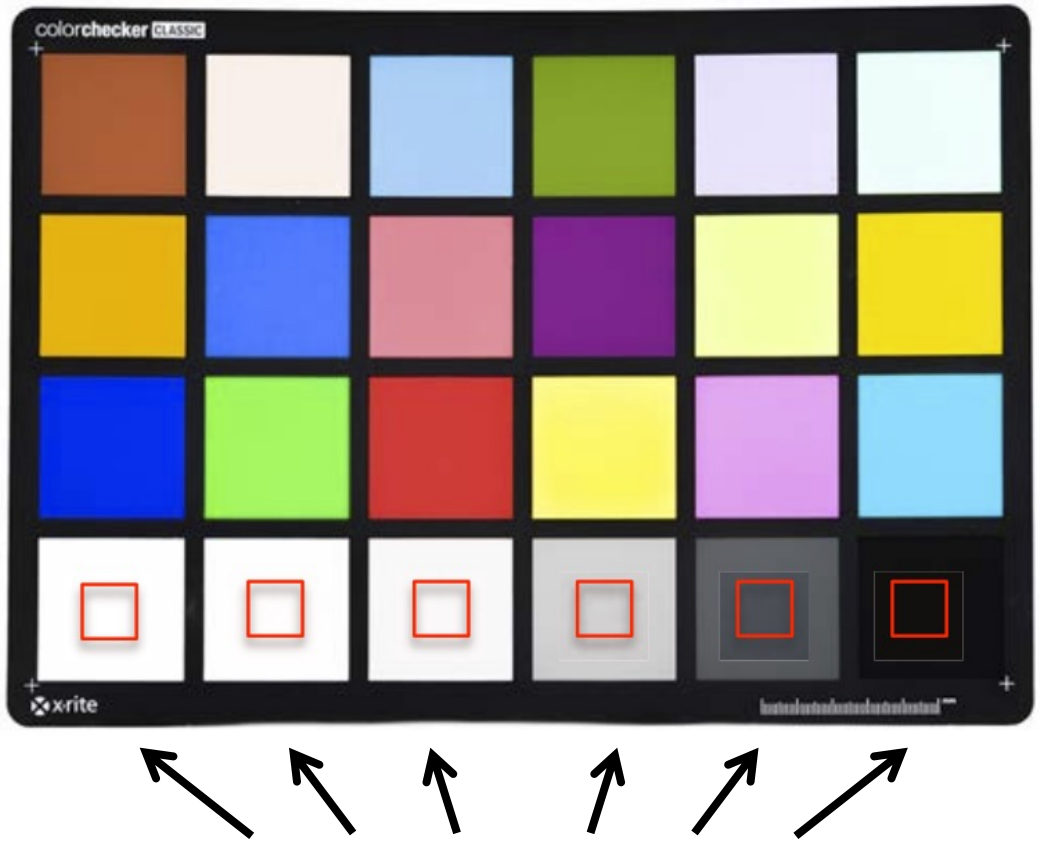
The image processing pipeline

The sequence of image processing operations applied by the camera's image signal processor (ISP) to convert a RAW image into a "conventional" image.

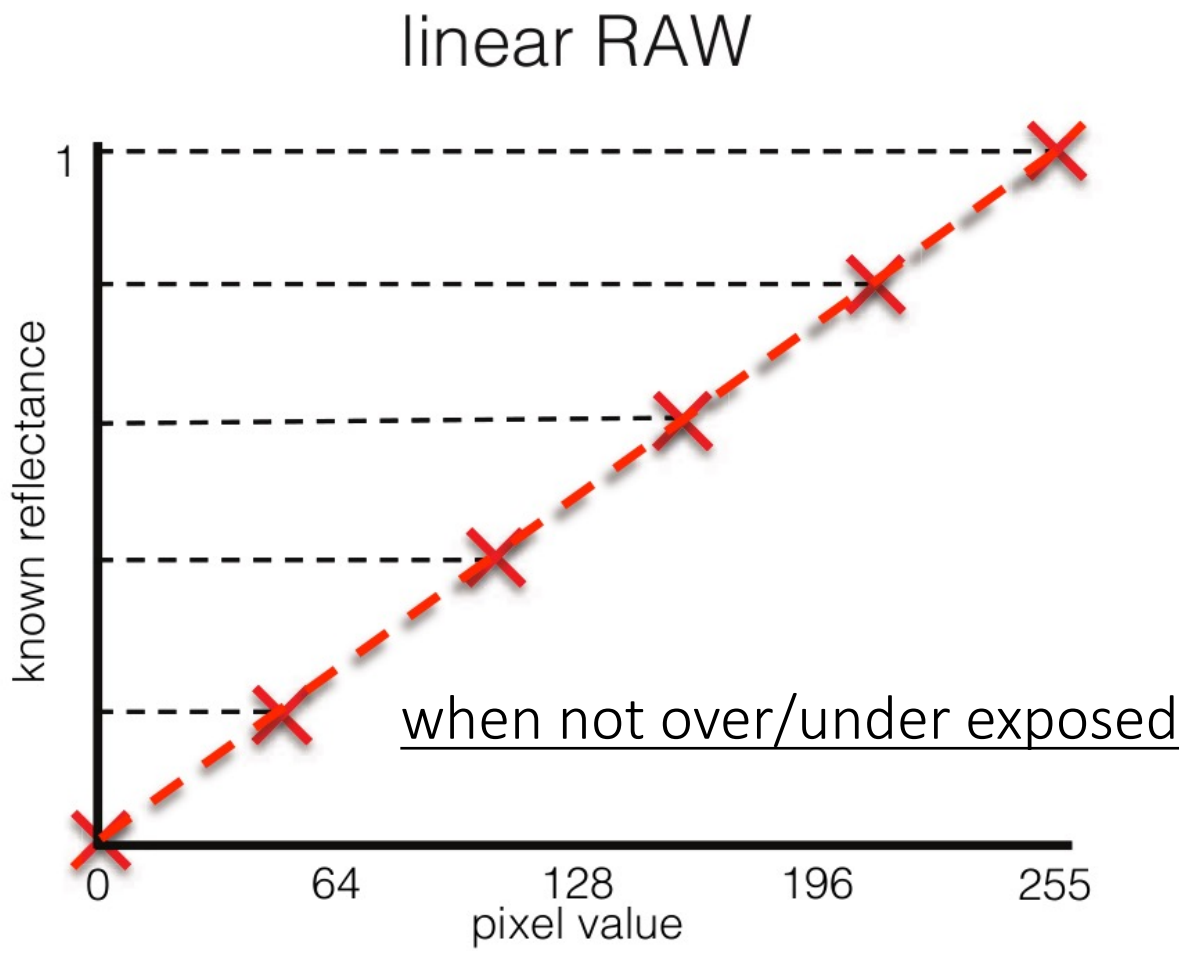


RAW images have a linear response curve

Colorchecker: Great tool for radiometric and color calibration.



Patches at bottom row have reflectance that increases linearly.

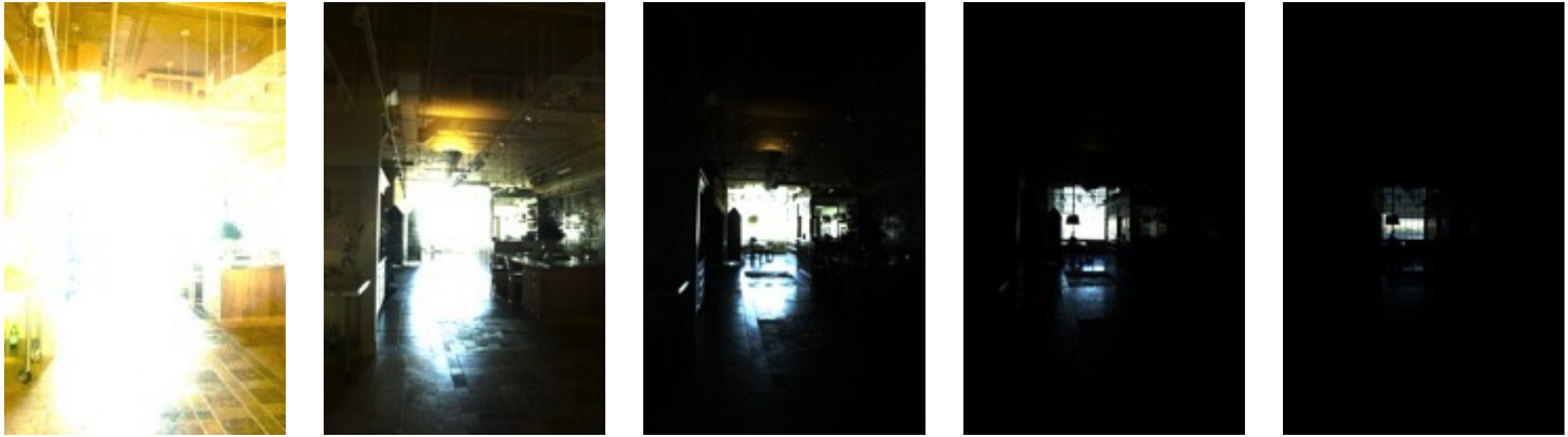


RAW (linear) image formation model

Real scene radiance for image pixel (x,y): L(x, y)

Exposure time:

t_5 t_4 t_3 t_2 t_1



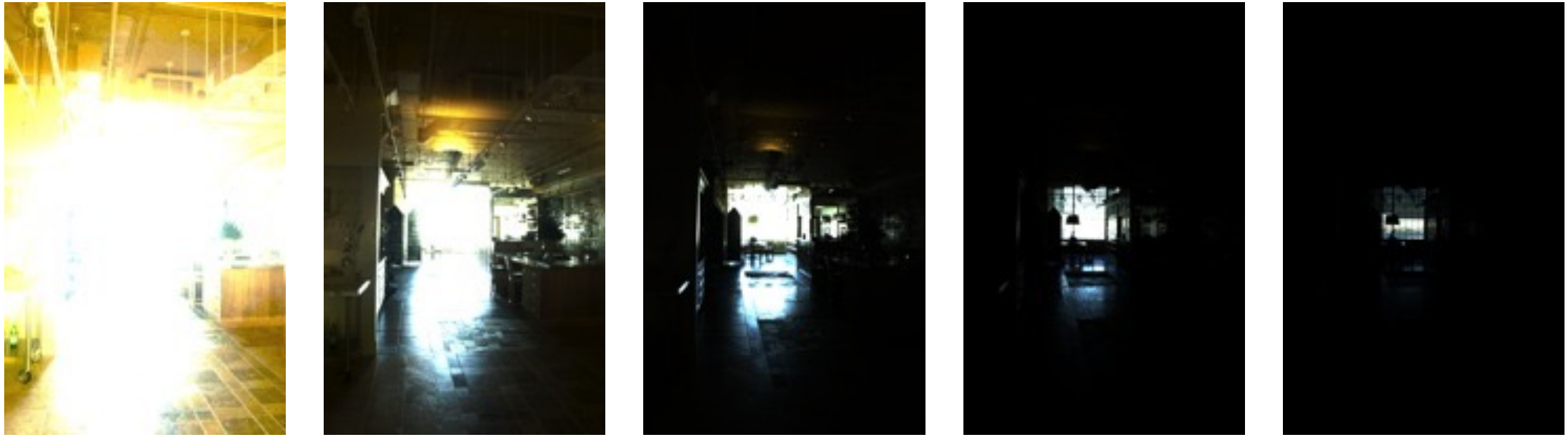
What is an expression for the image $I_{linear}(x,y)$ as a function of L(x,y)?

RAW (linear) image formation model

Real scene radiance for image pixel (x,y): $L(x, y)$

Exposure time:

t_5 t_4 t_3 t_2 t_1



What is an expression for the image $I_{linear}(x,y)$ as a function of $L(x,y)$?

$$I_{linear}(x,y) = \text{clip}[\, t_i \cdot L(x,y) + \text{noise} \,]$$

How would you merge these images into an HDR one?

Merging RAW (linear) exposure stacks

For each pixel:

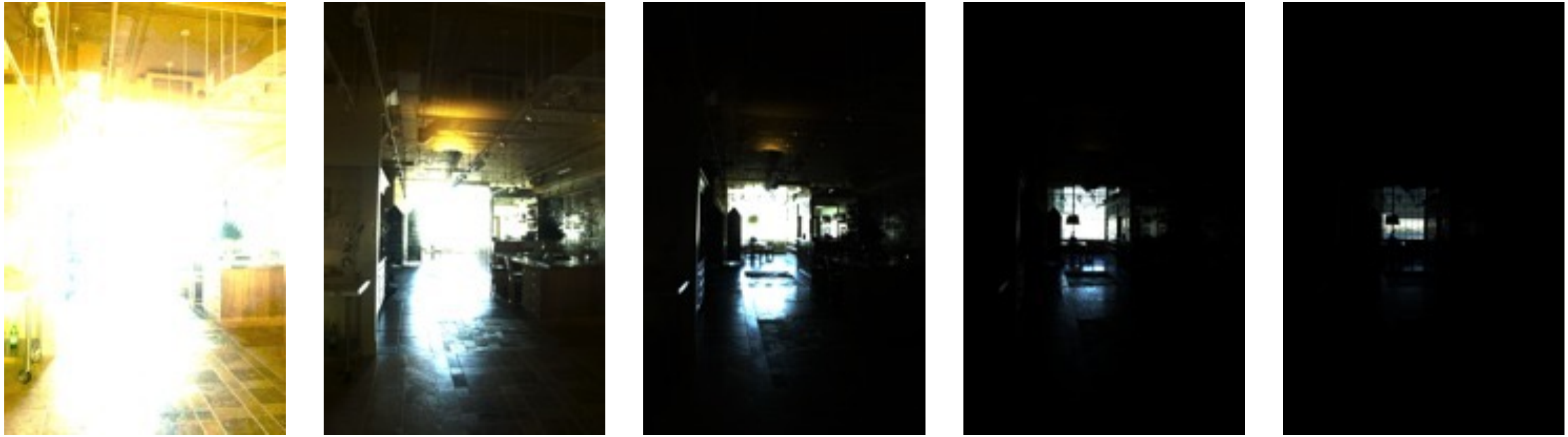
1. Find “valid” images

2. Weight valid pixel values appropriately

3. Form a new pixel value as the weighted average of valid pixel values

How would you implement steps 1-2?

t_5 t_4 t_3 t_2 t_1



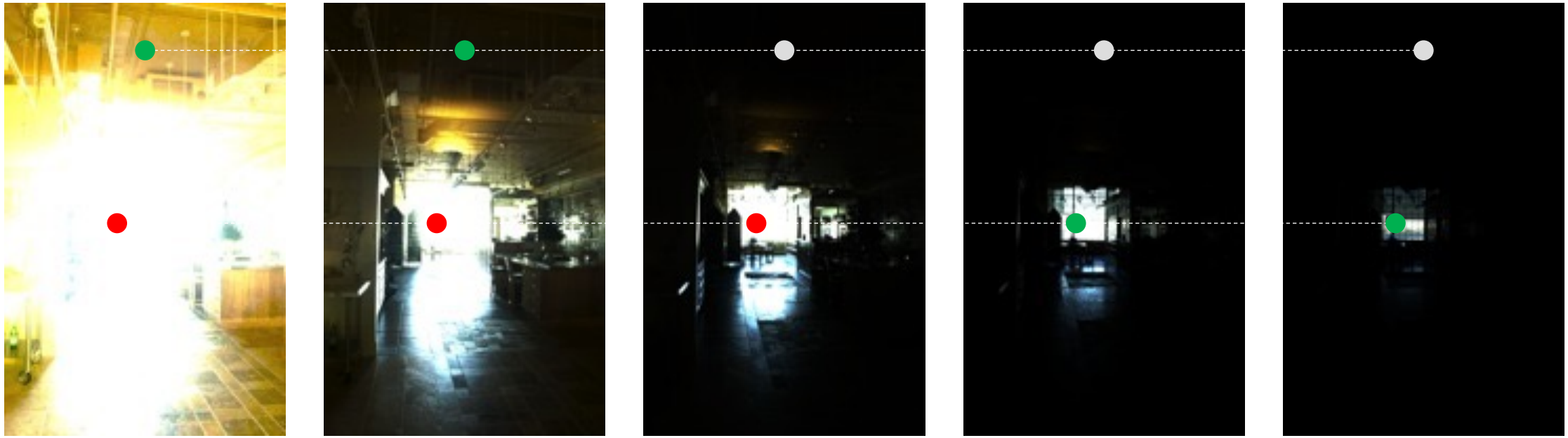
Merging RAW (linear) exposure stacks

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

noise
valid
clipped

t_5 t_4 t_3 t_2 t_1

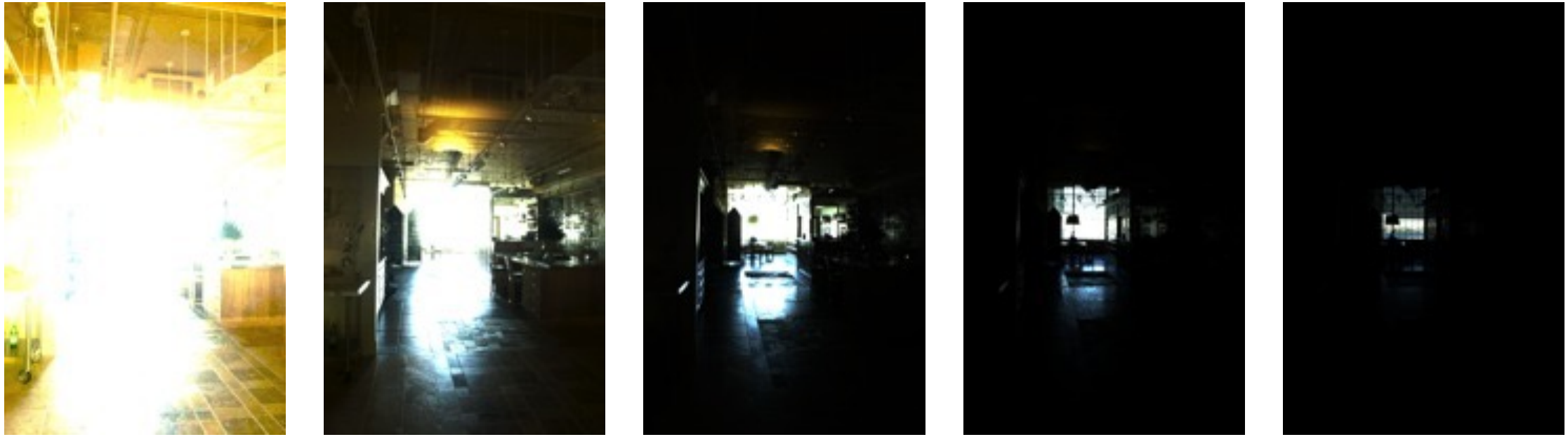


Merging RAW (linear) exposure stacks

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



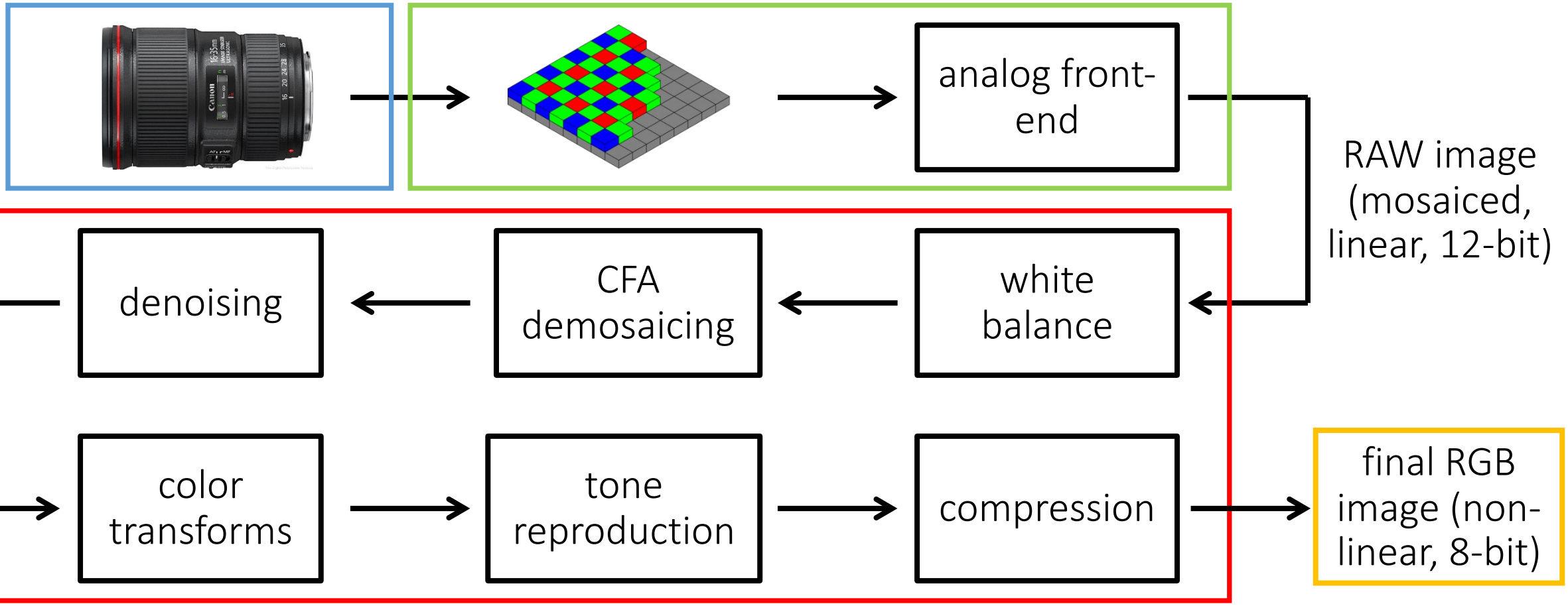
Merging result (after tonemapping)






The image processing pipeline

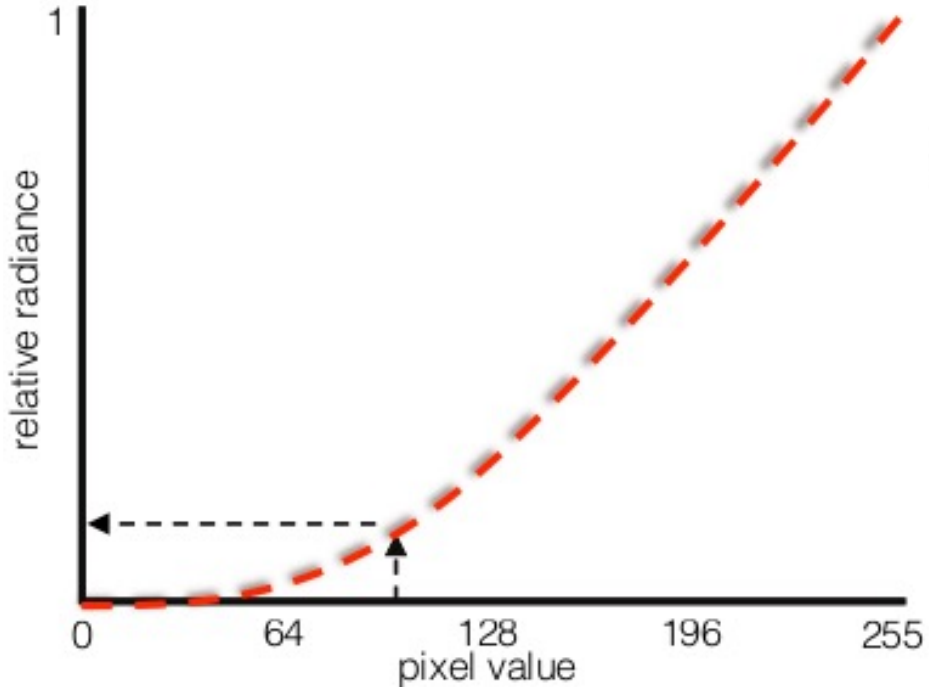
- Can you foresee any problem when we switch from RAW to rendered images?
- How do we deal with the nonlinearities?



Non-linear image formation model

Real scene radiance for image pixel (x,y): $L(x, y)$

Exposure time: t_i



$I_{linear}(x,y) = clip[\ t_i \cdot L(x,y) + noise\ ]$

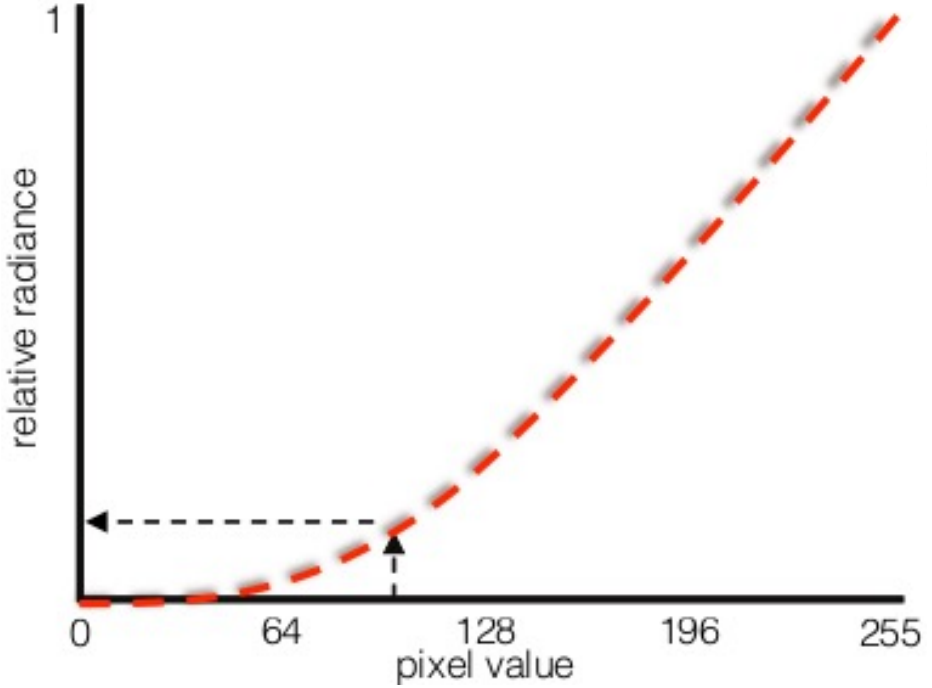
$I_{non\text{-}linear}(x,y) = f[\ I_{linear}(x,y)\ ]$

How would you merge the non-linear images into an HDR one?

Non-linear image formation model

Real scene radiance for image pixel (x,y): $L(x, y)$

Exposure time: t_i



$I_{linear}(x,y) = clip[\ t_i \cdot L(x,y) + noise\ ]$

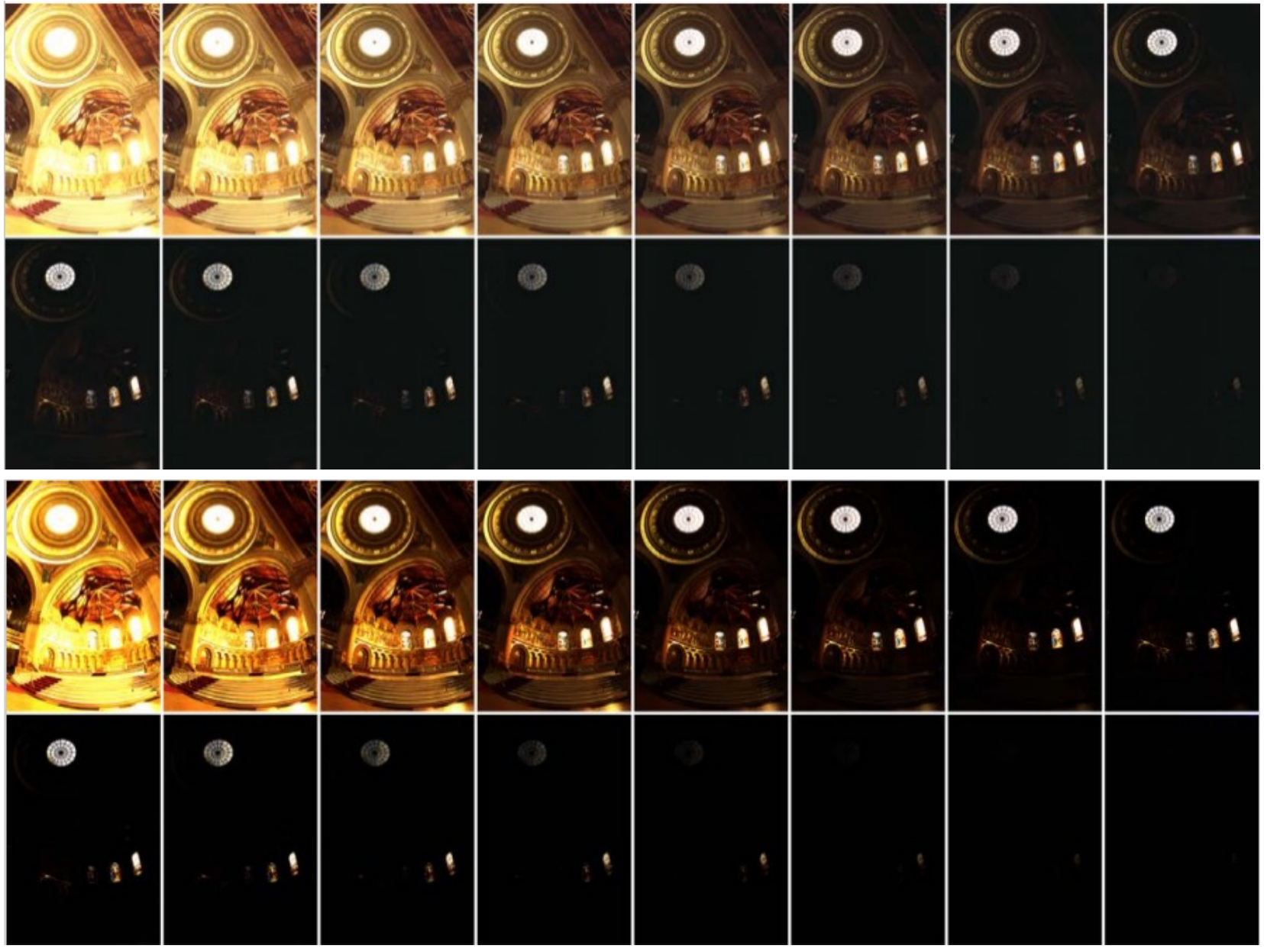
$I_{non\text{-}linear}(x,y) = f[\ I_{linear}(x,y)\ ]$ $\quad$ $I_{est}(x,y) = f^{-1}[\ I_{non\text{-}linear}(x,y)\ ]$

Use inverse transform to estimate linear image, then proceed as before

Linearization

$I_{non\text{-}linear}(x,y) = f[\ I_{linear}(x,y)\ ]$

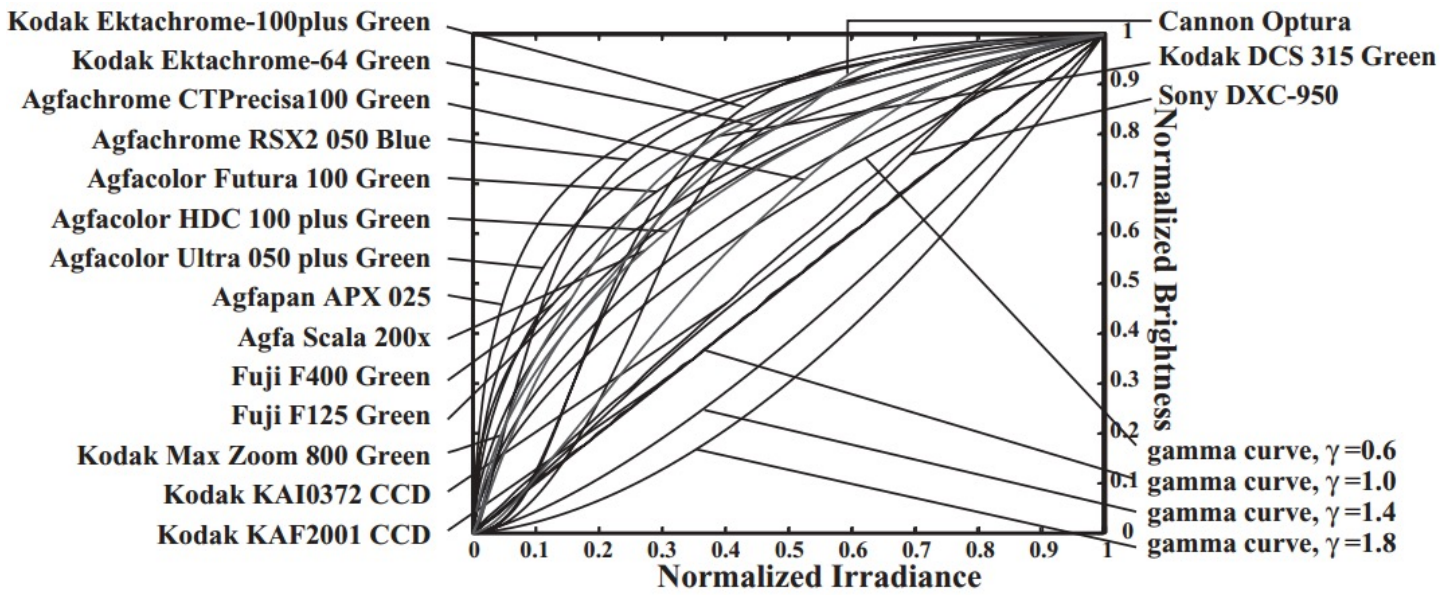
$I_{est}(x,y) = f^{-1}[\ I_{non\text{-}linear}(x,y)\ ]$



Tone reproduction curves

linear

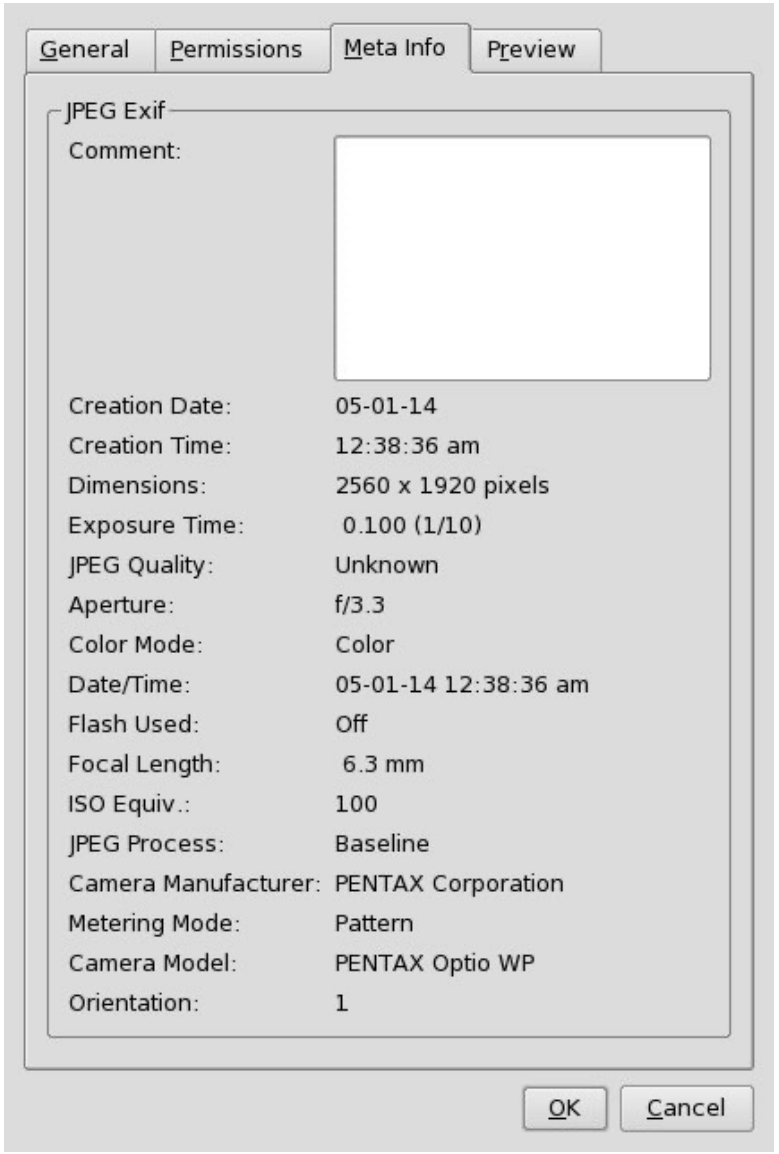
non-linear



You may find information in the image itself

If you cannot do calibration, take a look at the image's EXIF data (if available).

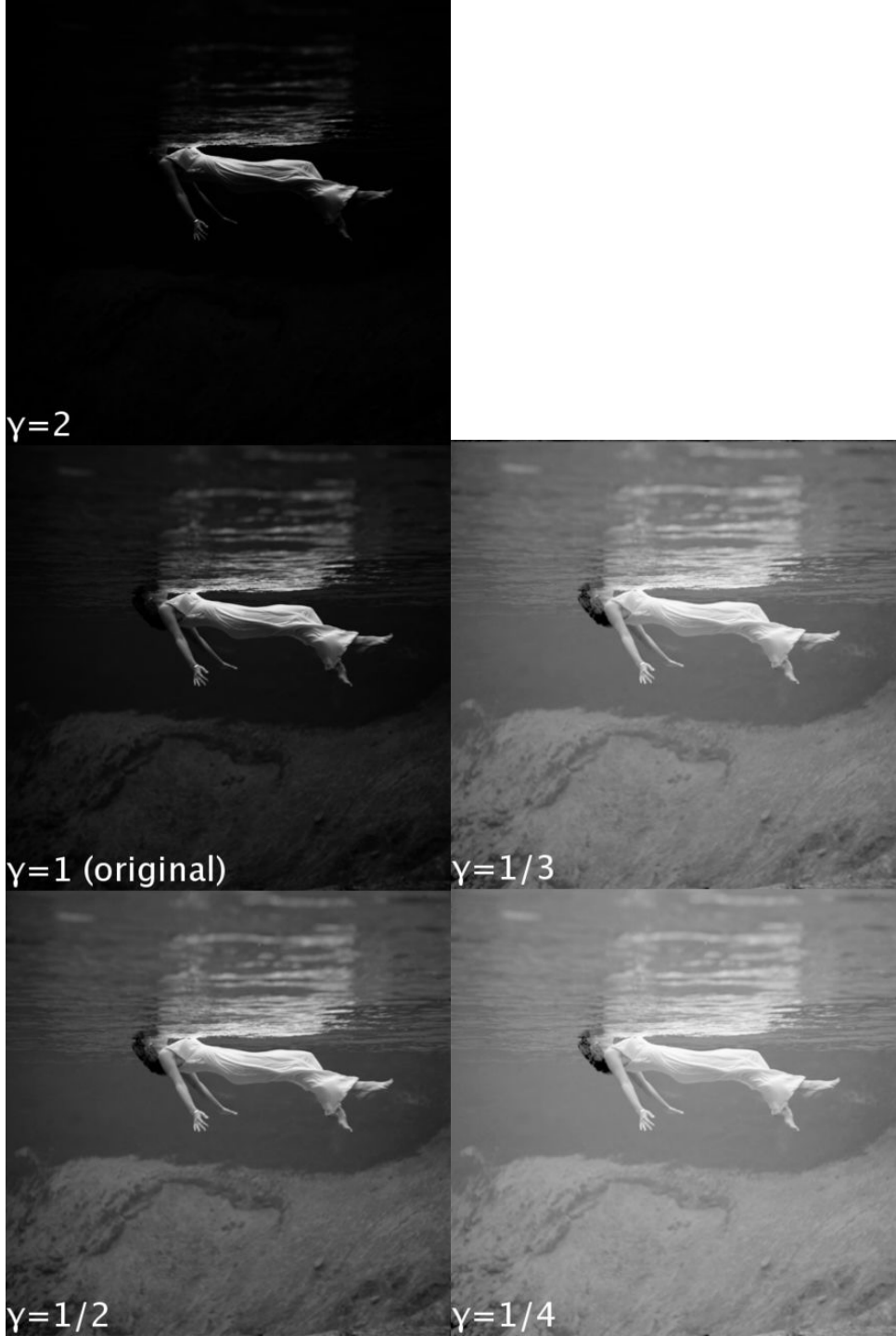
Often contains information about tone reproduction curve and color space.



Gamma Correction $V_{\text{out}} = AV_{\text{in}}^{\gamma},$

Linear raw-RGB images are tone mapped into non-linear sRGB space.

- Most images we work with are in sRGB space, i.e., already tone-mapped.
- Many Vision algorithms expects the image to be in linear space.
- sRGB -> Linear space conversion requires explicit knowledge of camera processing pipeline. Requires knowledge of tone-production curve.
- In absence of it it is very common to use $\gamma = 2.2$.
- Note: This is not accurate, just a cheap approximation that works for most Vision tasks.



credits: wiki

Merging non-linear exposure stacks

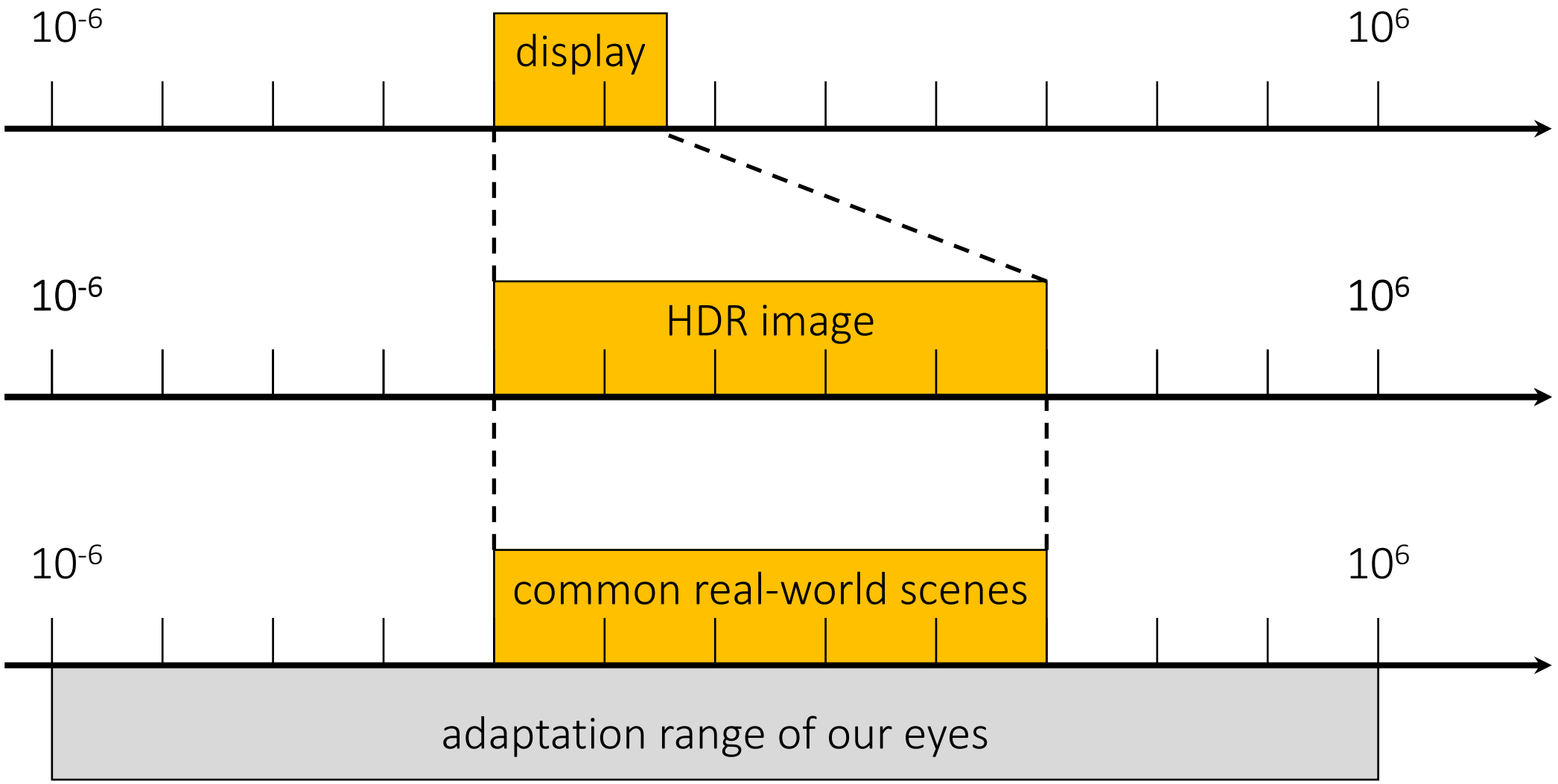
1. Calibrate response curve
2. Linearize images

For each pixel:

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

→ Same steps as in the RAW case.

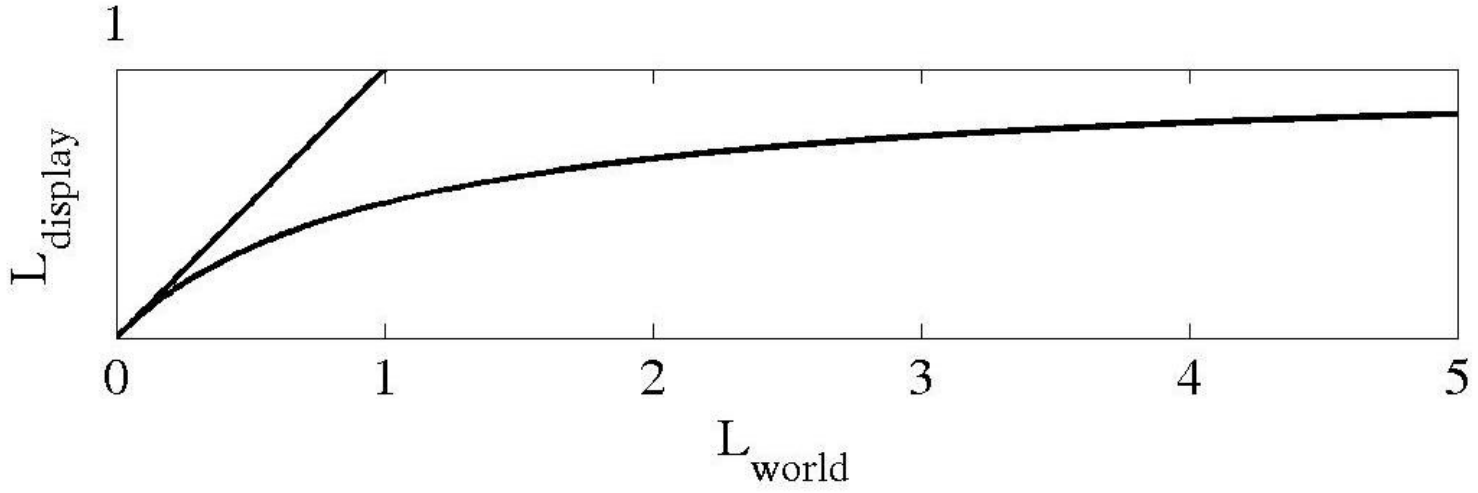
How do we display our HDR images?



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



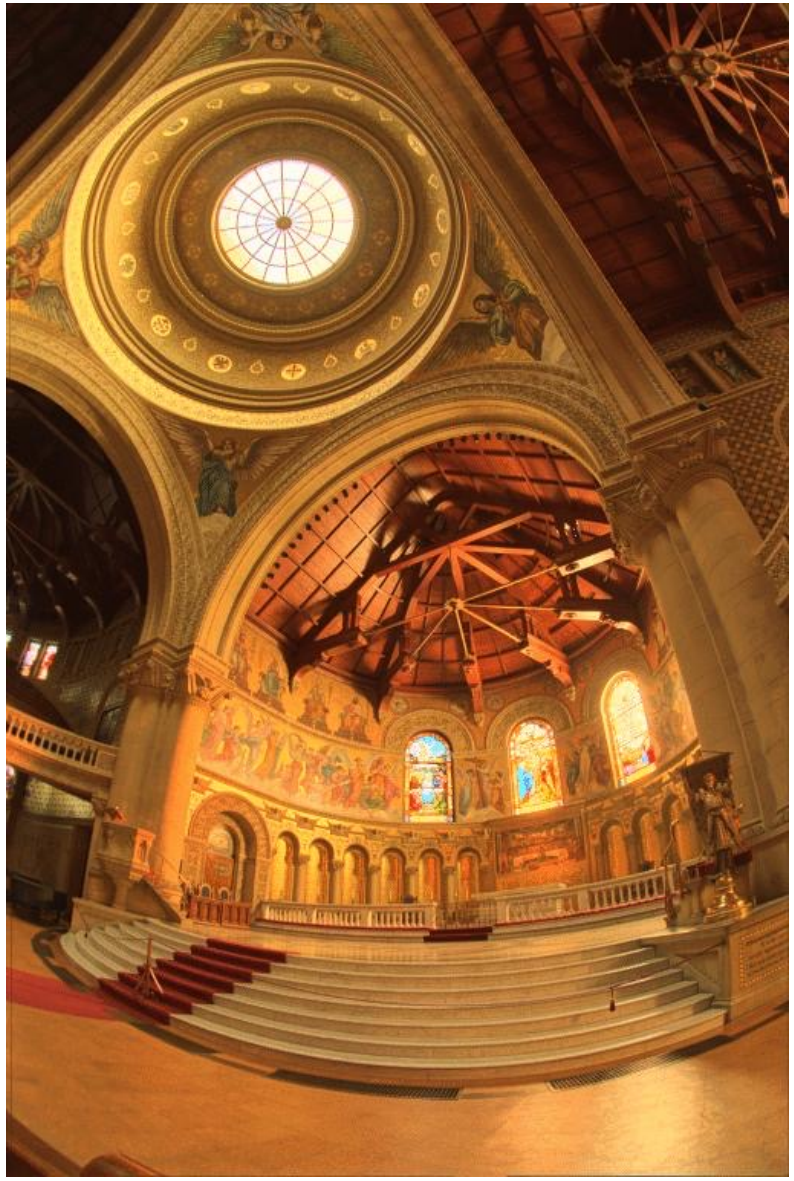
$$I_{display} = \frac{I_{HDR}}{1 + I_{HDR}}$$

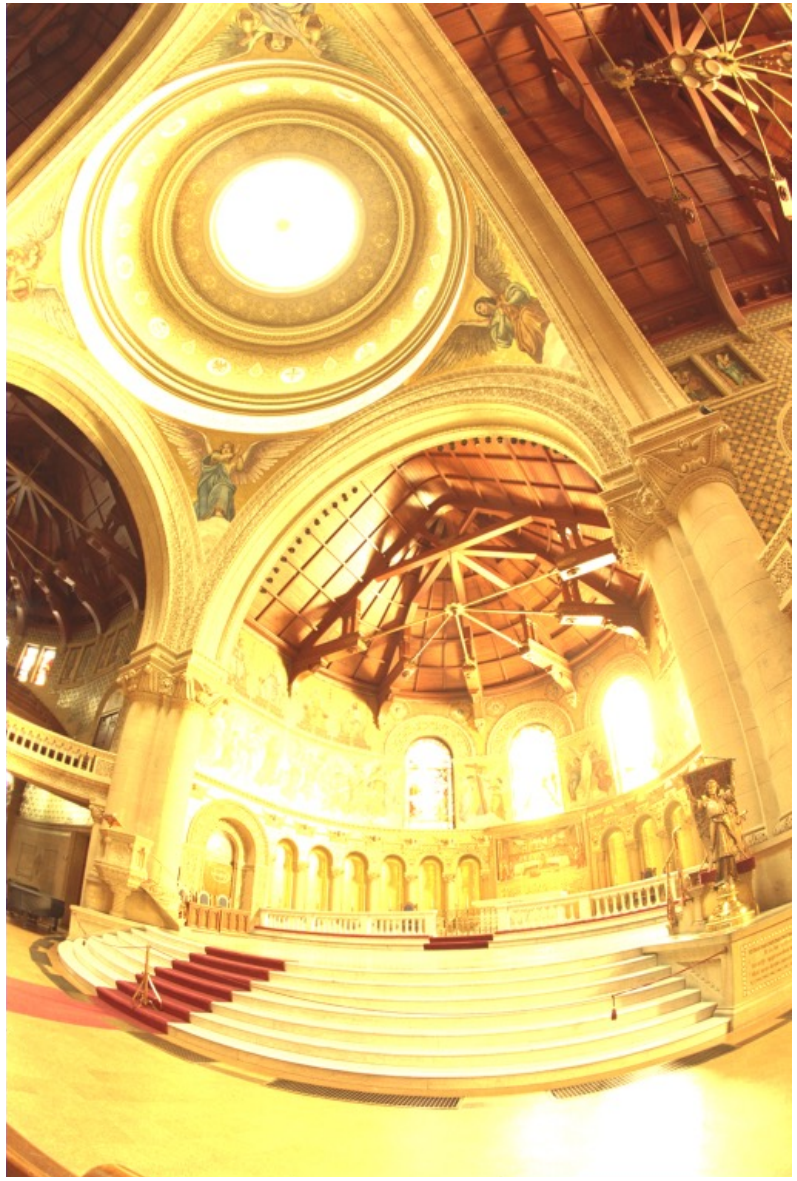
(exact formula more complicated)

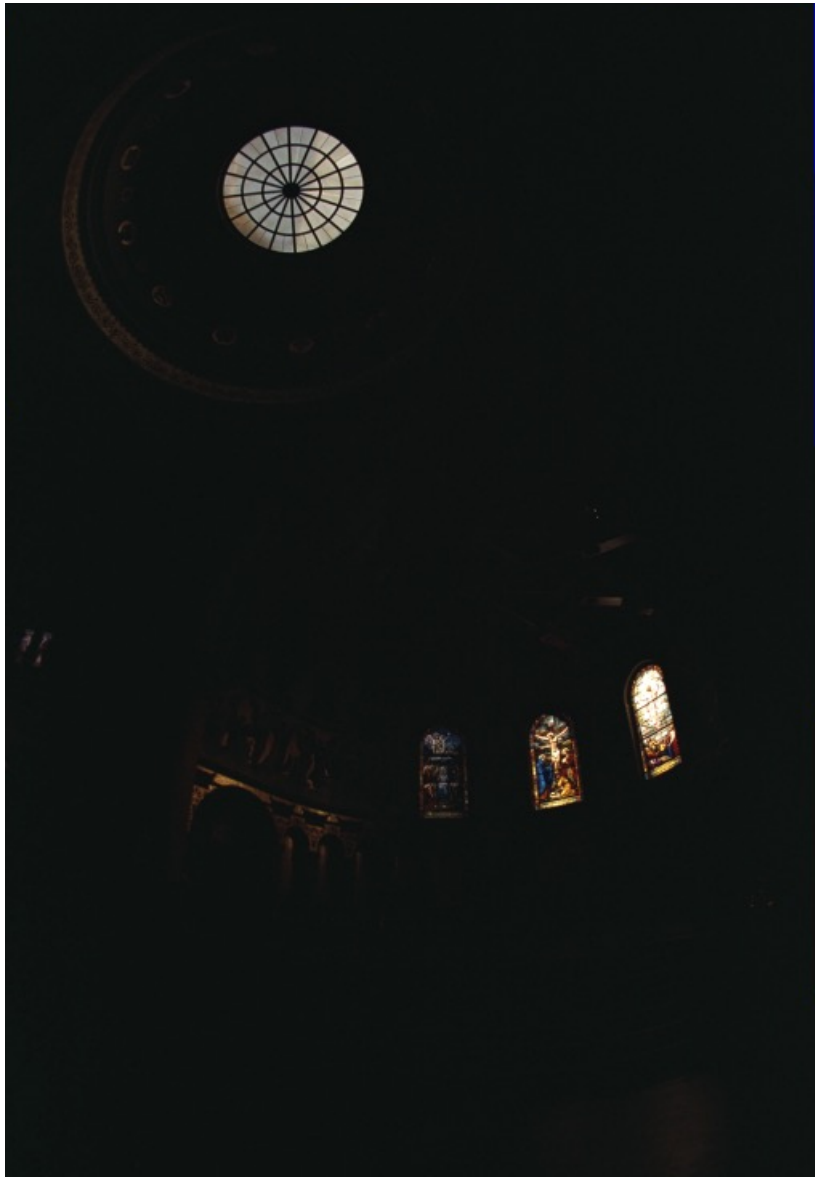
- Photographic because designed to approximate film zone system.
- Perceptually motivated, as it approximates our eye's response curve.

Compare with LDR images

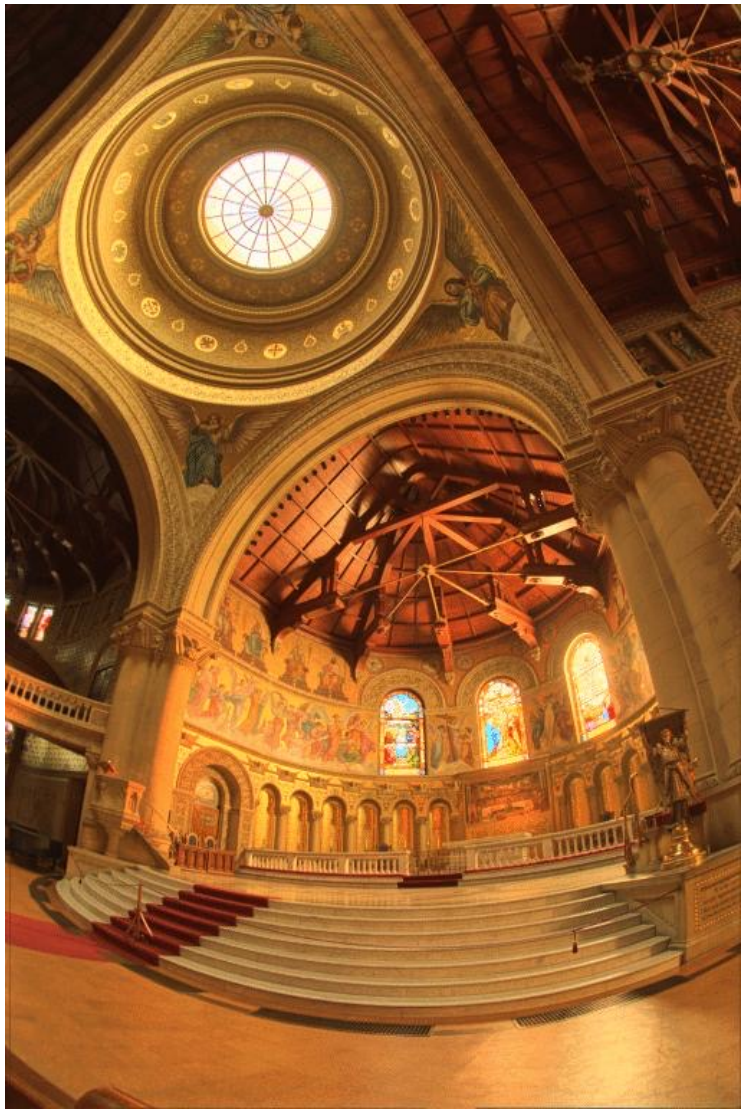
photographic tonemapping



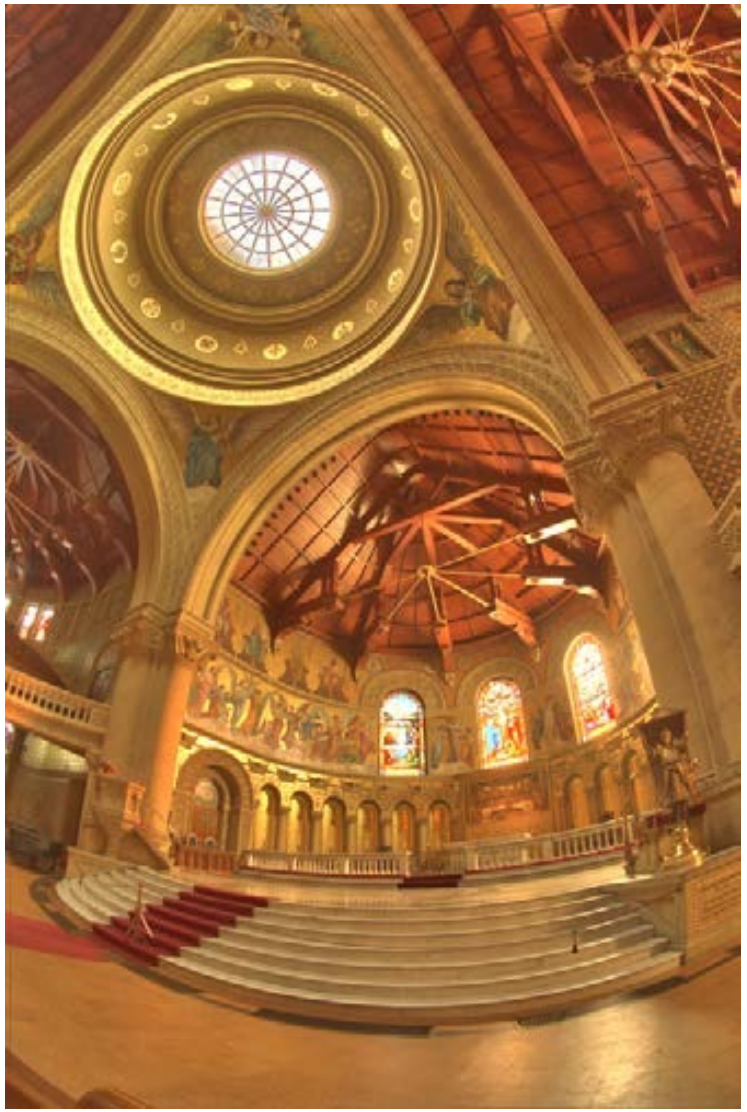




Comparison (which one do you like better?)



photographic



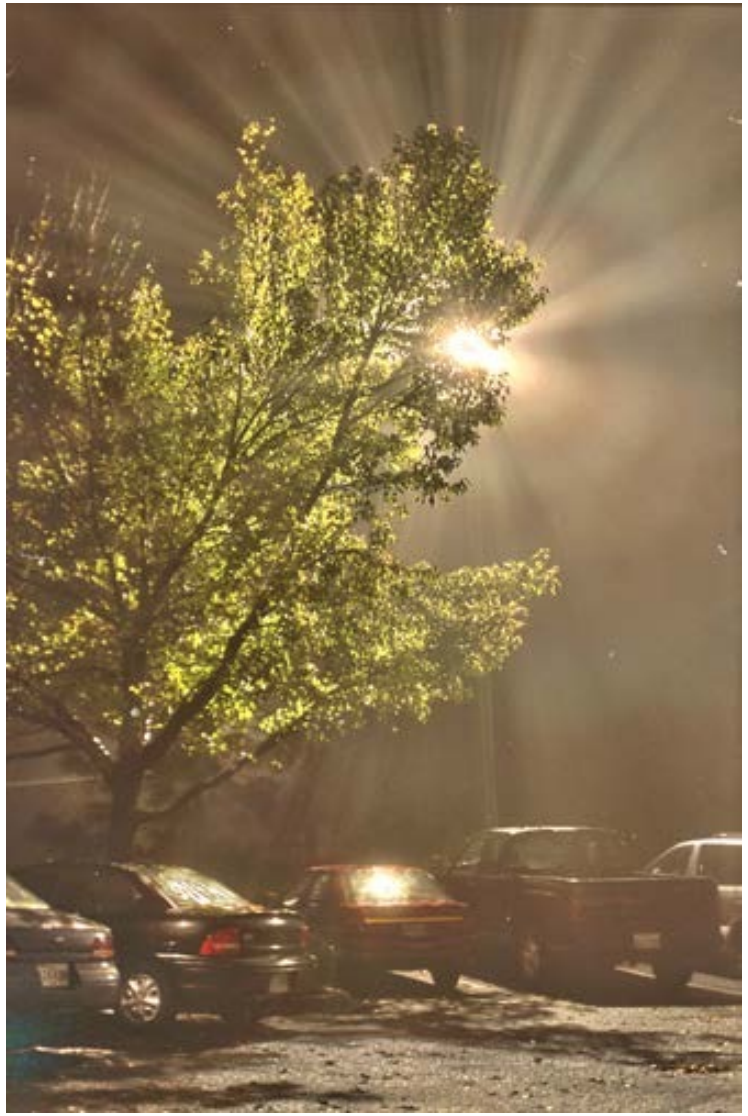
bilateral filtering

gradient-domain

See https://64.github.io/tonemapping/ for details.

Comparison (which one do you like better?)

photographic



bilateral filtering

gradient-domain

Comparison (which one do you like better?)

There is no ground-truth: which one looks better is entirely subjective

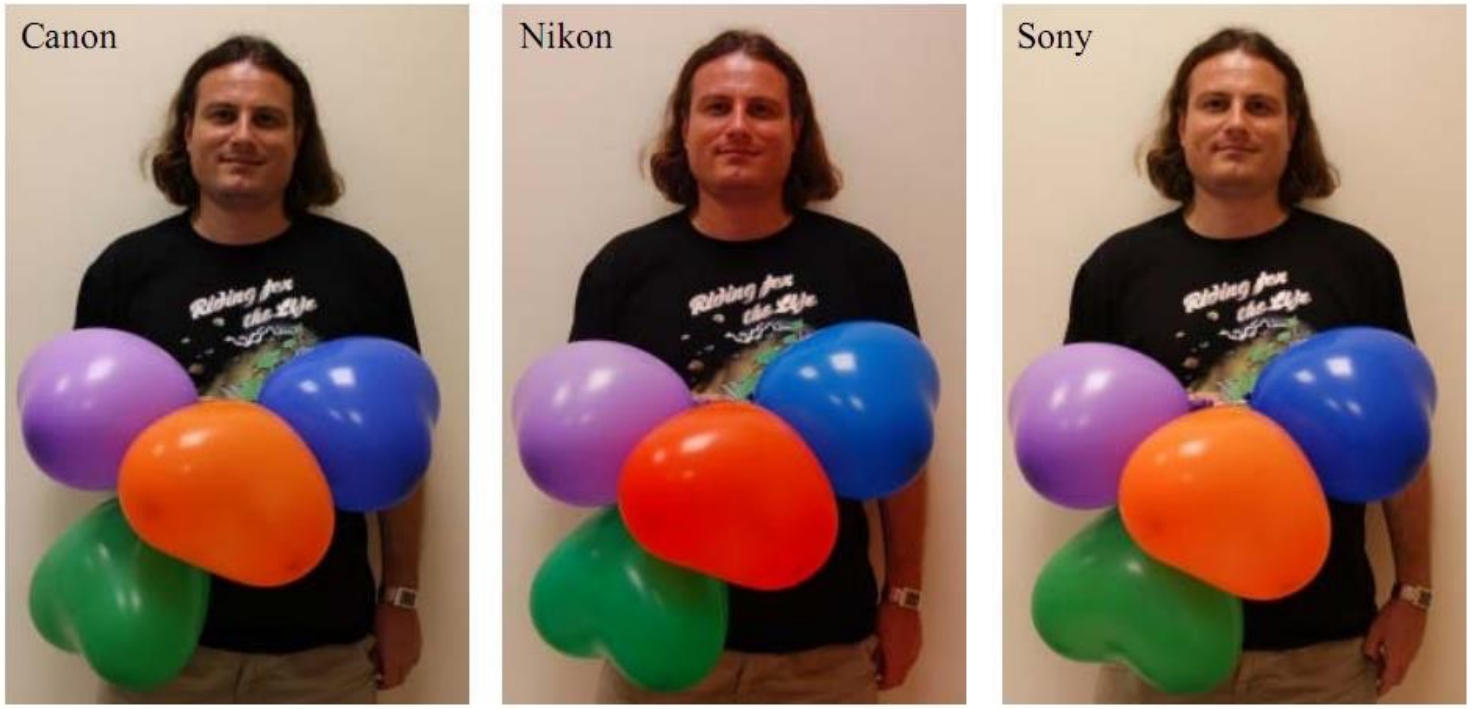
photographic

bilateral filtering

gradient-domain

"Take away" messages

1) Consumer cameras do not attempt to reproduce accurate color!



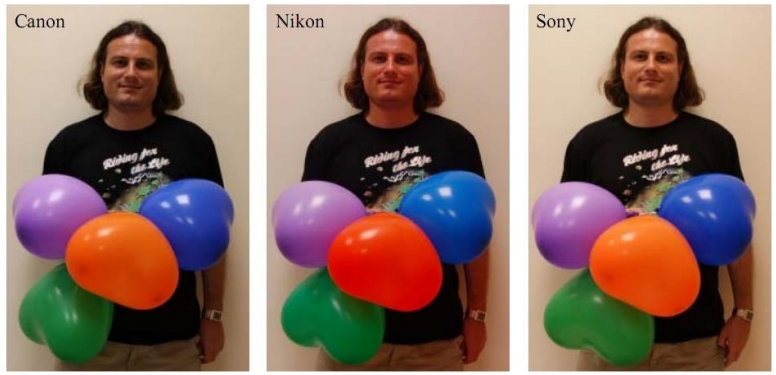
"Take away" messages

2) sRGB is a standard color space, but colors are not accurate with respect to the physical world.

Remember, sRGB values have been manipulated by your camera hardware and do not represent the physical world, they represent the "photo"!

sRGB output on the same camera, different photo options!

sRGB output on different cameras.

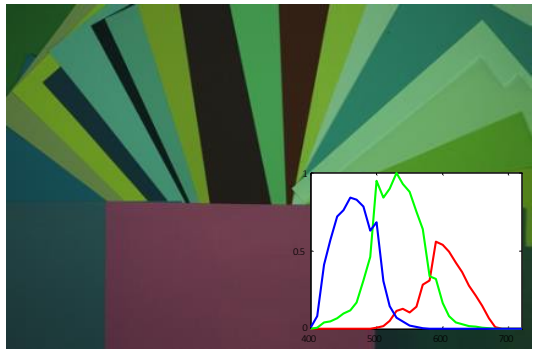


"Take away" messages

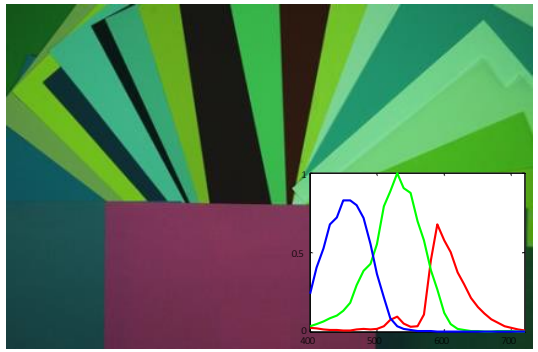
3) raw-RGB images are linear with respect to irradiance

If you need to measure the physical world, capture raw-RGB images.

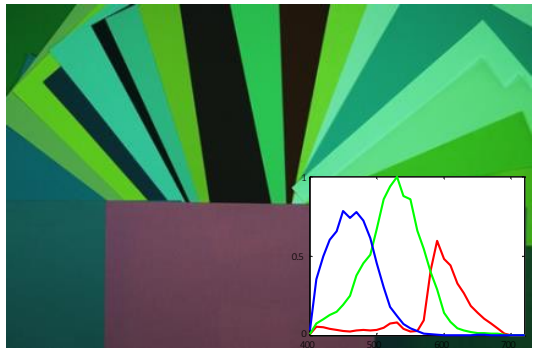
However, keep in mind that raw-RGB images are not standard between devices! The raw-RGB is device specific.



Canon 1D

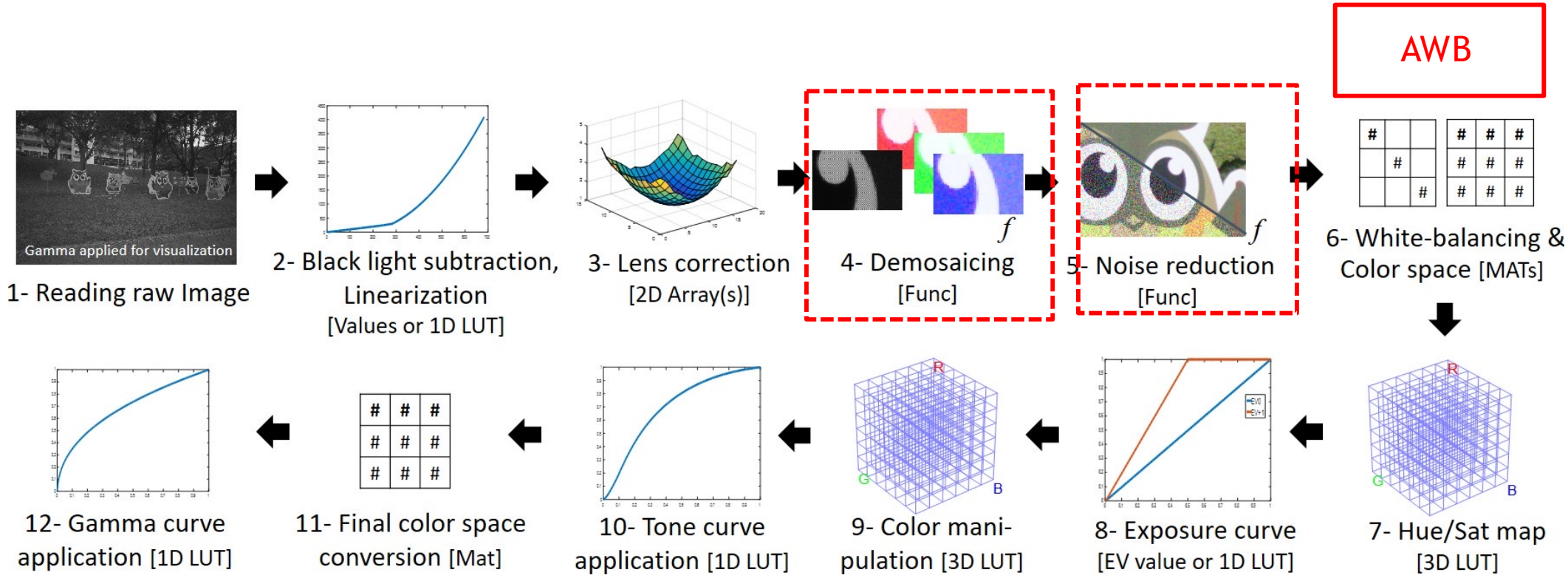


Nikon D40



Sony $\boldsymbol{\alpha 57}$

Many opportunities to improve the camera pipeline



Color reproduction notes

To properly reproduce the color of an image file, you need to convert it from the color space it was stored in, to a reference color space, and then to the color space of your display.

On the camera side:

- If the file is RAW, it *often* has EXIF tags with information about the RGB color space corresponding to the camera's color sensitivity functions.
- If the file is not RAW, you *may* be lucky and still find accurate information in the EXIF tags about what color space the image was converted in during processing.
- If there is no such information and you own the camera that shot the image, then you can do color calibration for the camera.
- If all of the above fails, assume sRGB.

On the display side:

- If you own a high-end display, it likely has accurate color profiles provided by the manufacturer.
- If not, you can use a spectrometer to do color profiling (not color calibration).
- Make sure your viewer does not automatically do color transformations.

Be careful to account for any gamma correction!

Amazing resource for color management and photography: https://ninedegreesbelow.com/

How do you convert an image to grayscale?

First, you need to answer two questions:

1) Is your image linear or non-linear?

- If the image is linear (RAW, HDR, or otherwise radiometrically calibrated), skip this step.
- If the image is nonlinear (PNG, JPEG, etc.), you must undo the tone reproduction curve.
    - i. If you can afford to do radiometric calibration, do that.
    - ii. If your image has EXIF tags, check there about the tone reproduction curve.
    - iii. If your image is tagged as non-linear sRGB, use the inverse of the sRGB tone reproduction curve.
    - iv. If none of the above, assume sRGB and do as in (iii).

2) What is the color space of your image?

- If it came from an original RAW file, read the color transform matrix from there (e.g., dcraw).
- If not, you need to figure out the color space.
    - i. If you can afford to do color calibration, use that.
    - ii. If your image has EXIF tags, check there about the color space.
    - iii. If your image is tagged as non-linear sRGB, use the color transform matrix for linear sRGB.
    - iv. If none of the above, assume sRGB and do (iii).

With this information in hand:

- Transform your image into the XYZ color space.
- Extract the Y channel.
- If you want brightness instead of luminance, apply the Lab brightness non-linearity.

Slide Credits

- “Understanding Color and the In-Camera Image Processing Pipeline for Computer Vision”, by Michael S. Brown, ICCV 2019 tutorial.
- CS 15-463, 663, 862, CMU, by Computational Photography, Ioannis Gkioulekas.