Lecture 2:

A [Simple] Camera Image Processing Pipeline

Visual Computing Systems
Stanford CS348K, Spring 2024

Theme of the next two lectures…

The pixels you see on screen are quite different than the values recorded by the sensor in a modern digital camera.

Computation (computer graphics, image processing, and ML) is a fundamental aspect of producing high-quality photographs.

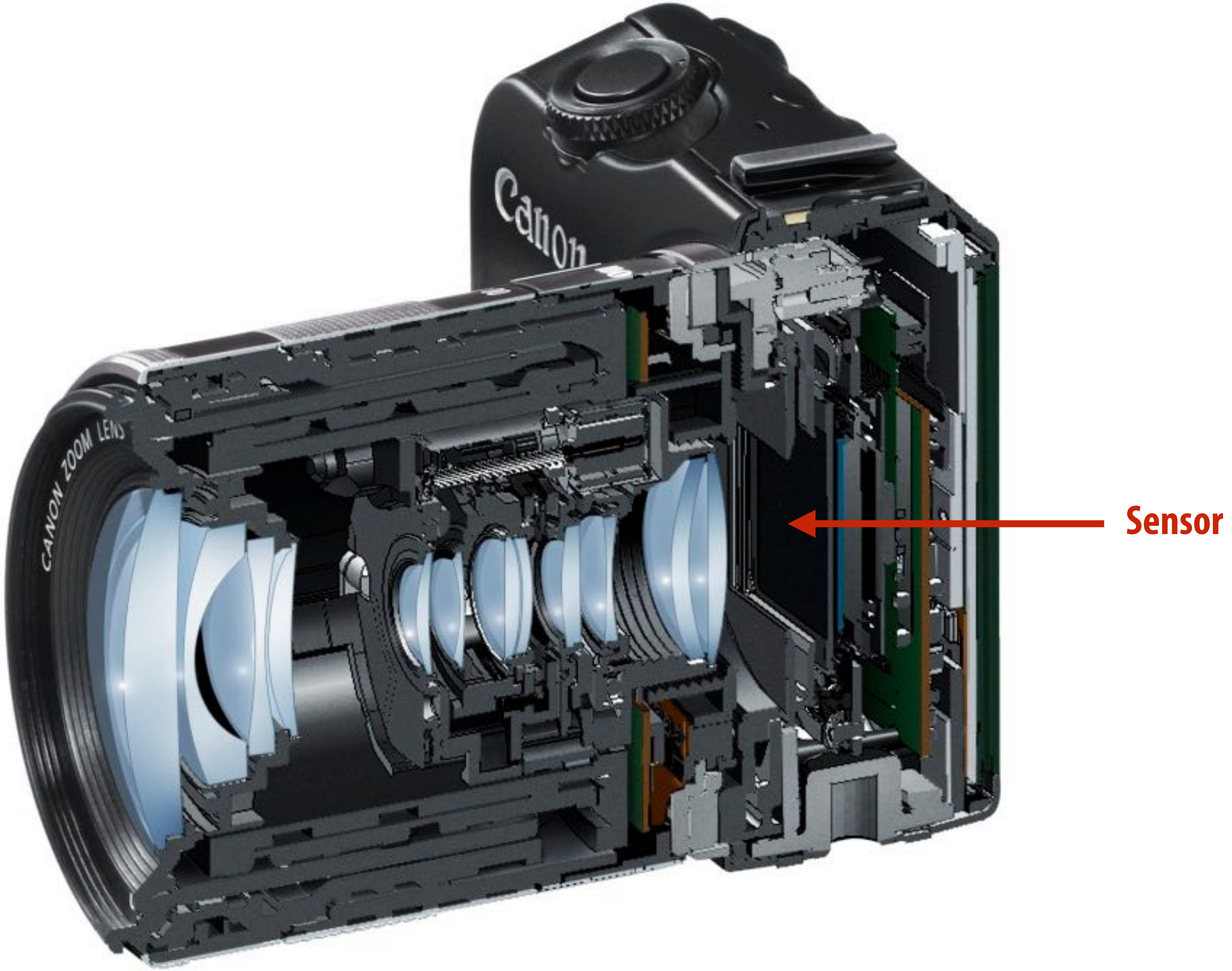
Sensor output ("RAW") → **Computation** →

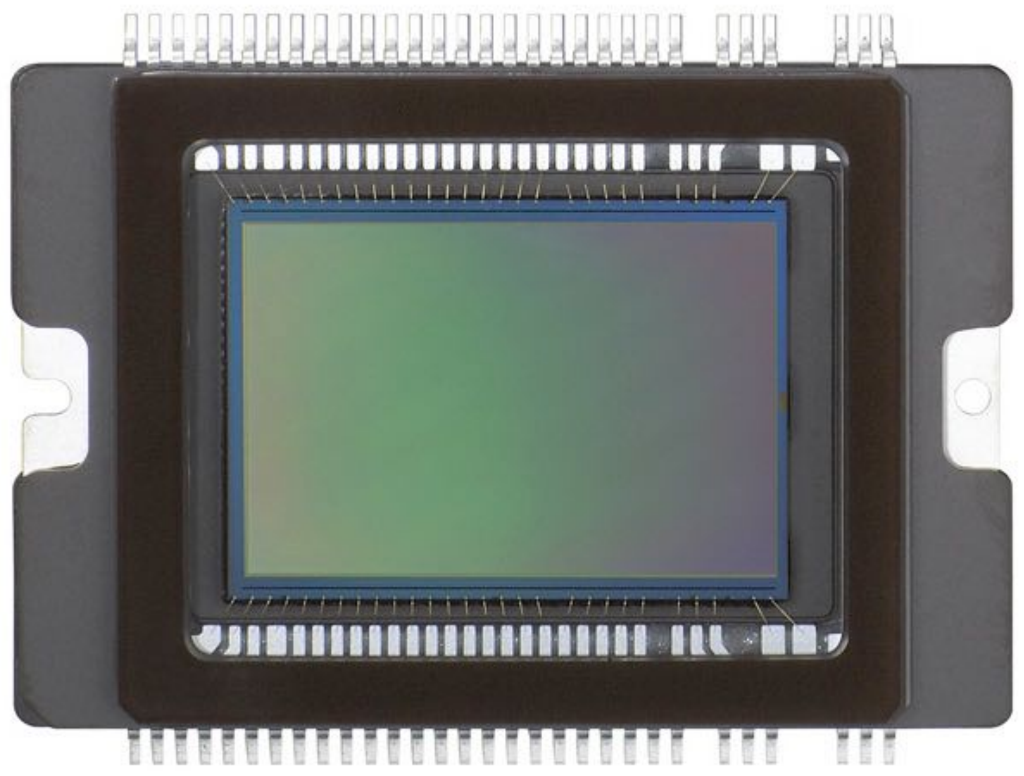
Beautiful image that impresses your Instagram friends

Part 1: image sensing hardware

(how a digital camera measures light,
and how physical limitations of these devices place challenges on software)

Camera cross section





Canon 14 MP CMOS Sensor
(14 bits per pixel)

Image credit: Canon (EOS M)

Camera cross section

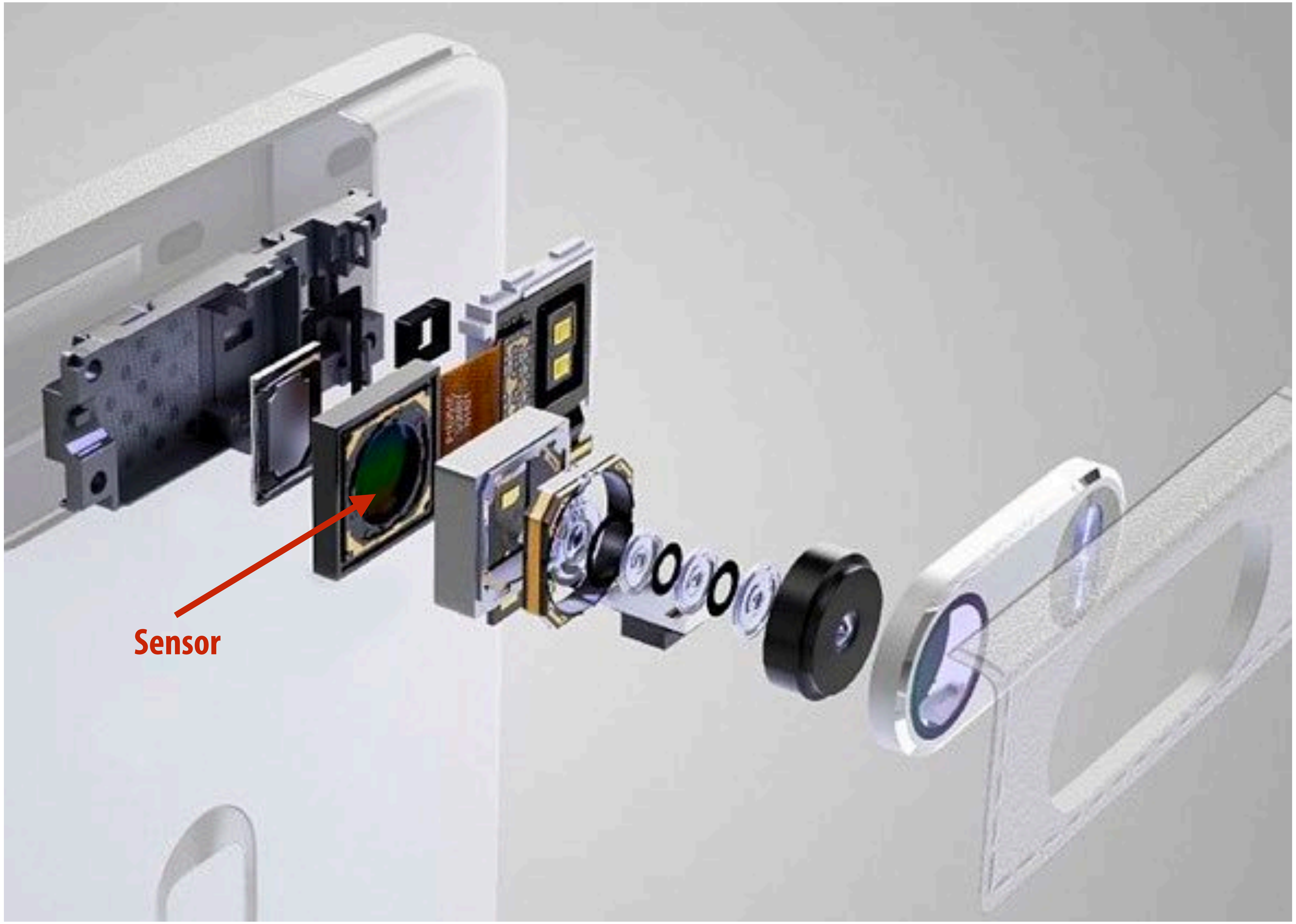
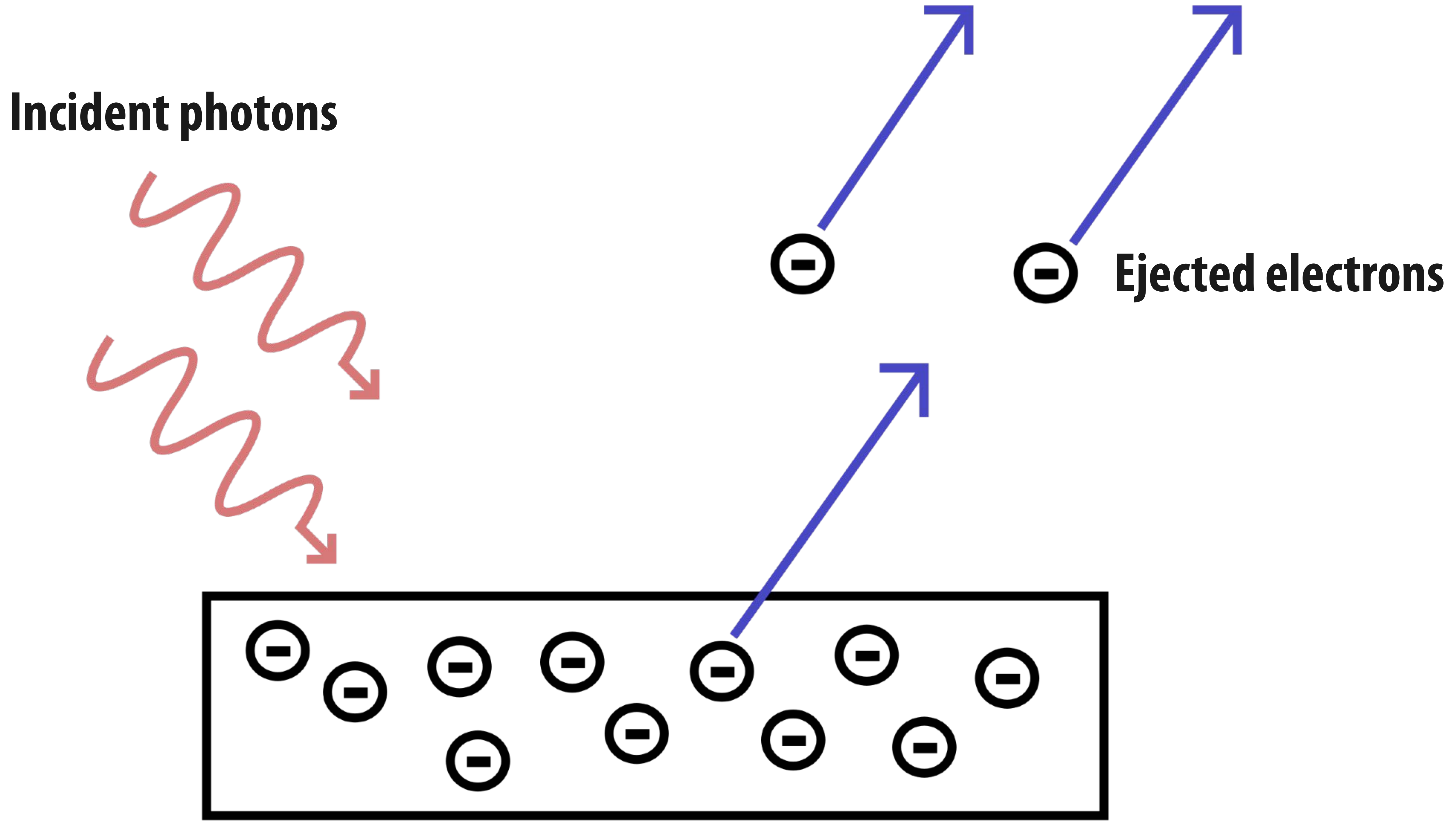


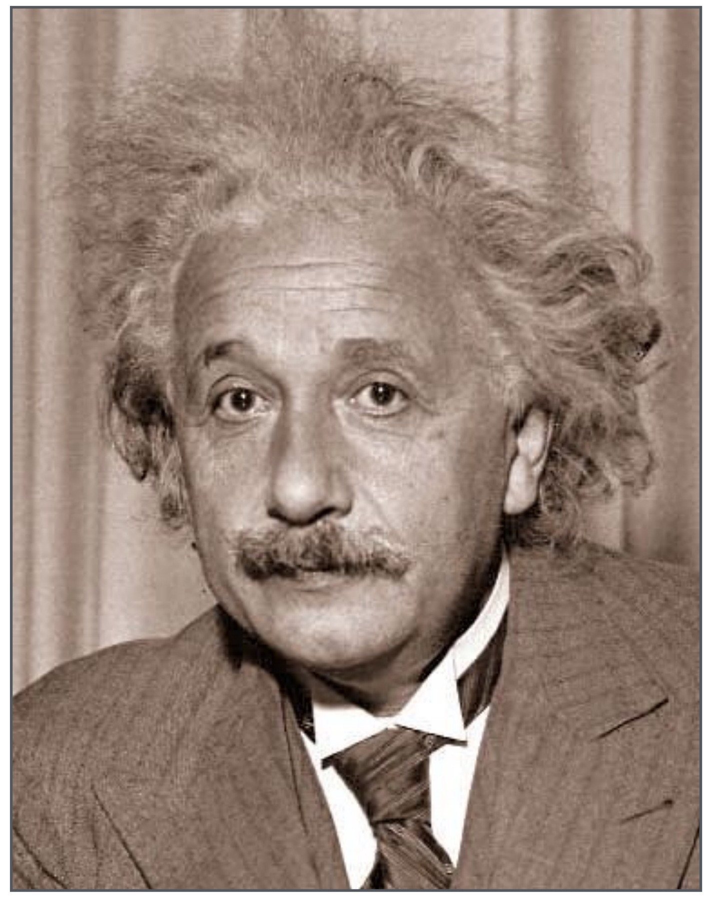
Image credit: https://www.dpreview.com/news/3717128828/the-future-is-bright-technology-trends-in-mobile-photography

The Sensor

Photoelectric effect

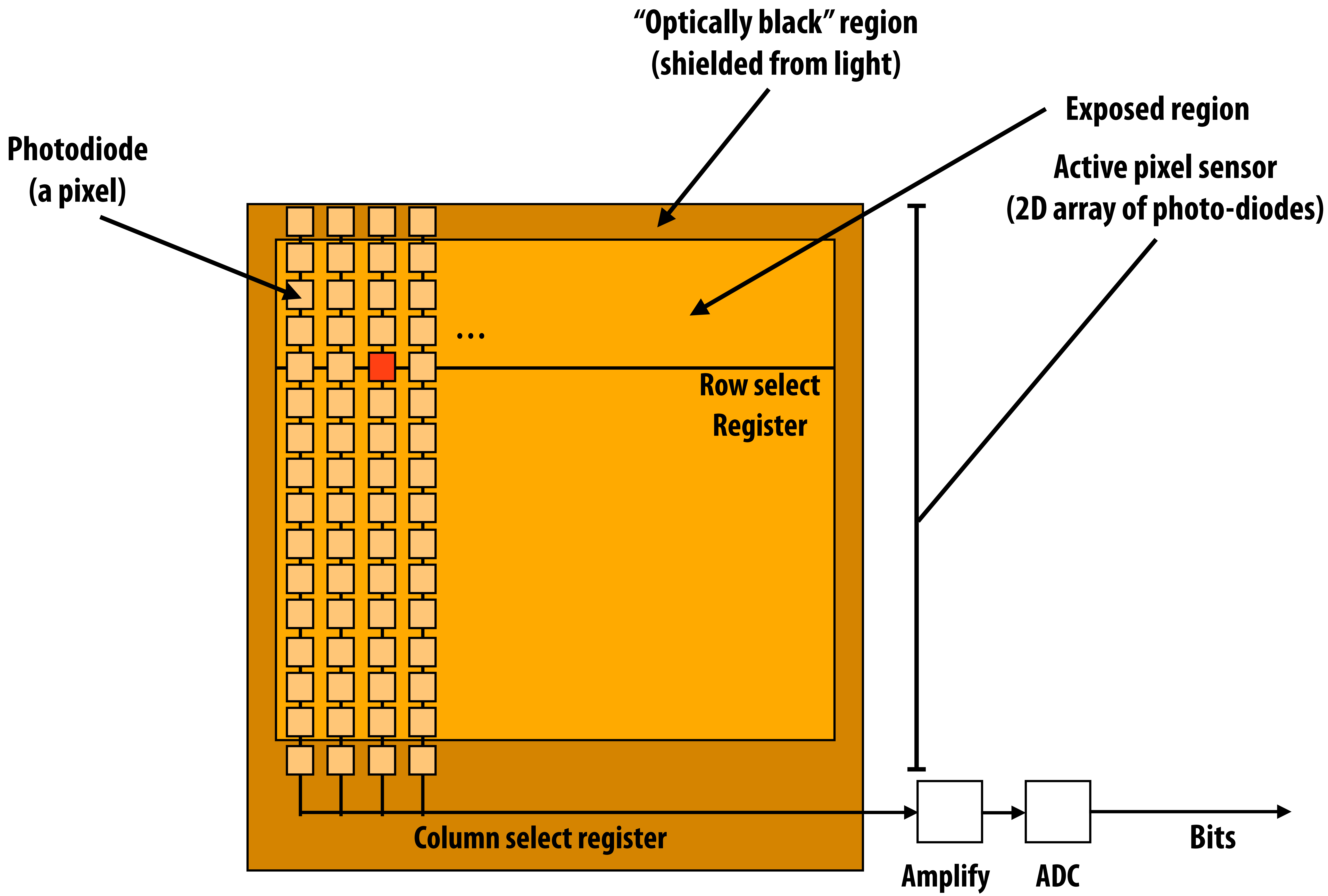
Einstein's Nobel Prize in 1921 "for his services to Theoretical Physics, and especially for his discovery of the law of the photoelectric effect"





Albert Einstein

CMOS sensor



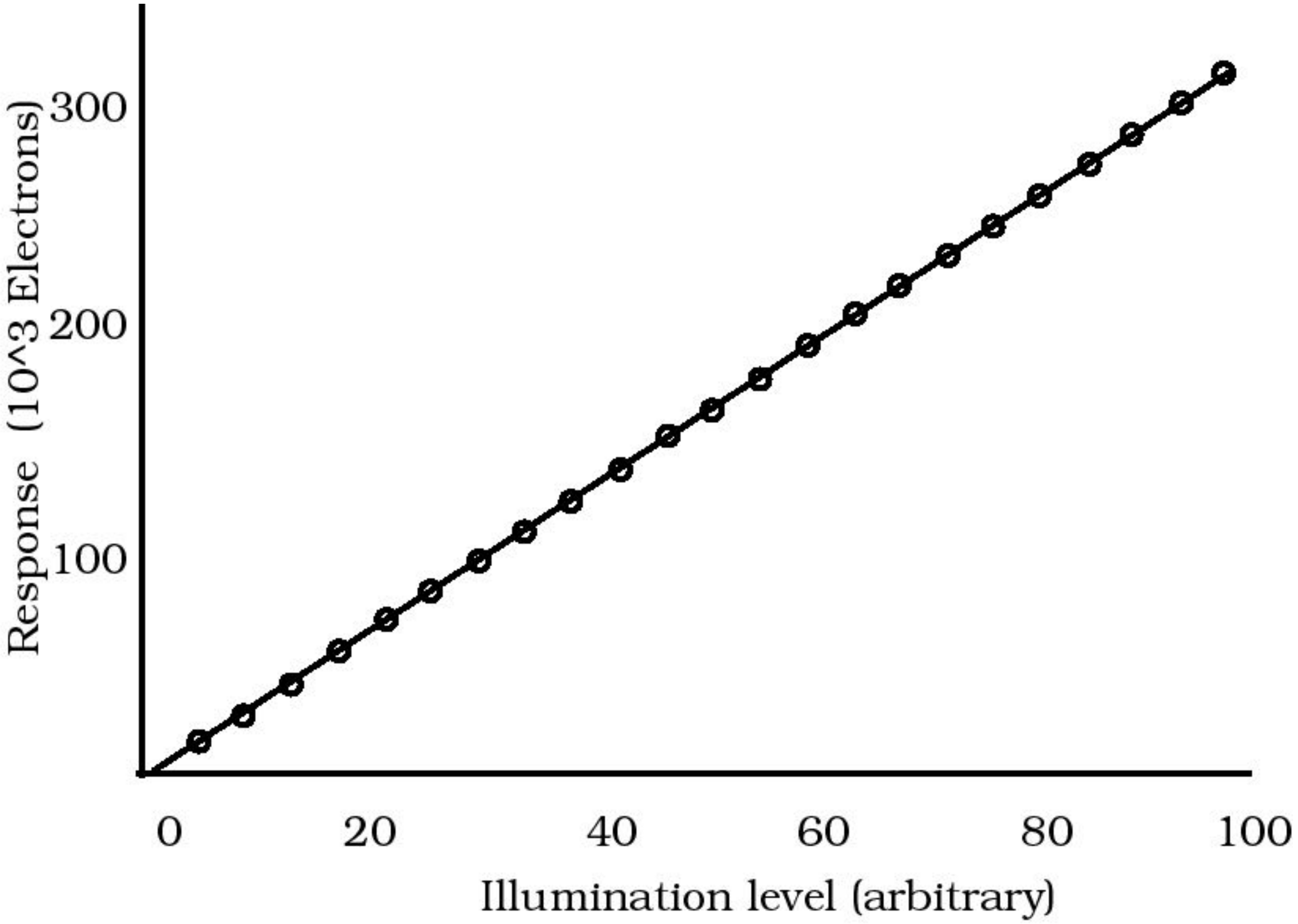
CMOS = complementary metal-oxide semiconductor

CMOS response functions are linear

Photoelectric effect in silicon:

- **Response function from photons to electrons is linear**

  (Some nonlinearity close to 0 due to noise and when close to pixel saturation)



(Epperson, P.M. et al. Electro-optical characterization of the Tektronix TK5 ..., Opt Eng., 25, 1987)

Quantum efficiency

- **Not all photons will produce an electron (depends on quantum efficiency of the device)**

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

- **Human vision:** **~15%**
- **Typical digital camera:** **< 50%**
- **Best back-thinned CCD:** **> 90%**
  (e.g., telescope)

Slide credit: Ren Ng

Sensing Color

Electromagnetic spectrum

Describes distribution of power (energy/time) by wavelength

Below: spectrum of various common light sources:

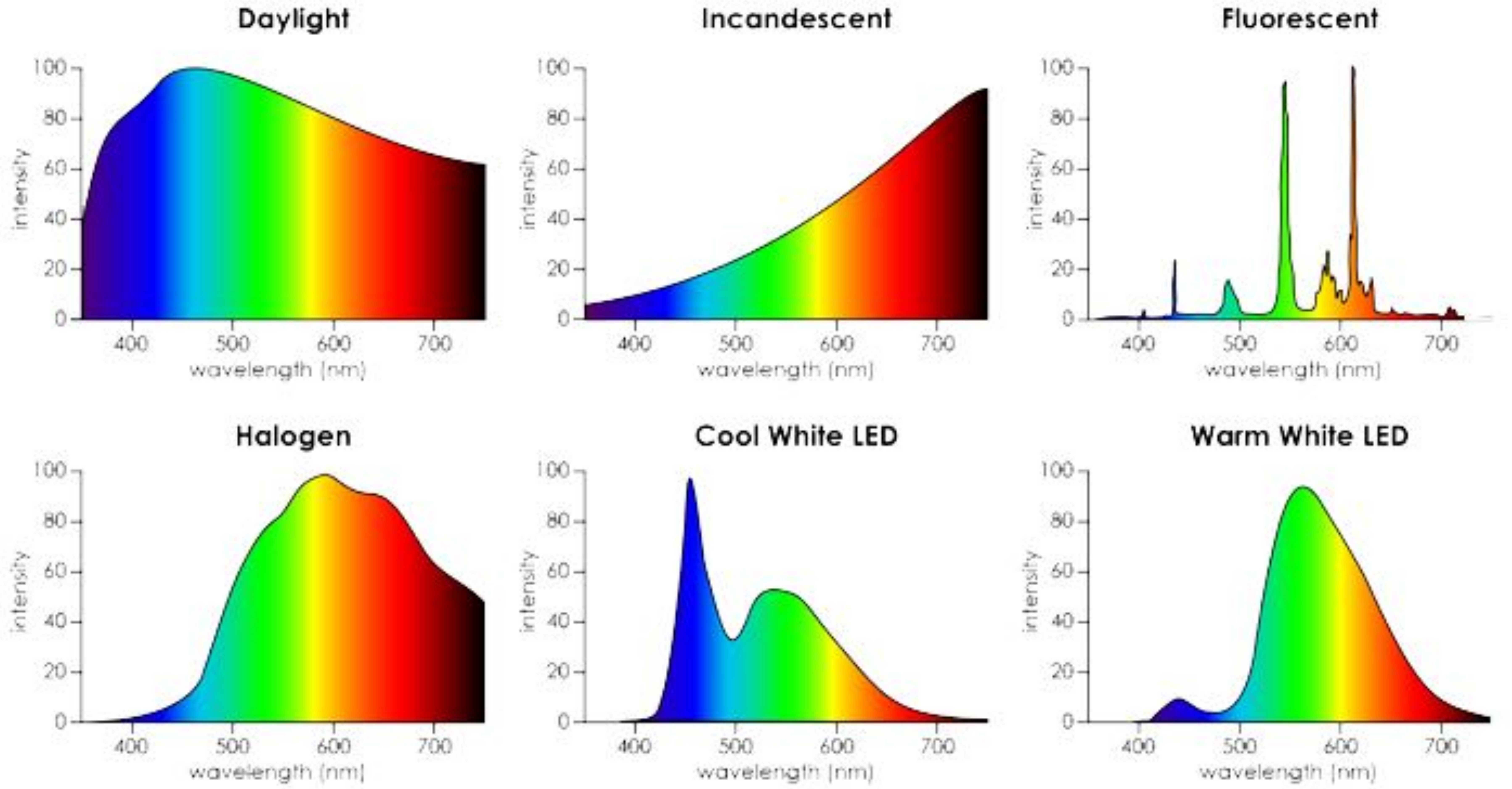


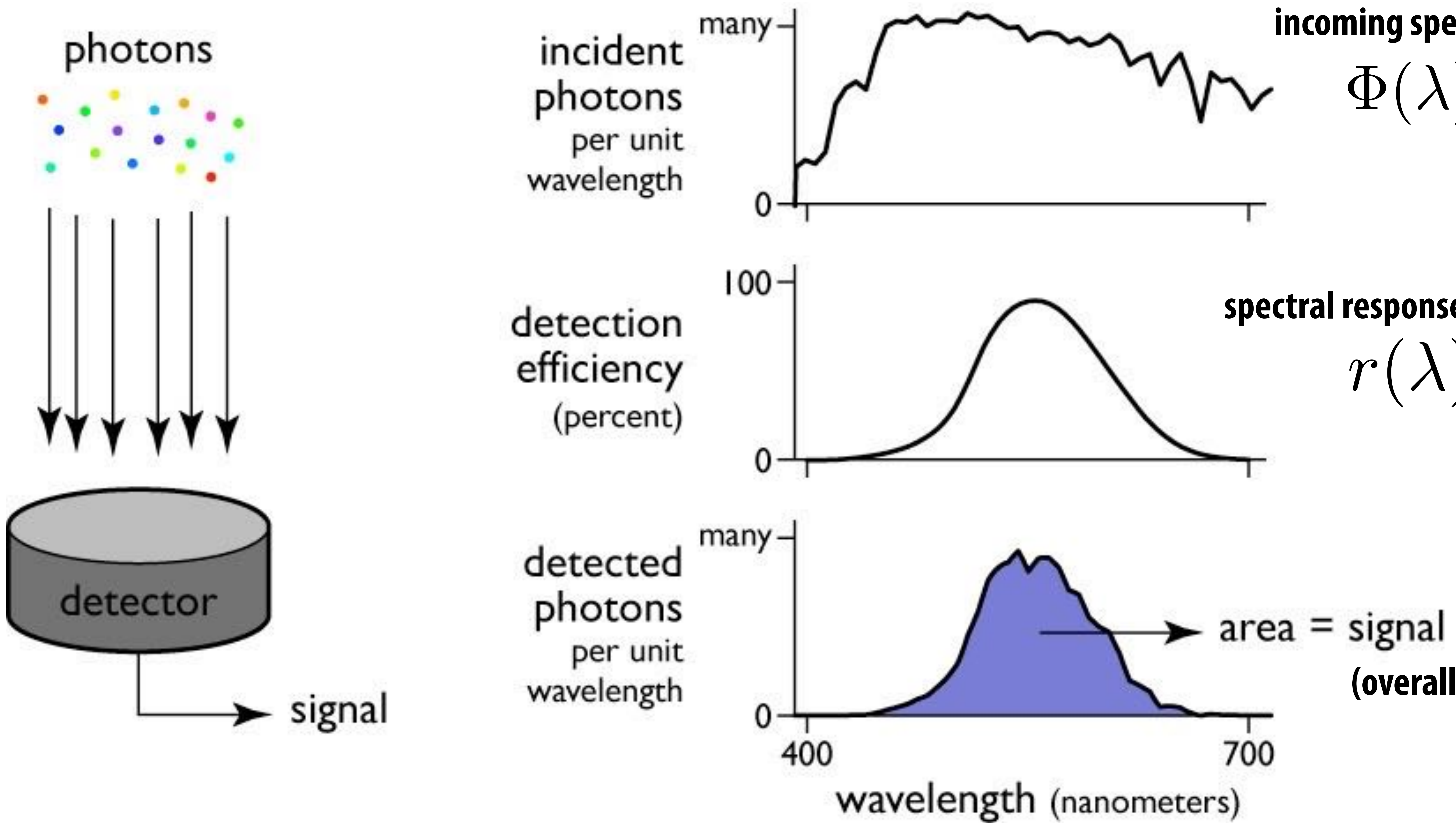
Figure credit:

admesy
ADVANCED MEASUREMENT SYSTEMS

Example: warm white vs. cool white

Image credit: (Oz Lighting: https://www.ozlighting.com.au/blog/what-is-warm-white-versus-cool-white/)

Simple model of a light detector



incoming spectrum

$\Phi(\lambda)$

spectral response function

$r(\lambda)$

(overall response)

$$R = \int_\lambda \Phi(\lambda) r(\lambda) d\lambda$$

Figure credit: Steve Marschner

Spectral response of cone cells in human eye

Three types of cells in eye responsible for color perception: S, M, and L cones (corresponding to peak response at short, medium, and long wavelengths)

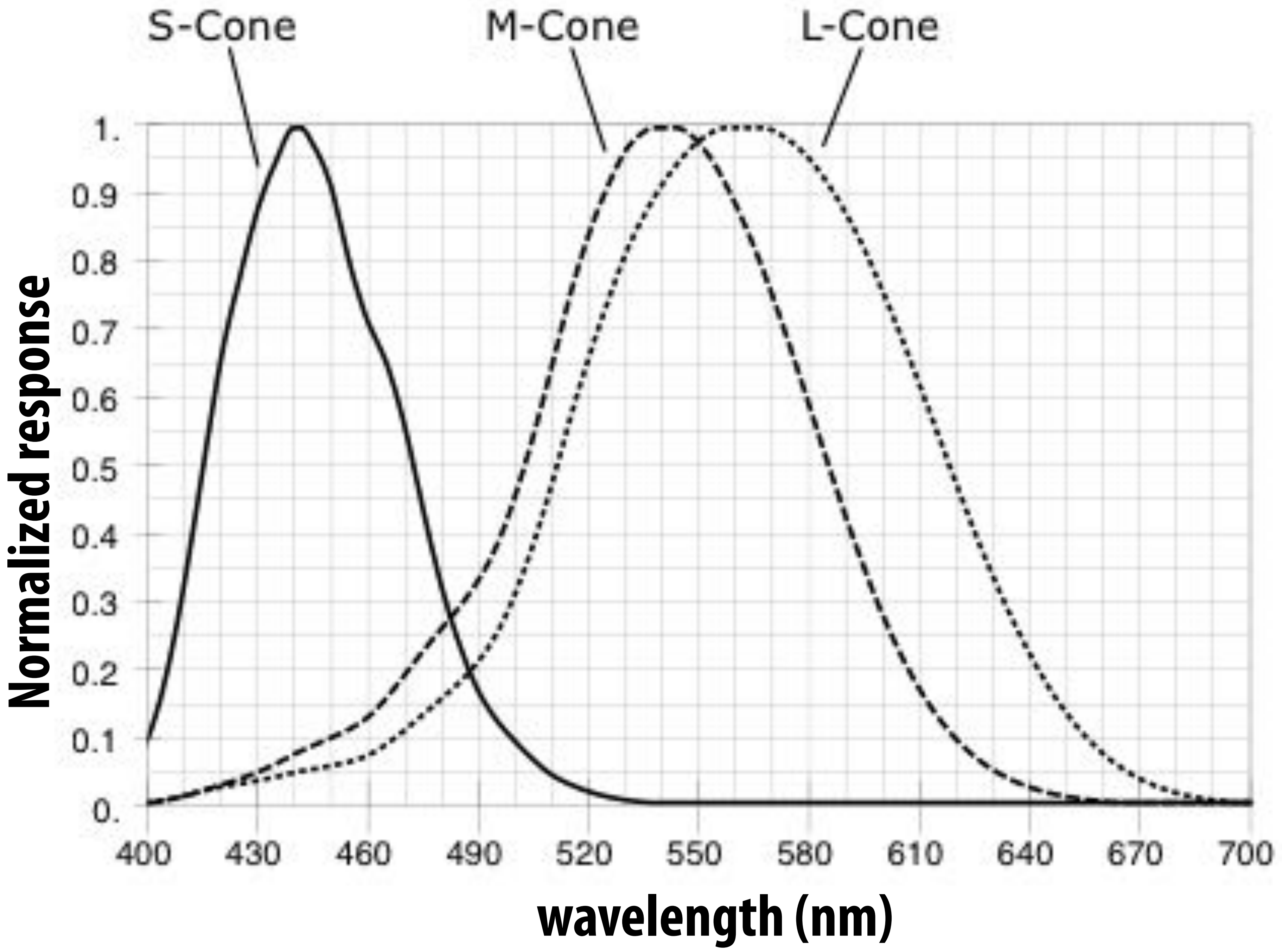
Implication: the space of human-perceivable colors is three dimensional

$$S = \int_\lambda \Phi(\lambda) S(\lambda) d\lambda$$

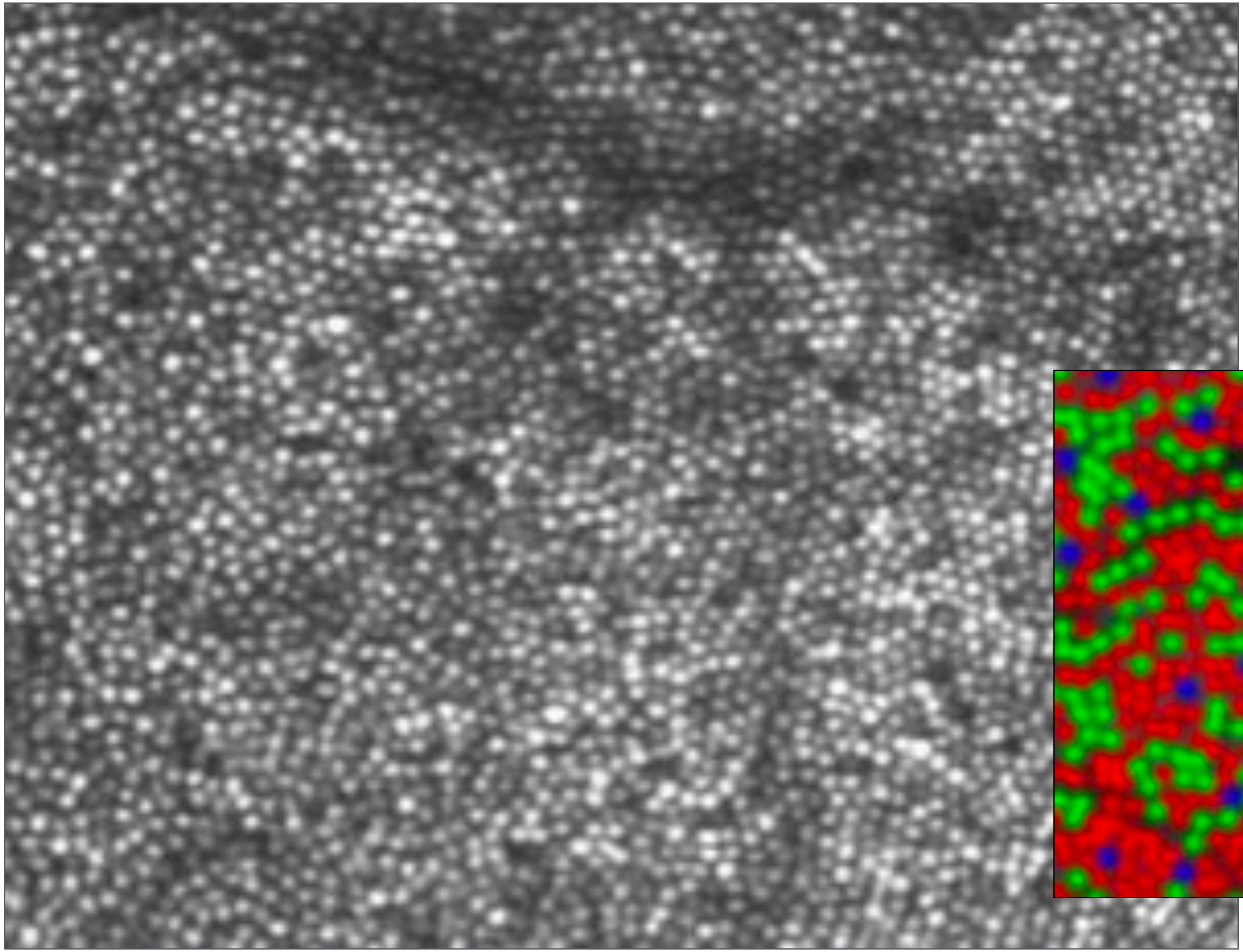
$$M = \int_\lambda \Phi(\lambda) M(\lambda) d\lambda$$

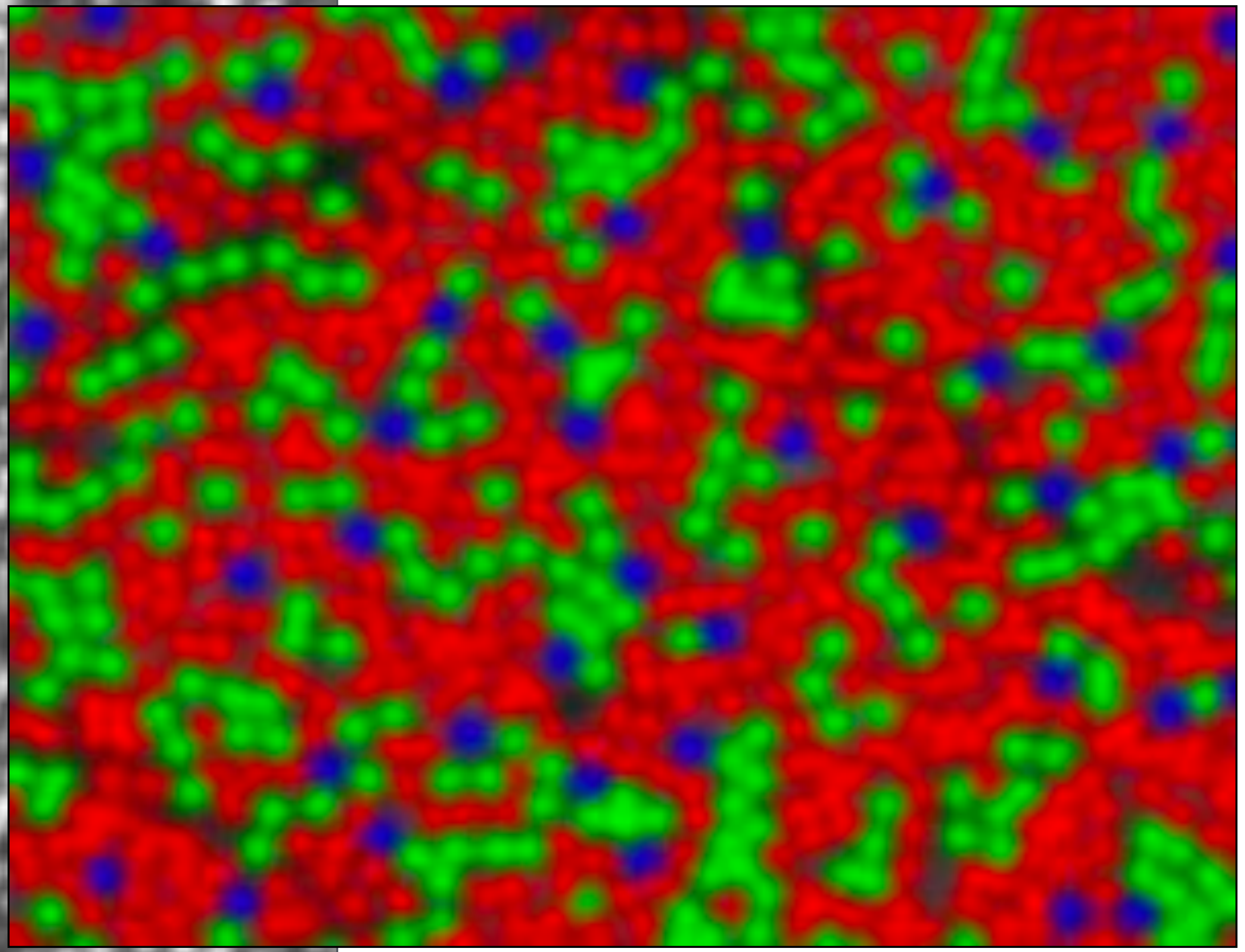
$$L = \int_\lambda \Phi(\lambda) L(\lambda) d\lambda$$

Response functions for S, M, and L cones



Human eye cone cell mosaic



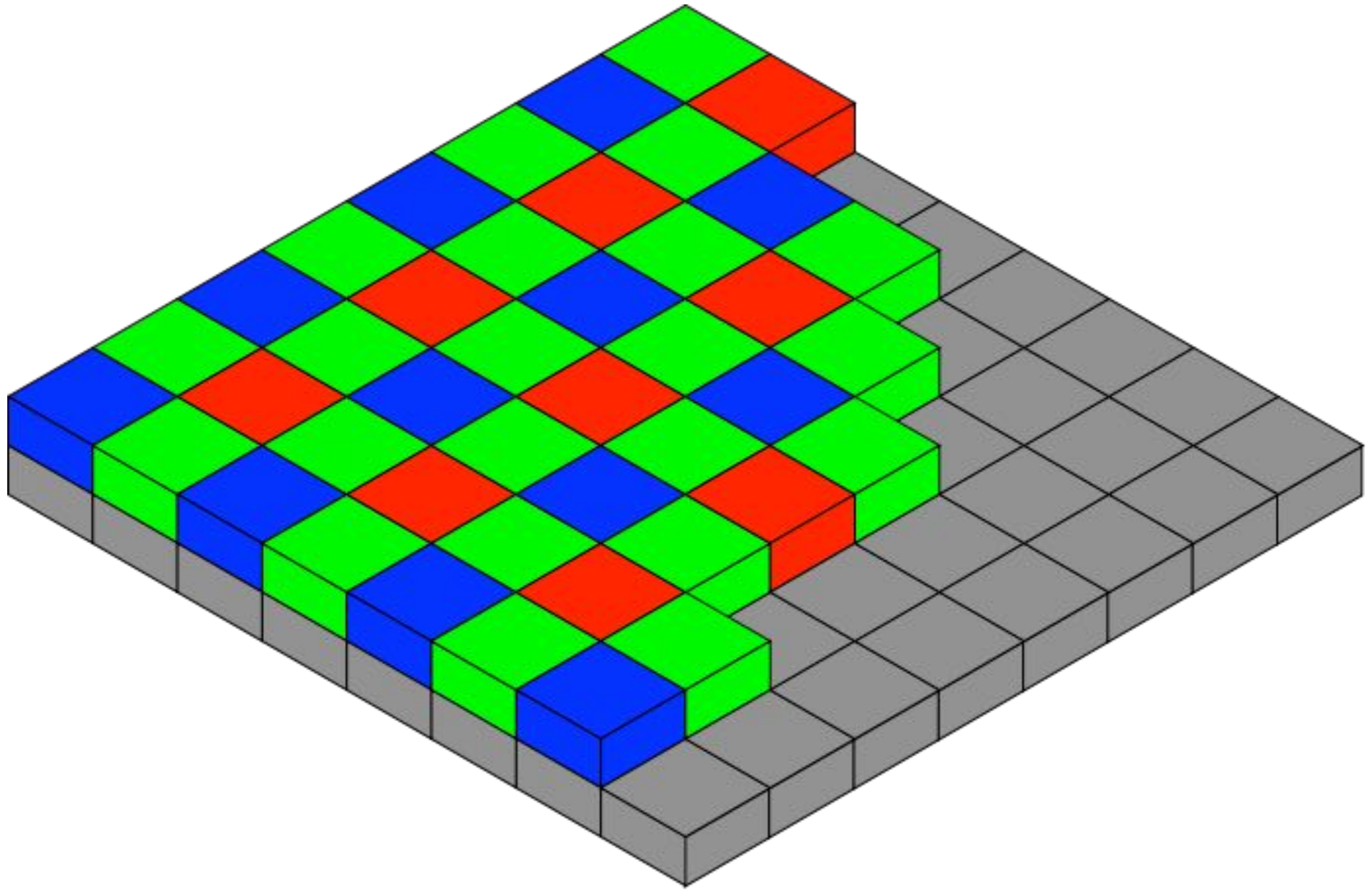


False color image:
red = L cones
green = M cones
blue = R cones

Image Credit: Ramkumar Sabesan Lab

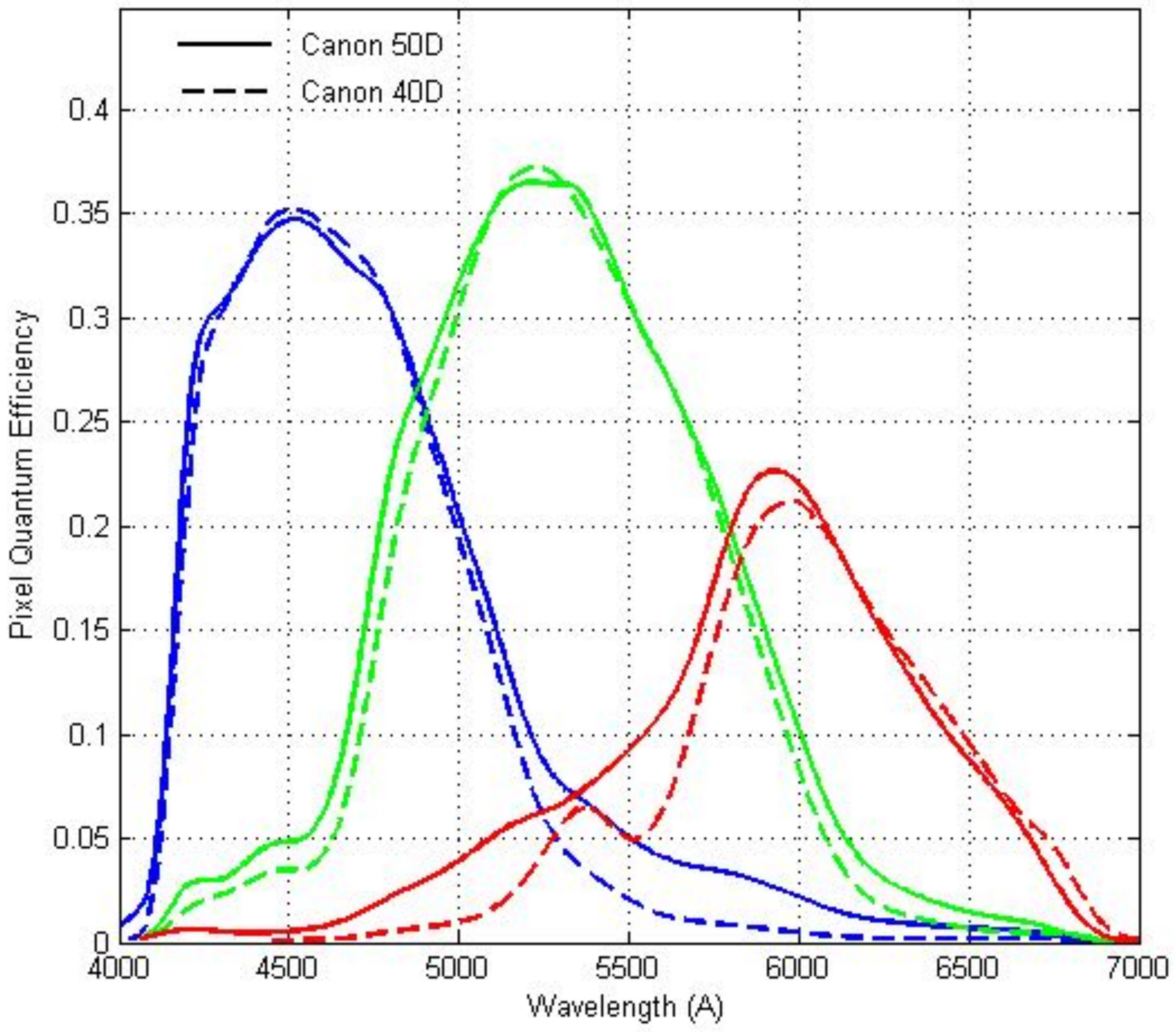
Color filter array (Bayer mosaic)

- Color filter array placed over sensor
- Result: different pixels have different spectral response (each pixel measures red, green, or blue light)
- 50% of pixels are green pixels



Traditional Bayer mosaic
(other filter patterns exist: e.g., Sony's RGBE)

Pixel response curve: Canon 40D/50D



$f(\lambda)$

Image credit:
Wikipedia, Christian Buil (http://www.astrosurf.com/~buil/cameras.htm)

Light incident on camera

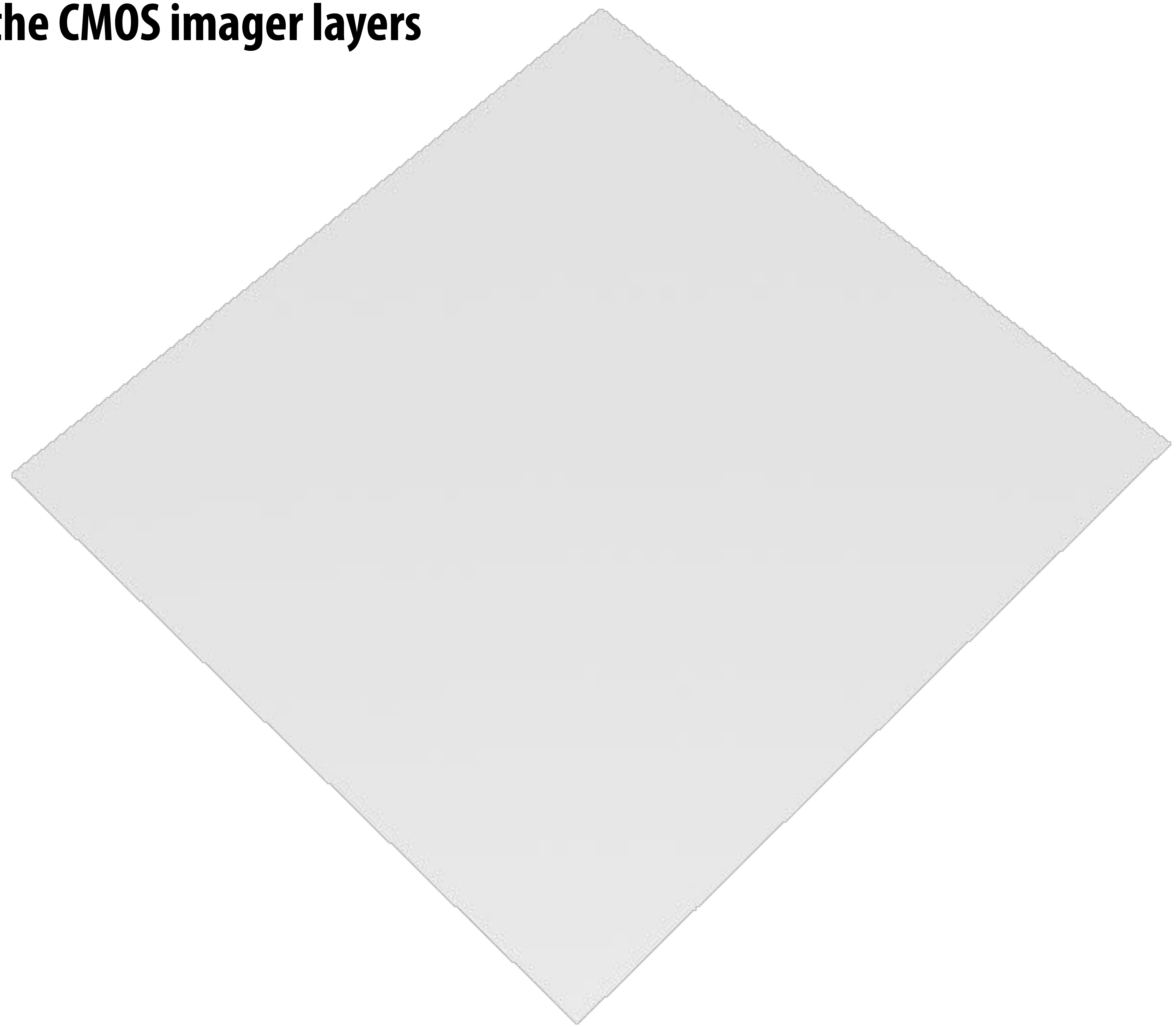
What sensor measures

What sensor measures (zoomed view)

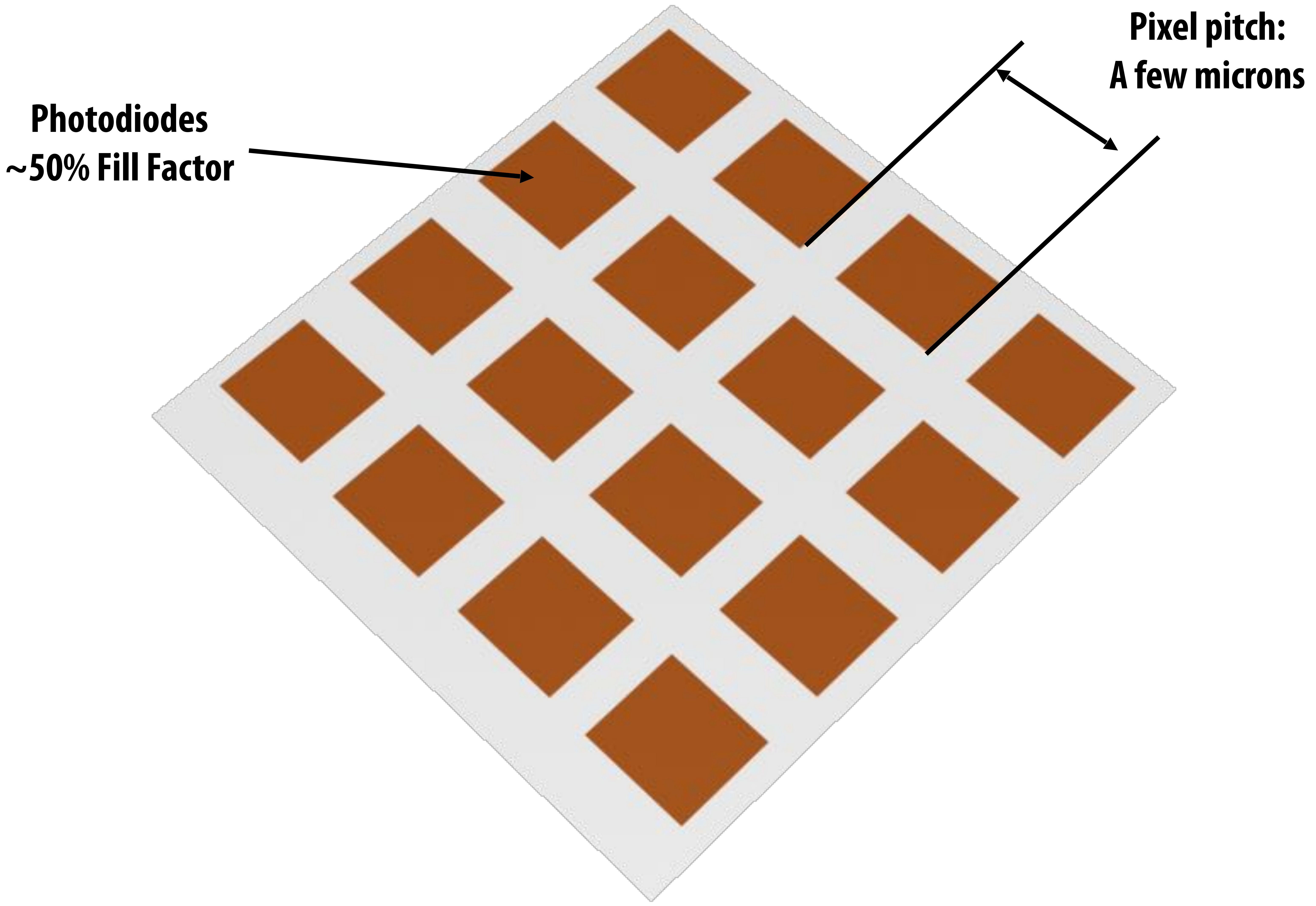
CMOS Pixel Structure

Front-side-illuminated (FSI) CMOS

Building up the CMOS imager layers

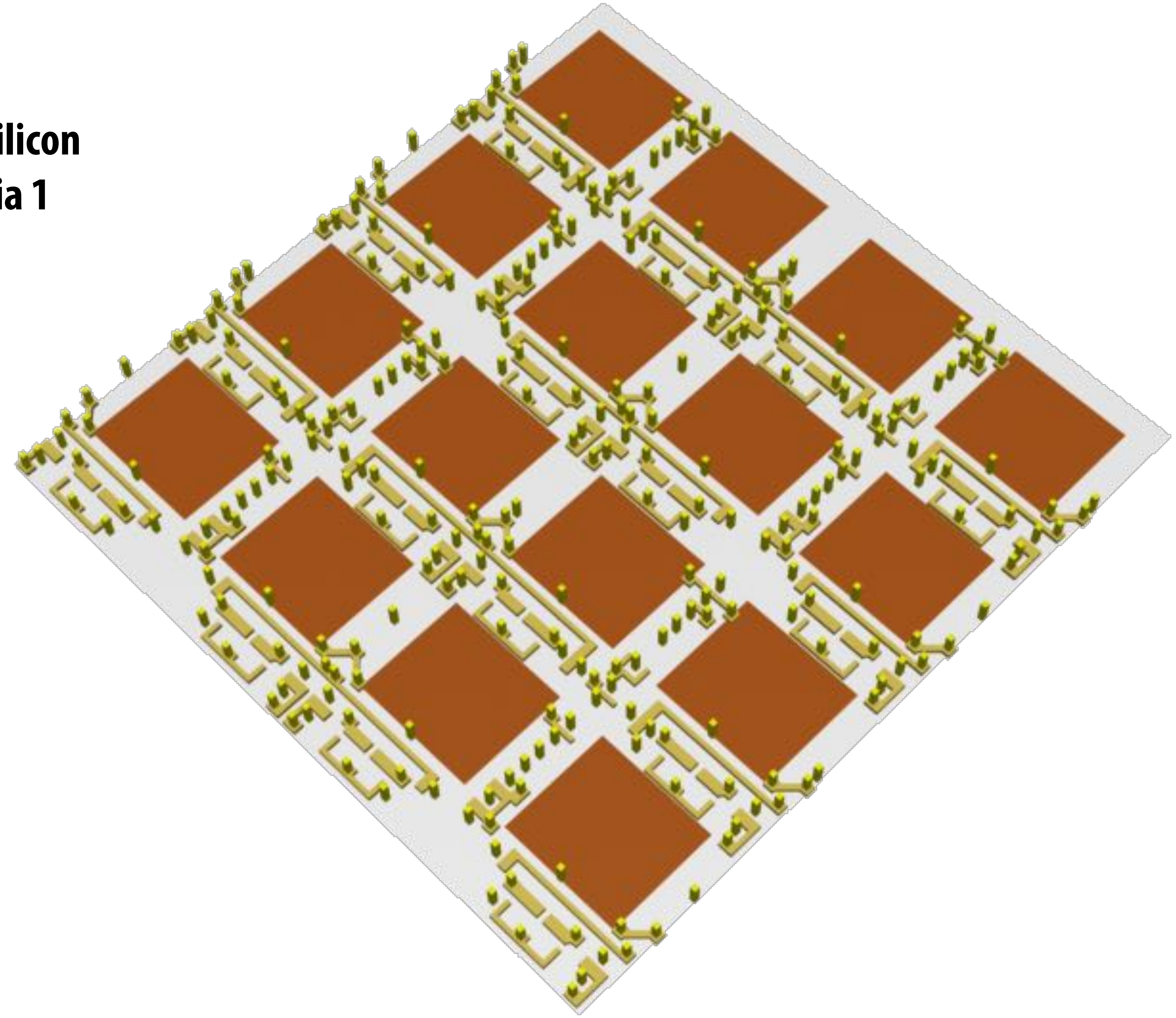


Courtesy R. Motta, Pixim



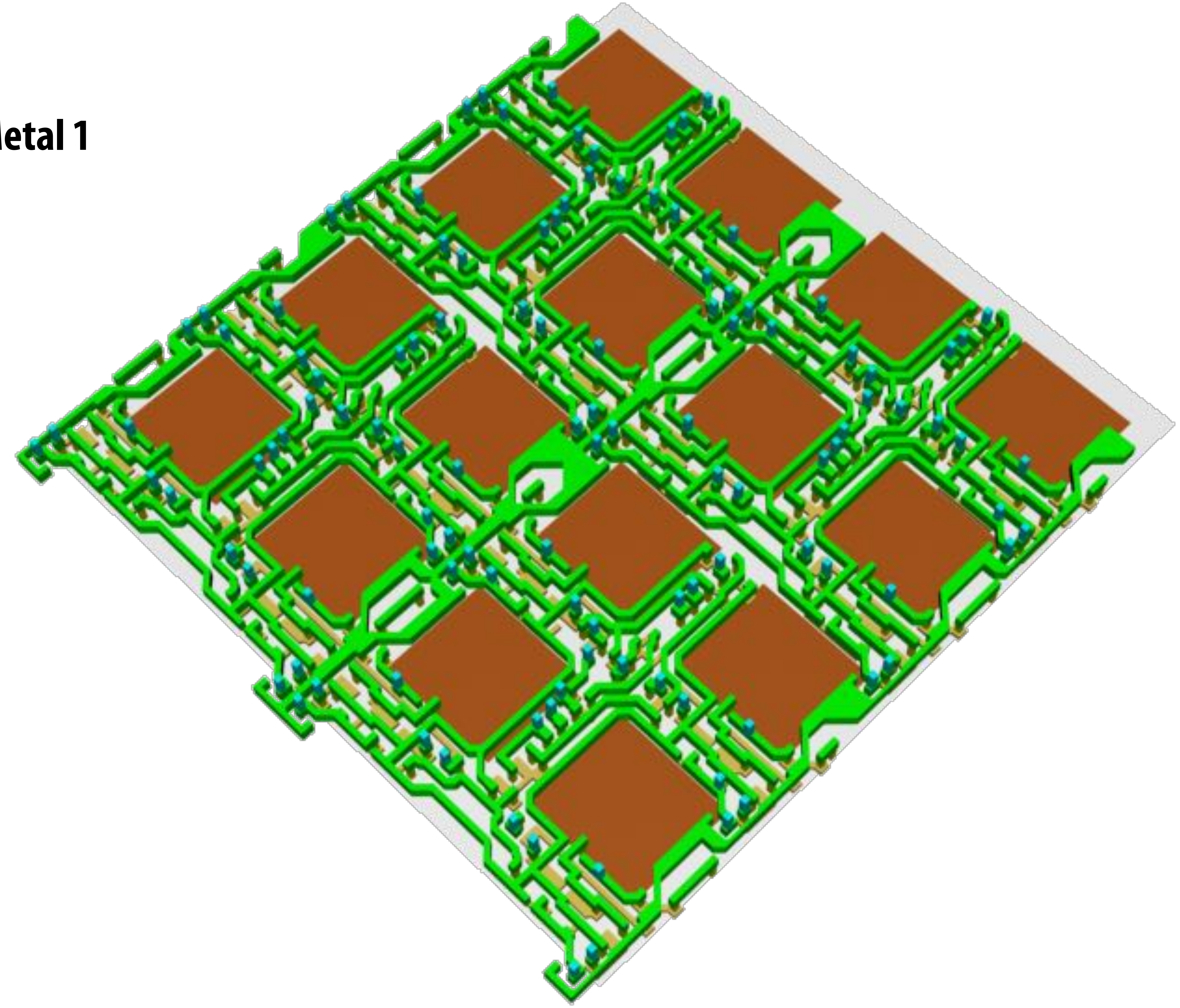
Courtesy R. Motta, Pixim

Polysilicon
& Via 1

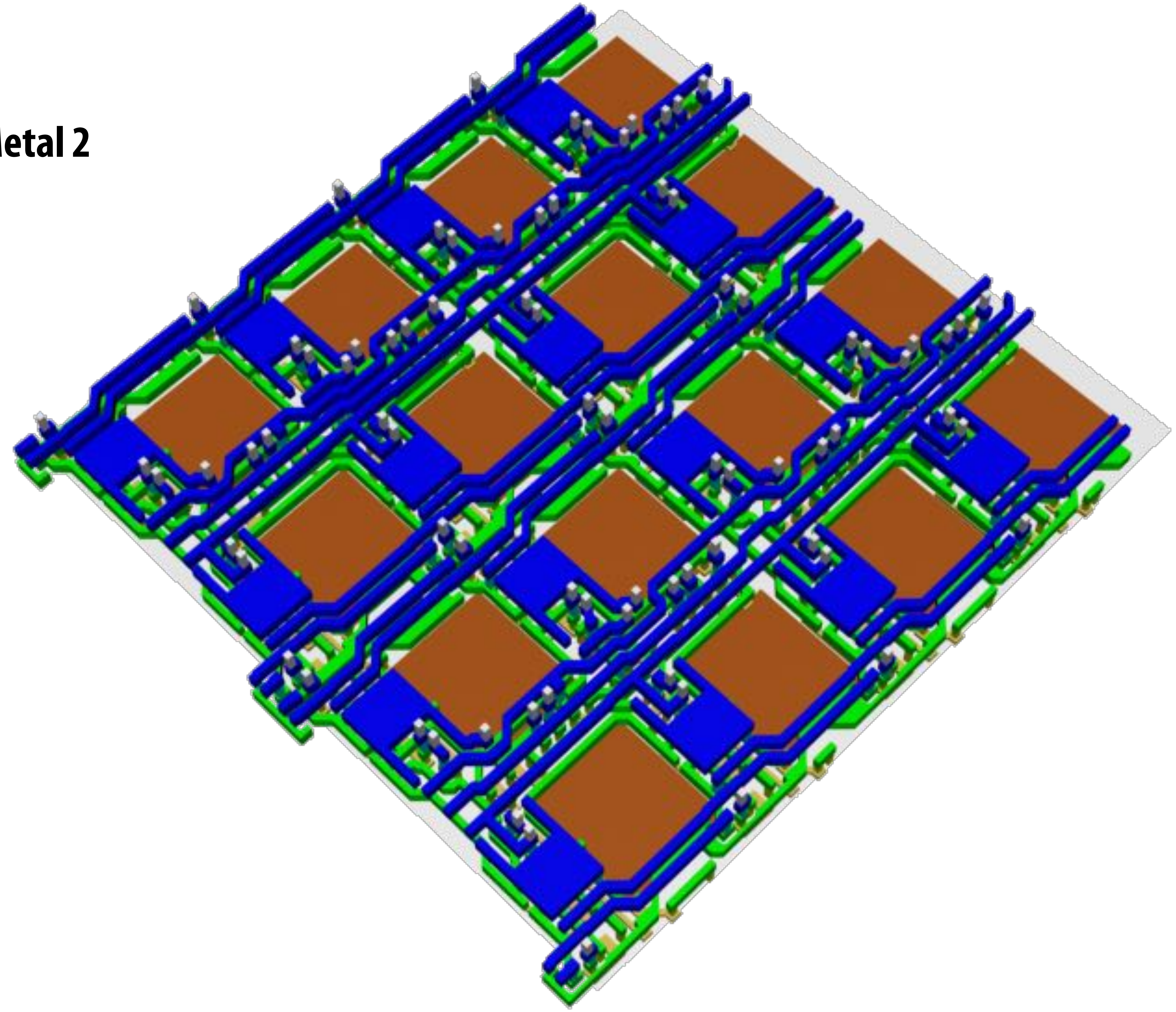


Courtesy R. Motta, Pixim

Metal 1

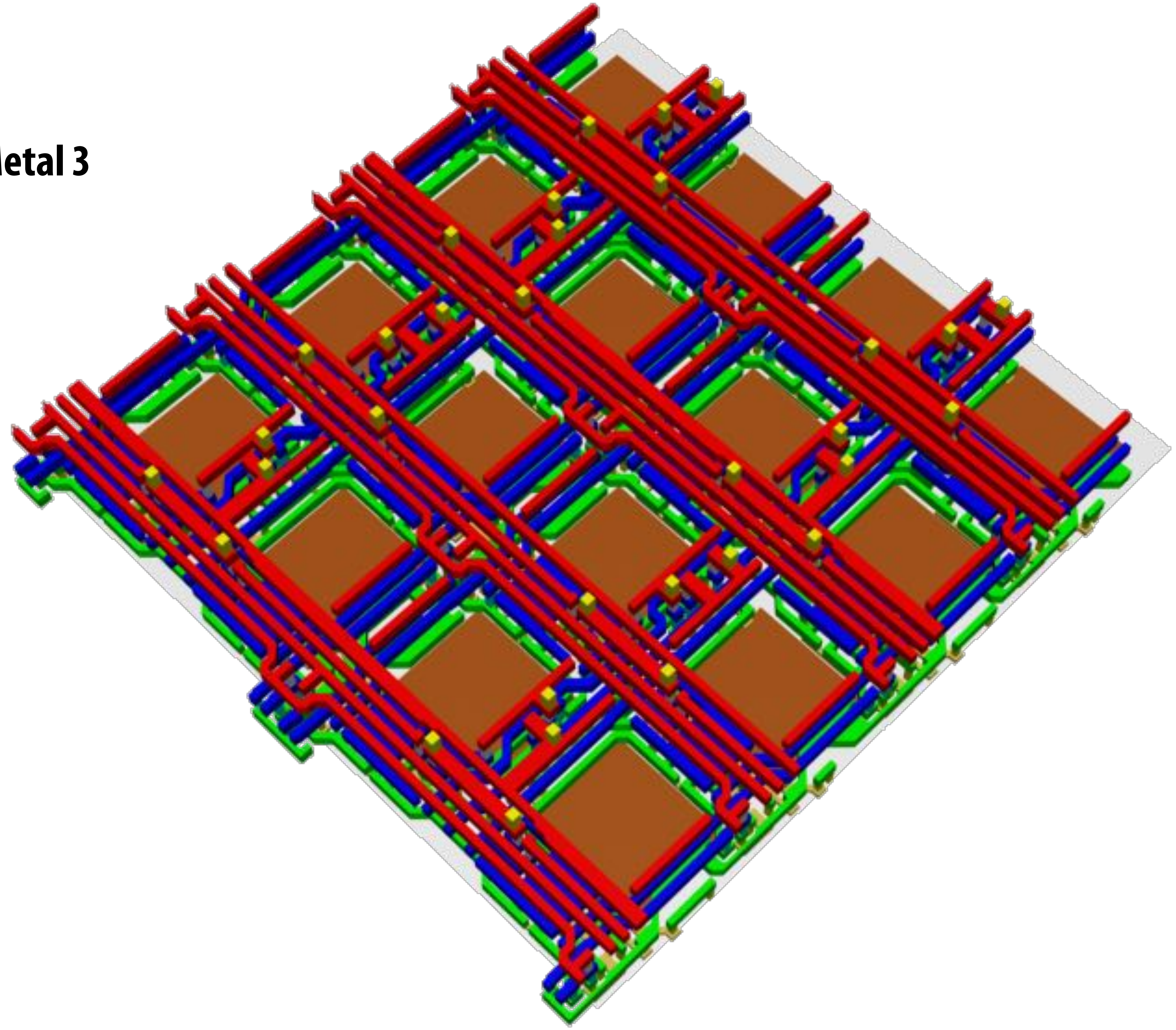


Courtesy R. Motta, Pixim

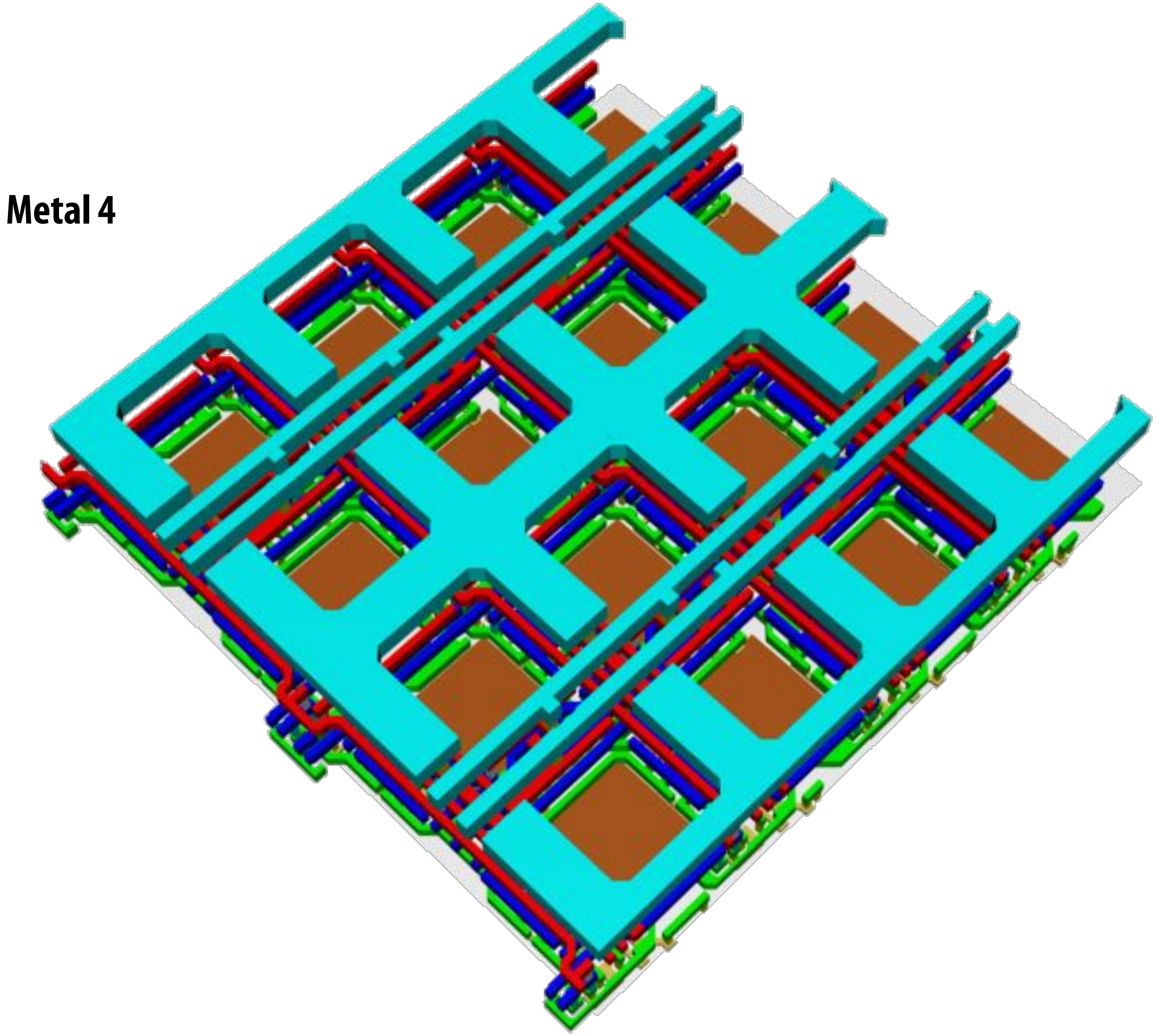


Courtesy R. Motta, Pixim

Metal 3

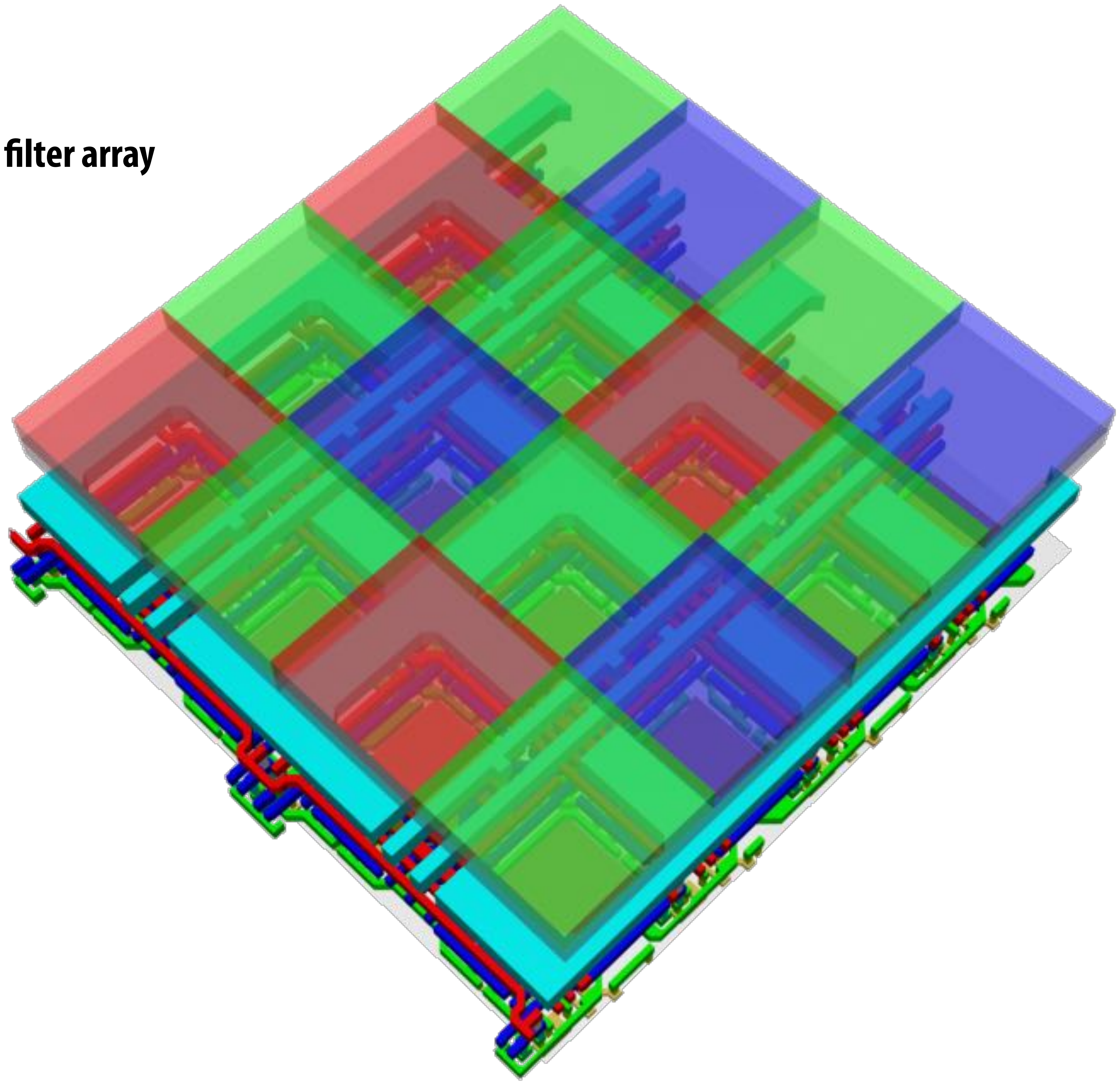


Courtesy R. Motta, Pixim



Courtesy R. Motta, Pixim

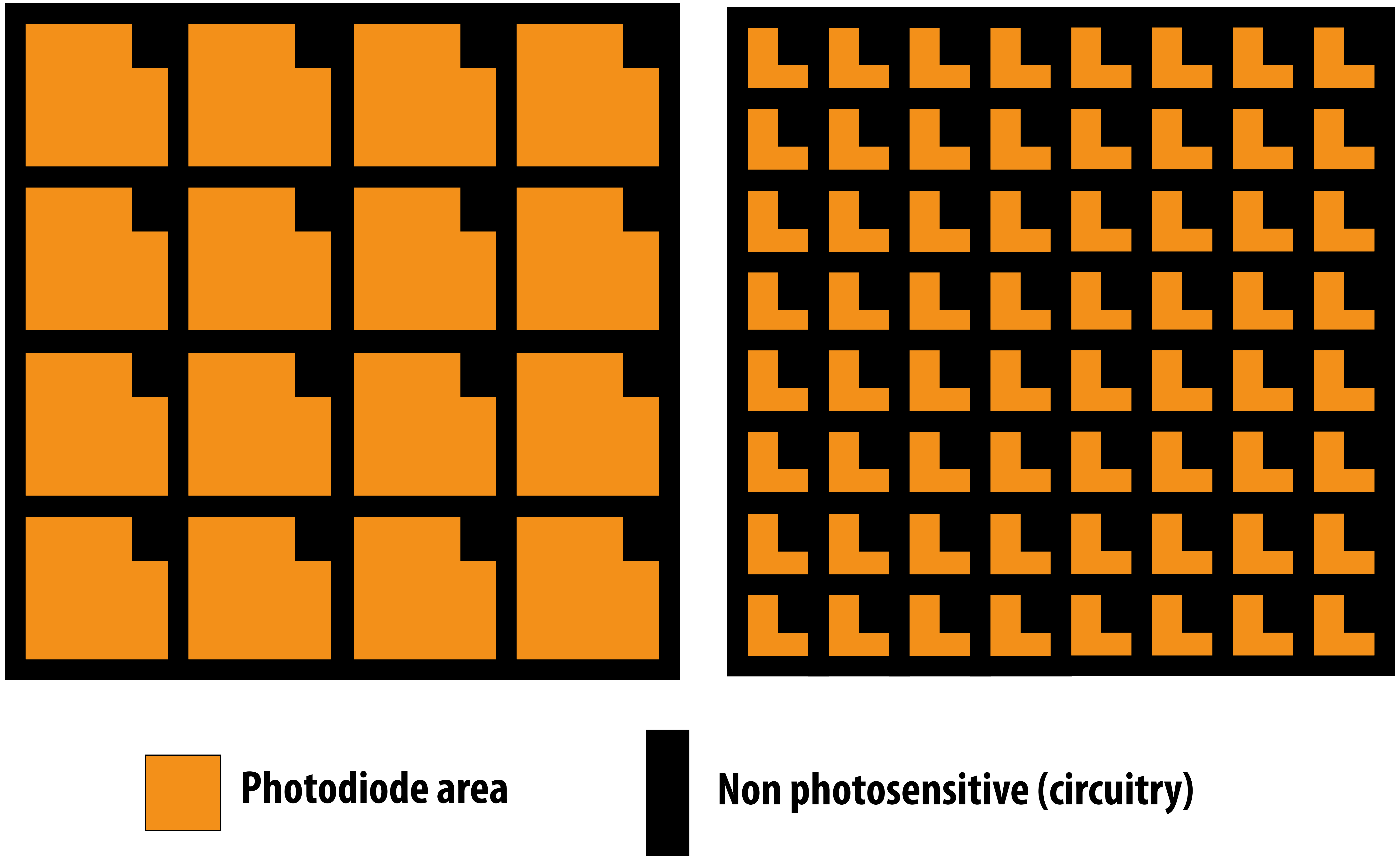
Color filter array



Courtesy R. Motta, Pixim

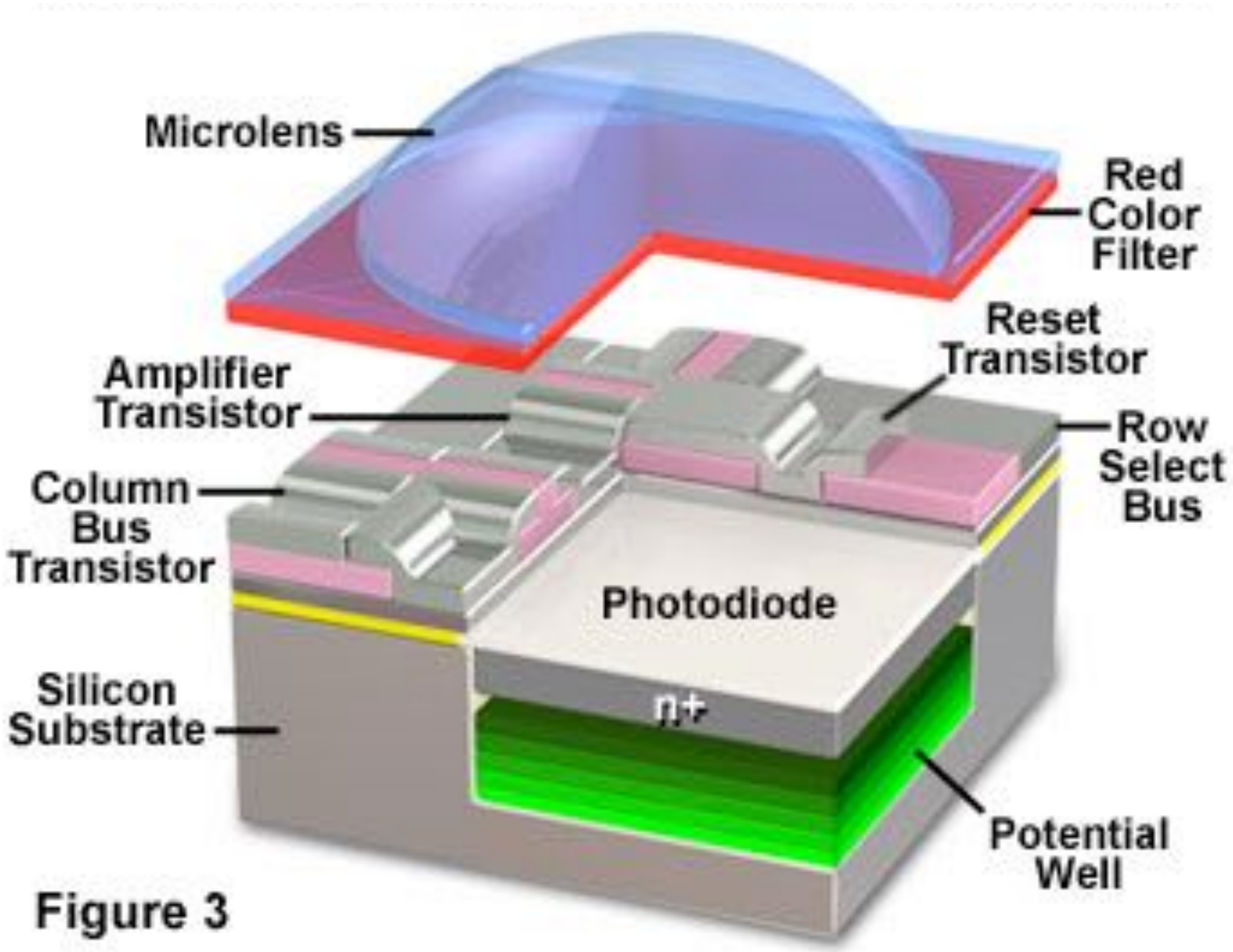
Pixel fill factor

Fraction of pixel area that integrates incoming light



Slide credit: Ren Ng

CMOS sensor pixel

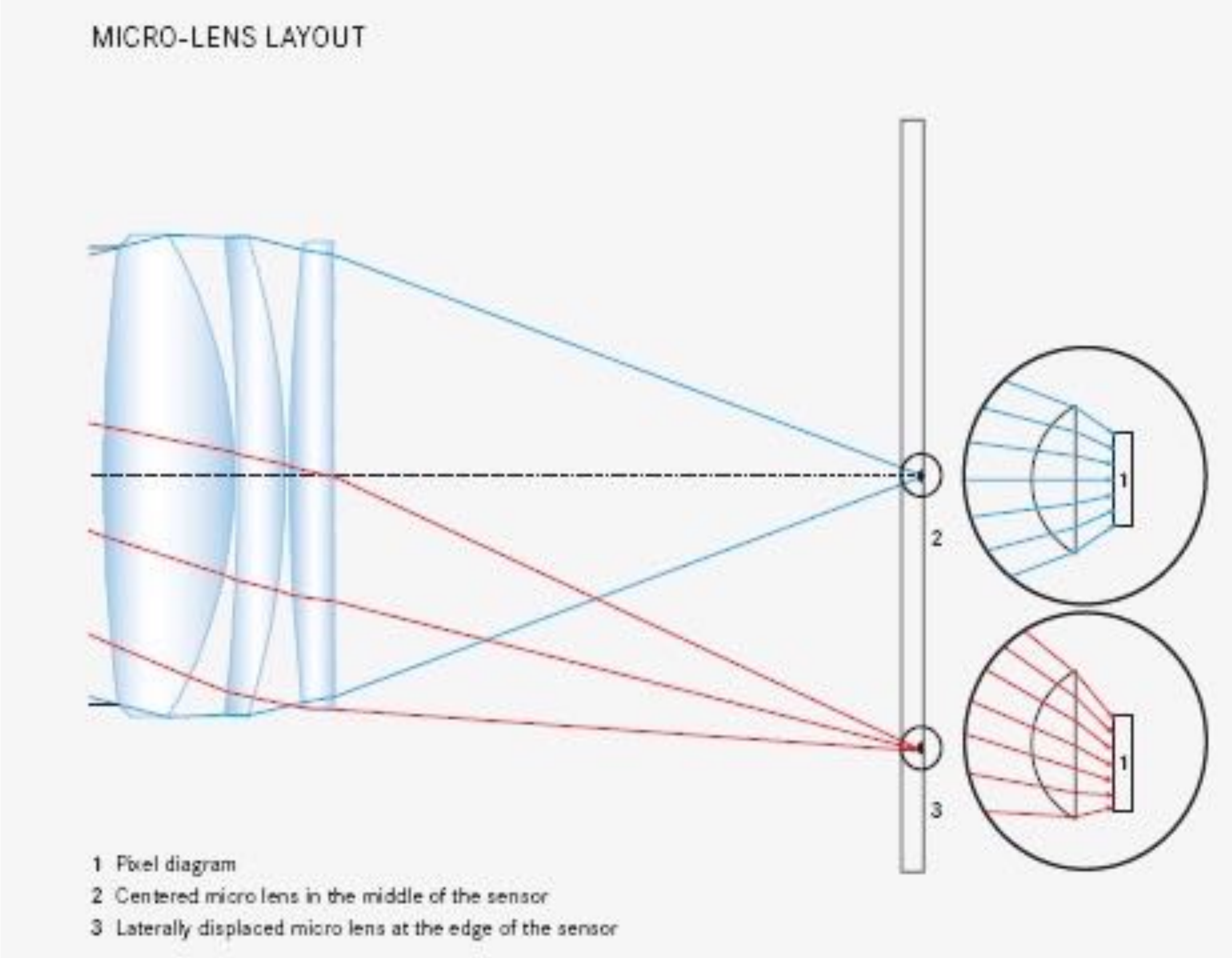


Color filter attenuates light

Microlens (a.k.a. lenslet) steers light toward photo-sensitive region (increases light-gathering capability)

Advanced question: Microlens also serves to reduce aliasing signal. Why?

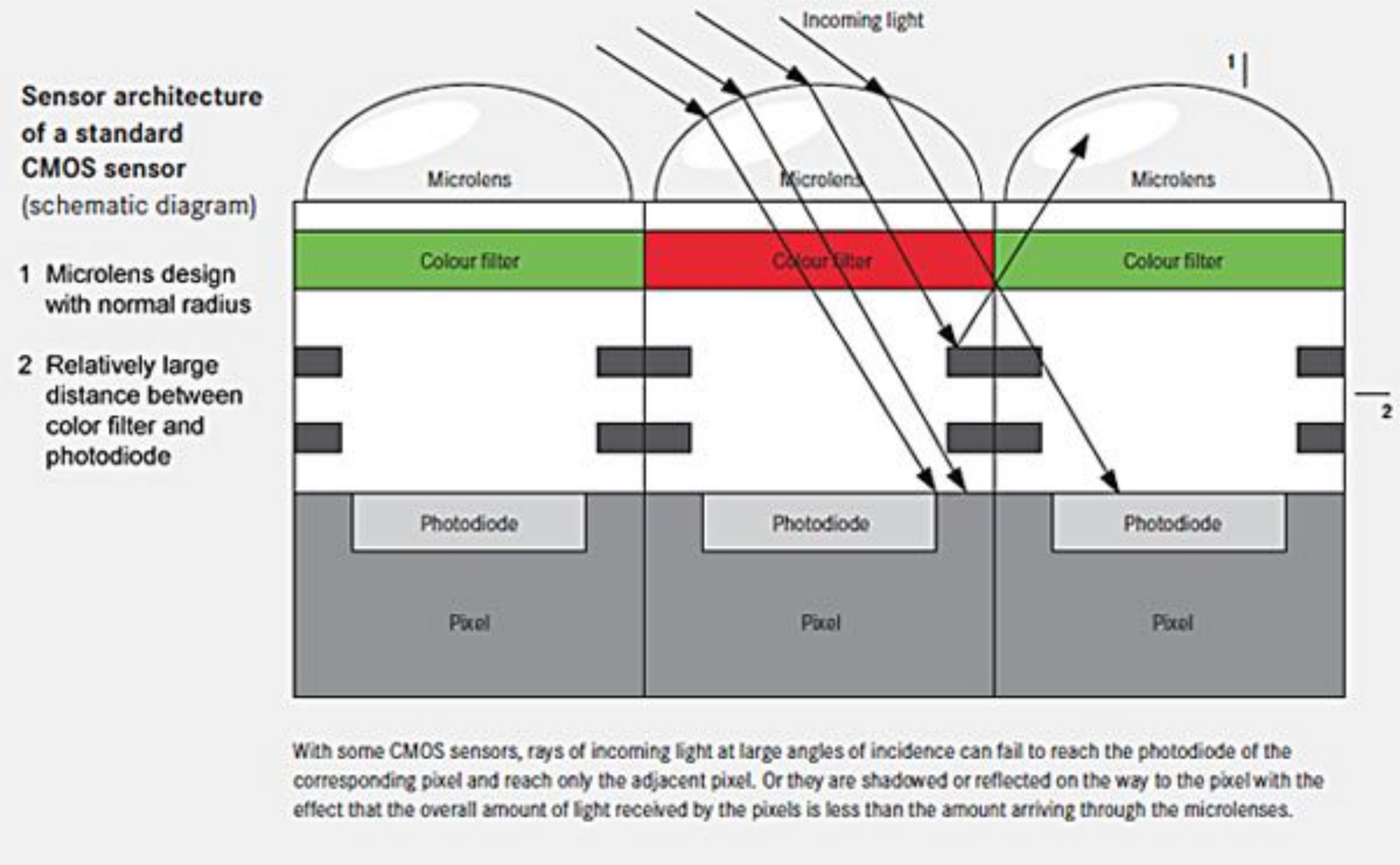
Using micro lenses to improve fill factor



Shifted microlenses on M9 sensor.

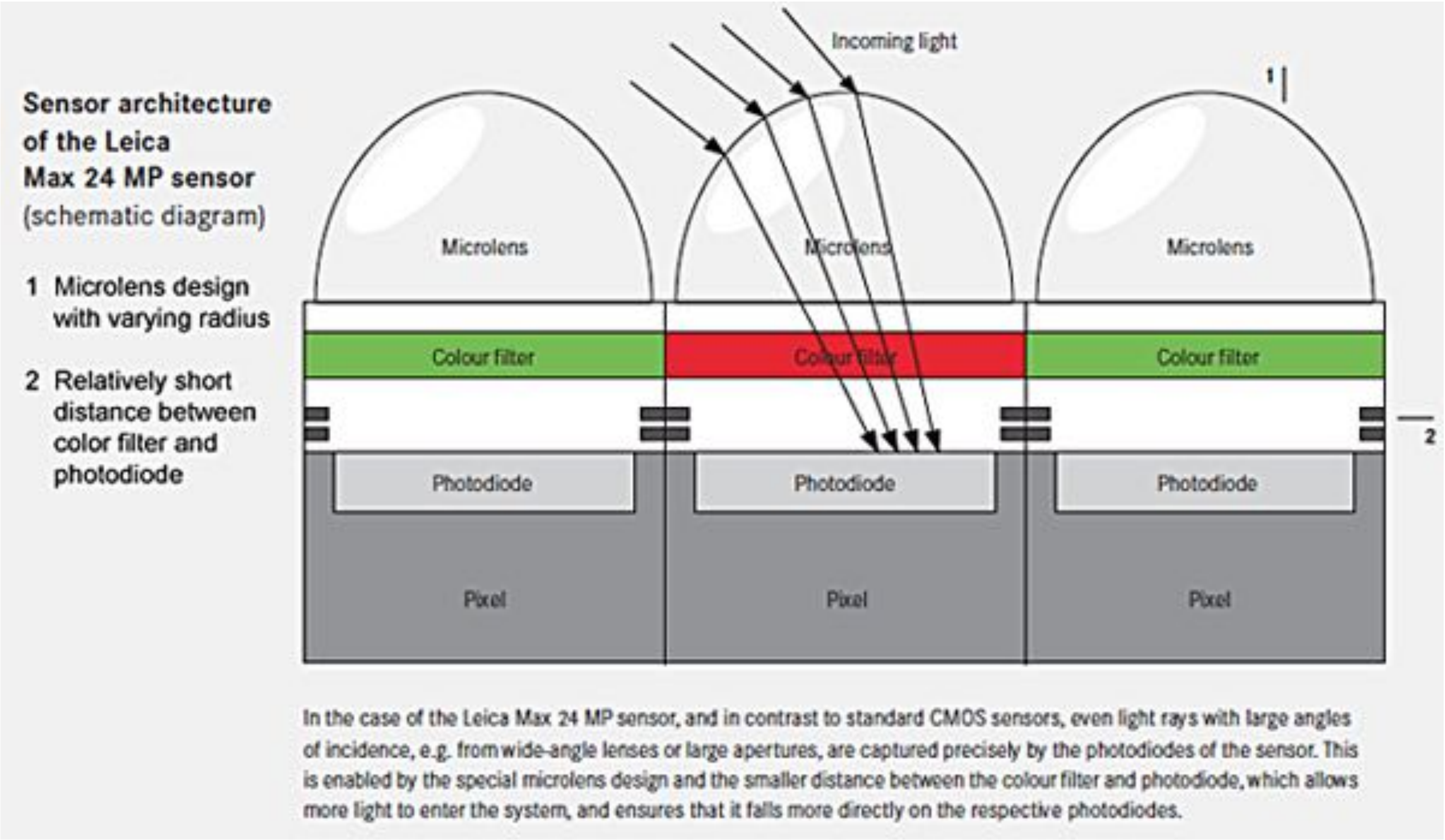
Leica M9

Optical cross-talk



Slide credit: Ren Ng
http://gmpphoto.blogspot.com/2012/09/the-new-leica-max-24mp-cmos-sensor.html

Pixel optics for minimizing cross-talk



Slide credit: Ren Ng

http://gmpphoto.blogspot.com/2012/09/the-new-leica-max-24mp-cmos-sensor.html

Backside illumination sensor

- Traditional CMOS: electronics block light
- Idea: move electronics underneath light gathering region
  - Increases fill factor
  - Reduces cross-talk due since photodiode closer to microns
  - Implication 1: better light sensitivity at fixed sensor size
  - Implication 2: equal light sensitivity at smaller sensor size (shrink sensor)

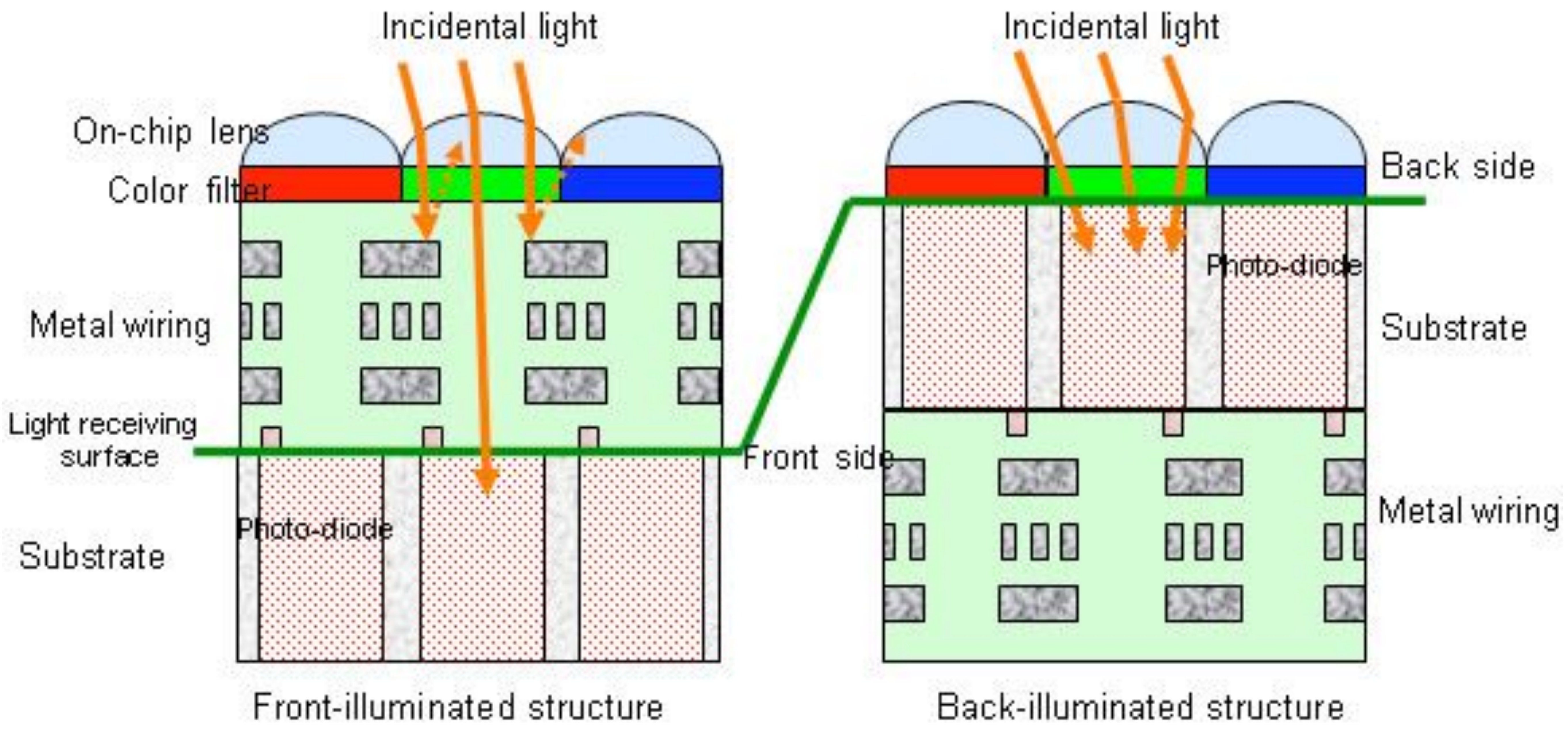
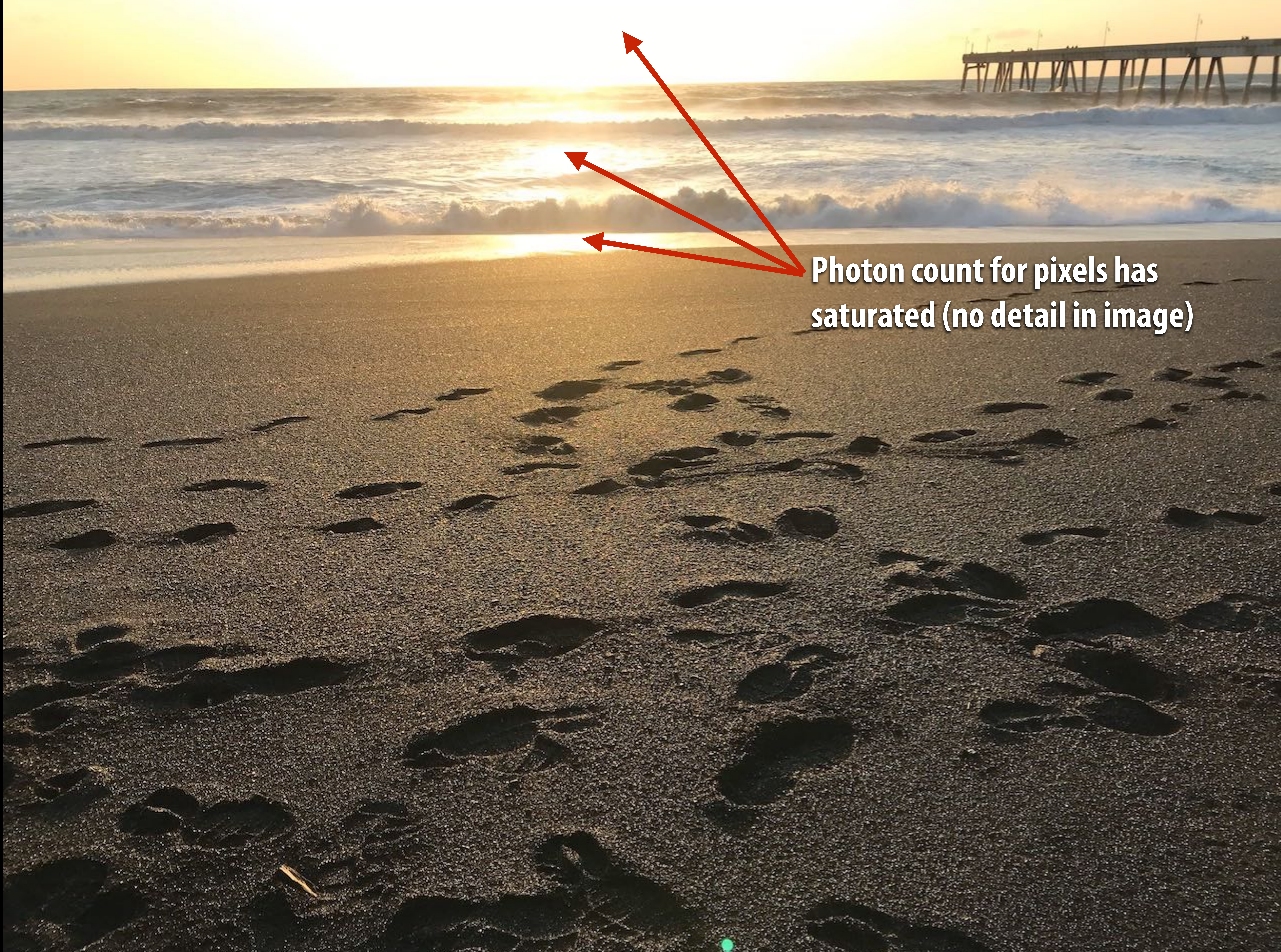


Illustration credit: Sony

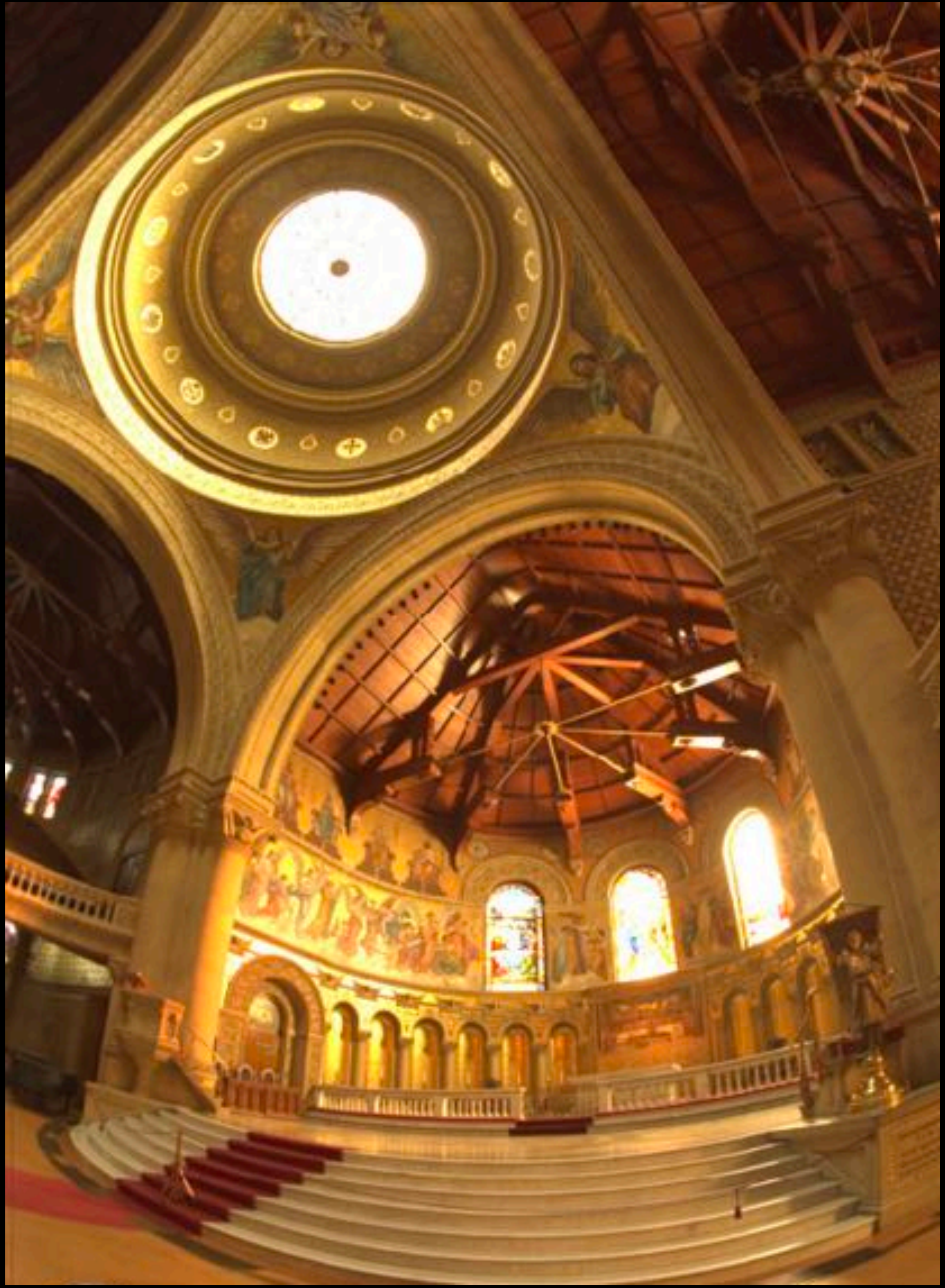
Pixel saturation and noise

Saturated pixels



Saturated pixels

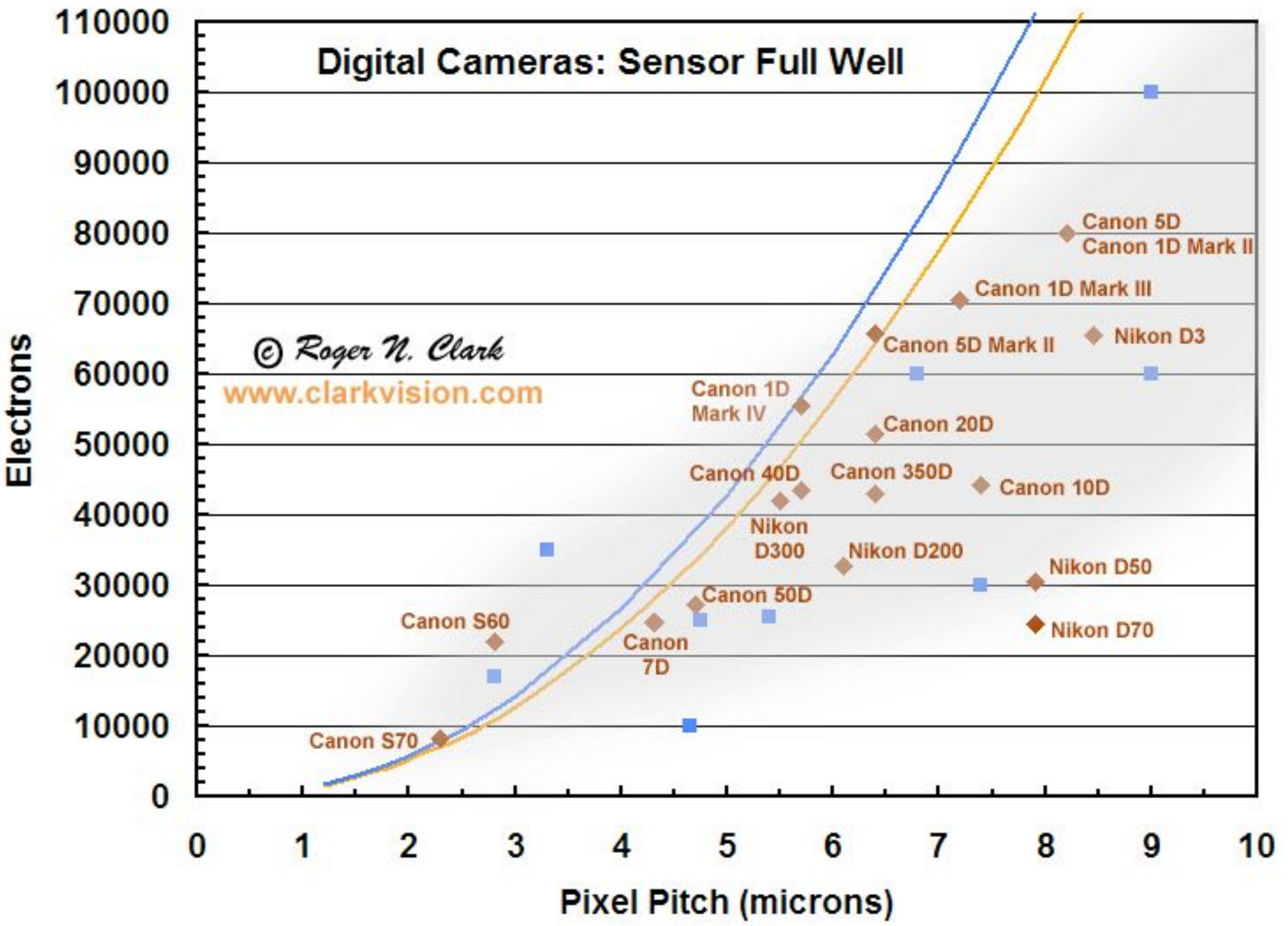
Saturated pixels



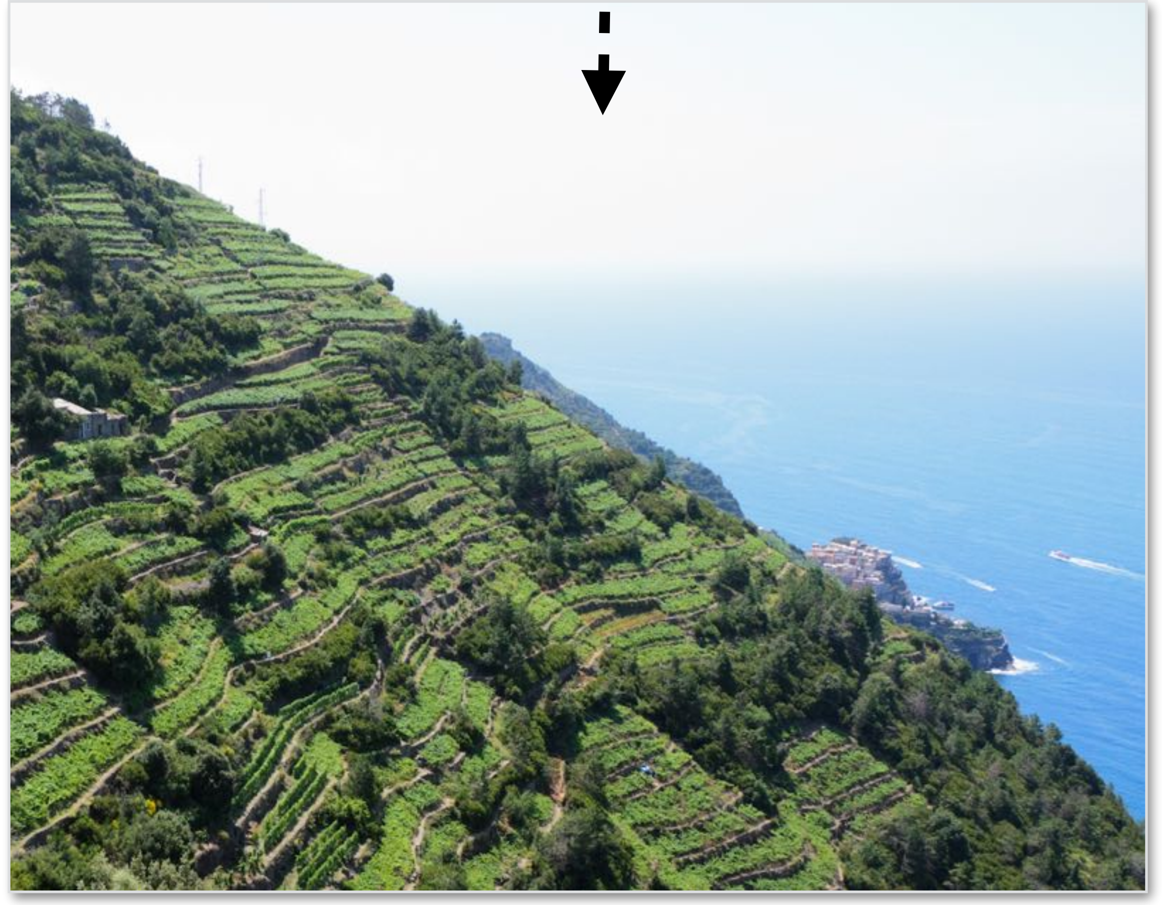
Credit: P. Debevec

Full-well capacity

Pixel saturates when photon capacity is exceeded



Saturated pixels



Graph credit: clarkvision.com

Bigger sensors = bigger pixels (or more pixels?)

- iPhone X (1.2 micron pixels, 12 MP)
- Nikon D7000 (APS-C)
  (4.8 micron pixels, 16 MP)
- Nikon D4 (full frame sensor)
  (7.3 micron pixels, 16 MP)
- Implication: very high pixel count sensors can be built with current CMOS technology
  - Full frame sensor with iPhone X pixel size ~ 600 MP sensor

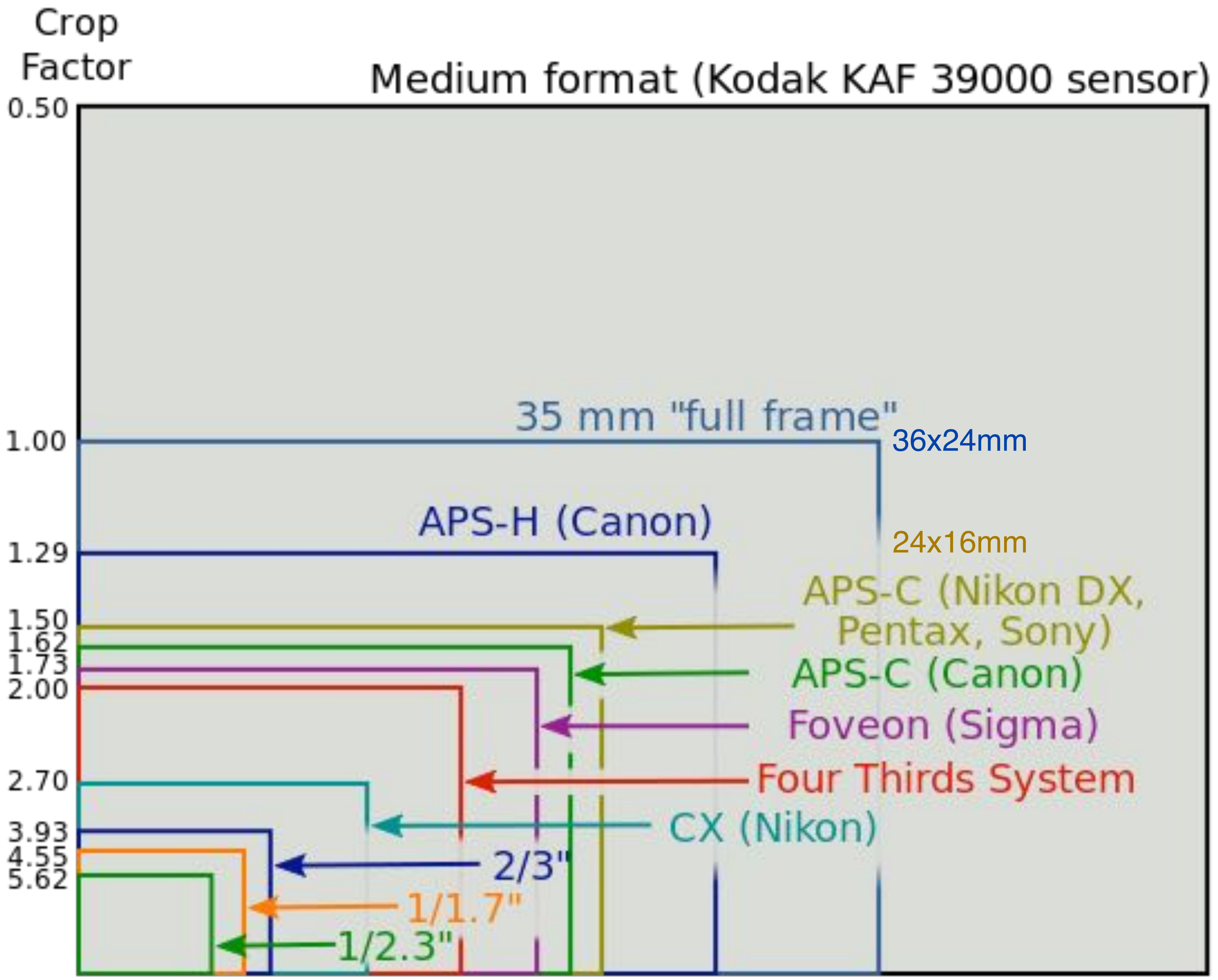
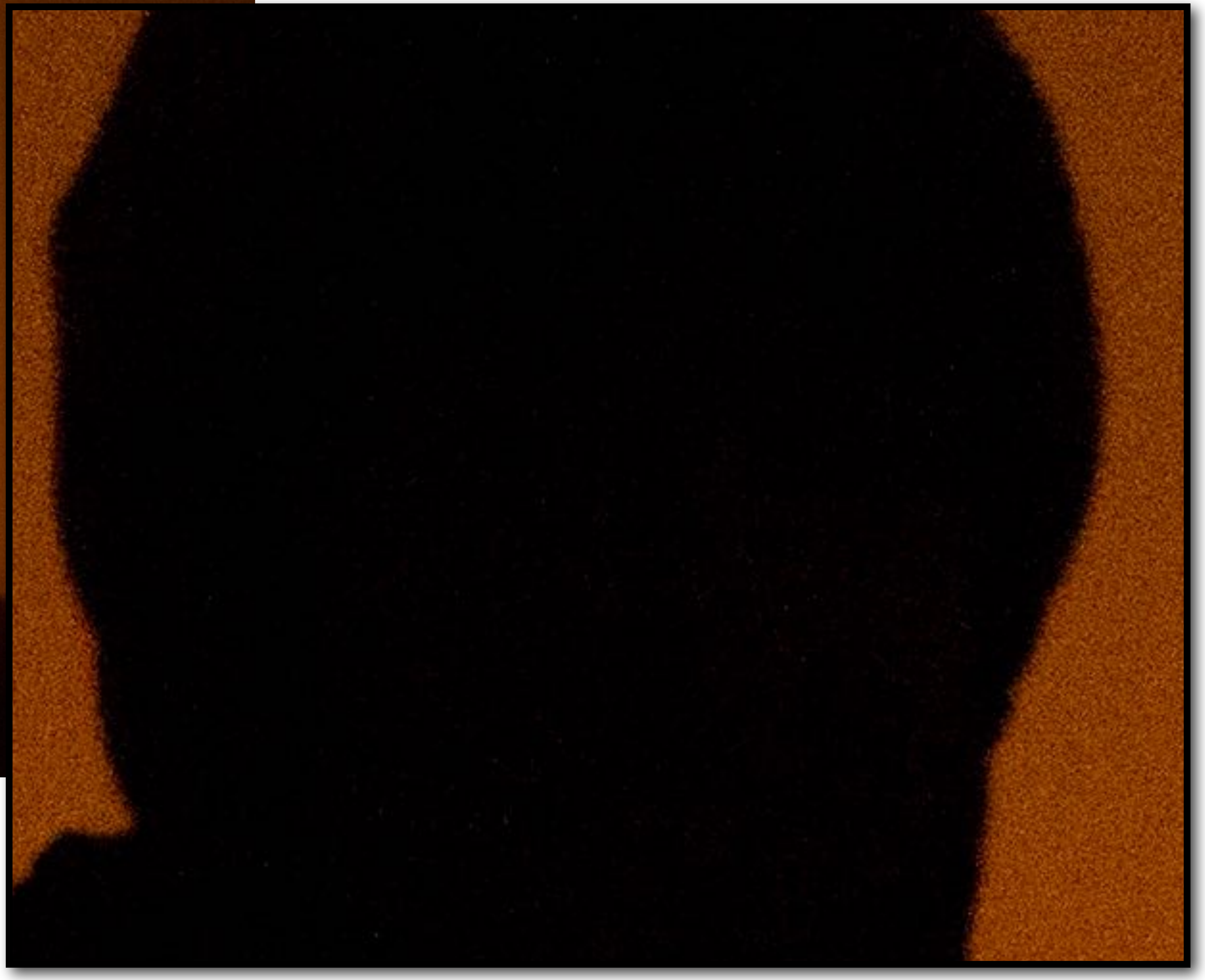


Image credit: Wikipedia

Measurement noise



We've all been frustrated by noise in low-light photographs

(or in shadows in day time images)

Measurement noise

Grand Teton National Park

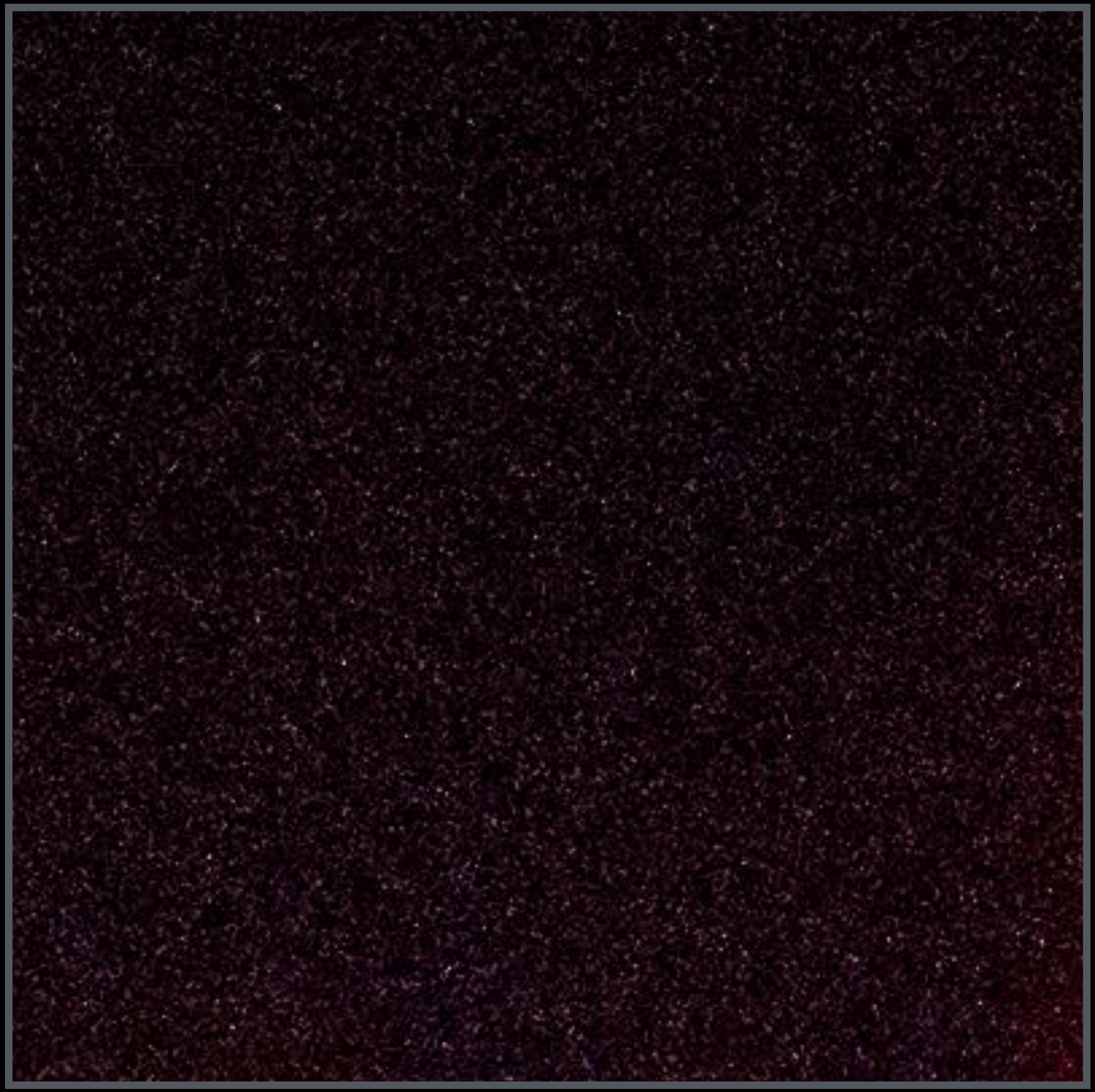
Measurement noise

Sources of measurement noise

- **Photon shot noise:**
  - Photon arrival rate takes on Poisson distribution
  - Standard deviation = sqrt(N)   (N = number of photon arrivals)
  - Signal-to-noise ratio (SNR) = N/sqrt(N)
  - Implication: brighter the signal, the higher the SNR
- **Dark-shot noise**
  - Due to leakage current in sensor
  - Electrons dislodged due to thermal activity (increases exponentially with sensor temperature)
- **Non-uniformity of pixel sensitivity (due to manufacturing defects)**
- **Read noise**
  - e.g., due to amplification / ADC

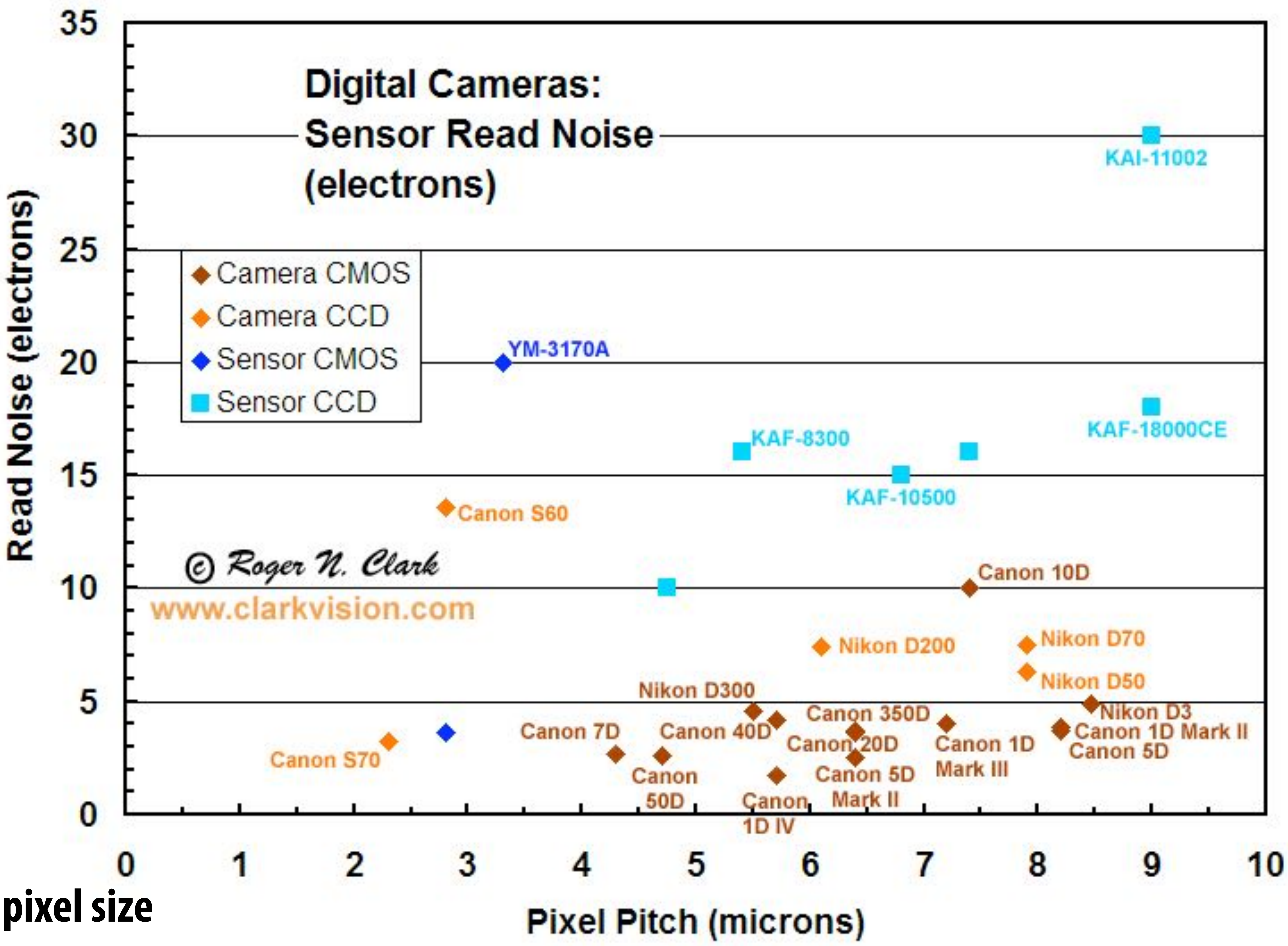
Dark shot noise / read noise

Black image examples: Nikon D7000, High ISO



1 sec exposure

Read noise



Read noise is largely independent of pixel size

Large pixels + bright scene = large N

So, noise determined largely by photon shot noise

Image credit: clarkvision.com

Maximize light gathering capability

- **Goal: increase signal-to-noise ratio**
  - Dynamic range of a pixel (ratio of brightest light measurable to dimmest light measurable) is determined by the noise floor (minimum signal) and the pixel's full-well capacity (maximum signal)

- **Use big pixels**
  - Nikon D4: 7.3 um
  - iPhone X: 1.2 um

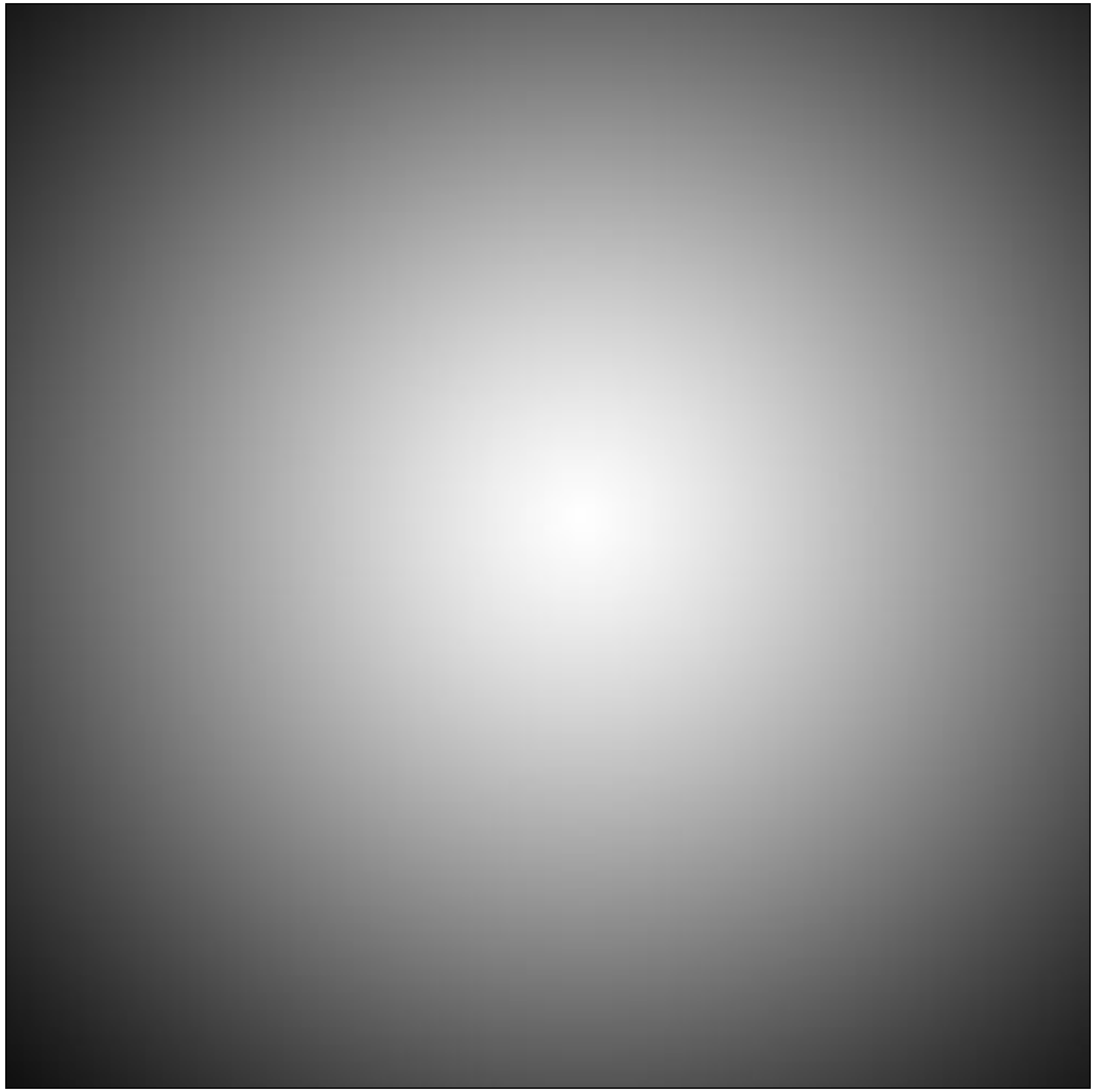
- **Manufacture sensitive pixels**
  - Good materials
  - High fill factor

Artifacts arising from lenses

Vignetting

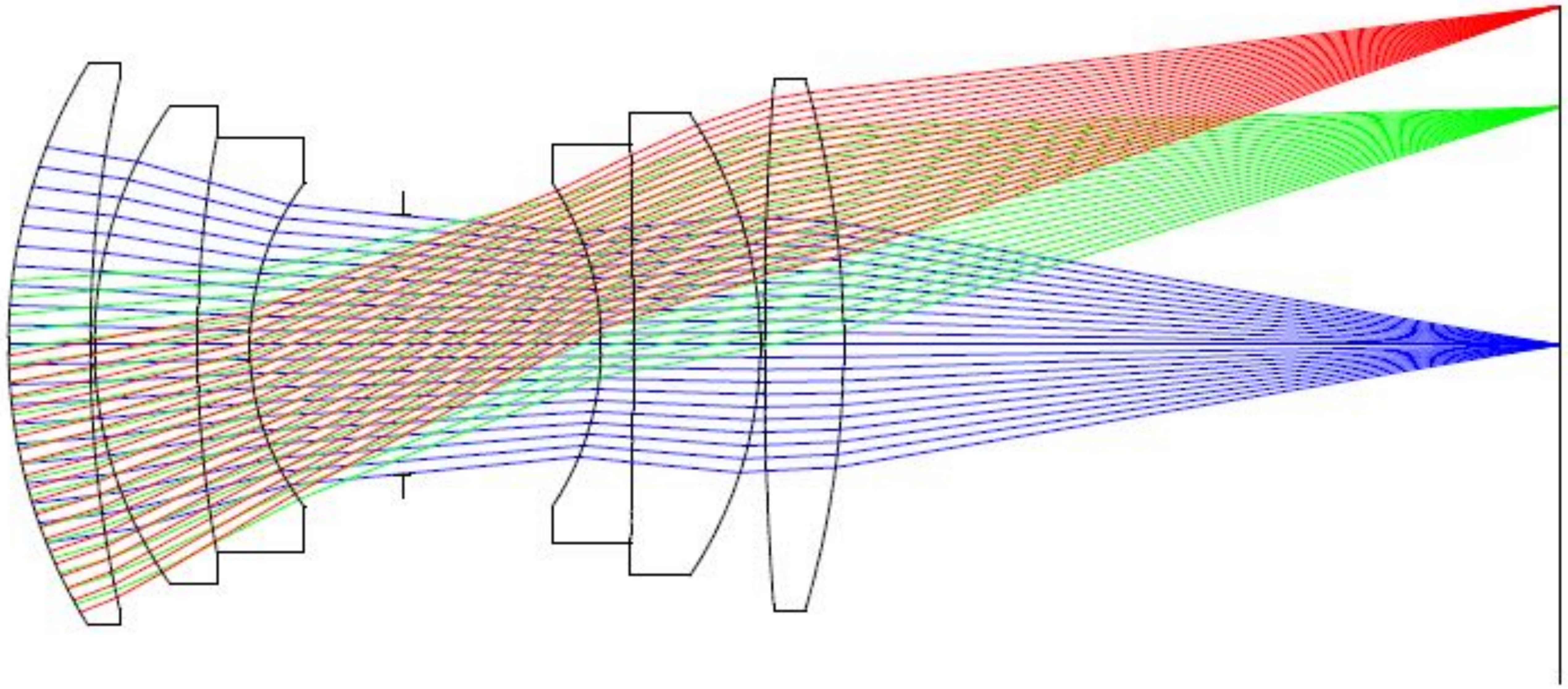
This is a photograph of a white wall

(Note: I contrast-enhanced the image to show effect more prominently)



Types of vignetting

Optical vignetting: less light reaches edges of sensor due to physical obstruction in lens



Pixel vignetting: light reaching pixel at an oblique angle is less likely to hit photosensitive region than light incident from straight above (e.g., obscured by electronics)

- Microlens reduces pixel vignetting

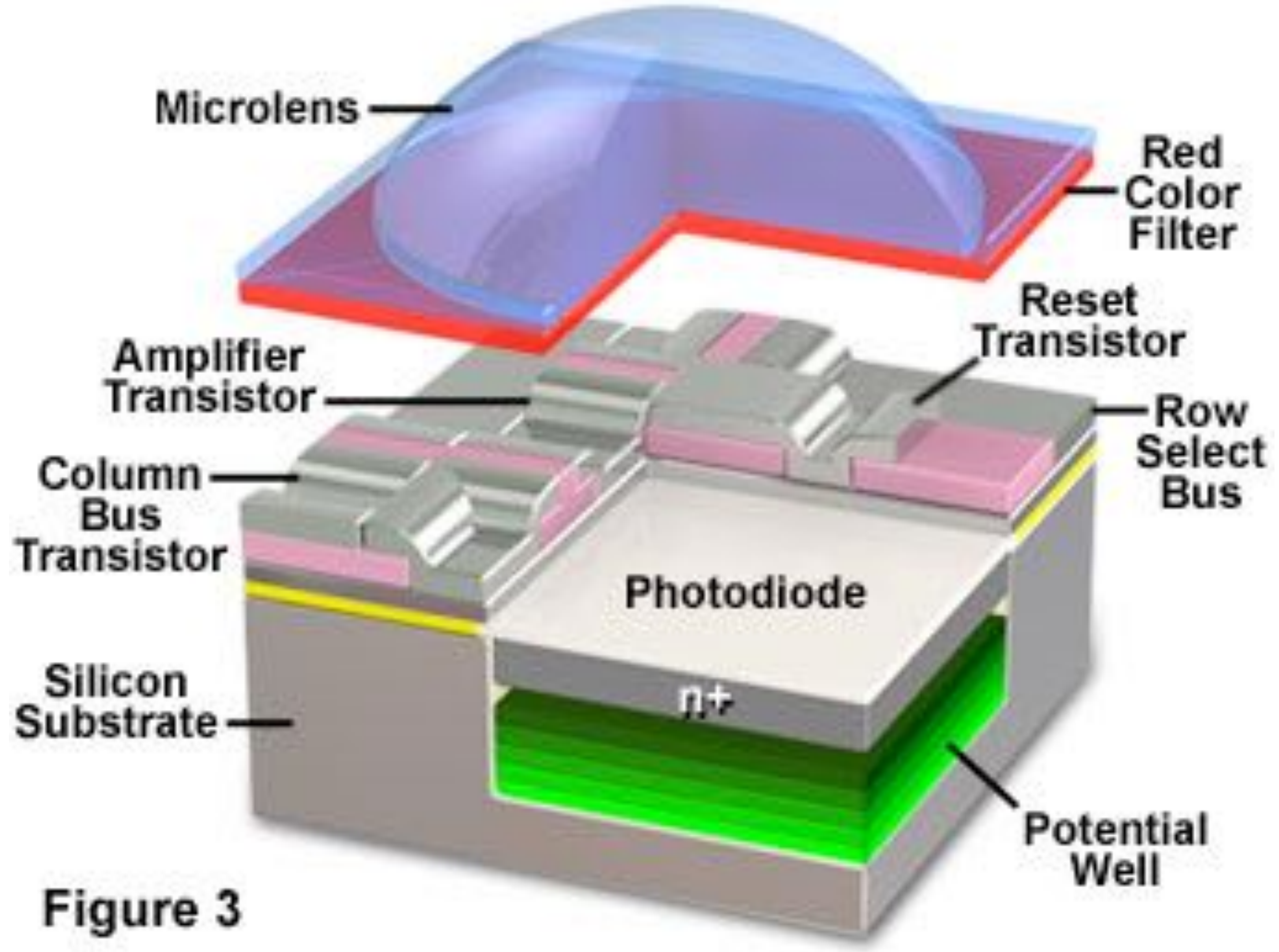
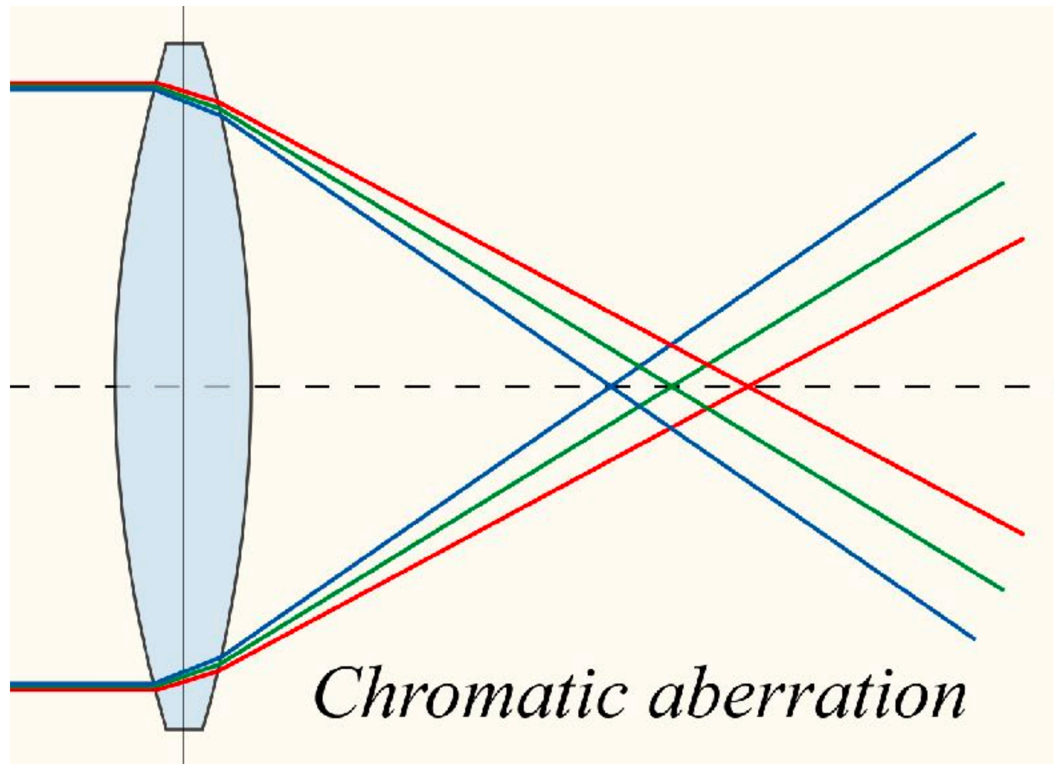


Figure 3

Image credit: Mark Butterworth

Chromatic aberration

Different wavelengths of light are refracted by different amounts



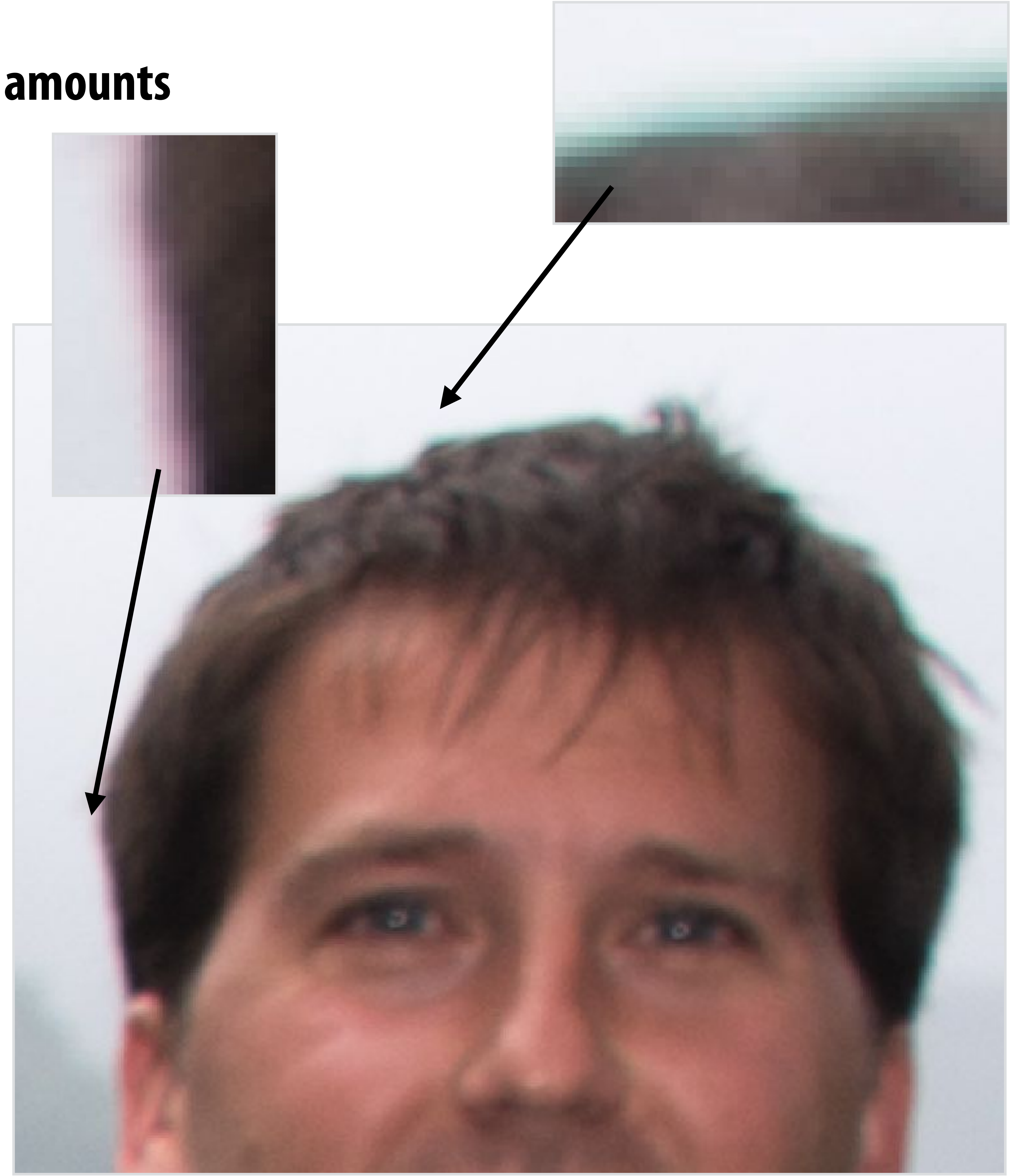
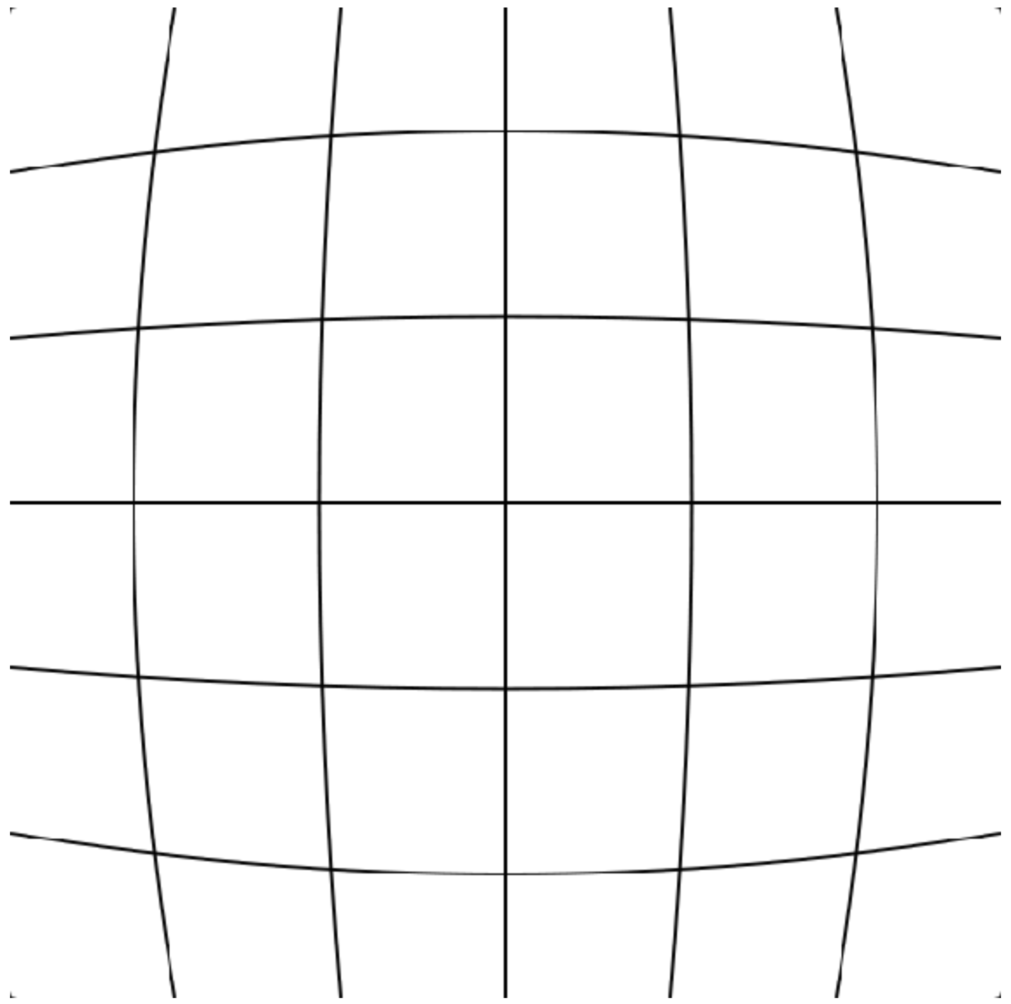


Image credit: Wikipedia

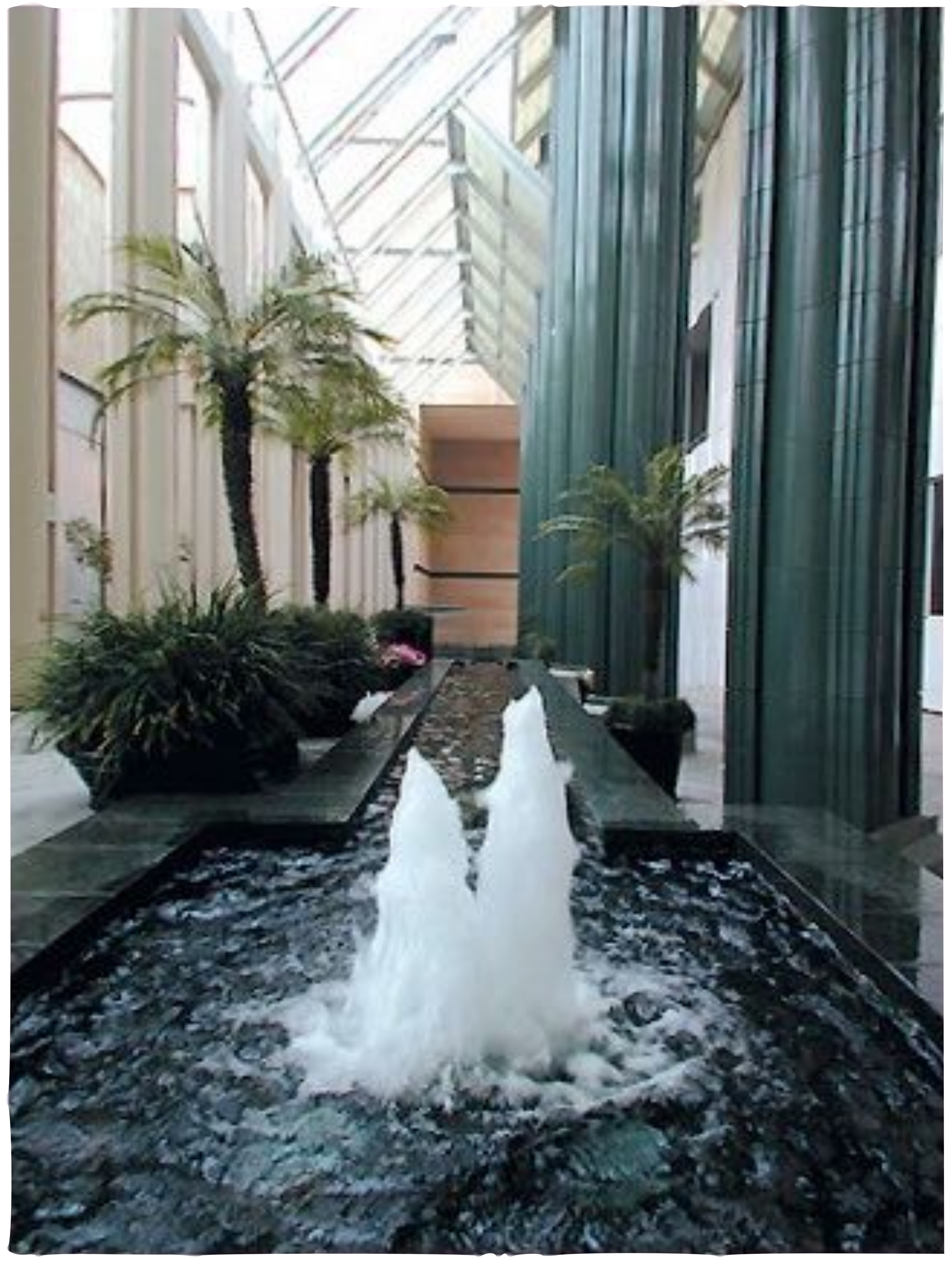
More challenges

- **Chromatic shifts over sensor**
  - Pixel light sensitivity changes over sensor due to interaction with microlens
    (Index of refraction depends on wavelength, so some wavelengths are more likely to suffer from cross-talk or reflection. Ug!)
- **Lens distortion**



Pincushion distortion

Captured Image



Corrected Image

Image credit: PCWorld

The message so far

- **Physical constraints of image formation by a camera create artifacts in the recorded image**

- **We are going to rely on processing to reduce / correct for these artifacts**

A simple RAW image processing pipeline

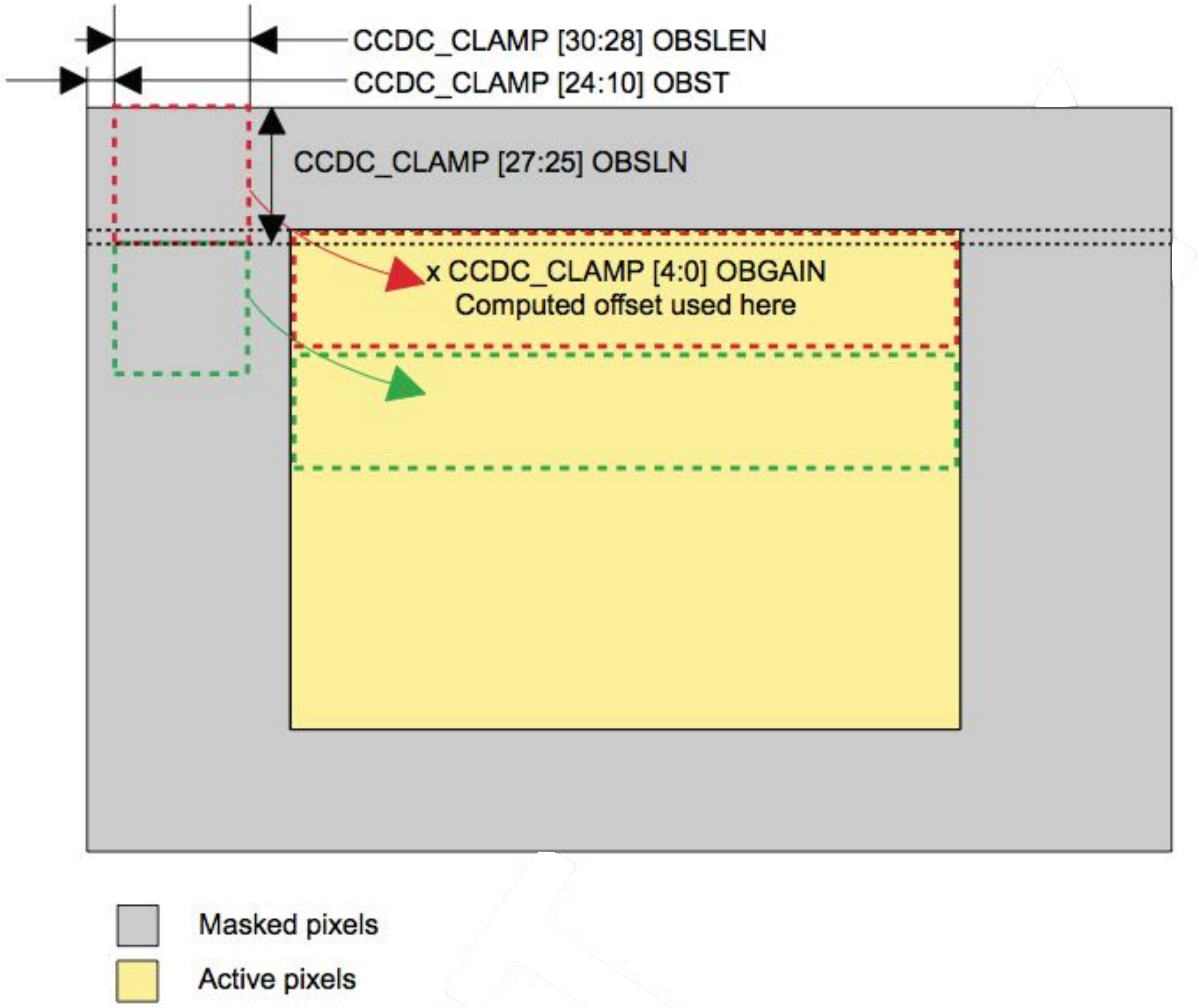
Given the physical reality of how a lens+sensor system works, now let's look at how software transforms raw sensor output into a high-quality RGB image.

Adopting terminology from Texas Instruments OMAP Image Signal Processor pipeline
(since public documentation exists)

Assume: receiving 12 bits/pixel Bayer mosaiced data from sensor

Optical clamp: remove sensor offset bias

```
output_pixel = input_pixel - [average of pixels from optically black region]
```



Remove bias due to sensor black level

(from nearby sensor pixels at time of shot)

Correct for defective pixels

- **Store LUT with known defective pixels**
  - e.g., determined on manufacturing line, during sensor calibration and test
- **Example correction methods**
  - Replace defective pixel with neighbor
  - Replace defective pixel with average of neighbors
  - Correct defect by subtracting known bias for the defect

```
output_pixel = (isdefectpixel(current_pixel_xy)) ?
                   average(previous_input_pixel, next_input_pixel) :
                   input_pixel;
```

“Hot pixel” suppression

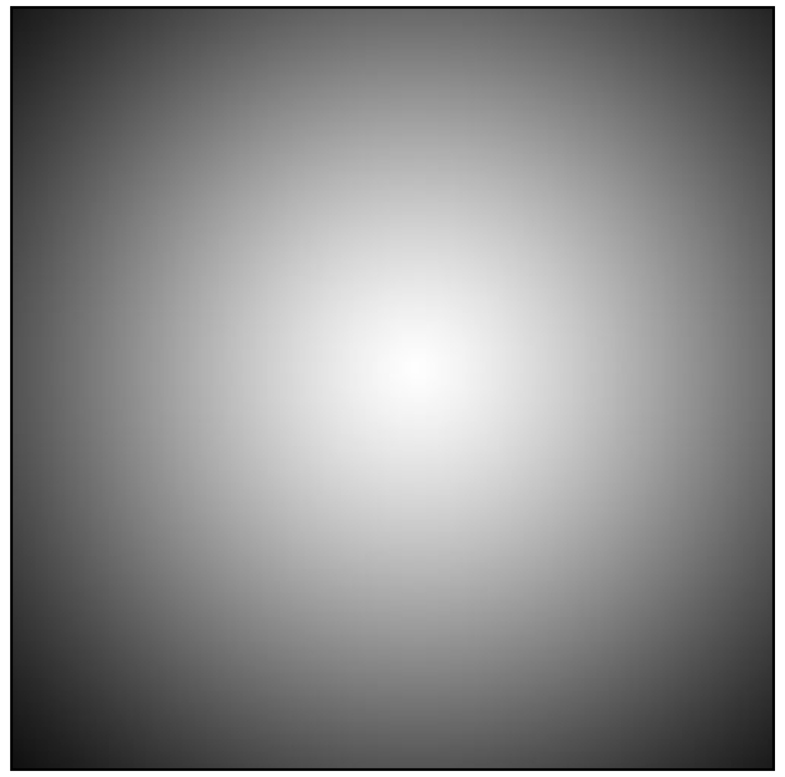
```
float input[(WIDTH+2) * (HEIGHT+2)];
float output[WIDTH * HEIGHT];

for (int j=0; j<HEIGHT; j++) {
   for (int i=0; i<WIDTH; i++) {
      float min_value = min( min(input[(j-1)*WIDTH + i], input[(j+1)*WIDTH + i]),
                             min(input[j*WIDTH + i-1], input[j*WIDTH + i+1]) );
      float max_value = max( max(input[(j-1)*WIDTH + i], input[(j+1)*WIDTH + i]),
                             max(input[j*WIDTH + i-1], input[j*WIDTH + i+1]) );
      output[j*WIDTH + i] = clamp(min_value, max_value, input[j*WIDTH + i]);
    }
}
```

This filter clamps pixels to the min/max of its cardinal neighbors
(e.g., hot-pixel suppression — no need for a lookup table)

Lens shading compensation

- **Correct for vignetting artifacts**
  - Good implementations will consider wavelength-dependent vignetting (that creates chromatic shift over the image)

Need to invert the vignetting effect



- **Possible implementations:**
  - Use "flat-field photo" stored in memory
    - e.g., lower resolution buffer, upsampled on-the-fly
  - Or use analytic function to model required correction

```
gain = upsample_compensation_gain_buffer(current_pixel_xy);
output_pixel = gain * input_pixel;
```

Demosiac

- Produce RGB image from mosaiced input image
- Basic algorithm: bilinear interpolation of mosaiced values (need 4 neighbors)
- More advanced algorithms:
  - Bicubic interpolation (wider filter support region… may overblur)
  - Good implementations attempt to find and preserve edges in photo

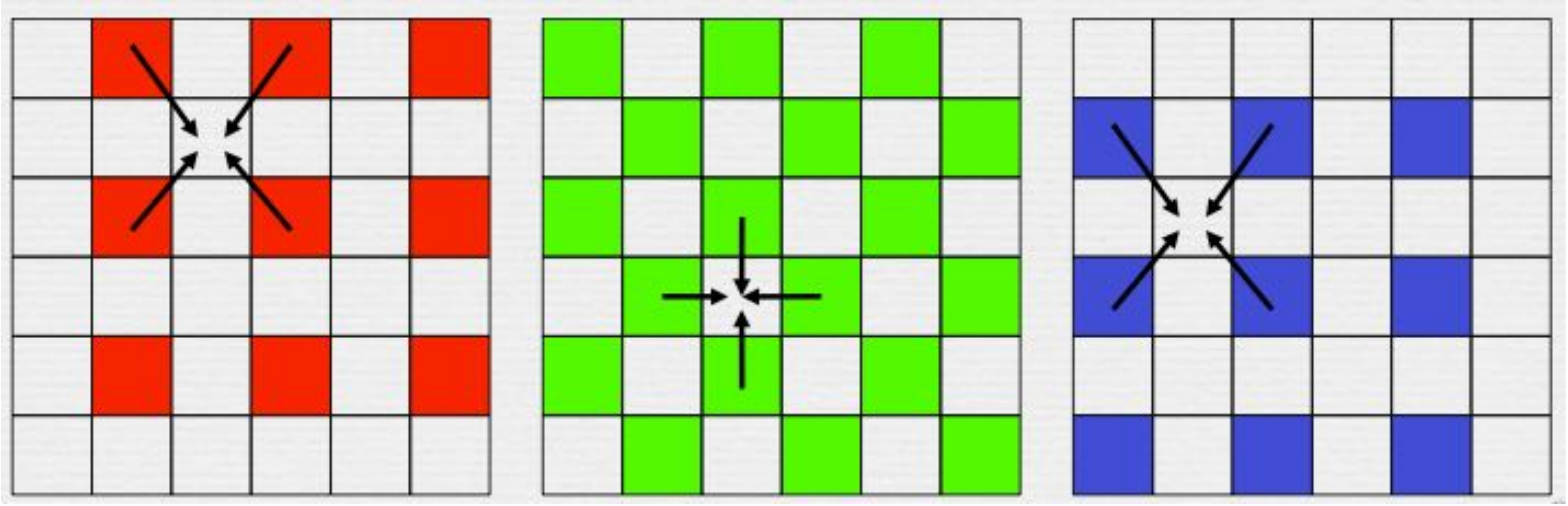
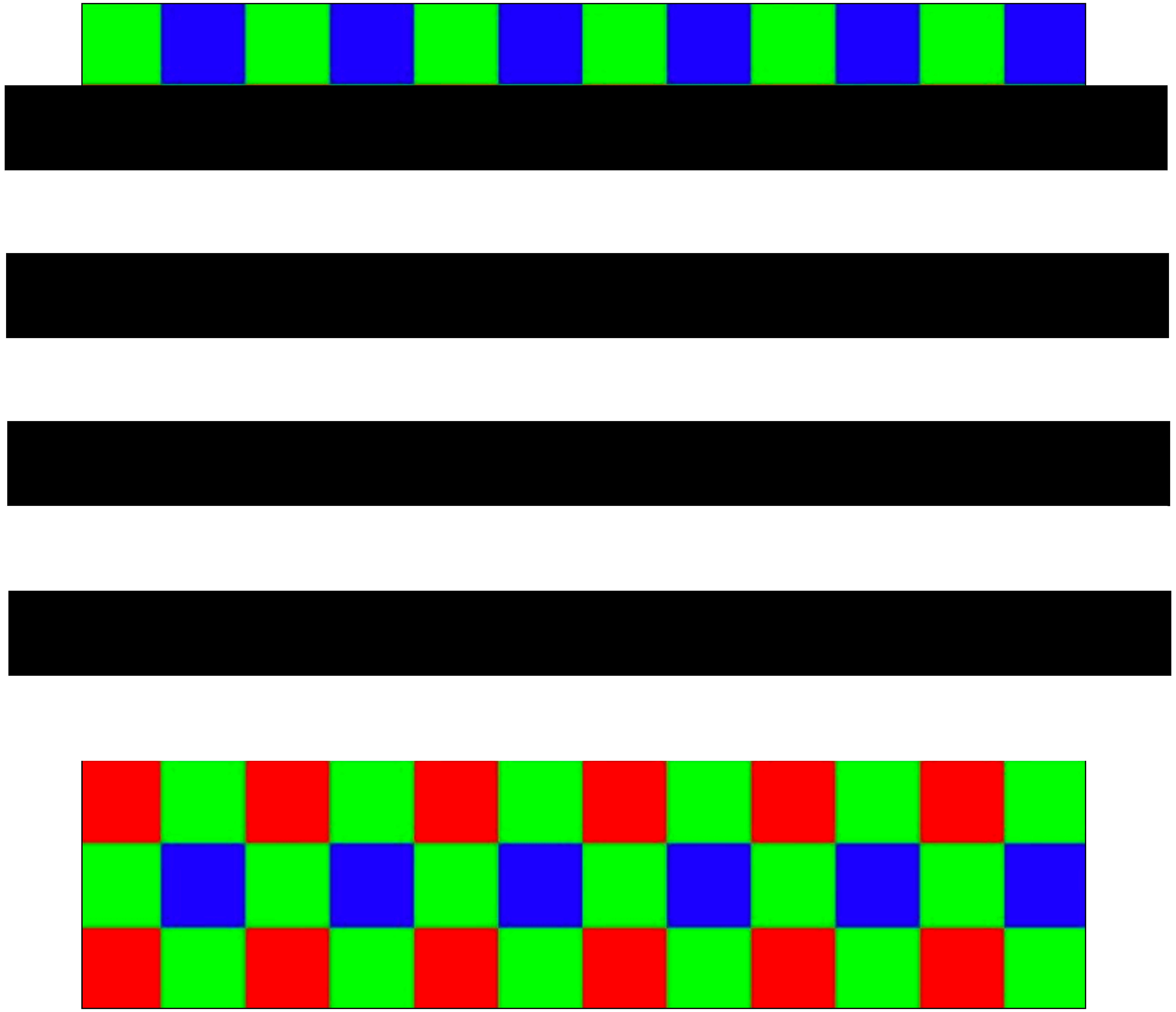


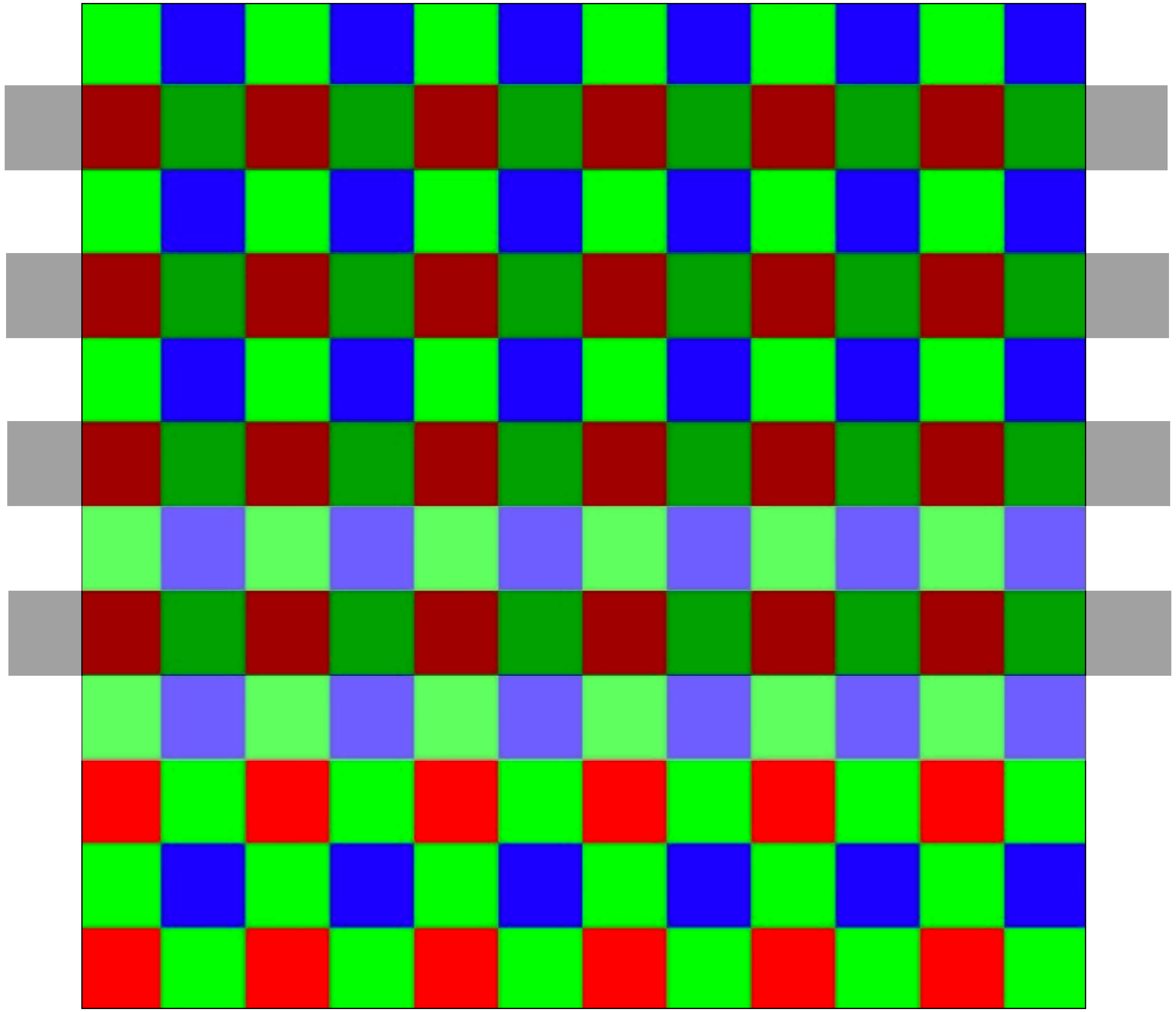
Image credit: Mark Levoy

Demosaicing errors



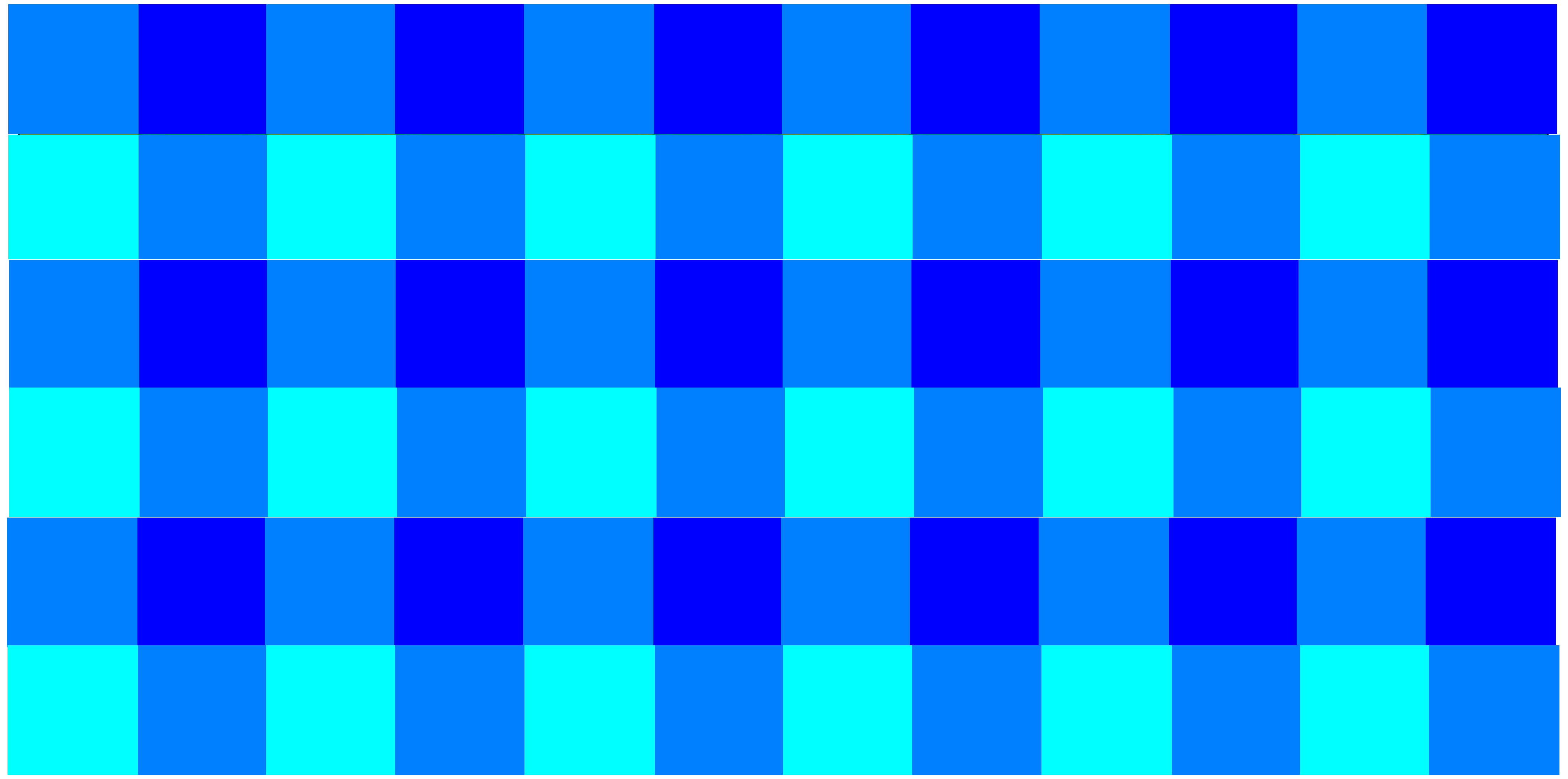
What will demosaiced result look like if this black and white signal was captured by the sensor?

Demosaicing errors



(Visualization of signal and Bayer pattern)

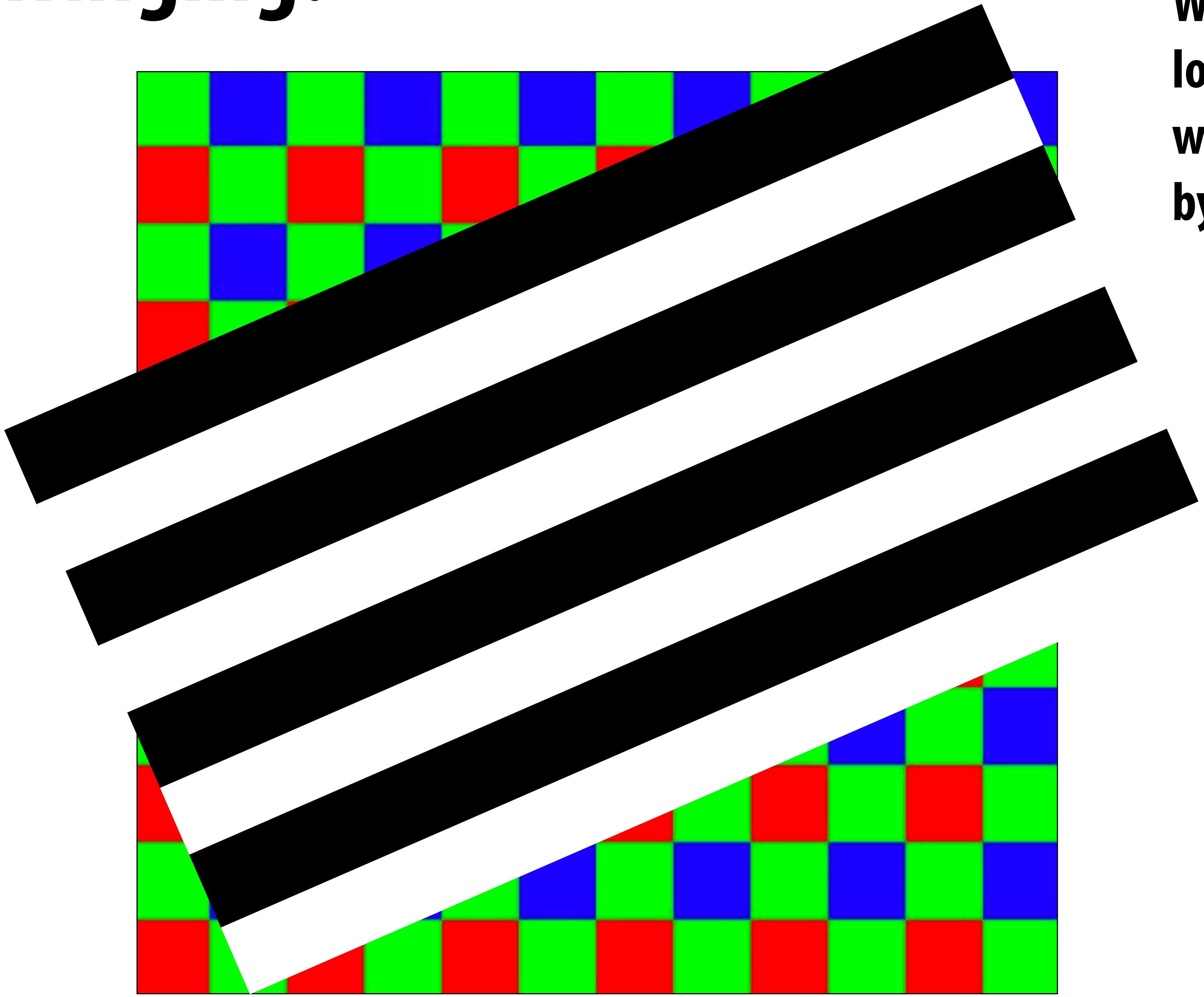
Demosaicing errors



No red measured.

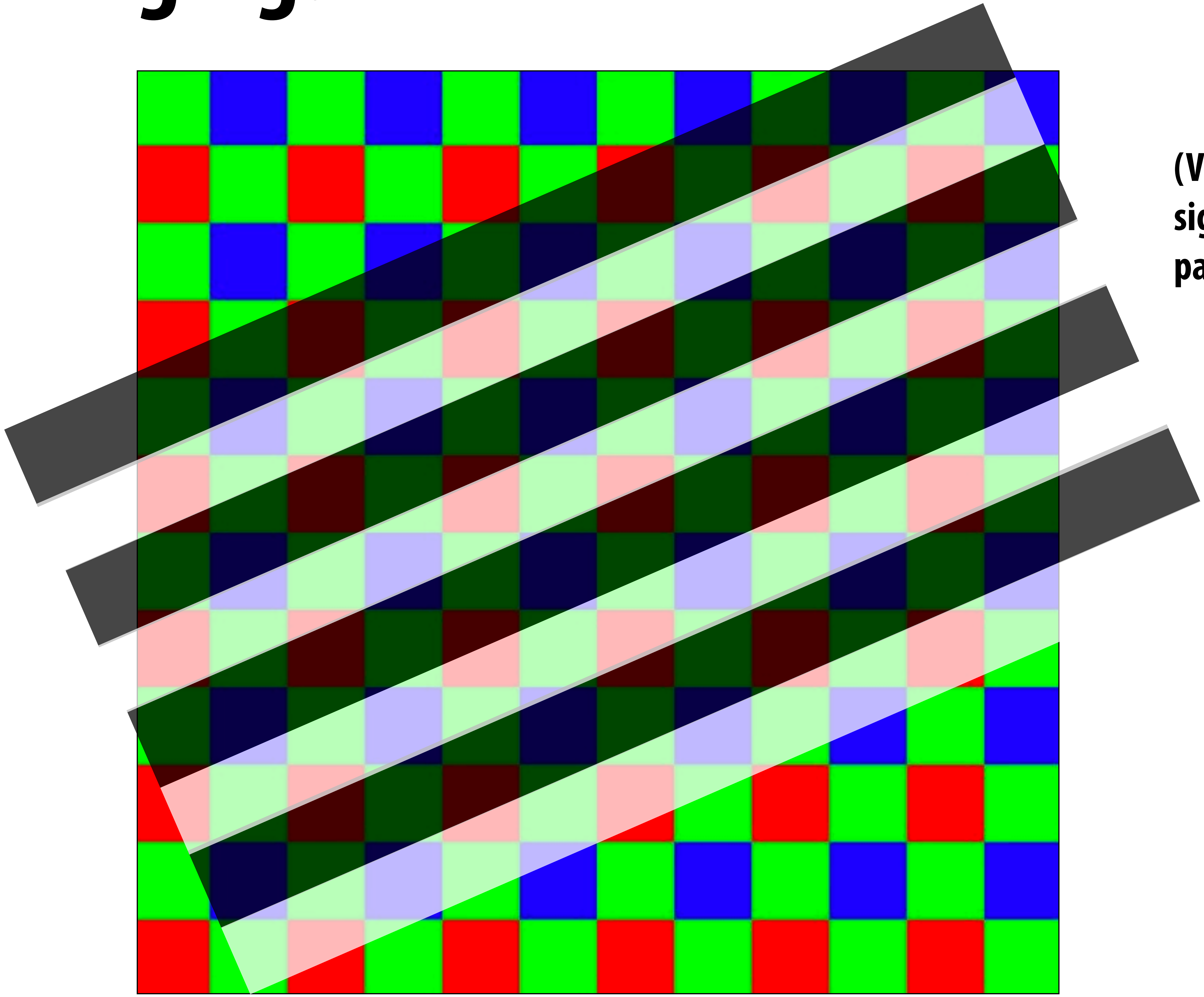
Interpolation of green yields dark/light pattern.

Why color fringing?



What will demosaiced result look like if this black and white signal was captured by the sensor?

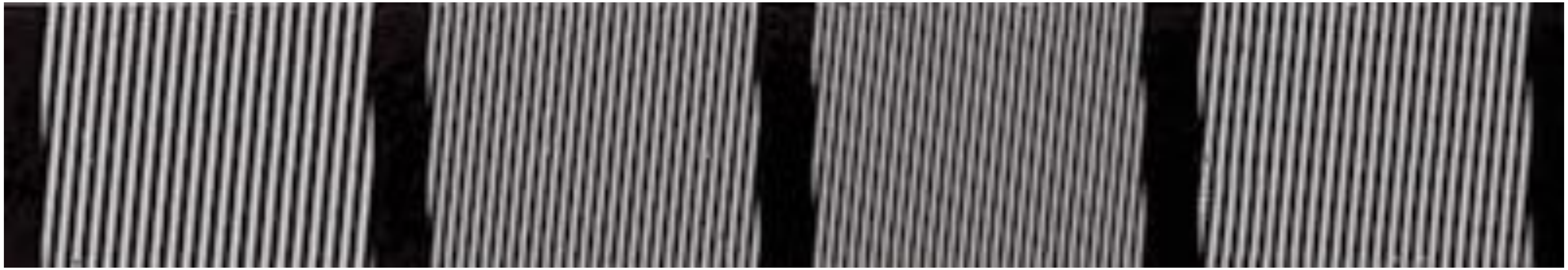
Why color fringing?



(Visualization of signal and Bayer pattern)

Demosaicing errors

- Common difficult case: fine diagonal black and white stripes
- Result: moire pattern color artifacts

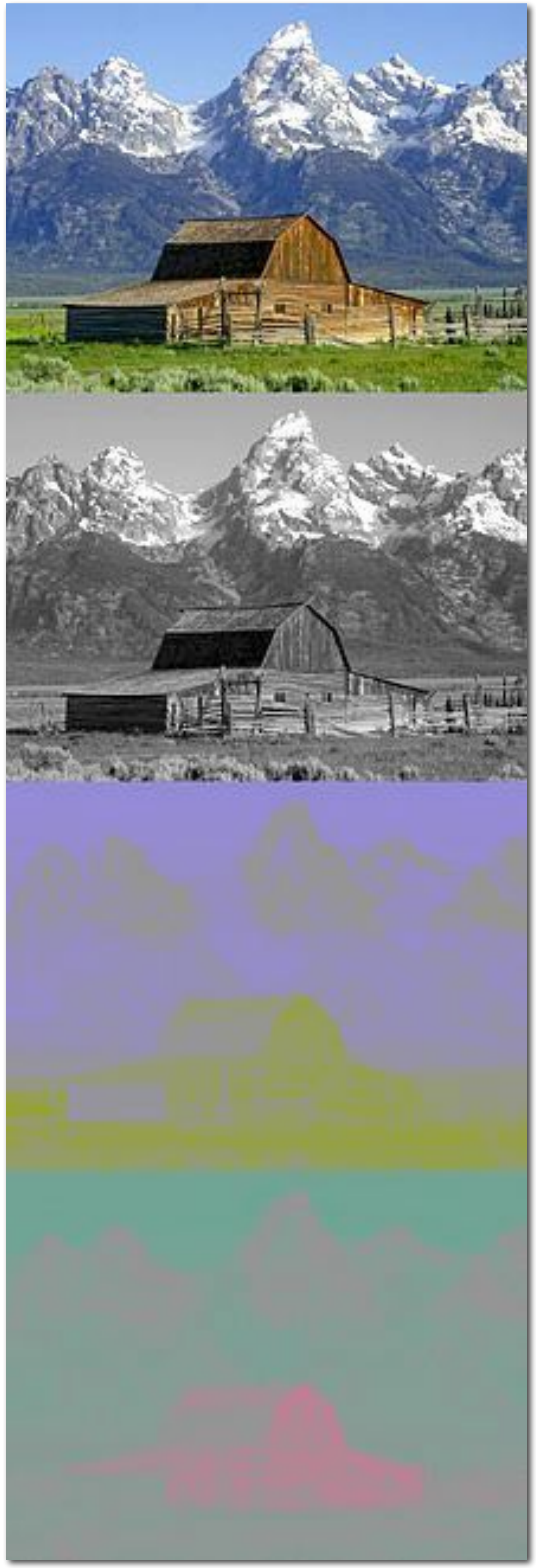


RAW data from sensor

RGB result after demosaic

Image credit: http://almanazir.typepad.com/almanazir/2006/11/how_a_camera_ph_1.html

Y’CbCr color space



Y’

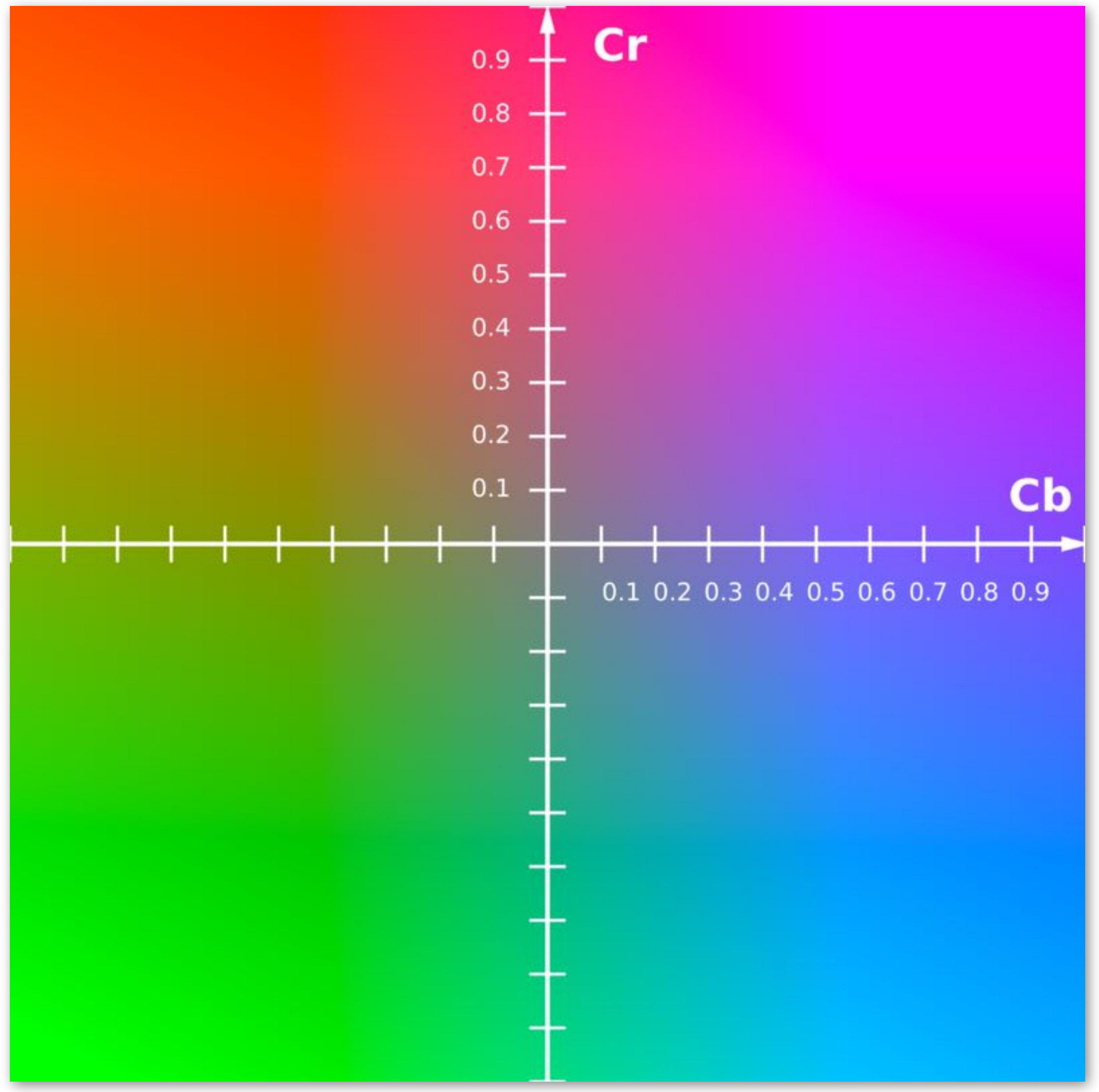
Cb

Cr

Colors are represented as point in 3-space

RGB is just one possible basis for representing color

Y’CbCr separates luminance from hue in representation



Y’ = luma: perceived luminance

Cb = blue-yellow deviation from gray

Cr = red-cyan deviation from gray

“Gamma corrected” RGB

(primed notation indicates perceptual (non-linear) space)

We’ll describe what this means this later in the lecture.

Conversion matrix from R’G’B’ to Y’CbCr:

$$
\begin{aligned}
Y' &= 16 + \frac{65.738 \cdot R'_D}{256} + \frac{129.057 \cdot G'_D}{256} + \frac{25.064 \cdot B'_D}{256} \\
C_B &= 128 + \frac{-37.945 \cdot R'_D}{256} - \frac{74.494 \cdot G'_D}{256} + \frac{112.439 \cdot B'_D}{256} \\
C_R &= 128 + \frac{112.439 \cdot R'_D}{256} - \frac{94.154 \cdot G'_D}{256} - \frac{18.285 \cdot B'_D}{256}
\end{aligned}
$$

Image credit: Wikipedia

Example: compression in Y'CbCr

Original picture of Kayvon

Example: compression in Y'CbCr

Contents of CbCr color channels downsampled by a factor of 20 in each dimension (400x reduction in number of samples)

Example: compression in Y'CbCr

Full resolution sampling of luma (Y')

Example: compression in Y'CbCr

Reconstructed result
(looks pretty good)

Better demosaic

- Convert demosaic'ed RGB value to YCbCr
- Low-pass filter (blur) or median filter CbCr channels
- Combine filtered CbCr with full resolution Y from sensor to get RGB

- Trades off spatial resolution of chroma information to avoid objectionable color fringing

White balance

- Adjust relative intensity of rgb values (goal: make neutral tones in scene appear neutral in image)

```
output_pixel = white_balance_coeff * input_pixel
// note: in this example, white_balance_coeff is vec3
// (adjusts ratio of red-blue-green channels)
```

- The same "white" object will generate different sensor response when illuminated by different spectra. Camera needs to infer what the lighting in the scene was.

Image credit: basedigitalphotography.com

White balance example

White balance example

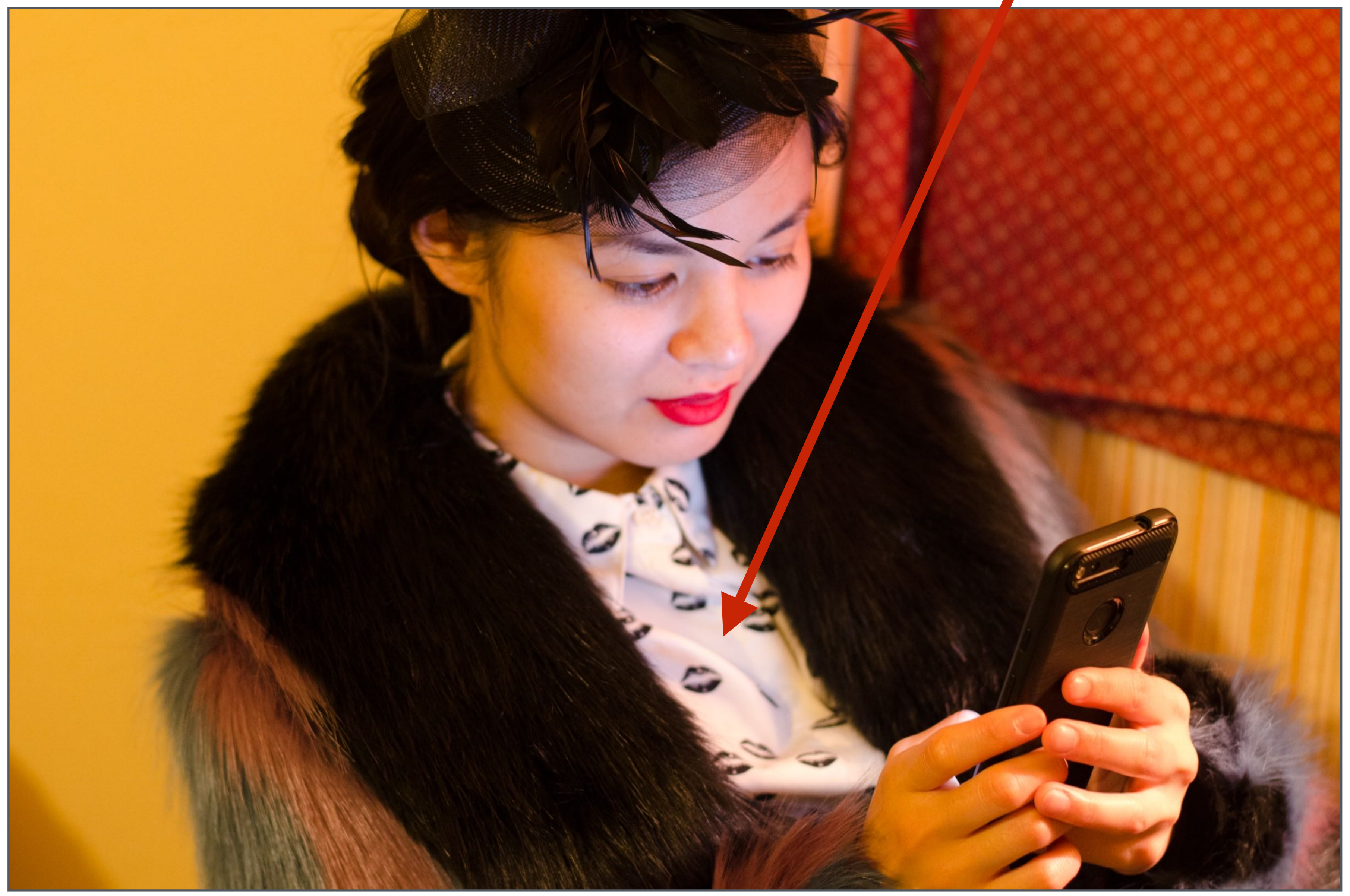
White balance example

White balance algorithms

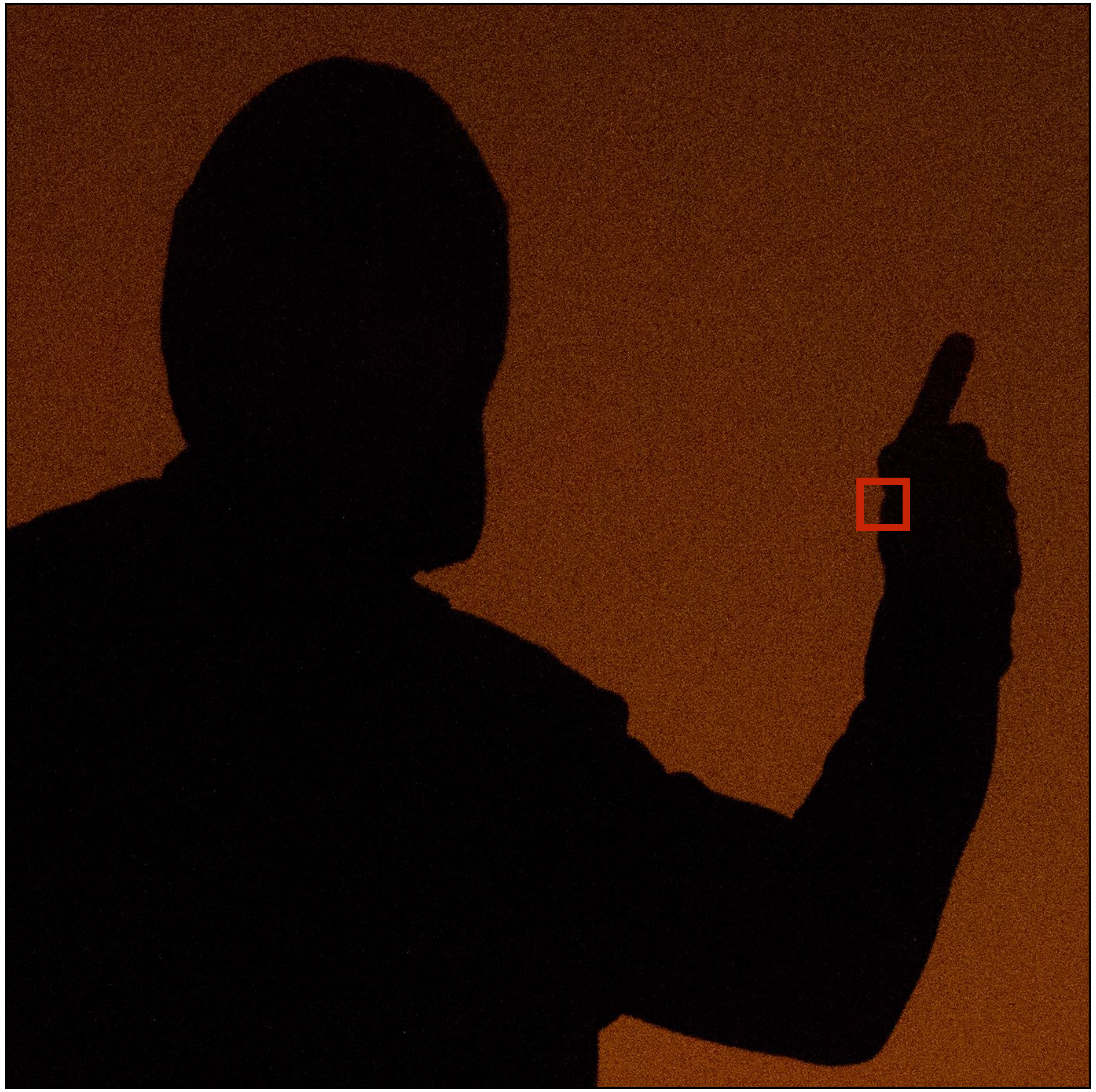
- White balance coefficients depend on analysis of image contents
  - Calibration based: get value of pixel of "white" object: (r_w, g_w, b_w)
    - Scale all pixels by ($1/r_w$, $1/g_w$, $1/b_w$)
  - Heuristic based: camera must guesse which pixels correspond to white objects in scene
    - Gray world assumption: make average of all pixels in image gray
    - Brightest pixel assumption: find brightest region of image, make it white ([1,1,1])

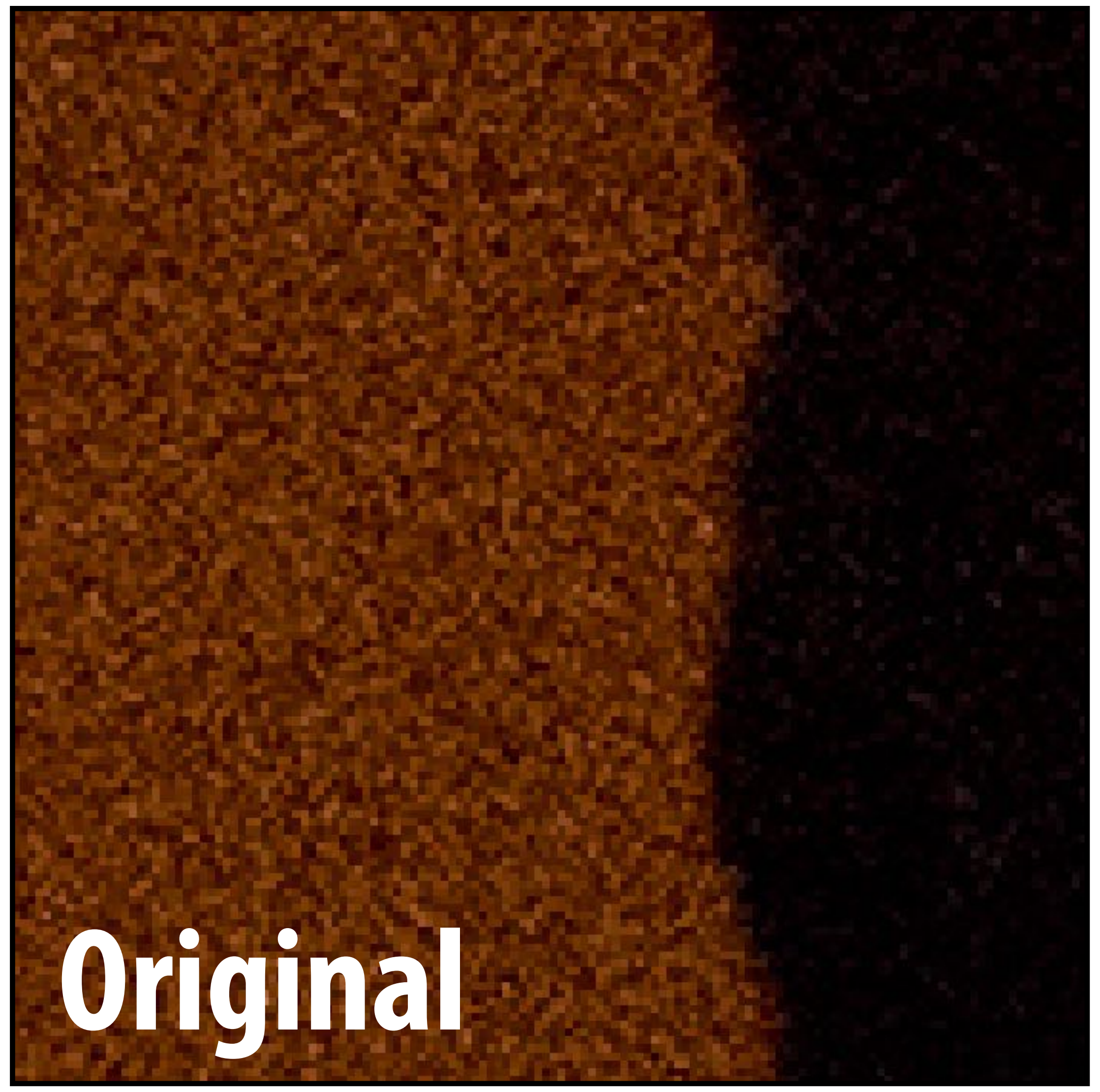
Scale r,g,b values so these pixels are close to (1,1,1)

- Modern white-balance algorithms are based on learning correct scaling from many "good photograph" examples
  - Create database of images for which good white balance settings are known (e.g., manually set by human)
  - Learn mapping from image features to white balance settings
  - When new photo is taken, use learned model to predict good white balance settings



Denoising





Low light conditions need long exposure…
blur due to camera shake

Image credit: https://www.colorexpertsbd.com/blog/how-to-fix-blurry-photos-induced-by-camera-shake-in-photoshop

Low light photo: many regions underexposed (short exposure) to avoid blur + some regions overexposed

Brightened image to see detail in dark regions, notice noise in dark regions

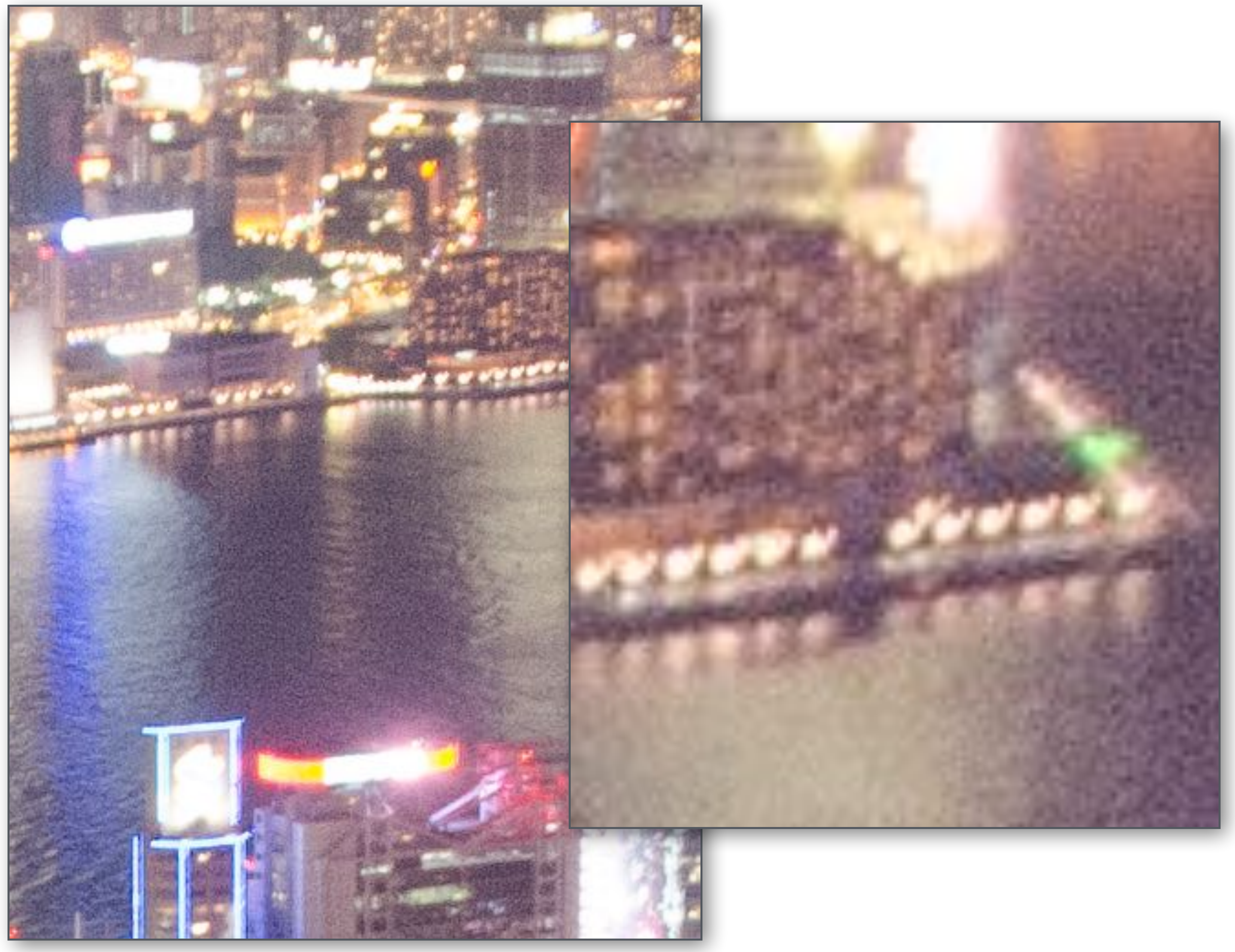
Attempt to denoise… splotchy effect remains

Long exposure: walking people are blurred…

Long exposure: walking people are blurred...

Also: still significant noise in dark regions

Reduce noise via image processing: denoising via downsampling



Downsample via point sampling

(noise remains)

Downsample via averaging

Noise reduced

Like a smaller number of bigger pixels!

Discrete 2D convolution

$$\underbrace{(f * I)(x,y)}_{\substack{\text{output image} \\ \text{(the result of convolving f with input image I)}}} = \sum_{i,j=-\infty}^{\infty} \underbrace{f(i,j)}_{\text{filter}} \underbrace{I(x-i, y-j)}_{\text{input image}}$$

Consider a $f(i,j)$ **that is nonzero only when:** $-1 \leq i,j \leq 1$

Then:

$$(f * g)(x,y) = \sum_{i,j=-1}^{1} f(i,j) I(x-i, y-j)$$

And we can represent f(i,j) as a 3x3 matrix of values where:

$$f(i,j) = \mathbf{F}_{i,j}$$

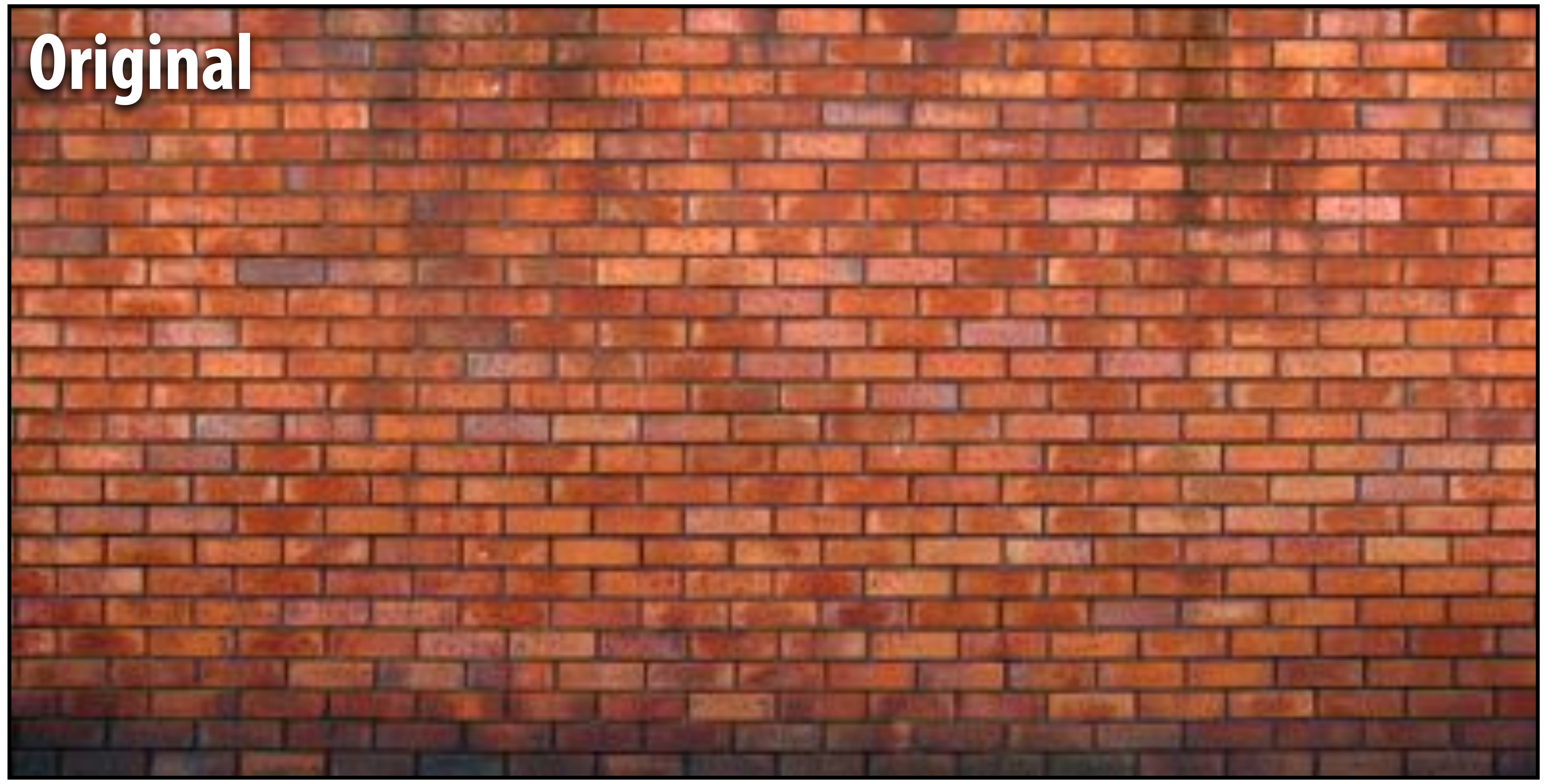
(often called: "filter weights", "filter kernel")

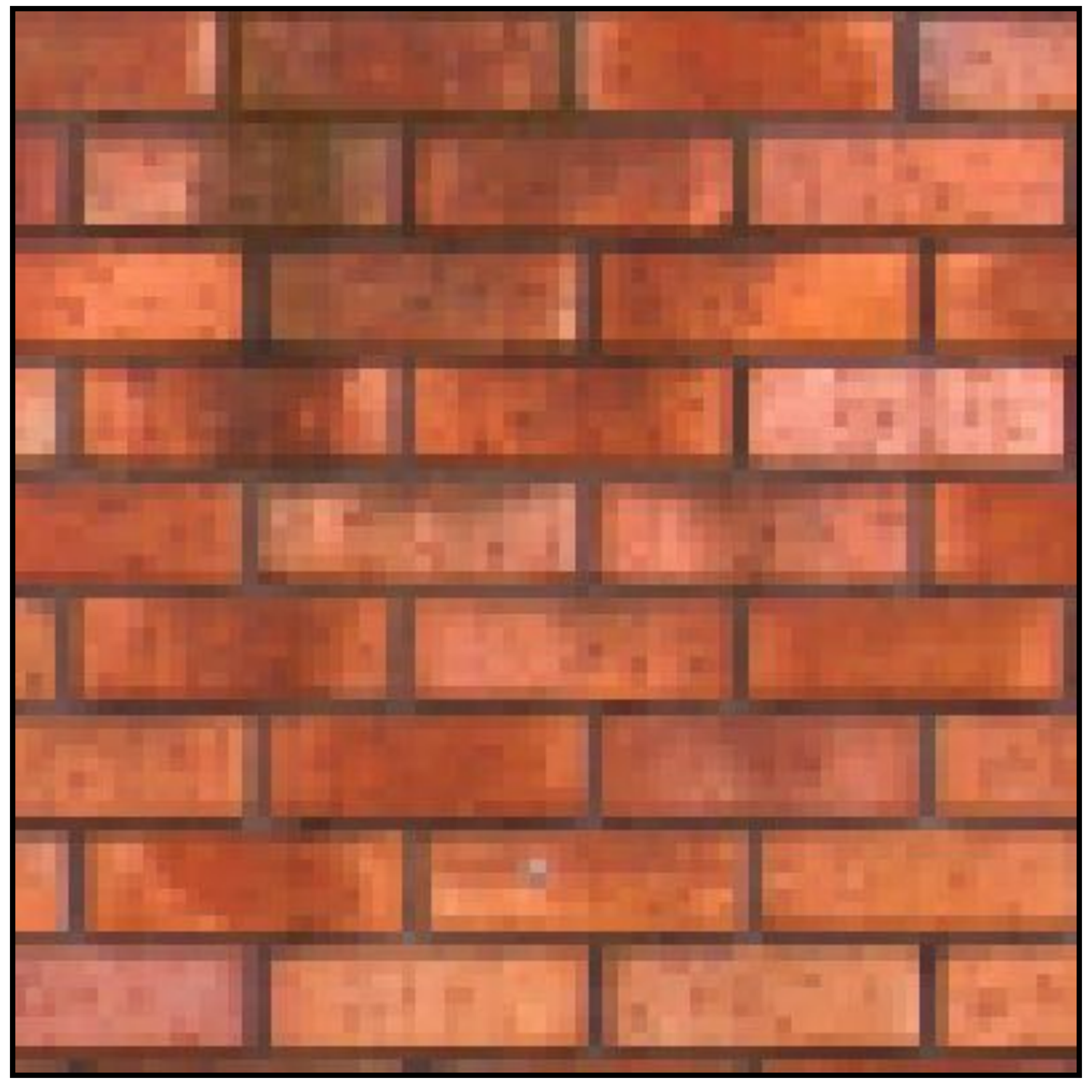
Simple 3x3 box blur in C code

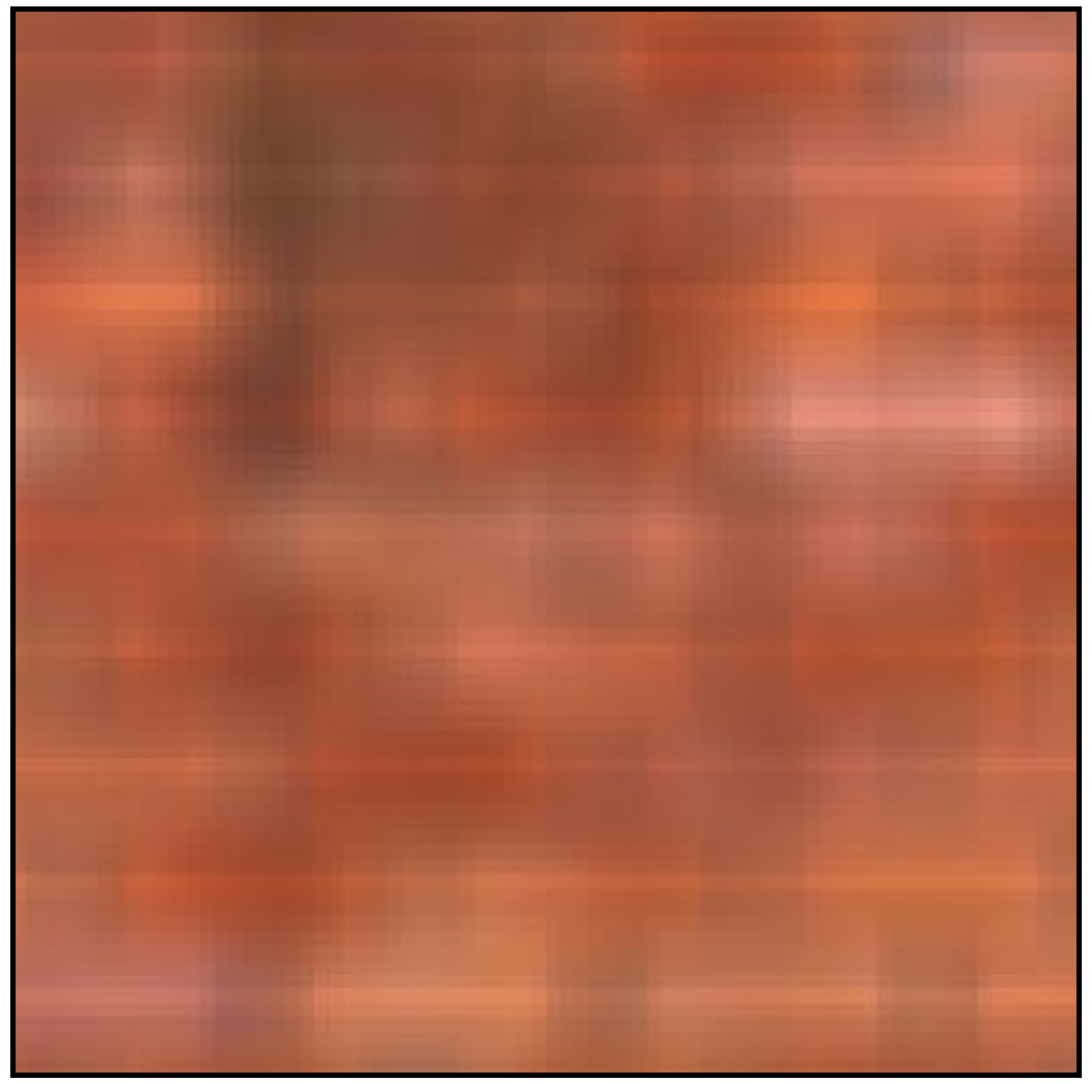
```
float input[(WIDTH+2) * (HEIGHT+2)];
float output[WIDTH * HEIGHT];

float weights[] = {1./9, 1./9, 1./9,
                   1./9, 1./9, 1./9,
                   1./9, 1./9, 1./9};

for (int j=0; j<HEIGHT; j++) {
   for (int i=0; i<WIDTH; i++) {
      float tmp = 0.f;
      for (int jj=0; jj<3; jj++)
         for (int ii=0; ii<3; ii++)
            tmp += input[(j+jj)*(WIDTH+2) + (i+ii)] * weights[jj*3 + ii];
      output[j*WIDTH + i] = tmp;
  }
}
```

For now: ignore boundary pixels and assume output image is smaller than input (makes convolution loop bounds much simpler to write)

7x7 box blur







Gaussian blur

- **Obtain filter coefficients from sampling 2D Gaussian**

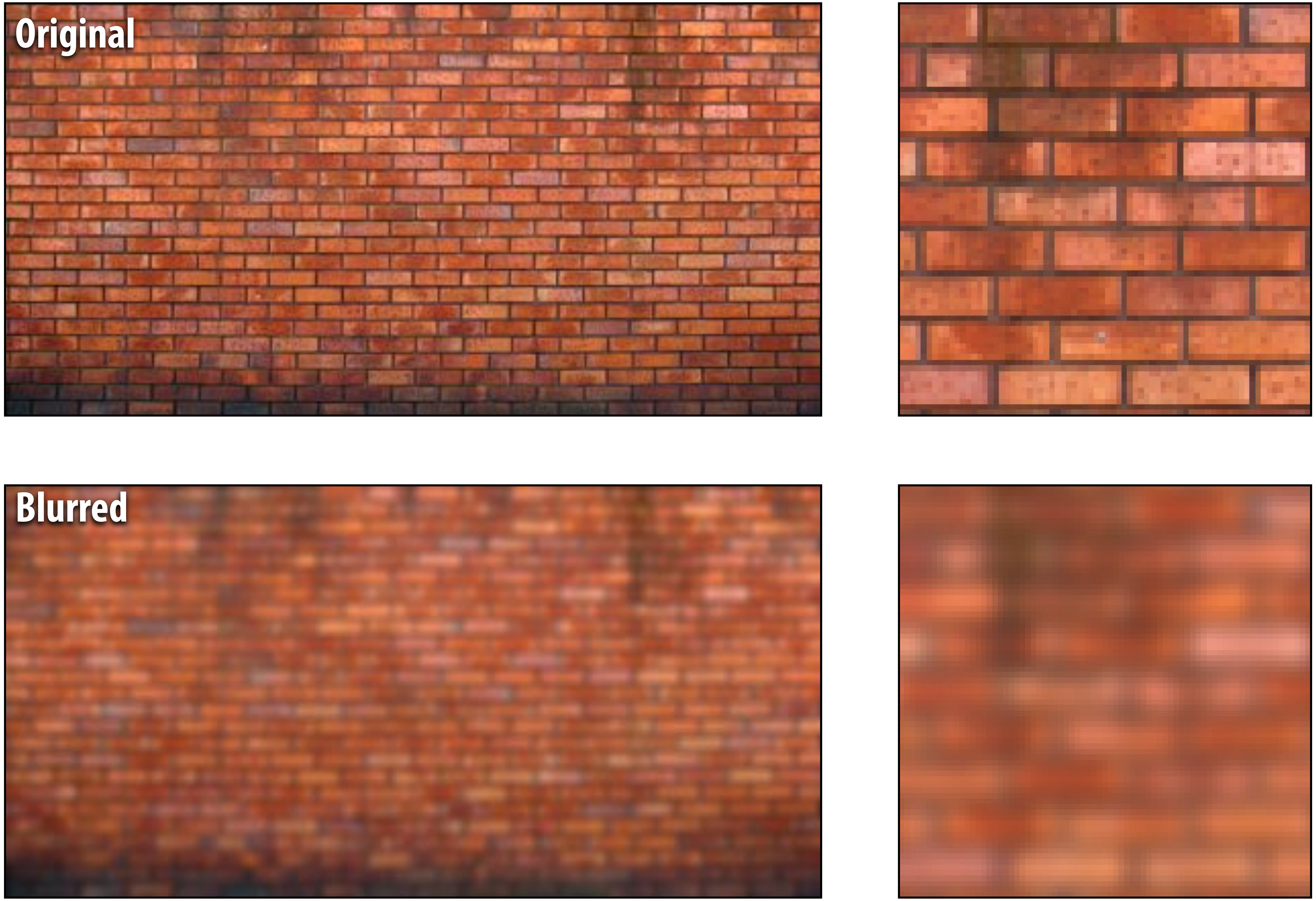
$$f(i,j) = \frac{1}{2\pi\sigma^2} e^{-\frac{i^2+j^2}{2\sigma^2}}$$

- **Produces weighted sum of neighboring pixels (contribution falls off with distance)**
  - **In practice: truncate filter beyond certain distance for efficiency**

$$\frac{1}{256} \cdot \begin{bmatrix} 1 & 4 & 6 & 4 & 1 \\ 4 & 16 & 24 & 16 & 4 \\ 6 & 24 & 36 & 24 & 6 \\ 4 & 16 & 24 & 16 & 4 \\ 1 & 4 & 6 & 4 & 1 \end{bmatrix}$$

Note: this is a 5x5 truncated Gaussian filter

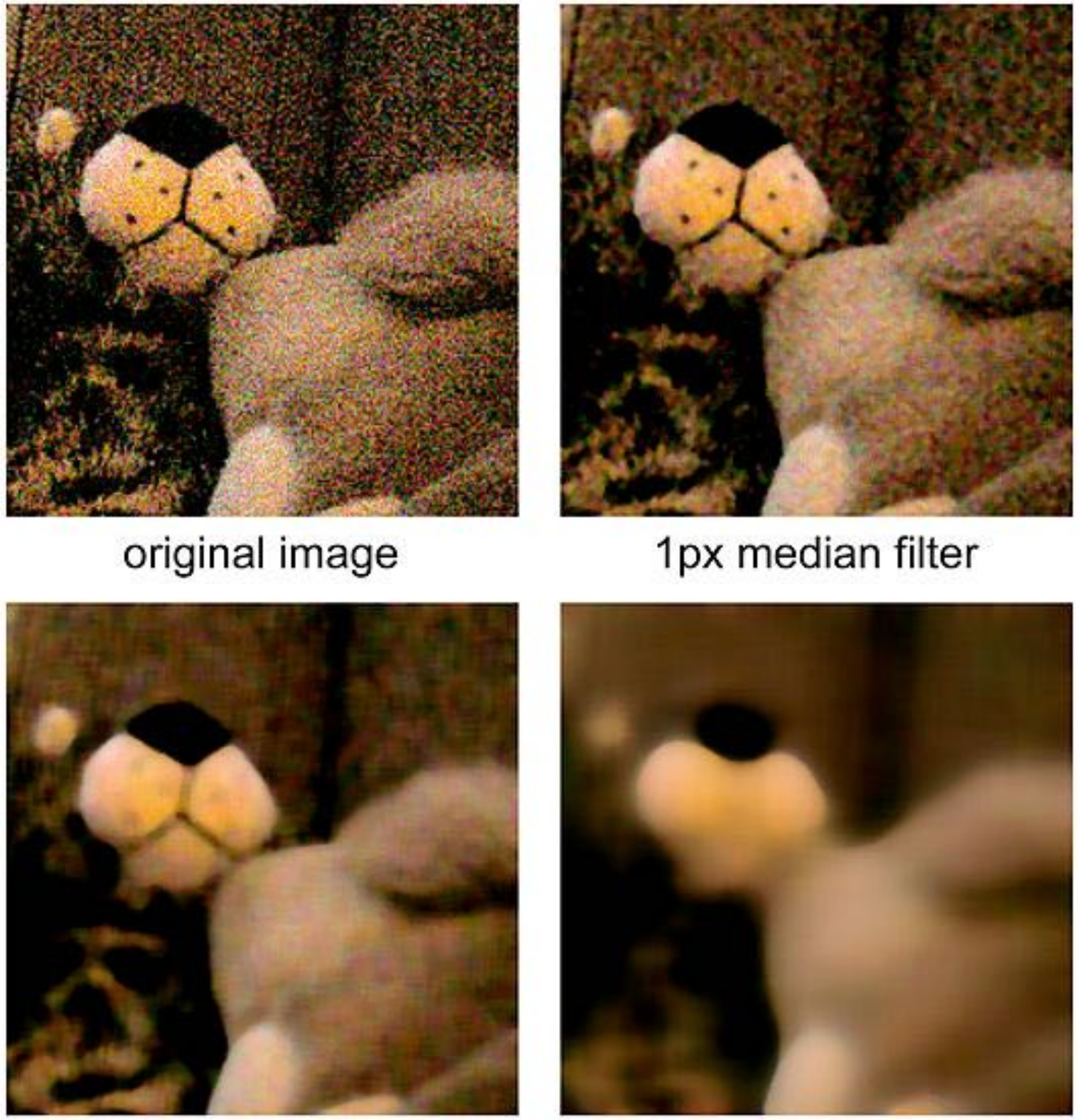
7x7 gaussian blur



Median filter

- Replace pixel with median of its neighbors
  - Useful noise reduction filter: unlike gaussian blur, one bright pixel doesn't drag up the average for entire region
- Not linear: filter weights are 1 or 0 (depending on image content)

```
uint8 input[(WIDTH+2) * (HEIGHT+2)];
uint8 output[WIDTH * HEIGHT];
for (int j=0; j<HEIGHT; j++) {
   for (int i=0; i<WIDTH; i++) {
      output[j*WIDTH + i] =
           // compute median of pixels
           // in surrounding 5x5 pixel window
   }
}
```



original image | 1px median filter | 3px median filter | 10px median filter

- Basic algorithm for NxN support region:
  - Sort N^2 elements in support region, then pick median: $O(N^2\log(N^2))$ work per pixel
  - Can you think of an $O(N^2)$ algorithm? What about $O(N)$?

Bilateral filter

Example use of bilateral filter: removing noise while preserving image edges

Bilateral filter

$$\mathrm{BF}[I](p) = \frac{1}{W_p} \sum_{i,j} f(\underbrace{|I(x-i,y-j) - I(x,y)|}_{\text{Re-weight based on difference in input image pixel values}})\overbrace{G_\sigma(i,j)}^{\text{Gaussian blur kernel}}\overbrace{I(x-i,y-j)}^{\text{Input image}}$$

Normalization

For all pixels in support region of Gaussian kernel

$$W_p = \sum_{i,j} f(|I(x-i,y-j) - I(x,y)|)G_\sigma(i,j)$$

- **The bilateral filter is an "edge preserving" filter: down-weight contribution of pixels on the "other side" of strong edges.** $f(x)$ **defines what "strong edge means"**
- **Spatial distance weight term** $f(x)$ **could itself be a gaussian**
  - **Or very simple:** $f(x) = 0$ if $x > threshold$, 1 $otherwise$

Value of output pixel (x,y) is the weighted sum of all pixels in the support region of a truncated gaussian kernel

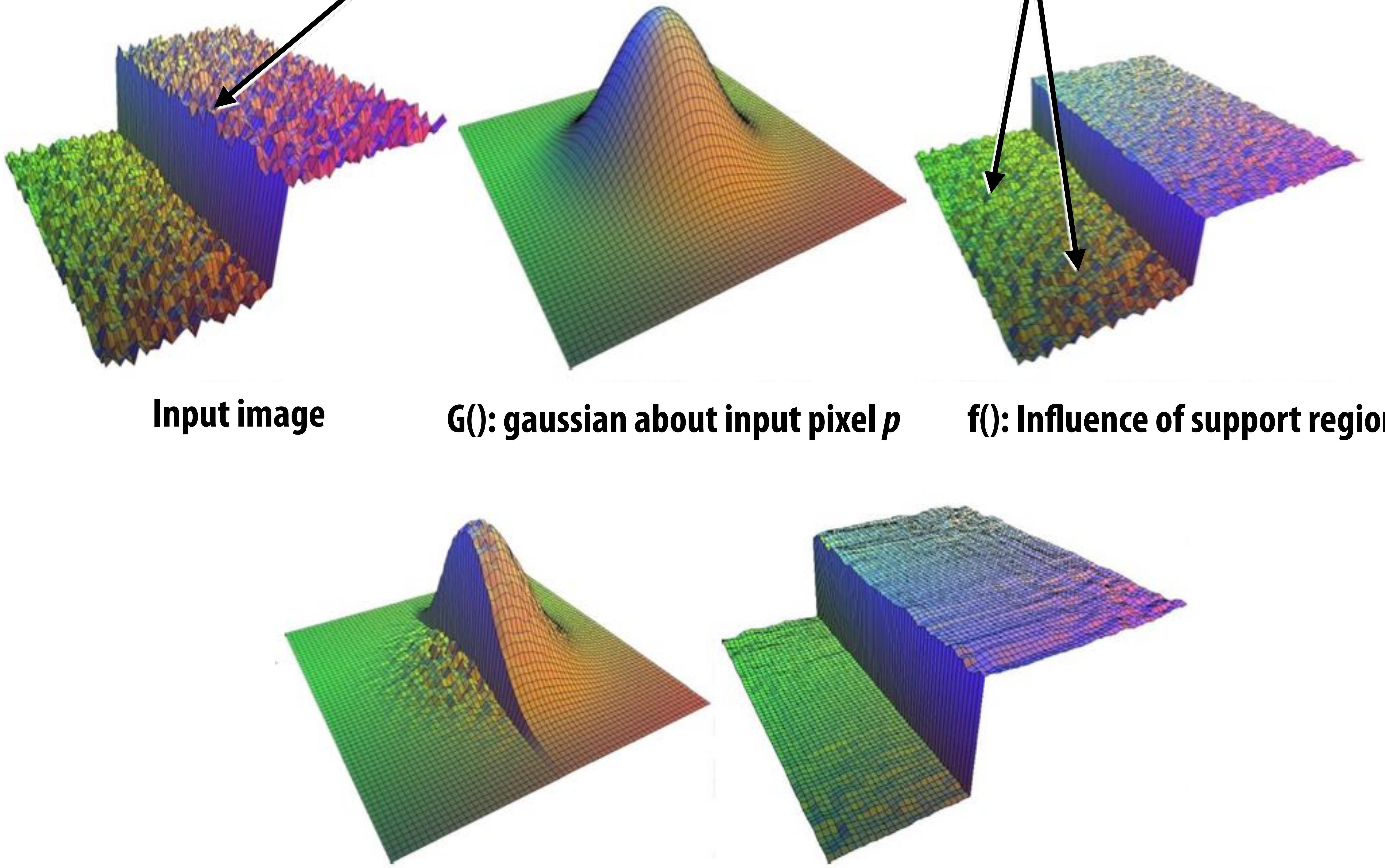
But weight is combination of <u>spatial distance</u> and <u>input image pixel intensity</u> difference. (non-linear filter: like the median filter, the filter's weights depend on input image content)

Bilateral filter

- Visualization of bilateral filter

Input pixel p

Pixels with significantly different intensity as p contribute little to filtered result (they are “on the “other side of the edge”



Input image

G(): gaussian about input pixel p

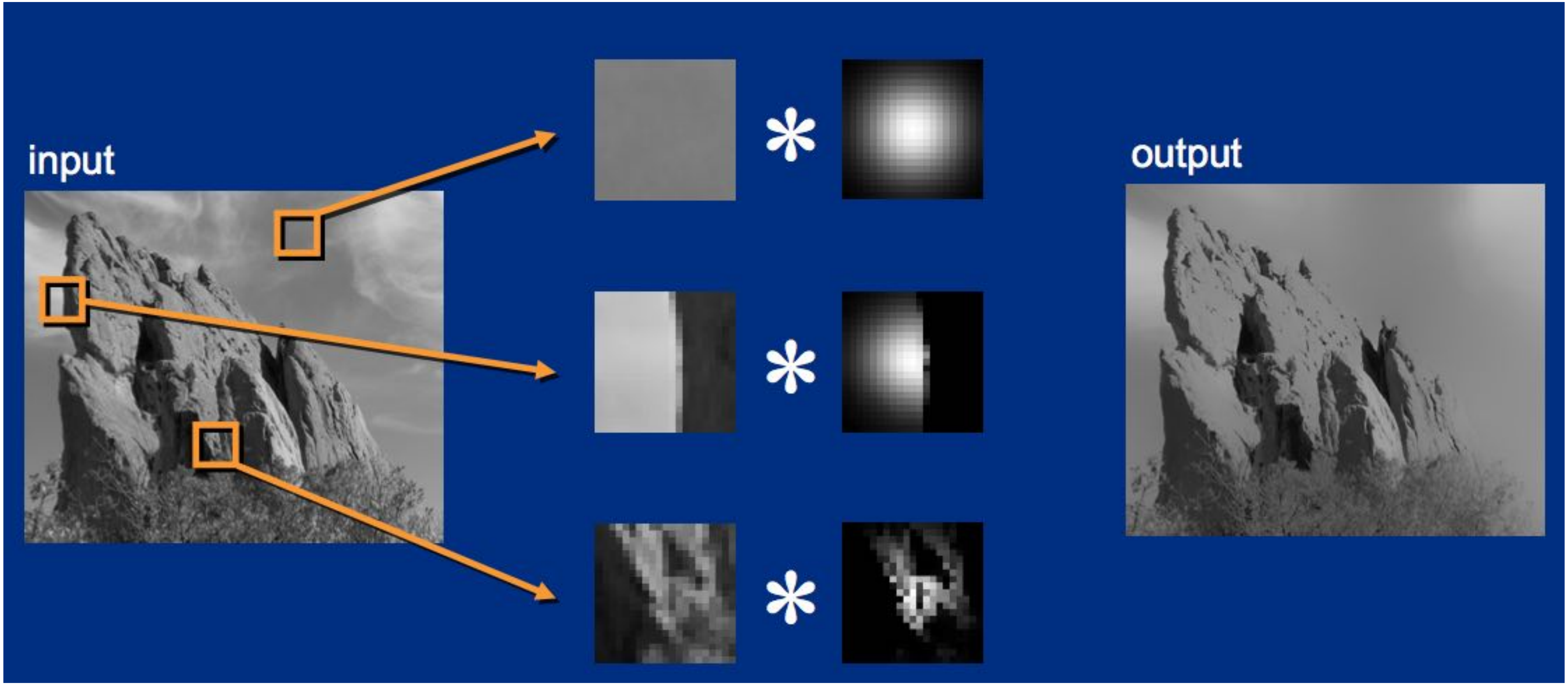
f(): Influence of support region

G x f: filter weights for pixel p

Filtered output image

Figure credit: Durand and Dorsey, “Fast Bilateral Filtering for the Display of High-Dynamic-Range Images”, SIGGRAPH 2002

Bilateral filter: kernel depends on image content



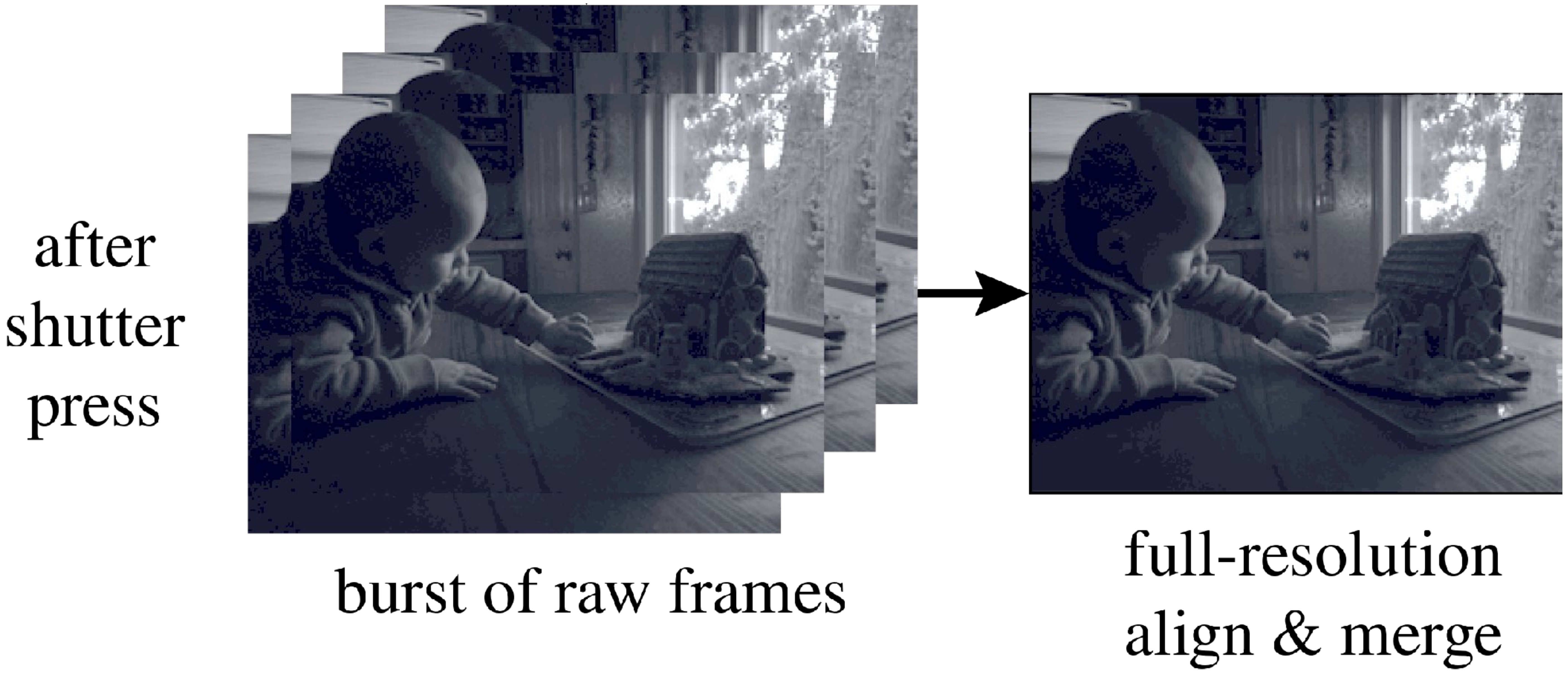
See Paris et al. [ECCV 2006] for a fast approximation to the bilateral filter

Figure credit: SIGGRAPH 2008 Course: "A Gentle Introduction to Bilateral Filtering and its Applications" Paris et al.

Better denoising idea: merge sequence of captures

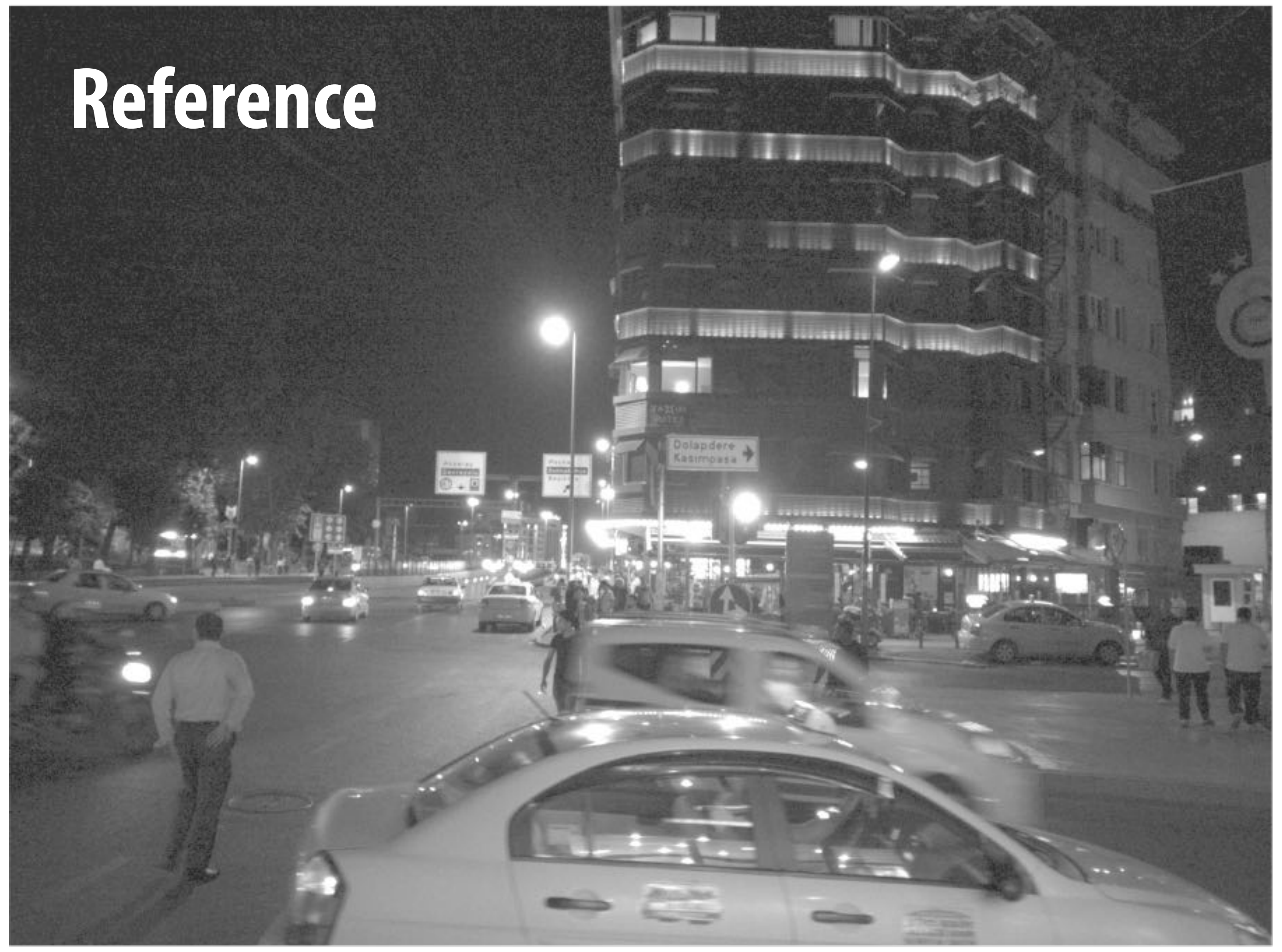
Algorithm used in Google Pixel Phones [Hasinoff 16]

- Long exposure: reduces noise (acquires more light), but introduces blur (camera shake or scene movement)
- Short exposure: sharper image, but lower signal/noise ratio
- Idea: take sequence of short full-resolution exposures, but align images in software, then merge them into a single sharp image with high signal to noise ratio

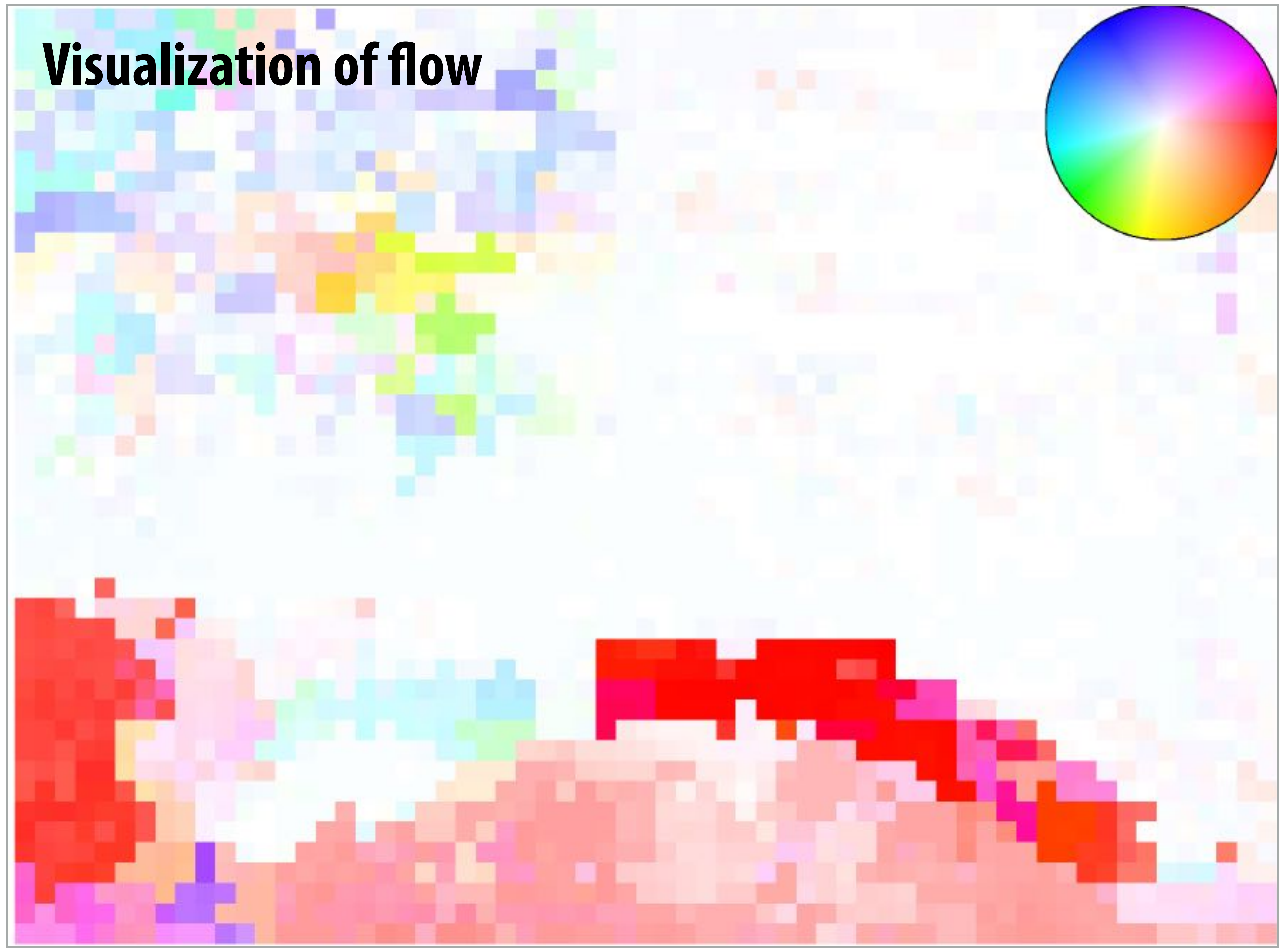


Google's align-and-merge algorithm

Image pair



- For each image in burst, align to reference frame (use sharpest photo as reference frame)
  - Compute optical flow field aligning image pair
- Simple merge algorithm: warp images according to flow, and sum
- More sophisticated techniques only merge pixels where confidence in alignment is high (tolerate noisy reference pixels when alignment fails)



[Image credit: Hasinoff 16]

Results of align and merge

[Hasinoff 16]

Full image

Successful alignment

Alignment failure

Reference frame

Temporal mean of images in burst (blurry)

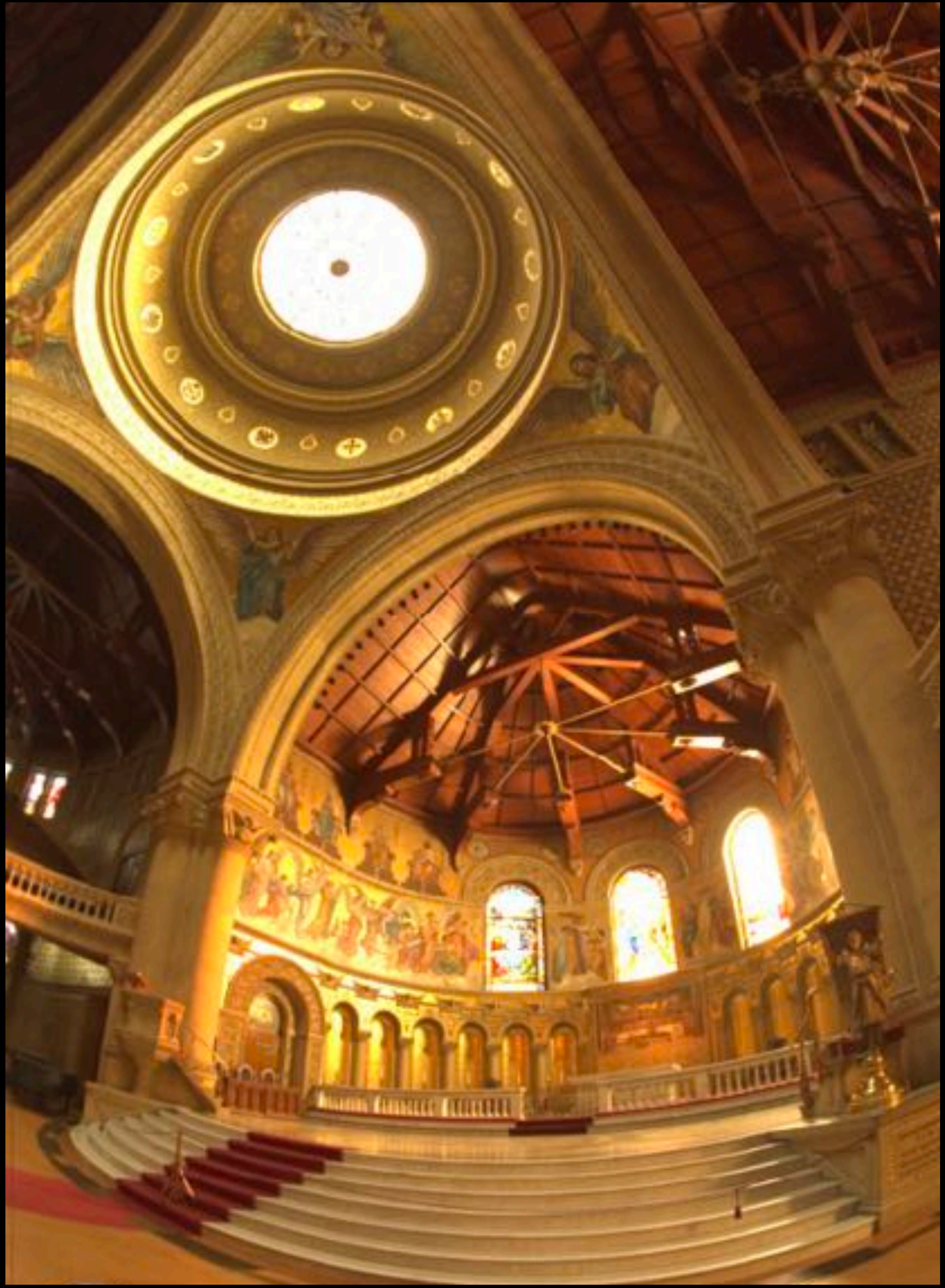
Temporal mean with alignment

Robust merge with alignment

[Image credit: Hasinoff 16]

Saturated pixels

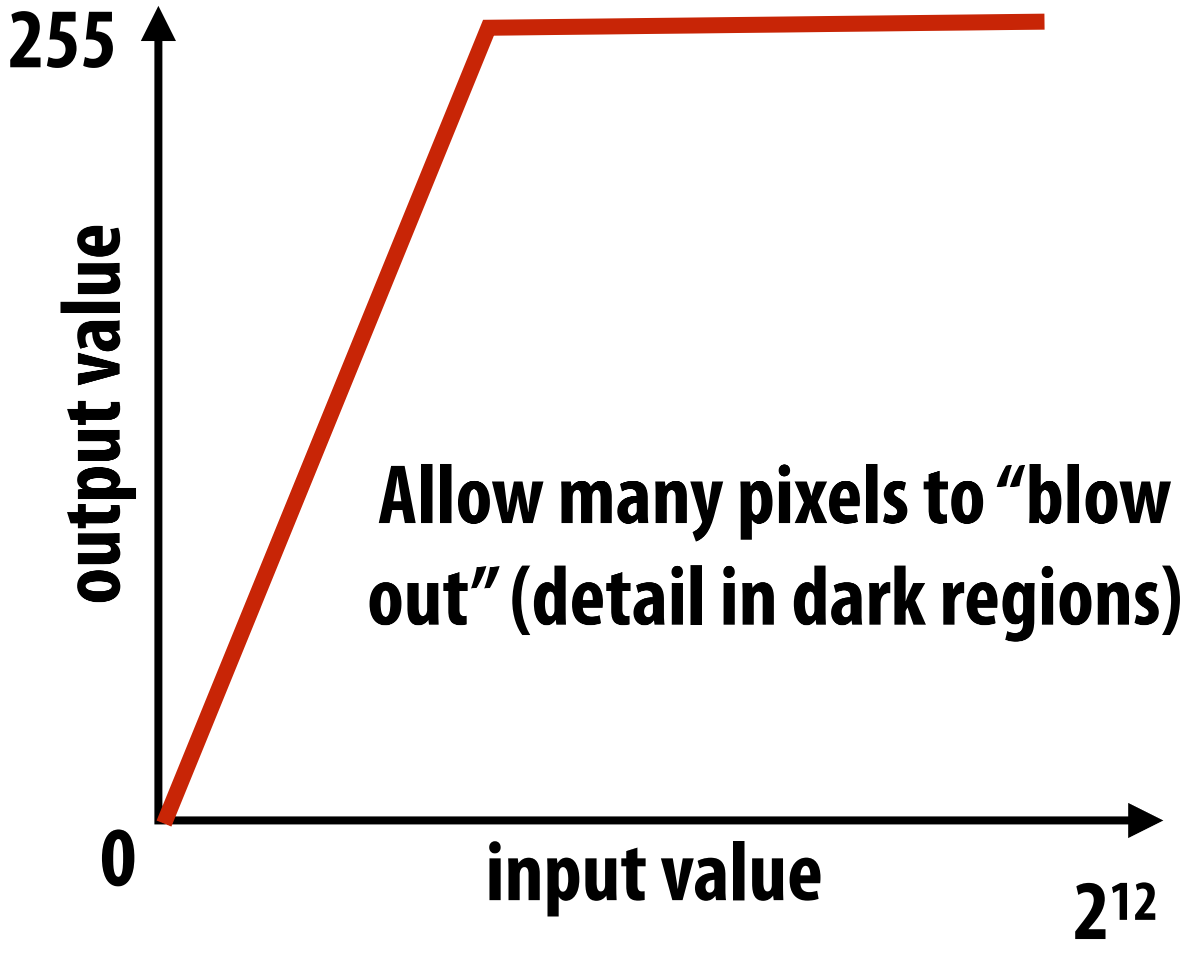
Saturated pixels

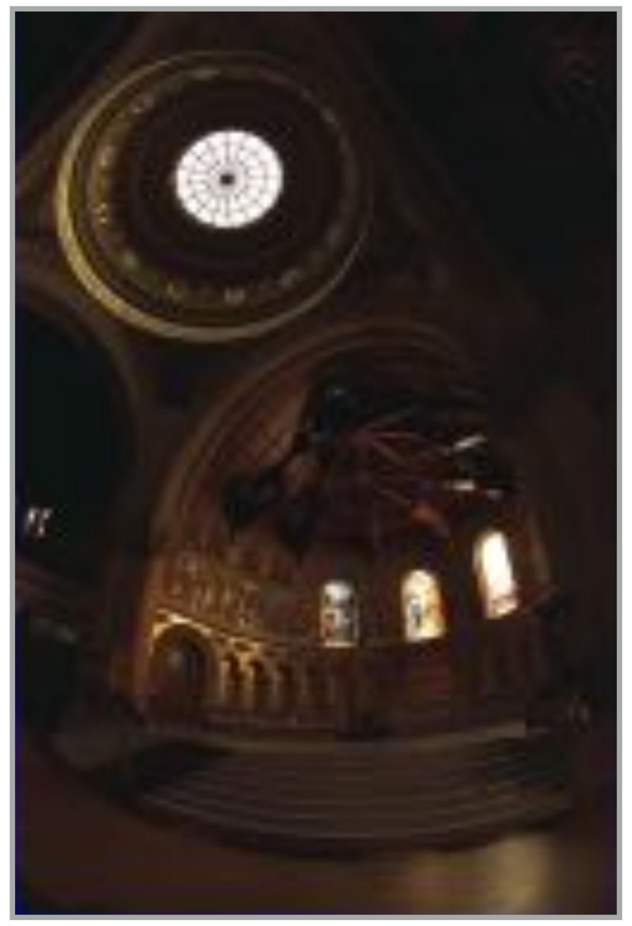


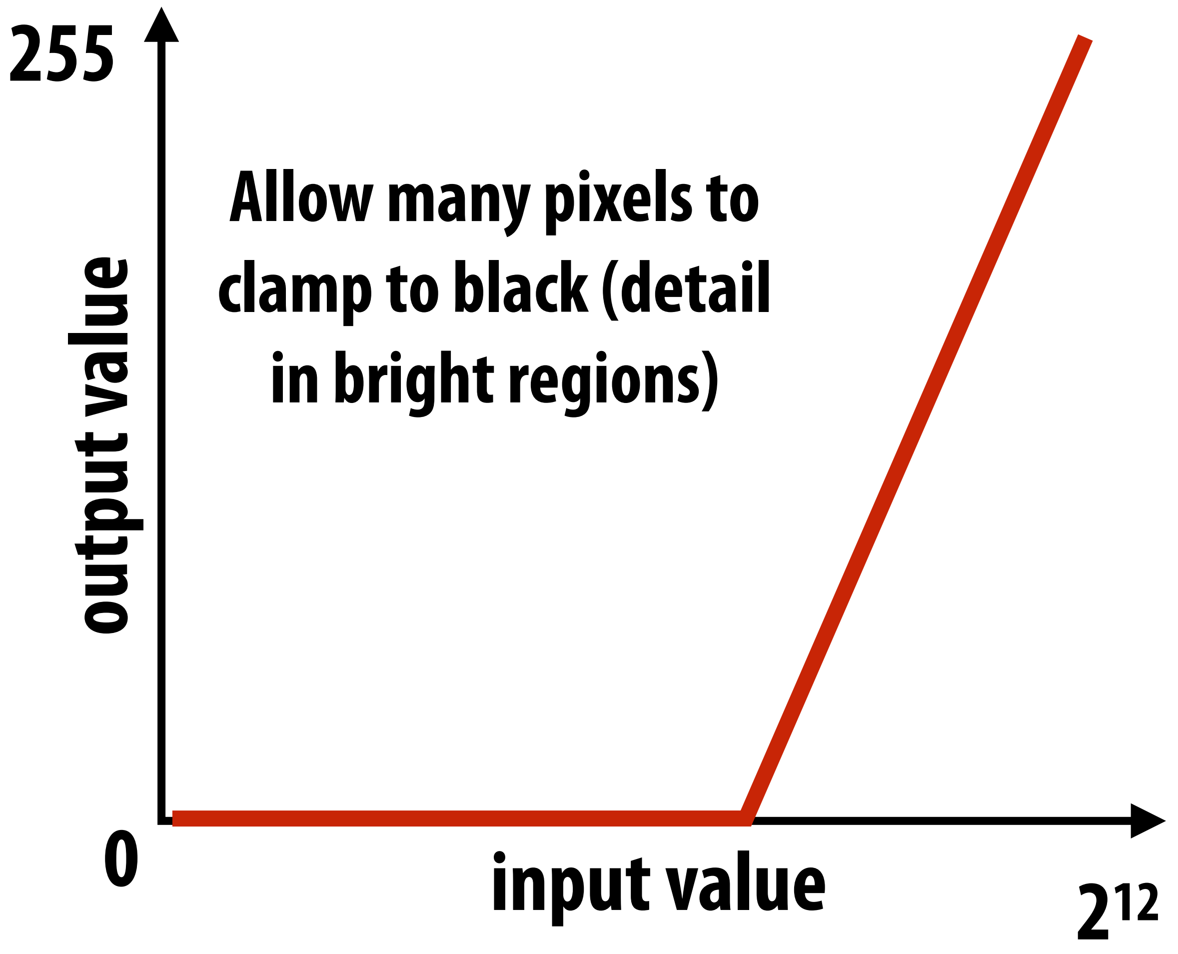
Credit: P. Debevec

Global tone mapping

- Measured image values (by camera's sensor): 10-12 bits / pixel, but common image formats are 8-bits/pixel
- How to convert 12 bit number to 8 bit number?







High dynamic range image (HDR)
Detail in dark and light images

Image credit: Wikipedia

Local tone adjustment

Pixel values

Weights

Improve picture's aesthetics by locally adjusting contrast, boosting dark regions, decreasing bright regions

(no physical basis for this)

Combined image
(unique weights per pixel)

Image credit: Mertens 2007

Challenge of merging images

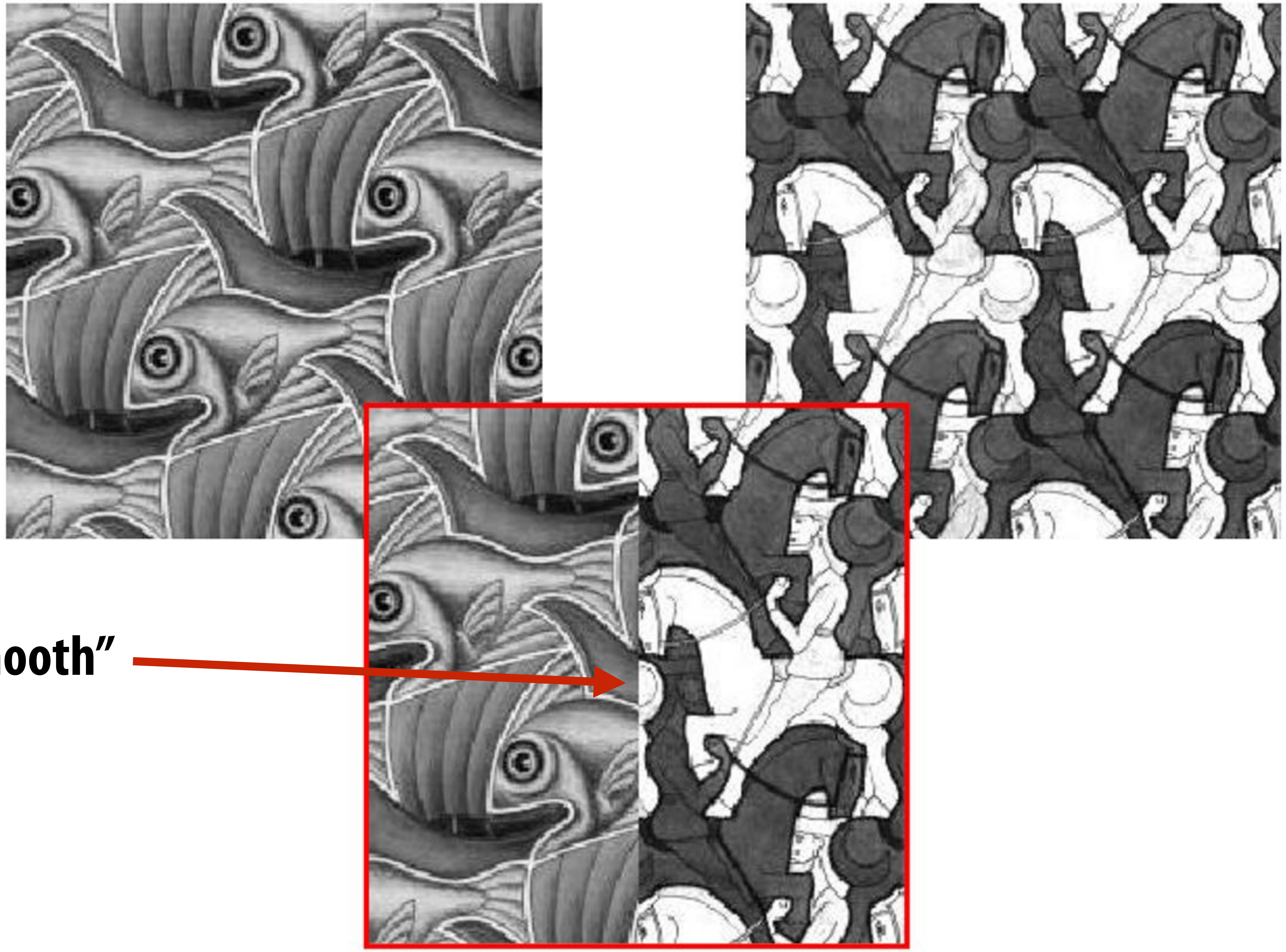
Four exposures (weights not shown)

Merged result (based on weight masks)
Notice heavy "banding" since absolute intensity of different exposures is different

Merged result (after blurring weight mask)
Notice "halos" near edges

Image blending

Consider a simple case where we want to blend two patterns:

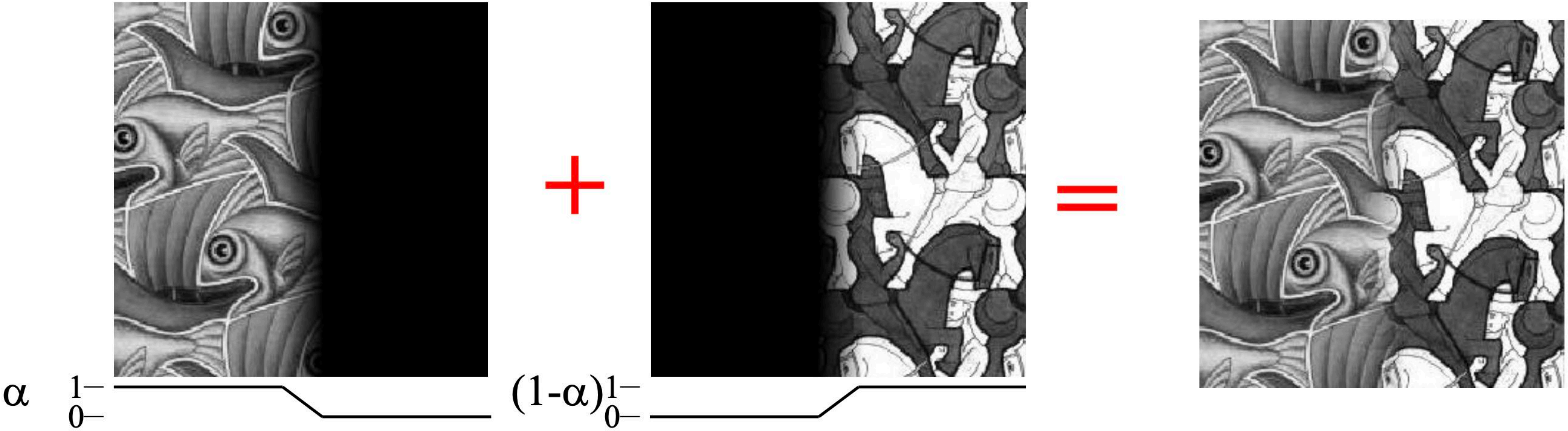


Problem: not “smooth”

Slide credit: Efros

“Feather” the alpha mask

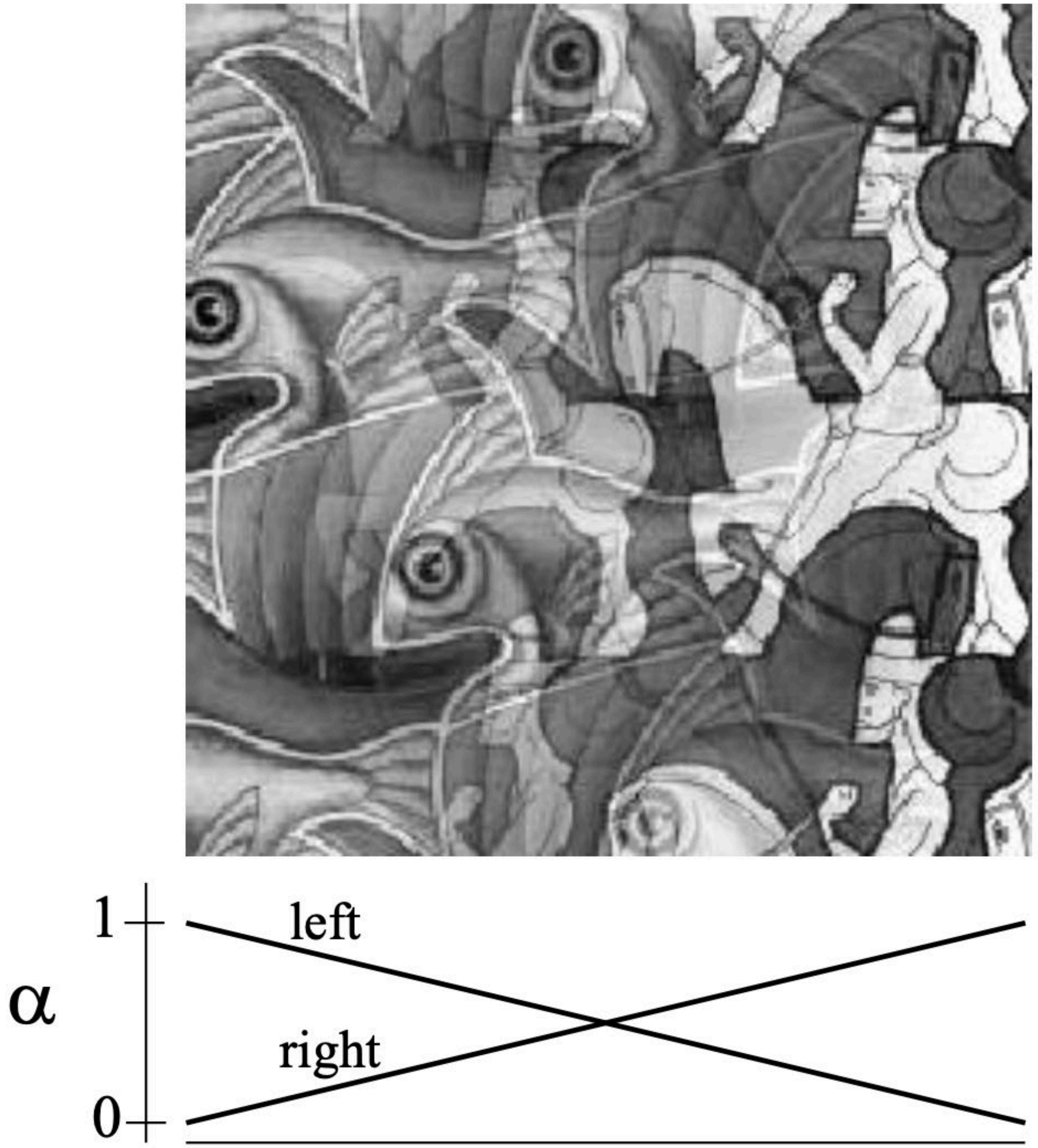
For a “smoother” look…

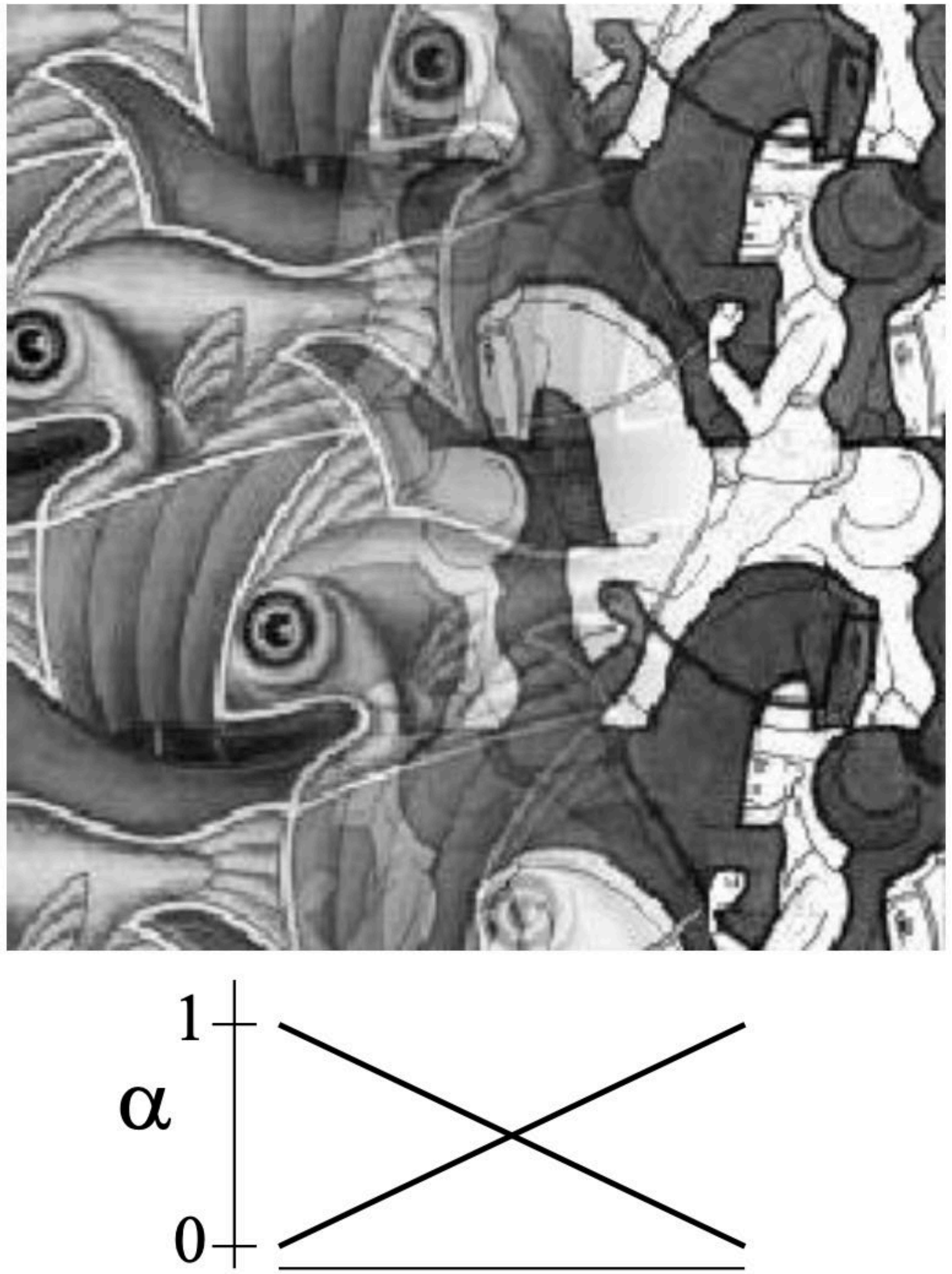


$$I_{\text{blend}} = \alpha\, I_{\text{left}} + (1-\alpha)\, I_{\text{right}}$$

Slide credit: Efros

Effect of feather window size

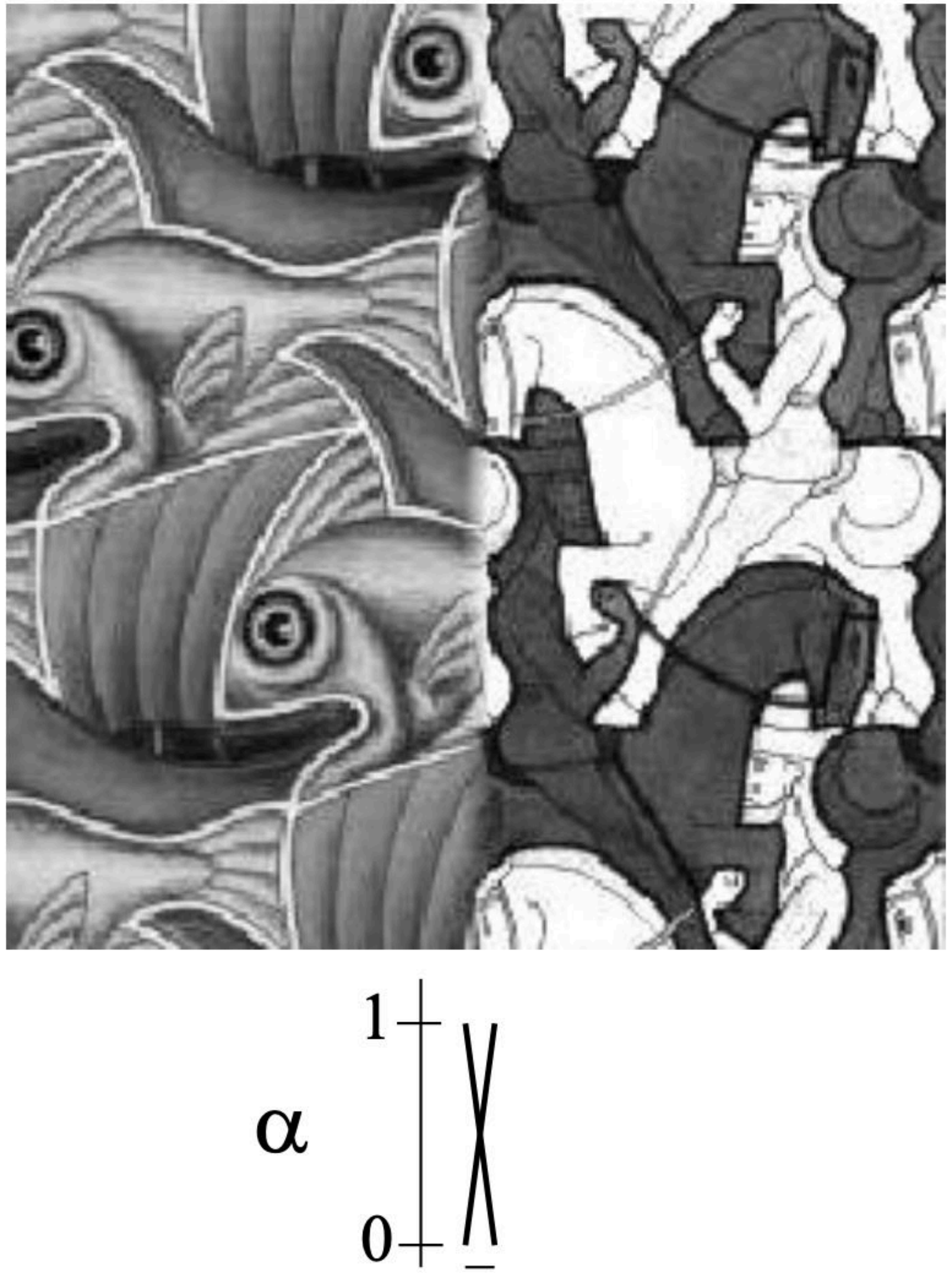


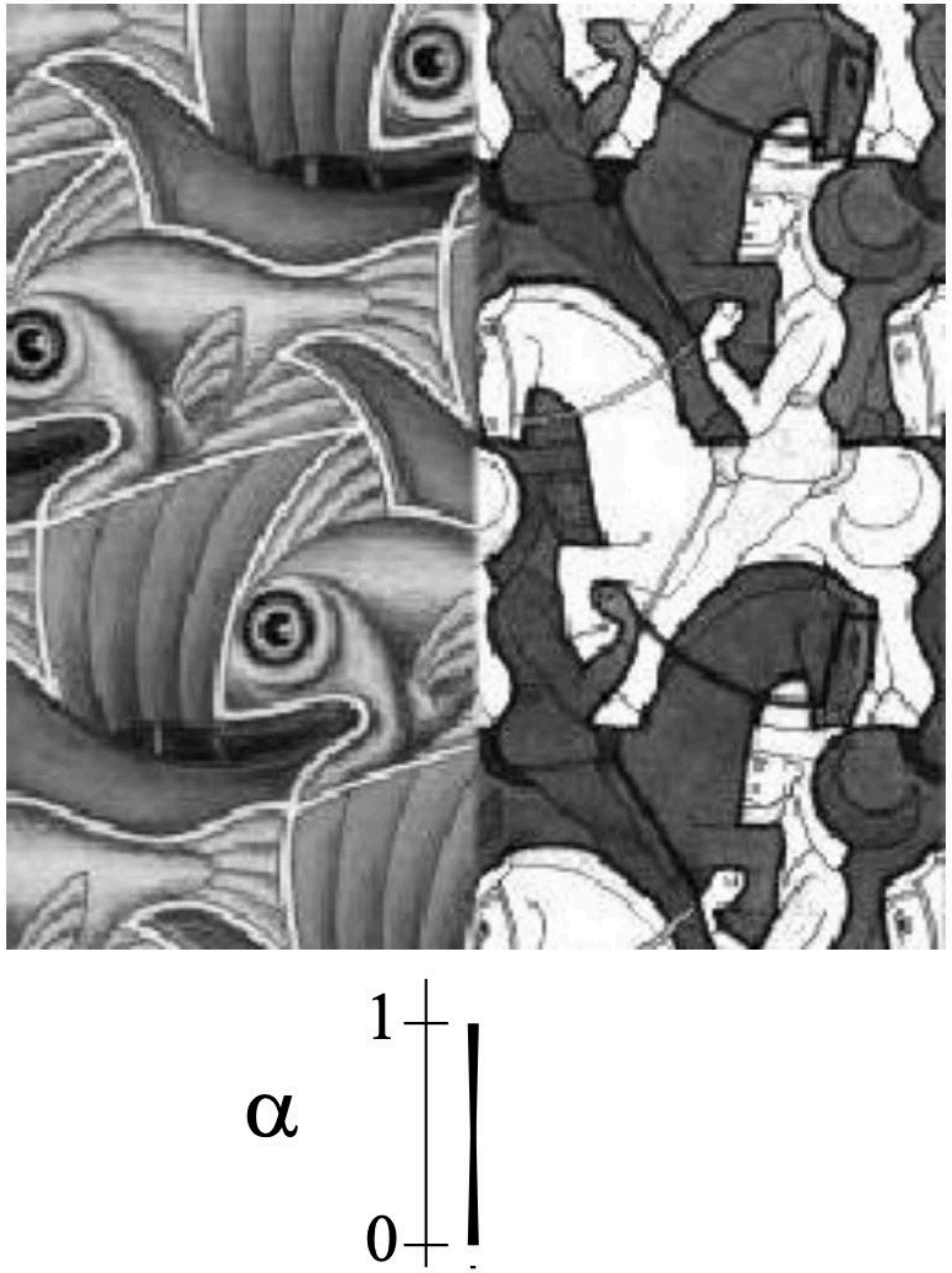


"Ghosting" visible is feather window (transition) is too large

Slide credit: Efros

Effect of feather window size





Seams visible is feather window (transition) is too small

What do we want

- To avoid seams, transition window should be >= size of largest prominent feature
- To avoid ghosting, transition window should be smaller than ~ 2X smallest prominent feature
- In other words, the largest and smallest features need to be within a factor of two for feathering to generate good results
- Intuition:
  - Coarse structure of images (large features) should transition slowly between images
  - Fine structure should blend quickly!

Slide credit: Efros, Guerzhoy

Gaussian pyramid

G_0 = image

$G_1 = \text{down}(G_0)$

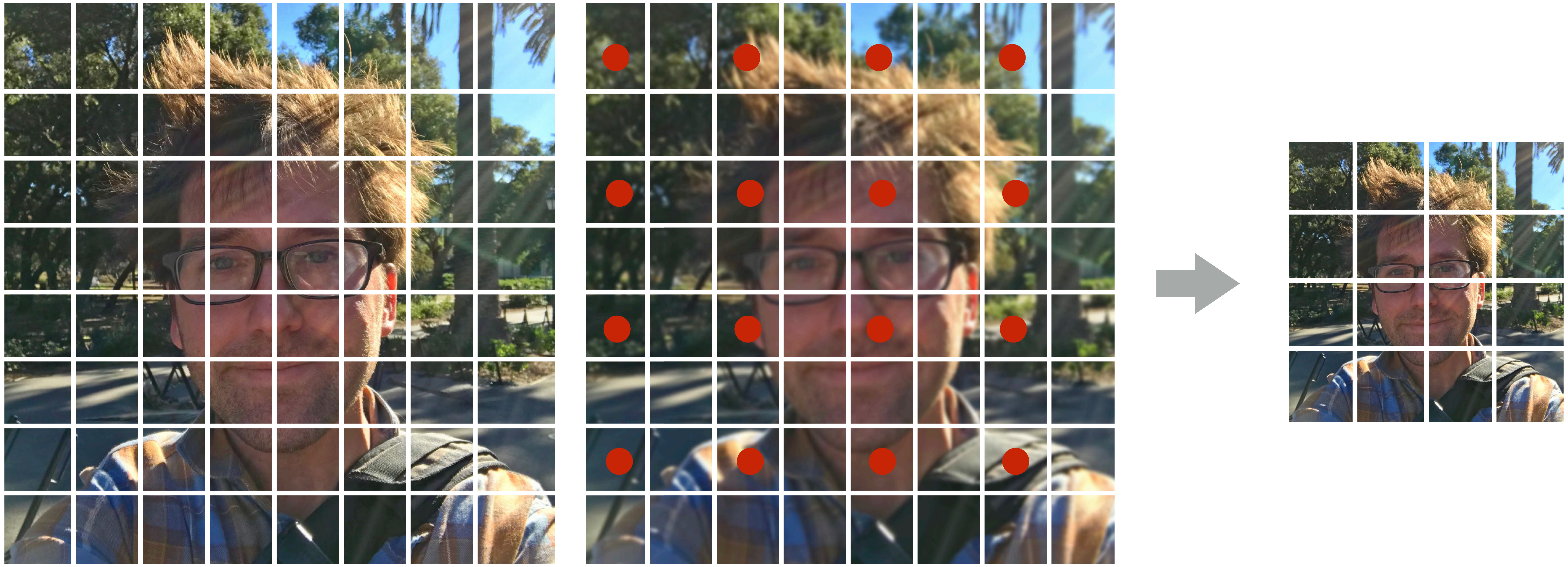
$G_2 = \text{down}(G_1)$

Each image in pyramid contains increasingly low-pass filtered signal

down() = image downsample operation

Downsample

- Step 1: Remove high frequency detail (blur)
- Step 2: Sparsely sample pixels (in this example: every other pixel)



Downsample

- **Step 1: Remove high frequencies (convolution)**
- **Step 2: Sparsely sample pixels (in this example: every other pixel)**

```
float input[(WIDTH+2) * (HEIGHT+2)];
float output[WIDTH/2 * HEIGHT/2];

float weights[] = {1/64, 3/64, 3/64, 1/64,    // 4x4 blur (approx Gaussian)
                   3/64, 9/64, 9/64, 3/64,
                   3/64, 9/64, 9/64, 3/64,
                   1/64, 3/64, 3/64, 1/64};

for (int j=0; j<HEIGHT/2; j++) {
   for (int i=0; i<WIDTH/2; i++) {
      float tmp = 0.f;
      for (int jj=0; jj<4; jj++)
         for (int ii=0; ii<4; ii++)
            tmp += input[(2*j+jj)*(WIDTH+2) + (2*i+ii)] * weights[jj*3 + ii];
      output[j*WIDTH/2 + i] = tmp;
  }
}
```

Gaussian pyramid

G_0

Gaussian pyramid

G_1

Gaussian pyramid

G_2

Gaussian pyramid

G_3

Gaussian pyramid

G_4

Gaussian pyramid

G_5

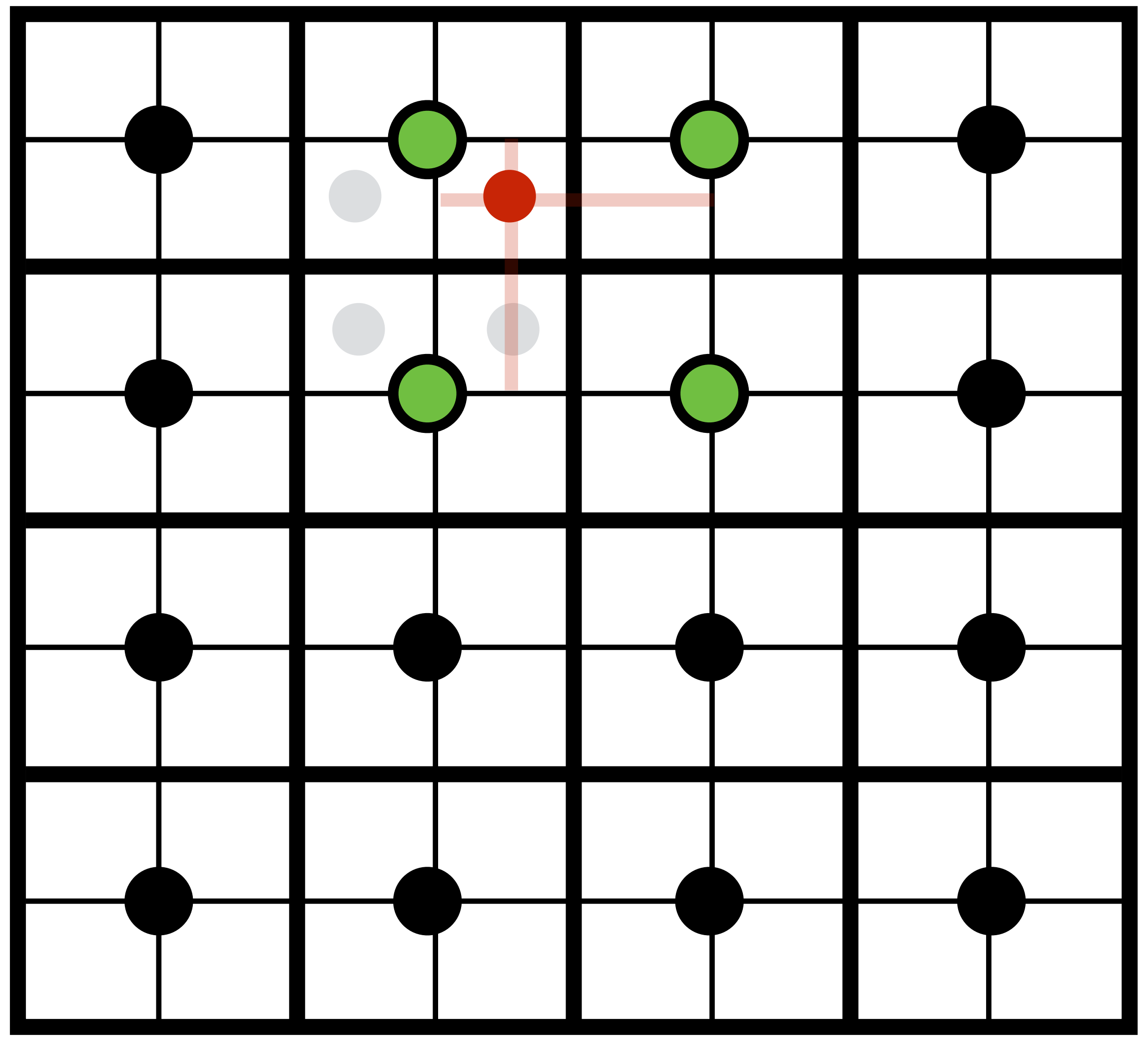
Upsample

Via bilinear interpolation of samples from low resolution image

Upsample

Via bilinear interpolation of samples from low resolution image

```
float input[WIDTH * HEIGHT];
float output[2*WIDTH * 2*HEIGHT];

for (int j=0; j<2*HEIGHT; j++) {
   for (int i=0; i<2*WIDTH; i++) {
      int row = j/2;
      int col = i/2;
      float w1 = (i%2) ? .75f : .25f;
      float w2 = (j%2) ? .75f : .25f;

      output[j*2*WIDTH + i] = w1 * w2 * input[row*WIDTH + col] +
                              (1.0-w1) * w2 * input[row*WIDTH + col+1] +
                              w1 * (1-w2) * input[(row+1)*WIDTH + col] +
                              (1.0-w1)*(1.0-w2) * input[(row+1)*WIDTH + col+1];
  }
}
```



Laplacian pyramid

$L_0 = G_0 - \mathrm{up}(G_1)$

G_0

$G_1 = \mathrm{down}(G_0)$

Each (increasingly numbered) level in Laplacian pyramid represents a band of (increasingly lower) frequency information in the image

[Burt and Adelson 83]

Laplacian pyramid

$L_0 = G_0 - up(G_1)$

$L_1 = G_1 - up(G_2)$

Laplacian pyramid

$L_0 = G_0 - up(G_1)$

$L_1 = G_1 - up(G_2)$

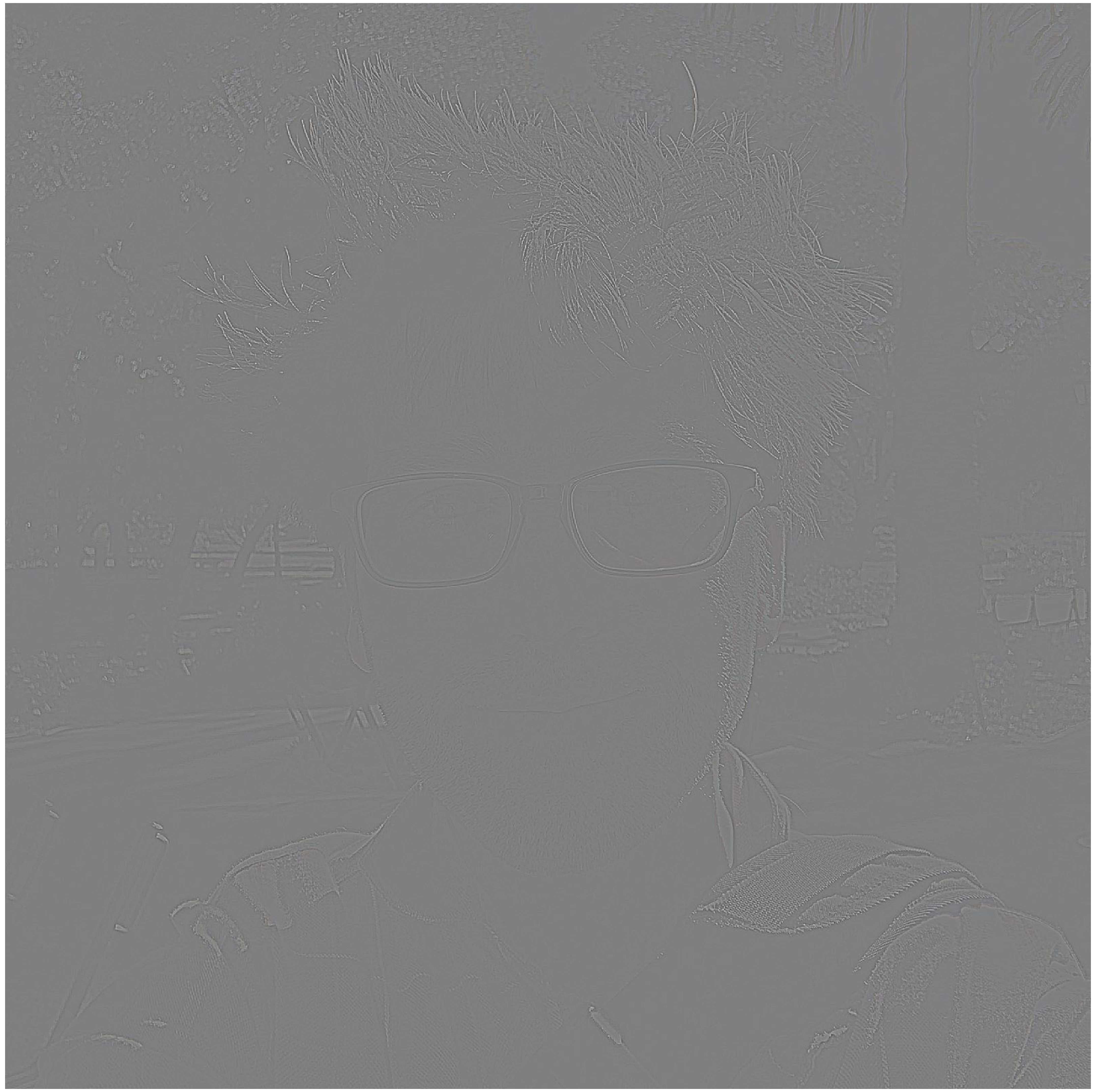
$L_2 = G_2 - up(G_3)$

$L_3 = G_3 - up(G_4)$

$L_4 = G_4$

Question: how do you reconstruct original image from its Laplacian pyramid?

Laplacian pyramid



$L_0 = G_0 - up(G_1)$

Laplacian pyramid

$L_1 = G_1 - up(G_2)$

Laplacian pyramid

$L_2 = G_2 - \text{up}(G_3)$

Laplacian pyramid

$L_3 = G_3 - \mathrm{up}(G_4)$

Laplacian pyramid

$L_4 = G_4 - \mathrm{up}(G_5)$

Laplacian pyramid

$L_5 = G_5$

Gaussian/Laplacian pyramid summary

- Gaussian and Laplacian pyramids are image representations where each pixel maintains information about frequency content in a region of the image

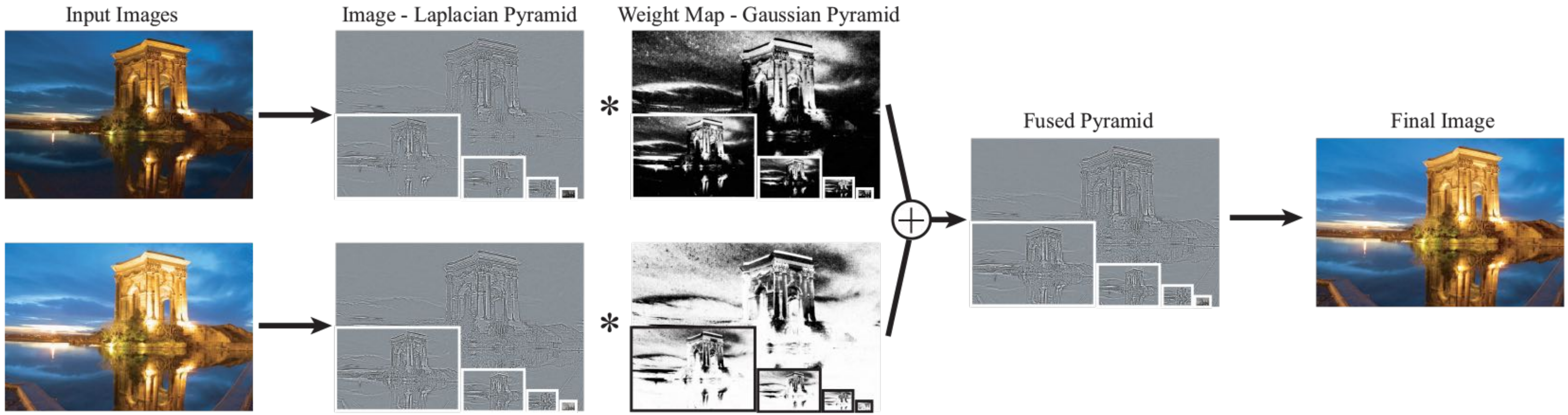
- $G_i(x,y)$ — frequencies up to limit given by *i*

- $L_i(x,y)$ — frequencies added to G_{i+1} to get G_i

- Notice: to boost the band of frequencies in image around pixel (x,y), increase coefficient $L_i(x,y)$ in Laplacian pyramid

Use of Laplacian pyramid in local tone mapping

- Compute weights for all Laplacian pyramid levels
- Merge pyramids (image features) not image pixels
- Then "flatten" merged pyramid to get final image



Merging Laplacian pyramids

Four exposures (weights not shown)

Merged result
(after blurring weight mask)
Notice "halos" near edges

Merged result
(based on multi-resolution pyramid merge)

Why does merging Laplacian pyramids work better than merging image pixels?

Summary: simplified image processing pipeline

- Correct pixel defects
- Align and merge (to create high signal to noise ration RAW image)
- Correct for sensor bias (using measurements of optically black pixels)
- Vignetting compensation
- White balance

(10-12 bits per pixel)
1 intensity value per pixel
Pixel values linear in energy

- Demosaic
- Denoise
- Gamma Correction (non-linear mapping)

3x10 bits per pixel
RGB intensity per pixel
Pixel values linear in energy

- Local tone mapping
- Final adjustments sharpen, fix chromatic aberrations, hue adjust, etc.

3x8-bits per pixel
Pixel values perceptually linear

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