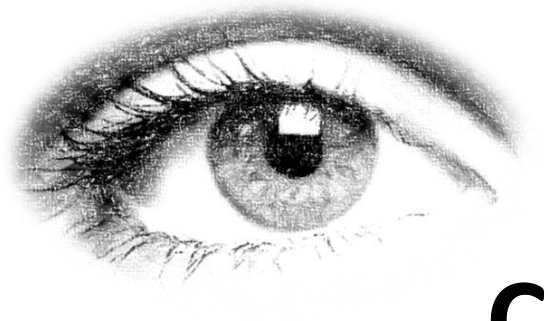


Camera Basics, Image Formation, and Image Processing

First version was created by Wei-Chih Tu, 2018

Vision

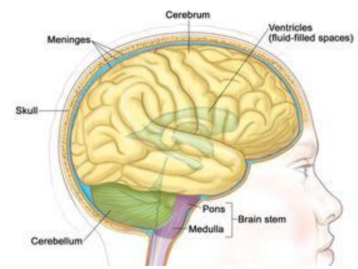
- How vision is formed

Physical world

Sensing device

Image formation

Interpreting device



CPU/GPU/DSP

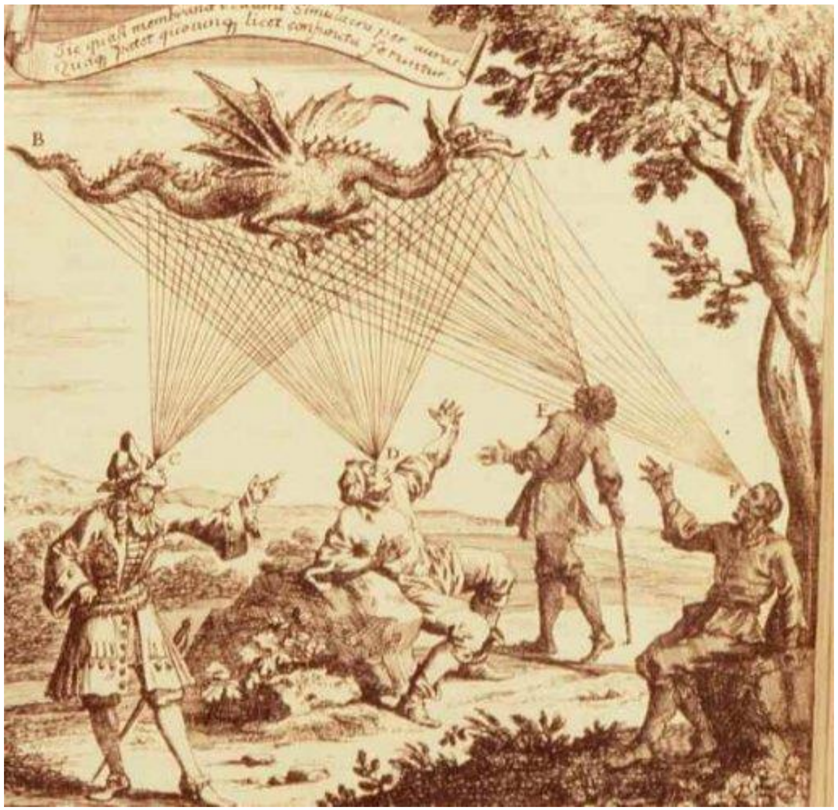
Image processing

Interpretations

cat, lovely, in a box

Image Formation

- Emission theory of vision



Eyes send out “feeling rays” into the world

Supported by:

- Empedocles
- Plato
- Euclid
- Ptolemy
- …
- 50% of US college students*

*http://www.ncbi.nlm.nih.gov/pubmed/12094435?dopt=Abstract

“For every complex problem there is an answer that is clear, simple, and wrong.”
-- H. L. Mencken

Image Formation

- The human eye is a camera
  - The image is inverted, but the spatial relationships are preserved

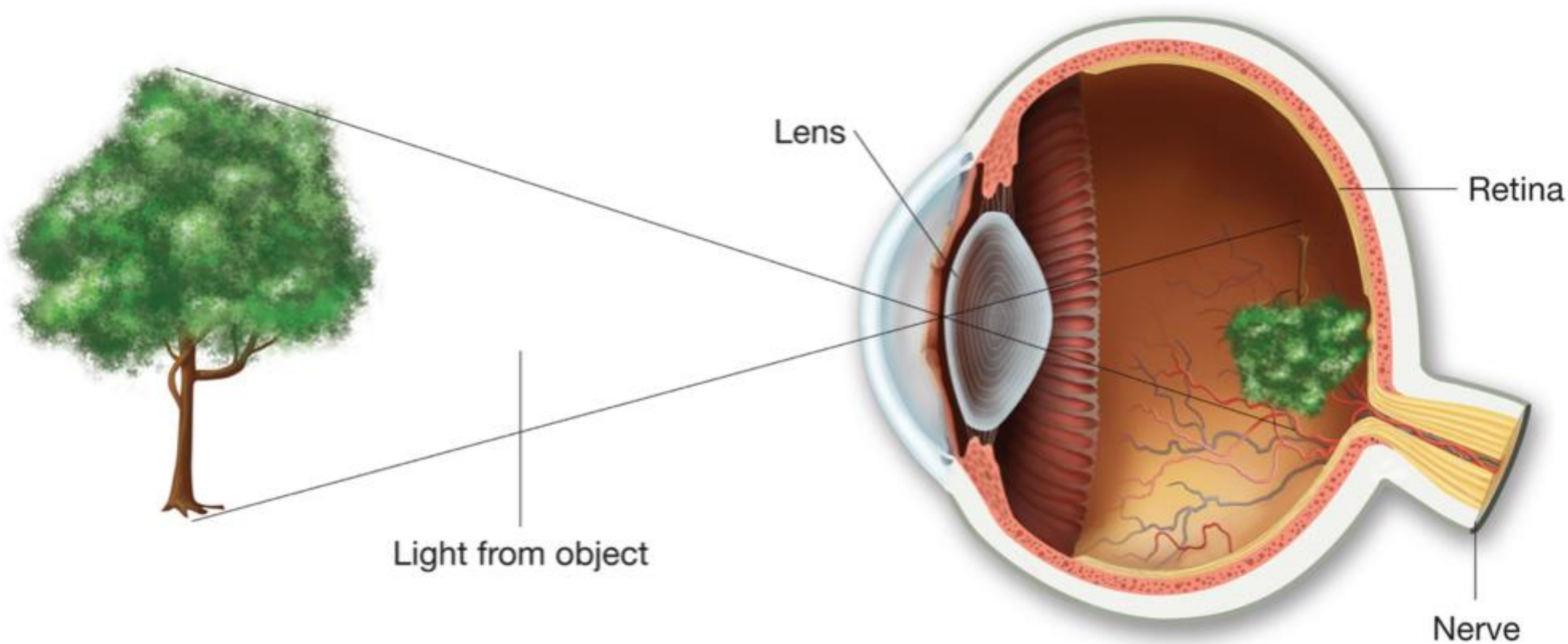


Image Formation

- Building a camera
  - Put a piece of film in front of an object

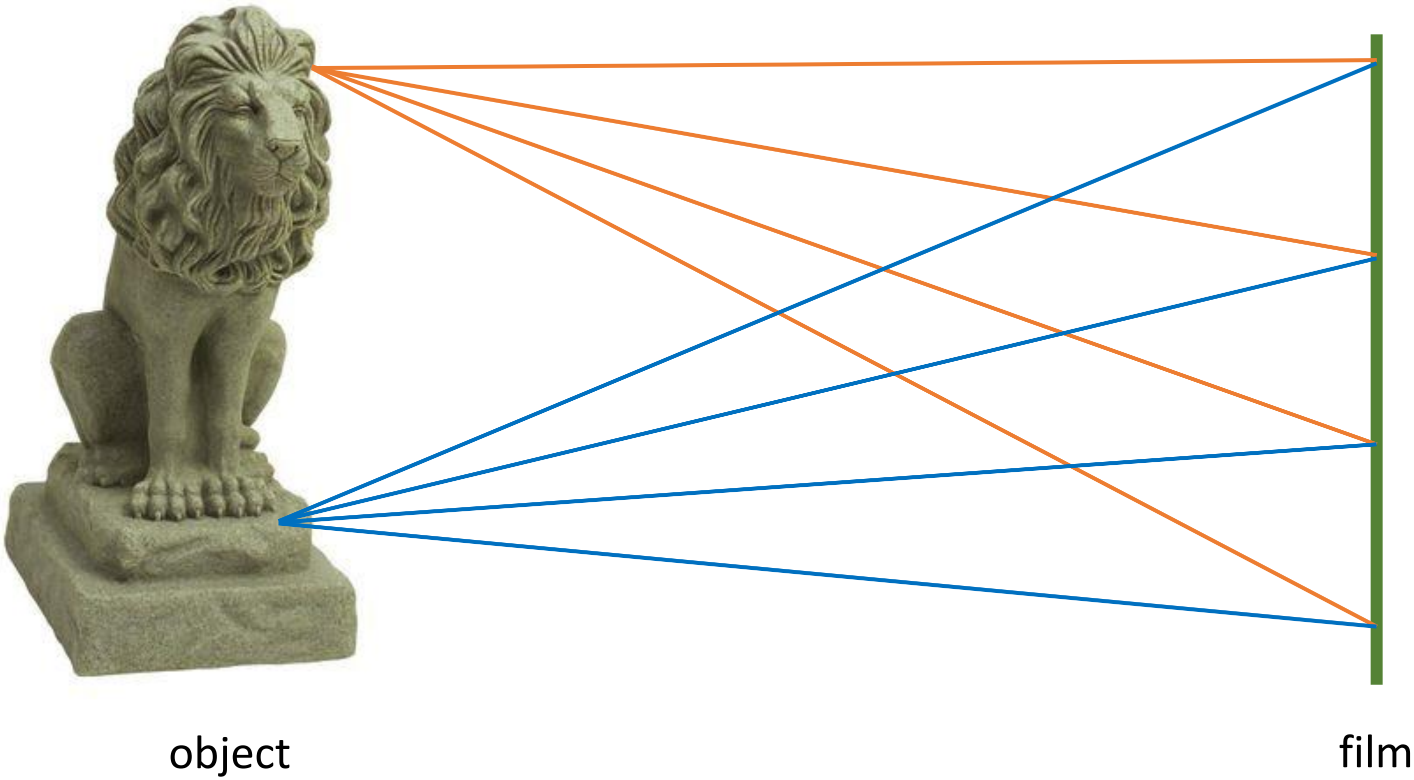
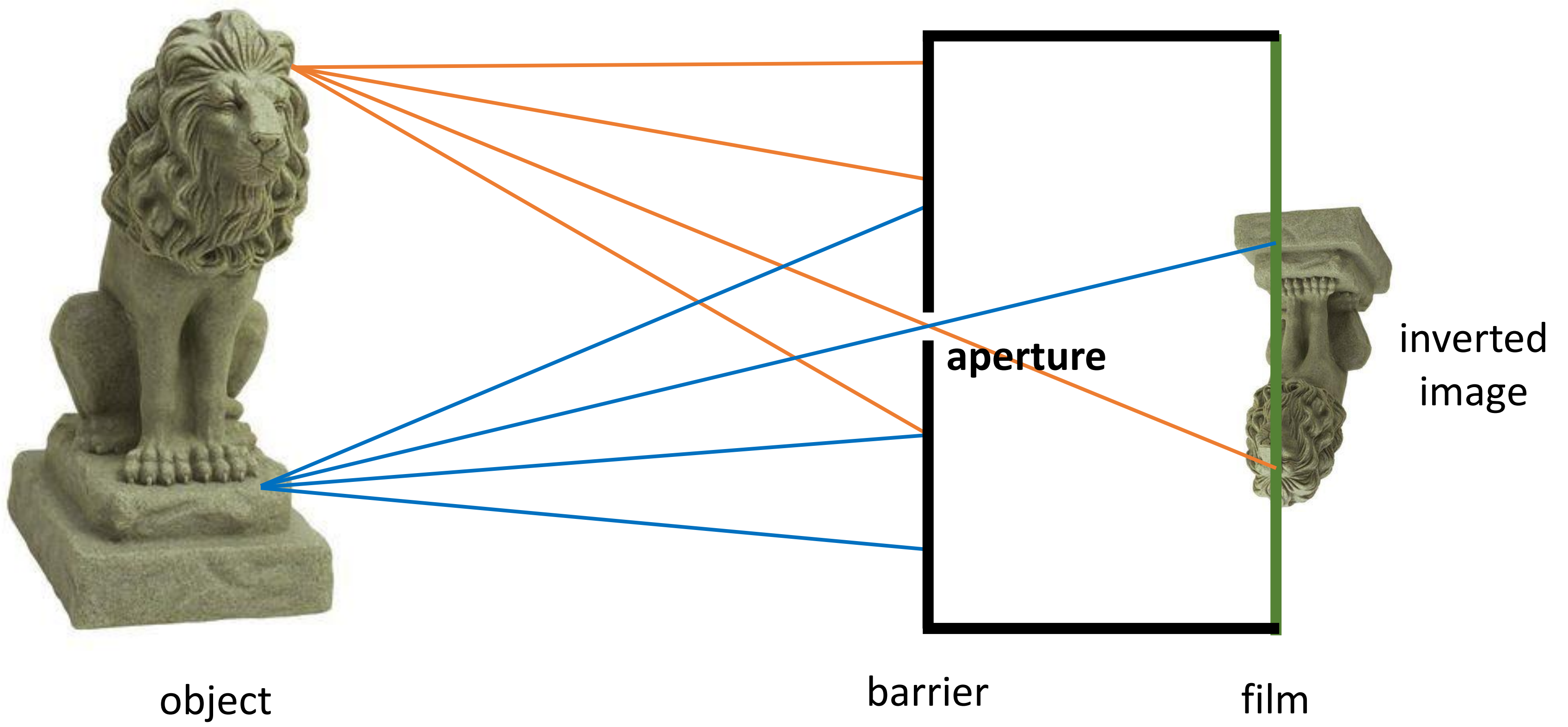


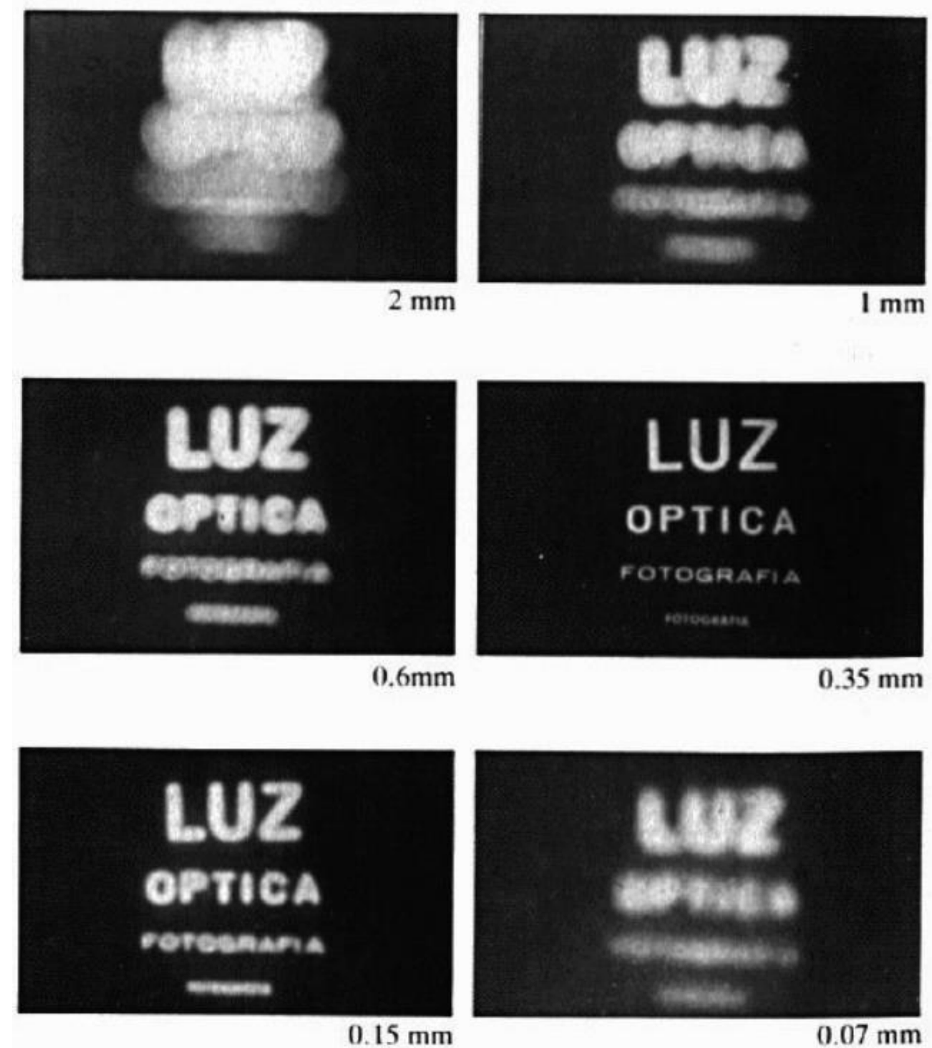
Image Formation

- Add a barrier to block off most of the rays
  - This reduces blurring



Aperture Size Matters

- Why not making the aperture as small as possible?
    - Less light get through
    - Diffraction effect



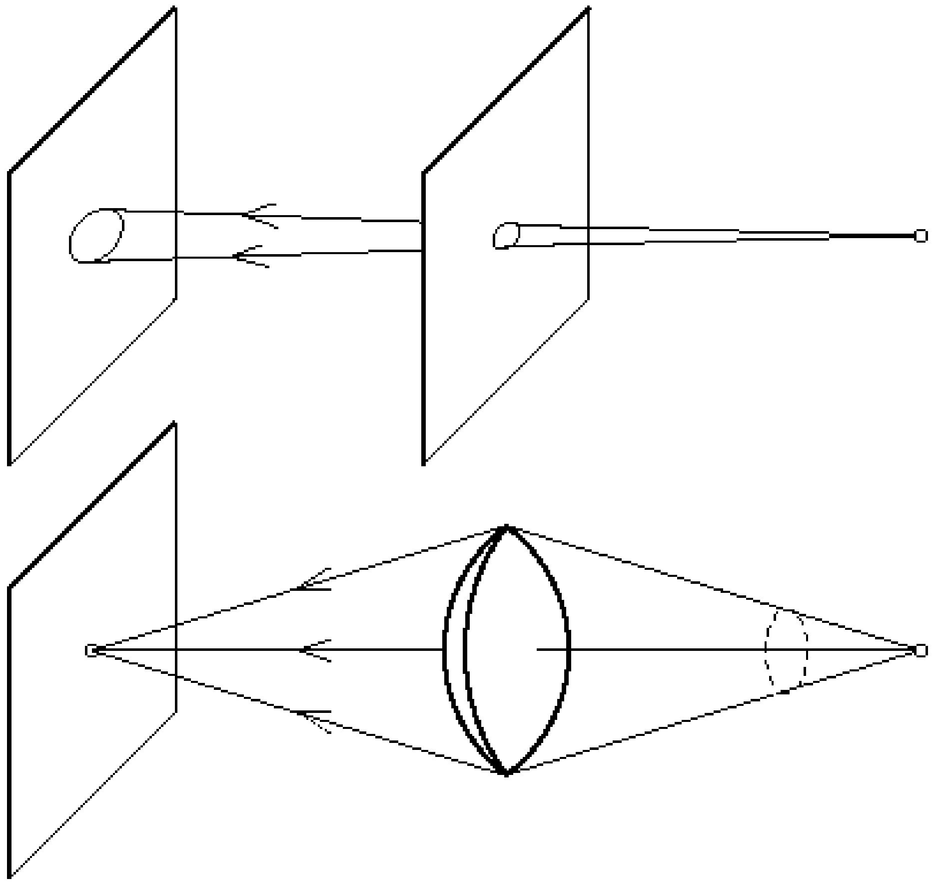
Slide by Steve Seitz

The “Trashcam” Project

https://petapixel.com/2012/04/18/german-garbage-men-turn-dumpsters-into-giant-pinhole-cameras/

Image Formation

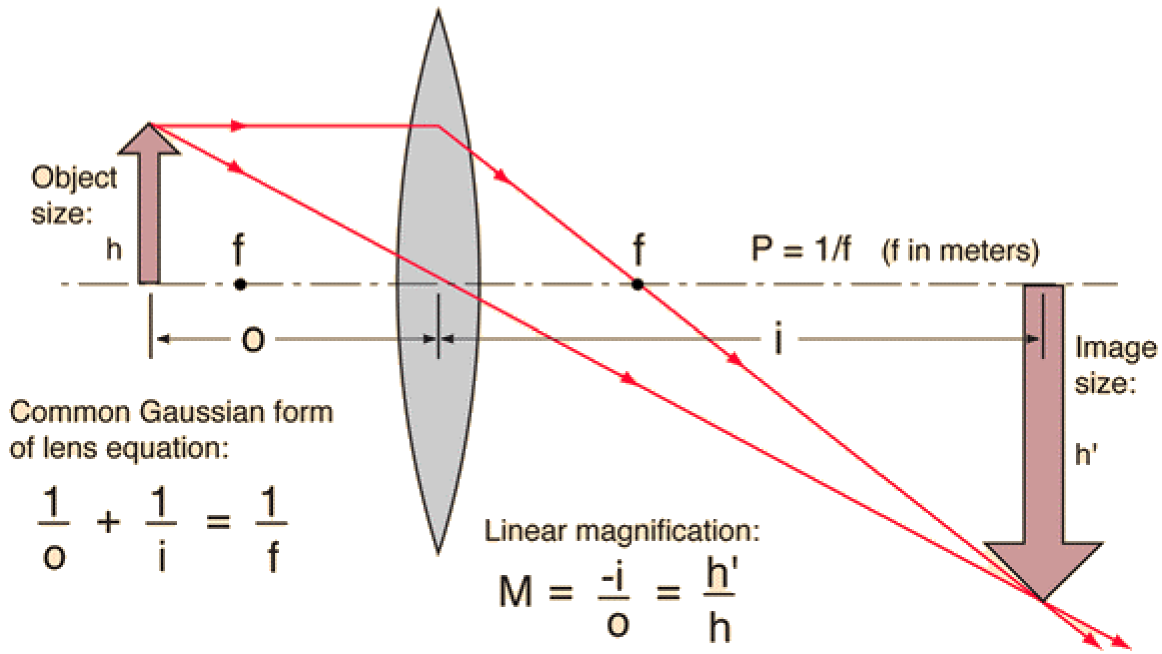
- Adding a lens



Slide by Steve Seitz

Image Formation

- Thin lens equation



Source: https://www.chegg.com/homework-help/questions-and-answers/theory-thin-lens-equation-written-1-f-1-0-1-f-focal-length-o-object-distance-image-distanc-q13090621

Image Formation

- The lens focuses light onto the film

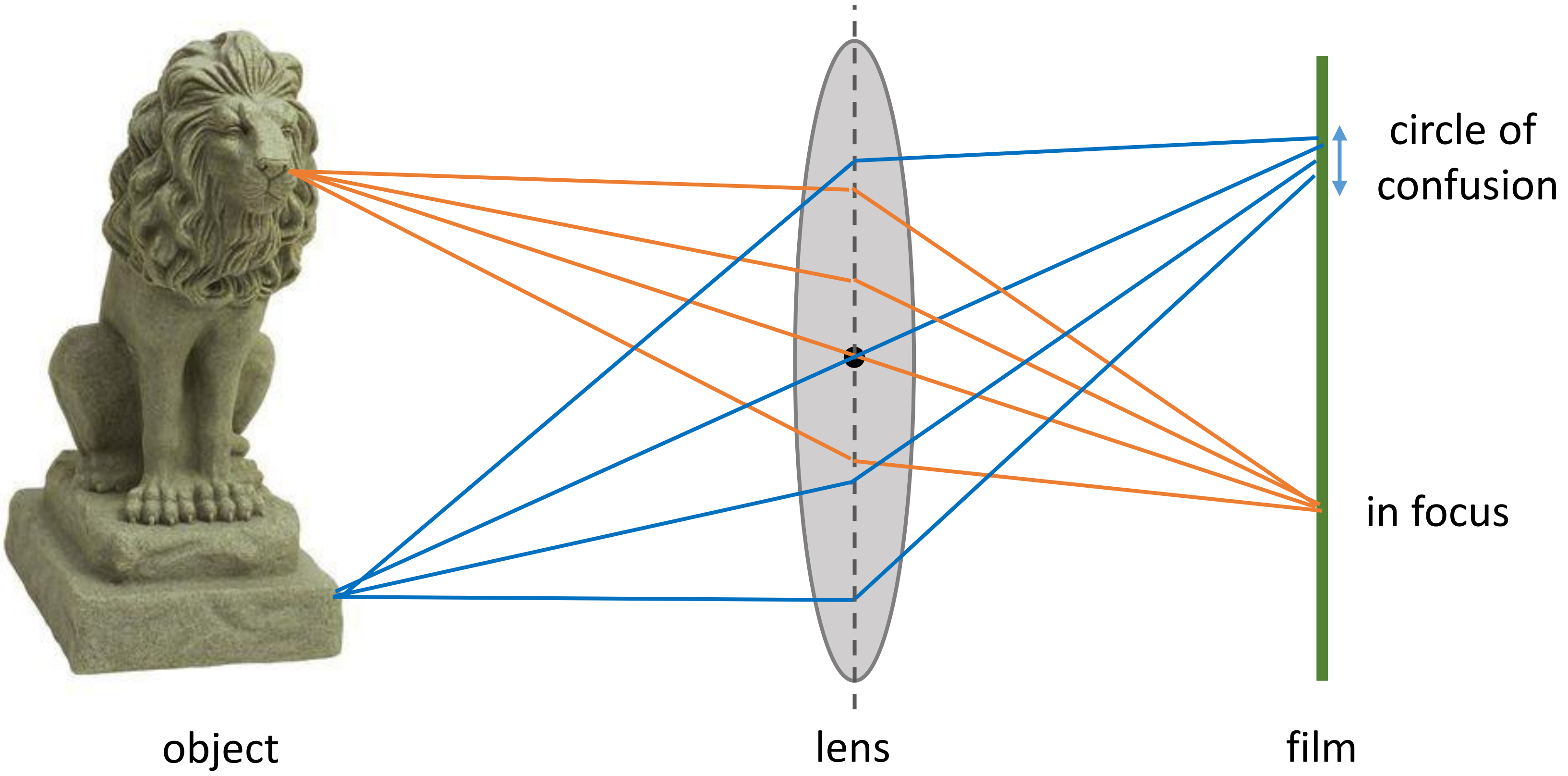
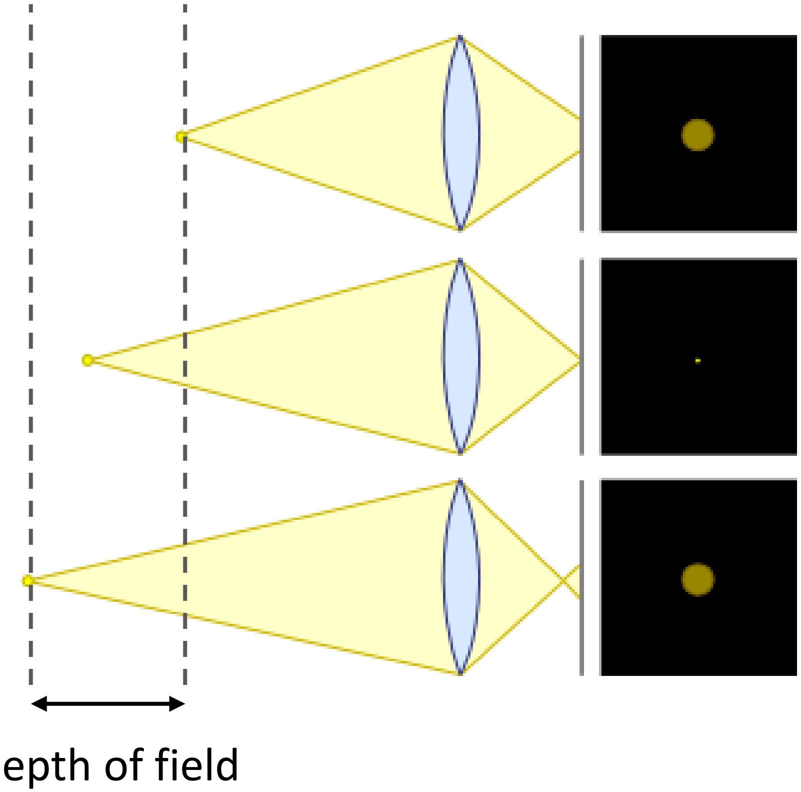


Image Formation

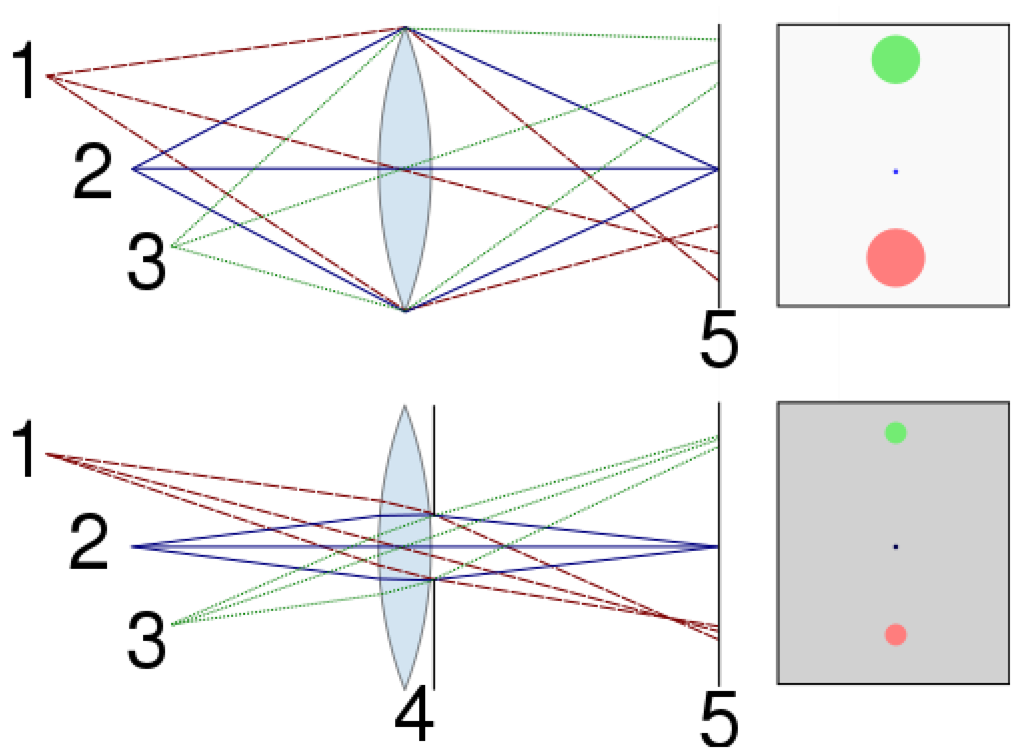
- Circle of confusion controls depth of field



Wiki: circle of confusion

Image Formation

- Aperture also controls depth of field



Wiki: depth of field

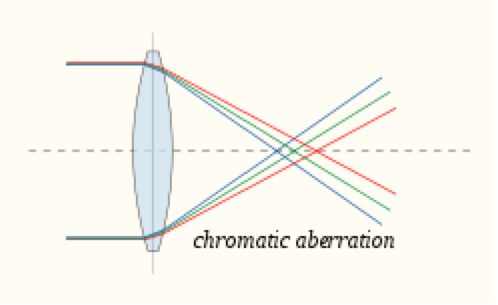
Image Formation

- Defocus

Source: AMC

Image Formation

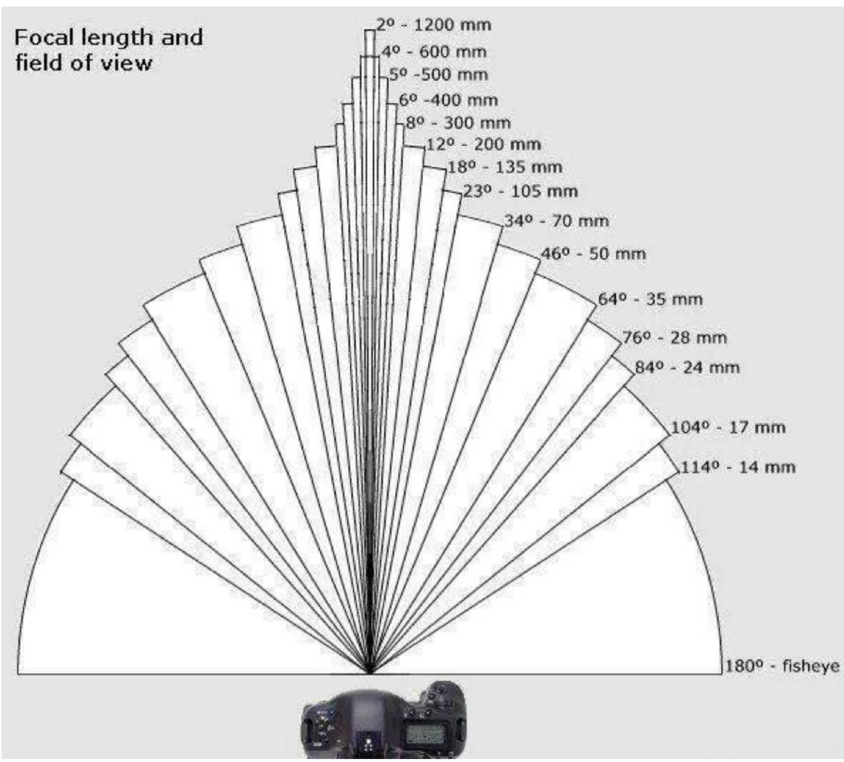
- Real lens consists of two or more pieces of glass
    - To alleviate chromatic aberration and vignetting

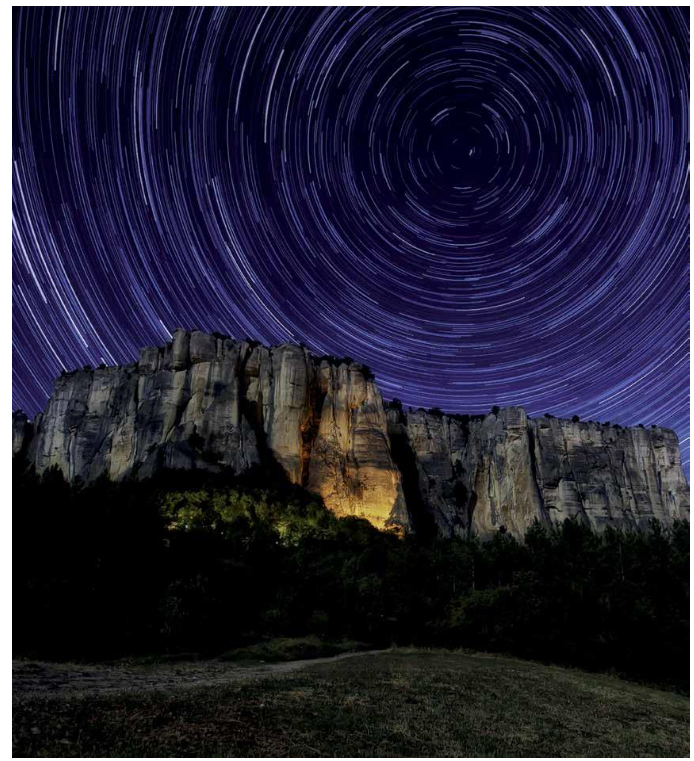


Vignetting

Image Formation

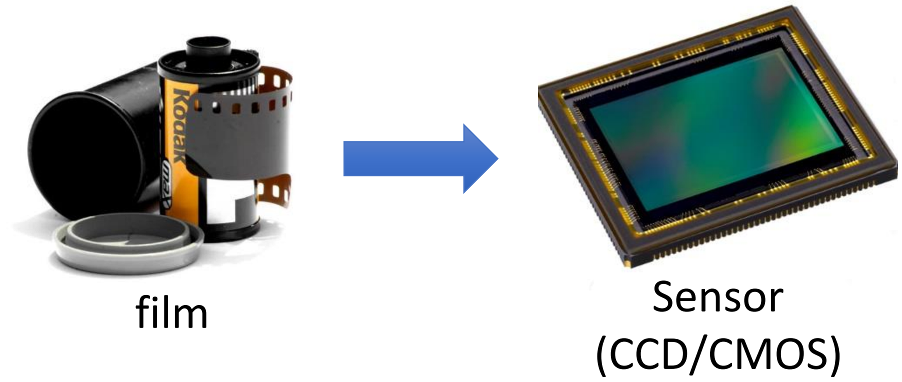
- Focal length controls field of view
- Shutter speed (exposure time) also matters

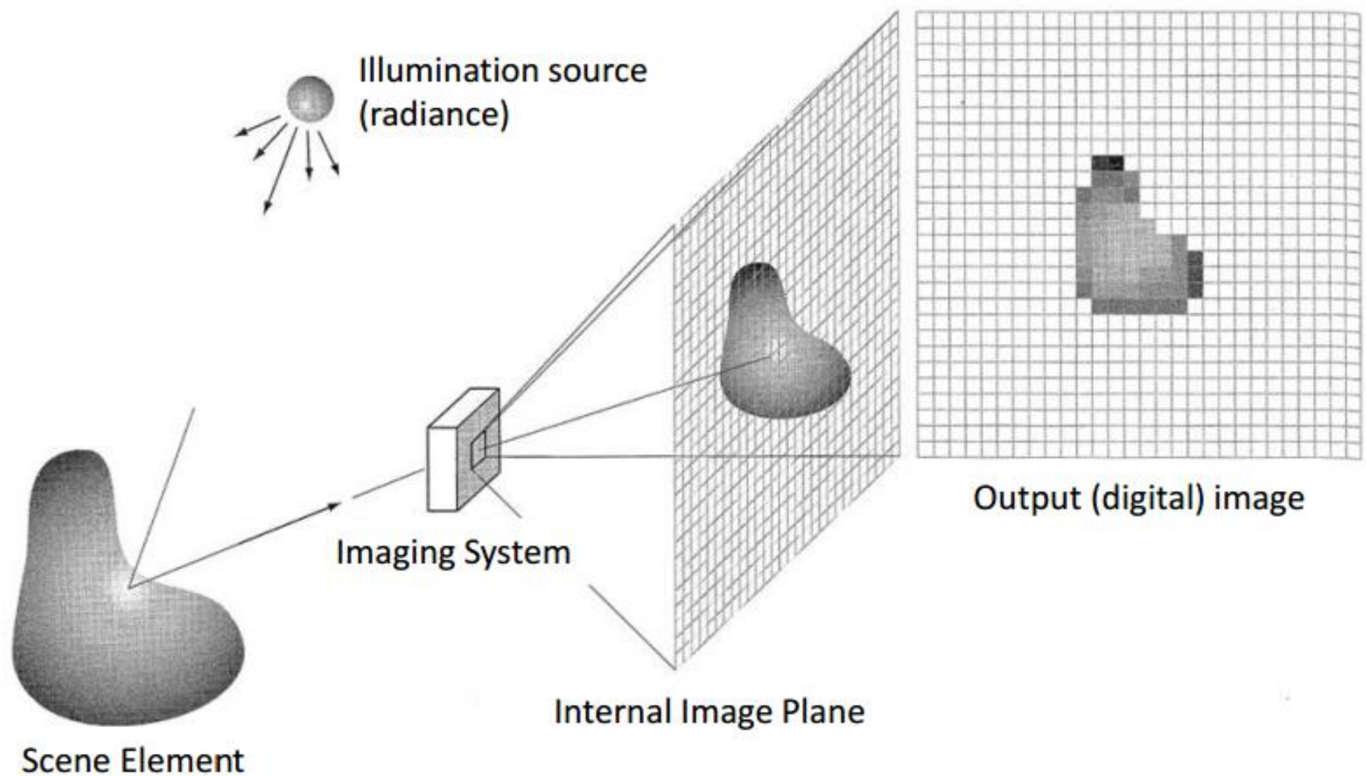




Source: National Geographic

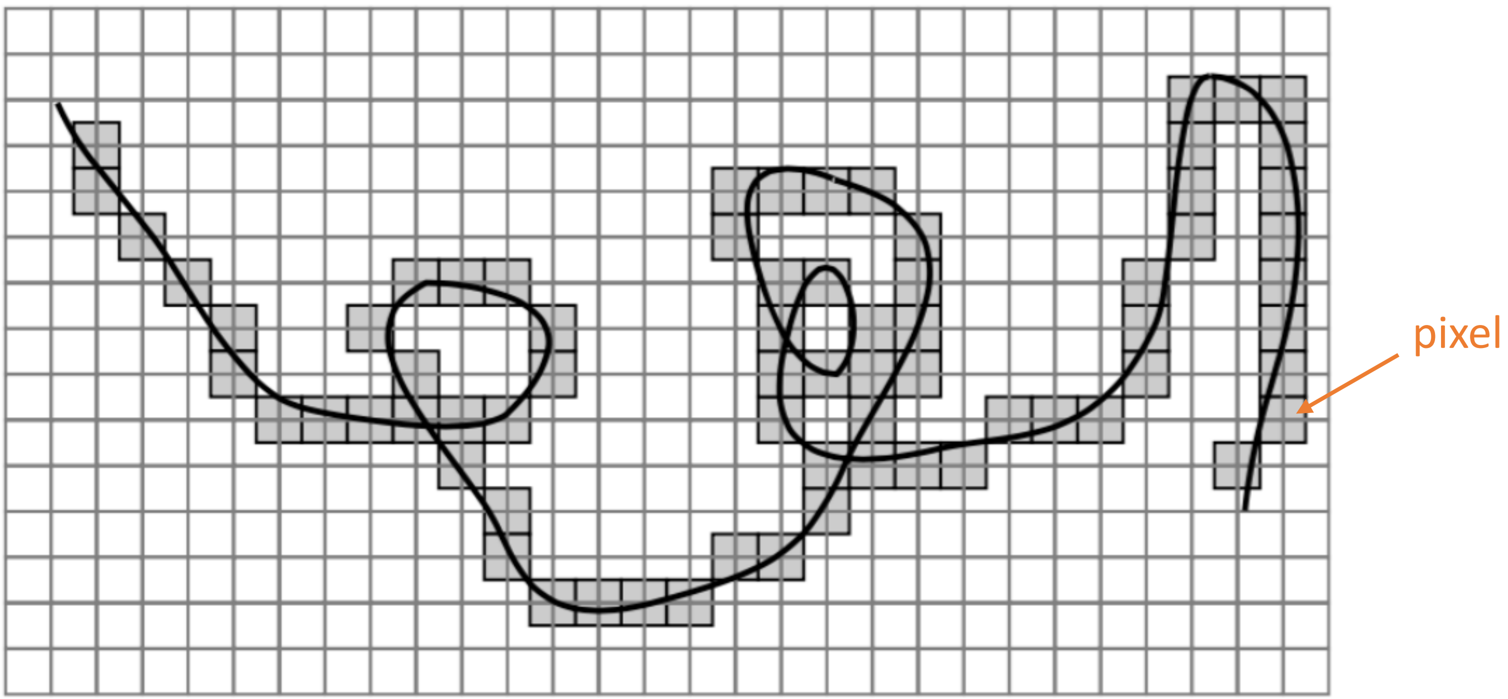
Digital Imaging





Digital Imaging

- Images are **sampled** and **quantized**
  - **Sampled:** discrete space (and time)
  - **Quantized:** only a finite number of possible values (*i.e.* 0 to 255)



Source: Ulas Bagci

Digital Imaging

- Camera pipeline

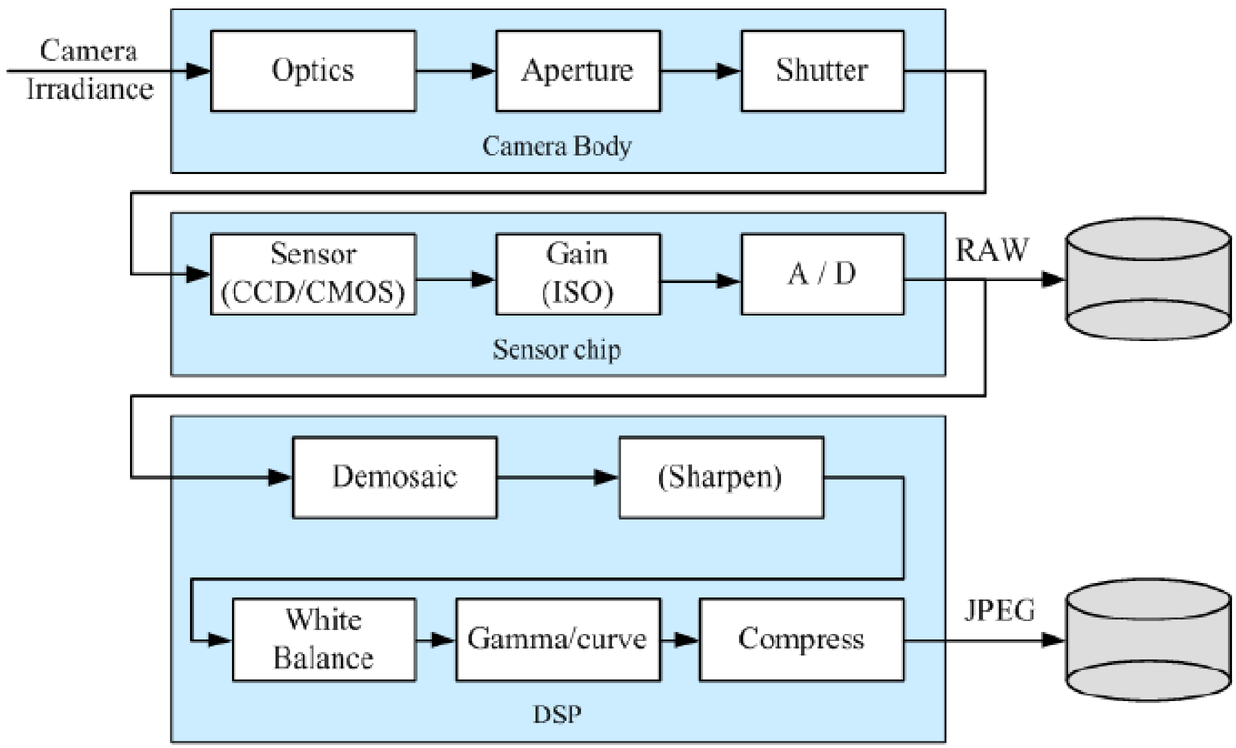


Figure 2.23 from *Computer Vision: Algorithms and Applications*

Digital Imaging

- Resolution
  - Image sensor samples and quantizes the scene

Low sampling rate may cause **aliasing** artifact

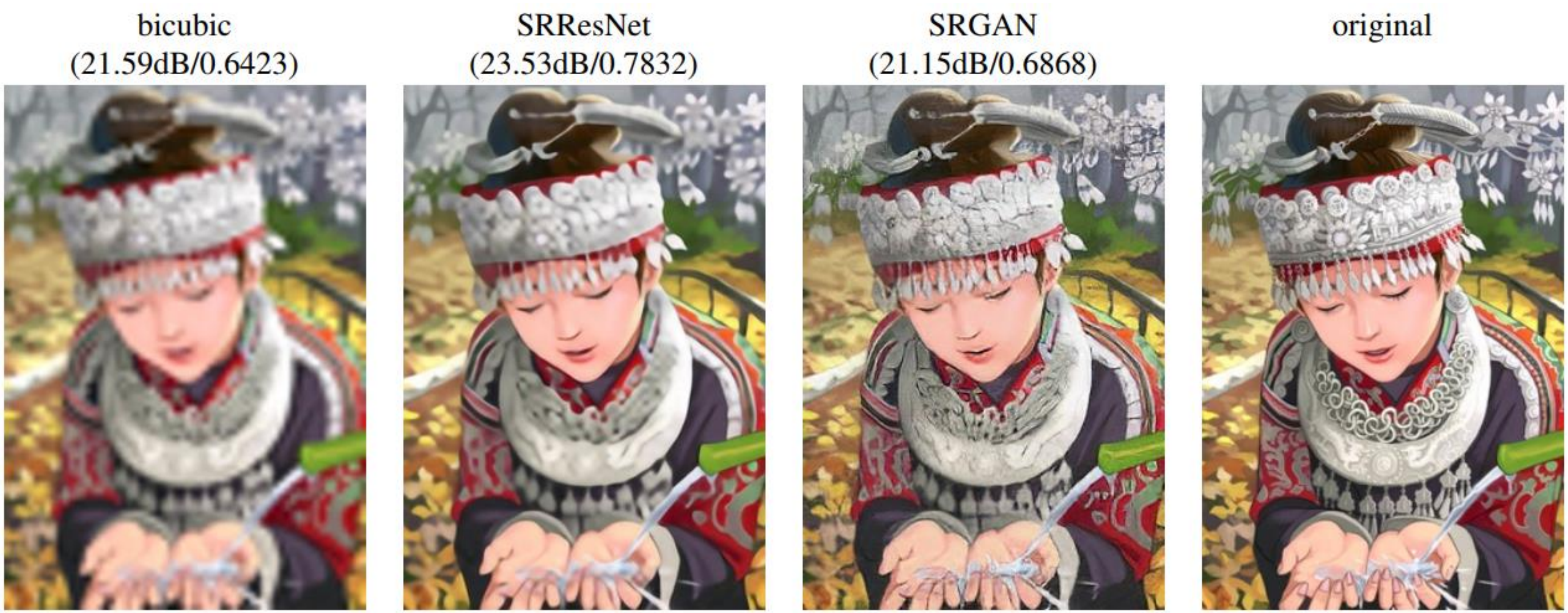
High resolution

Low resolution

Figure by Yen-Cheng Liu

Digital Imaging

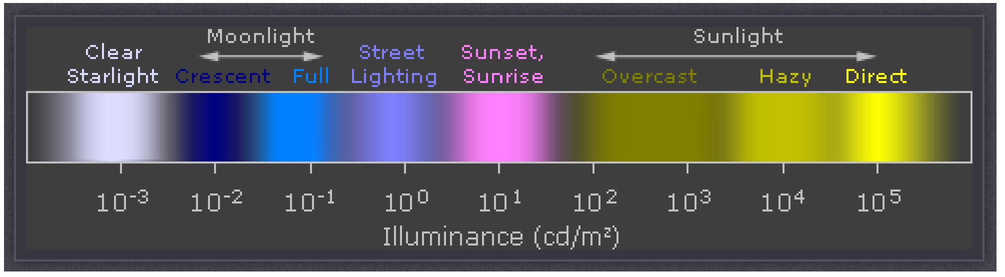
- Super resolution: the problem of resolving the high resolution image from the low resolution image



Example results of 4x upscaling. Figure from SRGAN [Ledig et al. CVPR 2017]

Digital Imaging

- Dynamic range
  - Information loss due to A/D conversion
  - Typical image: 8 bit ($0 \sim 255$)



The world is HDR and our eyes have great ability to sense it

An exposure bracketed sequence (Each picture is a LDR image)

Digital Imaging

- HDR imaging: LDRs → HDR
- Tone mapping: HDR → LDR

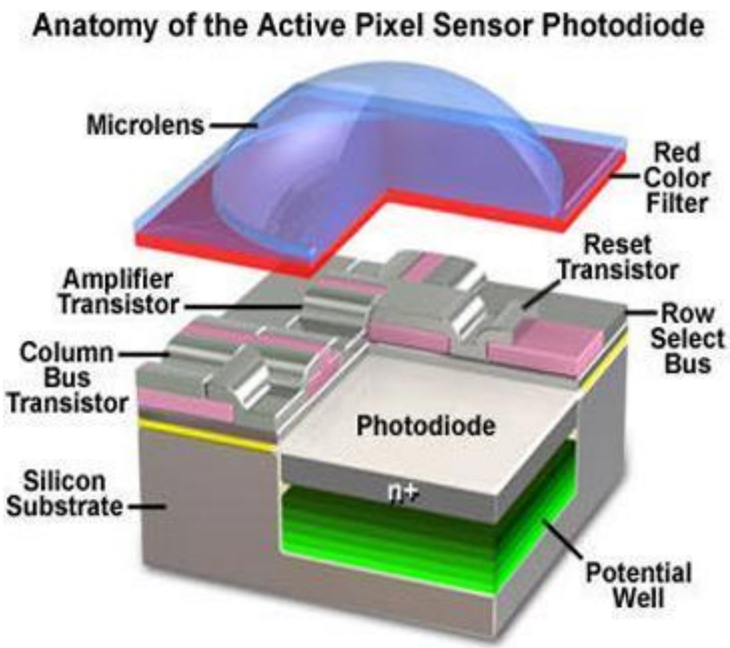
- Do we really need HDR?
  - Exposure fusion: LDRs → LDR
    [Mertens et al. PG 2007]

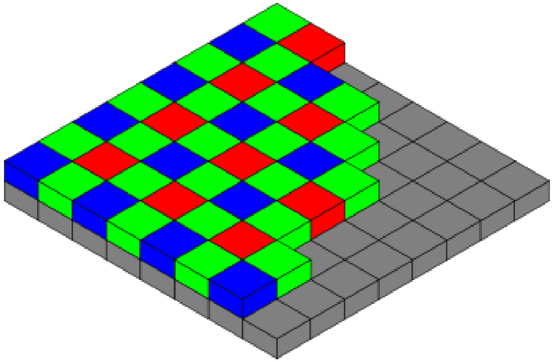
3 exposure (-2,0,+2) tone mapped image of a scene at Nippori Station.

Wiki: tone mapping

Digital Imaging

- Demosaicing: color filter array interpolation
  - The image sensor knows nothing about color!





Color filter array (CFA)
Bayer pattern: 1R1B2G in a 2x2 block

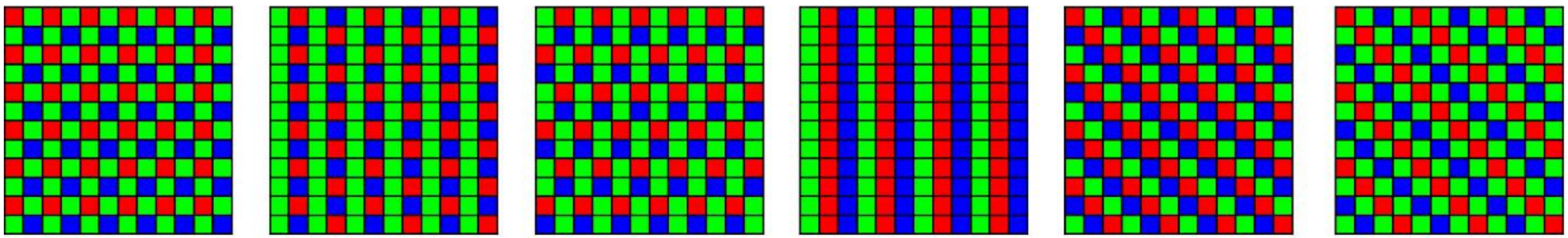
Digital Imaging

A picture of Alim Khan (1880-1944), Emir of Bukhara, taken in 1911.

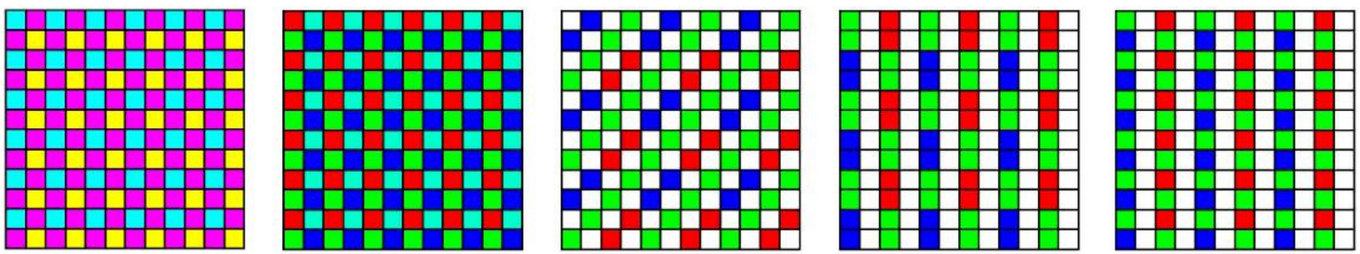
Wiki: Sergey Prokudin-Gorsky

Digital Imaging

- More CFA design



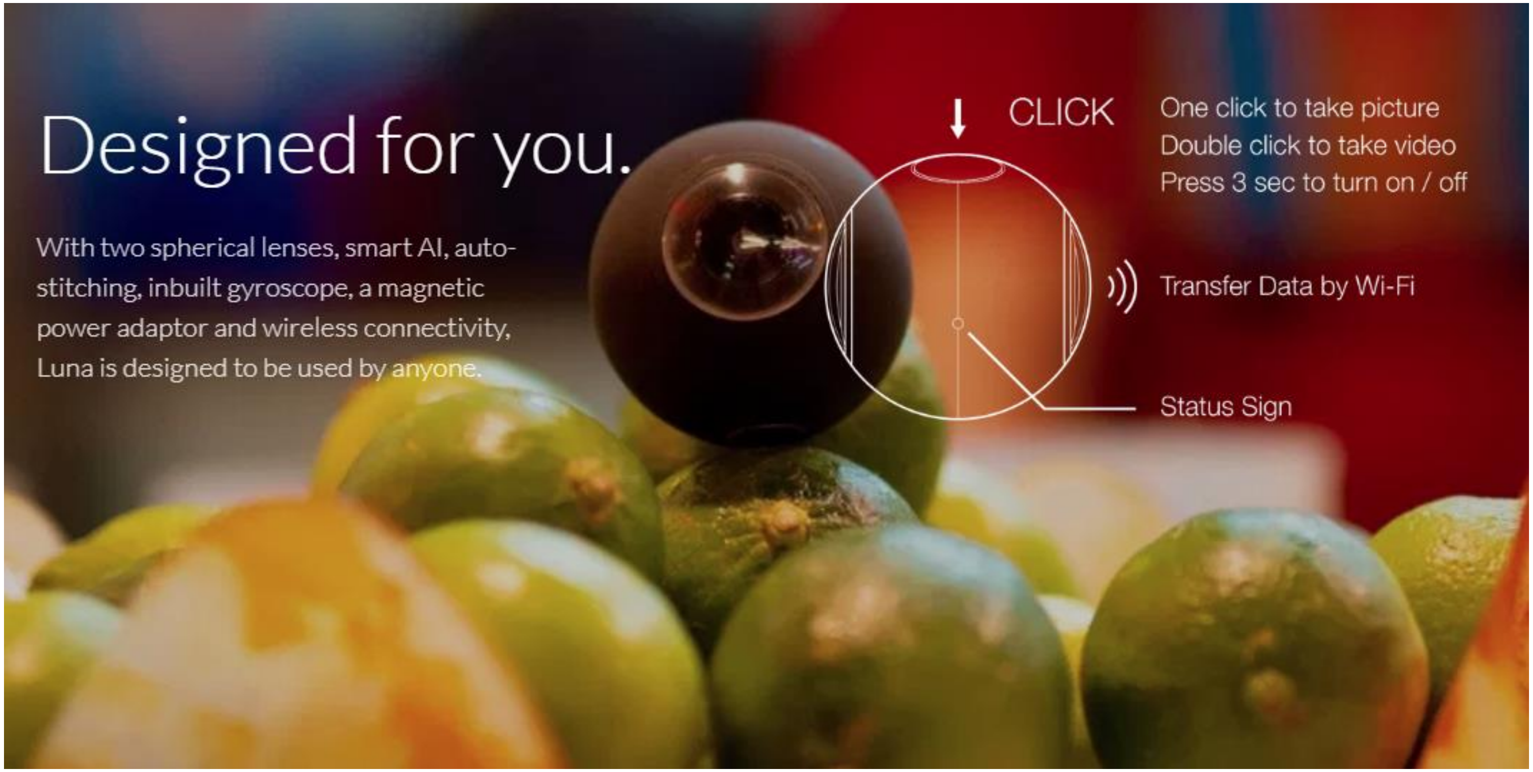
(a) Bayer [11] (b) Yamanaka [12] (c) Lukac [20] (d) Vertical (e) Diagonal (f) Modified Bayer [20]



(g) Cyan-Magenta-Yell. (h) Sony 4-Color [18] (i) Kodak Ver. 1 [22] (j) Kodak Ver. 2 [22] (k) Kodak Ver. 3 [22]

More Sensing Devices

- 360 camera



Source: LUNA

More Sensing Devices

- Infra-red camera

More Sensing Devices

- Depth camera

Kinect V2 (time of flight)

PointGrey Bumblebee 2 (stereo)

Vision

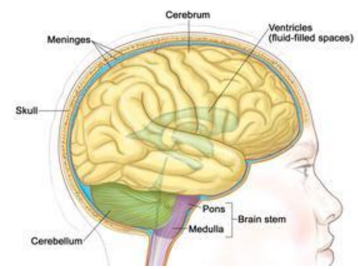
- How vision is formed

Physical world

Sensing device

Interpreting device

Interpretations



CPU/GPU/DSP

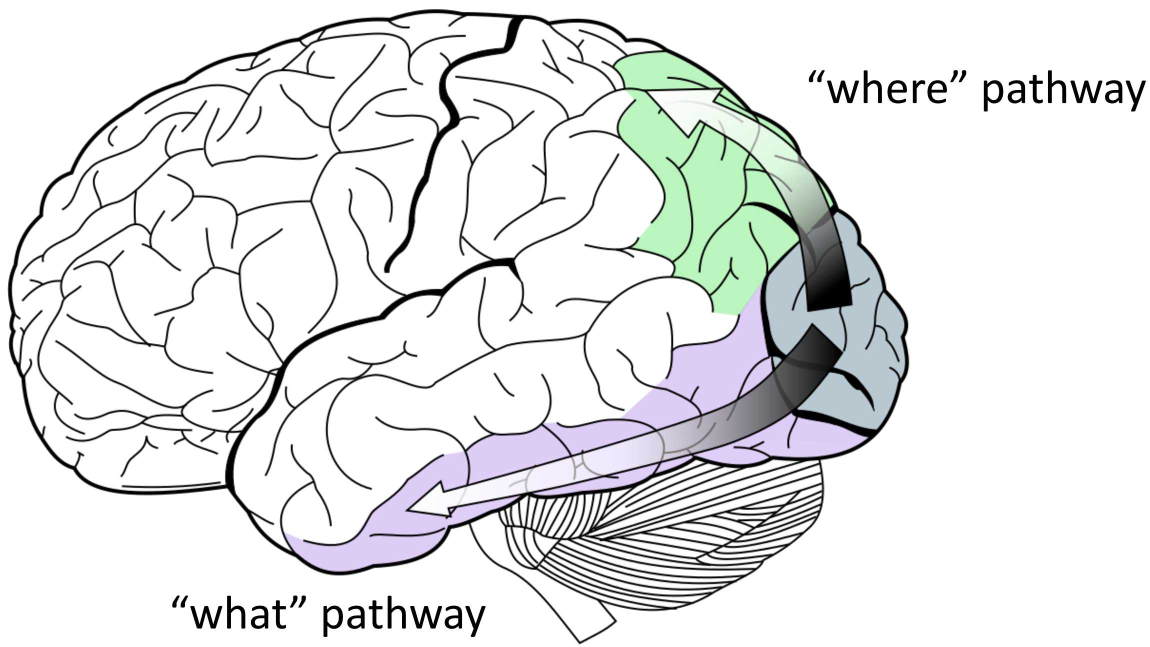
cat, lovely,
in a box

Image formation

Image processing

Image Processing in the Brain

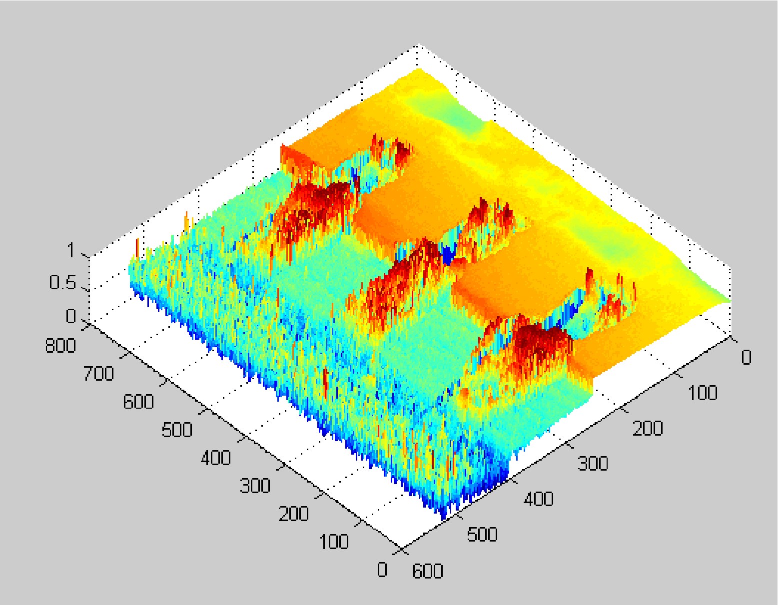
- The dorsal stream (green) and ventral stream (purple) are shown. They originate from a common source in the visual cortex.



Wiki: two-streams hypothesis

Digital Image Processing

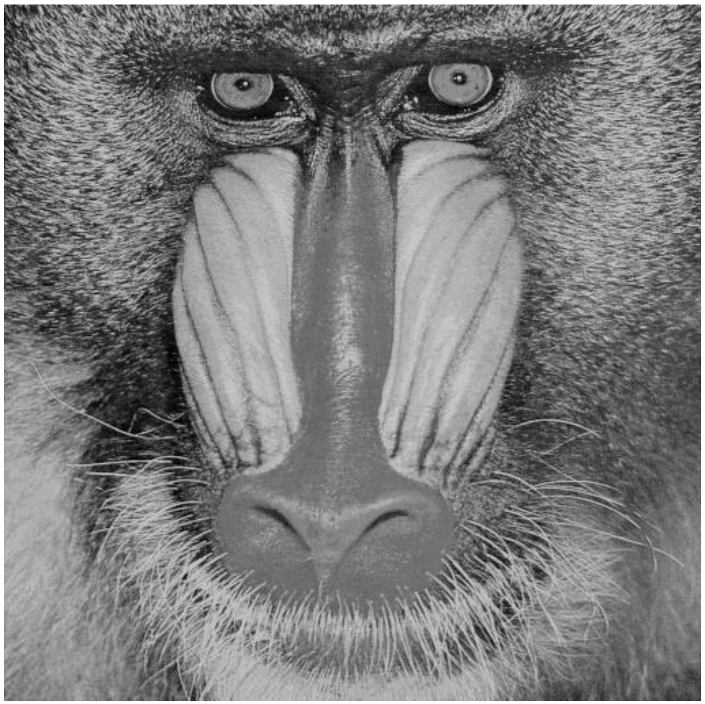
- Extract information (what and where) from digital images

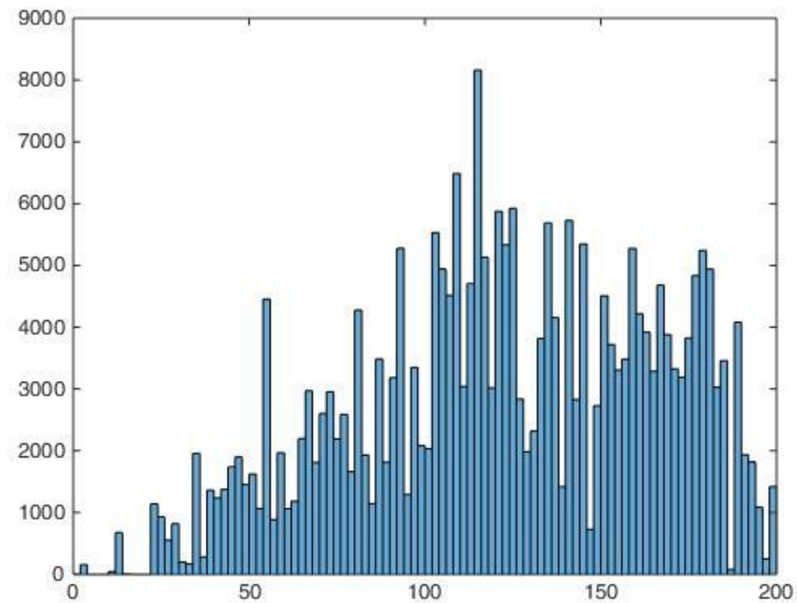


Digital Image Processing

- Some low-level image processing
  - Histogram
  - Morphological operations
  - Edge detection
  - Image filtering
- Topics to be covered in this course
  - Key point and feature descriptor
  - Matching
  - Geometric transformation
  - Semantic analysis
  - Learning-based techniques
  - …

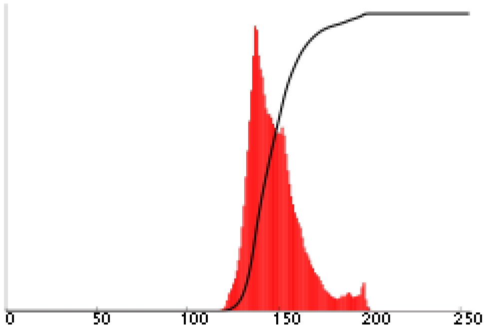
Histogram

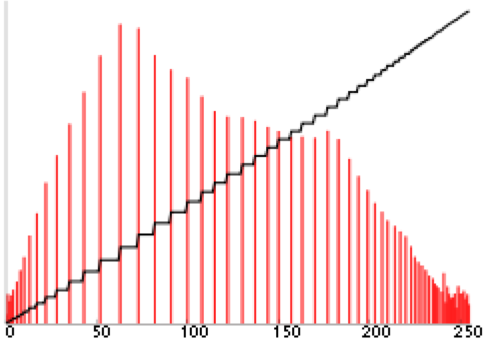




Histogram

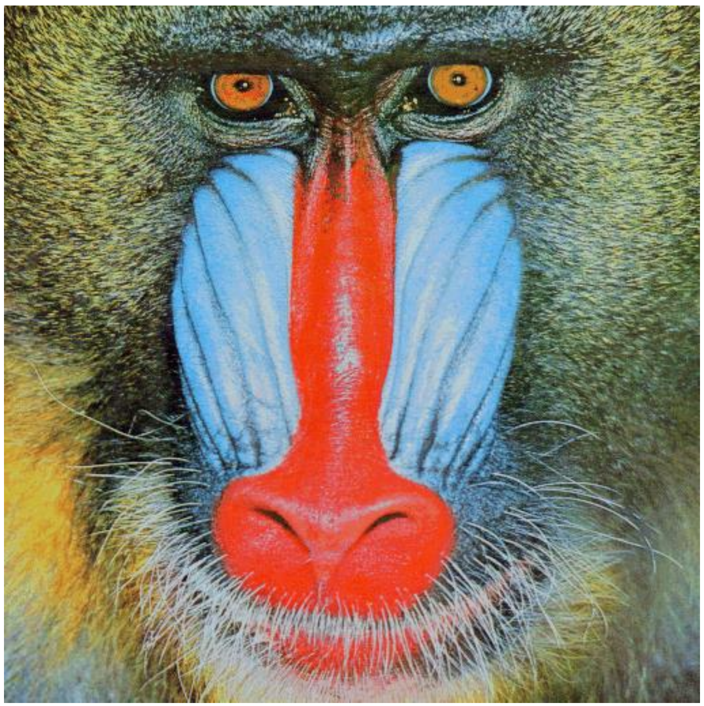
- Histogram equalization
  - By mapping CDF to the line $y = x$

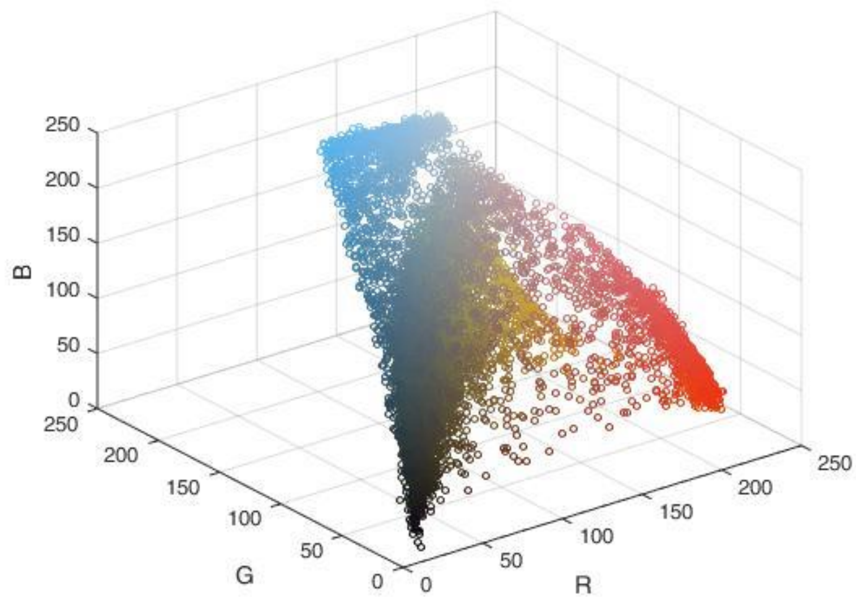




Histogram

- Understanding data distribution

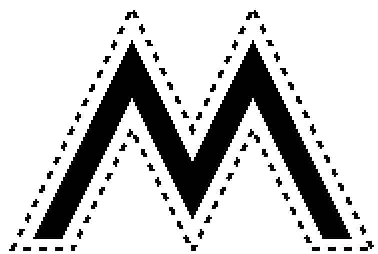




Morphological Operations

- Take a **binary image** and a **structuring element** as input.

Dilation



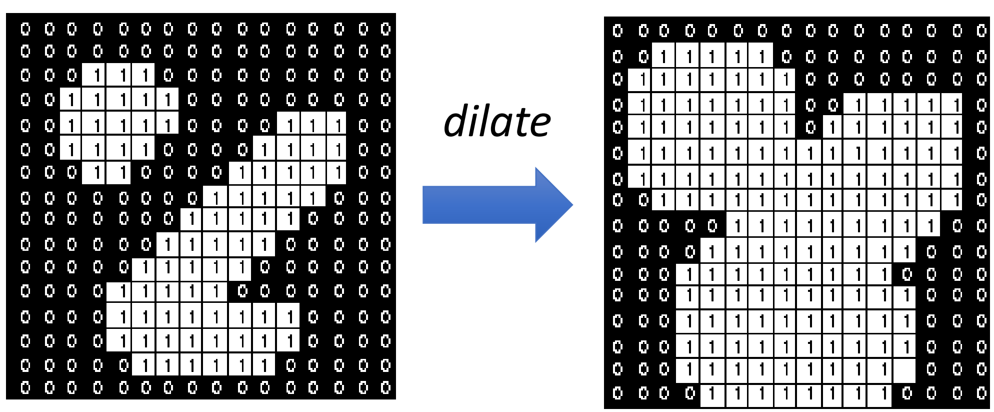
Erosion

1	1	1
1	1	1
1	1	1

Set of coordinate points =

{ (-1, -1), (0, -1), (1, -1),
(-1, 0), (0, 0), (1, 0),
(-1, 1), (0, 1), (1, 1) }

Example structuring element



https://homepages.inf.ed.ac.uk/rbf/HIPR2/morops.htm

Morphological Operations

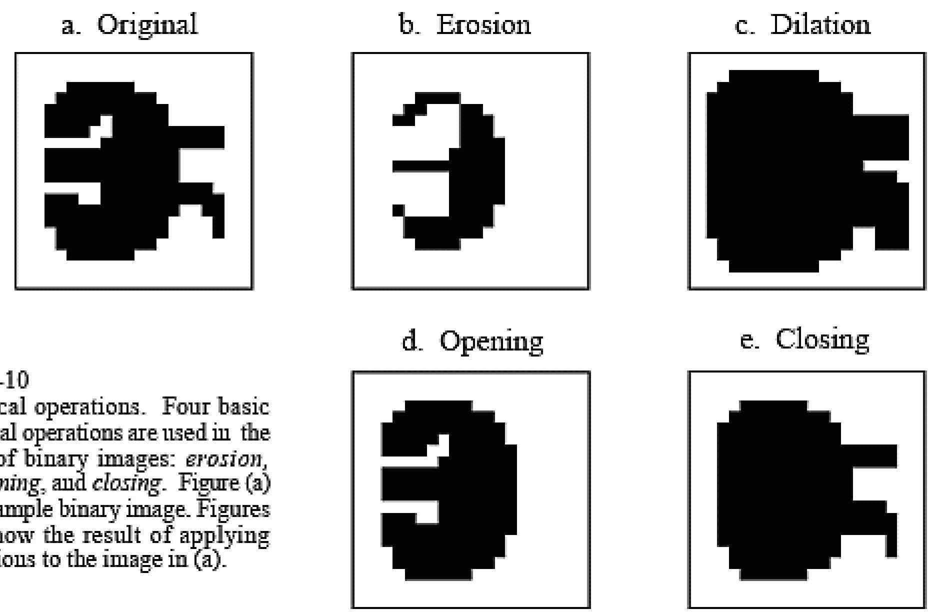


FIGURE 25-10
Morphological operations. Four basic morphological operations are used in the processing of binary images: *erosion*, *dilation*, *opening*, and *closing*. Figure (a) shows an example binary image. Figures (b) to (e) show the result of applying these operations to the image in (a).

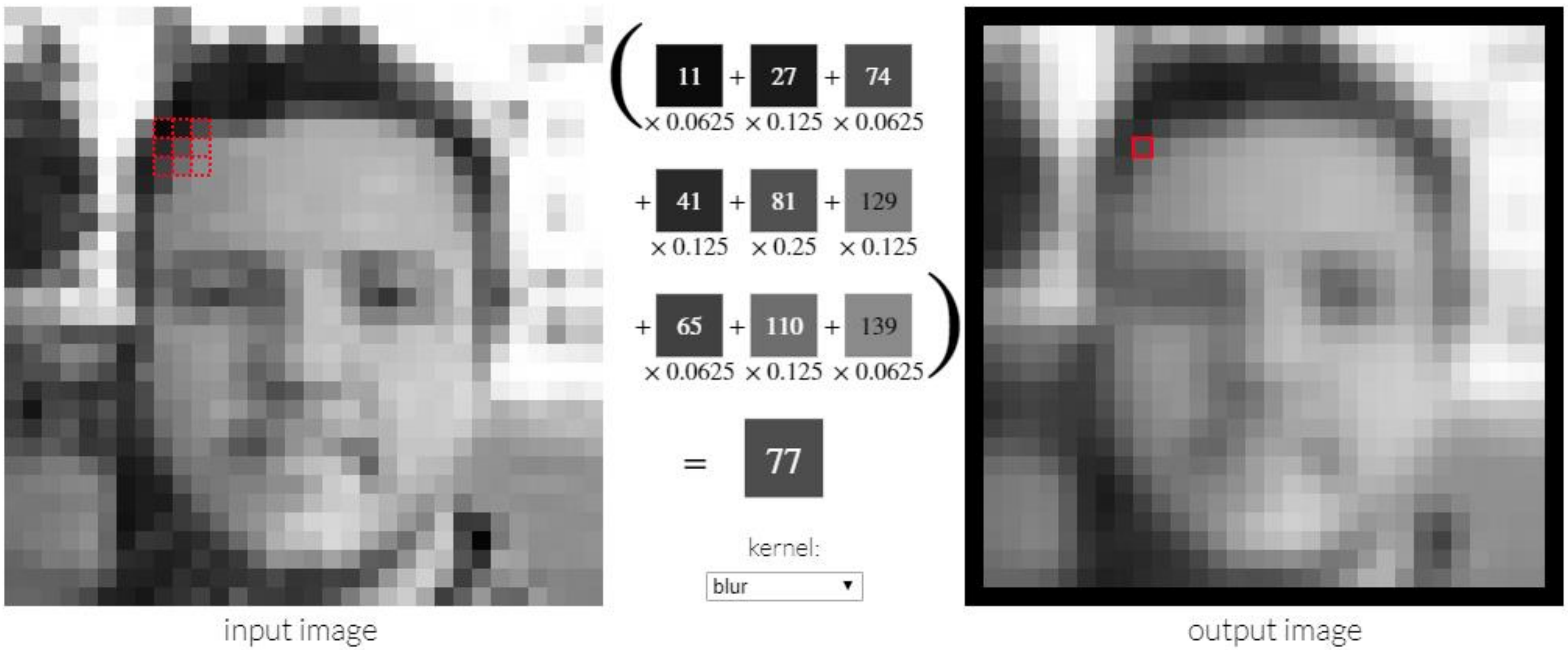
- Opening: erosion → dilation
- Closing: dilation → erosion

Image Filtering

- What is filtering?
  - Forming a new image whose pixel values are transformed from original pixel values
- Goals
  - To extract useful information from images
    - *e.g.* edges
  - To transform images into another domain where we can modify/enhance image properties
    - *e.g.* denoising, image decomposition

Image Filtering

- Try it yourself!



http://setosa.io/ev/image-kernels/

Image Filtering

$$g(x,y) = \frac{1}{W} \sum_{i,j \in [-r,r]} h(i,j) f(x-i, y-j)$$

$$W = \sum_{i,j \in [-r,r]} h(i,j)$$

- Convolution
  - Linear shift invariant (LSI)

Output size changed... ☹

$f(x,y)$

45	60	98	127	132	133	137	133
46	65	98	123	126	128	131	133
47	65	96	115	119	123	135	137
47	63	91	107	113	122	138	134
50	59	80	97	110	123	133	134
49	53	68	83	97	113	128	133
50	50	58	70	84	102	116	126
50	50	52	58	69	86	101	120

$*$

$h(x,y)$

0.1	0.1	0.1
0.1	0.2	0.1
0.1	0.1	0.1

$=$

$g(x,y)$

69	95	116	125	129	132
68	92	110	120	126	132
66	86	104	114	124	132
62	78	94	108	120	129
57	69	83	98	112	124
53	60	71	85	100	114

Figure 3.10 from *Computer Vision: Algorithms and Applications*

Image Filtering

- Padding

Zero padding

Symmetric

Replicate

Circular

Image Filtering

- Box filter
  - Average filter
  - Compute summation if ignoring $1/N$
  - Complexity: $O(r^2)$

$$g(x,y) = \frac{1}{N} \sum_{i,j \in [-r,r]} f(x-i, y-j)$$

45	60	98	127	132	133	137	133
46	65	98	123	126	128	131	133
47	65	96	115	119	123	135	137
47	63	91	107	113	122	138	134
50	59	80	97	110	123	133	134
49	53	68	83	97	113	128	133
50	50	58	70	84	102	116	126
50	50	52	58	69	86	101	120

$f(x,y)$

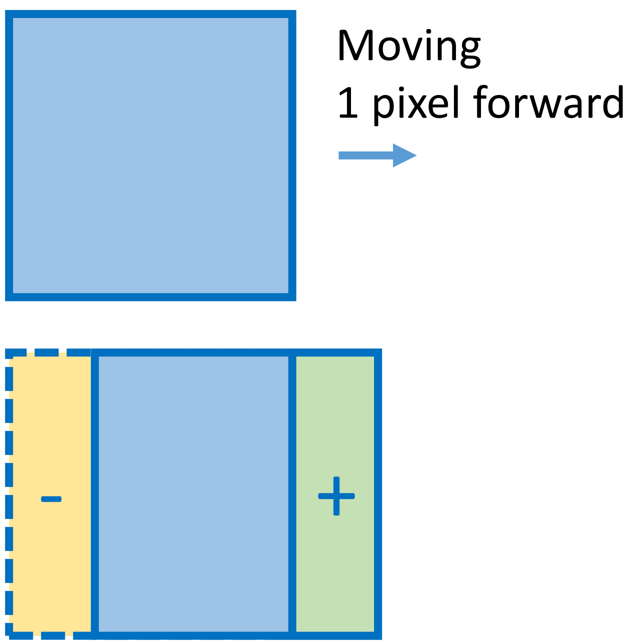
box filter

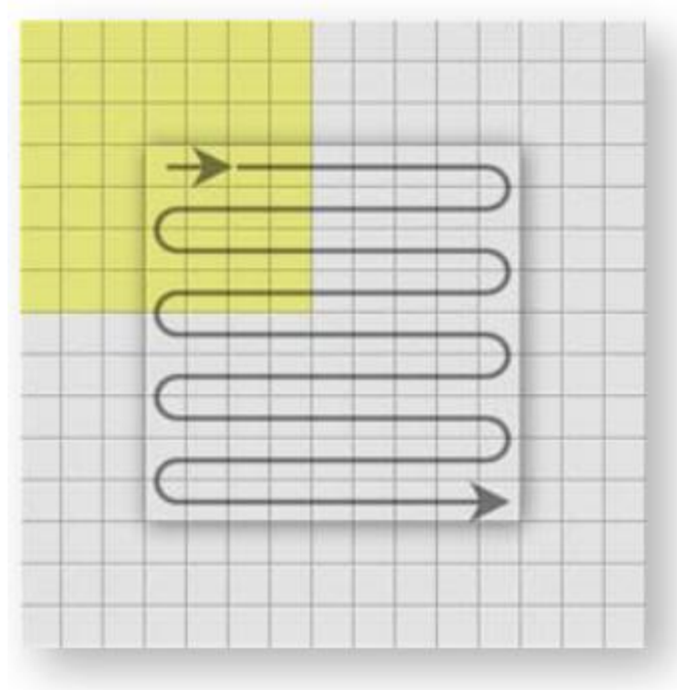
		$\frac{825}{9}$					

$g(x,y)$

Image Filtering

- Box filter in $O(r)$
  - Moving sum technique





Source: Ben Weiss

Note: $O(1)$ filter is also called **constant time** filter

Image Filtering

- Box filter in $O(1)$
  - Integral image (sum area table)
    - Computing integral image: 2 addition + 1 subtraction
    - Obtaining box sum: 2 subtraction + 1 addition
    - Regardless of box size ☺

3	2	7	2	3
1	5	1	3	4
5	1	**3**	5	1
4	3	2	1	6
2	4	1	4	8

Sum = 24

3	5	12	14	17
4	*11*	**19**	24	31
9	**17**	28	38	46
13	24	37	48	62
15	30	44	59	81

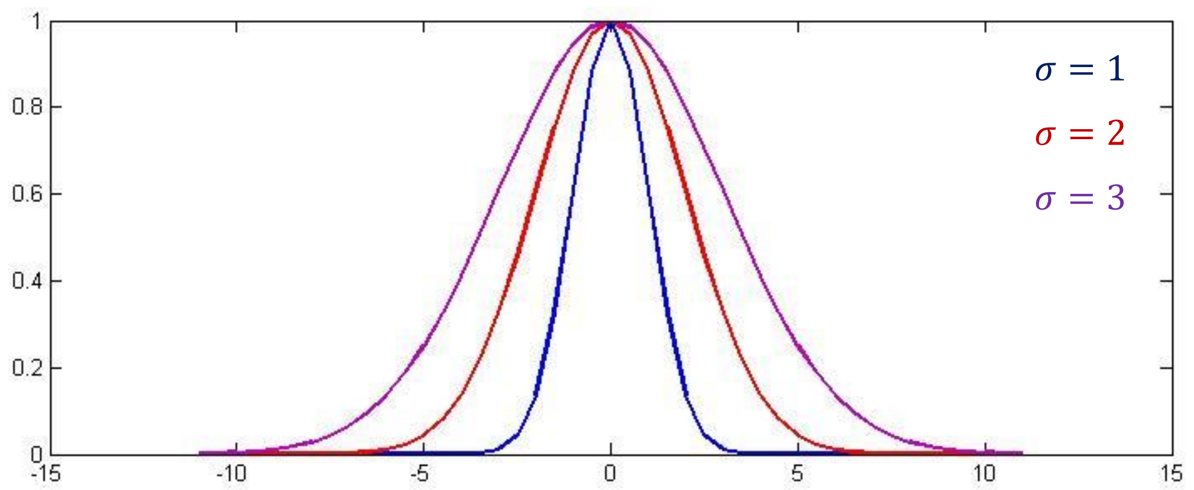
19 + 17 – 11 + 3 = 28

3	5	12	*14*	17
4	11	19	24	31
9	17	28	38	46
13	24	37	**48**	62
15	30	44	59	81

Sum = 48 – 14 – 13 + 3 = 24

Image Filtering

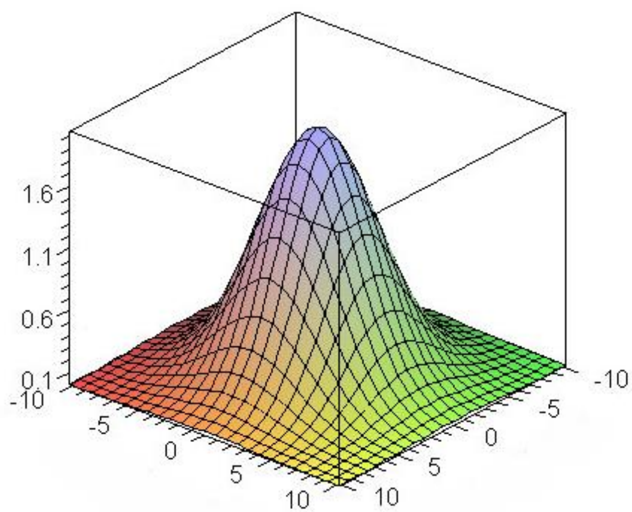
- Gaussian filter
  - The kernel weight is a Gaussian function $h(x) = e^{-\frac{x^2}{2\sigma^2}}$
  - Center pixels contribute more weights



1D illustration of Gaussian functions

Image Filtering

- Gaussian filter
  - 2D case: $h(x,y) = e^{-\frac{x^2+y^2}{2\sigma^2}}$
  - Complexity: $O(r^2)$



Original Image

Gaussian filtered image, σ = 2

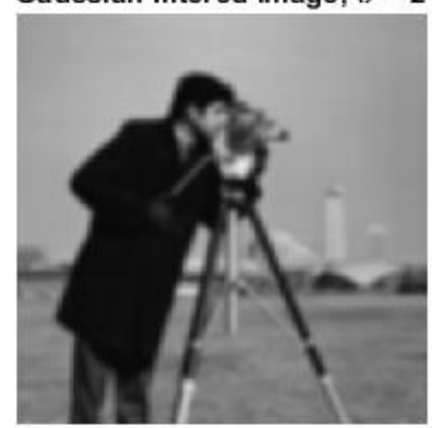


Image Filtering

$$g(x,y) = \frac{1}{W} \sum_{i,j \in [-r,r]} h(i,j) f(x-i, y-j)$$

$$W = \sum_{i,j \in [-r,r]} h(i,j)$$

- Gaussian filter in $O(r)$
  - Gaussian kernel is **separable**
    (The same technique can be applied to other separable kernels)

$$h(x,y) = e^{-\frac{x^2+y^2}{2\sigma^2}} = e^{-\frac{x^2}{2\sigma^2}} \cdot e^{-\frac{y^2}{2\sigma^2}}$$

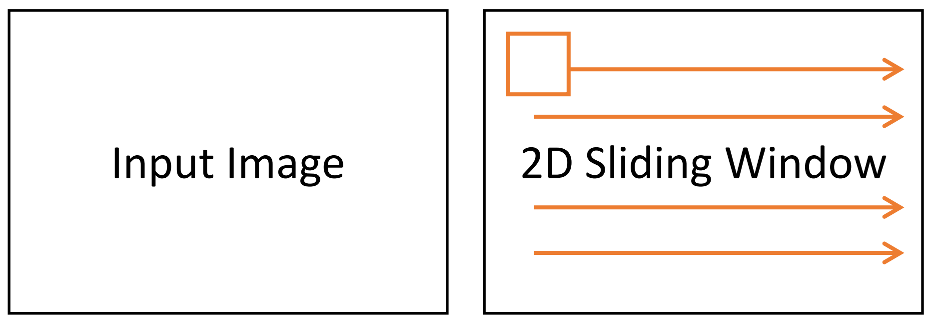
$$g(x,y) = \frac{1}{W} \sum_{i \in [-r,r]} \sum_{j \in [-r,r]} e^{-\frac{x^2+y^2}{2\sigma^2}} f(x-i, y-j)$$

$$g(x,y) = \frac{1}{W} \sum_{j \in [-r,r]} e^{-\frac{y^2}{2\sigma^2}} \sum_{i \in [-r,r]} e^{-\frac{x^2}{2\sigma^2}} f(x-i, y-j)$$

Image Filtering

- Gaussian filter in $O(r)$

Direct 2D implementation: $O(r^2)$



Separable implementation: $O(r)$

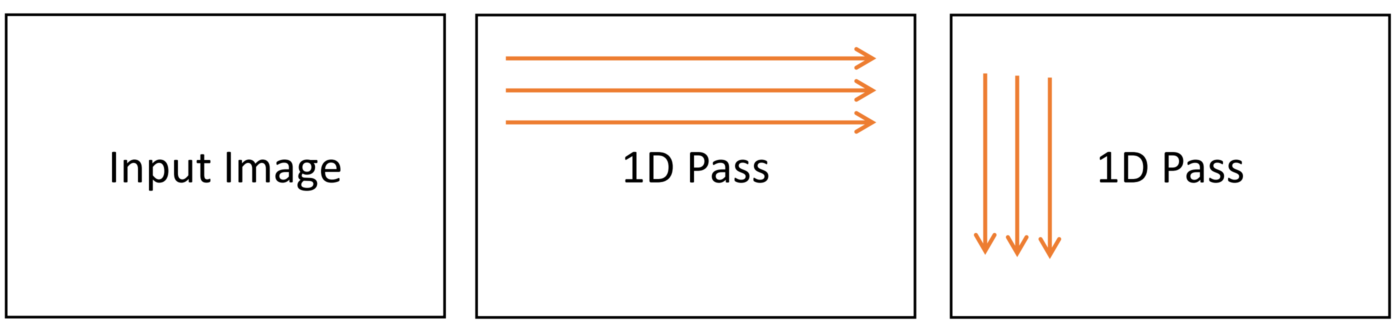


Image Filtering

- Gaussian filter in $O(1)$
  - FFT
  - Iterative box filtering
  - Recursive filter

Image Filtering

- $O(1)$ Gaussian filter by FFT approach

$$g = h * f$$

$$\mathcal{F}(g) = \mathcal{F}(h) \cdot \mathcal{F}(f)$$

$$g = \mathcal{F}^{-1}(\mathcal{F}(h) \cdot \mathcal{F}(f))$$

- Complexity:
  - Take FFT: $O(wh \ln(w) \ln(h))$
  - Multiply by FFT of Gaussian: $O(wh)$
  - Take inverse FFT: $O(wh \ln(w) \ln(h))$
  - Cost independent of filter size

Image Filtering

- $O(1)$ Gaussian filter by iterative box filtering
  - Based on the **central limit theorem**
  - Pros: easy to implement!
  - Cons: limited choice of box size (3, 5, 7, …) results in limited choice of Gaussian function σ^2

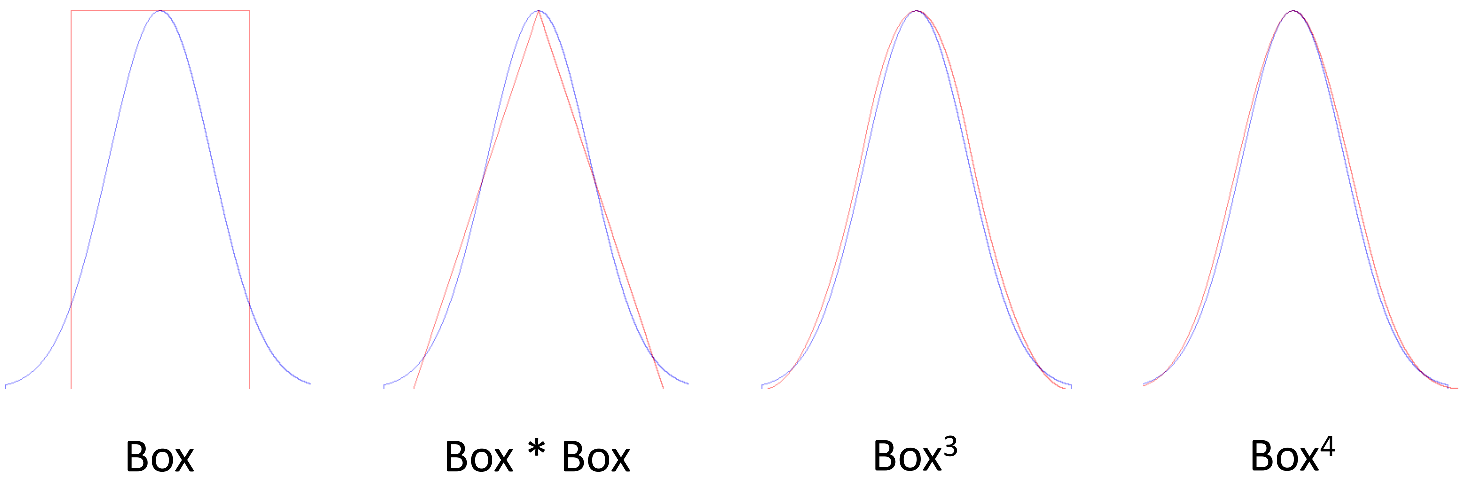


Image Filtering

- $O(1)$ Gaussian filter by recursive implementation
  - All filters we discussed above are FIR filters
  - We can use IIR (infinite impulse response) filters to approximate Gaussians…

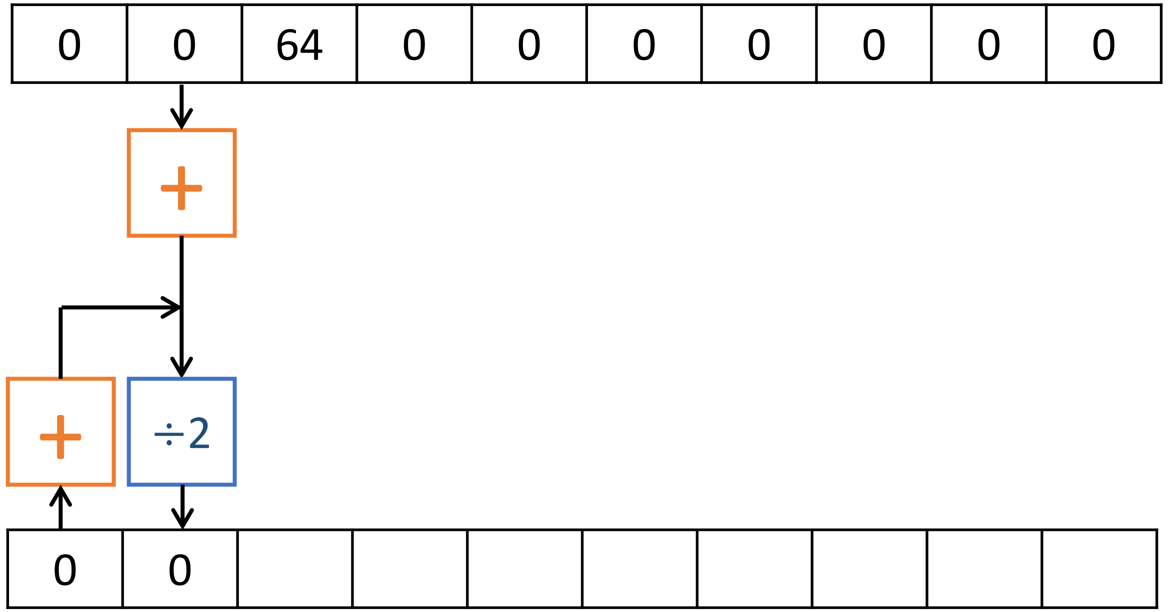
1st order IIR filter:

$$g(x) = a_0 \cdot f(x) - b_1 \cdot g(x-1)$$

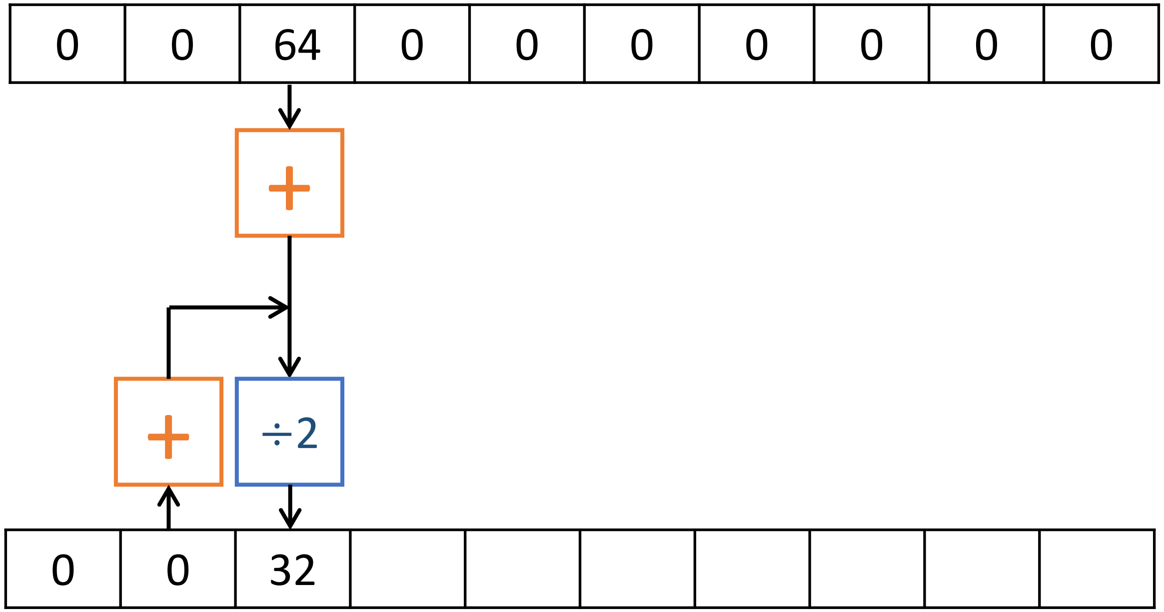
2nd order IIR filter:

$$g(x) = a_0 \cdot f(x) + a_1 \cdot f(x-1) - b_1 \cdot g(x-1) - b_2 \cdot g(x-2)$$

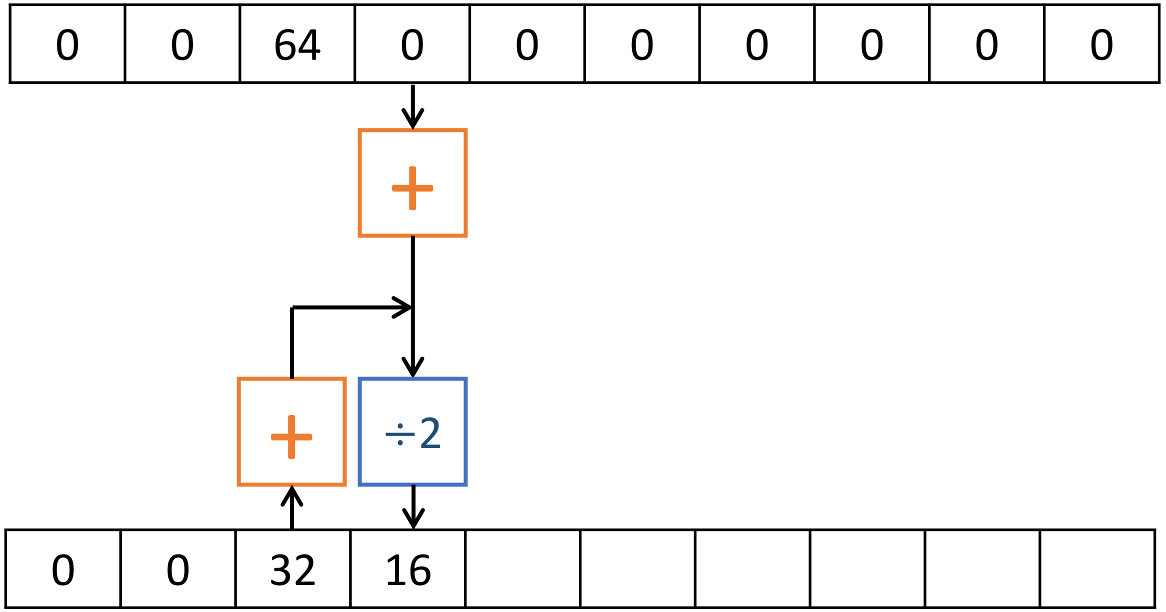
IIR Filters



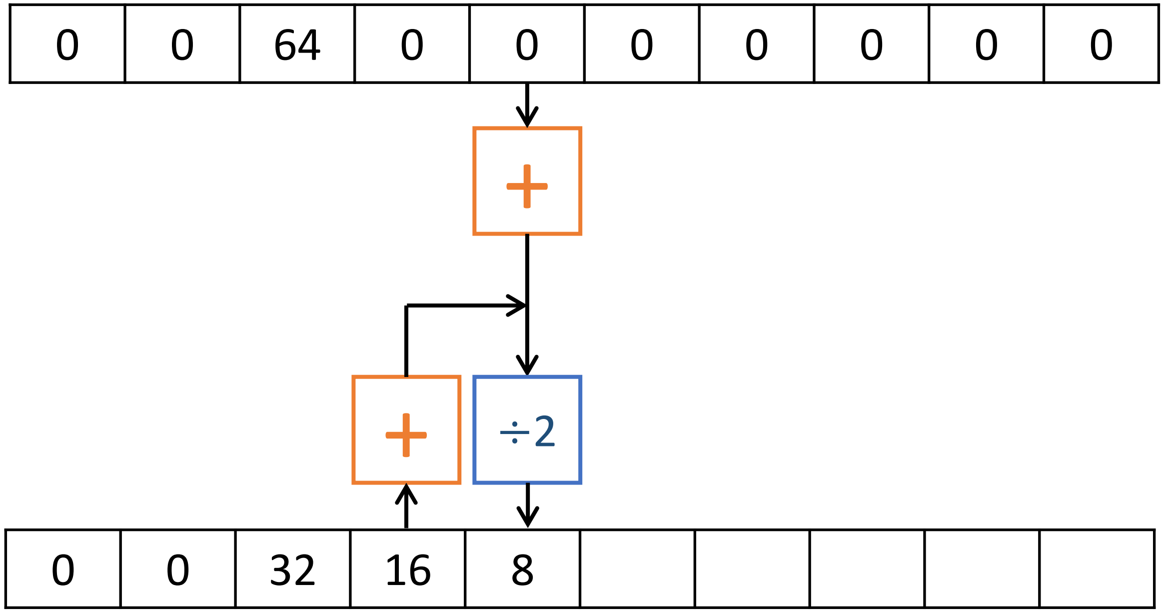
IIR Filters



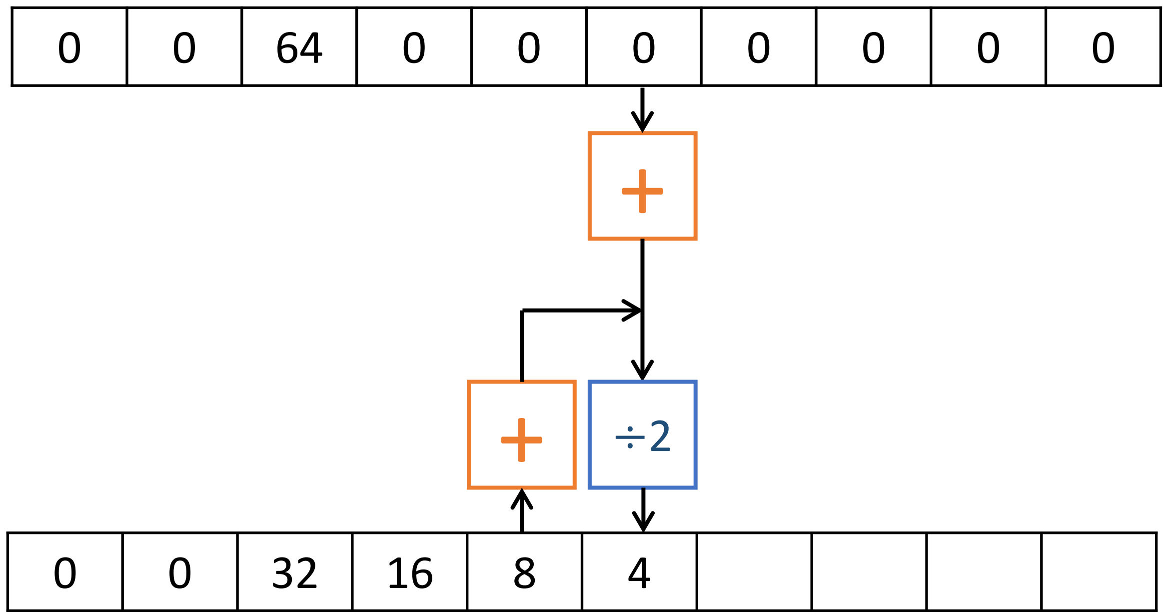
IIR Filters



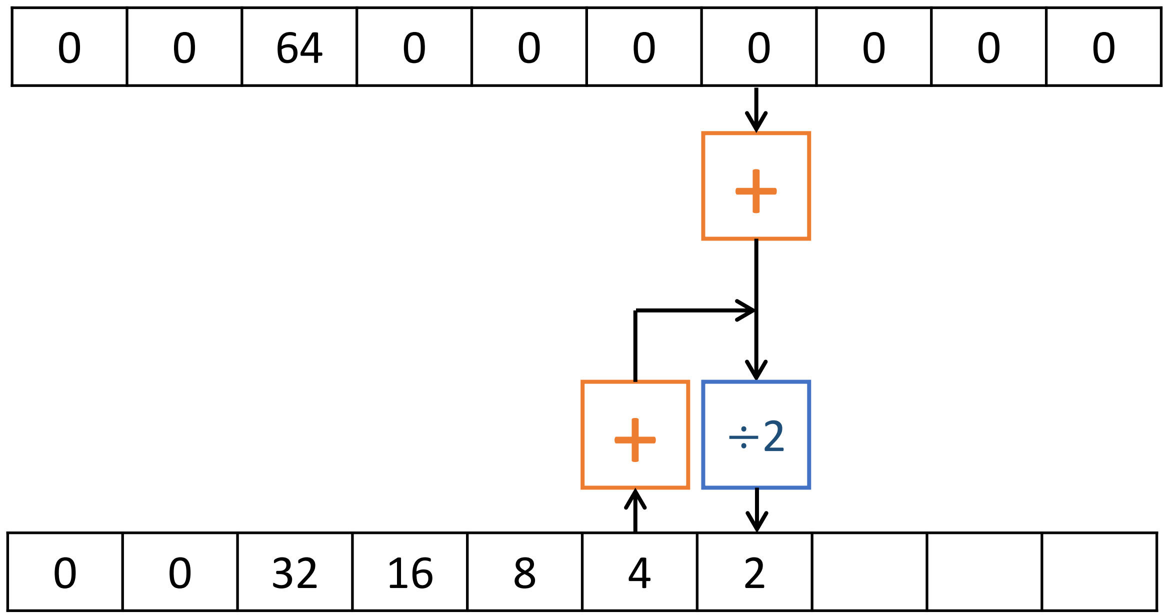
IIR Filters



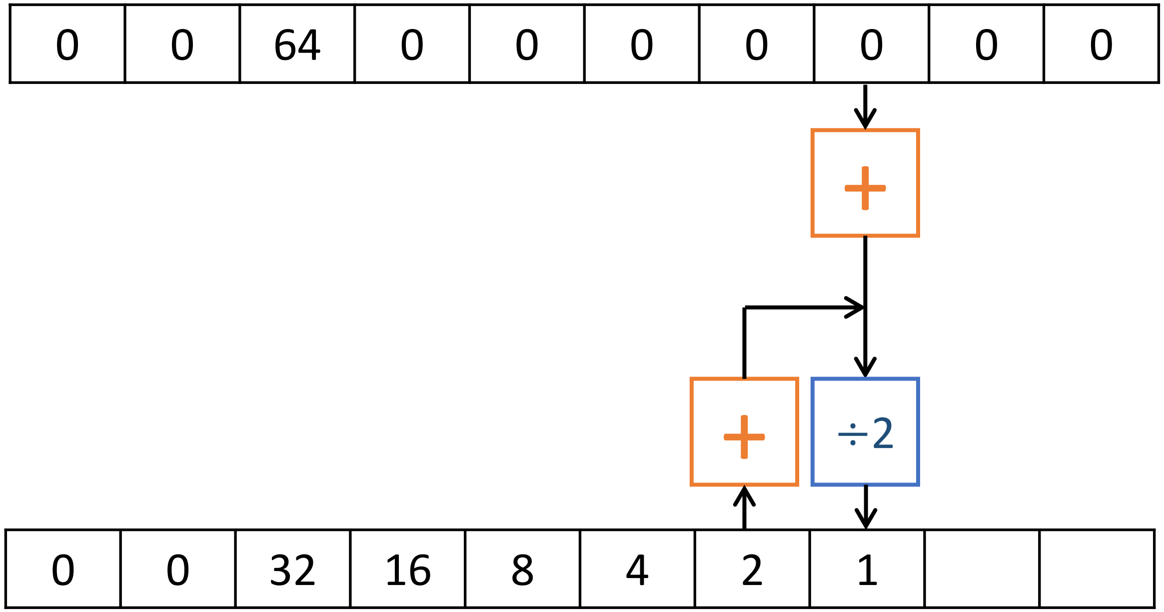
IIR Filters



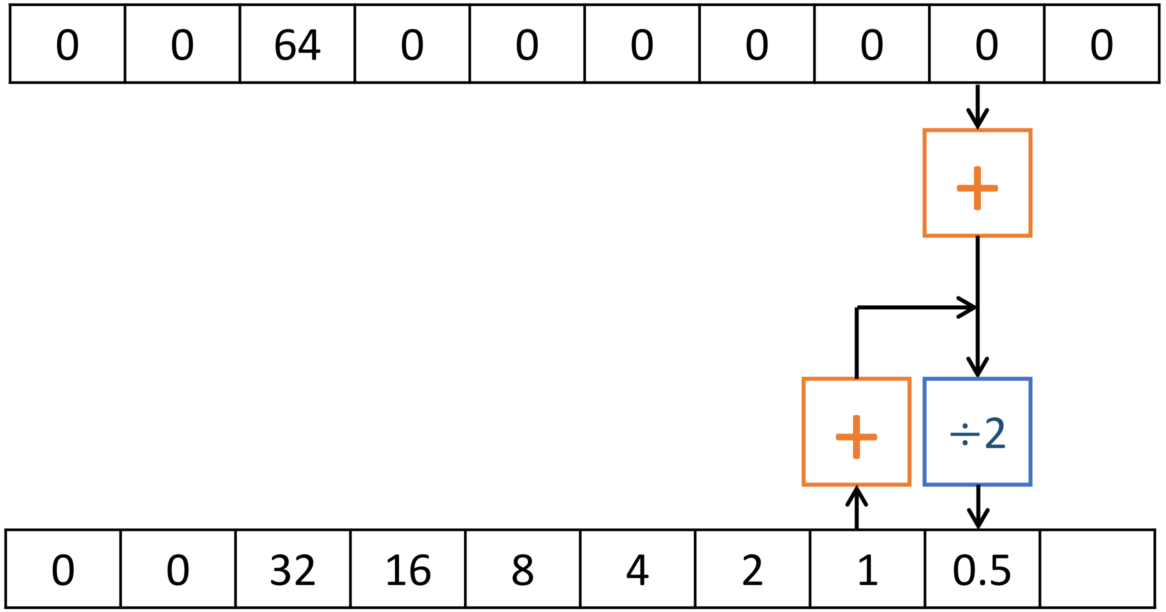
IIR Filters



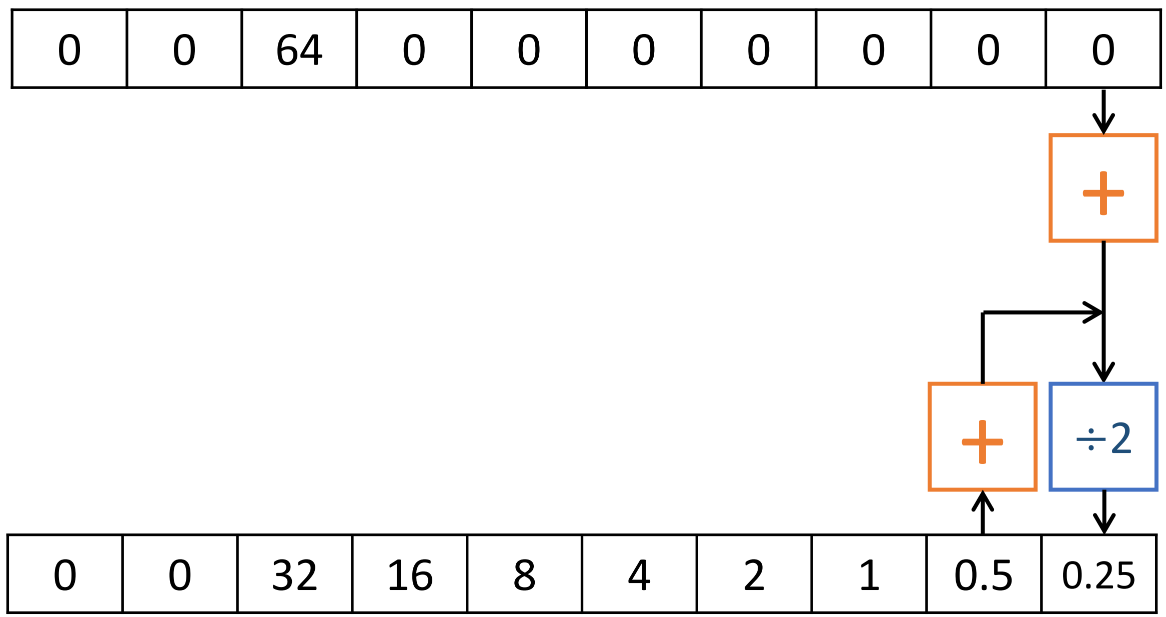
IIR Filters



IIR Filters

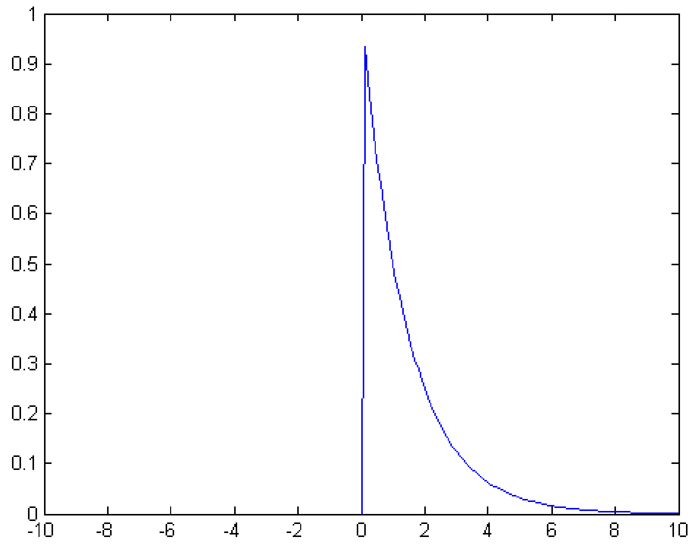


IIR Filters



IIR Filters

- The example above is an exponential decay
- Equivalent to convolution by:



IIR Filters

- Makes large, smooth filters with very little computation! ☺
- One forward pass (causal), one backward pass (anti-causal), equivalent to convolution by:

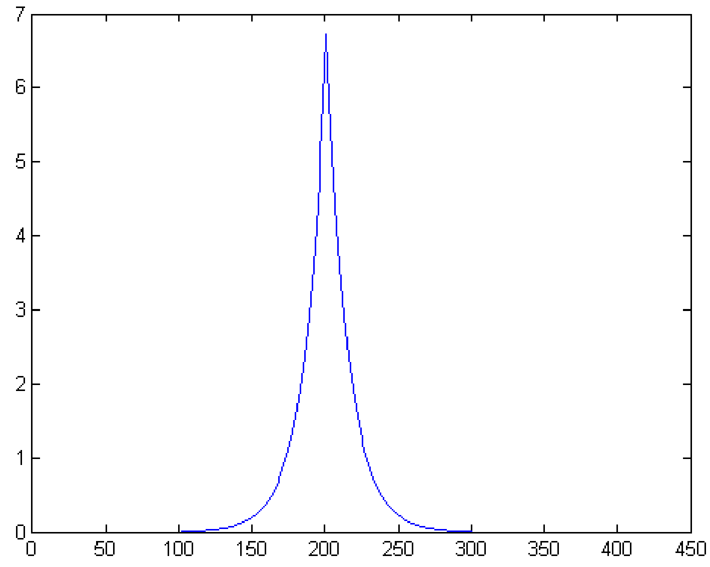


Image Filtering

- $O(1)$ Gaussian filter by recursive implementation
  - 2[nd] order IIR filter approximation

$$g(x) = a_0 \cdot f(x) + a_1 \cdot f(x-1) - b_1 \cdot g(x-1) - b_2 \cdot g(x-2)$$

$$g'(x) = a_2 \cdot f(x+1) + a_3 \cdot f(x+2) - b_1 \cdot g'(x+1) - b_2 \cdot g'(x+2)$$

$$a_0 = (1 - e^{-\frac{1.695}{\sigma_S}})^2 / (1 + 3.39 e^{-\frac{1.695}{\sigma_S}} / \sigma_S - e^{-\frac{3.39}{\sigma_S}})$$
$$a_1 = (1.695/\sigma_S - 1) e^{-\frac{1.695}{\sigma_S}} a_0,$$
$$b_1 = -2 e^{-\frac{1.695}{\sigma_S}},$$
$$b_2 = e^{-\frac{3.39}{\sigma_S}}.$$
$$a_2 = (1.695/\sigma_S + 1) e^{-\frac{1.695}{\sigma_S}} a_0 \text{ and } a_3 = -a_0 b_2$$

“Recursively implementing the Gaussian and its derivatives”, ICIP 1992

Image Filtering

- Median filter
  - 3x3 example:

11	19	22
12	25	27
18	26	23

A local patch

Sort

11, 12, 18, 19, 22, 23, 25, 26, 27

Replace center pixel value by median

11	19	22
12	22	27
18	26	23

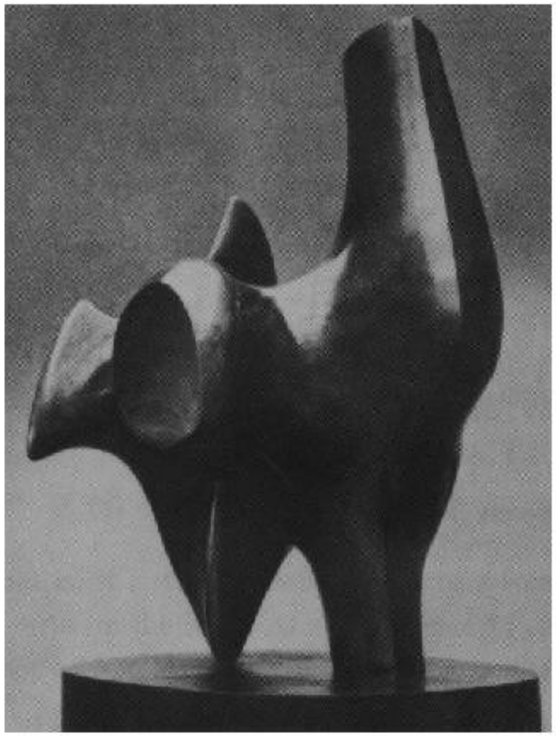
Image Filtering

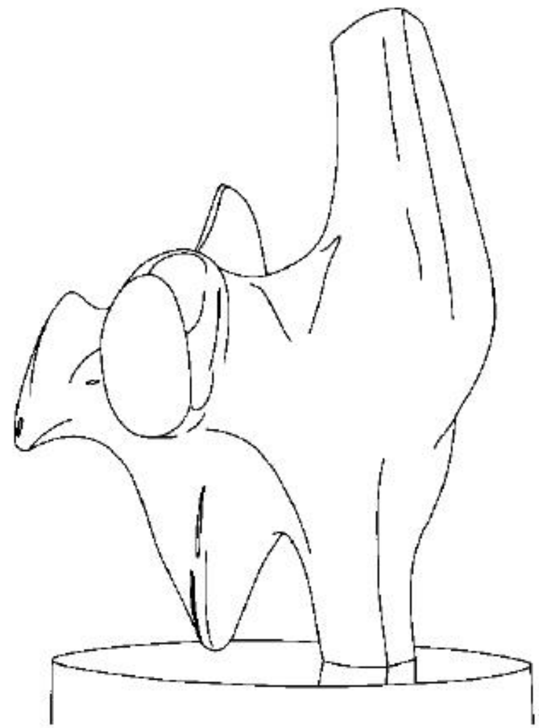
- Median filter
  - Useful to deal with **salt and pepper noise**

Original | Add salt & pepper | Gaussian filter | Median filter

Source: https://www.pinterest.com/pin/304485624782669932

Edge Detection





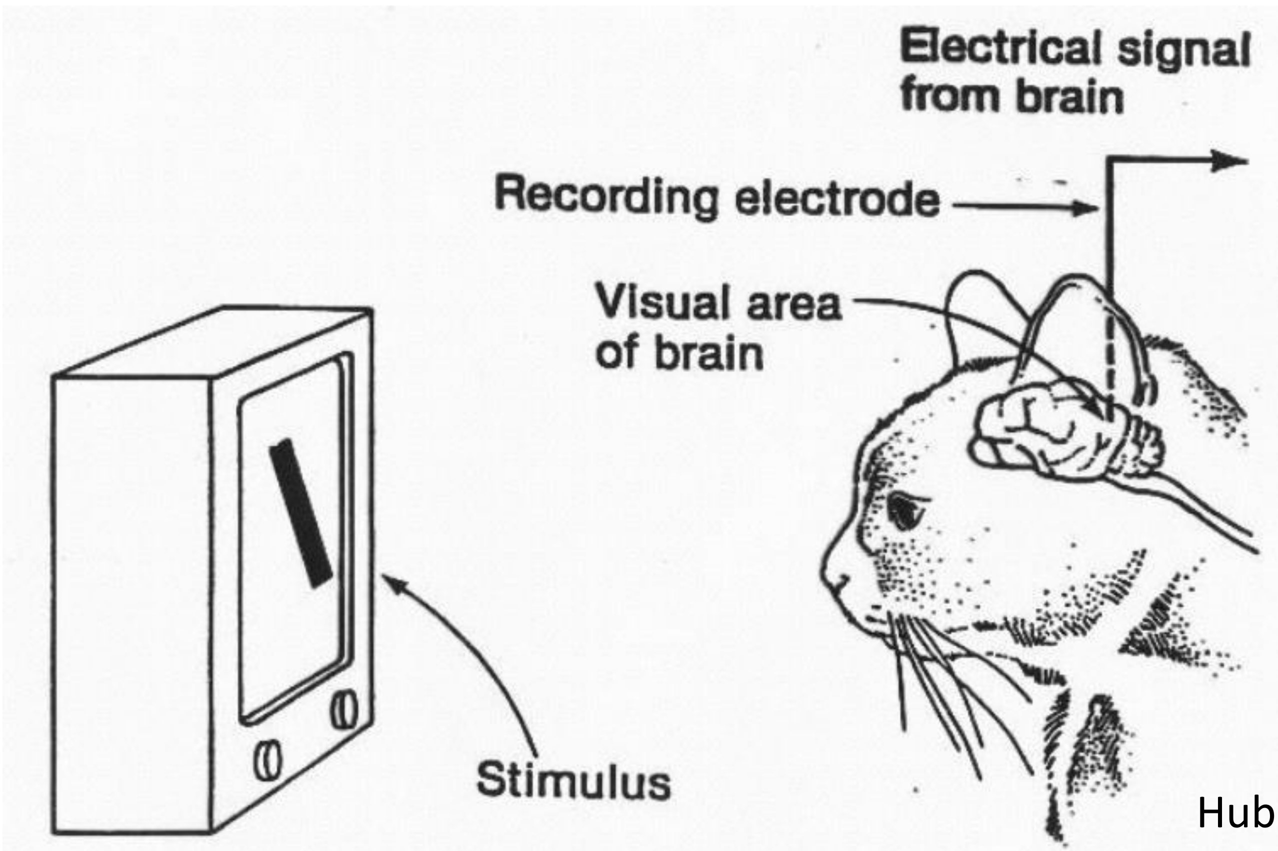
Convert a 2D image into a set of curves

- Extract salient features of the scene
- More compact than pixels

Slide by Steve Seitz

Edge Detection

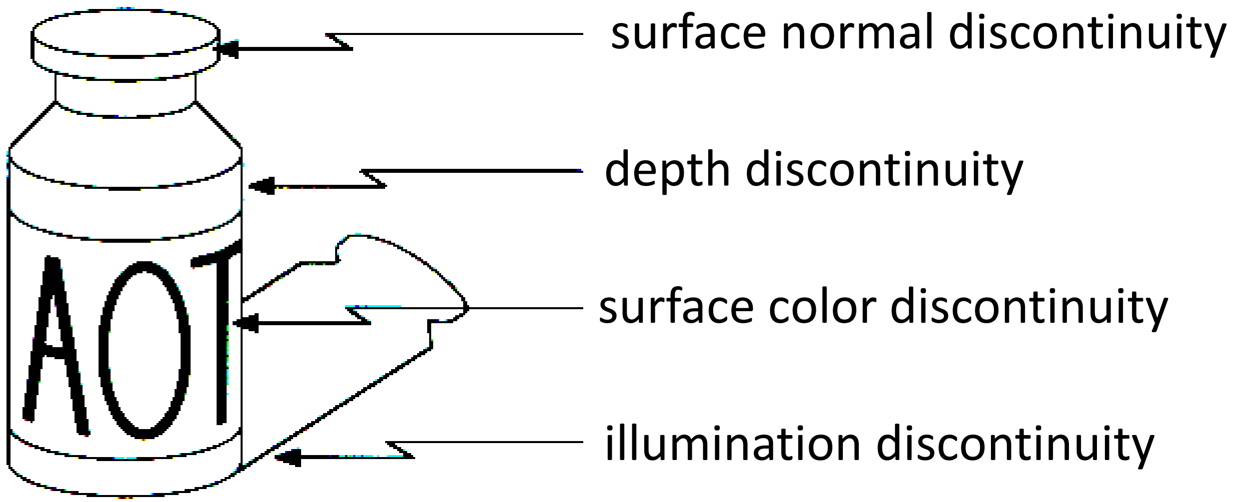
- We know edges are special from mammalian vision studies



Hubel & Wiesel (1962)

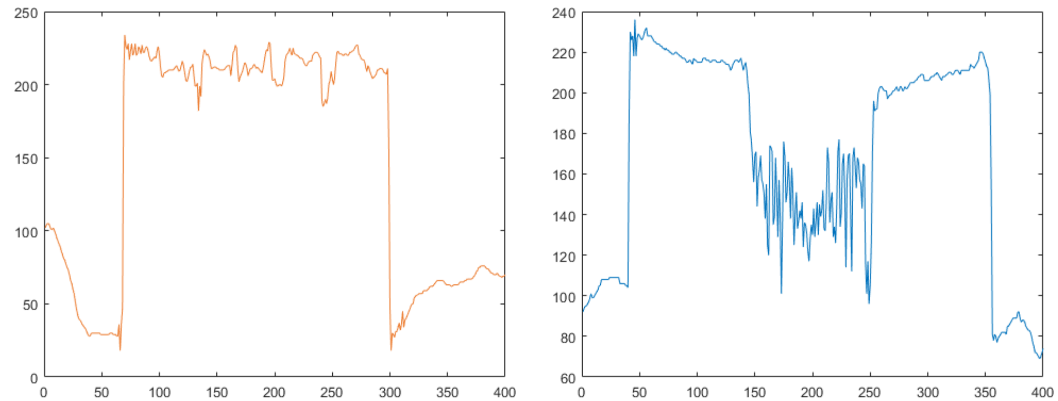
Edge Detection

- Origin of edges

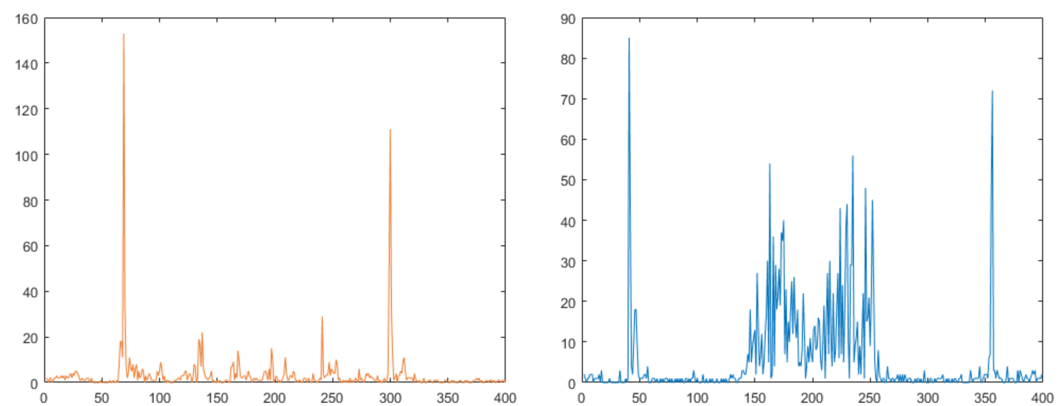


Edge Detection

- Characterizing edges



Intensity profile



Gradient magnitude

Edge Detection

- How to compute gradient for digital images?

$$\nabla f = [\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}]$$

  - Take **discrete derivative**

$$\frac{\partial f}{\partial x} \approx f(x+1, y) - f(x, y)$$

  - Gradient direction and magnitude

$$\theta = \tan^{-1}(\frac{\partial f / \partial y}{\partial f / \partial x}) \qquad \|\nabla f\| = \sqrt{(\frac{\partial f}{\partial x})^2 + (\frac{\partial f}{\partial y})^2}$$

Discrete Derivative

- Backward difference

$$\frac{df}{dx} = f(x) - f(x-1)$$

- Forward difference

$$\frac{df}{dx} = f(x) - f(x+1)$$

- Central difference

$$\frac{df}{dx} = f(x+1) - f(x-1)$$

Equivalent to convolve with:

[1, -1]

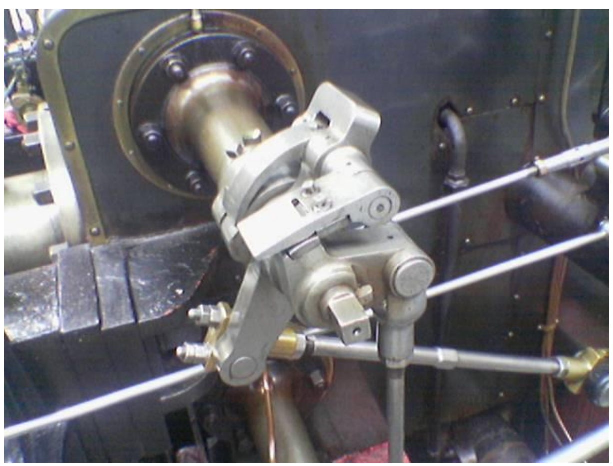
[-1, 1]

[1, 0, -1]

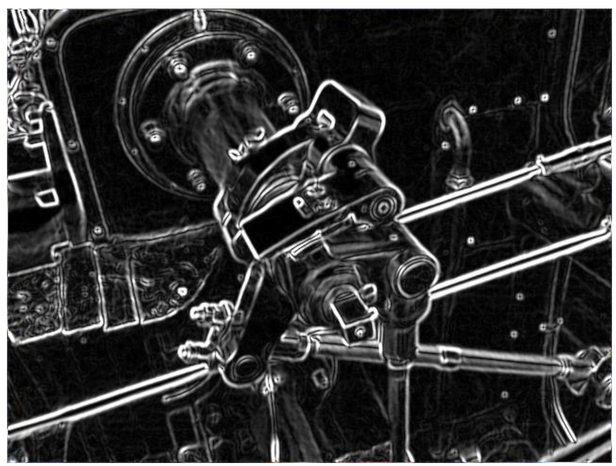
Edge Detection

- Sobel filter

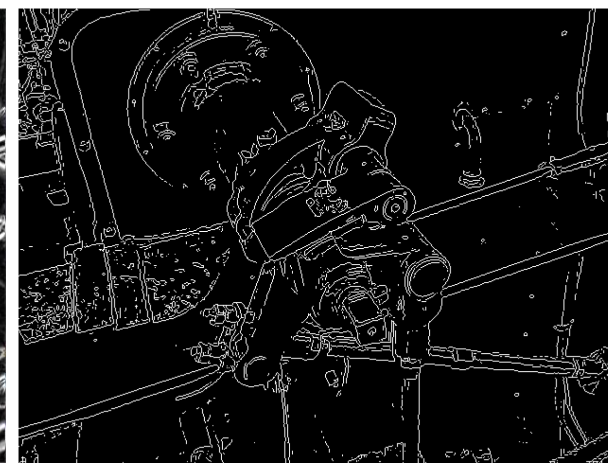
$$G_x = \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix} * f \qquad G_y = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} * f \qquad G = \sqrt{G_x^2 + G_y^2}$$



Input image



G

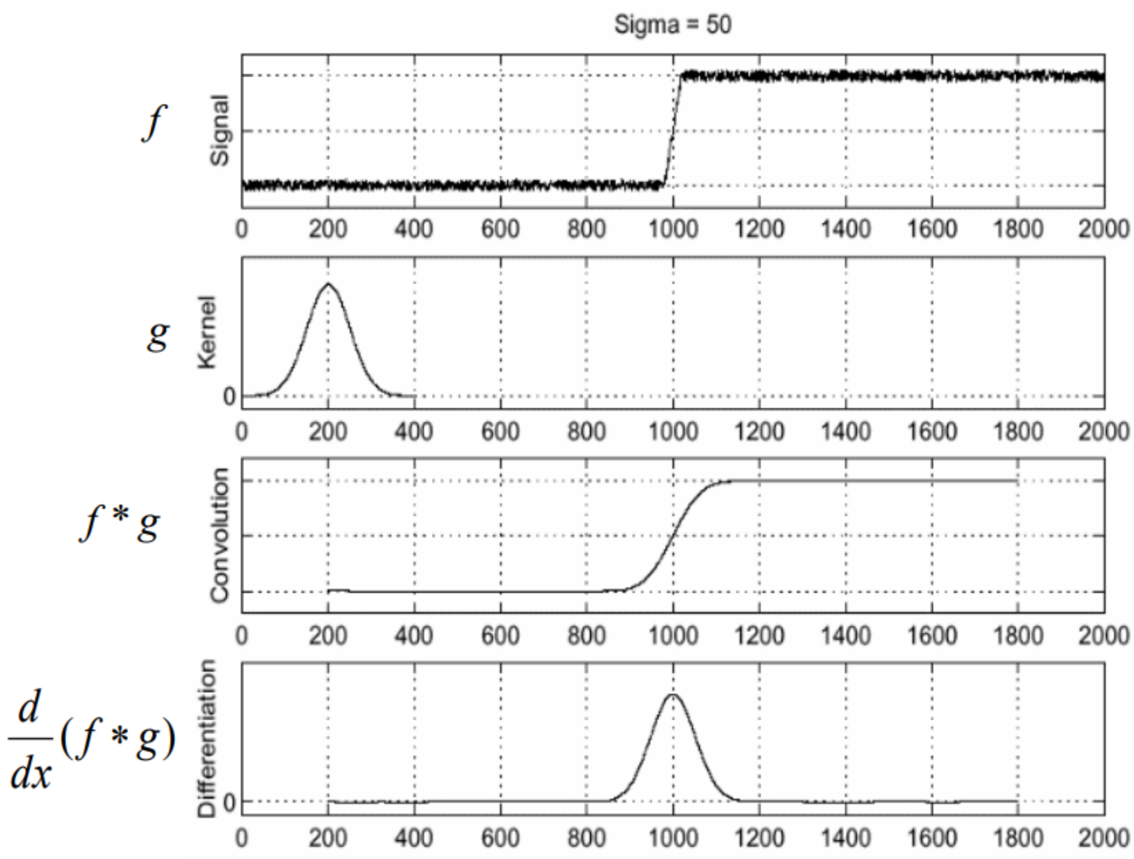


After thresholding

Wiki: Sobel operator

Edge Detection

- Effect of noise
  - Difference filters respond strongly to noise
  - Solution: smooth first



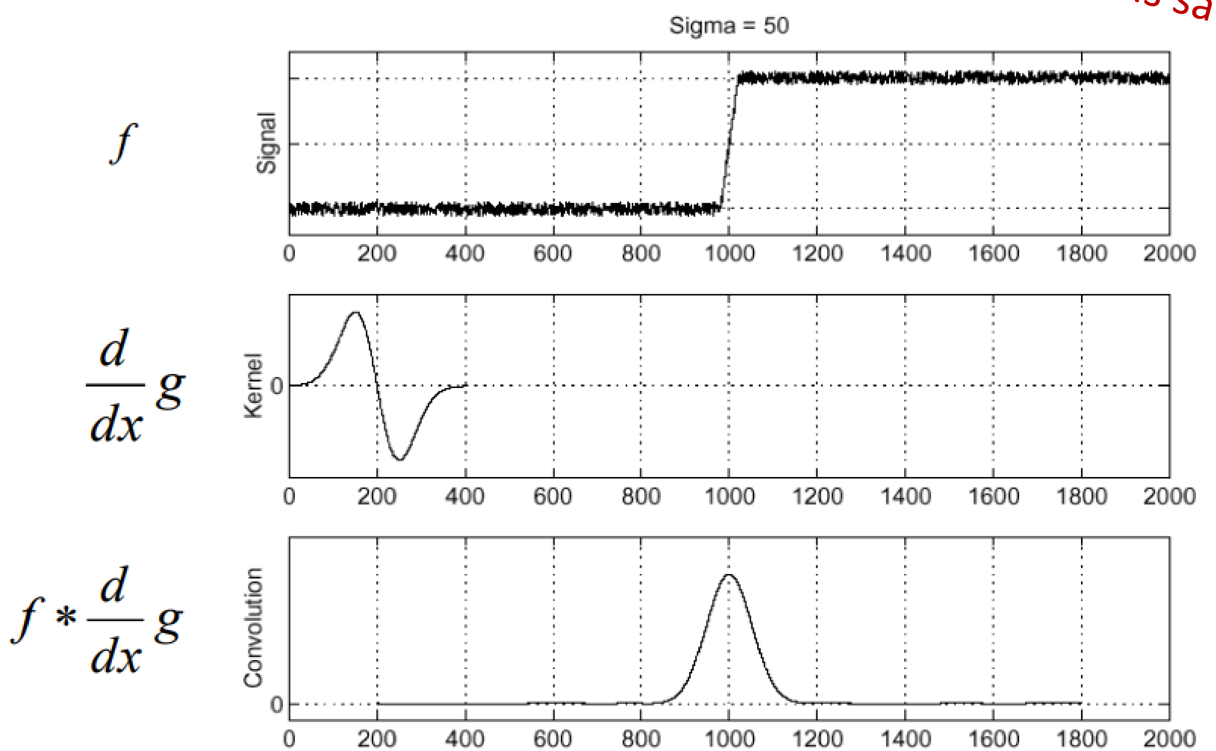
Slide by Steve Seitz

Derivative Theorem of Convolution

- Differentiation is convolution, which is associative:

$$\frac{d}{dx}(f * g) = f * (\frac{d}{dx}g)$$

This saves one operation!

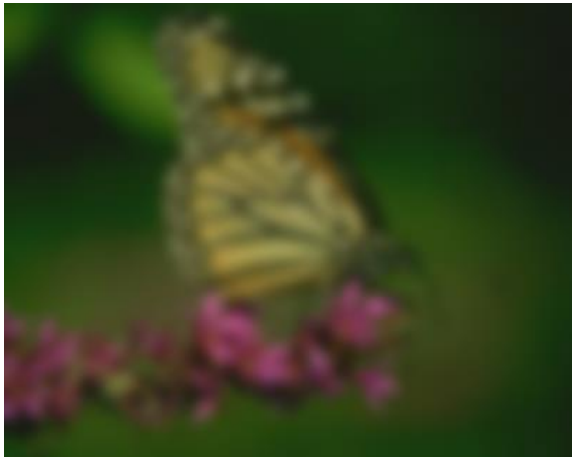


Edge Detection

- Tradeoff between smoothing and localization
  - Smoothing filter removes noise but blurs edges ☹

No filtering

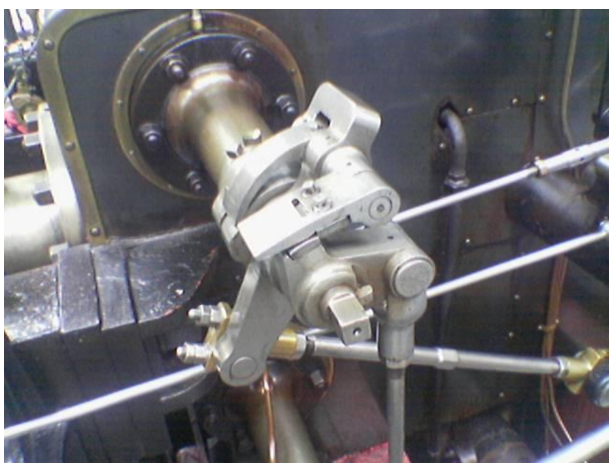
Gaussian filter, $\sigma = 2$



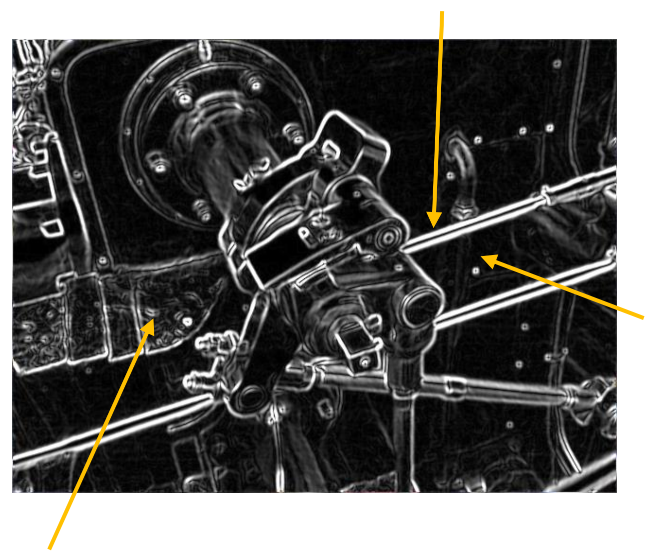
Gaussian filter, $\sigma = 5$

Edge Detection

- Criteria for a good edge detector
  - Good detection
    - Find all real edges, ignoring noise
  - Good localization
    - Locate edges as close as possible to the true edges
    - Edge width is only one pixel



Bad localization



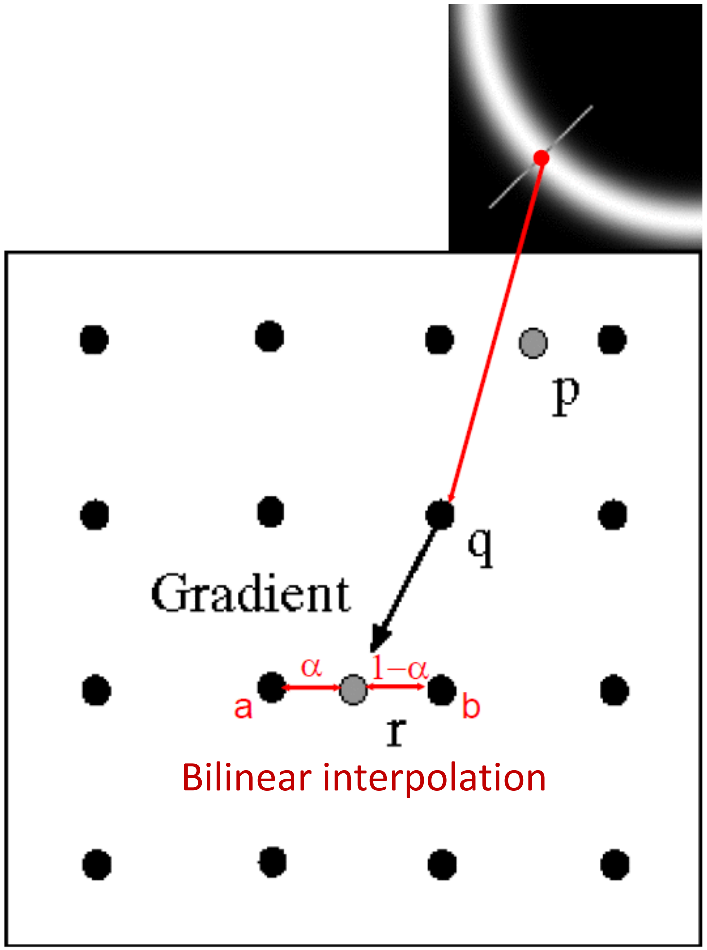
Missing edge

Not edge

Edge Detection

- Canny edge detector
  - The most widely used edge detector
  - The best you can find in existing tools like MATLAB, OpenCV…
- Algorithm:
  - Apply Gaussian filter to reduce noise
  - Find the intensity gradients of the image
  - Apply **non-maximum suppression** to get rid of false edges
  - Apply **double threshold** to determine potential edges
  - Track edge by **hysteresis**: suppressing weak edges that are not connected to strong edges

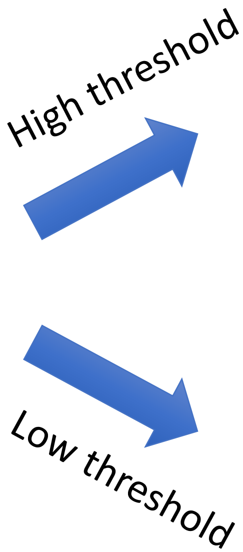
Non-Maximum Suppression



Gradient magnitude

After NMS

Double Thresholding

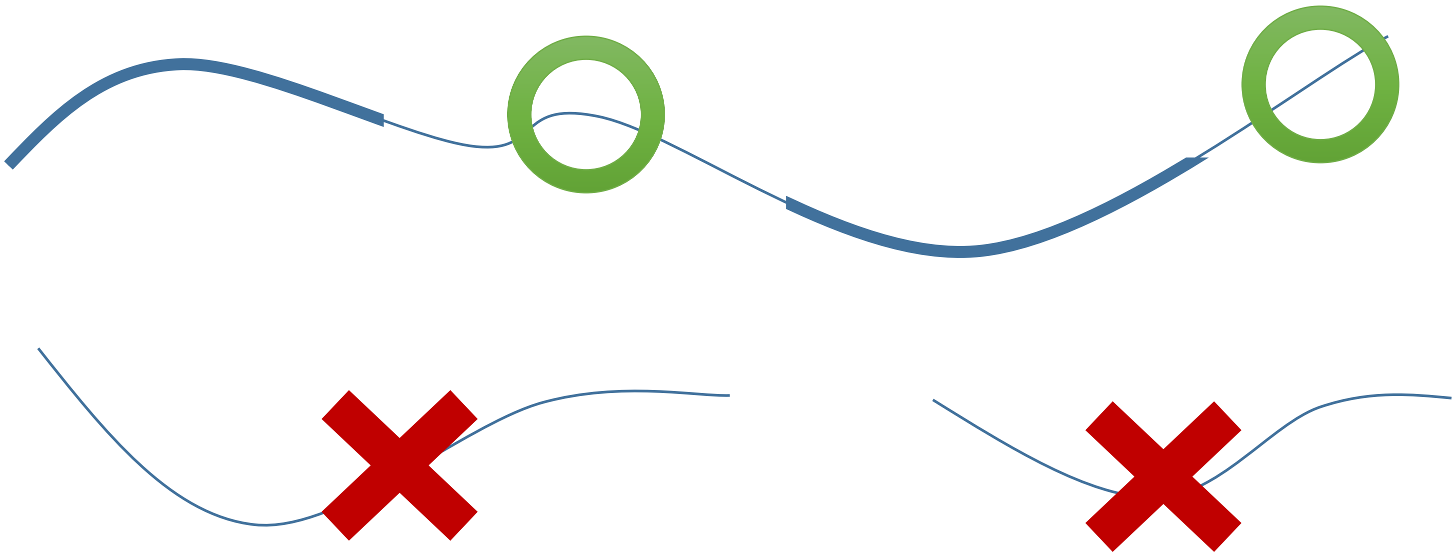


Strong edges

Weak edges

Hysteresis

- Find **connected components** from strong edge pixels to finalize edge detection



More Image Filtering

- Bilateral filter
  - Smoothing images while preserving edges

Edge remains sharp

Input

Output

Small fluctuations are removed

Bilateral Filtering

- Bilateral filter

$$g(x,y) = \frac{1}{W} \sum_{i,j \in [-r,r]} h(i,j) f(x-i, y-j)$$

Range kernel

$$g(x,y) = \frac{1}{W} \sum_{i,j \in [-r,r]} h_s(i,j) \cdot h_r(i,j) \cdot f(x-i, y-j)$$

Spatial kernel

  - **Spatial kernel**: weights are larger for pixels near the window center

$$h_s(i,j) = e^{-\frac{i^2+j^2}{2\sigma_s^S}}$$

  - **Range kernel**: weights are larger if the neighbor pixel has similar intensity (color) to the center pixel

$$h_r(i,j) = e^{-\frac{f(x-i)^2+f(y-j)^2}{2\sigma_r^S}}$$

Bilateral Filtering

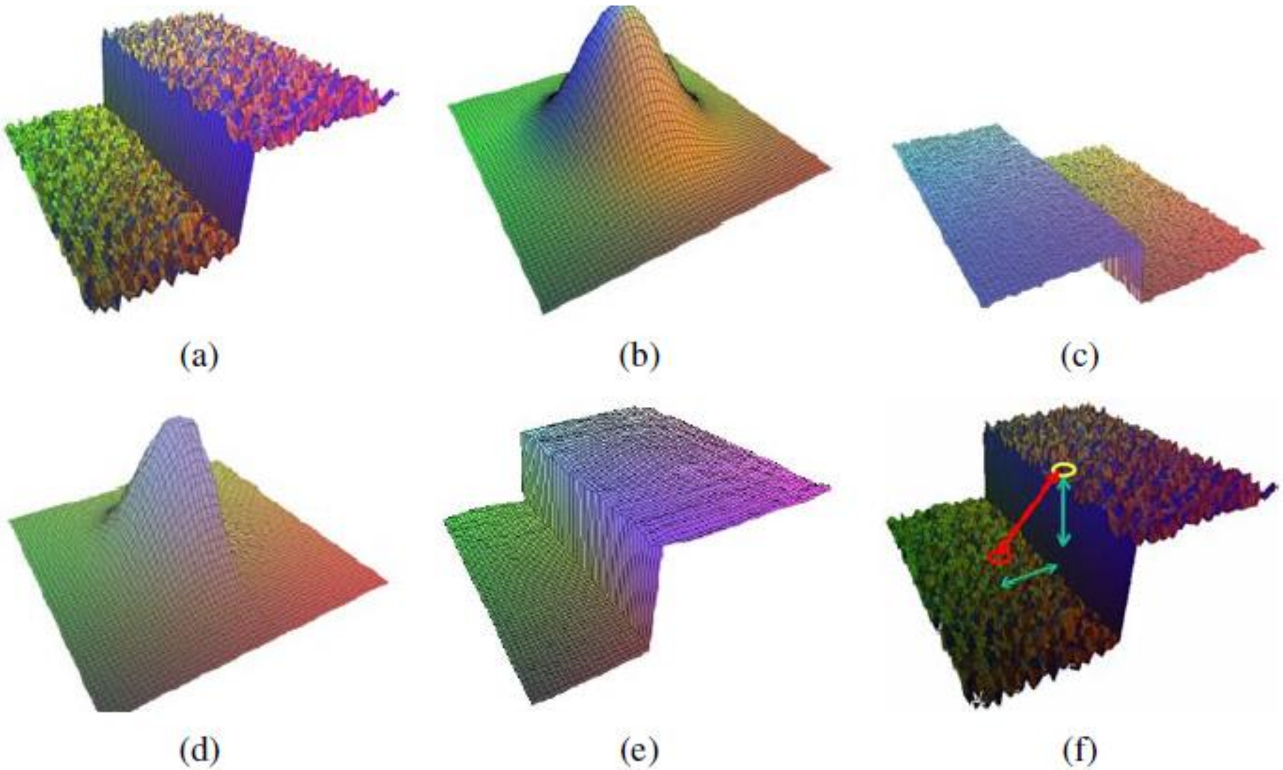


Figure 3.20 Bilateral filtering (Durand and Dorsey 2002) © 2002 ACM: (a) noisy step edge input; (b) domain filter (Gaussian); (c) range filter (similarity to center pixel value); (d) bilateral filter; (e) filtered step edge output; (f) 3D distance between pixels.

Joint Bilateral Filtering

- The range kernel takes another **guidance image** as reference

$$g(x, y) = \frac{1}{W} \sum_{i,j \in [-r,r]} h_s(i, j) \cdot h_r(i, j) \cdot f(x - i, y - j)$$

$$h_s(i, j) = e^{-\frac{i^2 + j^2}{2\sigma_s^s}} \qquad h_r(i, j) = e^{-\frac{f'(x-i)^2 + f'(y-j)^2}{2\sigma_r^s}}$$

Flash

No flash

Joint bilateral filtering

http://hhoppe.com/proj/flash/

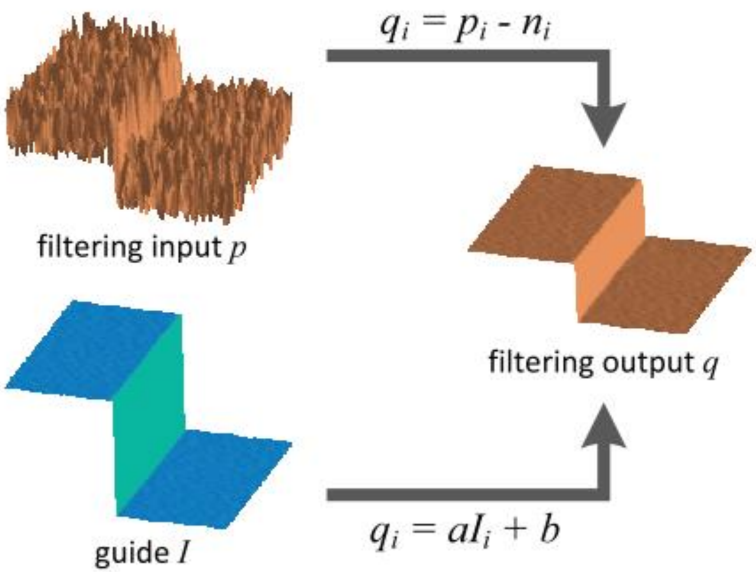
Bilateral Filtering

- Fast bilateral filtering also exists
  - "A fast approximation of the bilateral filter using a signal processing approach", ECCV 2006
  - "Constant time O(1) bilateral filtering", CVPR 2008
  - "Real-time O(1) bilateral filtering", CVPR 2009
  - "Fast high-dimensional filtering using the permutohedral lattice", EG 2010
  - and many more…
- We also contribute some works in this field
  - "Constant time bilateral filtering for color images", ICIP 2016
  - "VLSI architecture design of layer-based bilateral and median filtering for 4k2k videos at 30fps", ISCAS 2017

Guided Image Filtering

[He et al. ECCV 2010]

- Local linear assumption
- Per pixel $O(1)$



Algorithm 1. Guided Filter.

Input: filtering input image p, guidance image I, radius r, regularization ϵ

Output: filtering output q.

1: $\text{mean}_I = f_{\text{mean}}(I)$
   $\text{mean}_p = f_{\text{mean}}(p)$
   $\text{corr}_I = f_{\text{mean}}(I.*I)$
   $\text{corr}_{Ip} = f_{\text{mean}}(I.*p)$

2: $\text{var}_I = \text{corr}_I - \text{mean}_I.*\text{mean}_I$
   $\text{cov}_{Ip} = \text{corr}_{Ip} - \text{mean}_I.*\text{mean}_p$

3: $a = \text{cov}_{Ip}./(\text{var}_I + \epsilon)$
   $b = \text{mean}_p - a.*\text{mean}_I$

4: $\text{mean}_a = f_{\text{mean}}(a)$
   $\text{mean}_b = f_{\text{mean}}(b)$

5: $q = \text{mean}_a.*I + \text{mean}_b$

http://kaiminghe.com/eccv10/index.html

Edge-Preserving Filtering

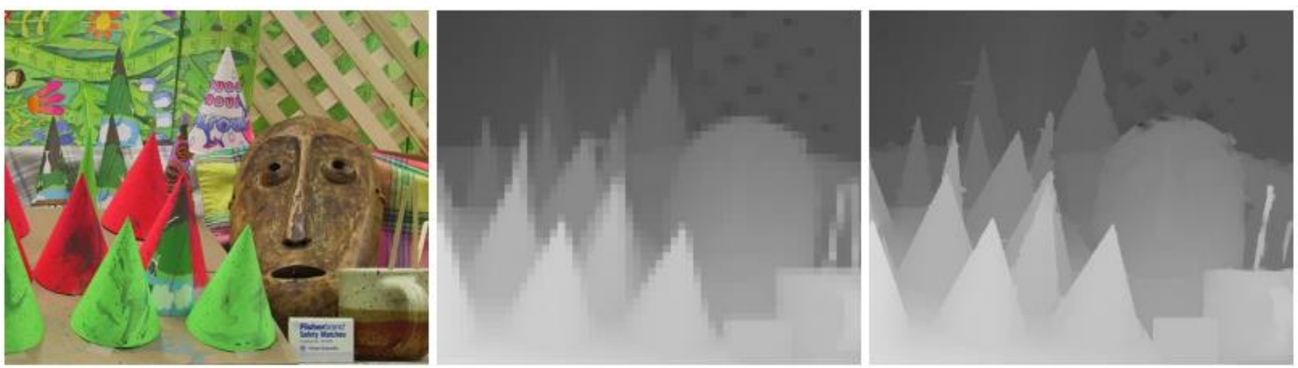
- Both the bilateral filter and the guided image filter are called **edge-preserving filters** (EPF)
  - They can smooth images while preserving edges
- Other widely used EPFs with source code
  - Weighted least square filter, SIGGRAPH 2008
  - Domain transform filter, SIGGRAPH 2011
  - L_0 filter, SIGGRAPH Asia 2011
  - Fast global smoothing filter, TIP 2014

Edge-Preserving Filtering

- Applications

Edit (*e.g.* color) propagation

Detail manipulation



Guided upsampling (depth maps, features, …, etc.)

What we have learned today

- Digital imaging
- Some low-level image processing

Physical world | Sensing device | Interpreting device | Interpretations

→

→ CPU/GPU/DSP → cat, lovely, in a box

Image formation
- Pinhole camera
- Photography
- Camera pipeline

Image processing
- Histogram
- Morphological operations
- Edge detection
- Image filtering
- …