



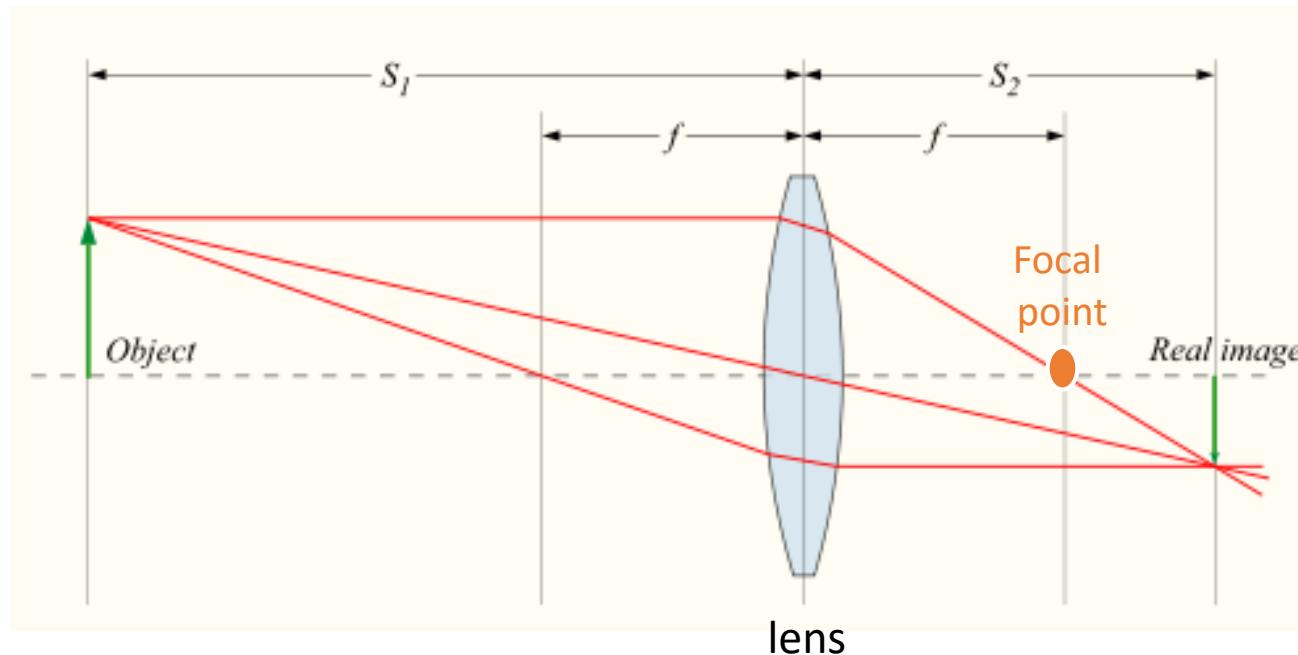
Mid-term Review

CPS592 – Visual Computing and Mixed Reality

Outline

- Imaging
- Color
- Image Operators
- Image Filtering
- Bilateral Filtering
- Color Transfer
- Visual Saliency
- Saliency Prediction Computational Models

Focal length

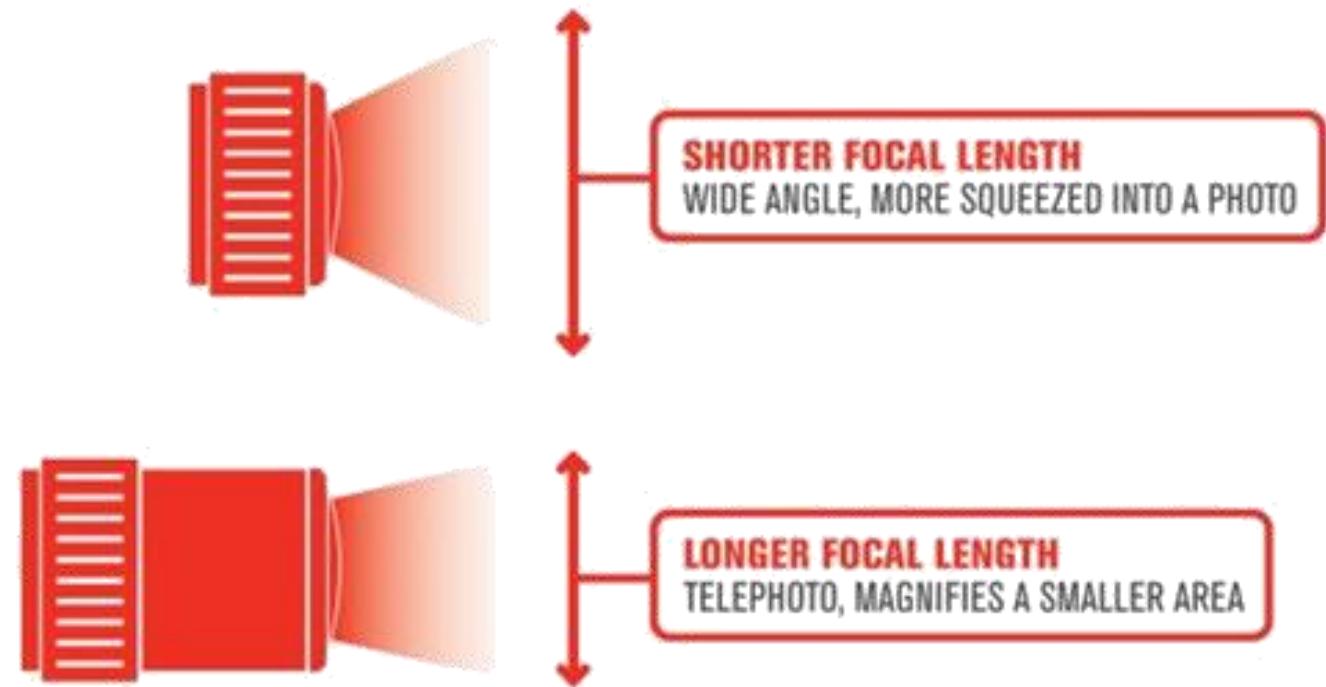


Thin lens equation:

$$\frac{1}{s_1} + \frac{1}{s_2} = \frac{1}{f}$$

Any object point satisfying this equation is in focus

Focal length



Exposure

- Exposure controls how much light hits the camera sensor
- Two ways to control this:
 - **Aperture**: the “hole” in the optical path for the light
 - **Shutter speed**: the time the “hole” is opened



Aperture



Controllable Shutter

Shutter speed

- Shutter speed
 - Expressed in fraction of a second:
 - $1/30, 1/60, 1/125, 1/250, 1/500$
 - (in reality, $1/32, 1/64, 1/128, 1/256, \dots$)

500 (1/500 sec)



60 (1/60 sec)



30 (1/30 sec)



8 (1/8 sec)



LONGER ← → **SHORTER**

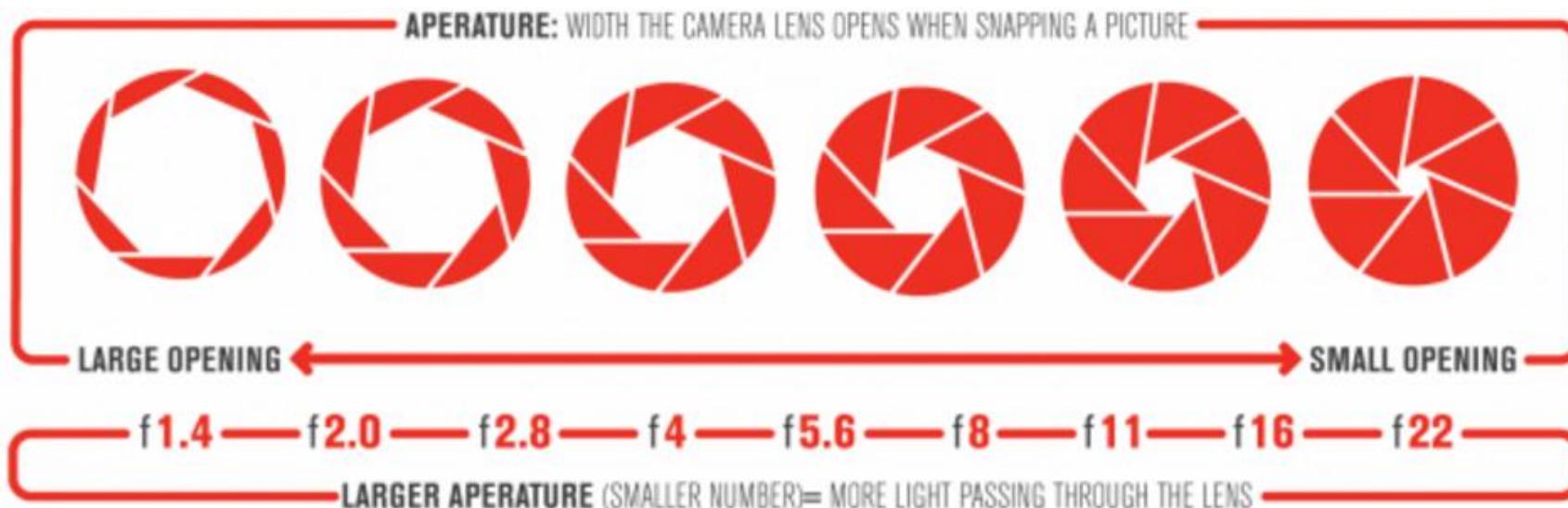


MORE MOTION

LESS MOTION Icon of a person walking, representing shorter shutter speeds.

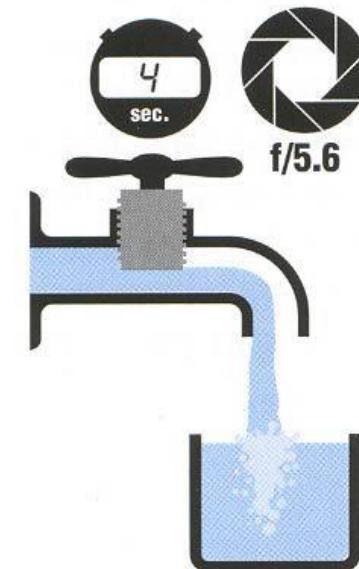
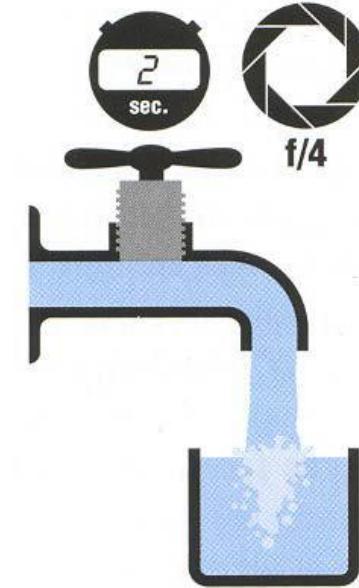
Aperture

- Aperture
 - Expressed as ratio of aperture size to focal length (f-stop)
 - f/2.0, f/2.8, f/4, f/5.6, f/8, f/11, f/16, f/22, f/32
 - f/**X**, means focal length is **X** times bigger than the aperture
 - Each f-stop reduces the area of the aperture by half
 - So, the larger the f-stop, the smaller the aperture



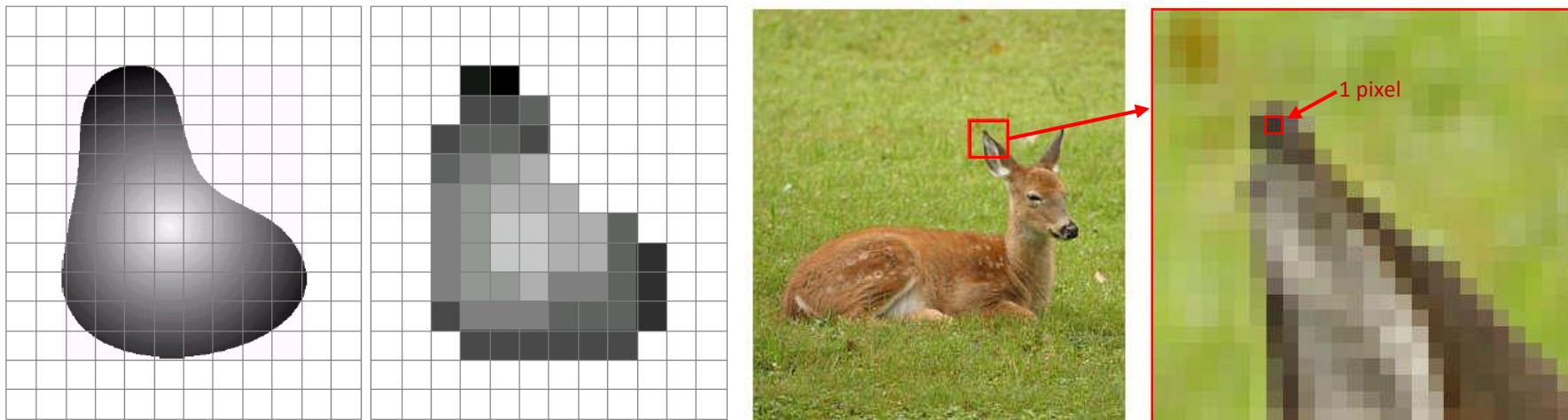
Exposure

- The play between f-stop and shutter:
 - Aperture (in f stop)
 - Shutter speed (in fraction of a second)
- Reciprocity
 - The same exposure is obtained with a shutter speed twice as long and an aperture area half as big



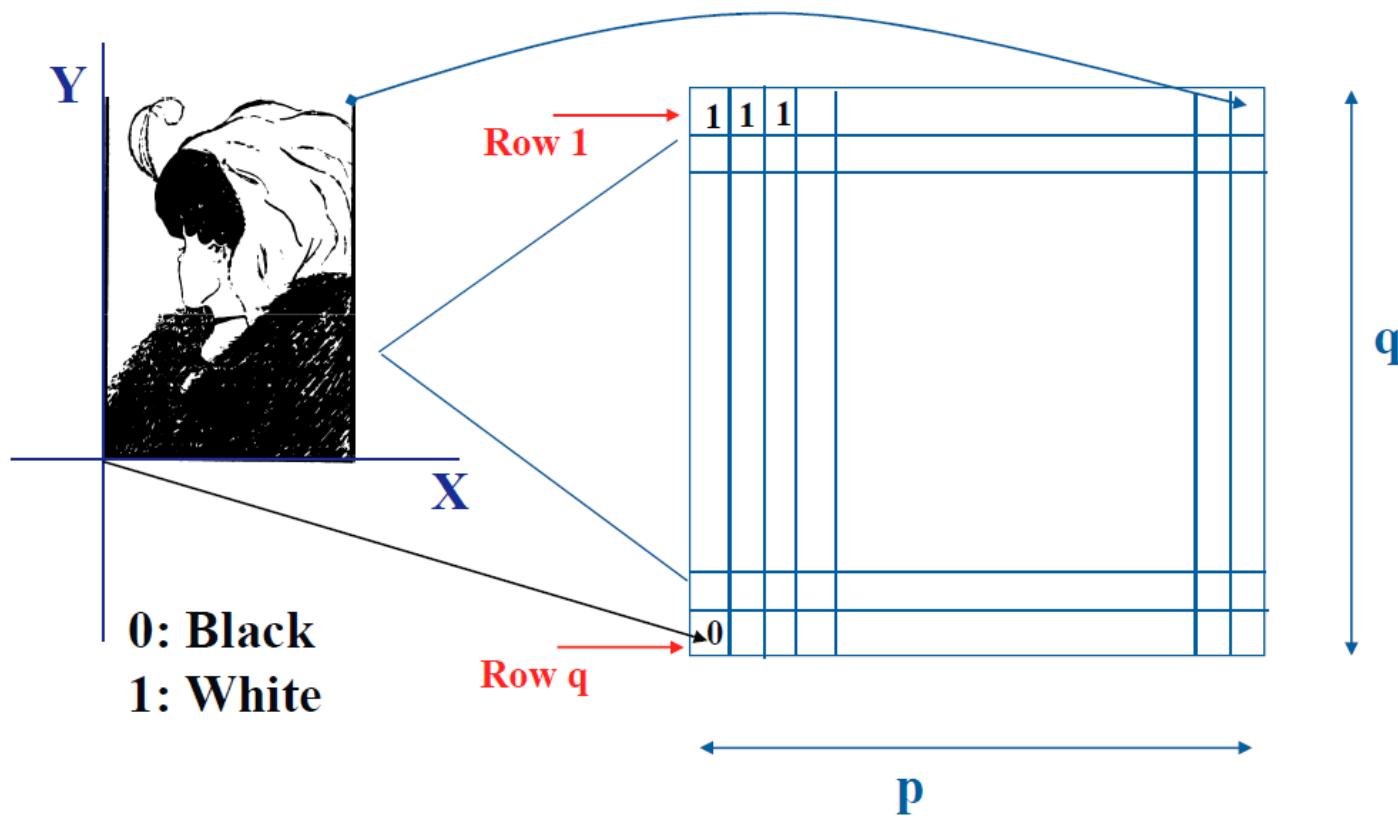
Digital Images

- A **digital image** is a representation of a two-dimensional image as a finite set of digital values, called picture elements or pixels.
- We can think of an **image** as a function, f , from \mathbb{R}^2 to \mathbb{R} :
 - $f(x, y)$ gives the **intensity** at position (x, y)

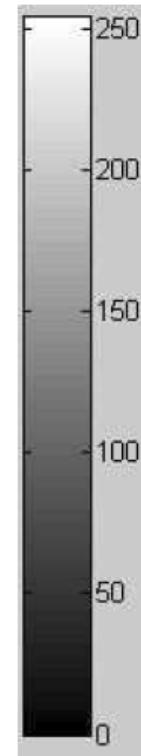
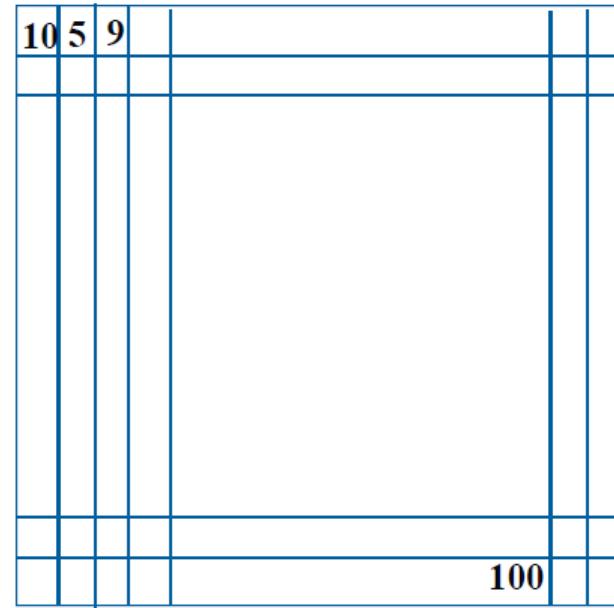


Digitization implies that a digital image is an approximation of a real scene.

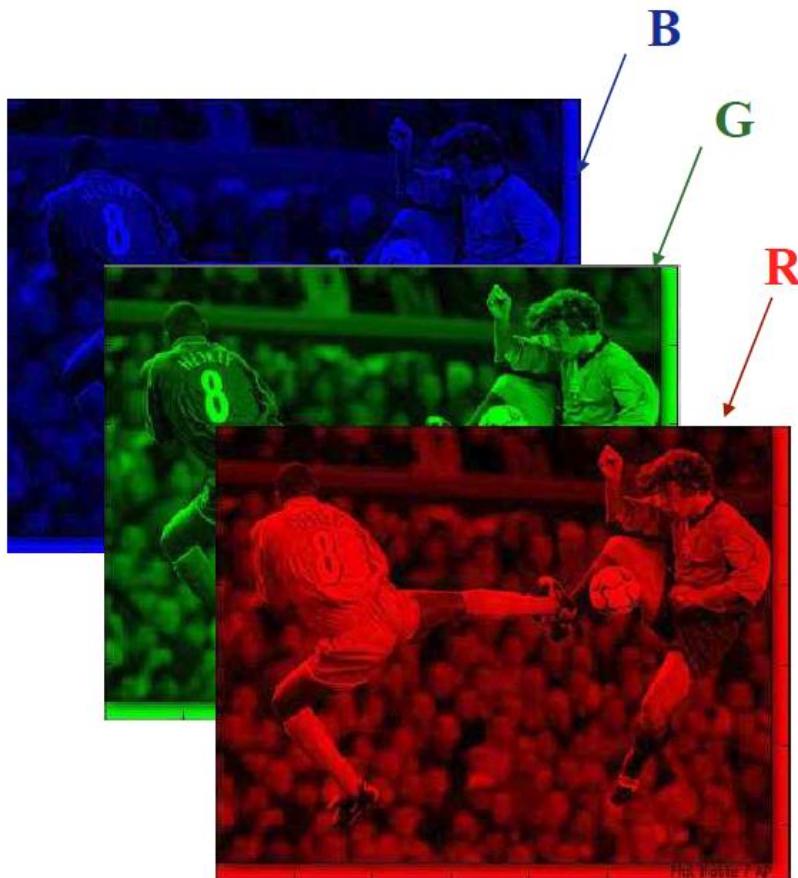
Binary Image



Grayscale Image

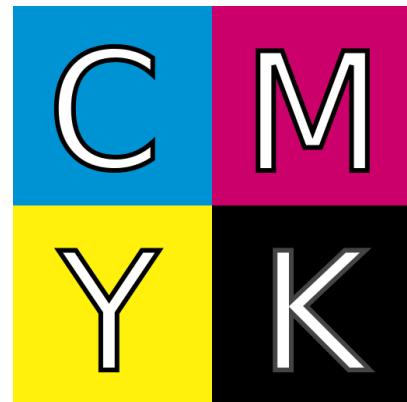


Color Image (RGB)



3-Component Color

- The de facto representation of color on screen display is RGB.
(additive color)
- Some printers use CMY(K), (subtractive color)



Main Color Spaces

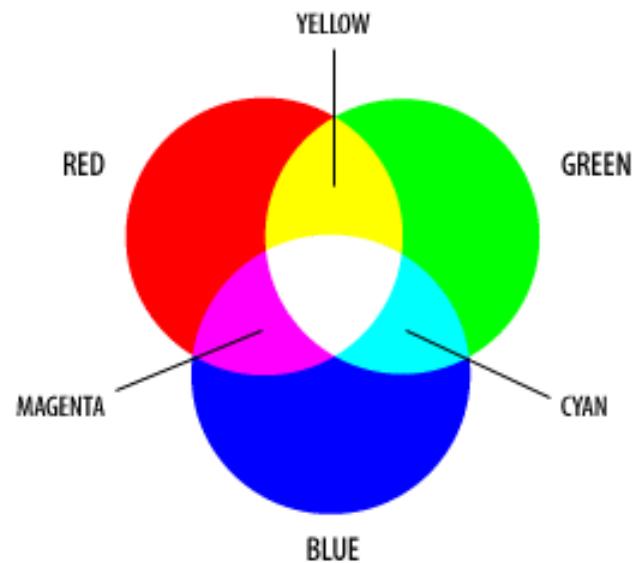
- RGB, CMYK
- HSV (Munsell, HSL, IHS)
- Lab, UVW, YUV, YCrCb, Luv,

Differences in Color Spaces

- What is the use?
 - Display,
 - Editing
 - Computation
 - Compression
- Several key (very often conflicting) features may be sought after:
 - Additive (RGB) or subtractive (CMYK)
 - Separation of luminance and chromaticity
 - Equal distance between colors are equally perceivable

RGB

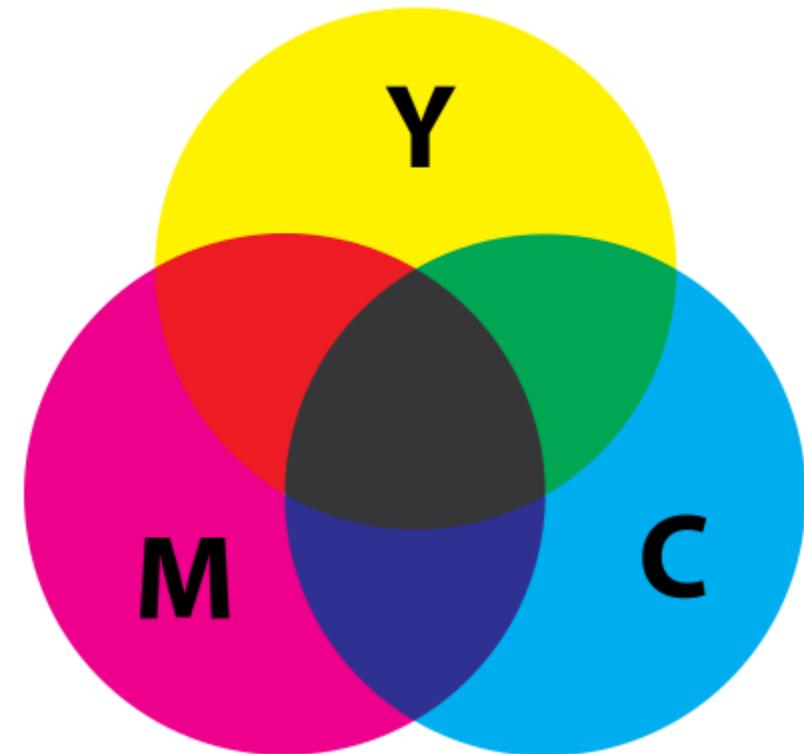
- The de facto standard



$$C = rR + gG + bB$$

CMY(K): printing

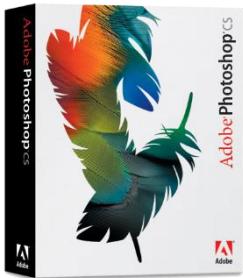
- Cyan, Magenta, Yellow (Black) – CMY(K)
- A subtractive color model



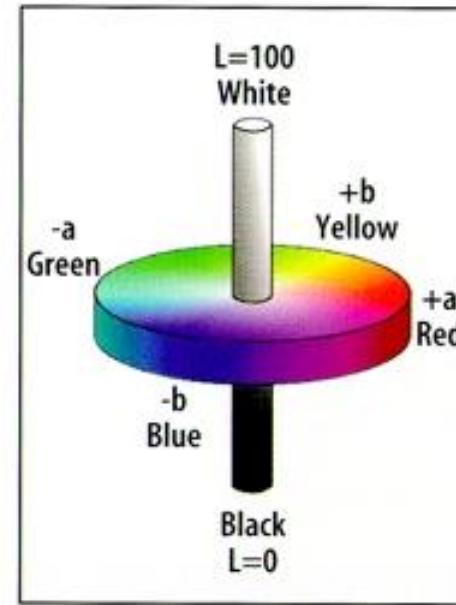
HSV

- This color model is based on polar coordinates, not Cartesian coordinates.
- HSV is a non-linearly transformed (skewed) version of RGB cube
 - Hue: quantity that distinguishes color family, say red from yellow, green from blue
 - Saturation (Chroma): color intensity (strong to weak). Intensity of distinctive hue, or degree of color sensation from that of white or grey
 - Value (luminance): light color or dark color

Lab: photoshop



- Photoshop uses this model to get more control over color
- Luminance: L
- Chrominance: a – ranges from green to red and b ranges from blue to yellow



Lab model

Yuv and YCrCb: digital video

- Initially, for PAL analog video, it is now also used in CCIR 601 standard for digital video

- Y (luminance) is the CIE Y primary.

$$Y = 0.299R + 0.587G + 0.114B$$

- *Chrominance* is defined as the difference between a color and a reference white at the same luminance. It can be represented by U and V -- the *color differences*.

$$U = B - Y; V = R - Y$$

- YCrCb is a scaled and shifted version of YUV and used in JPEG and MPEG (all components are positive)

$$Cb = (B - Y) / 1.772 + 0.5; Cr = (R - Y) / 1.402 + 0.5$$

Convert RGB to grayscale

- $\text{intensity} = 0.2989 * \text{R} + 0.5870 * \text{G} + 0.1140 * \text{B}$

Original RGB

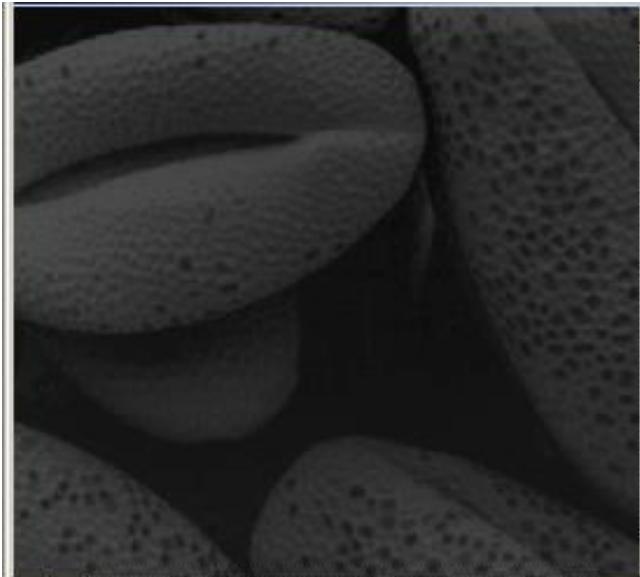


Grayscale Conversion



Image Histogram

- The shape of a histogram provides useful information for contrast enhancement.



```
>> clear;
[ix,map]=imread('Fig3_15a.jpg');
imshow(ix)
figure;
ix=double(ix);
h=histogram(ix);
figure
stem(0:255,h);
..'
```

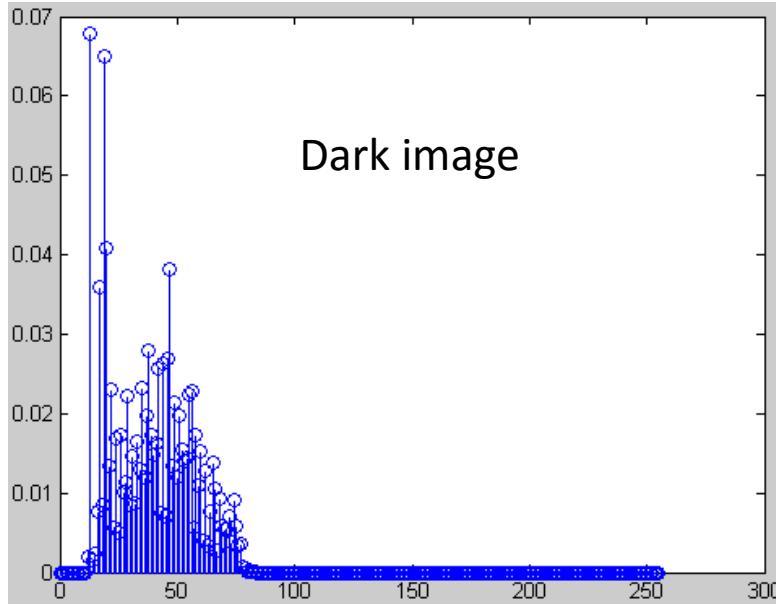
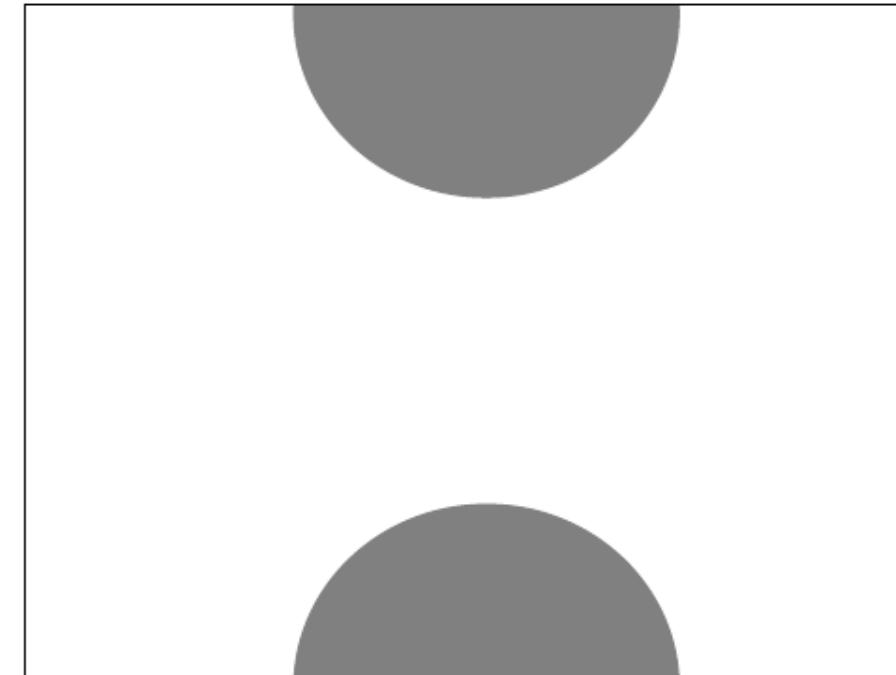
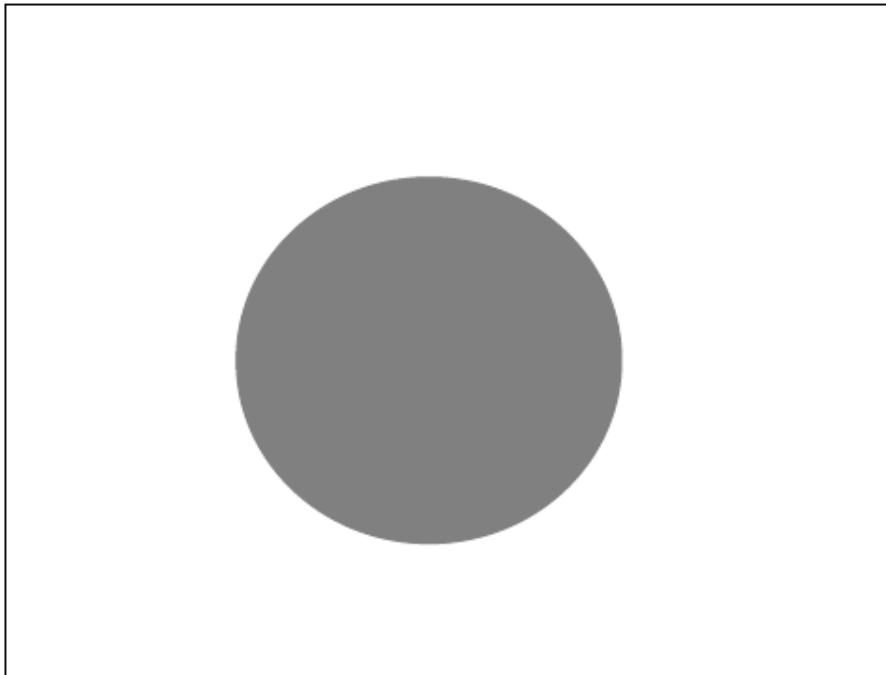


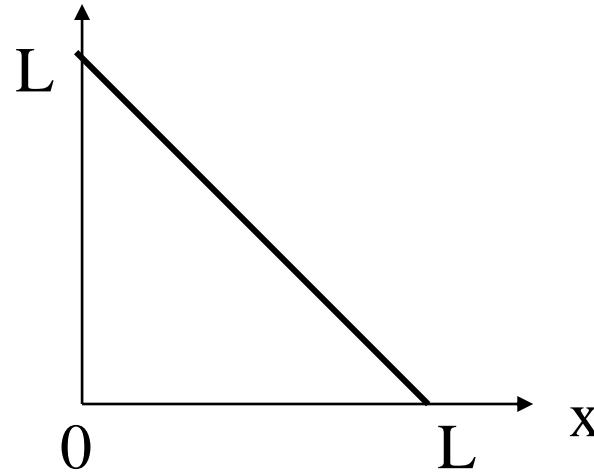
Image Histogram



- Keep in mind that histograms are not unique

Digital Negative

$$y = L - x$$



Histogram Stretching

- Stretch the histogram to increase the contrast.



[50,150] → [30,200]

Histogram Equalization

- Objective: we want an image with equally many pixels at every gray level
 - This makes the image look nice
 - Also maximizes pixel resources
 - We would say this has an “equal histogram”

Example

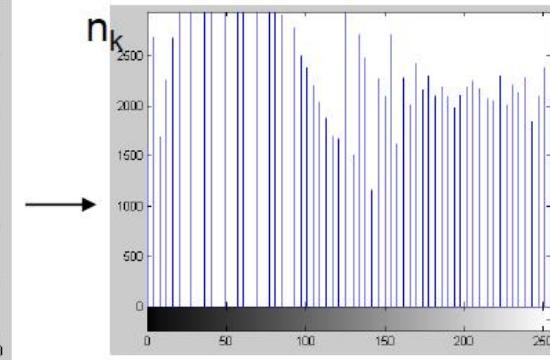
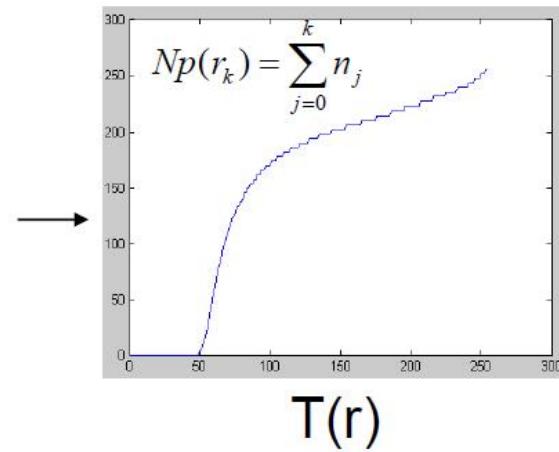
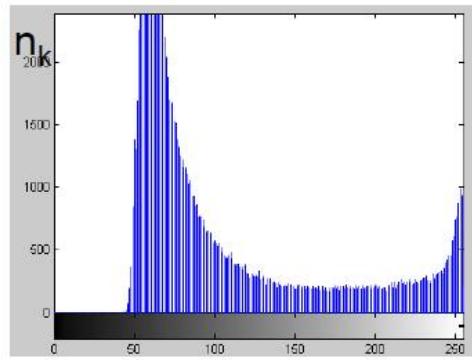


Image Filtering

- Modify the pixels in an image based on some function of a local neighborhood of each pixel

10	5	3
4	5	1
1	1	7

Local image data

Some function



?		

Modified image data

Example

\bar{H}

\bar{H}

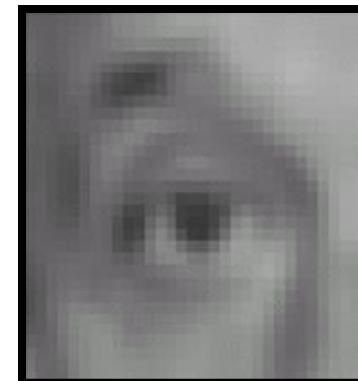
F

Mean filtering

$$\begin{matrix} & \begin{matrix} & & \end{matrix} \\ \begin{matrix} & & \end{matrix} & * \\ H & \begin{matrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 90 & 90 & 90 & 90 & 90 & 0 & 0 \\ 0 & 0 & 0 & 90 & 90 & 90 & 90 & 90 & 0 & 0 \\ 0 & 0 & 0 & 90 & 90 & 90 & 90 & 90 & 0 & 0 \\ 0 & 0 & 0 & 90 & 90 & 90 & 90 & 90 & 0 & 0 \\ 0 & 0 & 0 & 90 & 0 & 90 & 90 & 90 & 0 & 0 \\ 0 & 0 & 0 & 90 & 90 & 90 & 90 & 90 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{matrix} \end{matrix} = \begin{matrix} & \begin{matrix} & & \end{matrix} \\ \begin{matrix} & & \end{matrix} & * \\ F & \begin{matrix} 0 & 10 & 20 & 30 & 30 & 30 & 20 & 10 \\ 0 & 20 & 40 & 60 & 60 & 60 & 40 & 20 \\ 0 & 30 & 60 & 90 & 90 & 90 & 60 & 30 \\ 0 & 30 & 50 & 80 & 80 & 90 & 60 & 30 \\ 0 & 30 & 50 & 80 & 80 & 90 & 60 & 30 \\ 0 & 20 & 30 & 50 & 50 & 60 & 40 & 20 \\ 10 & 20 & 30 & 30 & 30 & 30 & 20 & 10 \\ 10 & 10 & 10 & 0 & 0 & 0 & 0 & 0 \end{matrix} \end{matrix}$$

$$G$$

$$\frac{1}{9} \begin{matrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{matrix}$$



Original

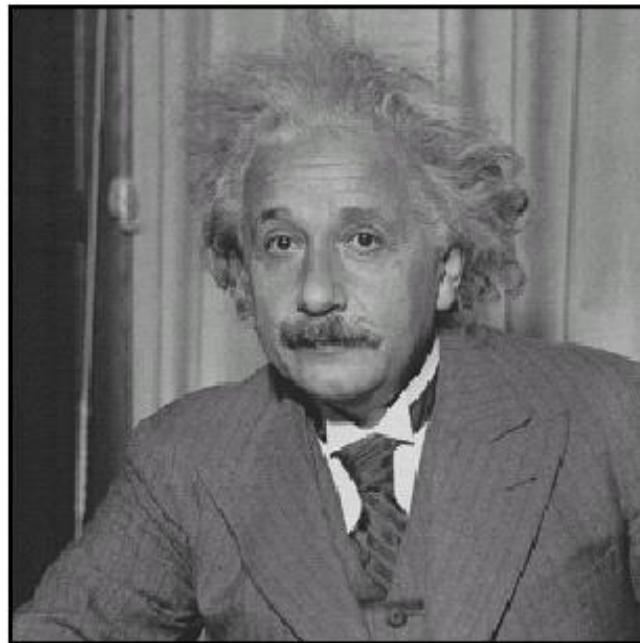
Blur (with a mean filter)

Linear filters: examples

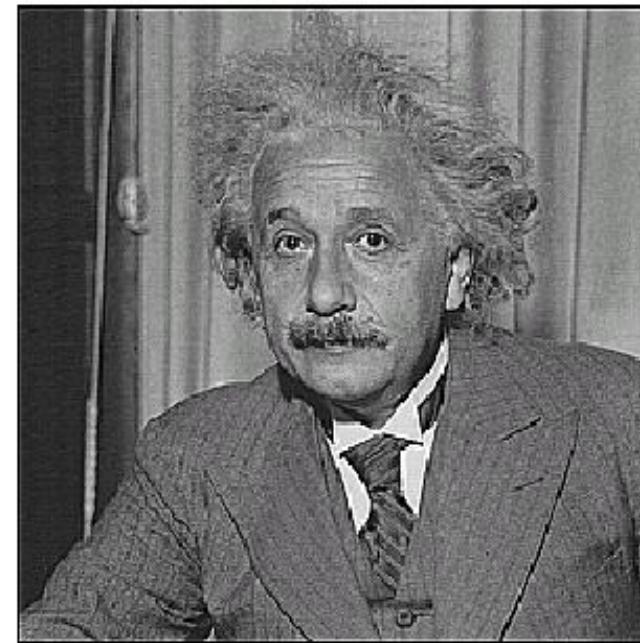
The diagram shows the mathematical operation of applying a linear filter to an image. On the left is a grayscale image of a face, labeled "Original". To its right is a convolutional operator symbol ($*$) followed by a large parentheses containing two matrices. The first matrix is a 3x3 kernel with values: $\begin{matrix} 0 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 0 \end{matrix}$. The second matrix is a 3x3 kernel with values: $\begin{matrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{matrix}$. A minus sign and a fraction $\frac{1}{9}$ are placed between the two matrices. An equals sign follows the second matrix. To the right of the equals sign is the resulting image, which appears sharper than the original, labeled "Sharpening filter (accentuates edges)".

$$\text{Original} \quad * \left(\begin{matrix} 0 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 0 \end{matrix} - \frac{1}{9} \begin{matrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{matrix} \right) = \text{Sharpening filter (accentuates edges)}$$

Sharpening



before



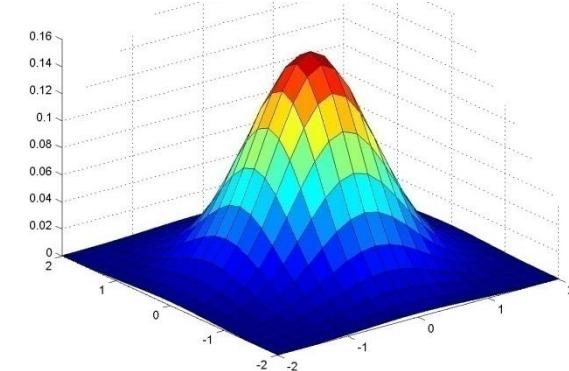
after

Gaussian filters

- A Gaussian kernel gives less weight to pixels further from the center of the window

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

$F[x, y]$



$$h(u, v) = \frac{1}{2\pi\sigma^2} e^{-\frac{u^2+v^2}{\sigma^2}}$$

Rank Filters: Median Filter

- One of the most popular non-linear filter
- Find the median of the window
- Preserves edges
- Removes impulse noise, avoids excessive smoothing

2	3	8
3	4	10
4	2	9

pixel values about (x,y) window 3x3

neighbor sort = {2,2,3,3,4,4,8,9,10}

$$f(x,y) = \text{median}$$

Rank Filters: Min/Max Filter

- Find the min or max of the neighborhood
- Not as “mainstream” as median filter
- Has various uses, will talk about these more later.

2	3	8
3	4	10
4	2	9

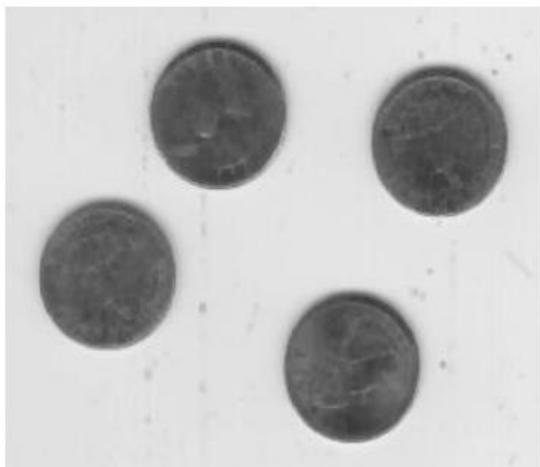
pixel values about (x,y) window 3x3

neighbor sort = {2,2,3,3,4,4,8,9,10}
 \uparrow \uparrow
 $f(x,y) = \min$ $f(x,y) = \max$

Examples



Original Image



Min



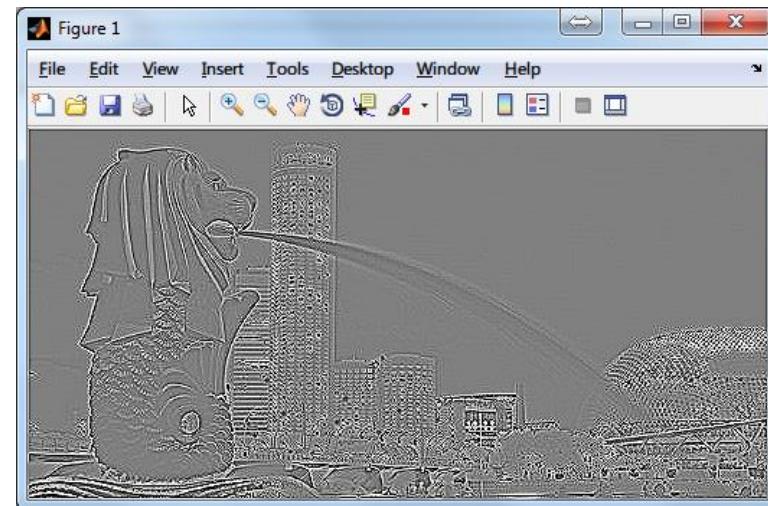
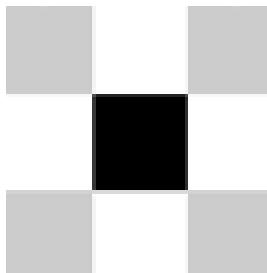
Median



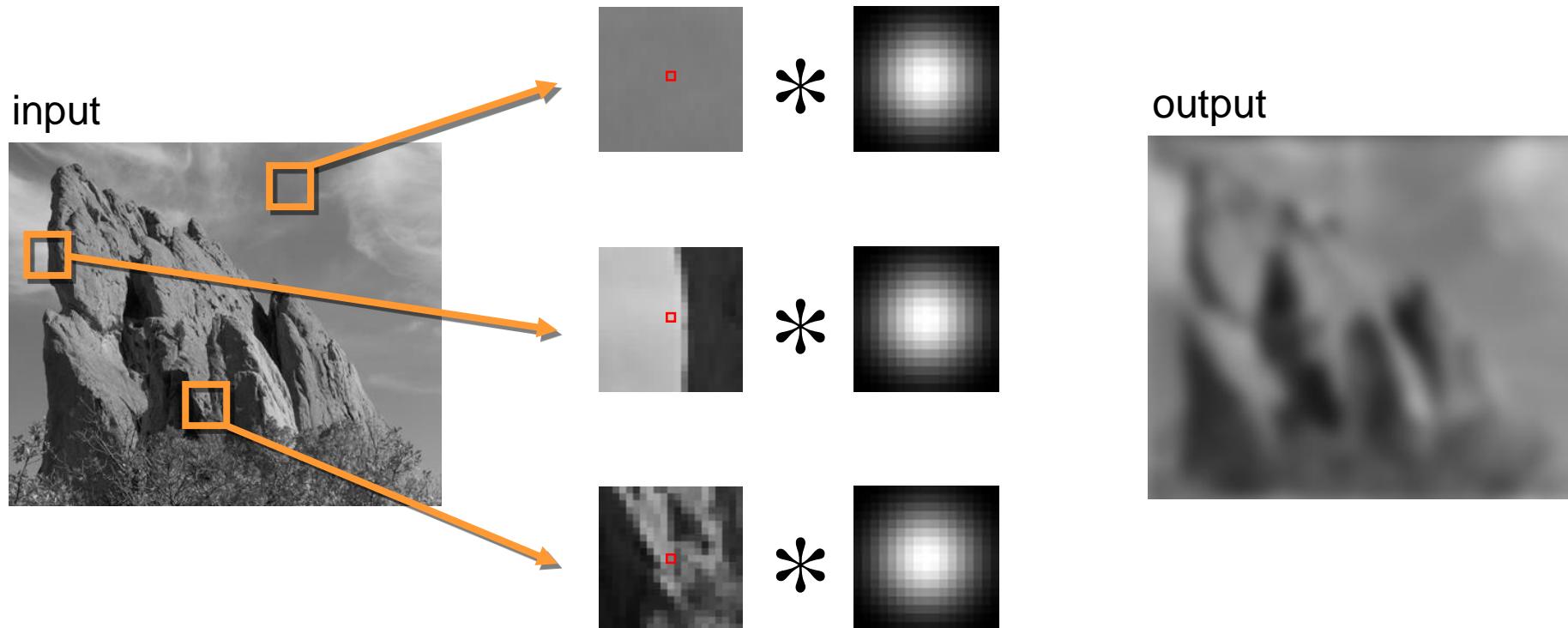
Max

Laplacian Filter

```
kernel = [0 1 0;  
          1 -4 1;  
          0 1 0];
```

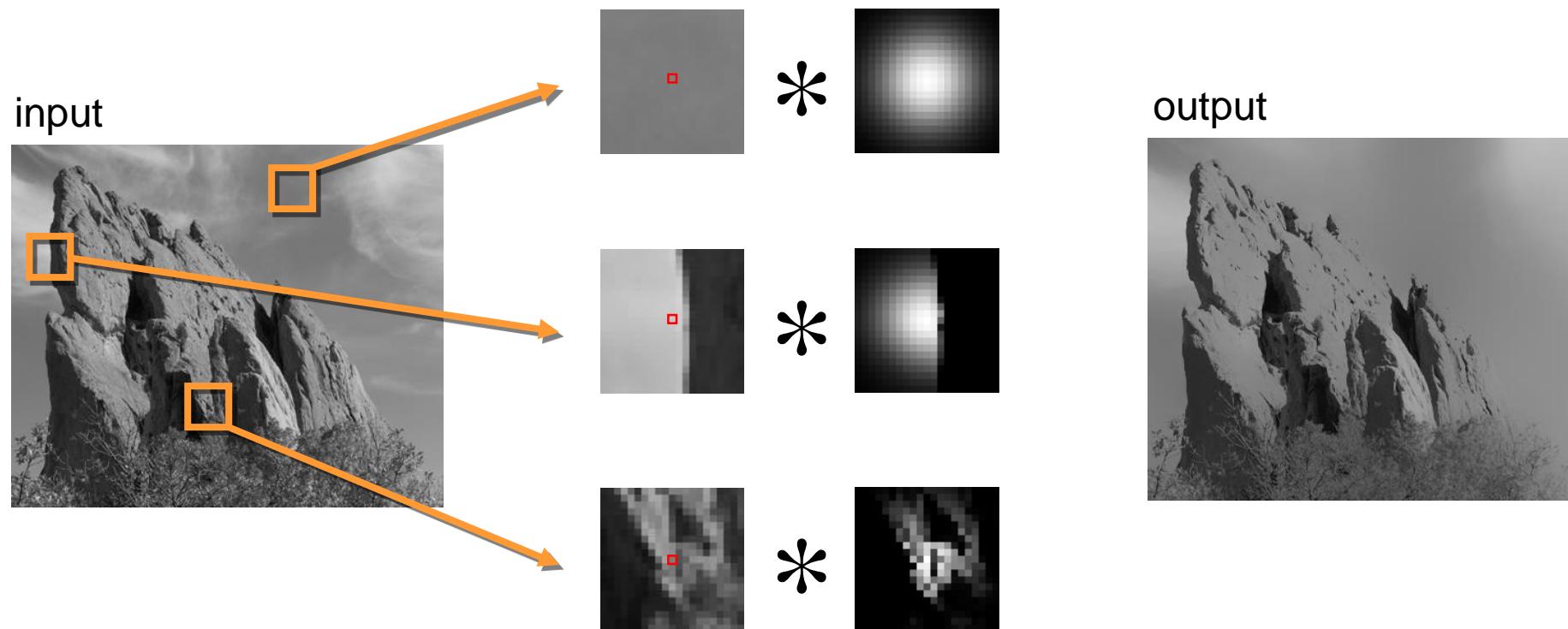


Gaussian Smoothing



Same Gaussian kernel everywhere
Averages across edges \Rightarrow blur

Bilateral Filtering



Kernel shape depends on image content
Avoids averaging across edges

Bilateral Filter Definition: an Additional Edge Term

Idea: **weighted average of pixels.**

$$BF[I]_p = \frac{1}{W_p} \sum_{q \in S} G_{\sigma_s}(\|p - q\|) G_{\sigma_r}(|I_p - I_q|) I_q$$

new
not new
new

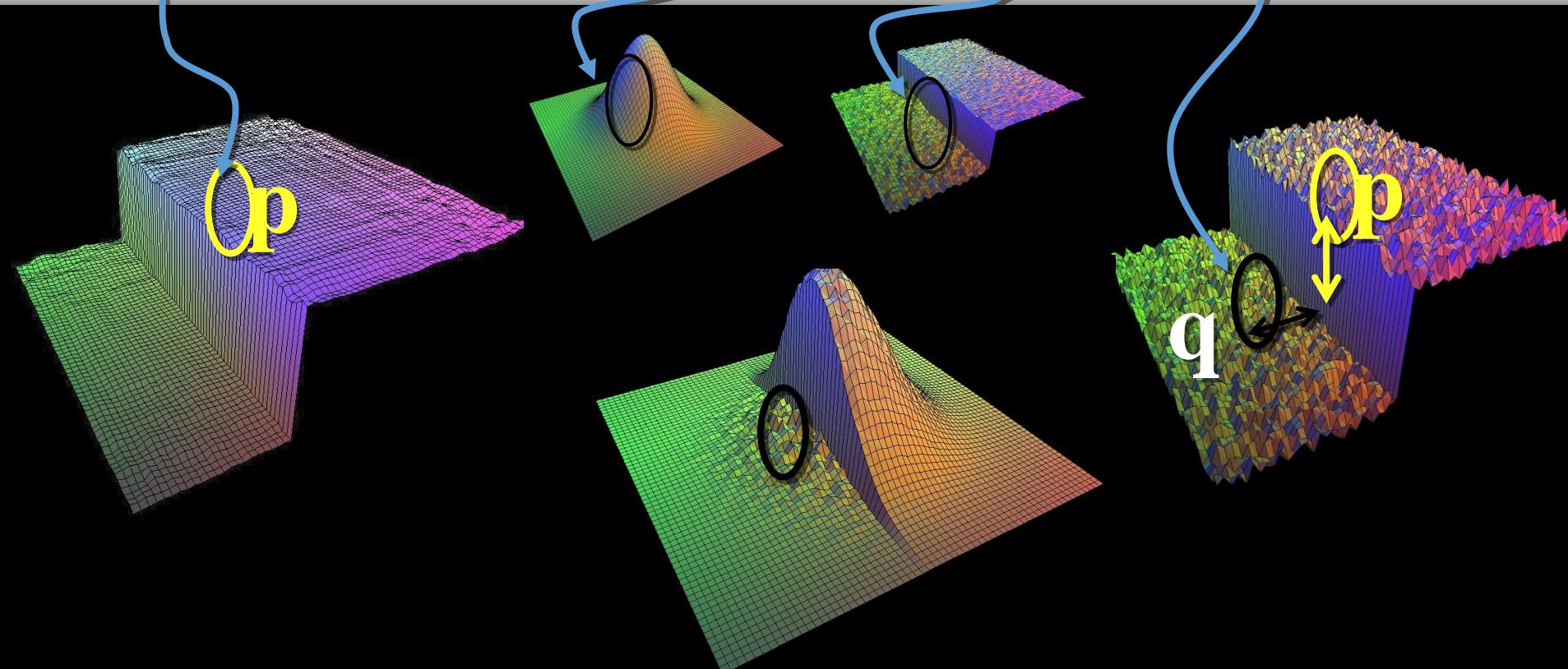
normalization factor *space* weight *range* weight

$$G_{\sigma_s}(\|p - q\|) = \frac{1}{2\pi\sigma^2} e^{-\frac{\|p-q\|^2}{\sigma^2}}$$
$$h(u, v) = \frac{1}{2\pi\sigma^2} e^{-\frac{u^2+v^2}{\sigma^2}}$$

$$W_p = \sum_{q \in S} G_{\sigma_s}(\|p - q\|) G_{\sigma_r}(|I_p - I_q|)$$

Bilateral Filter on a Height Field

$$BF[I]_p = \frac{1}{W_p} \sum_{q \in S} G_{\sigma_s}(\|p - q\|) G_{\sigma_r}(|I_p - I_q|) I_q$$



Implementation

- Brute-force Implementation
- Separable Kernel [Pham and Van Vliet 05]
- Box Kernel [Weiss 06]

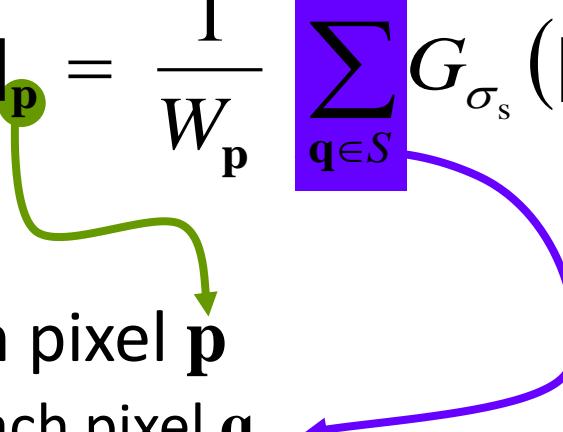
Brute-force Implementation

$$BF[I]_p = \frac{1}{W_p} \sum_{q \in S} G_{\sigma_s}(\|p - q\|) G_{\sigma_r}(|I_p - I_q|) I_q$$

For each pixel p

For each pixel q

Compute $G_{\sigma_s}(\|p - q\|) G_{\sigma_r}(|I_p - I_q|) I_q$

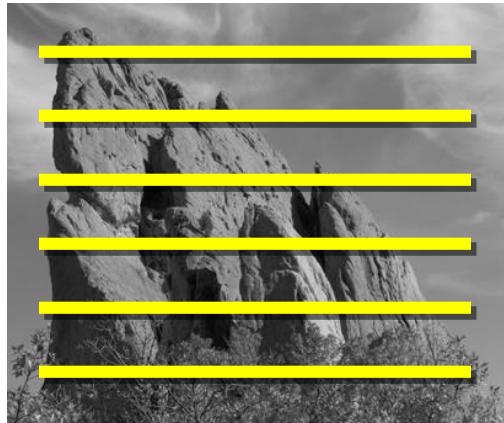


VERY SLOW!

Separable Kernel

[Pham and Van Vliet 05]

- Strategy: filter the rows then the columns



- Two “cheap” 1D filters
instead of an “expensive” 2D filter

Box Kernel

[Weiss 06]

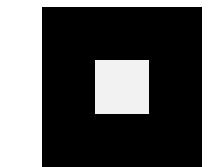
- Bilateral filter with a square box window

[Yarovlasky 85]

$$BF[I]_{\mathbf{p}} = \frac{1}{W_p} \sum_{\mathbf{q} \in S} G_{\sigma_s}(\|\mathbf{p} - \mathbf{q}\|) G_{\sigma_r}(|I_p - I_q|) I_q$$

restrict the sum

$$BF[I]_{\mathbf{p}} = \frac{1}{W_p} \sum_{\mathbf{q} \in B_{\sigma_s}} G_{\sigma_r}(|I_p - I_q|) I_q$$



box window

- The bilateral filter can be computed only from the list of pixels in a square neighborhood.

Color Transfer

- Make one image look like another



target image



source image



result image

Method

- For both images:
 - Transfer to new color space
 - Compute mean and standard deviation along each color axis
- Linear color transfer: scale and shift
 - Shift and scale the source image to have same statistics as the target image

Color Transfer Implementation

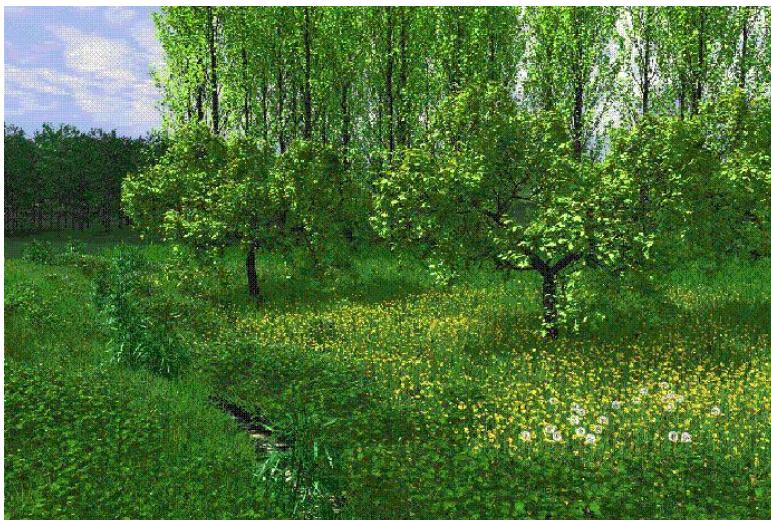
$$C' = \frac{\sigma_t}{\sigma_s} (C_s - \mu_s) + \mu_t$$

- Where
 - C' = new color
 - C_s = old color
 - σ_t = SD of target image
 - σ_s = SD of source image
 - μ_t = mean of target image
 - μ_s = mean of source image

Color Transfer Example



Color Transfer Example



What is Visual Saliency?

- Something is said to be **salient** if it **stands out**
- E.g. road signs should have high saliency



Introduction

- Trying to model visual attention
- Find locations of **Focus of Attention** in an image
- Use the idea of saliency as a basis for their model
- For primates focus of attention directed from:
 - **Bottom-up: rapid, saliency driven, task-independent**
 - Top-down: slower, task dependent

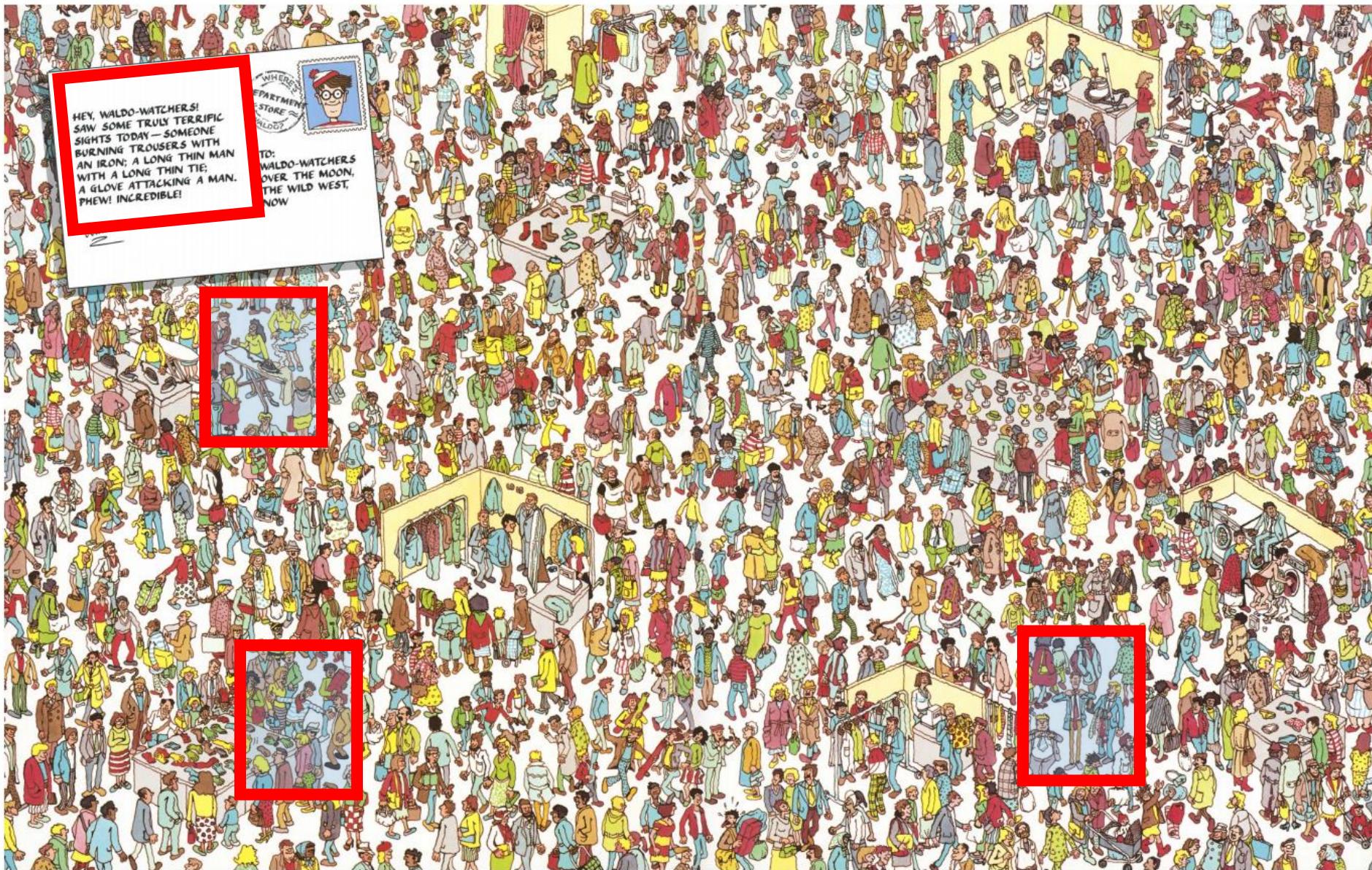
Bottom-up

- Task-independent



Top-down (Task dependent)

SOMEONE BURNING TROUSERS WITH AN IRON
A LONG THIN MAN WITH A LONG THIN TIE
A GLOVE ATTACKING A MAN



Purpose of visual saliency models

- Warning (animals, flashes, sudden motion)
- Exploration (find objects, verification)
- Inspection

Motivation - application

Image mosaicking: the salient details are preserved, with the use of smaller building blocks.



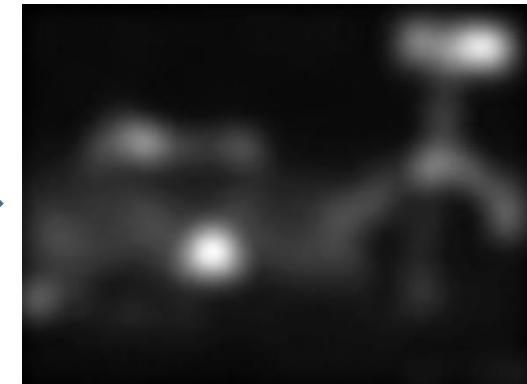
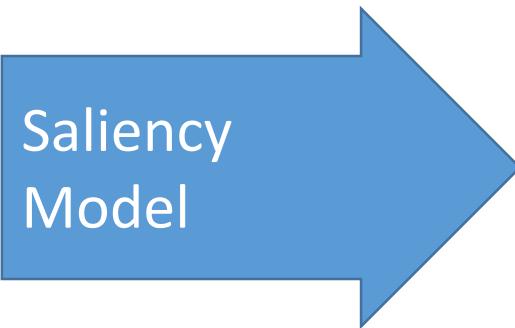
Input



Mosaic

Computational saliency models

Researchers create computational models to predict where people look.



A Model of Saliency-Based Visual Attention for Rapid Scene Analysis

Laurent Itti, Christof Koch, and Ernst Niebur



Itti's model

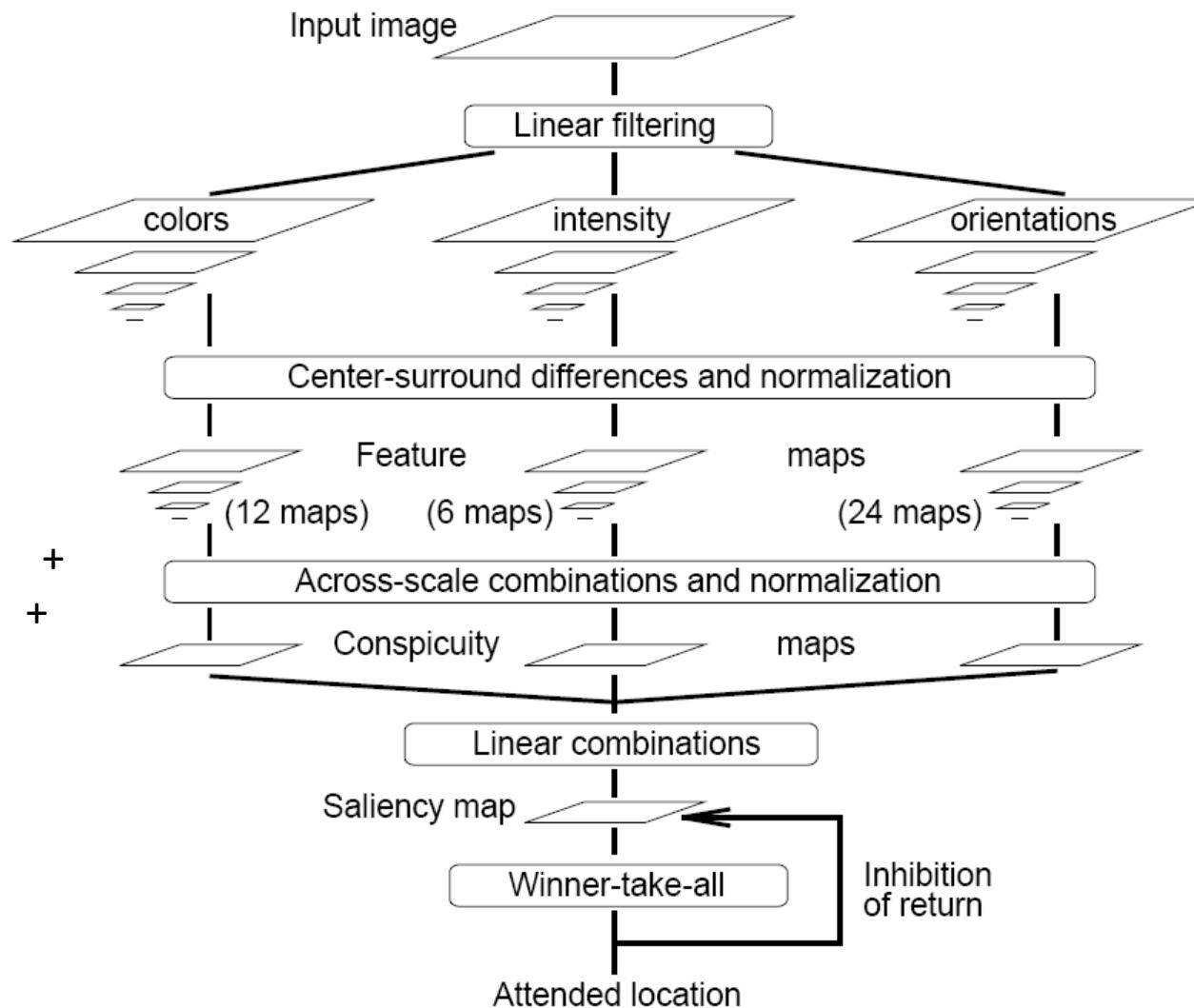
Gabor Pyramid +
Orientation Filters

Subtract low-res (3-4
octaves) from higher res

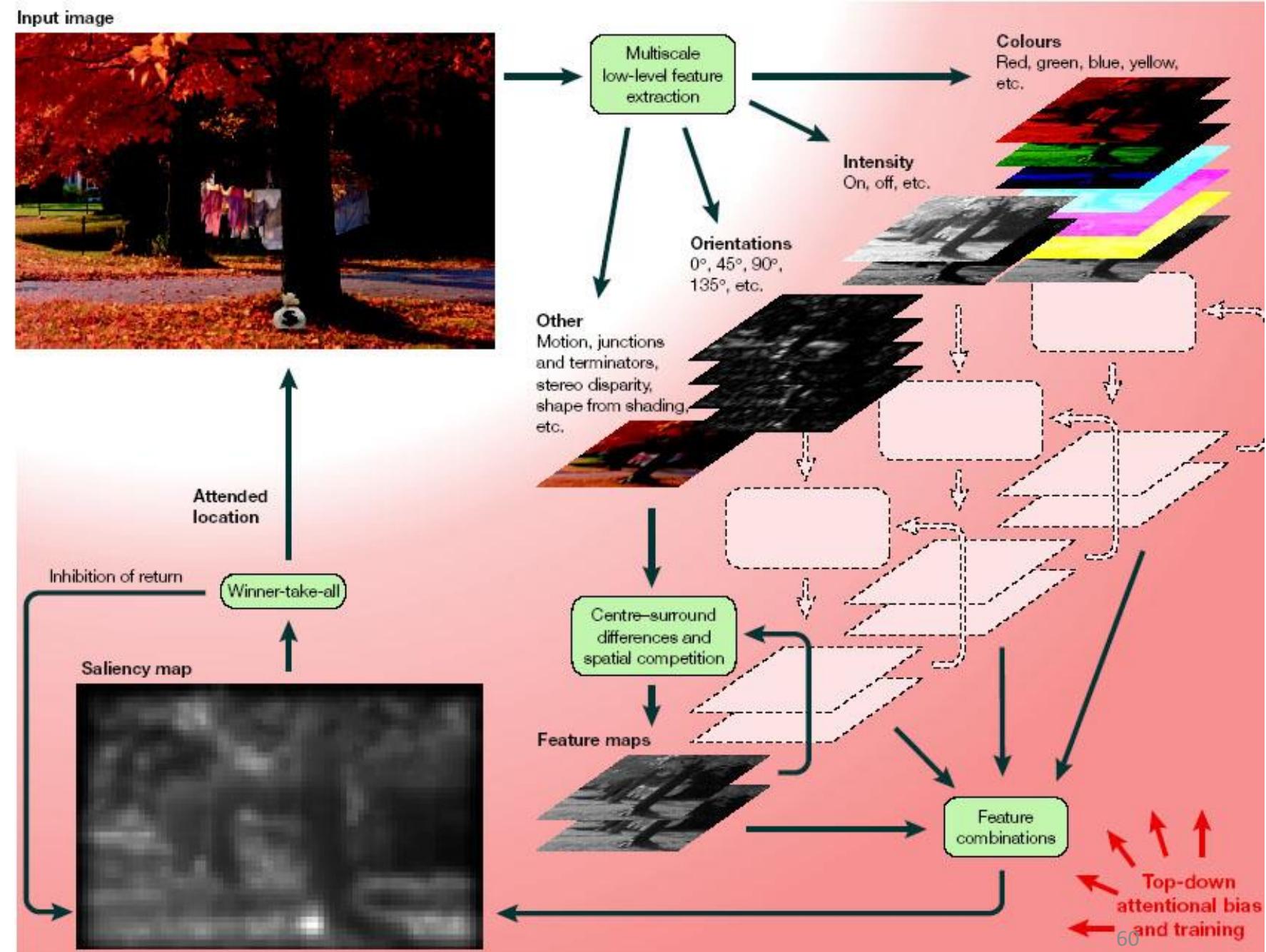
Normalize (0..1)
 $\text{map} * (1 - \max_{\text{ave}})^2$
add maps

Average Maps

Inhibition + Excitation



How it works



Frequency-tuned Salient Region Detection

Radhakrishna Achanta[†], Sheila Hemami[‡], Francisco Estrada[†], and Sabine Süsstrunk[†]

[†]School of Computer and Communication Sciences (IC)

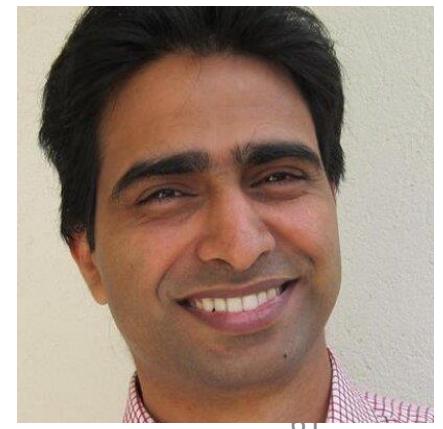
Ecole Polytechnique Fédérale de Lausanne (EPFL), CH-1015, Switzerland.

[radhakrishna.achanta, francisco.estrada, sabine.susstrunk]@epfl.ch

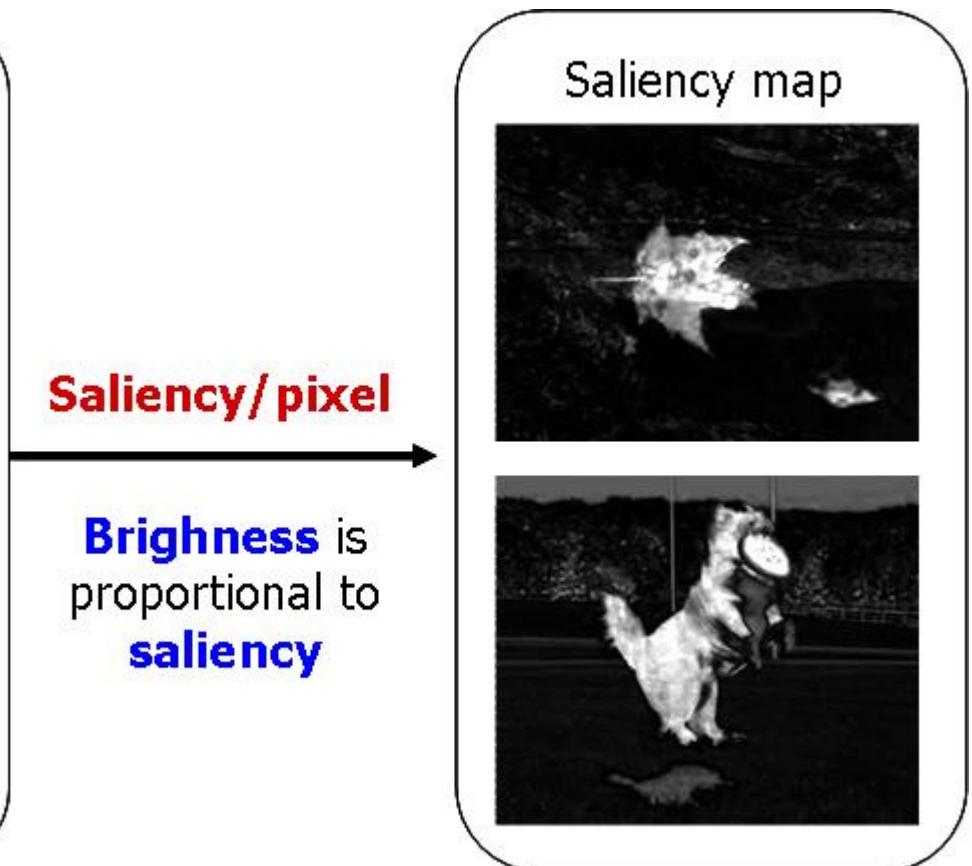
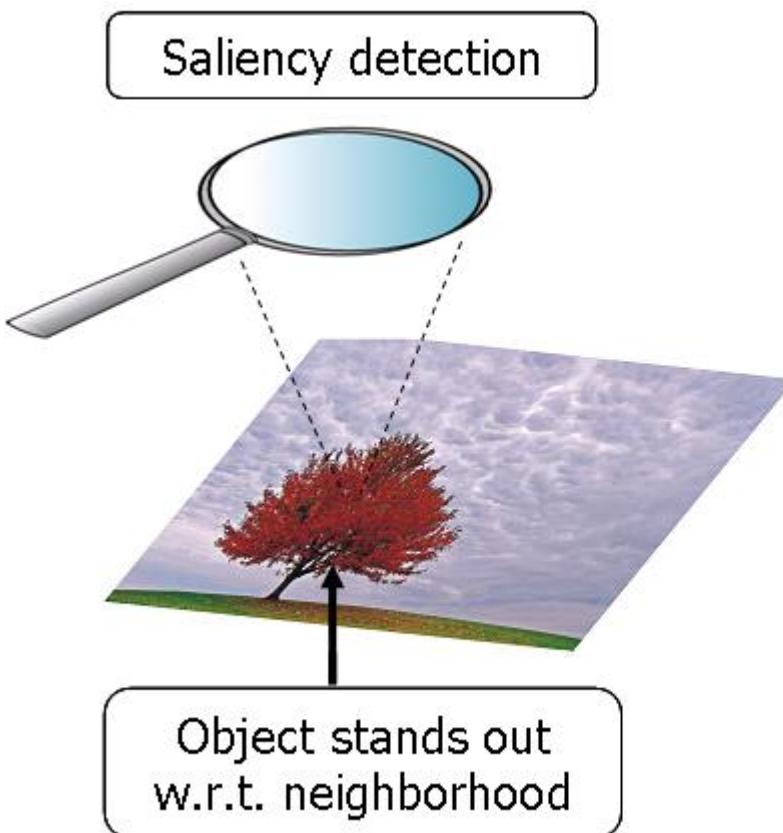
[‡]School of Electrical and Computer Engineering

Cornell University, Ithaca, NY 14853, U.S.A.

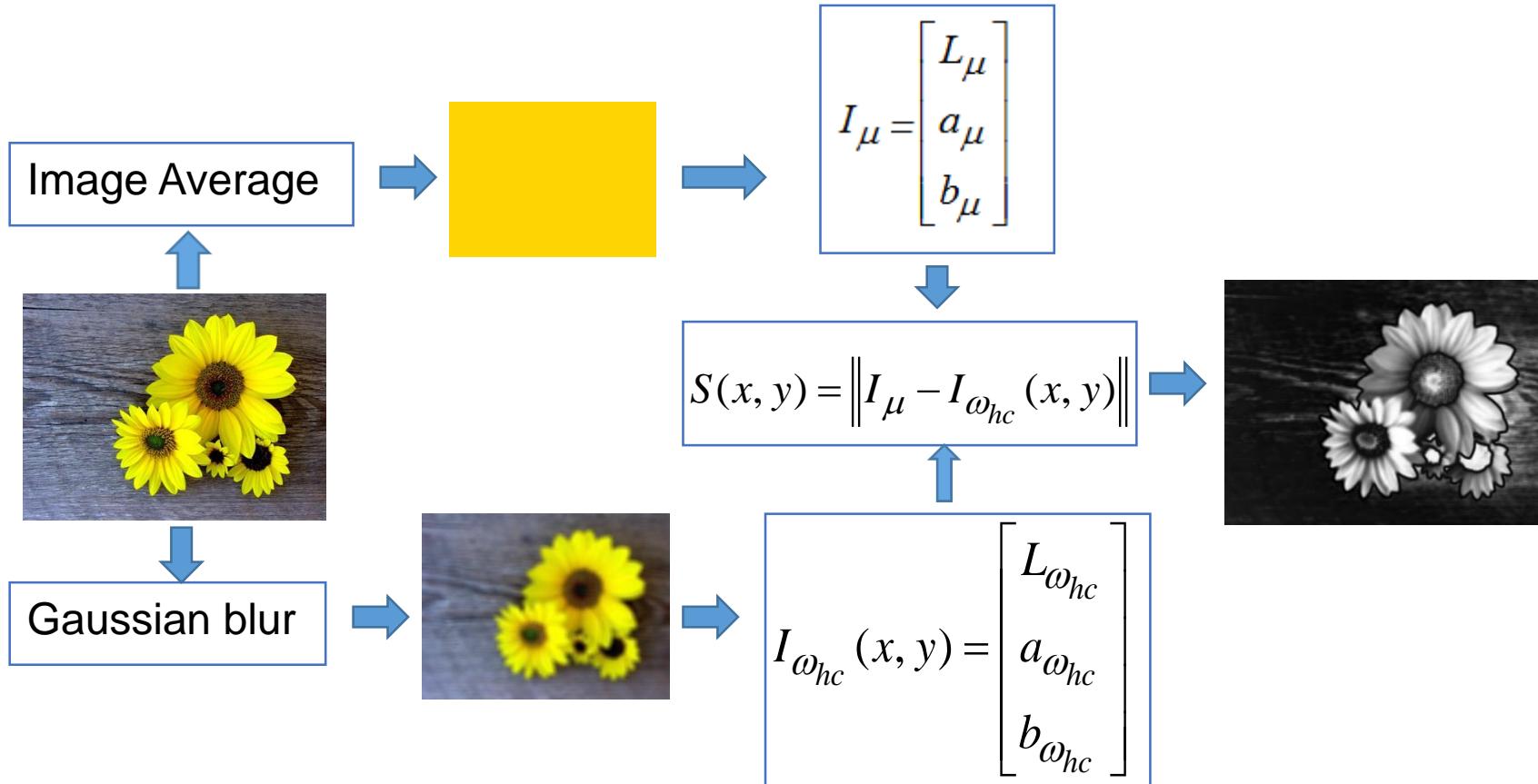
hemami@ece.cornell.edu



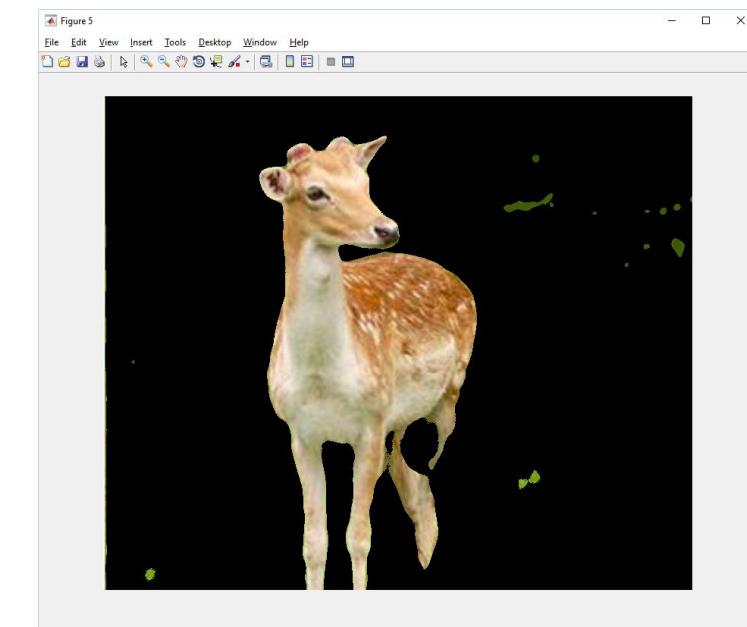
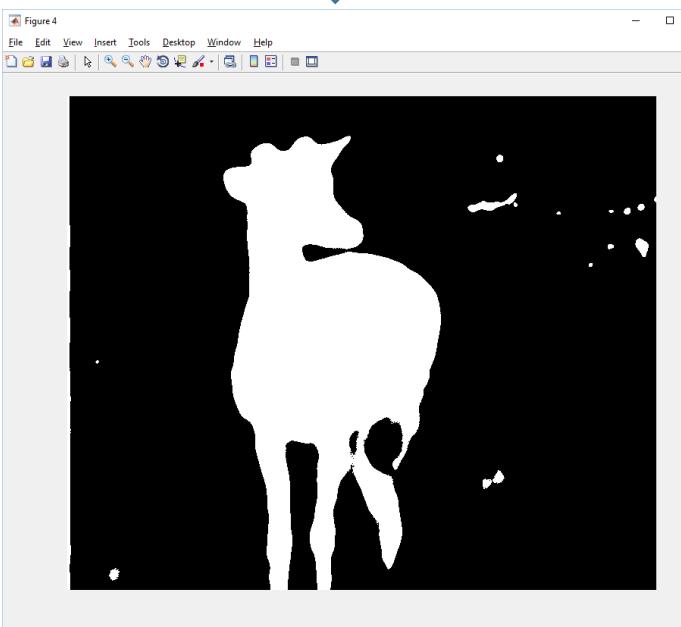
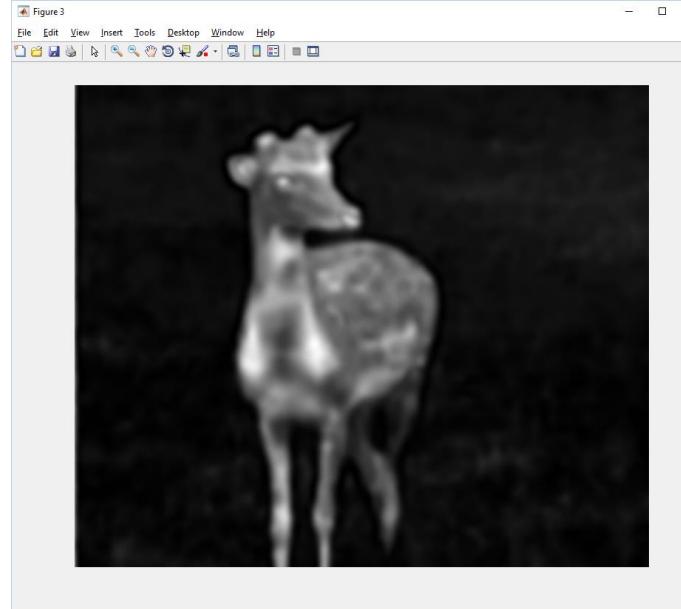
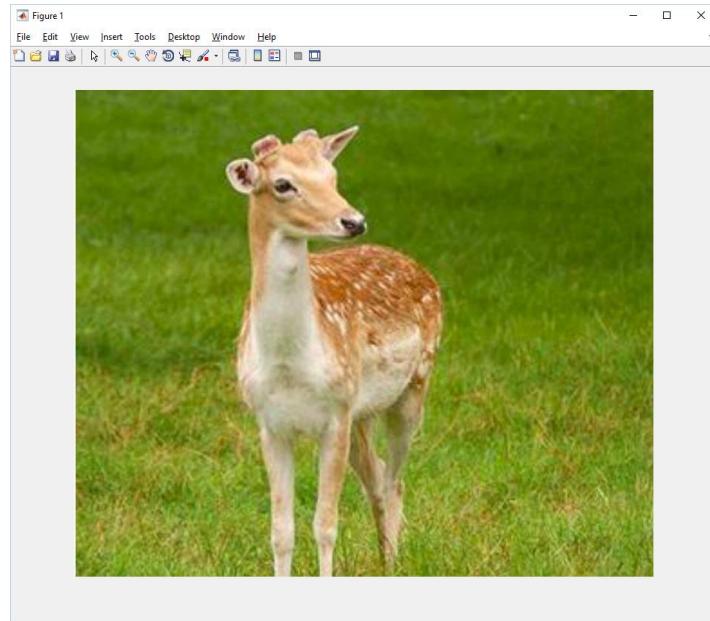
Idea



Frequency-tuned



Example



Context-Aware Saliency Detection

Stas Goferman
Technion

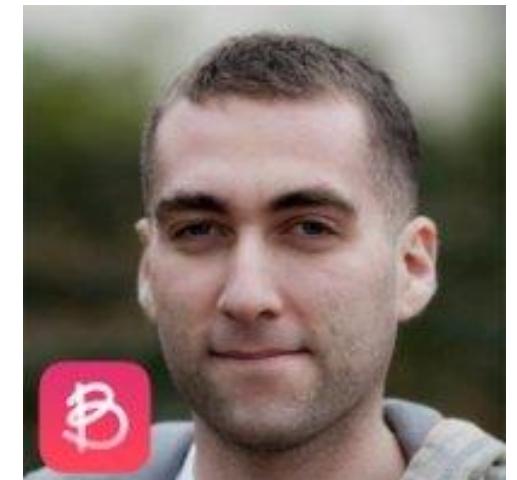
stasix@gmail.com

Lihi Zelnik-Manor
Technion

lihi@ee.technion.ac.il

Ayellet Tal
Technion

ayellet@ee.technion.ac.il



Frequency-tuned results



Input image

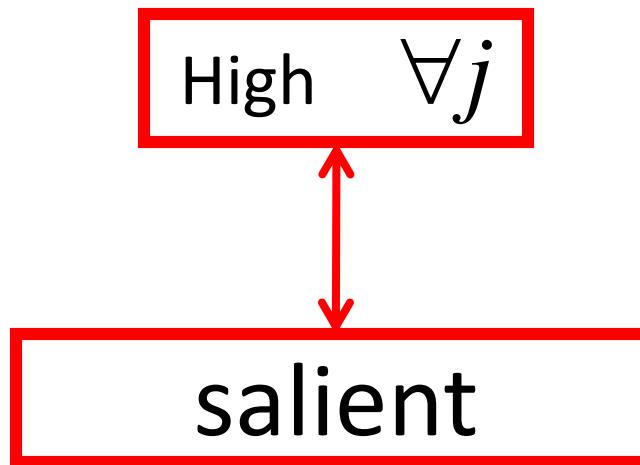
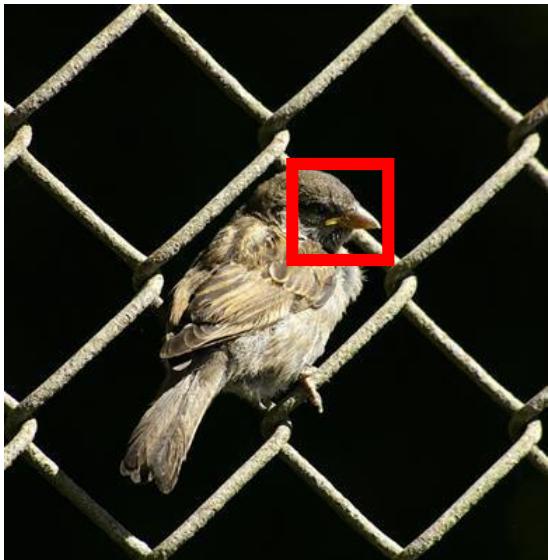


FT saliency map

Context-Aware

- Distance between a pair of patches:

$$d(p_i, p_j) = \frac{d_{color}(p_i, p_j)}{1 + c \cdot d_{position}(p_i, p_j)}$$



Q&A