

# EE XXX

## Design of Intelligent SoC Robot

<http://ssl.kaist.ac.kr/class/18fall/socrobotdesign>

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Computer Vision for Robot



# Outline

*-Computer Vision (CV) for Intelligent  
SoC Robot-*

*-Theoretical Part-*

1. *Introduction of CV for robot*
2. *Basic of Image*
3. *Image Processing Algorithm*

*-Practical Part-*

1. *Practical Algorithms for “Robot War”*

# Outline

**-Computer Vision (CV) for Intelligent SoC Robot-**

**-Theoretical Part-**

- 1. Introduction of CV for robot  
: Why does robot use CV?**
  
- 2. Basic of Image**
- 3. Image Processing Algorithm**

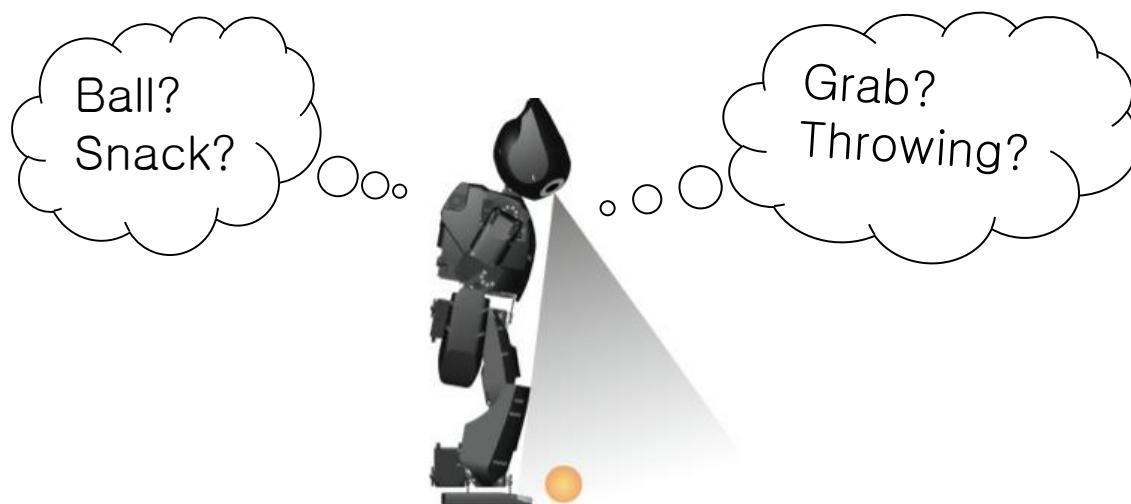
**-Practical Part-**

- 1. Practical Algorithms for “Robot War”**

# Why Computer Vision (CV) is required for Robot?

- For automatic understanding of images and video
  - Types of CV algorithms for robot
    - **Image Processing** : Obtaining the image information from digital images
    - **Image Recognition** : Identifying the types of and numbers of objects from an image
- Today's lecture

Next week's lecture

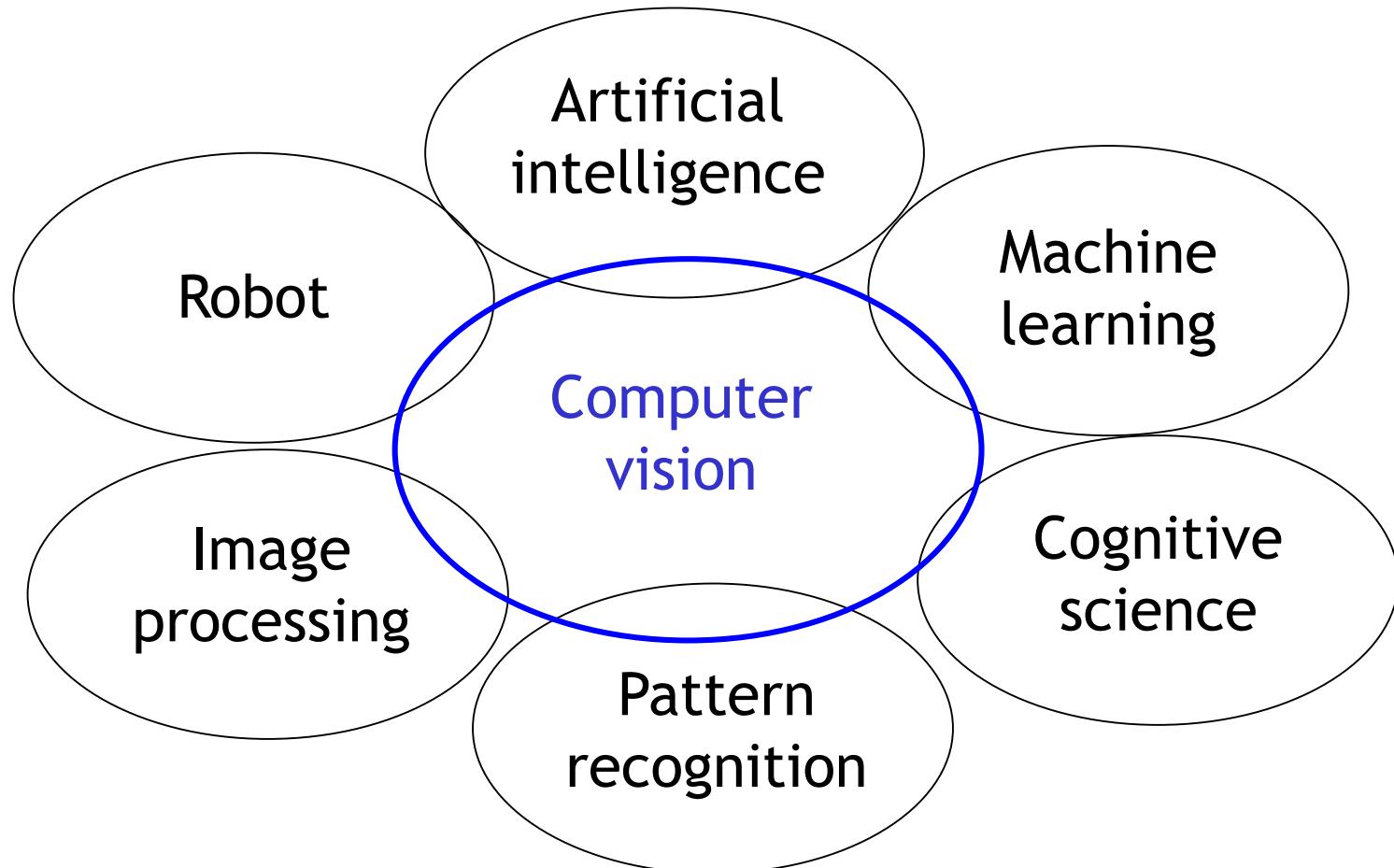


# What is computer vision?

- Automatic understanding of images and video
  - Properties of the 3D world from visual data  
*(measurement and modeling)*
  - Algorithms and representations to recognize objects, people, scenes, and activities.  
*(perception and interpretation)*



# Related disciplines

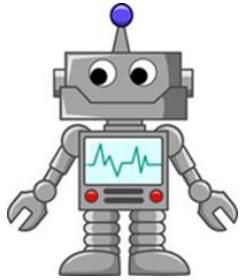


# Computer Vision and PR

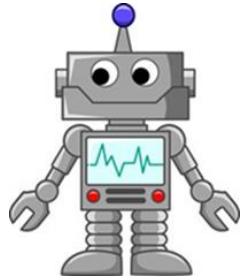


Slide by Fei-Fei, Fergus

# Detection: are there people?

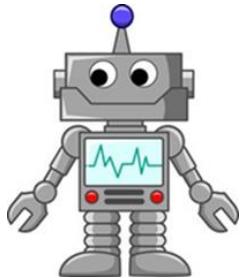


# Verification: is that a lamp?

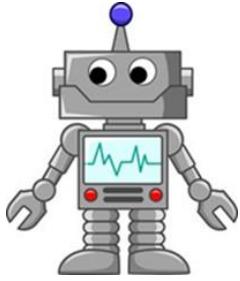


Slide by Fei-Fei, Fergus

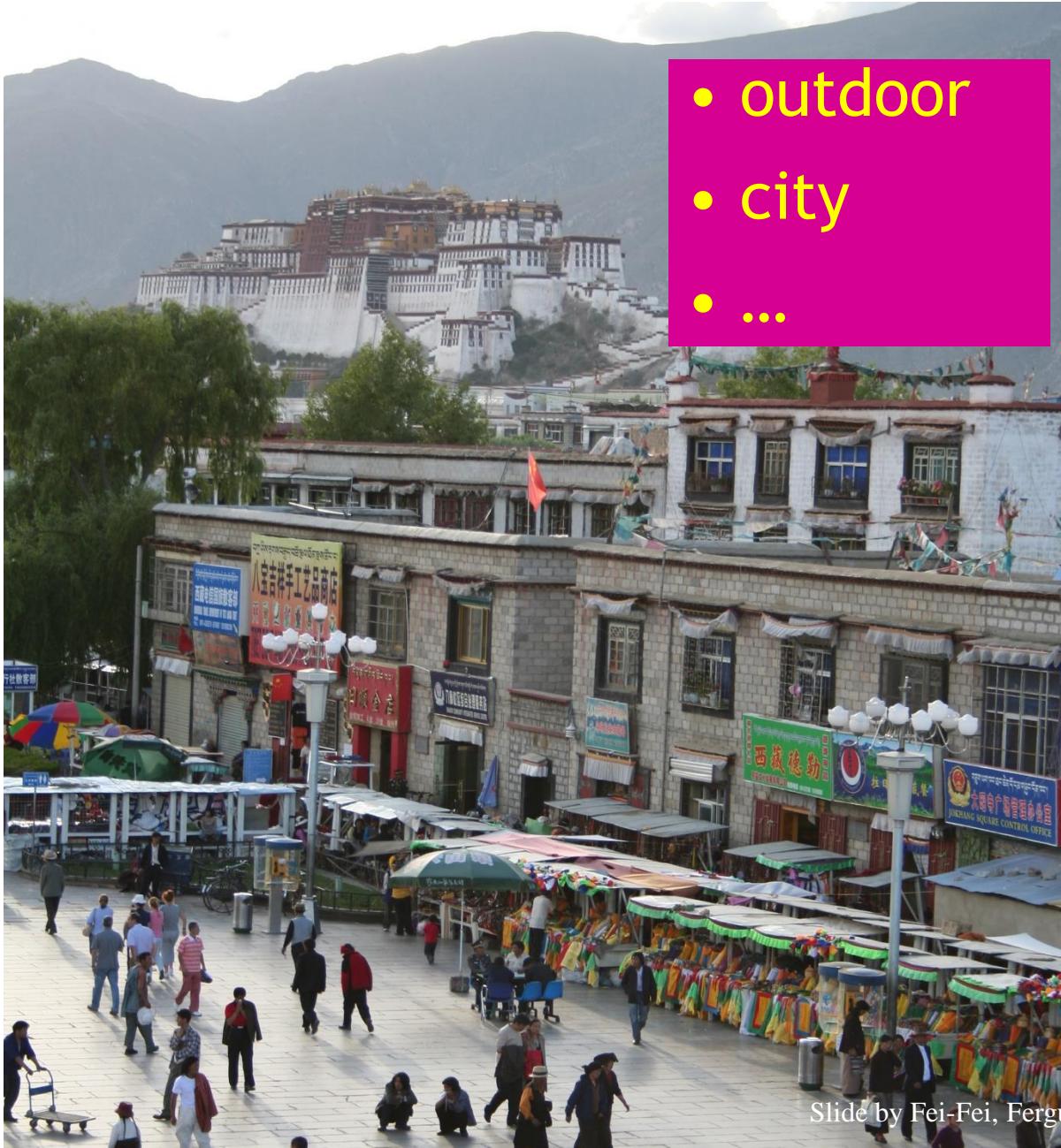
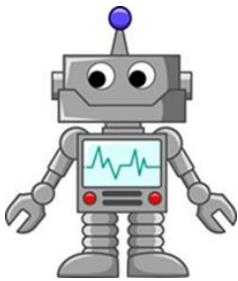
# Identification: is that Potala Palace?



# Object categorization

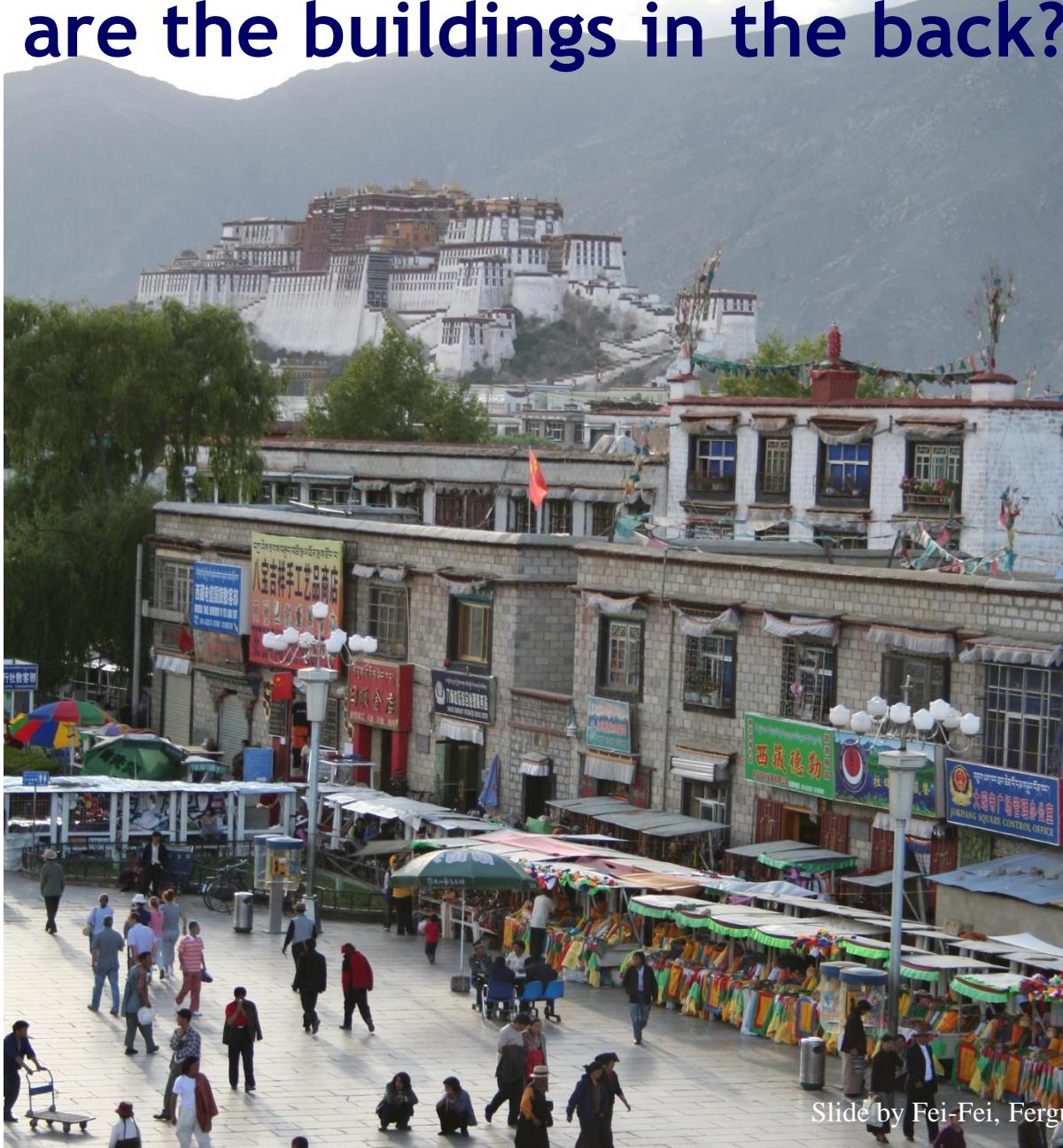
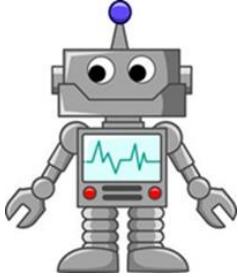


# Scene and context categorization

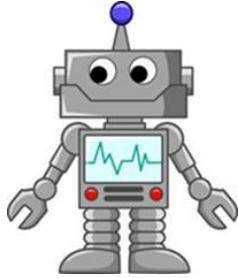


- outdoor
- city
- ...

# Is this space large or small? How far are the buildings in the back?



# Activity



What is this person doing? What are these two doing??



# Outline

## **-Computer Vision (CV) for Intelligent SoC Robot-**

### **-Theoretical Part-**

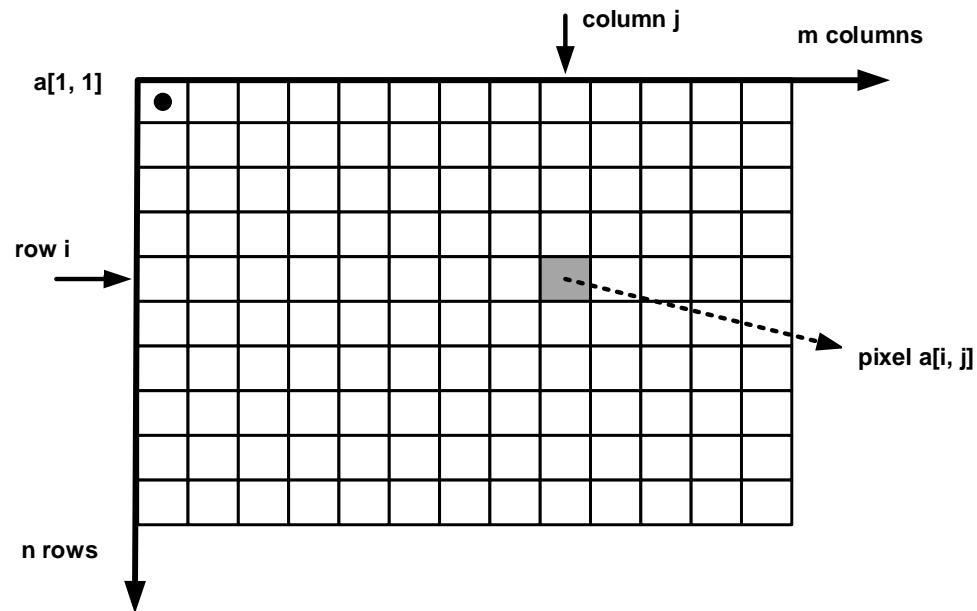
1. *Introduction of CV for robot*
2. **Basic of Image**  
*: What is a image? How can we get it?*
3. *Image Processing Algorithm*

### **-Practical Part-**

1. *Practical Algorithms for “Robot War”*

# What is Image?

- Definition of “Image”
  - A two-dimensional array of pixels
  - The indices  $[i, j]$  of pixels : values that specify the rows and columns in pixel values

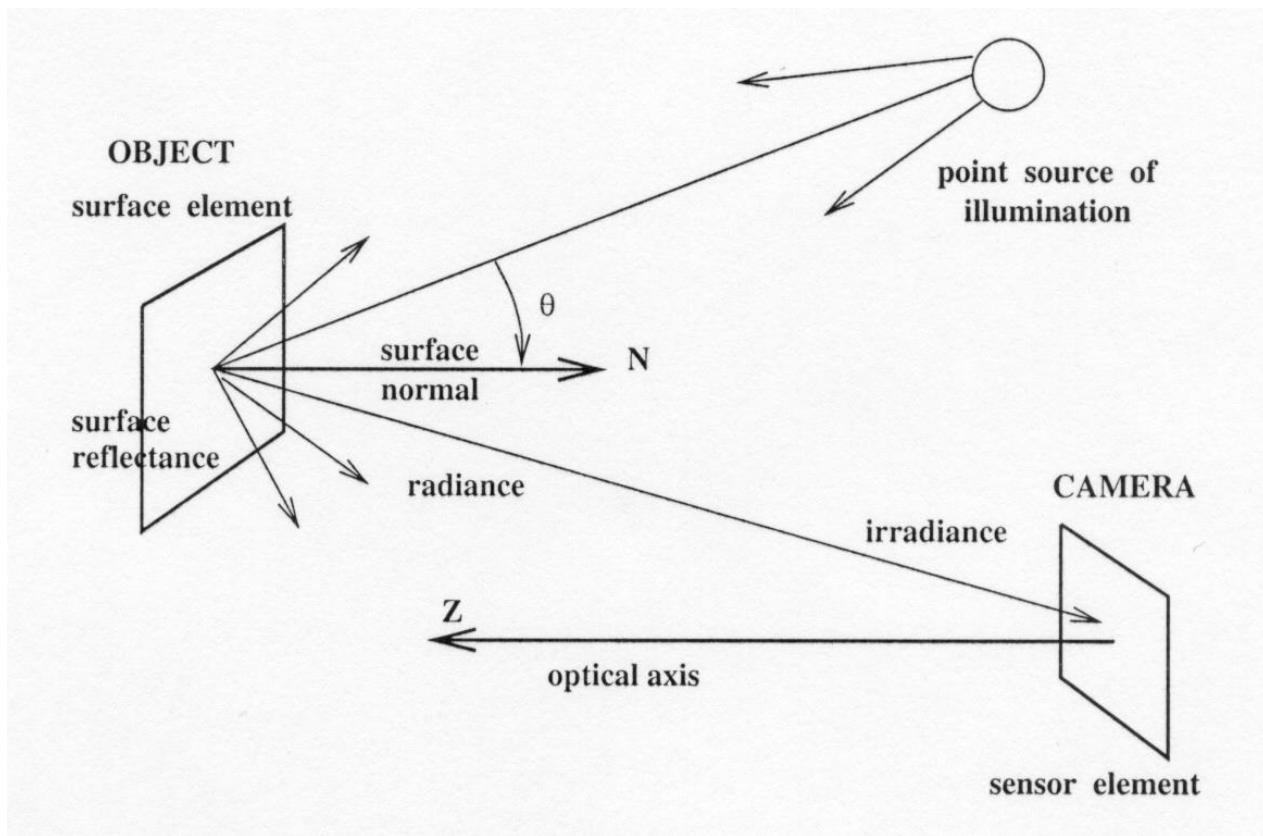


								155	155	155	110	120	120	0	0	0
								155	155	155	110	120	120	0	0	0
								155	155	155	110	120	120	0	0	0
								155	155	155	110	120	120	0	0	0
								155	155	155	110	120	120	0	0	0

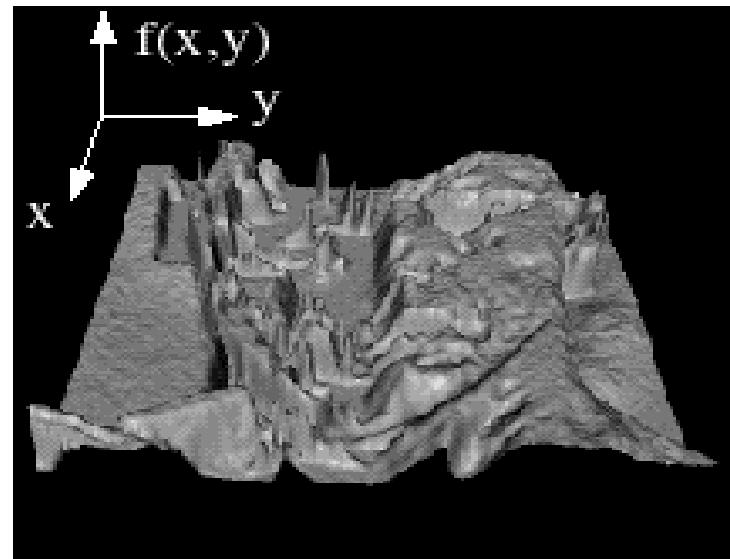
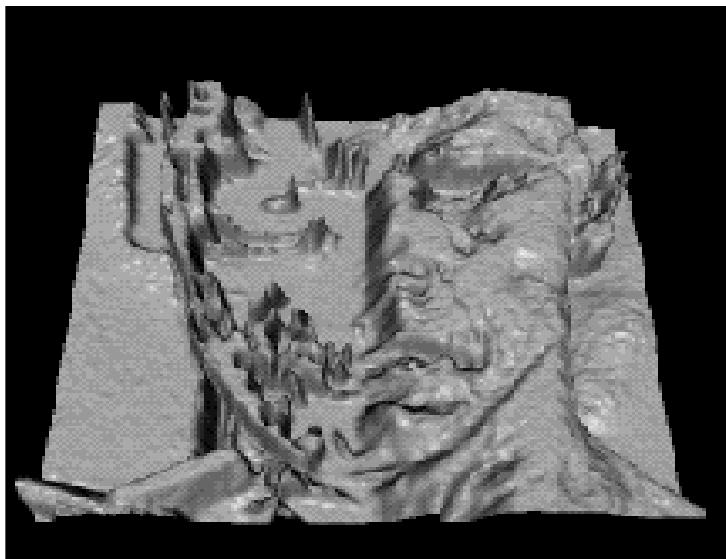
# A Simple model of image formation

The physics of light, which determines the brightness of a point in the image plane as a function of **illumination** and **surface properties**.

The geometry of image formation, which determines where a point of a scene will be projected on the image plane.



# Images as functions



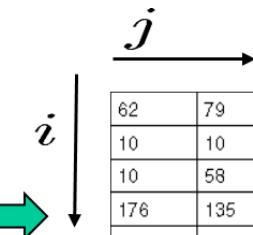
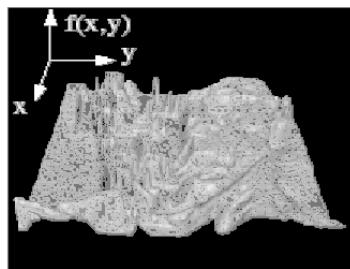
# Images as functions

- We can think of an image as a function,  $f$ , from  $\mathbf{R}^2$  to  $\mathbf{R}$ :
  - $f(x, y)$  gives the intensity at position  $(x, y)$
  - Realistically, we expect the image only to be defined over a rectangle, with a finite range:
- A color image is just three functions pasted together. We can write this as a “vector-valued” function:

$$f(x, y) = \begin{bmatrix} r(x, y) \\ g(x, y) \\ b(x, y) \end{bmatrix}$$

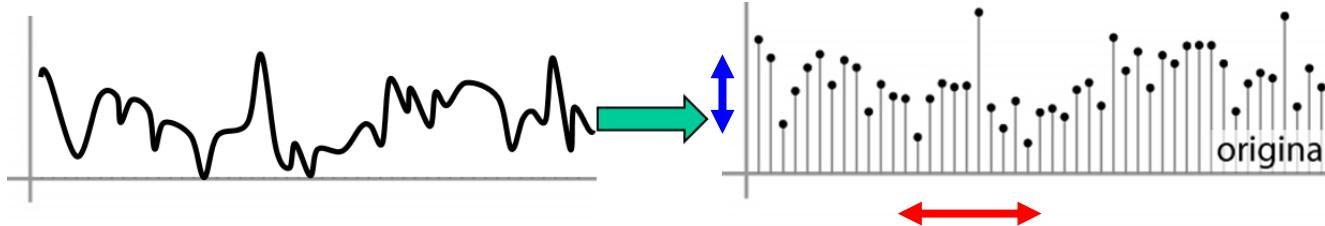
# How can we shift “light” to “digital image”

- Image digitization process
  - **1. Sampling**
    - measuring the value of an image **at a finite number of points.**
  - **2. Quantization**
    - Represent the measured value at the sampled point to the nearest **integer**.



62	79	23	119	120	105	4	0
10	10	9	62	12	78	34	0
10	58	197	46	46	0	0	48
176	135	5	188	191	68	0	49
2	1	1	29	26	37	0	77
0	89	144	147	187	102	62	208
255	252	0	166	123	62	0	31
166	63	127	17	1	0	99	30

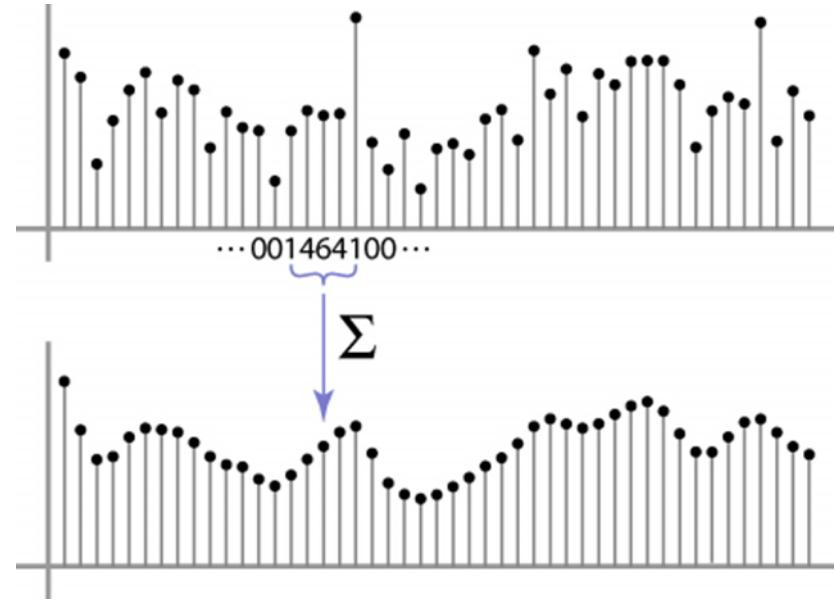
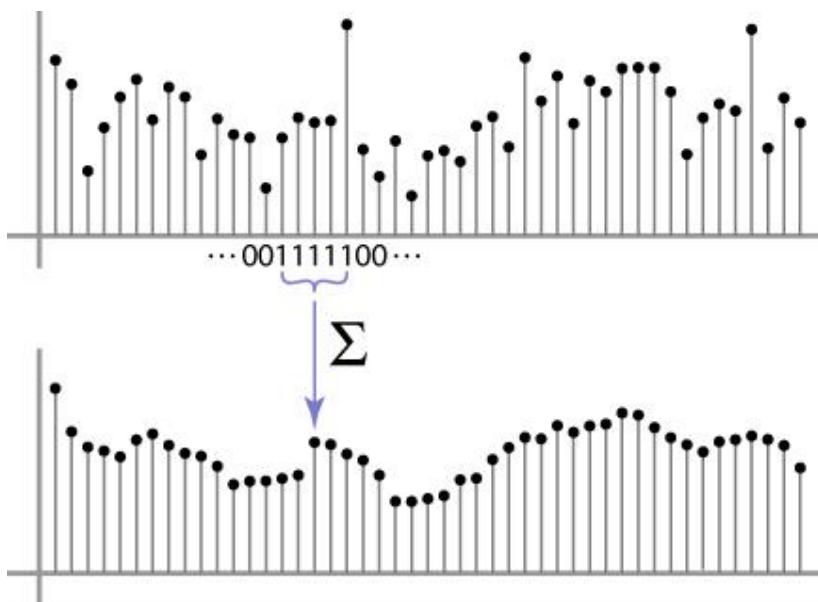
2D



1D

# Weighted Moving Average

- Let's replace each pixel with **an average of all the values in its neighborhood**
- Moving average in 1D:
- Can add weights to our moving average
- *Weights*  $[1, 1, 1, 1, 1] / 5$ , Non-uniform weights  $[1, 4, 6, 4, 1] / 16$



# Example of Image Sampling

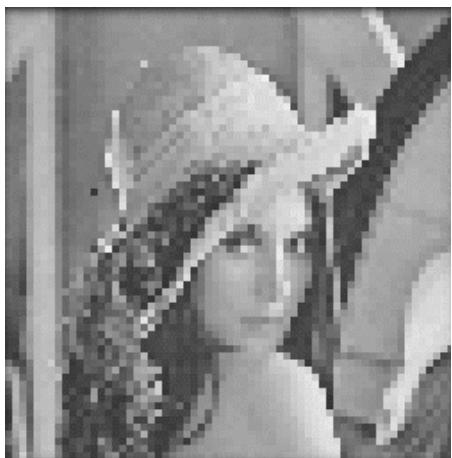
Original Image



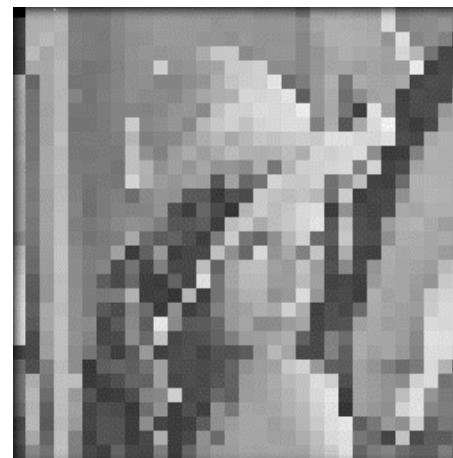
Sampled by  
a factor of 2



Sampled by  
a factor of 4



Sampled by  
a factor of 8



# Example of Image Quantization

256 gray levels  
(8bits/pixel)



32 gray levels  
(5bits/pixel)



16 gray levels  
(4bits/pixel)



8 gray levels  
(3bits/pixel)



4 gray levels  
(2bits/pixel)



2 gray levels  
(1bits/pixel)



# Colour or Monochrome?

- Monochrome images require 1 number - greyscale (0 - 255)
- Colour images require 3 numbers - red, green and blue values (0-255)
- Colour images require more work, but give more information.
- Examples are greyscale for simplicity. There is nothing harder about colour, it just requires more work.

# Outline

## **-Computer Vision (CV) for Intelligent SoC Robot-**

### **-Theoretical Part-**

1. *Introduction of CV for robot*
2. *Basic of Image*
3. ***Image Processing Algorithm***
  - ***Elementary Processing***
  - ***Applications of Elementary Processing***

### **-Practical Part-**

1. *Practical Algorithms for “Robot War”*

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1. *Introduction of CV for robot*
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3. ***Image Processing Algorithm***
  - ***Elementary Processing***  
***: Histogram Equalization, Filtering***

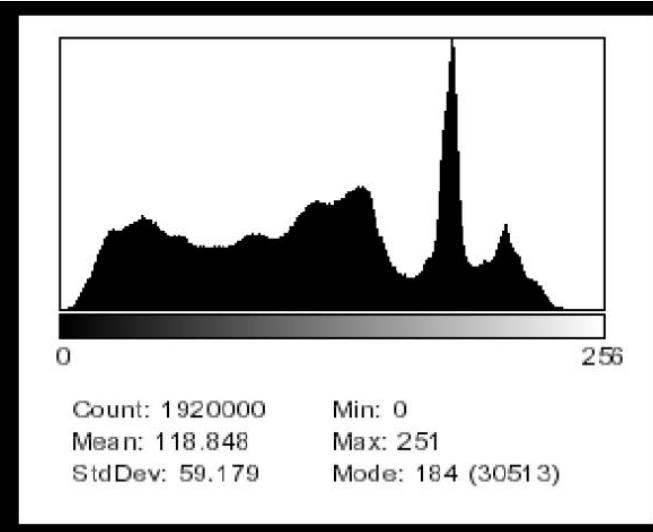
*- Applications of Elementary Processing*

### **-Practical Part-**

1. *Practical Algorithms for “Robot War”*

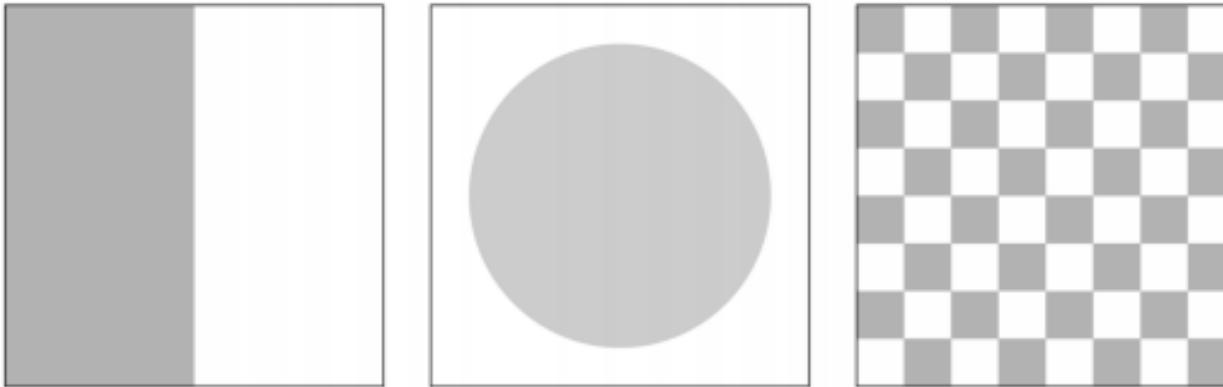
# Histograms

- Histogram: plots how many times (frequency) each intensity value in image occurs
- Example:
  - Image (left) has 256 distinct gray levels (8 bits)
  - Histogram (right) shows frequency (how many times) each gray level occurs



# Histograms

- Different images can have the same histogram
- 3 images below have same histogram



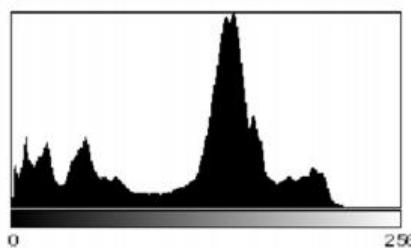
- Half of pixels are gray, half are white
  - Same histogram = same statistics
  - Distribution of intensities could be made the same → Histogram Equalization
- Can we reconstruct image from histogram? No!

# Application - Detecting Bad Exposure

- Exposures Are intensity values spread (good) out or bunched up (bad)

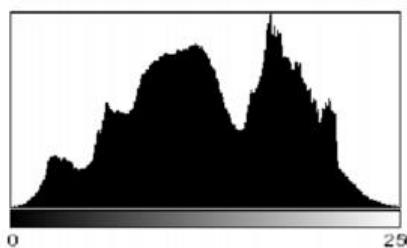


Image



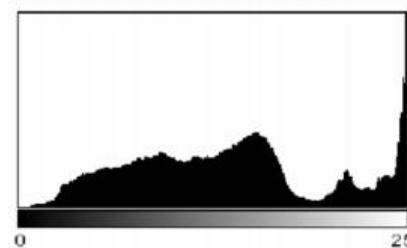
(a)

Underexposed



(b)

Properly  
Exposed



(c)

Overexposed

Histogram

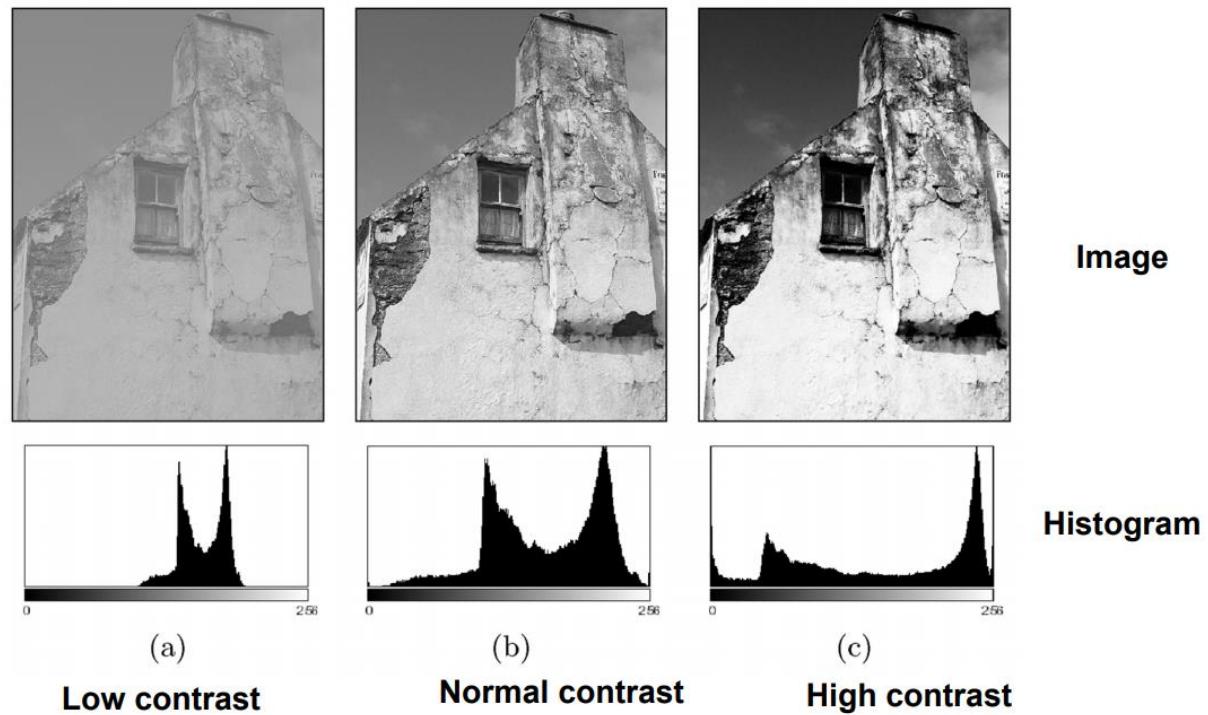
# Application - Image Contrast

- The contrast of a grayscale image indicates how easily objects in the image can be distinguished
- High contrast image: many distinct intensity values
- Low contrast: image uses few intensity values

Good Contrast?

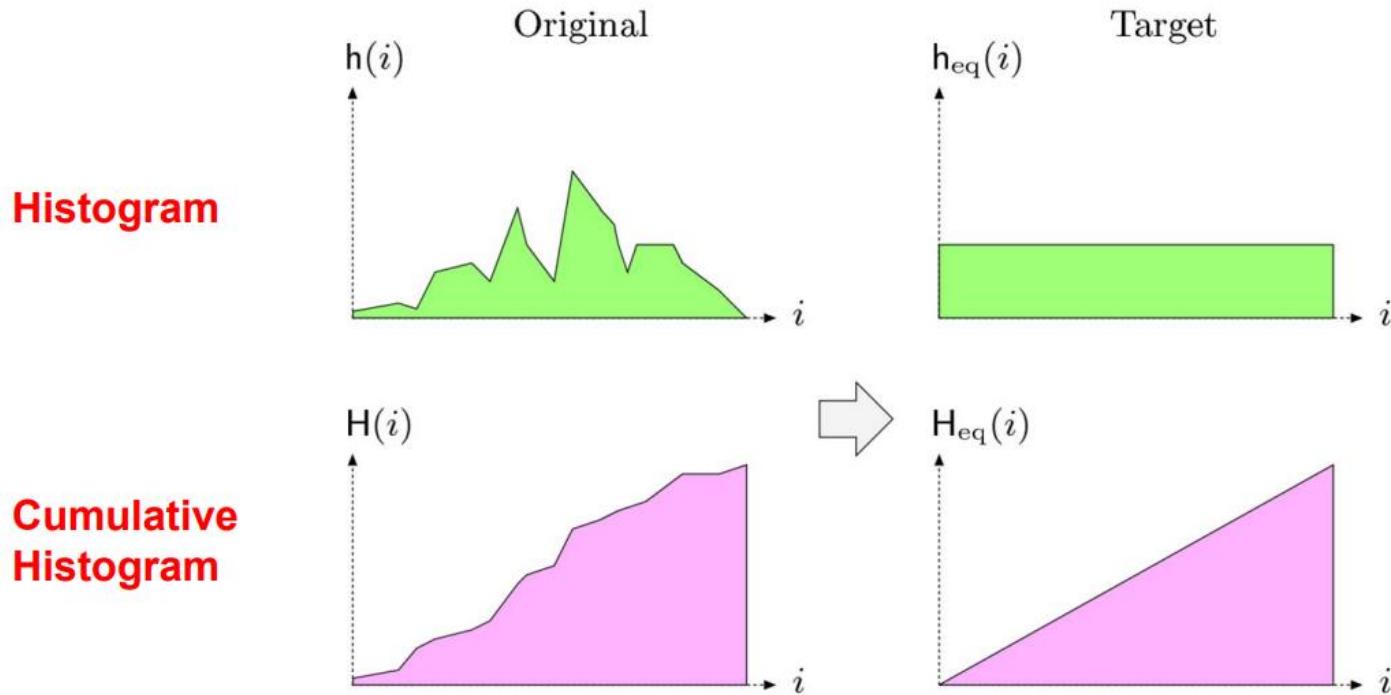
Widely spread  
intensity values

+ large difference  
between min and  
max intensity  
values

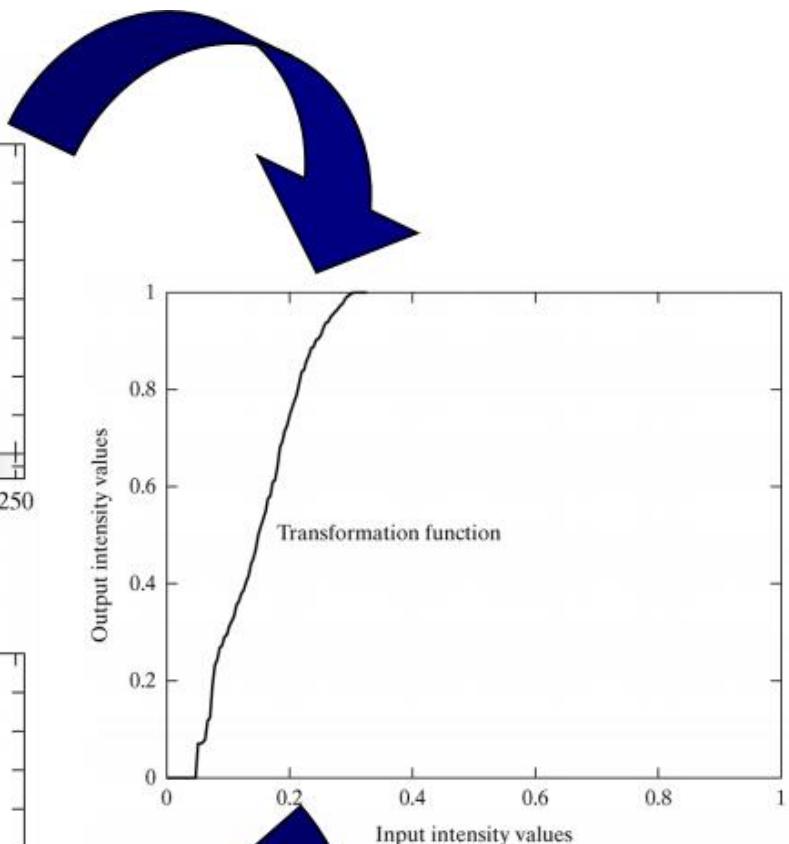
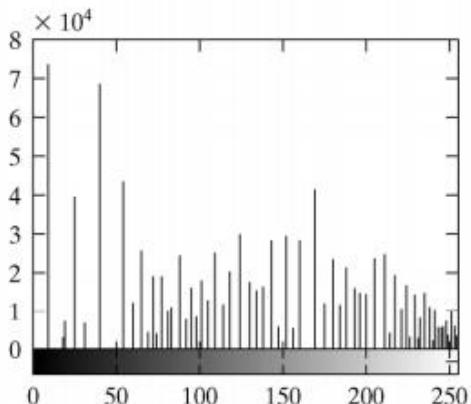
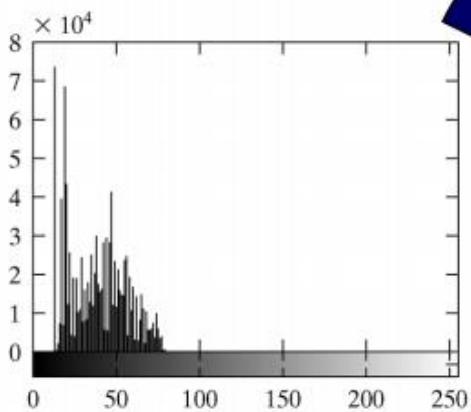
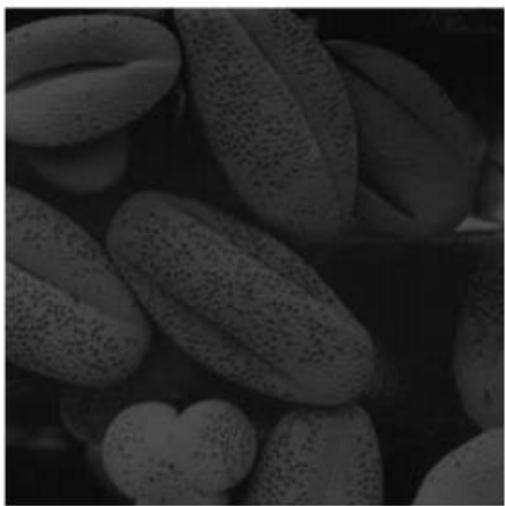


# Histogram Equalization

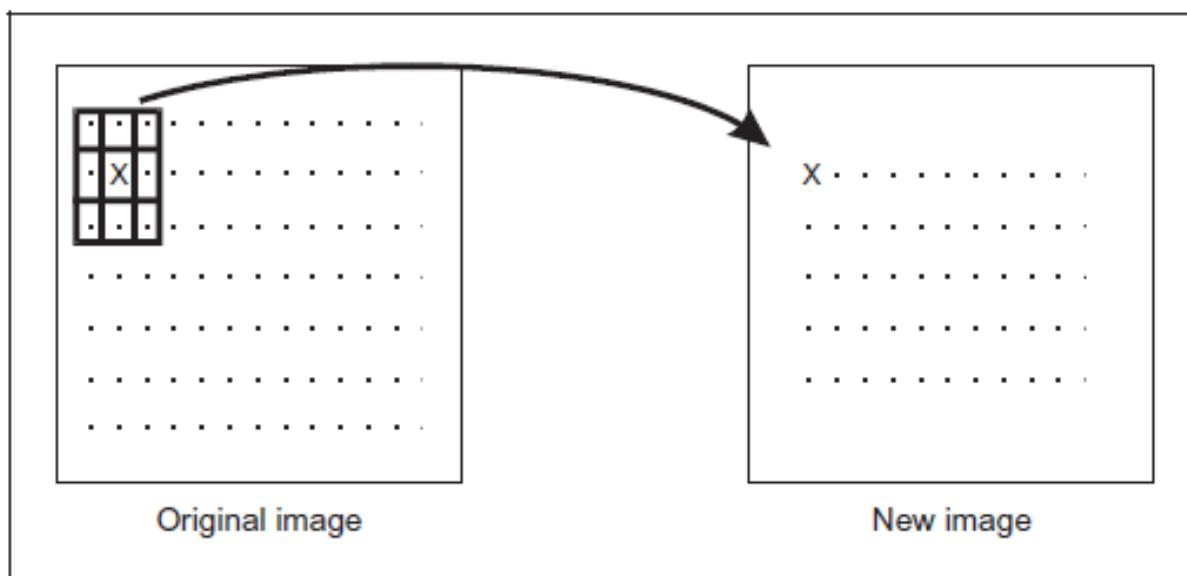
- Adjust 2 different images to make their histograms (intensity distributions) similar
- Apply a point operation that changes histogram of modified image into uniform distribution



# Histogram Equalization



# Filtering and Convolution Operation



1/9	1/9	1/9
1/9	1/9	1/9
1/9	1/9	1/9



# Moving Average In 2D

$$F[x, y]$$

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

$$G[x, y]$$

			0							

# Moving Average In 2D

$F[x, y]$

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

$G[x, y]$

0	10									

# Moving Average In 2D

$$F[x, y]$$

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

$$G[x, y]$$

			0	10	20					

# Moving Average In 2D

$$F[x, y]$$

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

$$G[x, y]$$


# Moving Average In 2D

$$F[x, y]$$

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

$$G[x, y]$$

			0	10	20	30	30			

# Moving Average In 2D

 $F[x, y]$ 

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

 $G[x, y]$ 

	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		

# Correlation filtering

Say the averaging window size is  $2k+1 \times 2k+1$ :

$$H(i, j) = \underbrace{\frac{1}{(2k+1)^2}}_{\text{Attribute uniform weight to each pixel}} \sum_{u=-k}^k \sum_{v=-k}^k F(i+u, j+v)$$

*Loop over all pixels in neighborhood around image pixel  $F[i,j]$*

Now generalize to allow different weights depending on neighboring pixel's relative position:

$$H(i, j) = \sum_{u=-k}^k \sum_{v=-k}^k G(u, v) \cdot \underbrace{F(i+u, j+v)}_{\text{Non-uniform weights}}$$

*Non-uniform weights*

# Correlation filtering

$$H(i, j) = \sum_{u=-k}^k \sum_{v=-k}^k G(u, v) \cdot F(i+u, j+v)$$

This is called cross-correlation, denoted  $H = G \times F$

Filtering an image: replace each pixel with a linear combination of its neighbors.

The filter “kernel” or “mask”  $G[u, v]$  is the prescription for the weights in the linear combination.

# Averaging filter

- What values belong in the kernel  $H$  for the moving average example?

$$F[x, y]$$

A 9x9 grid representing the input image  $F[x, y]$ . The central element is 90, which is highlighted by a red box. All other elements are 0.



$$G(u, v)$$

$$\frac{1}{9}$$

A 3x3 matrix representing the kernel  $G(u, v)$ . It has 1s in all positions except the center, where there is a question mark. The matrix is multiplied by  $\frac{1}{9}$ .

“box filter”

$$H(x, y)$$

A 9x9 grid representing the output image  $H(x, y)$ . The central element is 30, which is highlighted by a red box. All other elements are 0.

$$H = G \times F$$

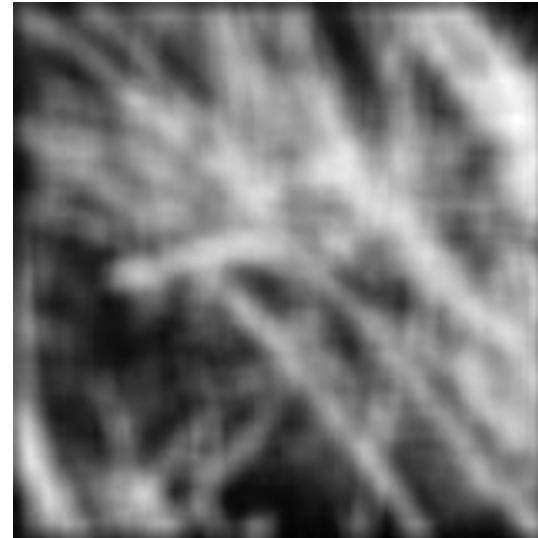
# Smoothing w/ Averaging Filter



← depicts box filter:  
white = high value, black = low value

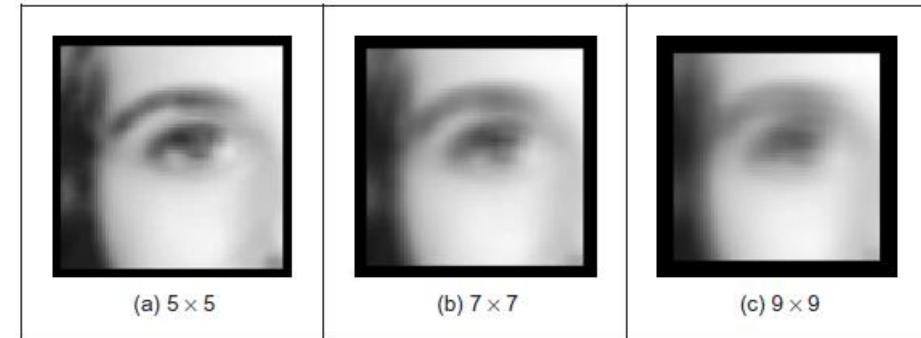


original



filtered

Averaging w/  
Different Filter Size



# Gaussian filter

- What if we want nearest neighboring pixels to have the most influence on the output?

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

$F[x, y]$

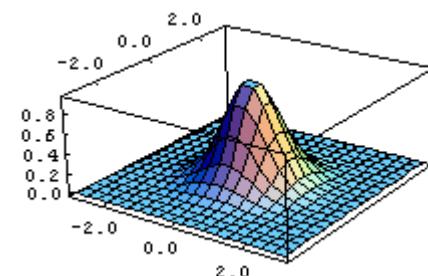
$$\frac{1}{16}$$

1	2	1
2	4	2
1	2	1

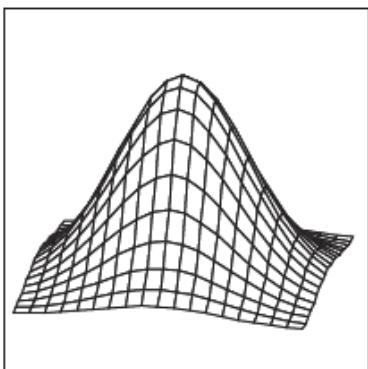
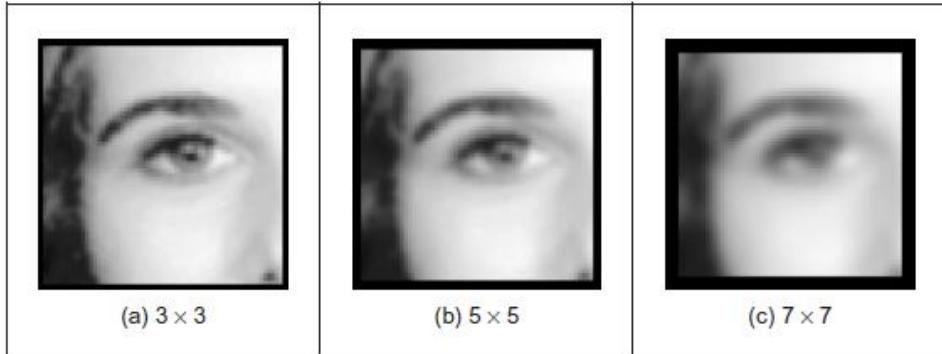
$G(u, v)$

This kernel is an approximation of a Gaussian function:

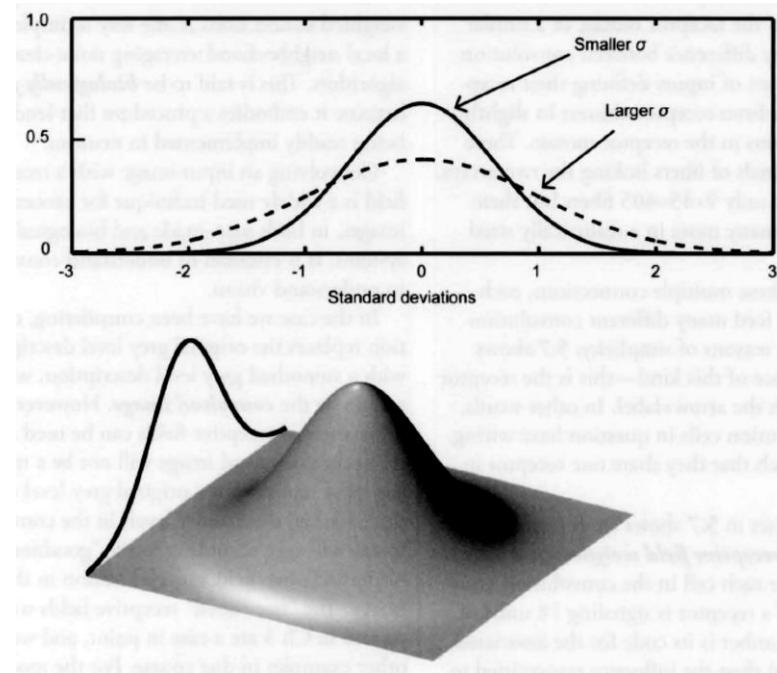
$$h(u, v) = \frac{1}{2\pi\sigma^2} e^{-\frac{u^2+v^2}{\sigma^2}}$$



# Gaussian Filter

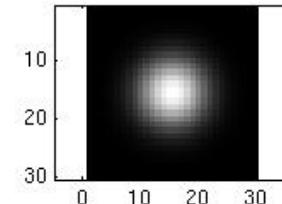
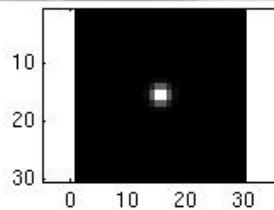


0.002	0.013	0.022	0.013	0.002
0.013	0.060	0.098	0.060	0.013
0.022	0.098	0.162	0.098	0.022
0.013	0.060	0.098	0.060	0.013
0.002	0.013	0.022	0.013	0.002

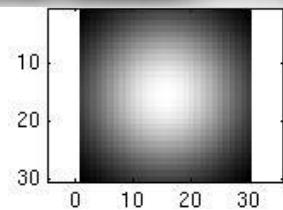


# Smoothing w/ a Gaussian

Parameter  $\sigma$  is the “scale” / “width” / “spread” of the Gaussian kernel, and controls the amount of smoothing.

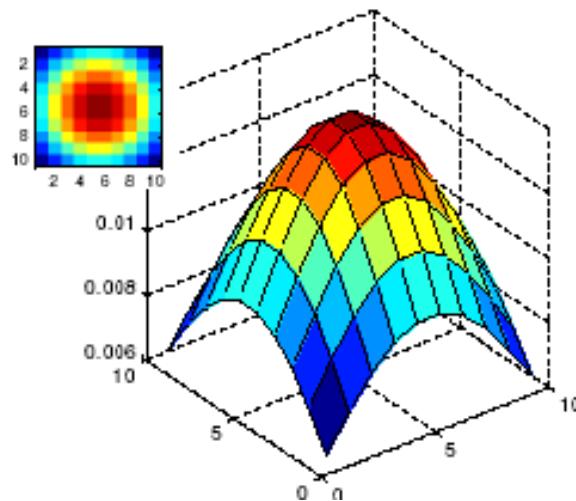


• • •

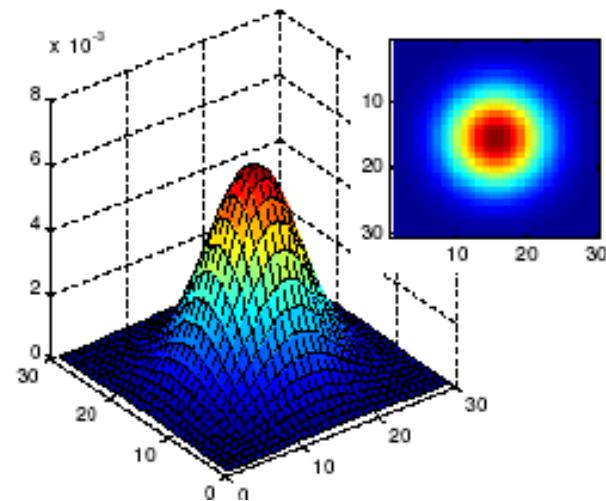


# Gaussian filters

- What parameters matter here?
- Size of kernel or mask
  - Note, Gaussian function has infinite support, but discrete filters use finite kernels



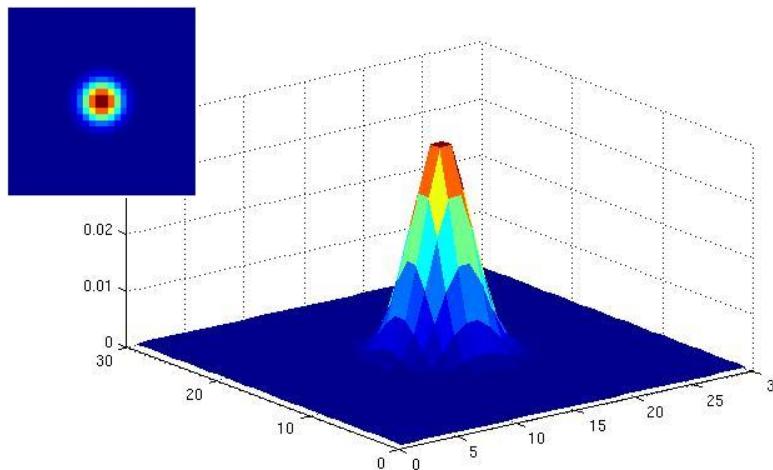
$\sigma = 5$  with 10  
x 10 kernel



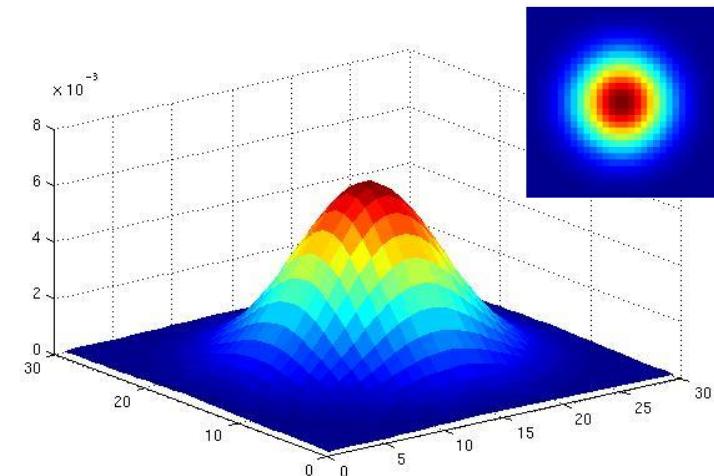
$\sigma = 5$  with 30  
x 30 kernel

# Gaussian filters

- What parameters matter here?
- **Variance of Gaussian:** determines extent of smoothing

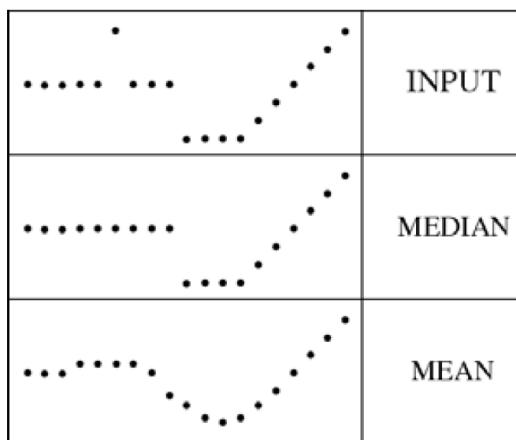
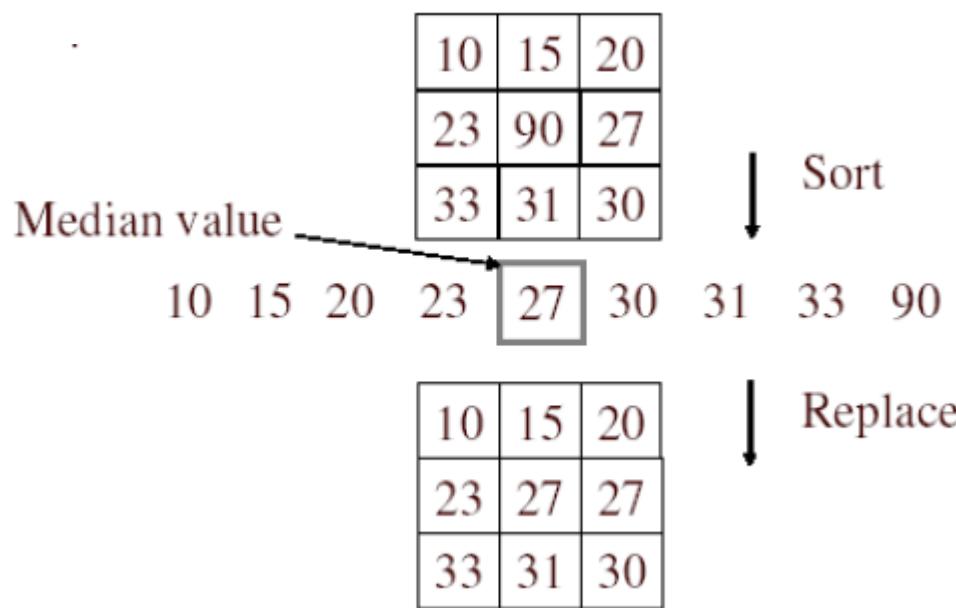


$\sigma = 2$  with 30  
x 30 kernel



$\sigma = 5$  with 30  
x 30 kernel

# Median filter

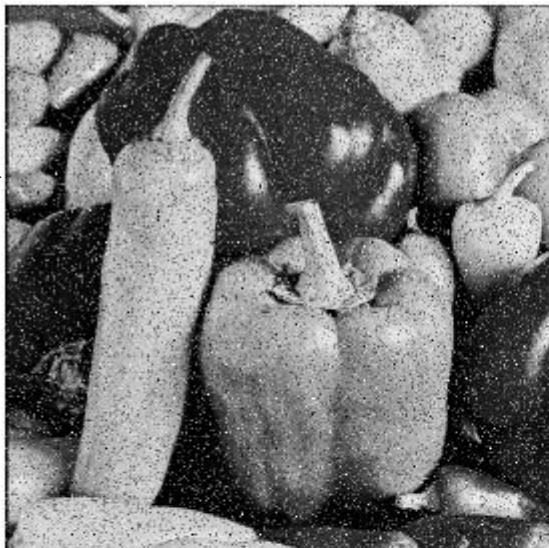


- No new pixel values introduced
- Removes spikes: good for impulse, salt & pepper noise

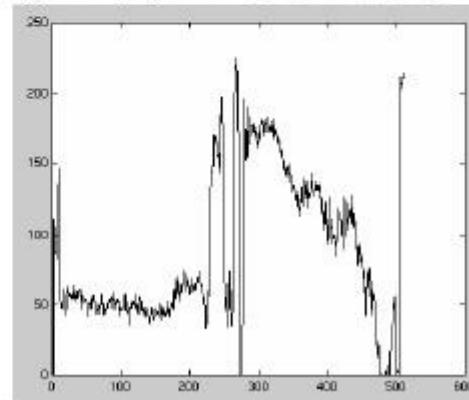
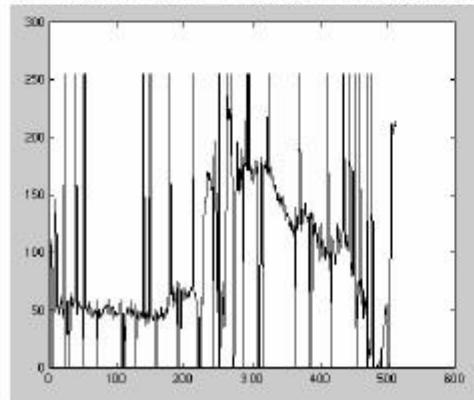
- Median filter is edge preserving

# Smoothing w/ Median filter

Salt and  
pepper  
noise

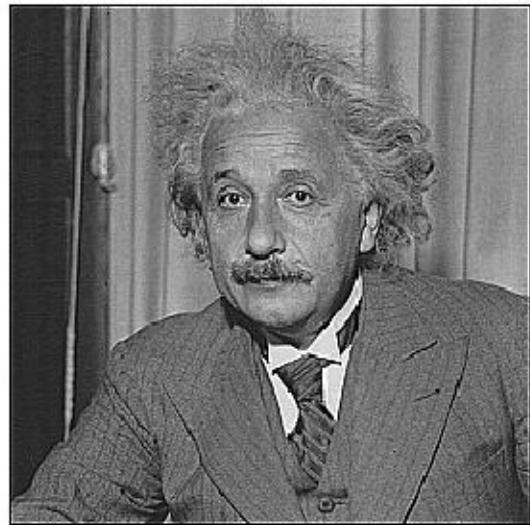
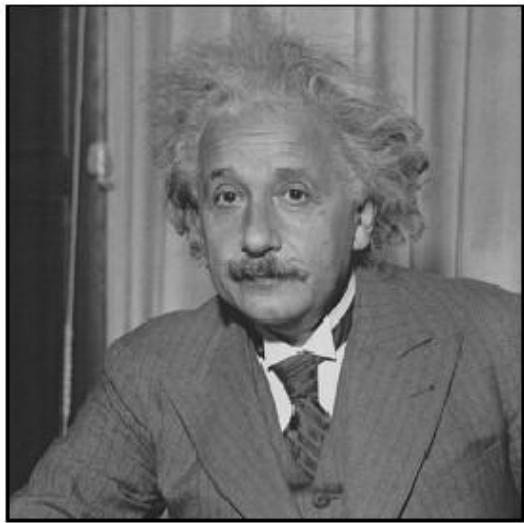


Median  
filtered



Plots of a row of the image

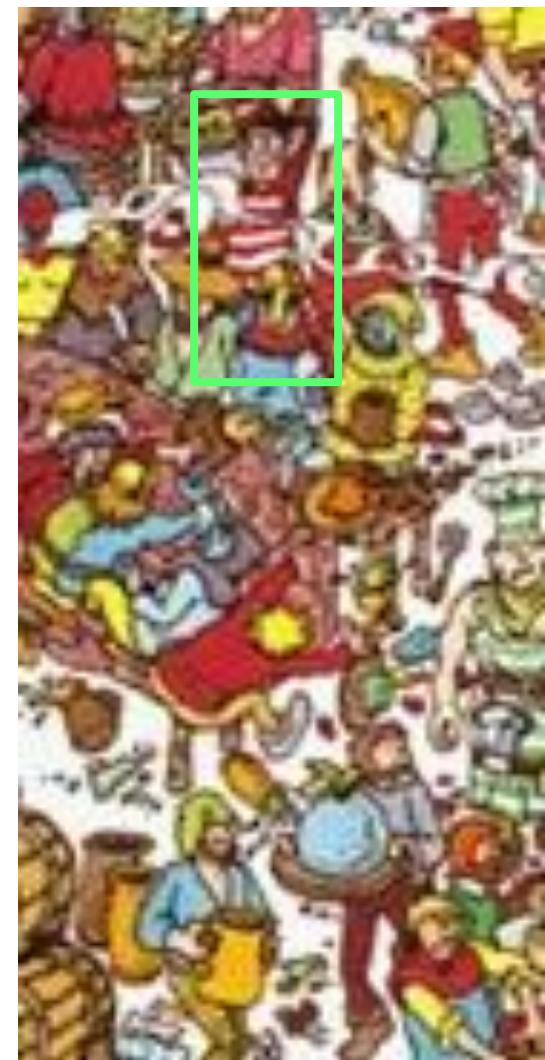
# Example of Applications using Convolution



*Smooth/Sharpen Images...*



*Find edges...*



*Find waldo...*

# Convolution and Cross-Correlation

- **Convolution:**

- Flip the filter (bottom to top, right to left)
- Then apply cross-correlation

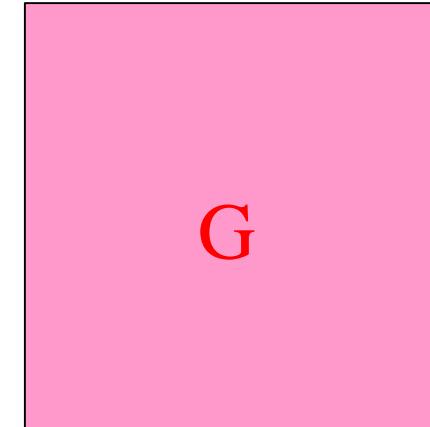
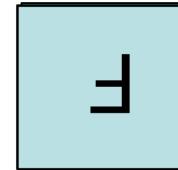
$$H(i, j) = \sum_{u=-k}^k \sum_{v=-k}^k G(u, v) \cdot F(i - u, j - v)$$

$$H = G * F = G \times F$$

↑                      ↑

*convolution  
operator*

*Cross-correlation  
operator*



# Convolution vs. Correlation

## Convolution

$$H(i, j) = \sum_{u=-k}^k \sum_{v=-k}^k G(u, v) \cdot F(i - u, j - v)$$

$$H = G * F$$

## Cross-correlation

$$H(i, j) = \sum_{u=-k}^k \sum_{v=-k}^k G(u, v) \cdot F(i + u, j + v)$$

$$H = G \times F$$

For a Gaussian or box filter, how will the outputs differ?  
If the input is an impulse signal, how will the outputs differ?

# Convolution Example using Linear Property



$$\begin{matrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{matrix}$$

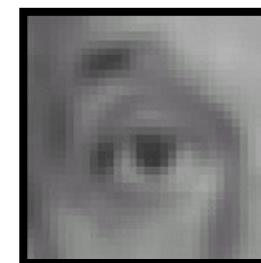
=



$$\frac{1}{9}$$

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

=



$$\begin{matrix} 0 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 0 \end{matrix}$$

$$- \frac{1}{9}$$

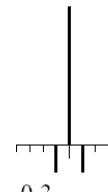
$$\begin{matrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{matrix}$$

=



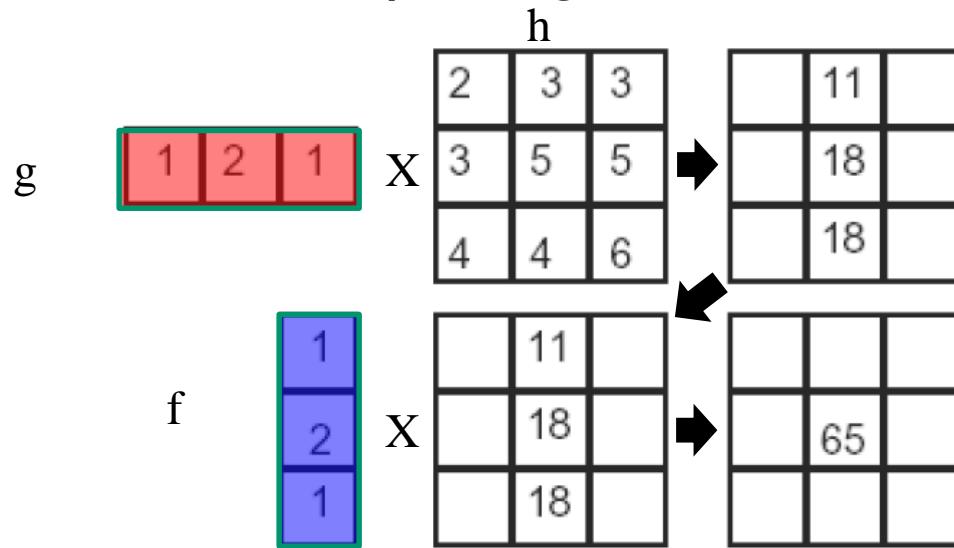
Original

Sharpening filter



# Separability

- In some cases, filter is separable, and we can factor into two steps: e.g.,



$$12+17+19=48$$

What is the computational complexity advantage for a separable filter of size  $k \times k$ , in terms of number of operations per output pixel?

$$\begin{array}{c} \begin{bmatrix} 1 \\ 2 \\ 1 \end{bmatrix} \times \begin{bmatrix} 1 & 2 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix} \rightarrow \begin{bmatrix} 2 & 3 & 3 \\ 3 & 5 & 5 \\ 4 & 4 & 6 \end{bmatrix} \\ \begin{array}{r} = 2 + 6 + 3 = 11 \\ = 6 + 20 + 10 = 36 \\ = 4 + 8 + 6 = 18 \end{array} \\ \hline 65 \end{array}$$

$$f * (g * h) = (f * g) * h$$

# Outline

## **-Computer Vision (CV) for Intelligent SoC Robot-**

### **-Theoretical Part-**

1. *Introduction of CV for robot*
2. *Basic of Image*
3. ***Image Processing Algorithm***
  - *Elementary Processing*
  - ***Applications of Elementary Processing***  
***: Edge, Distance, Optical Flow Detection***

### **-Practical Part-**

1. *Practical Algorithms for “Robot War”*

# Outline

## -Computer Vision (CV) for Intelligent SoC Robot-

### -Theoretical Part-

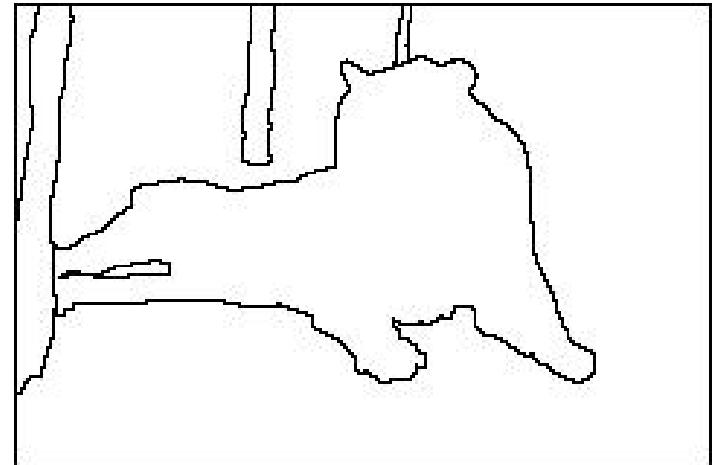
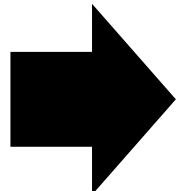
1. *Introduction of CV for robot*
2. *Basic of Image*
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***: Edge, Distance, Optical Flow Detection***

### -Practical Part-

1. *Practical Algorithms for “Robot War”*

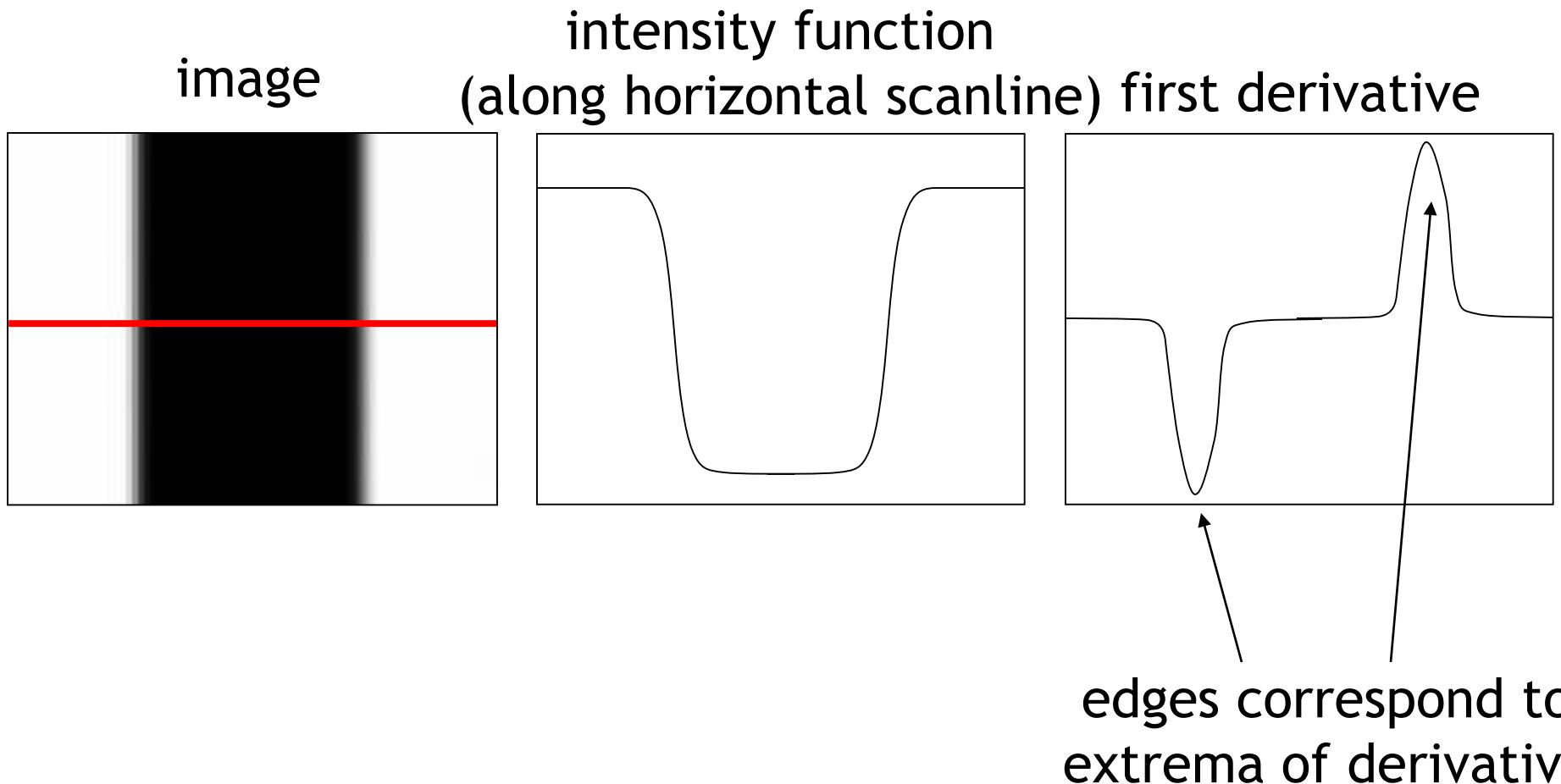
# Advanced Image Processing - Edge Detection

- Convert a 2D image into a set of curves
  - Reduce dimensionality of data, but preserve useful information
    - Extracts salient features of the scene
  - More compact than pixels
  - Useful in applications such as:
    - object detection, structure from motion, tracking, etc ...



# Derivatives and edges

An edge is a place of rapid change in the image intensity function.



# Differentiation and convolution

For 2D function,  $f(x,y)$ , the partial derivative is:

$$\frac{\partial f(x, y)}{\partial x} = \lim_{\varepsilon \rightarrow 0} \frac{f(x + \varepsilon, y) - f(x, y)}{\varepsilon}$$

For discrete data, we can approximate using finite differences:

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

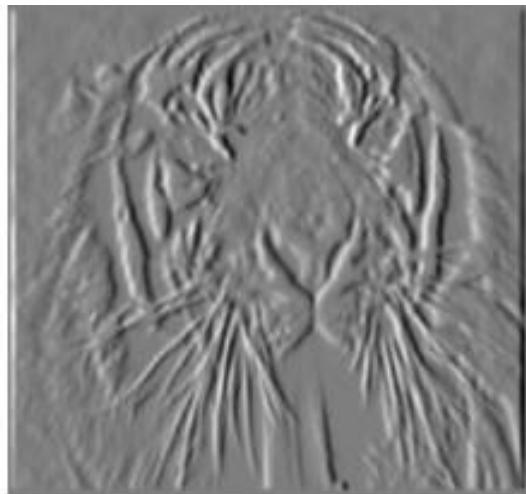
To implement above as convolution, what would be the associated filter?

# Partial derivatives of an image



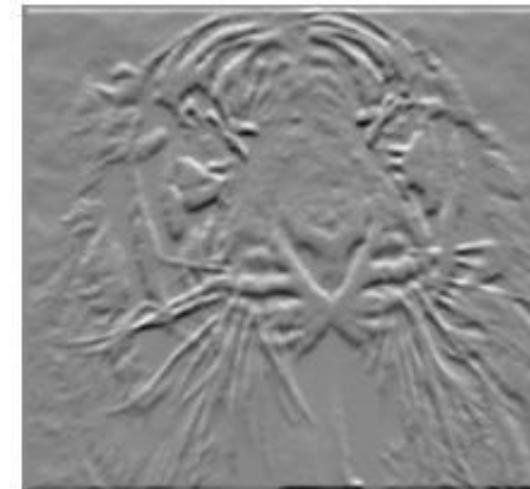
$$\frac{\partial f(x, y)}{\partial x}$$

-1	1
----	---



$$\frac{\partial f(x, y)}{\partial y}$$

-1	?	1
1	or	-1



Which shows changes with respect to x?  
(showing flipped filters)

# Edge Detection Filters

<table border="1"><tr><td>1</td><td>0</td><td>-1</td></tr></table>	1	0	-1	<table border="1"><tr><td>1</td></tr><tr><td>0</td></tr><tr><td>-1</td></tr></table>	1	0	-1
1	0	-1					
1							
0							
-1							
(a) $M_x$	(b) $M_y$						

First order difference

-1	2	-1
----	---	----

Second order difference

<table border="1"><tr><td>+1</td><td>0</td></tr><tr><td>0</td><td>-1</td></tr></table>	+1	0	0	-1	<table border="1"><tr><td>0</td><td>+1</td></tr><tr><td>-1</td><td>0</td></tr></table>	0	+1	-1	0
+1	0								
0	-1								
0	+1								
-1	0								
(a) $M^-$	(b) $M^+$								

Roberts

0	-1	0
-1	4	-1
0	-1	0

Laplacian

<table border="1"><tr><td>1</td><td>0</td><td>-1</td></tr><tr><td>1</td><td>0</td><td>-1</td></tr><tr><td>1</td><td>0</td><td>-1</td></tr></table>	1	0	-1	1	0	-1	1	0	-1	<table border="1"><tr><td>1</td><td>1</td><td>1</td></tr><tr><td>0</td><td>0</td><td>0</td></tr><tr><td>-1</td><td>-1</td><td>-1</td></tr></table>	1	1	1	0	0	0	-1	-1	-1
1	0	-1																	
1	0	-1																	
1	0	-1																	
1	1	1																	
0	0	0																	
-1	-1	-1																	
(a) $M_x$	(b) $M_y$																		

Prewitt

<table border="1"><tr><td>1</td><td>0</td><td>-1</td></tr><tr><td>2</td><td>0</td><td>-2</td></tr><tr><td>1</td><td>0</td><td>-1</td></tr></table>	1	0	-1	2	0	-2	1	0	-1	<table border="1"><tr><td>1</td><td>2</td><td>1</td></tr><tr><td>0</td><td>0</td><td>0</td></tr><tr><td>-1</td><td>-2</td><td>-1</td></tr></table>	1	2	1	0	0	0	-1	-2	-1
1	0	-1																	
2	0	-2																	
1	0	-1																	
1	2	1																	
0	0	0																	
-1	-2	-1																	
(a) $M_x$	(b) $M_y$																		

Sobel

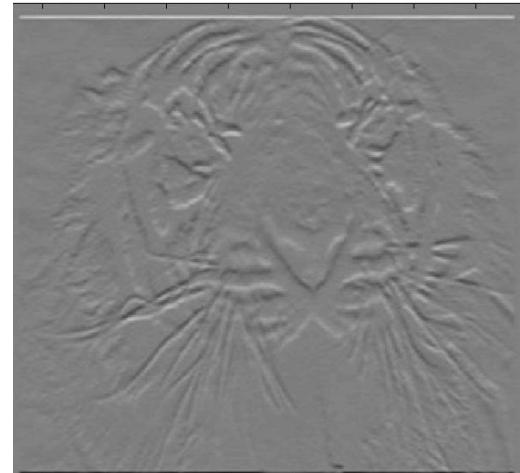
# Assorted finite difference filters

Prewitt:  $M_x = \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix}$  ;  $M_y = \begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix}$

Sobel:  $M_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$  ;  $M_y = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$

Roberts:  $M_x = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix}$  ;  $M_y = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$

```
>> My = fspecial('sobel');
>> outim = imfilter(double(im), My);
>> imagesc(outim);
>> colormap gray;
```

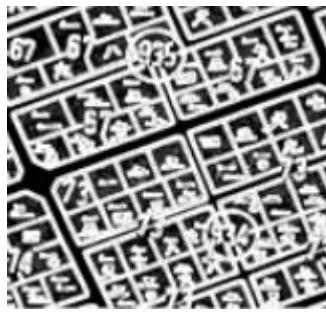


# Detail of Edge Detection

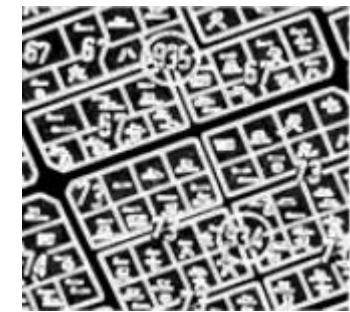
- How can we estimate edge?
  - Estimated as edges if the brightness difference between neighboring pixels exceeds the certain threshold
- Different Edge Detection with Different methods



Original Image



Sobel



Prewitt



Laplacian



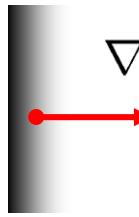
Canny

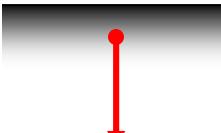
# Image gradient

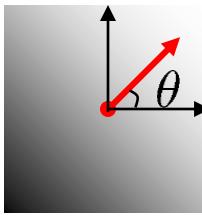
The gradient of an image:

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

The gradient points in the direction of most rapid change in intensity


$$\nabla f = \left[ \frac{\partial f}{\partial x}, 0 \right]$$


$$\nabla f = \left[ 0, \frac{\partial f}{\partial y} \right]$$


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

The gradient direction (orientation of edge normal) is given by:

$$\theta = \tan^{-1} \left( \frac{\partial f}{\partial y} / \frac{\partial f}{\partial x} \right)$$

The *edge strength* is given by the gradient magnitude

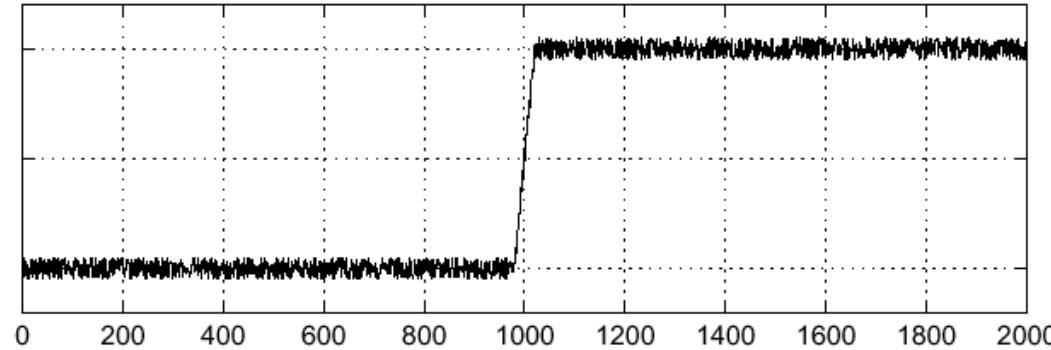
$$\|\nabla f\| = \sqrt{\left( \frac{\partial f}{\partial x} \right)^2 + \left( \frac{\partial f}{\partial y} \right)^2}$$

# Effects of noise

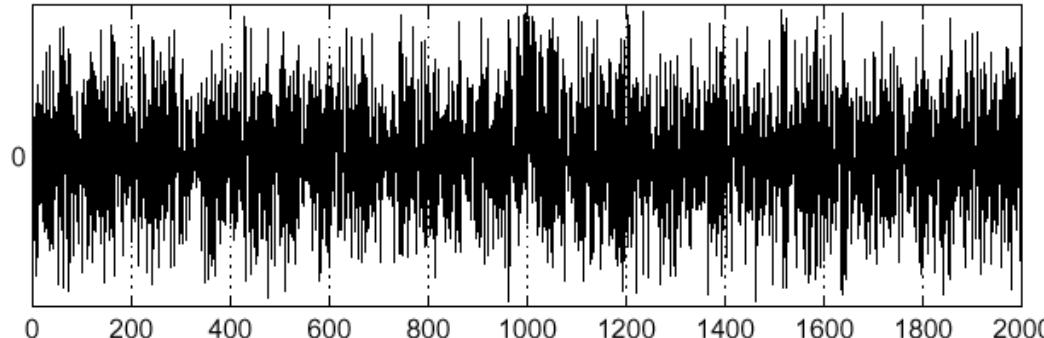
Consider a single row or column of the image

- Plotting intensity as a function of position gives a signal

$$f(x)$$



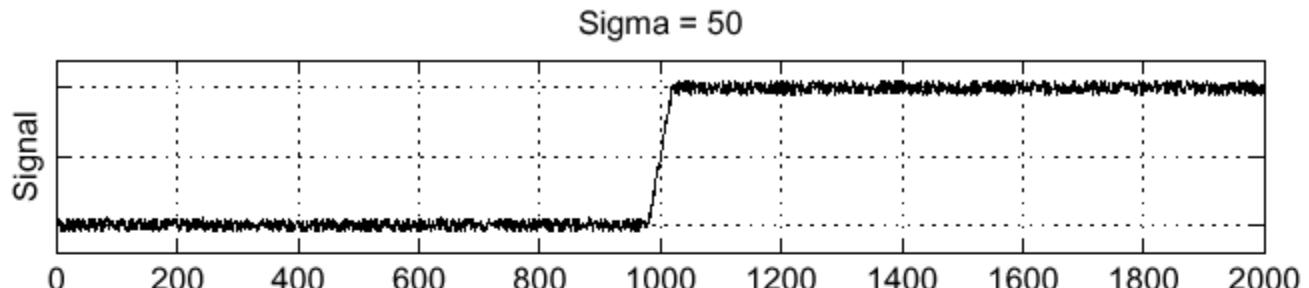
$$\frac{d}{dx}f(x)$$



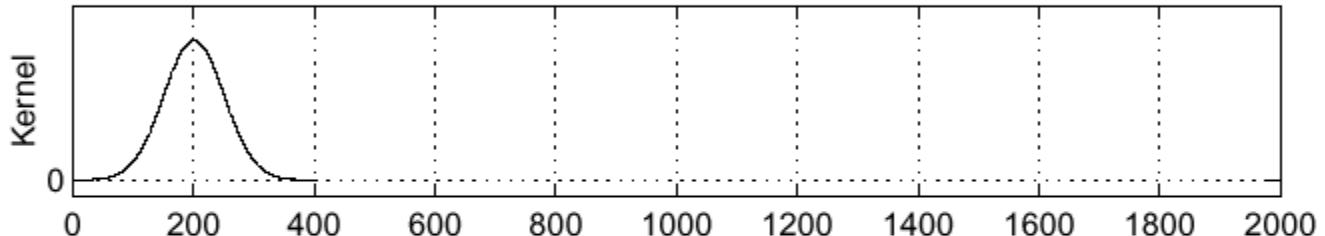
Where is the edge?

# Solution: smooth first

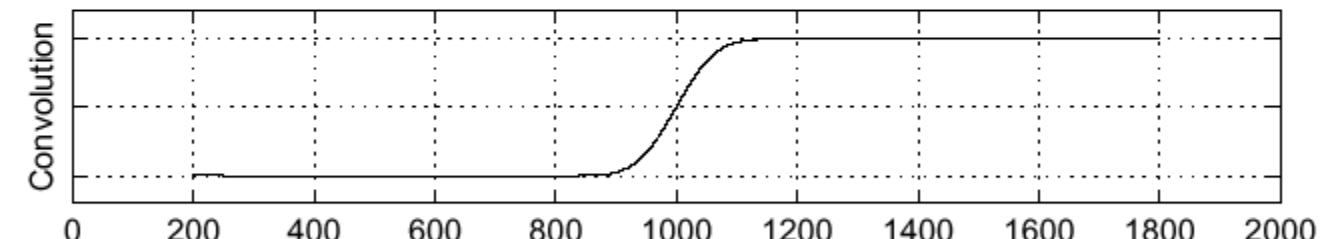
$f$



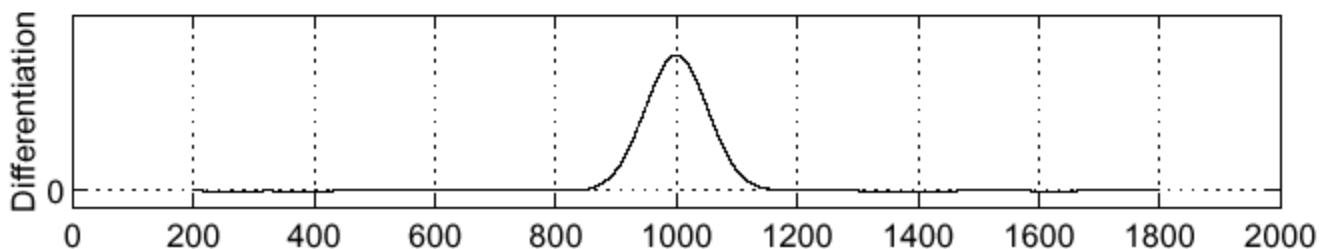
$h$



$h \star f$



$\frac{\partial}{\partial x}(h \star f)$

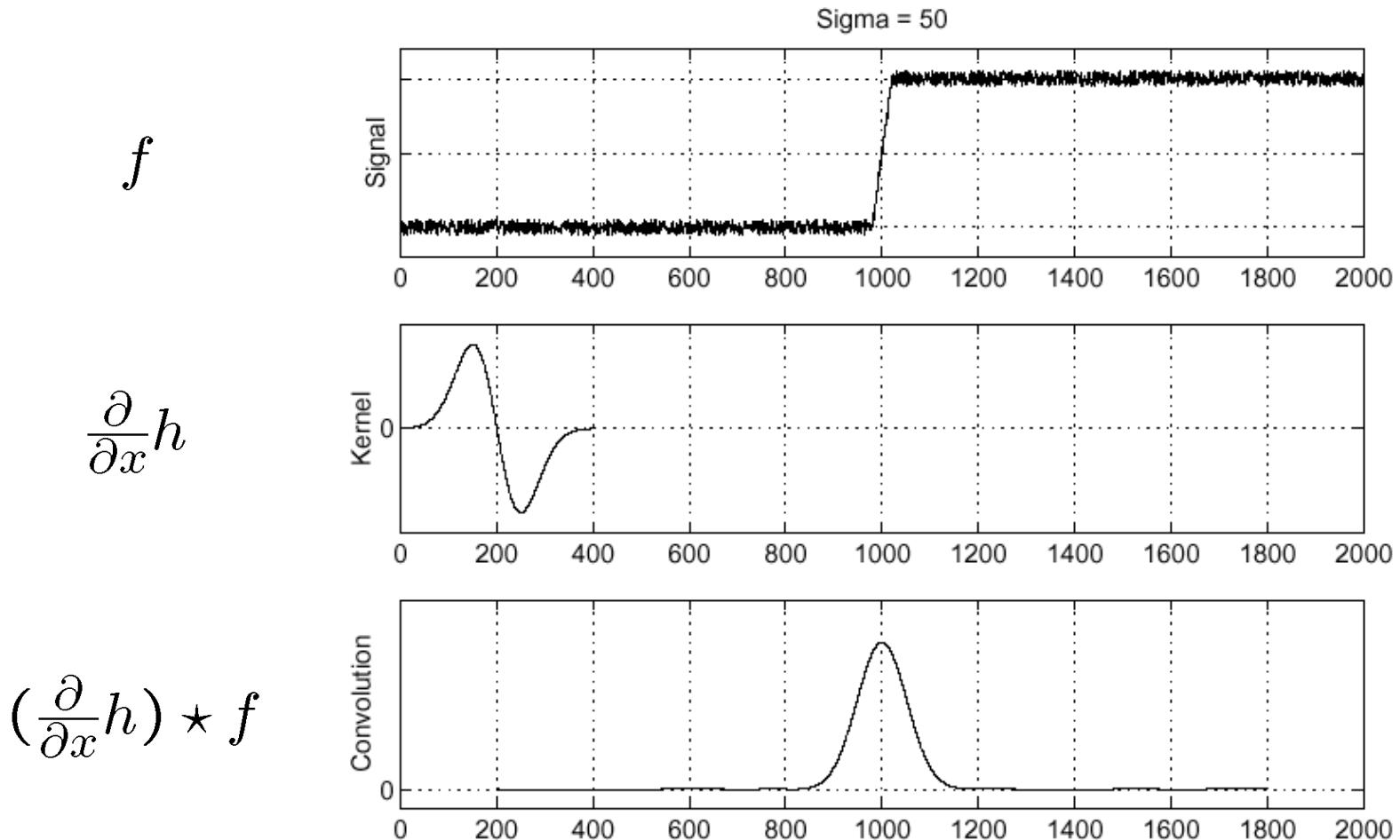


Where is the edge? Look for peaks in  $\frac{\partial}{\partial x}(h \star f)$

# Derivative theorem of convolution

$$\frac{\partial}{\partial x}(h \star f) = (\frac{\partial}{\partial x}h) \star f$$

Differentiation property of convolution.



# Derivative of Gaussian filter

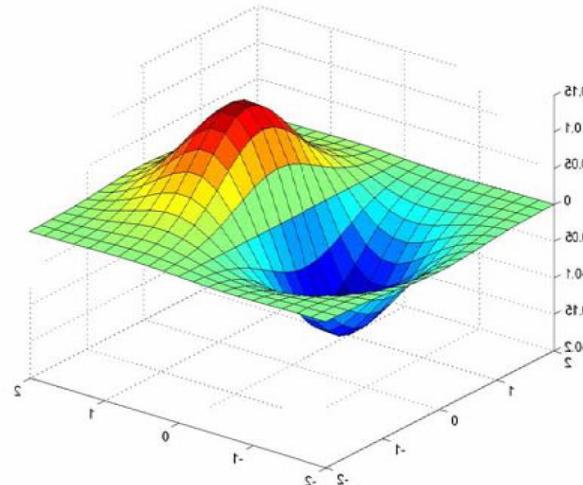
$$(I \otimes g) \otimes h = I \otimes (g \otimes h)$$

$$\begin{bmatrix} 0.0030 & 0.0133 & 0.0219 & 0.0133 & 0.0030 \\ 0.0133 & 0.0596 & 0.0983 & 0.0596 & 0.0133 \\ 0.0219 & 0.0983 & 0.1621 & 0.0983 & 0.0219 \\ 0.0133 & 0.0596 & 0.0983 & 0.0596 & 0.0133 \\ 0.0030 & 0.0133 & 0.0219 & 0.0133 & 0.0030 \end{bmatrix}$$

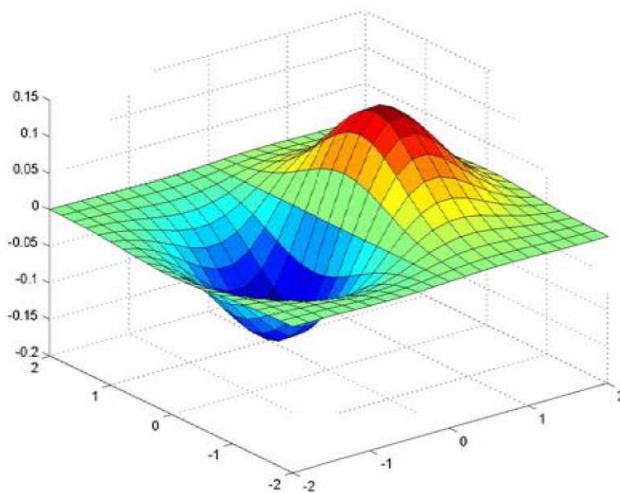
]

$\otimes$

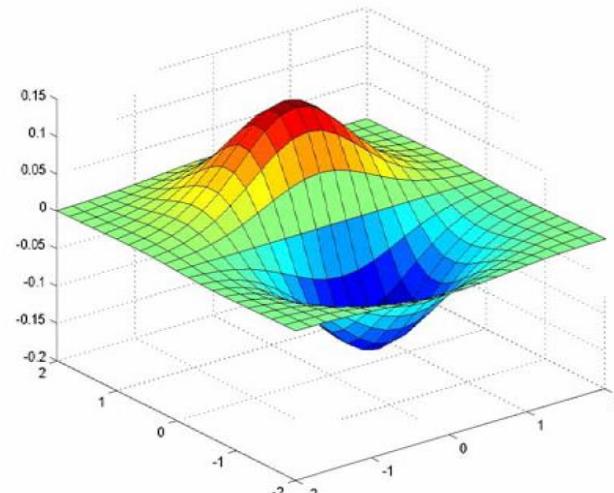
$$\begin{bmatrix} 1 & -1 \end{bmatrix}$$



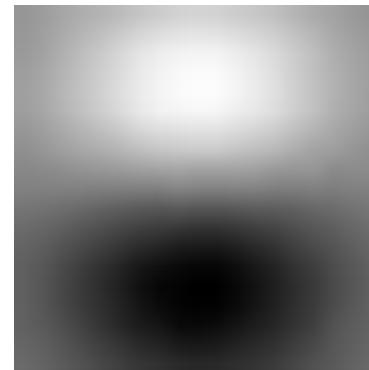
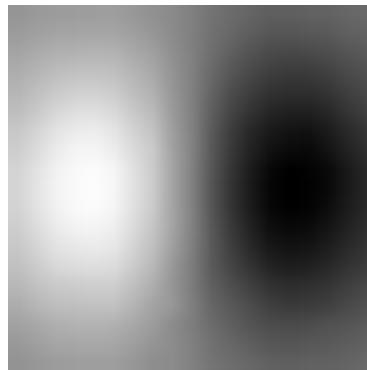
# Derivative of Gaussian filters



$x$ -direction



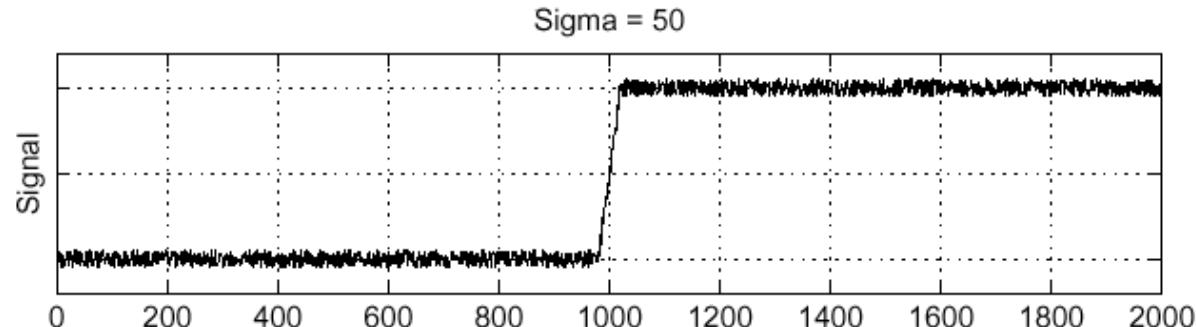
$y$ -direction



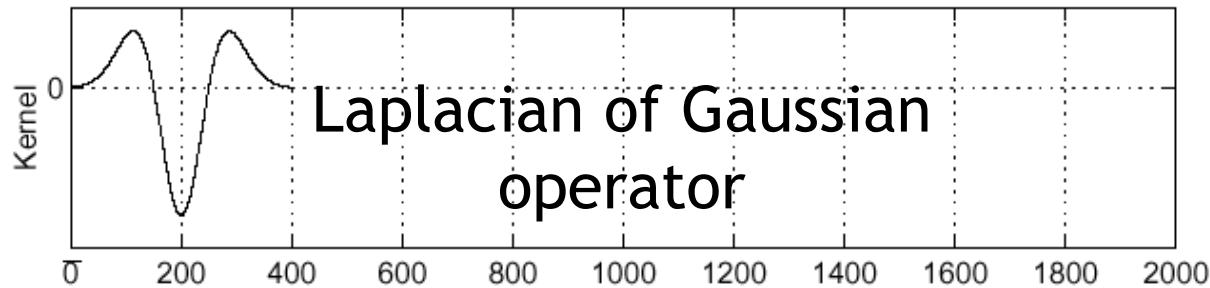
# Laplacian of Gaussian

Consider  $\frac{\partial^2}{\partial x^2}(h \star f)$

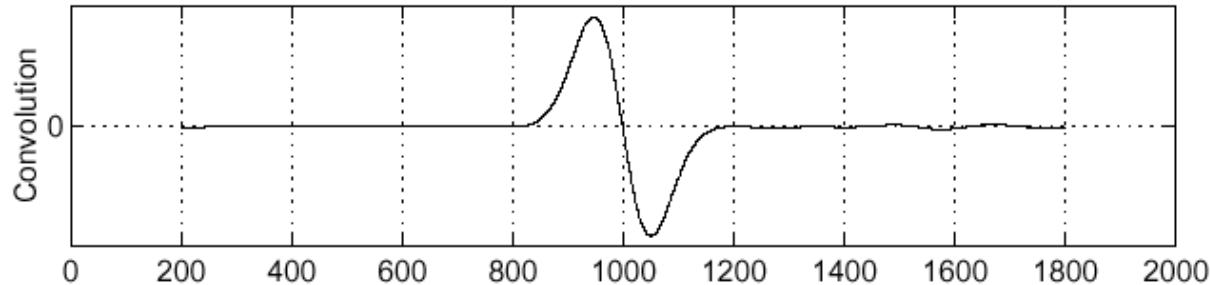
$f$



$\frac{\partial^2}{\partial x^2} h$



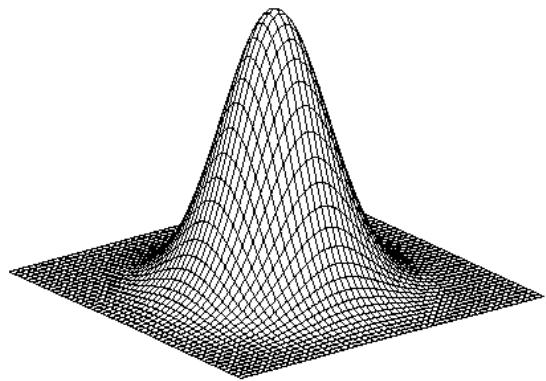
$(\frac{\partial^2}{\partial x^2} h) \star f$



Where is the edge?

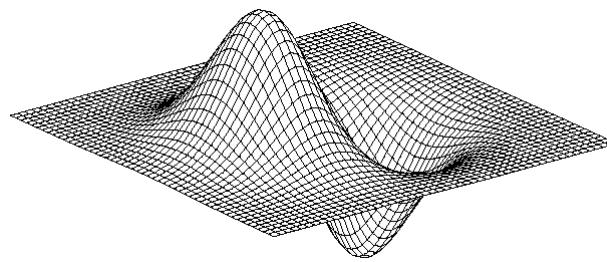
Zero-crossings of bottom graph

# 2D edge detection filters



Gaussian

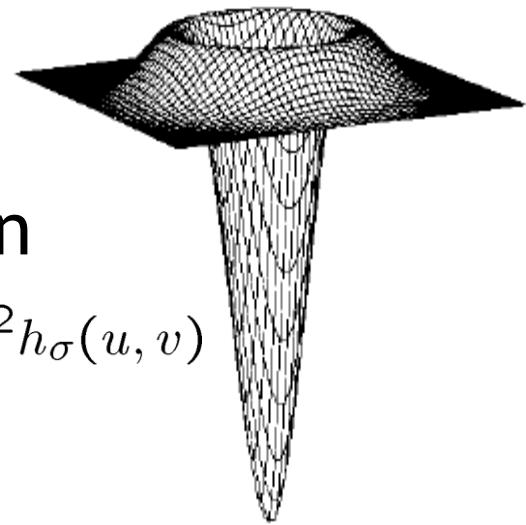
$$h_\sigma(u, v) = \frac{1}{2\pi\sigma^2} e^{-\frac{u^2+v^2}{2\sigma^2}}$$



Derivative of Gaussian

$$\frac{\partial}{\partial x} h_\sigma(u, v)$$

Laplacian of Gaussian



- $\nabla^2$  is the Laplacian operator:

$$\nabla^2 f = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2}$$

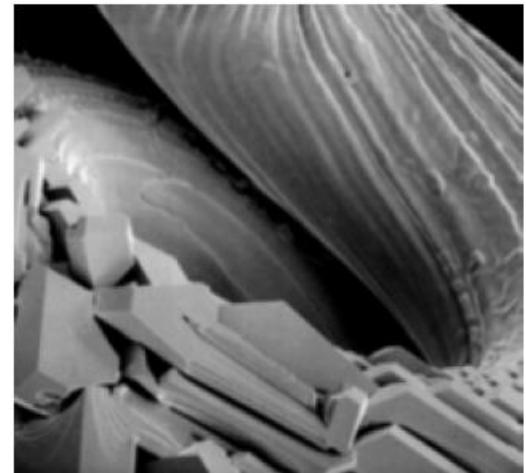
# Edge Detection w/ Laplacian Filter

0	1	0
1	-4	1
0	1	0

1	1	1
1	-8	1
1	1	1

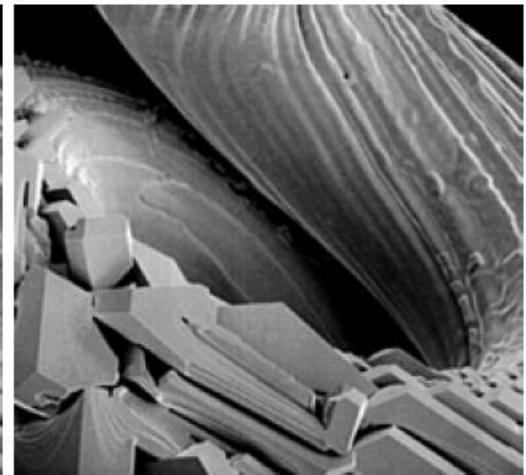
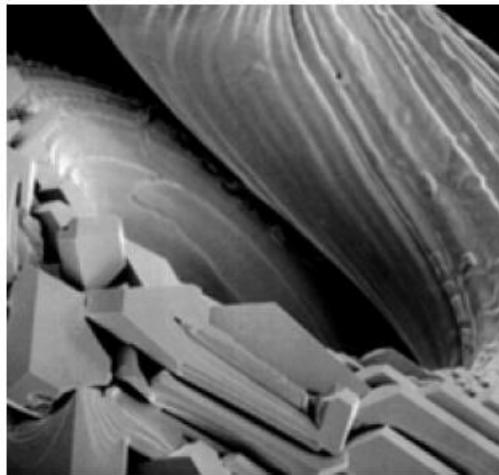
0	-1	0
-1	5	-1
0	-1	0

-1	-1	-1
-1	9	-1
-1	-1	-1



0	-1	0
-1	4	-1
0	-1	0

-1	-1	-1
-1	8	-1
-1	-1	-1



# Primary Edge Detection Steps

## 1. Smoothing:

- Suppress noise

## 2. Edge enhancement:

- Edge detection filters

## 3. Edge localization

- Determine which local maxima from filter output are actually edges vs. noise
- Threshold: if pixel value < threshold, pixel value =0, otherwise pixel value=1

# Original image



# Gradient magnitude image



# Thresholding gradient with a lower value



# Thresholding gradient with a higher value



# Outline

## -Computer Vision (CV) for Intelligent SoC Robot-

### -Theoretical Part-

1. *Introduction of CV for robot*
2. *Basic of Image*
3. ***Image Processing Algorithm***
  - *Elementary Processing*
  - ***Applications of Elementary Processing***  
*: Edge, Distance, Optical Flow Detection*

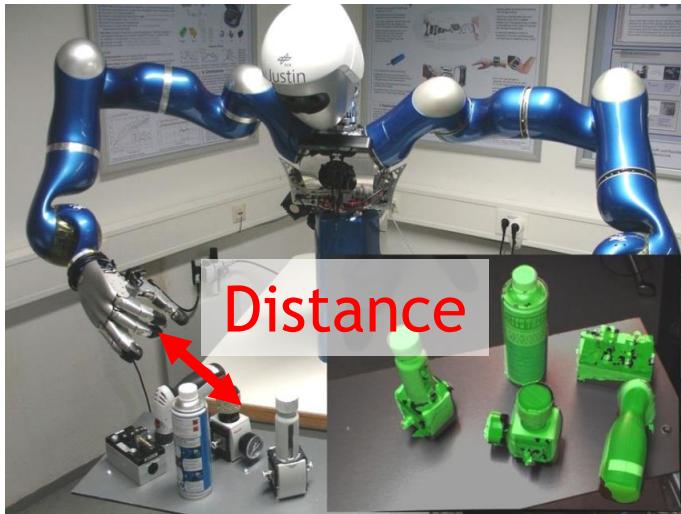
### -Practical Part-

1. *Practical Algorithms for “Robot War”*

# Advanced Image Processing - Distance Estimation

- Estimating distance Information is Essential!
  - Estimate the distance from the objects to move it
  - Estimate the distance from the obstacles to avoid it
- Time of flight (ToF) or stereo matching can be utilized

Distance information can be used for ...



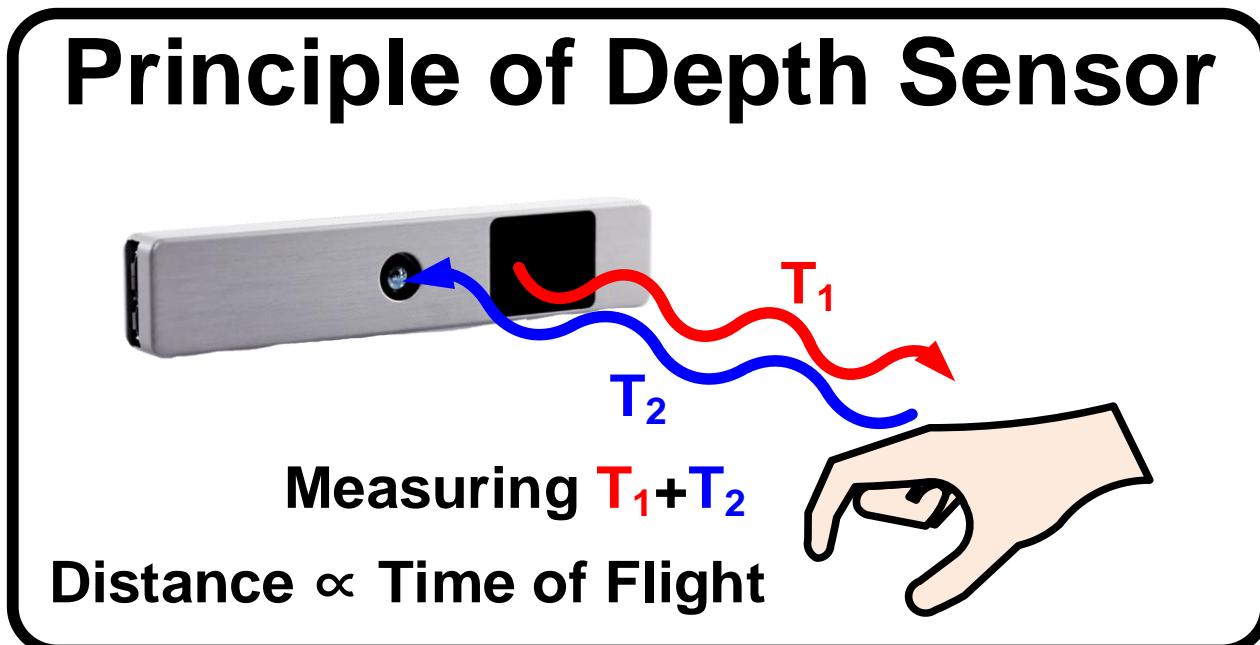
moving objects



avoid obstacles

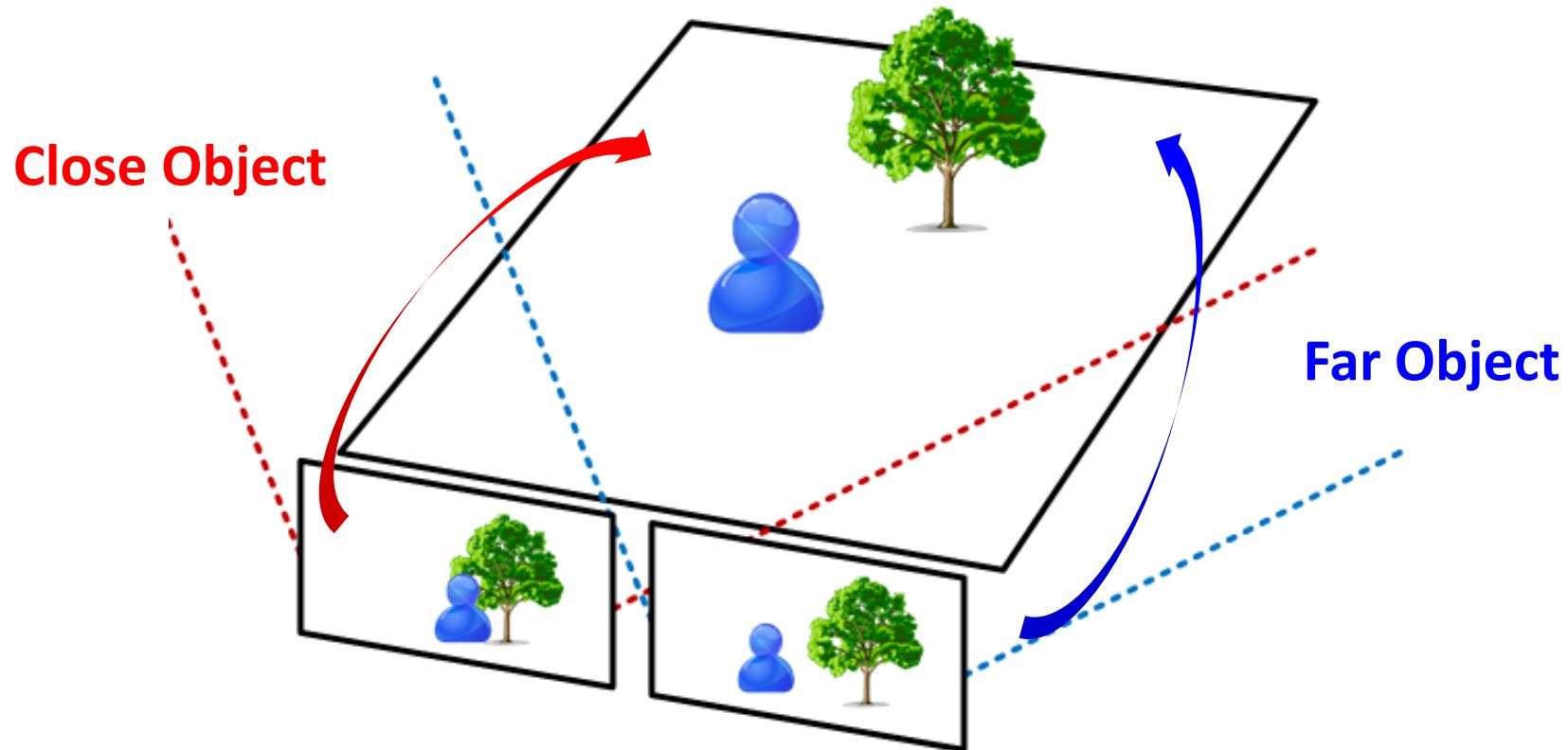
# Time of Flight (ToF)

- Basic idea: send out pulse of light (usually laser), time how long it takes to return
- Accurate, but large power consumption



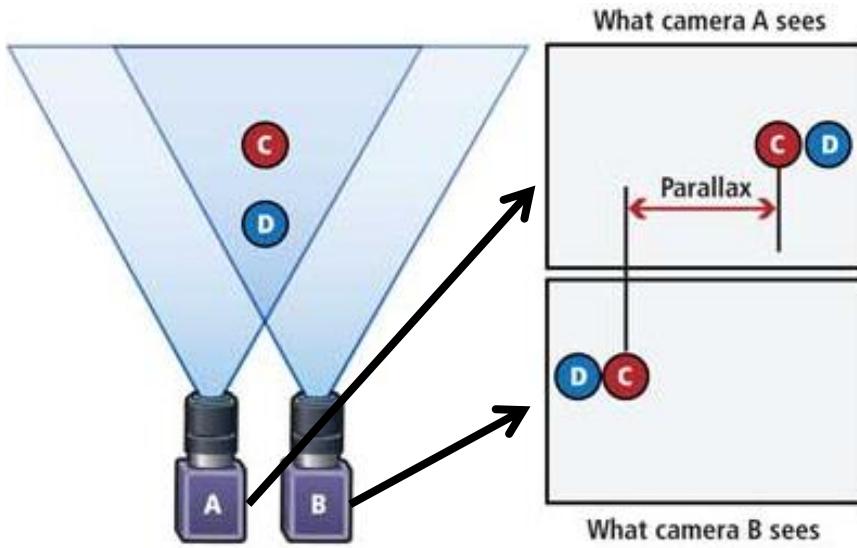
# Stereo Matching

- Basic Idea : Inferencing depth from two different views
  - Close object → Large displacement
  - Far object → Small displacement



# How can we do stereo matching?

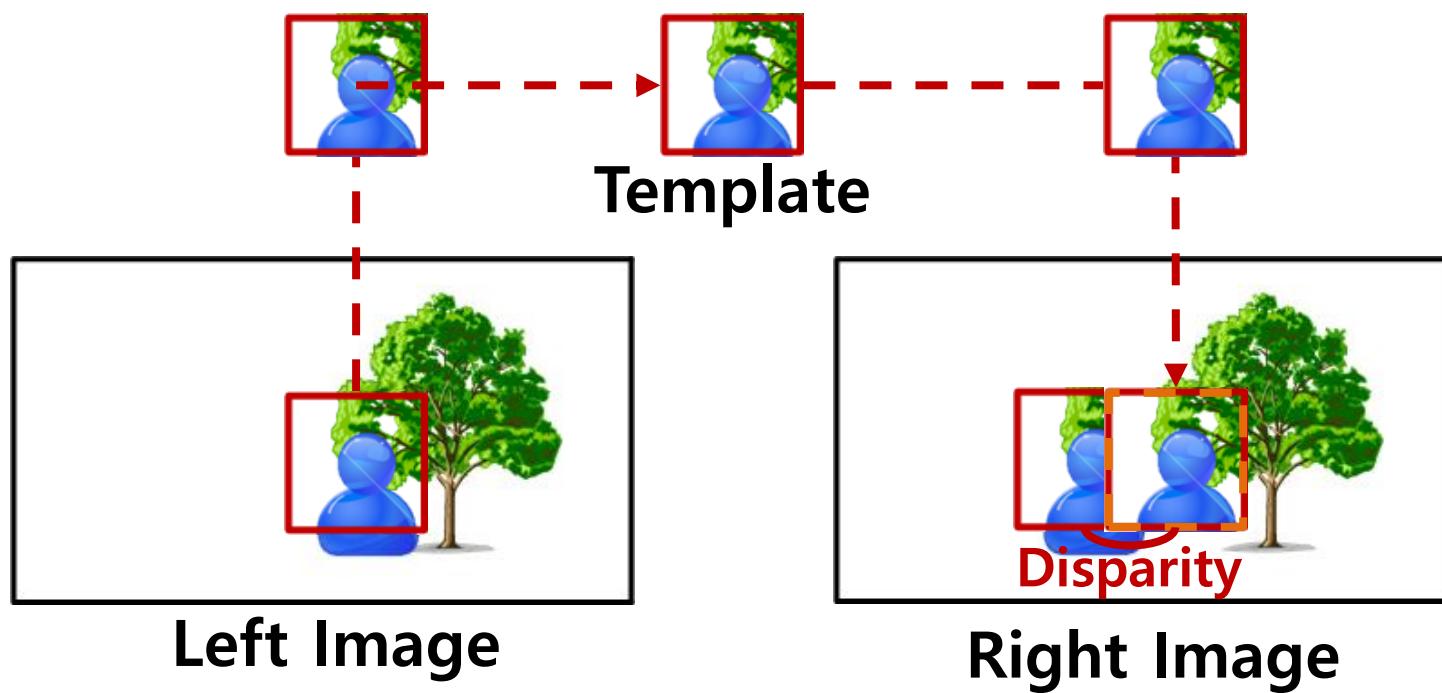
- By Using Stereo Camera
  - Measure the pixels distance from a left and right camera scene and estimate the depth using the ratio of equivalent triangles



Depth Map

# Detail of Stereo Matching Process

- Sliding Window Processing
  - Find best matched disparity between L & R images



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*: Edge, Distance, Optical Flow Detection*

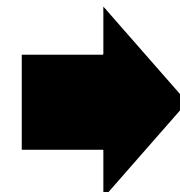
### *-Practical Part-*

1. *Practical Algorithms for “Robot War”*

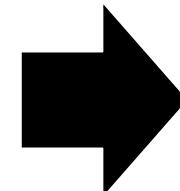
# Advanced Image Processing - Motion Information

- Motion Information is also useful in robot!
  - Segment only moving object from input video streams
  - Human action recognition from input video streams
  - Motion de-blurring on moving camera environment

Moving Object Segmentation



Motion De-blurring

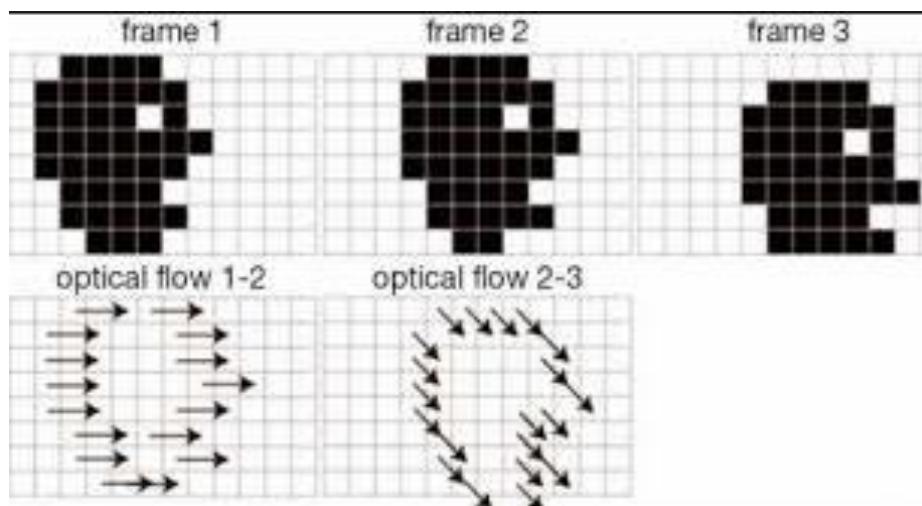


Segment!

De-blur!

# How can we get motion information?

- By Estimating Optical Flow!
  - Trace the object movement
  - Calculate the different pixels intensity from the adjacent frames and estimate the gradient components .



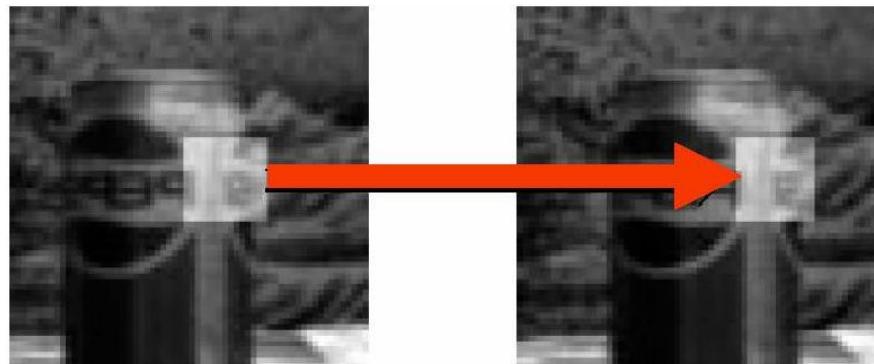
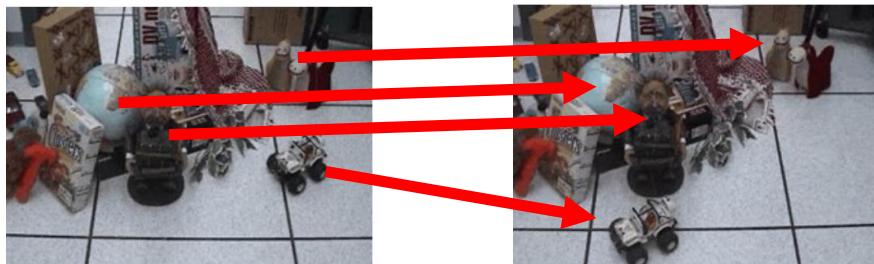
Original  
Image



Optical Flow  
Result

# Detail of Optical Flow Estimation Process

- Basic idea : Choose a small patch in previous frame ( $t$ ), and find similar one in next frame ( $t+1$ )
  - Assumption : The appearance of the image patches do not change (brightness constancy)



$$\frac{dI}{dt} = 0$$

$I(x,y) = \text{grey level value}$   
 $\text{Velocity vector is } (v_1, v_2)$

$$\frac{\partial I}{\partial x} v_1 + \frac{\partial I}{\partial y} v_2 + \frac{\partial I}{\partial t} = 0$$

# Outline

**-Computer Vision (CV) for Intelligent SoC Robot-**

**-Theoretical Part-**

1. *Introduction of CV for robot*
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3. *Image Processing Algorithm*

**-Practical Part-**

1. ***Practical Algorithms for “Robot War”***  
*: Which CV techniques will help you?*

# Image Processing and Image Recognition

- **Image Processing**

- Subcategory of digital signal processing
- Computer algorithms to obtain the image information from images
  - Ex) Resolution enhancement, image restoration, compression, recognition, etc.

1920s

- Transfer the newspapers between America and Europe  
→ Beginning of image processing

1964

- The Jet Propulsion Laboratory  
→ Image restoration from satellite images

1980s

- Development of medical imaging like CT, MRI

1990s

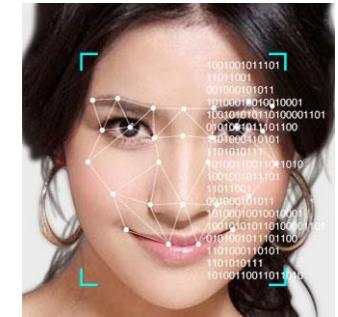
- The fast computers  
→ The common for the computer vision and graphics broadcasting

# Image Processing and Image Recognition

- **Image Recognition**

- Identify the types of and numbers of objects from an image

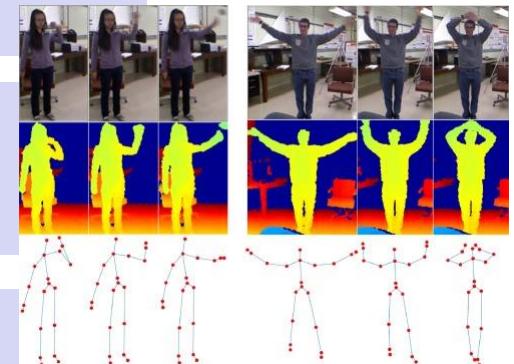
- Face recognition  
→ Security, digital camera, smartphone



- Lane line recognition  
→ Autonomous navigation (Driving, Parking)

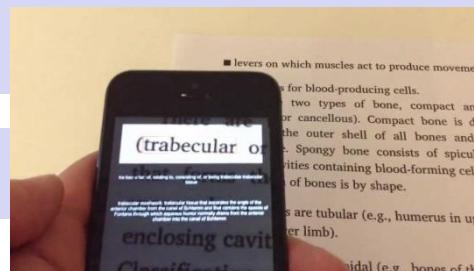


- Environment recognition  
→ Robot, forest fire



- Action recognition  
→ Game

- Text recognition



# SoC Robot - Image Processing

Processing/ Recognition	Methods / Results	Remarks
Color Conversion	Because RGB format is vulnerable to illumination change, <b>YCbCr</b> or HIS is mainly used for image processing / recognition	<b>Brightness changes with place / time</b>
Noise Reduction	Remove noise from the input video from camera	<b>Camera noise</b>
Opponent Robot recognition	Because Color-based recognition is sensitive to environment variation, image recognition using feature extraction is required	<b>Environment changes with place / time</b>
Opponent Robot motion recognition	By recognizing the motion (movement) of the robot, it is possible to predict the next motion, thereby determining the attack / defense	<b>Attack / defense strategy</b>
Location recognition	Recognize the opponent robot's and my position for various strategies	<b>Attack / defense strategy</b>
Distance recognition	By measuring the distance between the robot and my position, it can estimate the distance that can be attacked or defended, and can take various attack or evasion actions	<b>Attack / defense strategy</b>

# Program Analysis

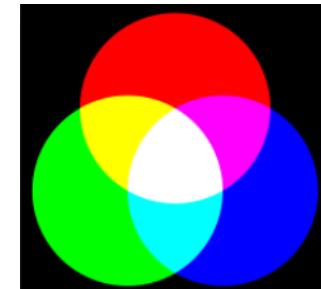
Source Code Analysis for Intelligent SoC Robot (HDL: H / C language: C)

Technique	Details	Team								
		A	B	C	D	E	F	G	H	I
Filtering	Noise Filtering	H		C	C	C		C		
Color Conversion	Resolution Conversion		H			H			H	
	Format (RGB-YUV) Conversion			H	H	C	H	H	H	C
Color Recognition	Black line Recognition	H	C	C		C	H	H	H	
	Opponent Robot Recognition	H	C	C	C	C		C		C
Motion Recognition	Opponent Attack Motion Recognition									
	Opponent Defense Motion Recognition									
	Opponent Standing Motion Recognition							C		
	Opponent Sitting Motion Recognition							C		
Location Recognition	Opponent Location Recognition	H	C	C	C	C	H	C	C	C
Distance Recognition	Opponent Distance Recognition	H	C	C	C	C	H	C		
Object Tracking	Opponent Object Tracking	H	C	C	C					

# Image Processing - Color

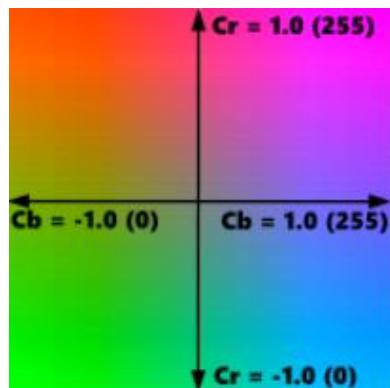
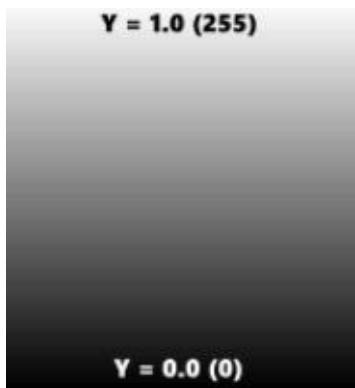
- **RGB**

- Mix colors of three primary colors, RED, GREEN, BLUE
- Sensitive to brightness
- Correlation of color elements is too large



- **YCbCr**

- Y: Luminance, Cb, Cr: Difference chrominance components
- Robust to brightness by using Cb and Cr for color recognition
- Compression effect in color information compared to RGB

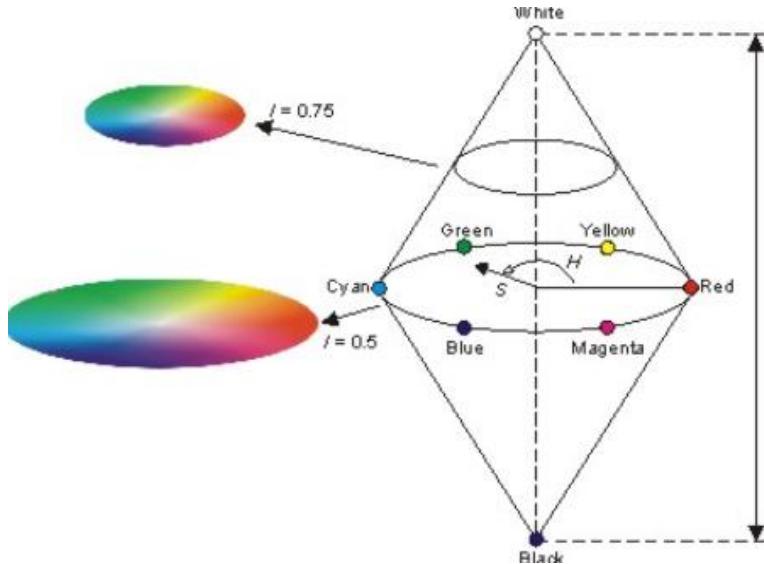


$$\begin{pmatrix} Y \\ U \\ V \end{pmatrix} = \begin{pmatrix} 0.299 & 0.587 & 0.114 \\ -0.147 & -0.289 & 0.436 \\ 0.615 & -0.514 & -0.101 \end{pmatrix} \begin{pmatrix} R \\ G \\ B \end{pmatrix}$$

# Color Processing

- HIS

- Same way human feels color
- Hue: The feeling of color. 6 basic colors (red, yellow, green, cyan, blue, magenta) are interpolated to make other colors
- Saturation: Degree of color how much diluted with white color
- Intensity: The intensity (the amount of light)



# Spatial Filter

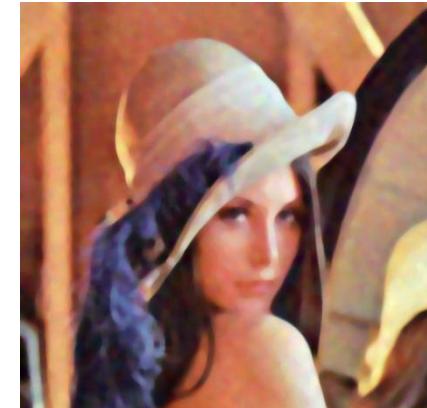
- Uses one pixel of the input image and its surrounding pixels as the input



Input Image

$h_1$	$h_2$	$h_3$
$h_4$	$h_5$	$h_6$
$h_7$	$h_8$	$h_9$

Mask



Filtering Result

- Since the image is a two-dimensional signal, the filter used in the image processing is also two-dimensional
- Constructing spatial filter is called as “Mask” or “Window”

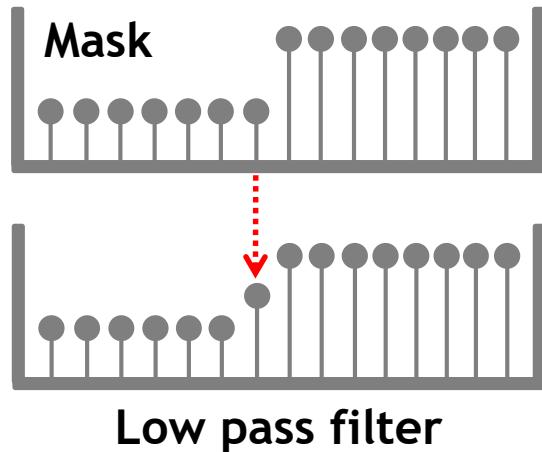
# Spatial Filter

- **Image Smoothing**

- A preprocessing that eliminates image noise and softens the image

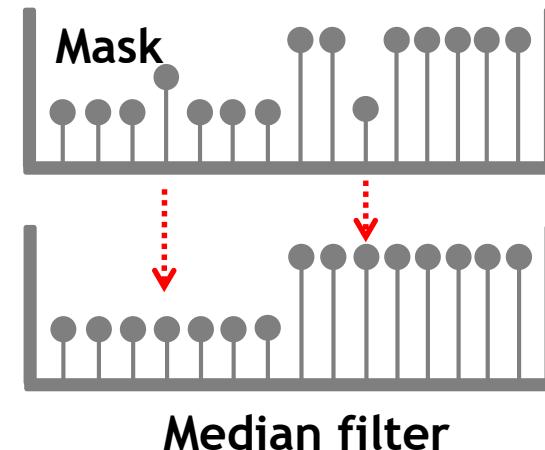
- **Low-pass filter**

- Eliminate high frequency components
  - Smoothing original Image



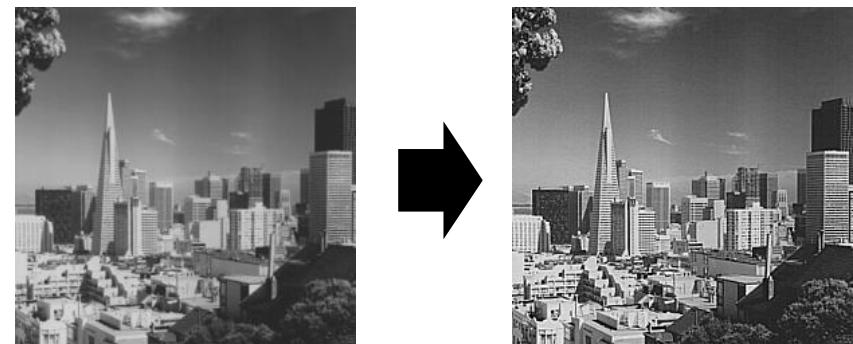
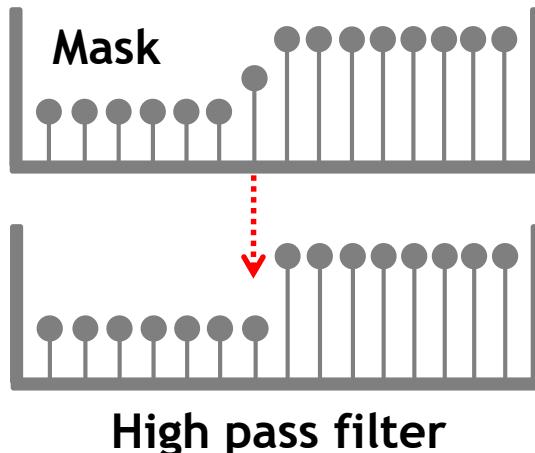
- **Median Filter**

- Sort by size and select the median value
  - Preserve the edge and remove noise



# Spatial Filter

- **Image Sharpening**
  - Improvement of the specific information of the image
- **High-pass Filter**
  - Eliminate low frequency components
  - Emphasize the edges



# Morphology

- Process that changes the shape while maintaining the basic characteristics of the image
  - Operation of Erosion and Dilation
  - Operation of Opening and Closing
  - Used for image segmentation and preprocessing
    - Ex) noise reduction, feature extraction

$$A = \begin{matrix} 1 & 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 & 1 \end{matrix}$$

$$B = \begin{matrix} 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 & 1 \end{matrix}$$

Union Operation  
-  $A \oplus B, A \cup B$

$$\triangleq \quad \doteq \ll \begin{matrix} 1 & 0 & 1 & 1 & 1 \\ 0 & 1 & 0 & 1 & 1 \\ 1 & 0 & 1 & 1 & 1 \end{matrix}$$

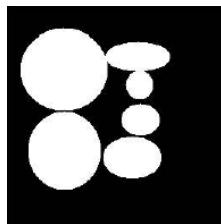
Intersection Operation  
-  $A \otimes B, A \cap B$

$$\triangleq \quad \doteq \ll \begin{matrix} 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{matrix}$$

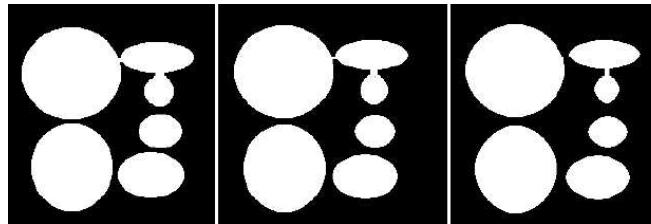
# Morphology (cont.)

- **Operation of Erosion**

- Intersection operation when template and binary image are matched
- Remove the edge protrusion, and reduce the size of the object



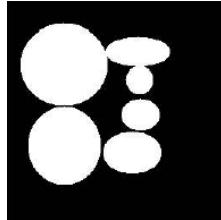
Original Image



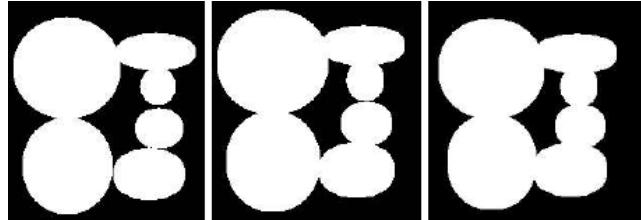
1 Erosion 2 Erosion 3 Erosion

- **Operation of Dilation**

- Union operation when template and binary image are matched
- Remove the depth of the hole or edge, and enlarge the size of the object



Original Image

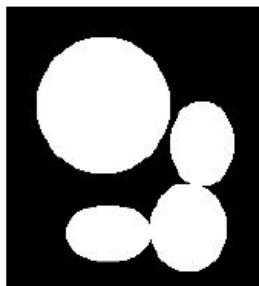


1 Dilation 2 Dilation 3 Dilation

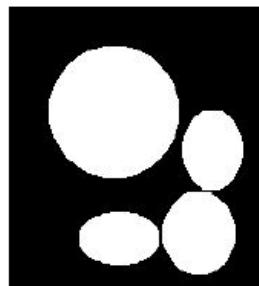
# Morphology (cont.)

- **Operation of Opening**

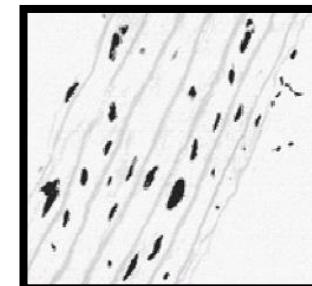
- Apply the dilation operation after the erosion
- Useful for separating the objects



Original Image



After Opening



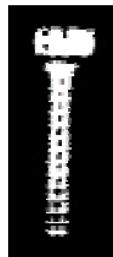
Original Image



After Opening

- **Operation of Closing**

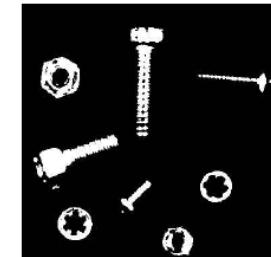
- Apply the erosion operation after the dilation
- Use for combining the objects



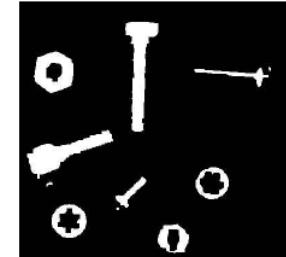
Original Image



After Closing



Original Image



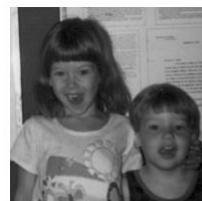
After Closing

# SoC Robot - Image Processing

- **Edge Detection**
  - Edge or contour
  - Estimated as an edges if the brightness difference between neighboring pixels exceeds the certain threshold

- **Condition for edge detection mask**

- Width and height of mask have to be equal, and odd numbers
- Vertical symmetry based on center coefficient
- The values of the center coefficient are always positive or zero
- The others of the center coefficient are negative
- The sum in all coefficients is zero



(a) Original image



(b) Robert operator



(c) Sobel operator



(d) Prewitt operator



(e) Laplacian operator



(f) Kirsch operator



(g) Robinson operator

# SoC Robot - Image Processing

- **Sobel Mask**

- Widely used for edge detection with weighting the pixel edges
- Edge detection in all direction is possible and strong in noise

-1	0	1
-2	0	2
-1	0	1

Vertical Mask

1	2	1
0	0	0
-1	-2	-1

Horizontal Mask

- **Prewitt Edge Detection**

- Fast responsibility
- Less detecting edge due to smaller weighting than Sobel mask
- More sensitive to vertical / horizontal edge than diagonal

-1	0	1
-1	0	1
-1	0	1

Vertical Mask

1	1	1
0	0	0
-1	-1	-1

Horizontal Mask

# SoC Robot - Image Processing

- **Labeling**
  - Labeling the same number to all adjacent pixels and another number to the other segments

			255	255	255		
			255	255	255		
			255	255	255		
255	255						
255	255				255		
255	255			255	255	255	
255	255		255	255	255	255	255

Grayscale Image

						10	10	10
						10	10	10
						10	10	10
						9	9	
						9	9	
						9	9	

Labeling Image

- **Grassfire Algorithm**
  - Algorithm for labeling pixels like spreading fire in the grass

# SoC Robot - Image Processing

- **Feature:** Geometric properties of the object for recognition and separation
- **Features for recognizing objects**
  - Average brightness
  - Max. and min. brightness
  - Area / Thinness / Shape Ratio
  - Circumference: the total number of pixels around the region
  - Diameter: The farthest distance between two pixels that are at the edge of an object
  - Center of gravity: The average of x- and y-coordinate pixels in the region
  - Moment: Significant direction features in the center of gravity coordinate
  - The degree of curvature around the object
  - Hole in the object / Chain code

# SoC Robot - Image Processing

- **Recognition**
  - Finding and identifying the target objects in the region
- **Template matching**
  - A recognizing method of comparing with the standard model which stored previously an image of an object or processed results
  - Recognition fails easily from different camera angle and distance
- **Bayesian theorem**
  - Impossible to obtain the same recognition results with same object features due to the method's stochastic characteristic.
- **Neural network**
  - **Training:** Adjust the connection weights by the pattern classes
  - **Inference:** Classify the nearest class by calculating the distance from the input vector and trained vectors
  - => Learning skills like human: Pattern Classification, Recognition, Optimization, Prediction

# SoC Robot - Image Processing

- **Object Tracking**
  - Track the path of an arbitrarily moving object
  - Use position and size of the object in the frame of the image
- **Mean-Shift**
  - Find new center by comparing histogram in certain region with histogram in the next frame
- **CAMShift (Continuous Adaptive Mean Shift)**
  - Extend Mean-Shift Algorithm to the video image
  - Robust to rotation and zooming
  - Fast, Simple, Efficient

