Information Technology Institute

Mct/ROB/200 Robotics, Spring Term 12-13

Lecture 11 – Friday April 5, 2013

Visual Servoing

Most of the slides of this lecture are based on material from the following books:

- P. McKerrow. *Introduction to Robotics*. Addison-Wesley, 1991.
- C. Ray Asfahl. *Robots and Manufacturing Automation*. 2nd Ed., Wiley, 1992.
- M. Lee. *Intelligent Robotics*. Halsted Press and Open University Press Robotics Series, 1989.
- Saeed Benjamin Niku. *Introduction to Robotics*. 2nd Ed., Wiley, 2011.
- A. Khamis, "How to Build a Real Robot-11: Robotic Vision," Arab Electricity Magazine, issue 81, 2005, Egypt.

Objectives

When you have finished this lecture you should be able to:

- Understand the fundamentals of machine vision.
- Understand the basics of vision-based robot control (visual servoing).

Outline

- Introduction
- Digital Image Presentation [For Reading]
- Machine Vision
- Visual Servoing
- Summary

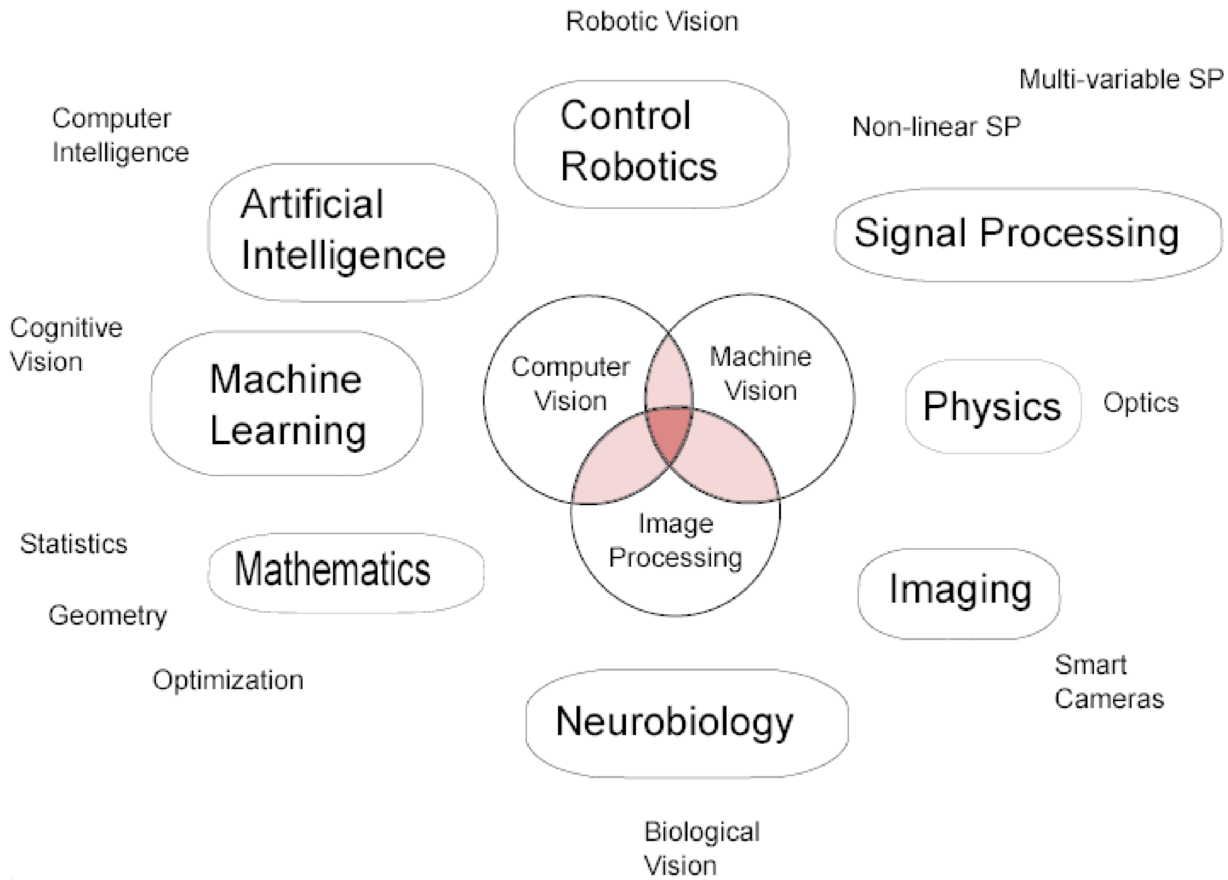
Outline

- **<u>Introduction</u>**
- Digital Image Presentation
- Machine Vision
- Visual Servoing
- Summary

Introduction

• **Computer Vision**

The goal of computer vision is inferring the properties of the world from one or more images.



Introduction

- **Computer Vision: Industrial Applications**

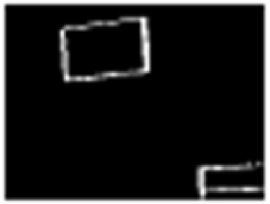
Object Location	**Used in object handling and processing**
	- Position - Orientation
Object Properties	**Used in inspection, identification, measurement**
	- Size - Area - Shape - Periphery length/area ratio - Degree of concavity - Texture - Repetition of pattern - Properties of internal features
Spatial Relations	**Used in measurement & task verification**
	- Relative positions - Relative orientations - Occlusions - Alignments - Connectivity
Action Monitoring	**Used in actuator control & verification**
	- Direct feedback - Error measurement - Action confirmation - Inspection - Collision avoidance planning

Introduction

- **Computer Vision: Research Fields**

Image Processing

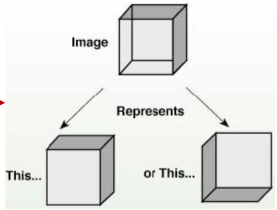
Results in new image



Concerns the transmission, storage, enhancement and restoration of images

Pattern Recognition

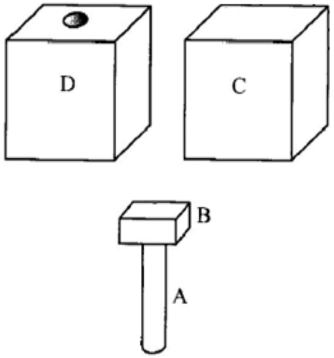
Results in image classification



Involves the interpretation of an image in terms of pre-defined classification of patterns

Image Understanding

Results in image description

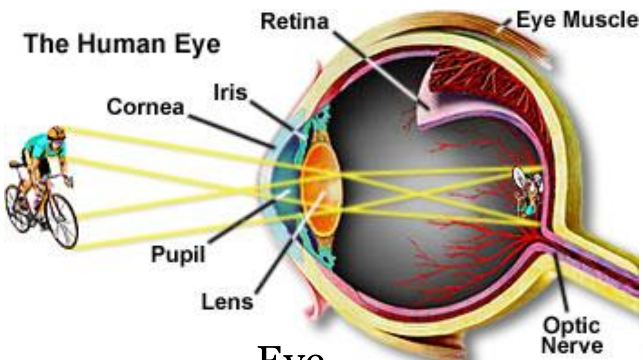


Deals with the perception and interpretation of three-dimensional scenes. The output is a description of the scene or image rather than a simple classification result

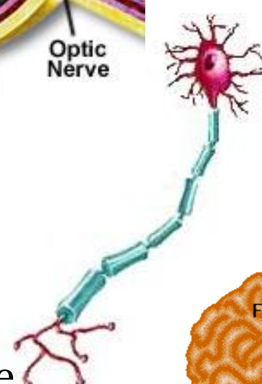
Introduction

- **What is an Image?**

  An image is a **spatial representation** of an object, a two-dimensional or a three-dimensional scene.

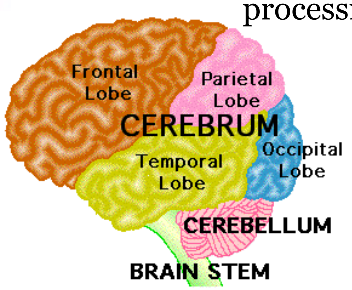


Eye
(The input sensor)



Optic Nerve
(The transmission path)

Occipital Lobe of the Brain
(The information processing unit)



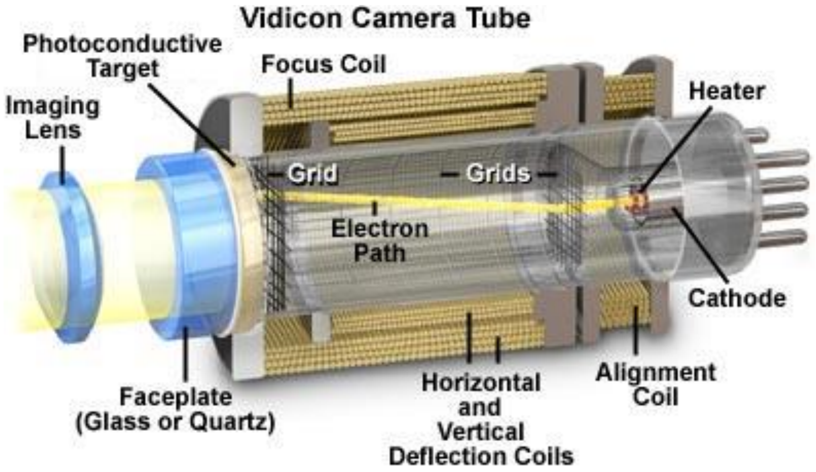
Introduction

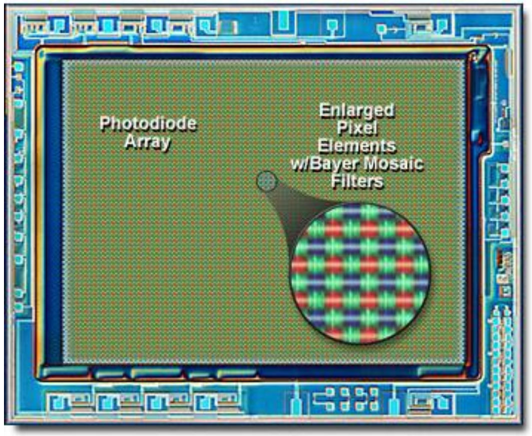
- **What is an Image?**
  - ◊ Intensity image
  - ◊ Tactile Image
  - ◊ Range Image
  - ◊ Thermal Image

Introduction

- **What is an Image?**

Photographic Sensors: an image is typically proportional to the radiant energy received in the electromagnetic band to which the sensor or detector is sensitive. In this case, the image is called an **intensity image**.





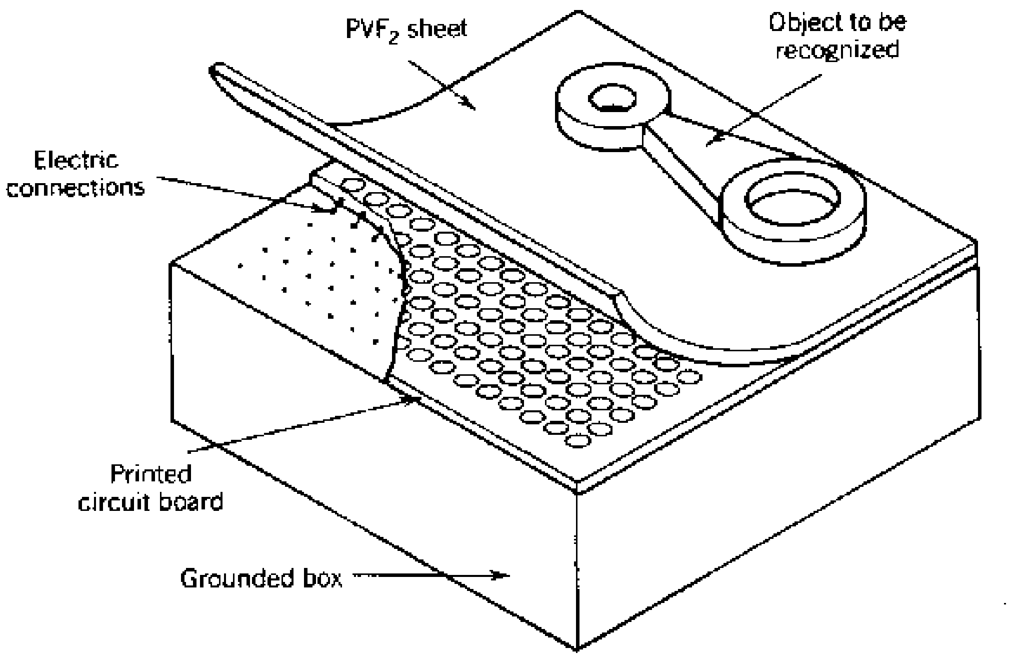
CCD (Charge Coupled Device)

More Info: http://micro.magnet.fsu.edu/optics/lightandcolor/vision.html

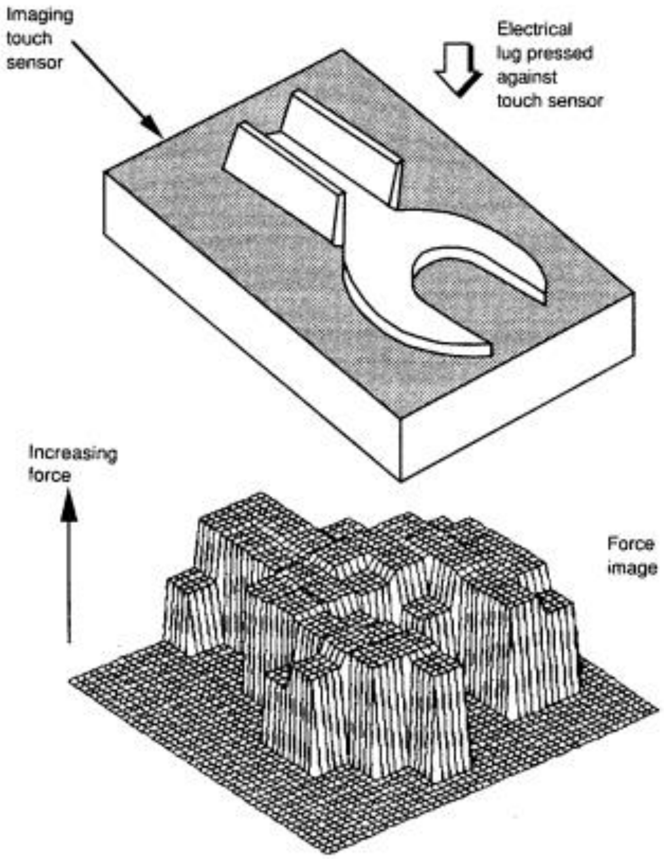
Introduction

- **What is an Image?**

  Tactile Sensors: an image is typically proportional to the sensor deformation caused by the surface of or around of an object.



Measuring 2-D pressure distribution

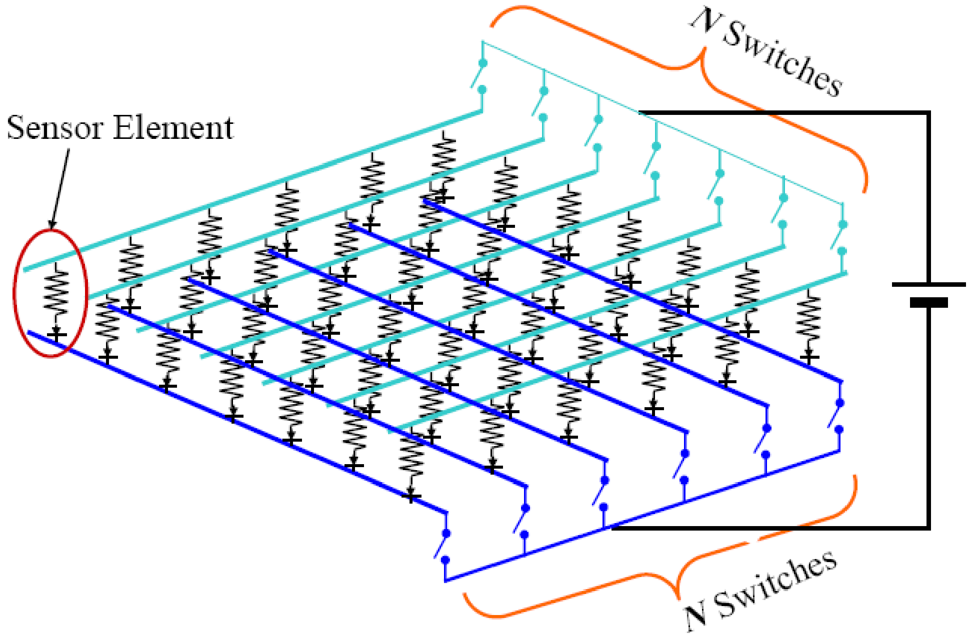


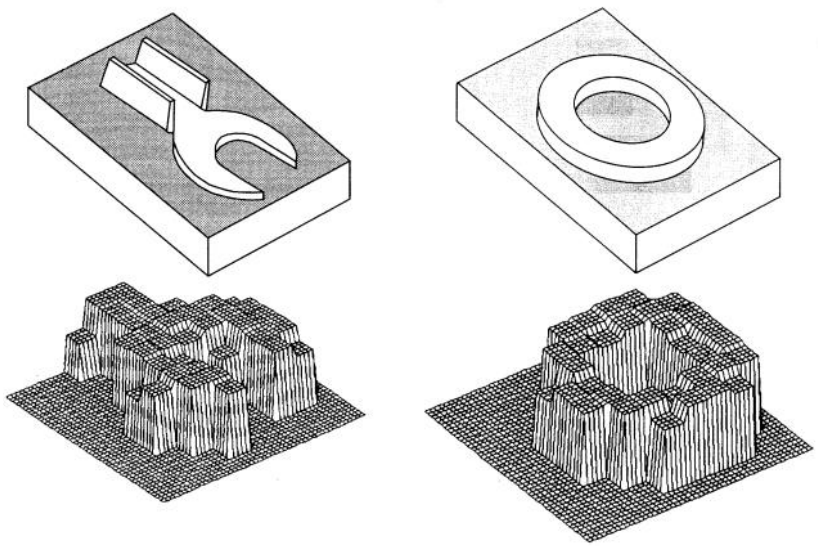
Introduction

- **What is an Image?**

Tactile sensors are able to detect an object and recognize its shape.

Artificial skin can be formed by aggregating multiple sensing points in form of digital sensor array using VLSI.

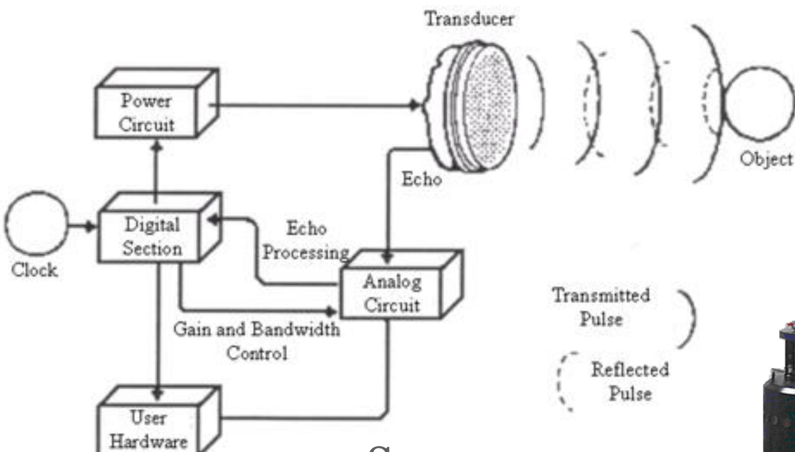




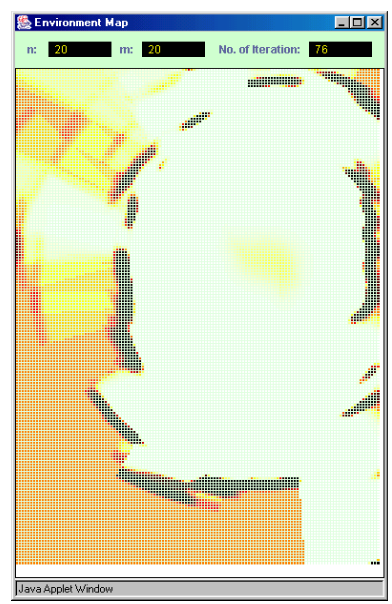
Introduction

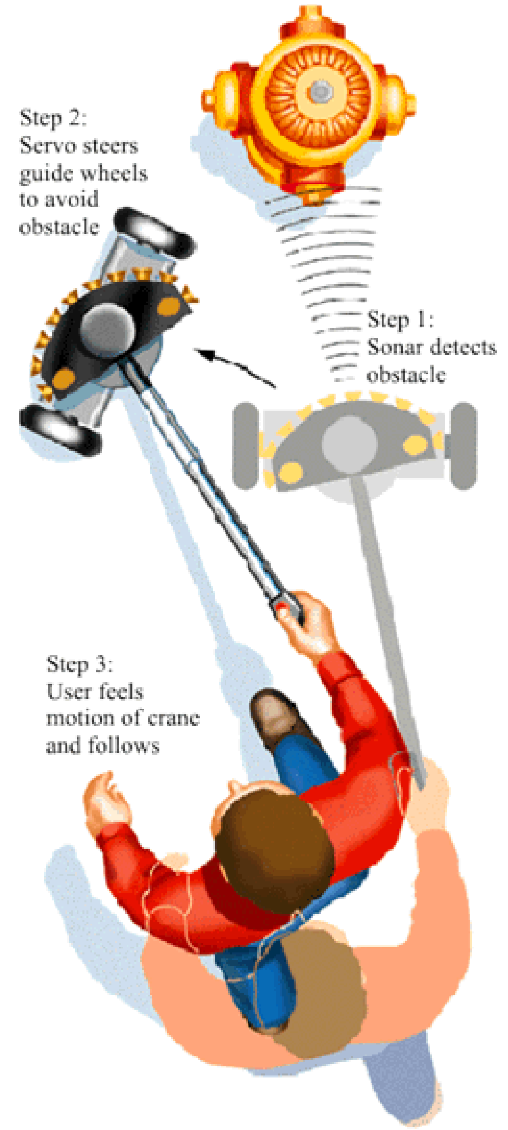
- **What is an Image?**

  Range Finder Sensors: an image is a function of the line-of-sight distance from the sensor position to an object in the three-dimensional world. This image is called **range image**.



Sonar





$$d = \frac{1}{2} * Vt, \ \text{V} = \text{speed of sound} = 331 + 0.6\text{T m/s}$$

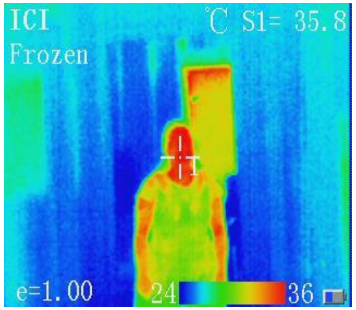
T is the temperature in ^{o}C, t is the time of travel

Introduction

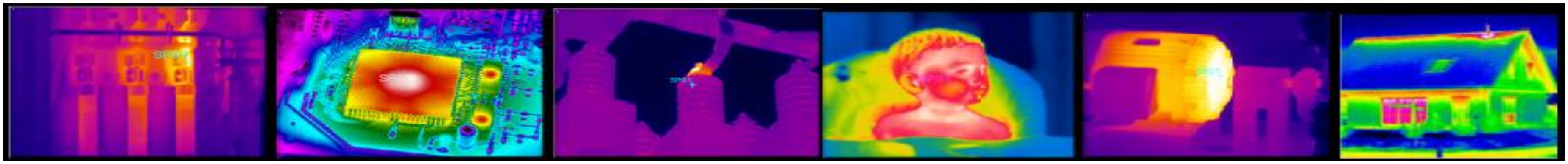
- **What is an Image?**

Thermal Imagining: Thermographic cameras detect radiation in the **infrared** range of the electromagnetic spectrum and produce images of that radiation. Since infrared radiation is emitted by all objects based on their temperature, according to the black body radiation law, **thermography** makes it possible to "see" one's environment with or without visible illumination.

IR Night Vision Camera



Military application (firefighters), Maintenance operation (localizing overheating joints and parts in power lines), luxury cars to aid the driver (Cadillac DeVille).



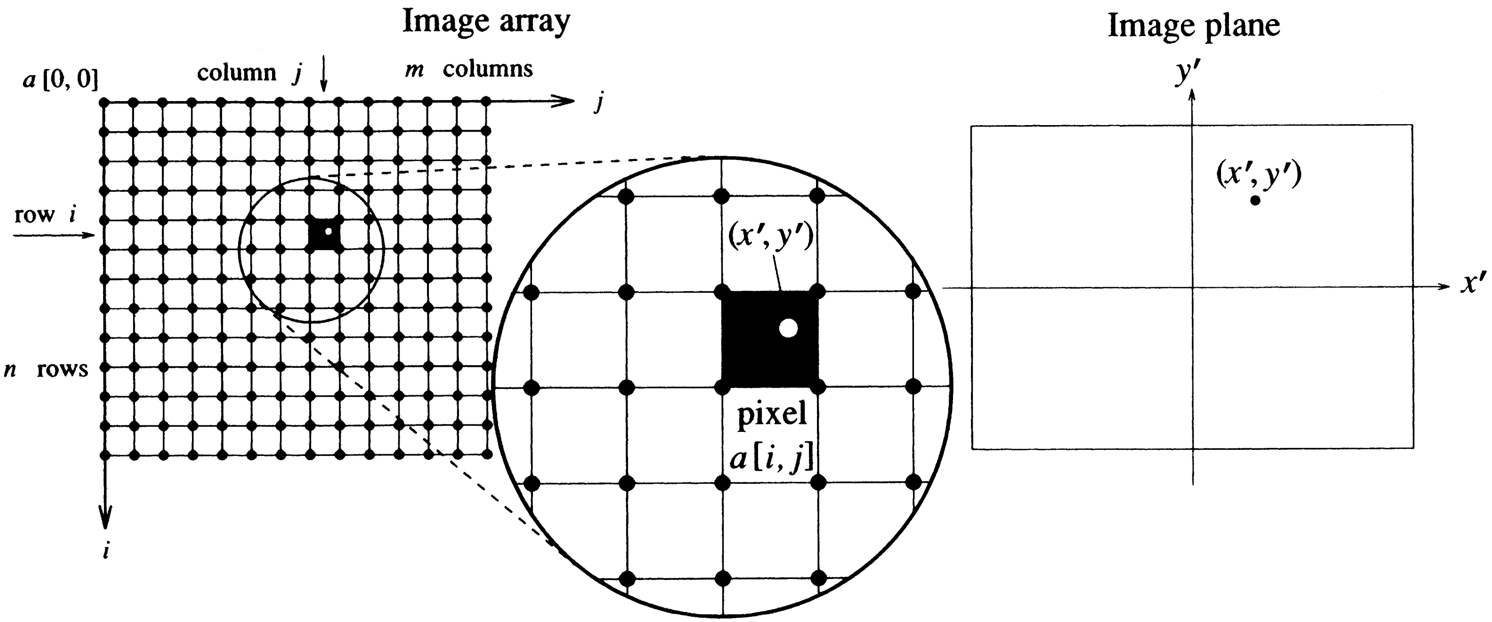
Outline

- Introduction
- **Digital Image Presentation**
- Machine Vision
- Visual Servoing
- Summary

Digital Image Representation

For Reading

Digital Image: A digital image is represented by a matrix of numeric values each representing a quantized intensity value.



- When **a** is a two-dimensional matrix, then **a(i,j)** is the intensity value at the position corresponding to row **i** and column **j** of the matrix.

- Pixels: the points at which an image is sampled are known as **picture elements** or **pixels**.

Digital Image Representation

For Reading

A **voxel** is a volume element, representing a value on a regular grid in three dimensional space.

This is analogous to a pixel, which represents 2D image data.

Some volumetric displays use voxels to describe their resolution. For example, a display might be able to show 512×512×512 voxels

3D Image

Digital Image Representation

For Reading

- **1-Bit/Binary/bi-level/two-level/B&W/Monochrome/ Monochromatic Images**

  A 1-bit image is the simplest type of image and consists of ON and OFF bits only. Each pixel is stored as a single bit (0 or 1).

A 1-bit monochrome Lena* image

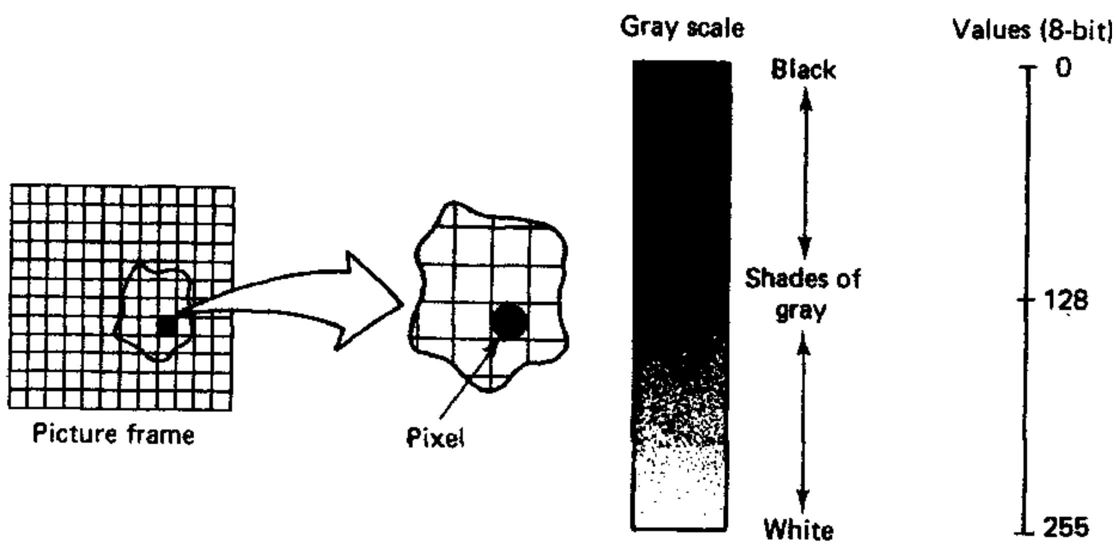
- A 640X480 monochrome image requires 38.4 KB of storage (640X480/8)

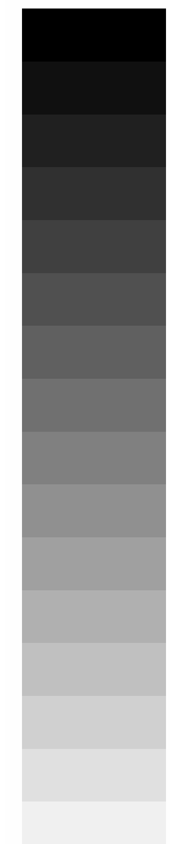
Digital Image Representation

For Reading

- **8-bit Gray-level Images**

Each pixel has a gray-value between 0 and 255. Each pixel is represented by a single byte; e.g., a dark pixel might have a value of 10, and a bright one might be 230.





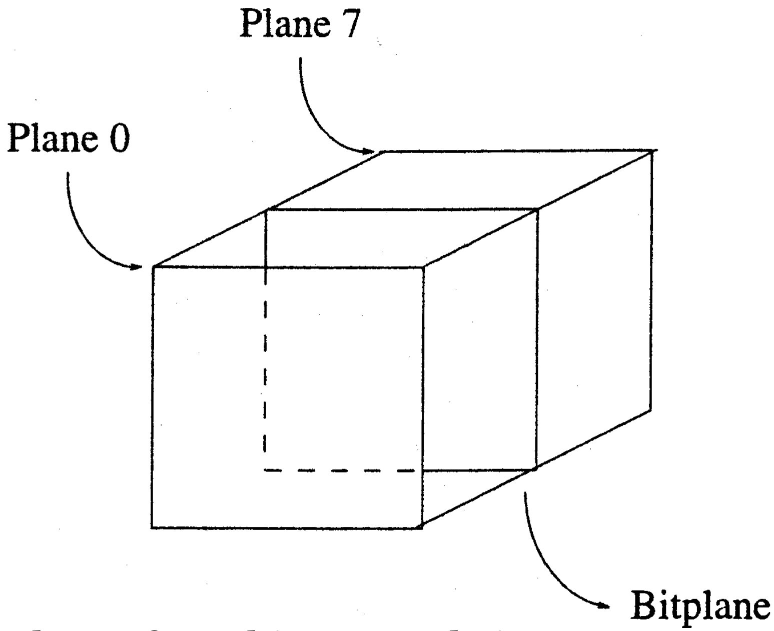
◇ The entire image can be thought of as two-dimensional array of pixel values. This array is called **bitmap**.

◇ Bitmap: The two-dimensional array of pixel values that represents the graphics/image data.

Digital Image Representation

For Reading

- **8-bit Gray-level Images**
  - ◇ 8-bit image can be thought of as a set of 1-bit bit-planes.
  - ◇ Each bit-plane consists of a 1-bit representation of the image at higher and higher levels of “elevation”: a bit is turned on if the image pixel has a nonzero value that is at or above that bit level.



Bit-planes for 8-bit grayscale image

Gray-scale Image

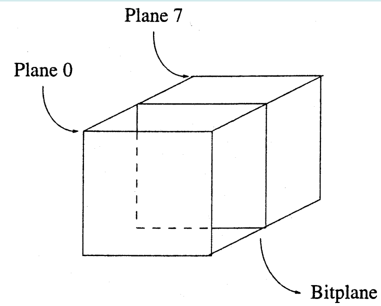
First Bit Plane

For 8-bit data representation there are 8 bit-planes. The first bit-plane contains the set of the most significant bits and the 8th contains the least significant bits.

Digital Image Representation

For Reading

- **8-bit Gray-level Images**



Bit-planes for 8-bit grayscale image

Original, 8-bit image

Bit-plane 7, the most significant bit

Bit-plane 6

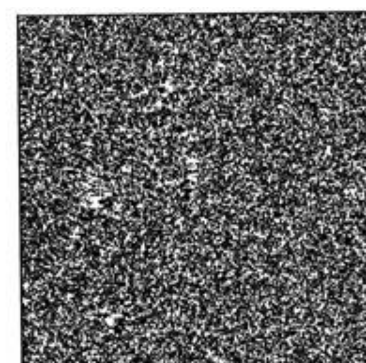
Bit-plane 5

Bit-plane 4

Bit-plane 3

Bit-plane 2

Bit-plane 1



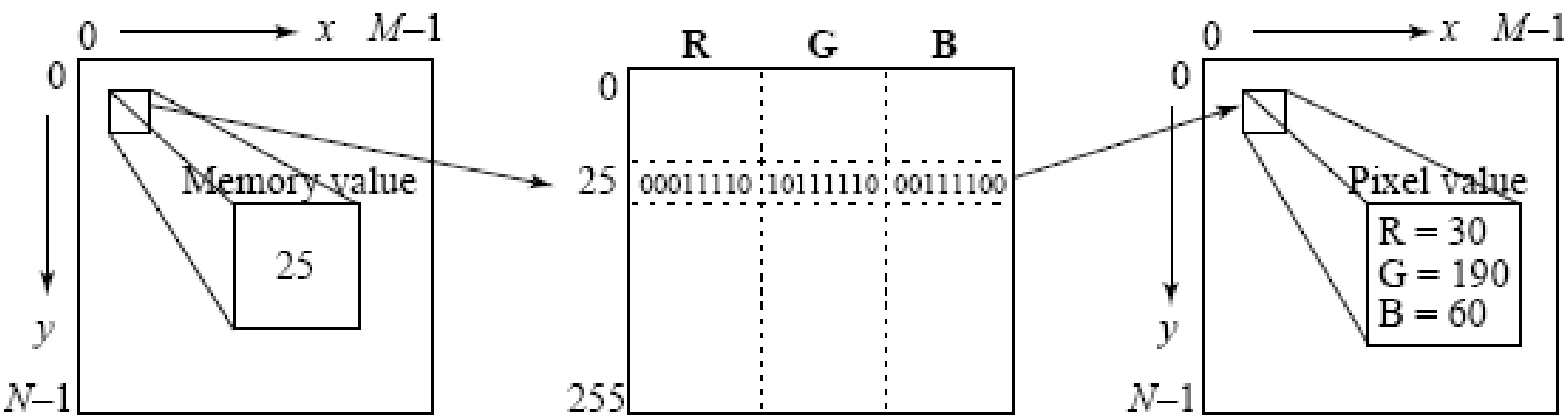
Bit-plane 0, the least significant

Digital Image Representation

For Reading

- **Color Look-up Tables (LUTs)**

The idea used in 8-bit color images is to store only the index, or code value, for each pixel. Then, e.g., if a pixel stores the value 25, the meaning is to go to row 25 in a color look-up table (LUT).



Color LUT for 8-bit color images

Outline

- Introduction
- Digital Image Presentation [For Reading]
- **Machine Vision**
- Visual Servoing
- Summary

Machine Vision

Machine Vision (MV) is the analysis of images to extract data for controlling a process or activity.

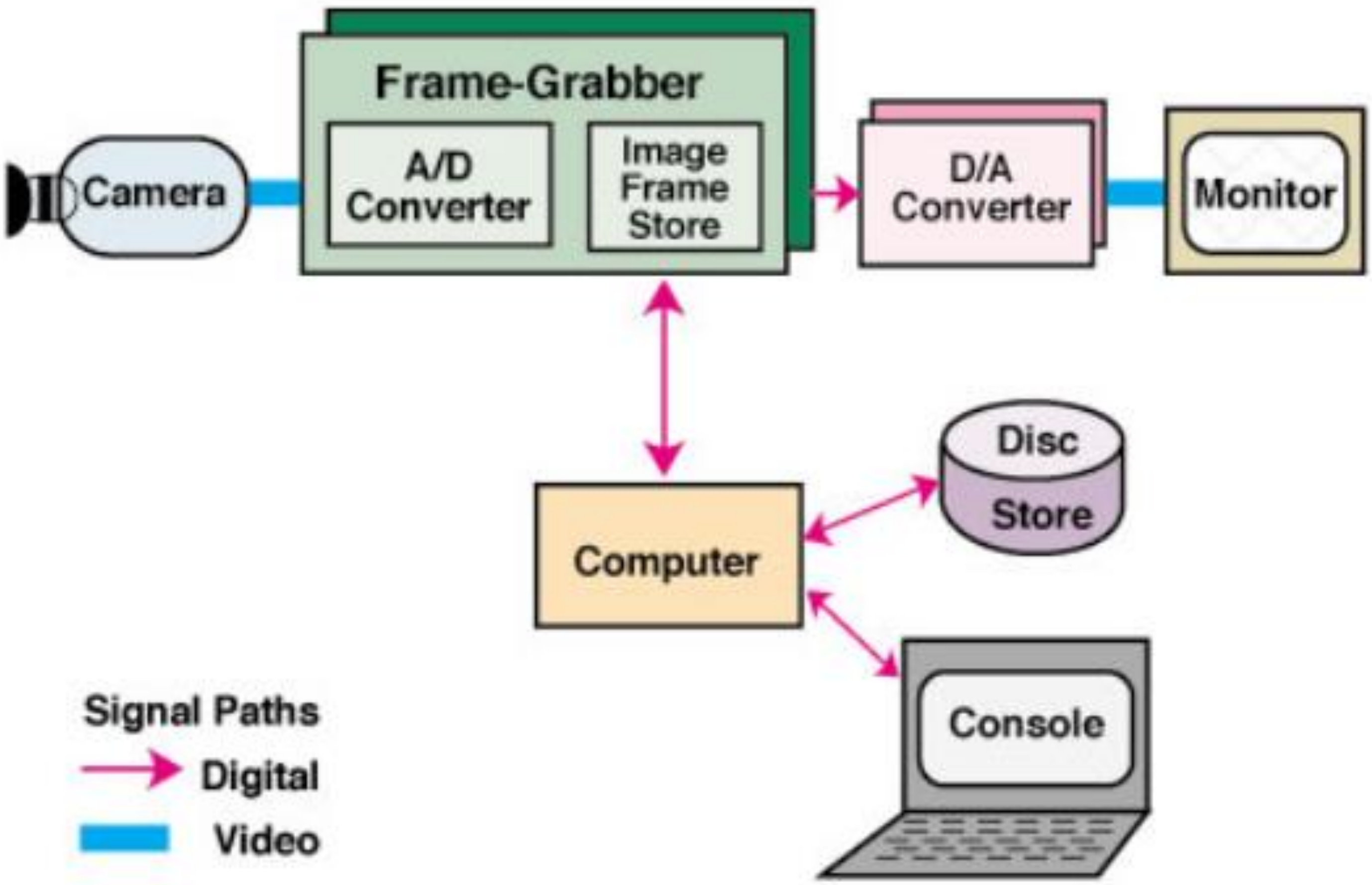
G. Christopher . *Image Acquisition and Processing with LabVIEW*. CRC Press, 2004.

Machine Vision Processes

- **Image Acquisition**
  - Camera
  - Lighting
  - Digitization
- **Image Analysis**
  - windowing
  - Thresholding
  - Histogramming
  - Shape Identification
  - Template Matching
  - Edge Detection

Machine Vision

- **Image Acquisition**

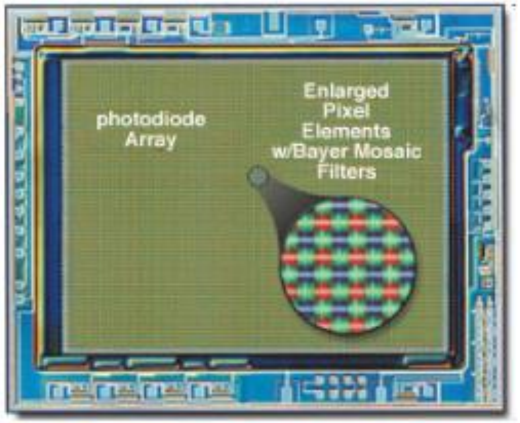


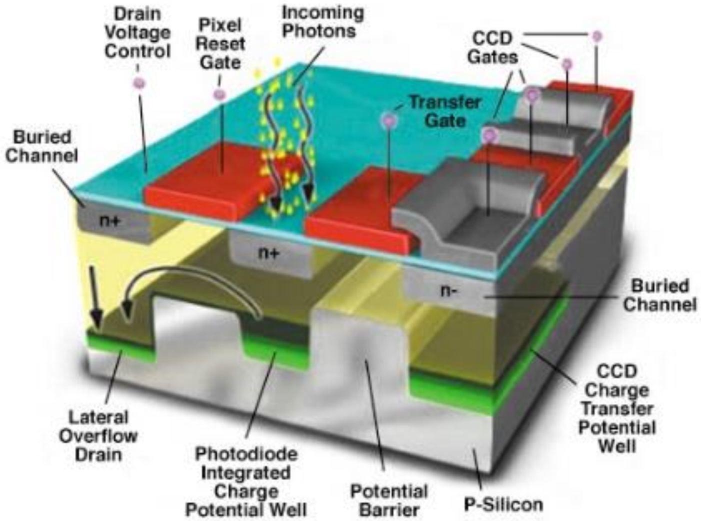
Machine Vision

- **Image Acquisition: CCD Cameras**

A **CCD (Charge Coupled Devices)** camera lens arrays an image on a glass faceplate that consist of a very fine grid of photosensitive material. Each tiny spot on the grid is electrically charges in proportion to the light that impinges upon it.

This tiny sports are the source of the most basic picture elements (pixels). The electric charge for each pixel is gathered by the system, usually a scanning electron gun (raster scan).





Machine Vision

- **Image Acquisition: CCD Cameras**

Manufacturer and model	Format (pixels)	Pixel Size (Microns)	Array Size (Millimeters)
Kodak KAF-2001CE	1732 x 1172	13 x 13	22.5 x 15.2
Kodak KAF-3000CE	2016 x 1512	9 x 9	18.1 x 13.6
Kodak KAF-3040CE	2144 x 1432	6.8 x 6.8	14.6 x 9.7
Kodak KAF-6302CE	3052 x 2016	9 x 9	27.5 x 18.1
Kodak KAI-4000	2048 x 2048	7.4 x 7.4	15.16 x 15.16
Sony ICX205AK	1392 x 1040	4.65 x 4.65	7.6 x 6.2
SITe ST-002[a]	2048 x 4096	15 x 15	30.72 x 30.72
Marconi CCD 42-90	4608 x 2048	13.5 x 13.5	27.6 x 62.2
Marconi CCD 48-20	1028 x 1033	13 x 13	13.3 x 13.3
Philips FTF3020-C	3072 x 2048	12 x 12	36.8 x 24.6
Philips FT18	1024 x 1024	7.5 x 7.5	7.68 x 7.68

Machine Vision

- **Image Acquisition: Lighting**

Lighting of the subject should be considered an important element of image acquisition system.

Experience with machine vision systems leads the designer to choose **dedicated lighting system** rather than relying upon ambient light.

Dedicated light may consist of a **point source** that enhances sharp features or takes advantage of sharp shadows.

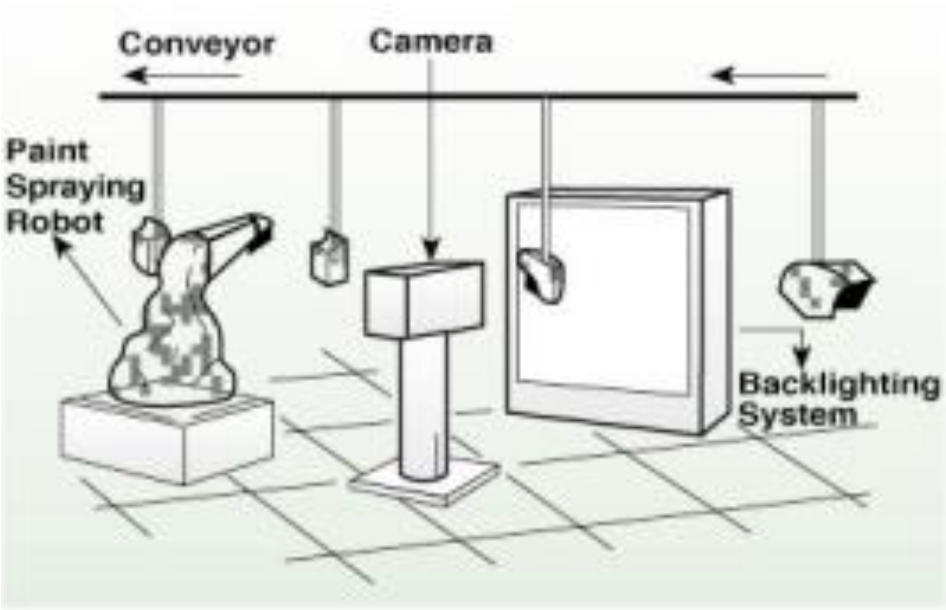
For other applications the object may be surrounded with **multiple source light** to eliminate the **presence of shadows** that may give rise to dark pixels that can be falsely interpreted.

Machine Vision

- **Image Acquisition: Lighting**

Sometimes a **silhouette** is desired so that edges can be detected; in this case **backlighting** may be desirable.

But if the object has an important feature to be detected on its face, such as a hole or a groove, backlighting will be counterproductive.



Machine Vision

- **Image Acquisition: Lighting**

  Another lighting problem is **glare**. Black, **shiny surfaces** can be sensed as white owing the **reflection of the light source**.

  The human eye more easily distinguishes between glare and white background than does a machine vision sensor.

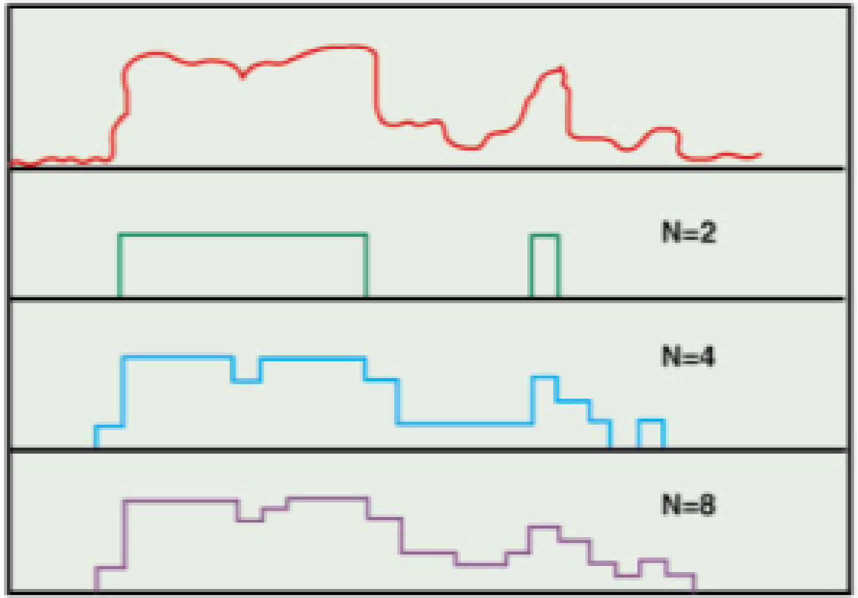
  Although glare from a black surface can be brilliantly white, the human eye (and brain) can recognize the context of the scene and ignore glare much as the human ear (and brain) can interpret speech from context. Because humans take this capability for granted, they sometimes fail to adequately deal with the problem of glare when designing a machine vision system.

Machine Vision

- **Image Acquisition: Digitization**

The sensor that gathers the image for a machine vision system is typically an analog device.

However, the computer version of the image must be digital. A central problem of automated manufacturing is the gathering of analog signals and converting them to digital approximations for storage and analysis by computer.



Three digital approximations to the same continuous analog signal representing light intensity in the scan of an image. The value N is the number of binary digits used to represent the digital values.

Machine Vision

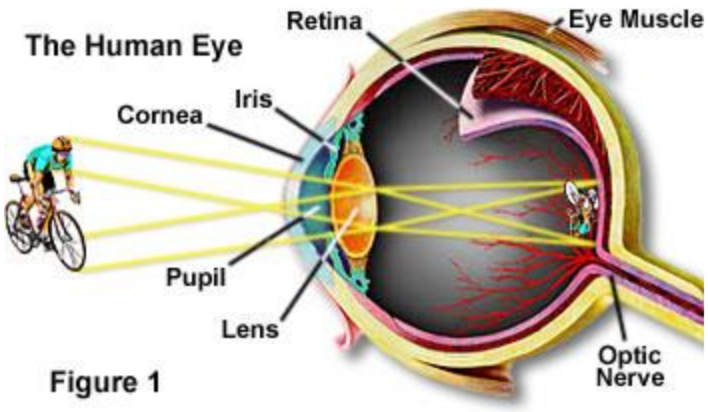
- **Image Analysis: Windowing**

  Windowing is a means of **concentrating** vision system analysis **on a small field of view**, thereby conserving computer resources of run time and storage.

Machine Vision

- **Image Analysis: Windowing**

Our **human vision** systems are constantly performing a **windowing process**. Although largely taking for granted, the human system has an amazing facility for looking directly at a small field while maintaining a much larger field within the range of peripheral vision.



The human brain quietly monitors the peripheral field and ignores it unless unexpected motion or something out of place interrupts the attention span and brings the disturbing influence to the full attention of the observer.

Machine Vision

- **Image Analysis: Windowing**

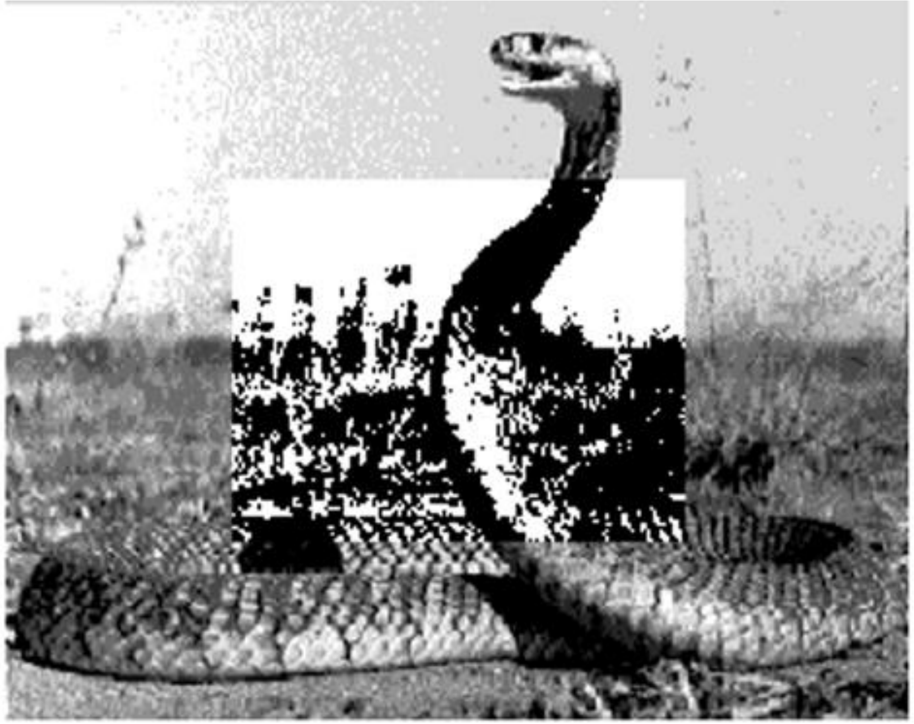
The most practical applications of windowing employ **fixed windows**, that is, the window is always set up in the same place within the image.

More sophisticated machine vision systems are able to employ **adaptive windowing**, in which the system is able to select the appropriate window out of context. In such systems a search of the entire image detects known landmarks that identify the position and orientation of the subject workpiece. The landmarks can then be used by the system to find the window area of interest and proceed as in a fixed window scheme.

Machine Vision

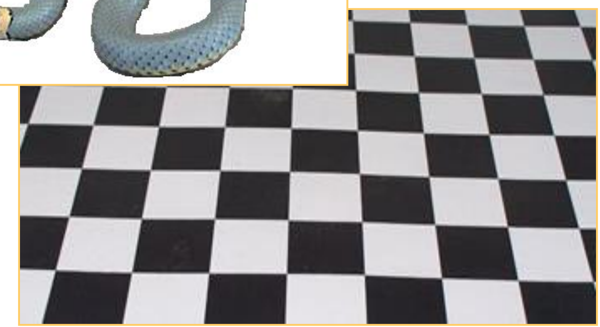
- **Image Analysis: Thresholding**

Thresholding is **reducing** an image **to binary black or white pixels**. Any binary imaging system is usually designated as thresholding, though the system is not necessarily limited to a single threshold.



Machine Vision

- **Image Analysis: Thresholding**



Consider the problem of capturing the image of a **gray snake** on a **black-and-white checked tile floor**. Black and white pixels could both be assigned a value 1 (white) and only pixels in the gray region between two thresholds could be transformed to a value 0 (black).

This would convert the image to a **black snake on a white floor**. Perhaps robots do not need to worry about snakes on the floor, but in an industrial setting two well-chosen thresholds could be used to select a band of gray level and thus pick up only a specifically desired object, perhaps of a different color from the undesired objects or the background.

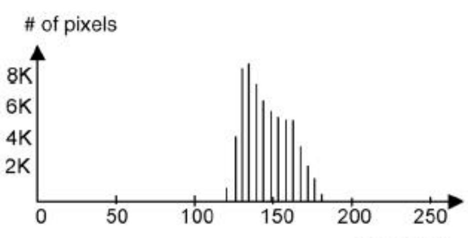
Machine Vision

- **Image Analysis: Histogramming**

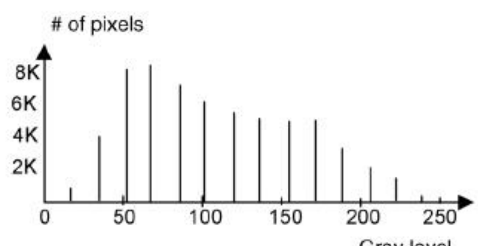
A histogram is a representation of the total number of pixels of an image at each gray level.

(a)

(b)



(c)



(d)

The Actual Grayness Values and # of Pixels for Images in Figure (a) and (b).

Levels	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
# of Pixels	0	750	5223	8147	8584	7769	6419	5839	5392	5179	5185	3451	2078	1692	341	0
For (b)	0	17	34	51	68	85	102	119	136	153	170	187	204	221	238	256
For (a)	120	124	128	132	136	140	144	148	152	156	160	164	168	172	176	180

Machine Vision

- **Image Analysis: Histogramming**

  Histogram information is used:

  ◇ In **thresholding**: for example, histogram information can help in determining a **cutoff point** for converting the image into binary form.

  ◇ To decide if there are any prevalent gray levels in an image. For instance, suppose a **systematic source of noise** in an image causes many pixels to have one **“noisy” gray level**. Histogramming can be used to determine the **noisy gray level** in order to attempt to **remove or neutralize the noise**.

Machine Vision

- **Image Analysis: Histogramming**

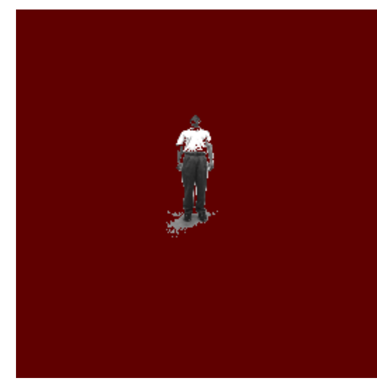
  Histogram information is used:

  ◊ To **separate** an **object** from the **background** so long as they have distinctly different colors or gray values.

  A background image may be used to establish a baseline of irrelevant imagery. Anything that differs from the background is considered relevant.

minus

equals



Machine Vision

- **Image Analysis: Shape Identification**

The selection of shape is stretching the limits of capability for histogramming and thresholding techniques. There are other clever ways to identify a desired shape or to perceive its orientation, and a variety of algorithms have these purposes.

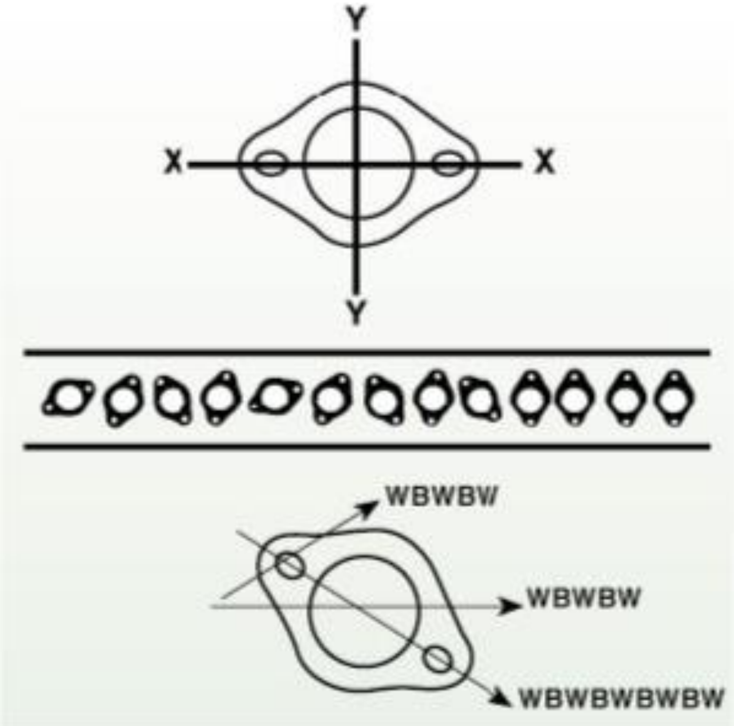
One method of **finding the orientation** of a known shape is to scan a series of straight lines across a binary image looking for characteristic “**run-lengths**” of black or white pixels.

Machine Vision

- **Image Analysis: Shape Identification**

Suppose, for instance, that it is desired to properly **orient gaskets** as shown here.

The task is to align the mirror axis of symmetry (**y-y in the top diagram**) with the direction of travel of the conveyor.



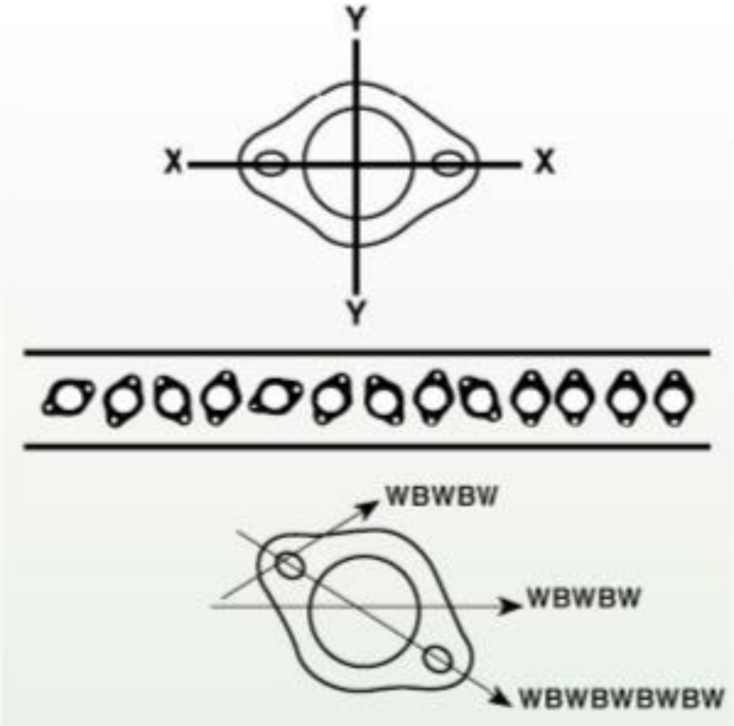
A simple approach takes advantage of the computational speed of the system computer to quickly strike a variety of scan lines across the image at various, perhaps random, angles.

Machine Vision

- **Image Analysis: Shape Identification**

The system is attempting to find the major axis (x-x) by the following series of runs:

white-black-white-black-white-black-white-black-white



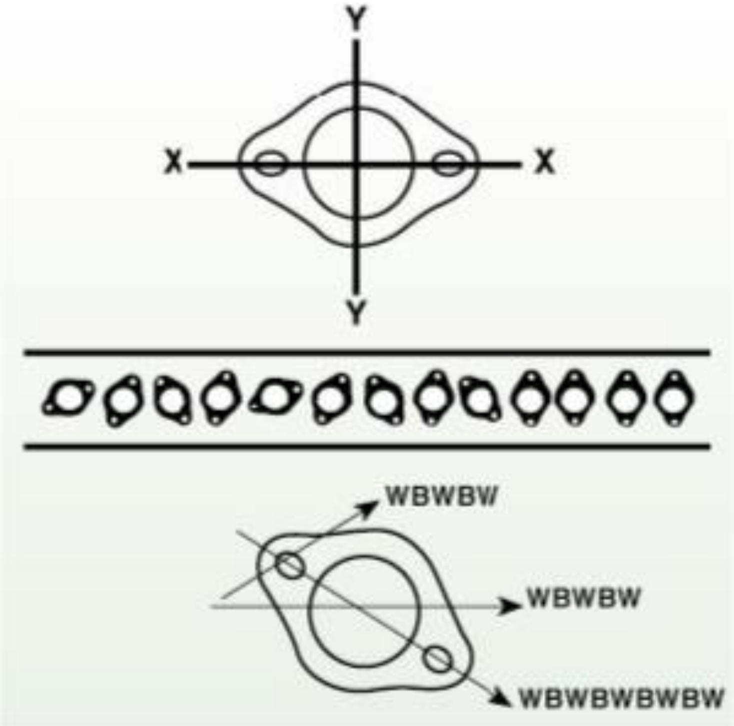
The two white runs at the series extremes represent the background. Besides these beginning and ending white runs, there are three white runs in the series – one for each of the two small holes and one longer run for the larger center hole.

Machine Vision

- **Image Analysis: Shape Identification**

Perhaps even simpler than looking for the series having the correct number of **black-white run transitions** would be a search for the longest straight line pixel run of the following patter:

black-white-black-white-black-white-black

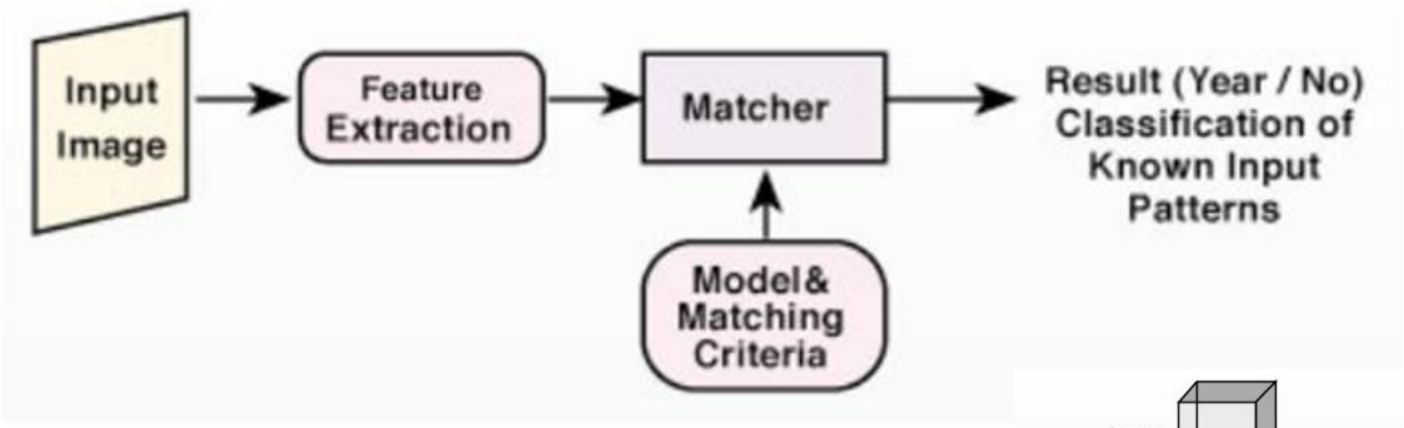


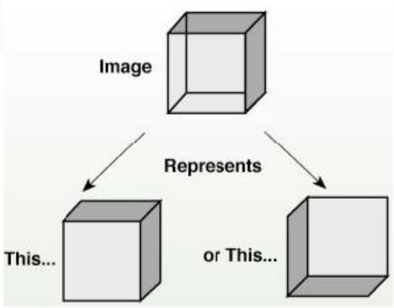
Here the interior transitions are ignored and the objective of the search is to find the first and the last black pixels and maximize their separation. Once this maximum is found , the major axis of the gasket will have been identified.

Machine Vision

- **Image Analysis: Template Matching**

Images features are extracted and simply compared against a **prototype model** to see if the required features are there in sufficient evidence. Such a system is acceptable for pre-determined inputs and pre-determined classes of output.

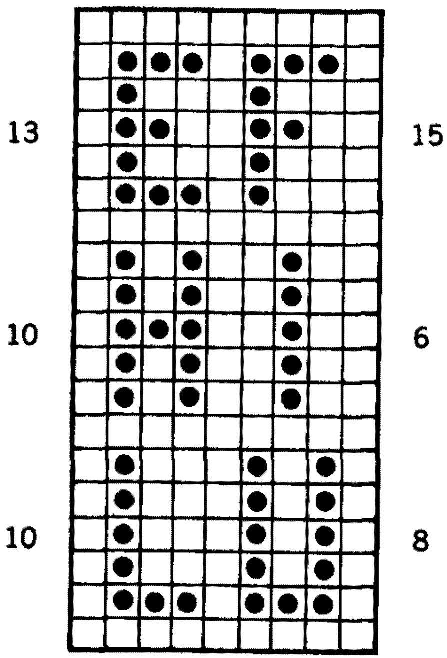




Machine Vision

- **Image Analysis: Template Matching**

Example: Consider the 171-pixel matrix that contains six familiar pattern –six letters of the alphabet.

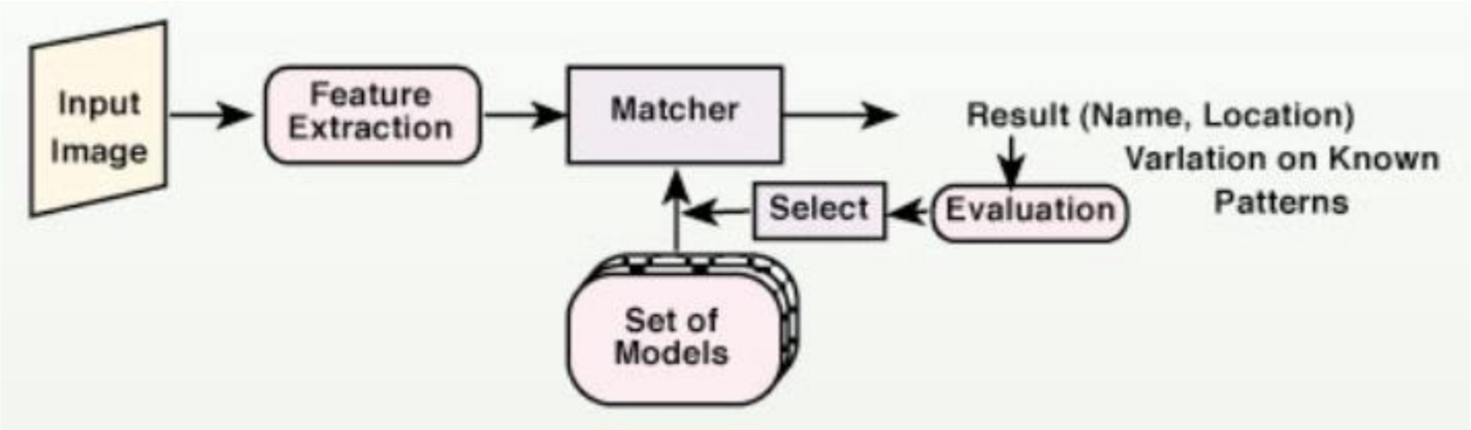


The task is to locate the letter F using 3x5 pixel template of comparison. In nested iterations throughout the matrix 3x5 set of pixels can be examined for degree of match with the template.

As suspected, the letter E is a close match, attaining a score of 13 out of a possible 15. the letter F, of course, rates a perfect 15.

Machine Vision

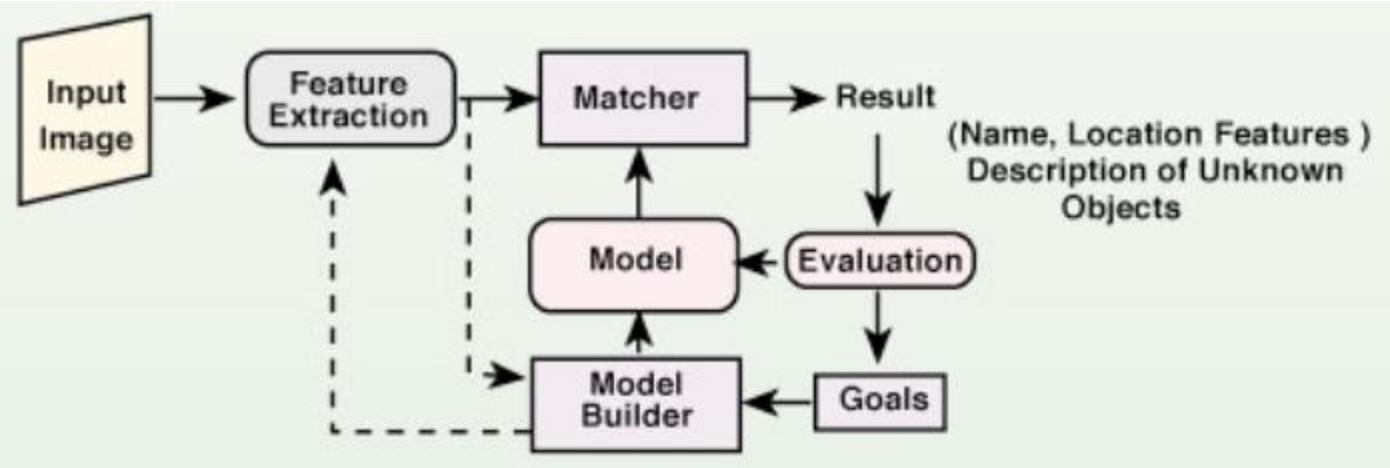
- **Image Analysis: Template Matching**



This level shows **the matcher** can have access to a set of models and an evaluation, based on the results of matching, can then **select different models** if it didn't find a good match. In other words, if it doesn't appear to have a very good apple, it can try to match it against pear and see if this produces a better result. Such a system is useful for variations on known classes of things.

Machine Vision

• **Image Analysis: Template Matching**



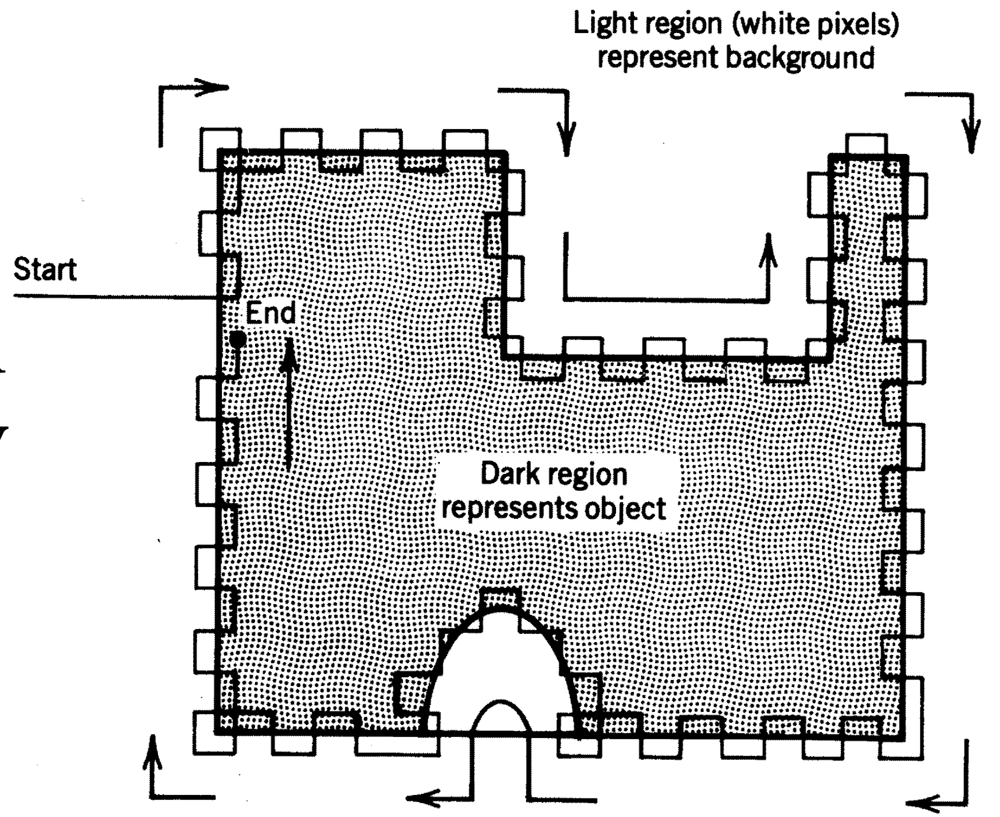
This level shows a more complex system, with more feedback paths, in which a goal is specified to a **model builder** that allows classes of **models to be generated**. This type of system is useful for building descriptions of **unknown items** until sufficient evidence can be amassed to produce an output result.

Machine Vision

- **Image Analysis: Edge Detection**

Edge detection is a procedure that uses **binary logic** to guide a search through an image**, one pixel at a time**, as it **first finds an edge** and **then follows it completely around the object until it repeats itself**.

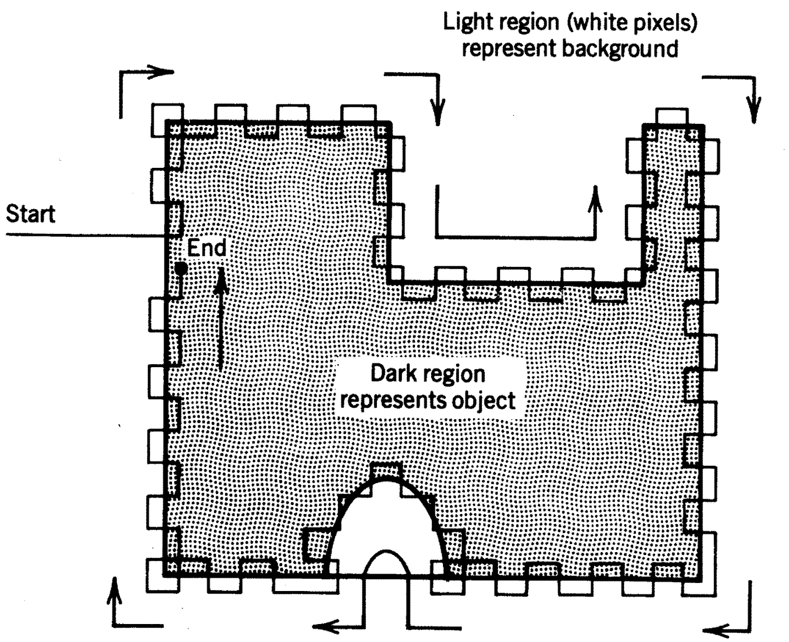
At the point of repeat the conclusion is reached that the entire object has been circumscribed.

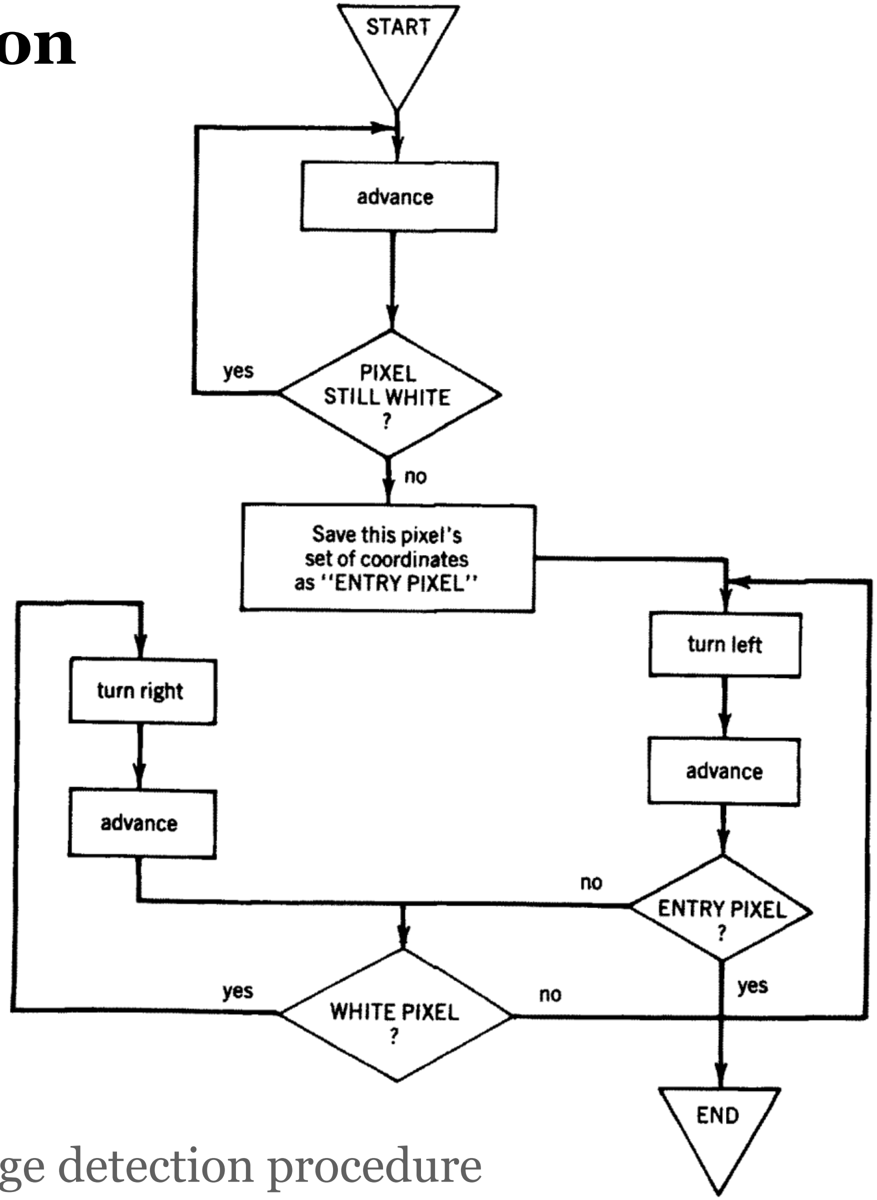


An edge detection algorithm finds and the, by continually cross it, follows the edge completely around the object.

Machine Vision

- **Image Analysis: Edge Detection**





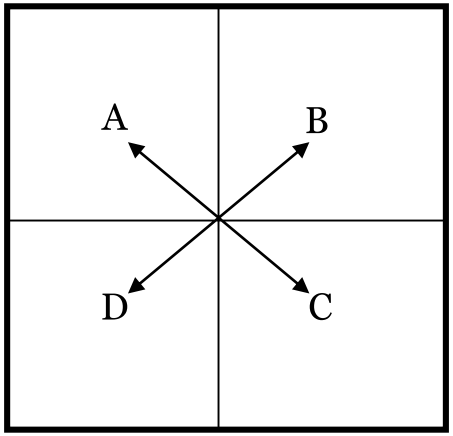
Logic flow diagram for edge detection procedure

Machine Vision

- **Image Analysis: Edge Detection**

Roberts Cross-Operator: An algorithmic method of edge detection makes use of this operator. The algorithm computes the square root of the sum of the squares of the adjacent diagonal differences between pixels gray-scale values.

The idea is to identify a transition (edge) by finding points at which the diagonal differences are greatest.



$$R_A = \sqrt{(A-C)^2 + (B-D)^2}$$

Machine Vision

- **Image Analysis: Edge Detection**

Example-1: Calculate the Roberts Cross-Operator for the following pixel matrix.

$$\begin{pmatrix} 3 & 1 & 2 \\ 2 & 3 & 3 \\ 0 & 2 & 3 \end{pmatrix}$$

Solution

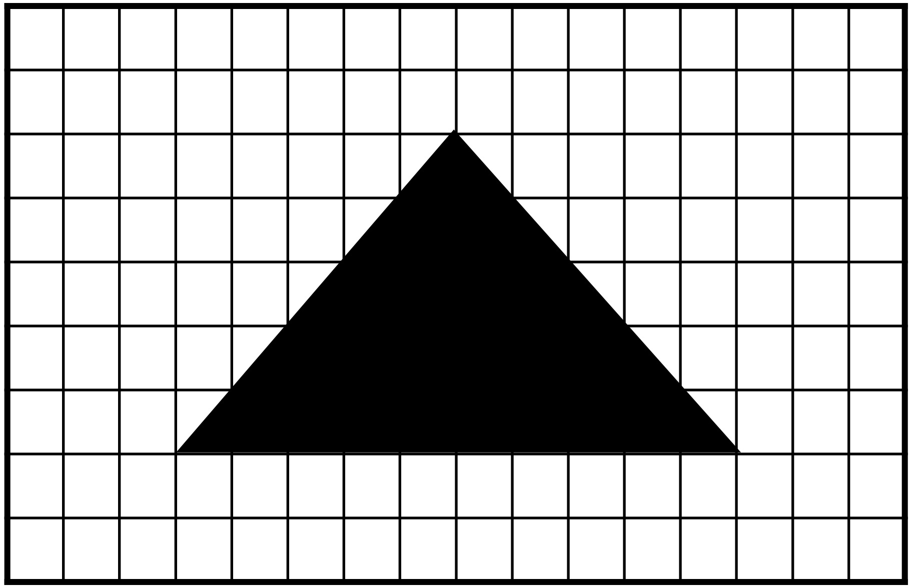
$$R_A = \sqrt{(A-C)^2 + (B-D)^2}$$

$$\begin{pmatrix} 1 & \sqrt{5} & - \\ 3 & 1 & - \\ - & - & - \end{pmatrix}$$

Machine Vision

- **Image Analysis: Edge Detection**

Example-2: On a 16x9 pixel ideal white field let us place a carefully selected ideal black image –an isosceles triangle with based exactly equal to 10 pixels and height exactly 5 pixels.



Machine Vision

- **Image Analysis: Edge Detection**

Let us use a gray-scale range of 2^6 so that ideally all white pixels will be gray scale 63 and all black pixels gray scale 0. Since these pixels are exactly half-in and half-out in our idealized model, we will assign each of them a gray scale of exactly 31.

						63	63	63	63						
					63	63	31	31	63	63					
				63	63	31	0	0	31	63	63				
			63	63	31	0	0	0	0	31	63	63			
			63	31	0	0	0	0	0	0	31	63			
			63	31	0	0	0	0	0	0	31	63			
			63	63	63	63	63	63	63	63	63	63			

Machine Vision

- **Image Analysis: Edge Detection**

After calculating the Roberts cross-operator for each feasible pixel in the matrix.

						0	0	0	0						
					0	32	45	32	0	0					
				0	32	63	44	63	32	0	0				
			0	32	63	31	0	31	63	32	0	0			
		0	32	63	31	0	0	0	31	63	32	0	0		
	0	32	63	31	0	0	0	0	0	31	63	32	0	0	
	0	32	71	89	89	89	89	89	89	89	71	32	0	0	
	0	0	0	0	0	0	0	0	0	0	0	0	0	0	

Machine Vision

- **Image Analysis: Edge Detection**

Using carefully selected thresholds, outline of the triangle can be detected.

						0	0	0	0						
					0	32	45	32	0	0					
				0	32	63	44	63	32	0	0				
			0	32	63	31	0	31	63	32	0	0			
		0	32	63	31	0	0	0	31	63	32	0	0		
	0	32	63	31	0	0	0	0	0	31	63	32	0	0	
	0	32	71	89	89	89	89	89	89	89	71	32	0	0	
	0	0	0	0	0	0	0	0	0	0	0	0	0	0	

If pixel intensity≥44, pixel→dark, otherwise pixel →light

Machine Vision

- **Image Analysis: Edge Detection**

Various threshold selection

						0	0	0	0						
					0	32	45	32	0	0					
				0	32	63	44	63	32	0	0				
			0	32	63	31	0	31	63	32	0	0			
		0	32	63	31	0	0	0	31	63	32	0	0		
	0	32	63	31	0	0	0	0	0	31	63	32	0	0	
	0	32	71	89	89	89	89	89	89	89	71	32	0	0	
	0	0	0	0	0	0	0	0	0	0	0	0	0	0	

If pixel intensity$\geq$0, pixel$\rightarrow$dark, otherwise pixel $\rightarrow$light

Machine Vision

- **Image Analysis: Edge Detection**

Threshold selection can be critical to the success of a Roberts cross-operator analysis.

						0	0	0	0						
					0	32	45	32	0	0					
				0	32	63	44	63	32	0	0				
			0	32	63	31	0	31	63	32	0	0			
		0	32	63	31	0	0	0	31	63	32	0	0		
	0	32	63	31	0	0	0	0	0	31	63	32	0	0	
	0	32	71	89	89	89	89	89	89	89	71	32	0	0	
	0	0	0	0	0	0	0	0	0	0	0	0	0	0	

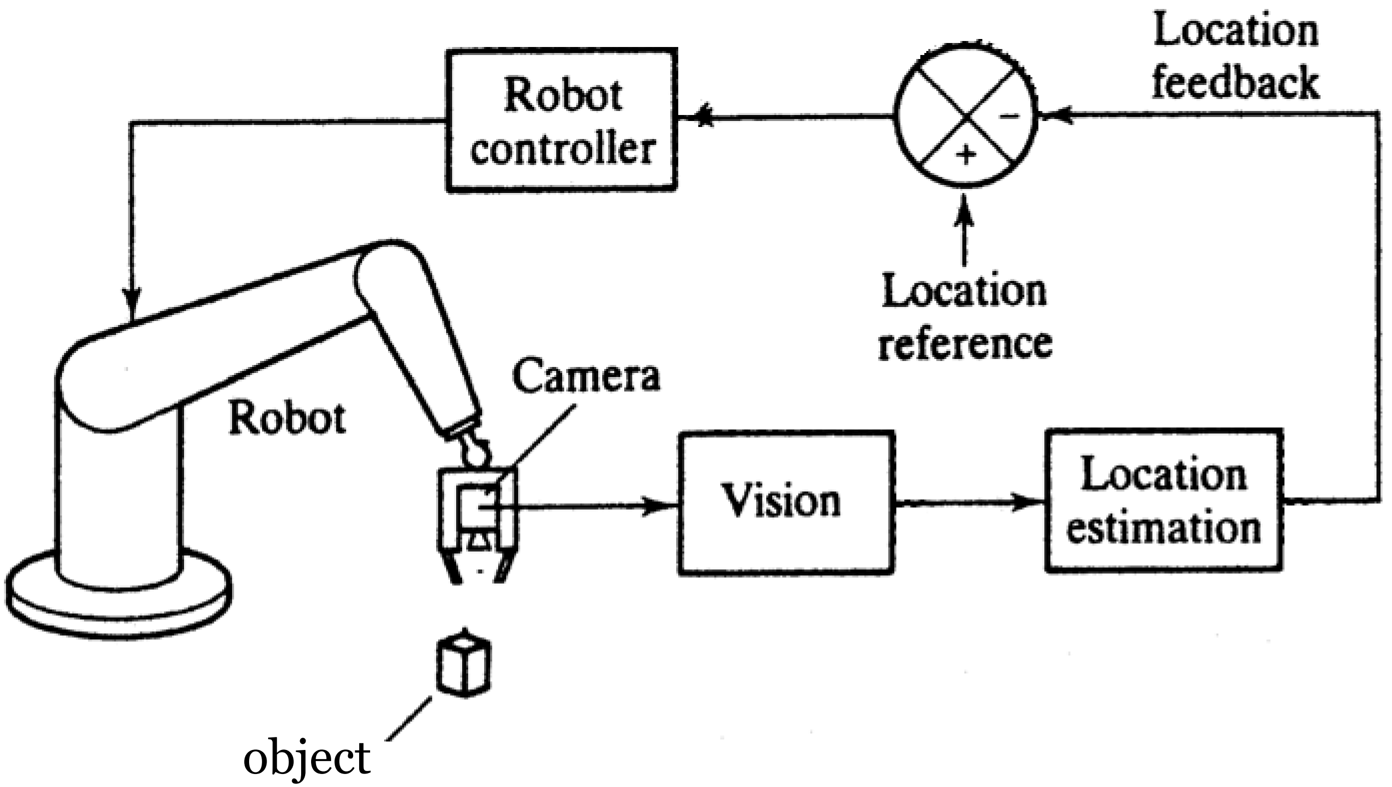
If pixel intensity≥64, pixel→dark, otherwise pixel →light

Outline

- Introduction
- Digital Image Presentation
- Machine Vision
- **Visual Servoing**
- Summary

Visual Servoing

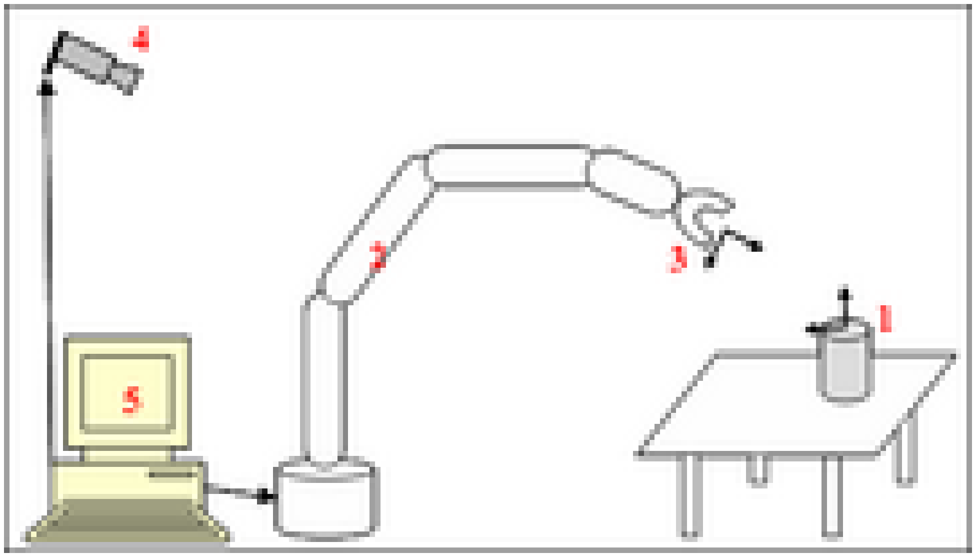
Visual servoing (VS), also known as Vision-Based Robot Control, is a technique which uses **feedback** information extracted from a **vision sensor** to control the motion of a robot.



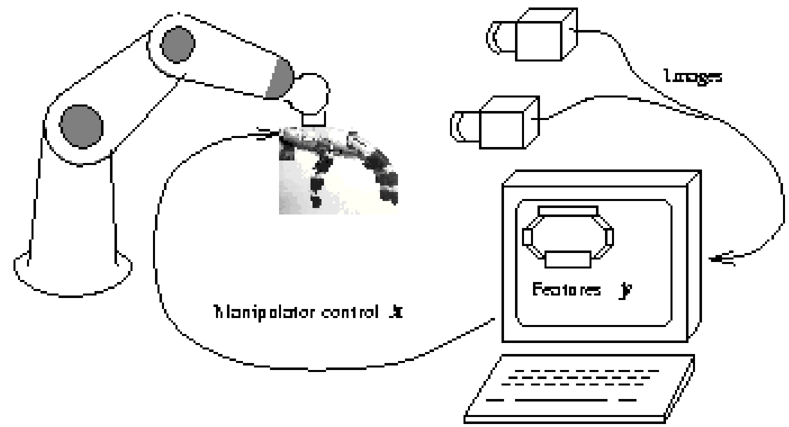
Vision-based Object Grasping

The vision data may be acquired from a camera that is mounted directly on a robot manipulator or on a mobile robot, in which case motion of the robot induces camera motion

Visual Servoing



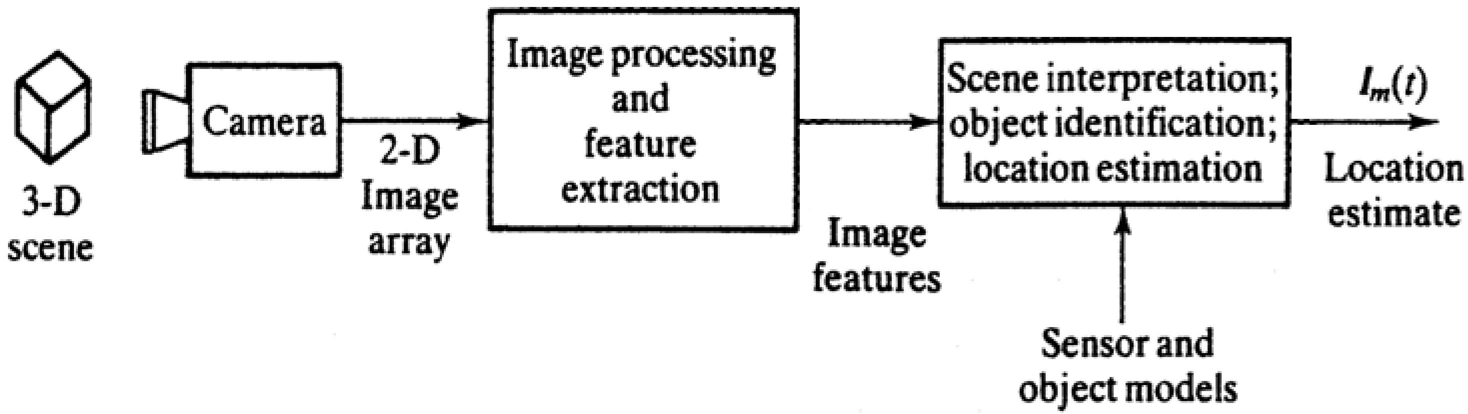
The camera can be fixed in the workspace so that it can observe the robot motion from a stationary configuration.



Other configurations can be considered such as, for instance, several cameras mounted on pan-tilt heads observing the robot motion.

Visual Servoing

The camera capture a 2D image, from which the vision processing software must extract image features.

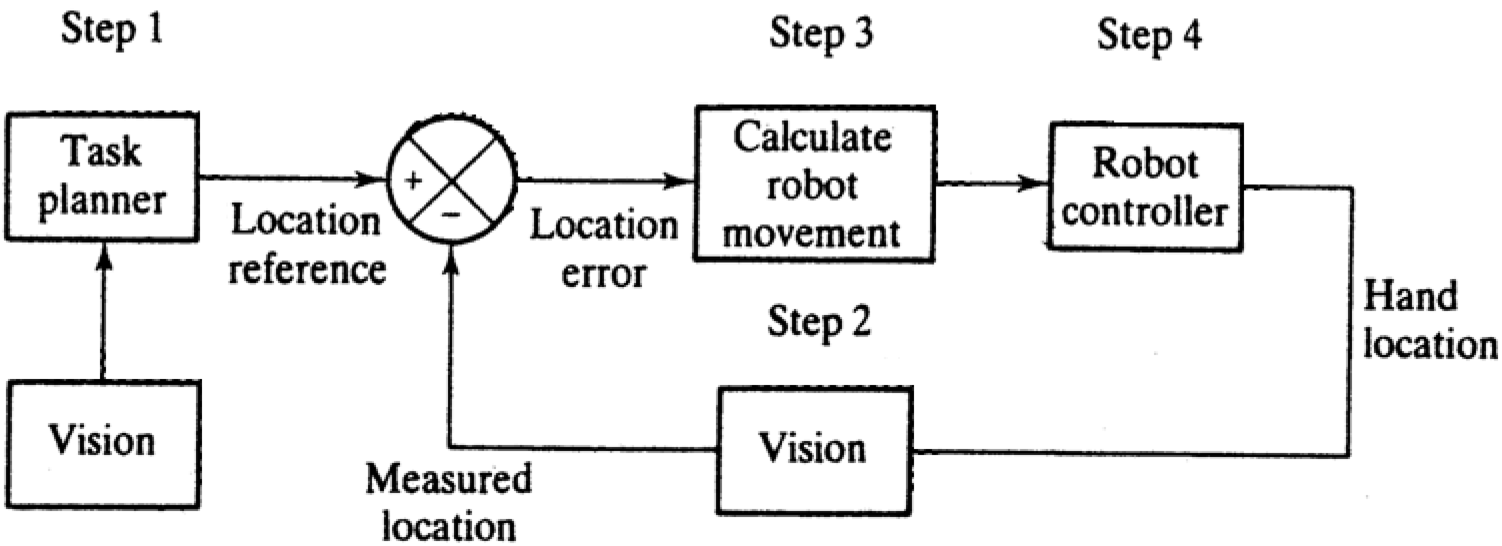


These features are **compared to models** of the objects to identify the object of interest, and the location of grasp points.

The **location (position and orientation)** of the object relative to hand, and/or relative to world coordinates is then estimated to produce an object location signal.

Visual Servoing

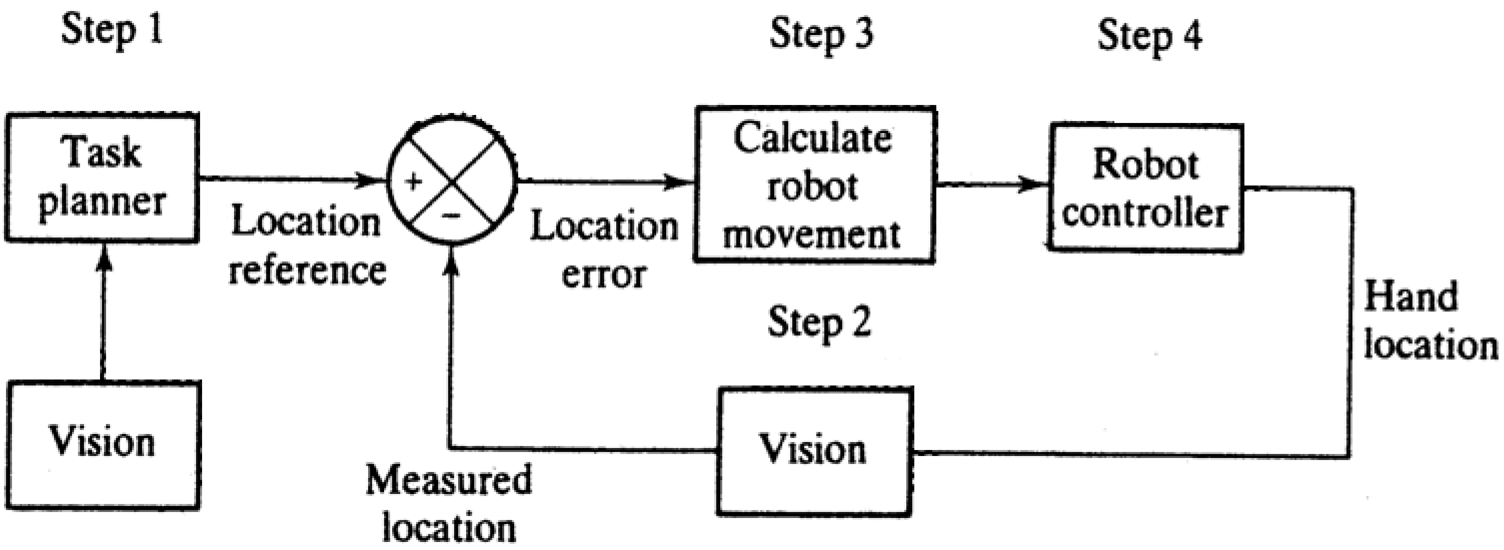
The most common used control system is the **static look and move** system.



Step-1: the task planner generated a position reference using visual information.

Step-2: the vision system estimates the location of the hand relative to world coordinates.

Visual Servoing



Step-3: the task computer calculates the Cartesian motions required to move the hand to the desired location.

Step-4: the robot controller moves the hand.

These steps are repeated until the robot hand is in the correct position to grasp the object.

Visual Servoing

For Reading

- **Visual Servoing Approaches**

  ◊ Position-based Visual Control Approach

  ◊Image-based Visual Control Approach

Visual Servoing

For Reading

- **Visual Servoing Tutorial**
  - ◊ FRANÇOIS CHAUMETTE AND SETH HUTCHINSON, "**Visual Servo Control Part I: Basic Approaches**," IEEE Robotics & Automation Magazine, DECEMBER 2006.
  - ◊ FRANÇOIS CHAUMETTE AND SETH HUTCHINSON, "**Visual Servo Control Part II: Advanced Approaches**," IEEE Robotics & Automation Magazine, MARCH 2007.

Outline

- Introduction
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- **Summary**

Summary

- Vision systems are commonly used for operations that require information from the work environment and include inspection, navigation, part identification, assembly operations, surveillance, control, and communication.
- Machine vision functions can be divided into two categories: image acquisition and image interpretation.
- The acquisition phase has two principal parameters: resolution and contrast.
- The interpretation and analysis phase is where specific objectives are being pursued with a variety of specialized techniques.
- Visual servo control refers to the use of computer vision data to control the motion of a robot.

End of the course

Best wishes!